Pass-through Mutual Funds, Flow of Funds, and Low-Risk Anomaly*

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Abstract

We explain the low-risk anomaly in stock returns, attributing it to demand pressure from mutual funds that pass through the flows from their investors. Our analysis shows that when investors chase returns, mutual funds with high-beta assets receive significantly larger flows following market fluctuations than those with low-beta assets, leading to greater demand pressure on high-beta assets. Due to the substantially inelastic demand for high-beta assets relative to low-beta assets, this pressure leads to more pronounced price impacts on high-beta stocks. Notably, we show that the beta anomaly is present only following uptrend markets, with the CAPM holding otherwise. Investors persistently allocate capital to high-beta funds during uptrends but adopt a more conservative approach in downtrends. This accumulated demand pressure leads to overpricing of high-beta stocks and lower expected returns. By controlling for market trends and related demand pressure, we effectively eliminate the negative risk-adjusted returns of high-beta stock portfolios.

Keywords: Low-risk anomaly, Inelastic Market Hypothesis, Mutual fund flows, Demand pressure, Price impact

JEL Codes:

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1 Introduction

Friend and Blume (1970) and Black et al. (1972) document that the security market line (SML) for U.S. equities is flatter than predicted by the Capital Asset Pricing Model (CAPM). This empirical irregularity, known as the "beta anomaly," has persisted to the present day. We demonstrate that a substantial portion of the beta anomaly stems from mutual funds' demand pressure. Following market fluctuations, retail investors' return-chasing behavior triggers larger capital flows into funds holding high-beta assets than those with low-beta assets.[1] These flows, when passed through by funds, exert significant demand pressure on high-beta assets, influencing their equilibrium prices.[2] Due to the substantially inelastic demand for high-beta assets relative to low-beta assets, this demand pressure causes greater price impacts on high-beta stocks. Consequently, market fluctuations themselves contribute to the beta anomaly through flow-driven demand pressures' differential price impacts on assets with varying systematic risk profiles. This mechanism contributes to the flattening of the security market line.

We explain the beta anomaly through two key mechanisms: market fluctuations and pass-through mutual funds. Market fluctuations act as a coordinating device, aggregating capital flows from return-chasing retail investors and channeling them into mutual funds that optimally tilt toward high-beta assets. These mutual funds, in turn, pass through a substantial portion of these flows by reinvesting in existing holdings, creating significant demand pressure on high-beta assets. Given the relatively inelastic demand for high-beta assets, this flow-driven demand pressure results in substantial price impacts, reducing their expected returns.

[1]Black (1972) and Frazzini and Pedersen (2014) theoretically demonstrate that leverage-constrained investors optimally tilt their investments toward riskier assets rather than holding the market portfolio. Employing the demand system asset pricing approach (Koijen and Yogo, 2019), we confirm that mutual funds' optimal portfolio holdings, on average, favor high-beta assets, even when controlling for other asset characteristics. We estimate each fund's logit demand coefficient on asset beta quarterly, using institutional holdings data from SEC form 13F. Figure 1 illustrates that the cross-sectional mean coefficients of market beta are consistently positive, both statistically and economically significant over time. This finding implies that the average mutual fund manager's strategy optimally tilts toward high-beta assets.

[2]The literature documents that funds are approximately "pass-through vehicles" that trade in roughly one-to-one fashion in response to investor flows (e.g., Lou (2012), Li (2022) and references therein). Precisely, fund managers tend to expand or liquidate their existing holdings proportionally in response to new capital inflows or outflows. We empirically verify this claim by running fund-level panel regressions in Section 3. (See also Table 1).

Using mutual fund flow data, we demonstrate distinct investor behaviors across market trends. In uptrend markets, return-chasing investors consistently allocate capital to mutual funds with high-beta assets, accumulating significant demand pressures on these securities. This demand pressure leads to more pronounced price impacts on high-beta stocks due to their less elastic demand than low-beta assets. The equilibrium prices of high-beta assets rise, reducing their expected future returns and yielding a flatter estimated security market line than the CAPM predicts. Conversely, in downtrend markets, investors react more conservatively and cautiously to market fluctuations. Flows to funds become both economically and statistically insignificant across all beta quintiles, making the demand pressures exerted by funds negligible.

We find strong evidence for inelatic asset demand curves, leading to the economically significant price impacts of flow-induced demand pressure. In theory, if arbitrageurs could bear unlimited risk, they would take infinitely large positions to fully absorb any demand pressure, resulting in flat demand curves and no price impact. However, our results, consistent with Gabaix and Koijen (2022), demonstrate that capital markets are sufficiently inelastic to generate substantial effects on asset returns from demand pressure.[3]

We show that market trend conditions primarily drive the low-risk anomaly. We demonstrate that the beta anomaly manifests only following uptrend markets, while the CAPM holds following downtrend markets. Standard Fama-MacBeth regression results reveal that after uptrend markets, the CAPM-predicted price of risk ($\bar{r}_m^e$) substantially exceeds the estimated price of risk ($\hat{\lambda}$), with both economic and statistical significance (difference of 0.94% per month with t-statistic 3.44 in Table 9). Conversely, this difference becomes economically and statistically insignificant following downtrend markets (0.06% per month with t-statistic 0.2). We define uptrend and downtrend markets based on whether the cumulative past 24-month market

[3] Wurgler and Zhuravskaya (2002), Coval and Stafford (2007), Koijen and Yogo (2019) also shows empirical evidence of the downward-sloping asset demand curve. The microfoundation of inelastic asset demands can be traced back to the seminal work of Kyle (1989), who pioneered a model of imperfectly competitive financial markets using a demand submission game. In this framework, informed traders strategically choose their demand schedules, considering the price impact of their trades. Downward-sloping demand curves for assets characterize the resulting perfect Bayesian equilibrium.

returns are above or below the median, respectively.[4]

Our analysis of mutual fund flows reveals several important findings. First, we find that the funds with high-beta assets consistently receive significantly larger capital flows than those with low-beta assets following market fluctuations. The results are both statistically significant and economically sizeable. To illustrate, in January 2022, the average assets under management (AUM) of the top 20% high-beta funds is $3.9 billion. The monthly market volatility is about 4.4%. Given a one standard deviation increase in the market return, on average, a median AUM fund with high beta assets receives 12 million dollars more than those with low beta assets, holding the fund's other characteristics constant. With about 600 funds falling into the high-beta category, this translates to an influx of approximately $7.2 billion in new capital compared to the funds with low-beta assets.

Secondly, we demonstrate that high-beta assets experience larger demand pressure from funds for a given change in market returns compared to low-beta assets. This aligns with our observation that funds tilting toward high-beta assets experience larger flows in response to market fluctuations relative to low-beta funds. To quantify the demand pressure from mutual fund flows on individual stocks, we employ the Flow-Induced Trading (FIT) measure introduced by Lou (2012). Conceptually, FIT treats the entire mutual fund industry as a single giant fund and measures the magnitude of trading in each stock induced by the aggregate fund's inflows and outflows. To examine the relationship between FIT and market returns across stocks with different beta profiles, we conduct a panel regression analysis. We sort stocks into quintiles based on their monthly beta and perform a panel regression of the monthly FIT measures on market returns for each beta quintile, including firm-fixed effects to control for unobserved heterogeneity across firms. The regression results reveal a significant disparity in the market-to-FIT relationship between high-beta and low-beta stocks. Specifically, the market-to-FIT estimate of the highest-beta quintile (0.048) is economically more sizeable and statistically robust than that of the lowest-beta quintile (0.029).

[4]We also use an alternative definition of uptrend and downtrend markets based on past 12-month cumulative market returns. Our results remain economically and statistically robust under this alternative definition.

Notably, we show that long-term market fluctuations significantly affect fund flows only during uptrends, while flows remain unresponsive to market fluctuations during downtrends. Specifically, the coefficients relating long-run market fluctuations to cumulative flow-driven demand pressures across all assets are economically sizeable and statistically significant only in uptrend markets. In downtrend markets, these coefficients become both economically and statistically insignificant across all assets, rendering the demand pressures exerted by funds negligible. This pattern reveals that investors persistently invest in high-beta funds, accumulating large demand pressures on these securities exclusively during uptrend markets. Conversely, in downtrend markets, investors react more conservatively to market fluctuations and curtail their investments. As we will discuss shortly, this cumulative demand pressure leads to the overpricing of high-beta stocks and their subsequent underperformance because the demand for high-beta assets is much less elastic than that for low-beta assets.

In the third part of our analysis, we examine the differential price impact of flow-induced trades on stocks with varying betas. We employ a panel regression of monthly stock returns on current FIT measures (representing unanticipated contemporaneous demand surprise) and average-lagged FIT measures (capturing cumulative realized demand pressure) for each beta quintile while controlling for market returns and firm-fixed effects. The results demonstrate a significant disparity in the price impact of flow-induced trades between high-beta and low-beta stocks. Specifically, a one-standard-deviation increase in the contemporaneous demand pressure of high-beta stocks leads to an additional 1.37% increase in monthly returns (equivalent to 16.44% per annum) compared to low-beta stocks. We also demonstrate that for a given level of cumulative demand pressure, high-beta stocks exhibit a higher reversion rate (-0.13) than low-beta assets (-0.08), indicating a more pronounced reversal effect. Our findings confirm that the demand for high-beta stocks is more inelastic than for low-beta stocks.

Furthermore, our analysis reveals that the substantial reversal effect for high-beta assets is predominantly observed following uptrend markets. The coefficients of average lagged FIT-to-return are economically sizeable and statistically significant across all beta quintiles only after uptrend periods. In contrast, these coefficients become both economically and statistically negligible following downtrend markets. This asymmetry, coupled with our earlier finding that long-term market fluctuations significantly affect fund flows only during uptrends, provides robust evidence that uptrend markets are the primary driver of the beta anomaly.

To further quantify the mechanism underlying the differential price impact of flow-induced trading on high-beta and low-beta stocks, we employ a structural vector autoregressive (SVAR) model (Blanchard and Quah, 1989). This model captures the joint dynamics of market returns, fund flows (and consequently, FIT), and stock returns. Figure 3 illustrates the dynamic responses of portfolio returns to a unit impulse in FIT.[5] A flow shock, represented by a shock to FIT, has an economically sizeable impact on high-beta portfolio returns (Panel A). This positive price impact is statistically robust and appears to dissipate gradually over time, indicating a slow reversal. In contrast, the impact of flow-induced trading on low-beta portfolio returns is both economically and statistically insignificant (Panel B).

These findings corroborate the results from our previous stock-level panel regressions and align with existing literature. Studies by Wurgler and Zhuravskaya (2002), Greenwood (2005), and Gromb and Vayanos (2010) suggest that securities with greater risk or more specialized characteristics are associated with steeper demand curves, likely due to limited substitutability and higher arbitrage risk. Our results, showing larger price impacts of flow-induced trading for high-beta stocks, are consistent with and extend these prior findings.

Next, we examine how the patterns observed in our panel regressions contribute to explaining the beta anomaly. Our time-series test confirms the anomaly, revealing that market-neutral portfolio returns of high-beta stocks exhibit a significant negative alpha of -41bps (-5% annualized).[6] Based on our panel regression results, we hypothesize that this negative alpha is primarily driven by cumulative demand pressure. To test this hypothesis, we remove stock-month observations in the top 30% of past average FIT over the previous 24 months, thus eliminating

[5]Precisely, the impulse response functions are computed by injecting a unit impulse of structural error of the FIT component.

[6]We define market-neutral returns as the return of market hedged position $r^e_{it} - \beta_{it} r^e_{mt}$ where r^e_{it} is the excess return of portfolio i at time t, β_{it} is its beta, and r^e_{mt} is the market excess return.

stocks likely to experience negative return reversals. The impact of removing these high-FIT stocks is substantial: the high-beta portfolio's alpha decreases by nearly 80% to -9bps (about -1% annually). This significant reduction strongly supports our hypothesis that cumulative demand pressure largely accounts for the negative alpha observed in high-beta stocks, thus explaining a considerable portion of the beta anomaly.

We then conduct Fama and MacBeth (1973) cross-sectional regressions on beta-quintile portfolios using the single-factor market model. Consistent with prior studies, we find the estimated Security Market Line (SML) is flatter than the average market excess return. Analyzing subsamples, we observe that following market uptrends, the difference between the estimated SML slope and average market excess returns is both economically sizeable and statistically significant. Conversely, following downtrend markets, this difference becomes economically and statistically insignificant.

These findings from both time-series and cross-sectional tests strongly support our hypothesis: the beta anomaly is primarily driven by mutual funds' demand pressure, which passes through return-chasing investors' flows in response to market fluctuations

In the last section, we present a theoretical model to provide a micro-foundation for our empirical analyses. Our model builds upon the work of Black (1972) and Frazzini and Pedersen (2014), incorporating leverage-constrained mutual funds that optimally tilt their portfolios toward high-beta assets. We introduce risk-neutral arbitrageurs (representing hedge funds) who, while not leverage-constrained, face a value-at-risk (VaR) constraint. The shadow cost of this VaR constraint acts as the arbitrageurs' time-varying risk appetite, effectively limiting their risk-bearing capacity. Crucially, these arbitrageurs cannot fully absorb the mutual funds' demand pressure for high-beta assets. As a result, in equilibrium, the expected returns of high-beta assets are reduced relative to CAPM predictions (Proposition 1).

When flows to mutual funds increase, the net worth of the mutual funds expands, while that of hedge funds contracts. This shift enhances the risk-bearing capacity of leverage-constrained mutual funds, intensifying their excessive demand for high-beta assets. The resulting excess demand leads to a greater price impact, which is further exacerbated by the diminished risk-bearing capacity of the hedge funds due to their reduced net worth (Corollary 2).

Related literature

Our study contributes to the extensive literature addressing the beta anomaly. Black (1972) and Frazzini and Pedersen (2014) theoretically demonstrate that leverage-constrained investors optimally tilt towards riskier assets, flattening the equilibrium security market line. Boguth and Simutin (2018) provides empirical evidence supporting the notion that leverage constraints determine the anomaly. Hong and Sraer (2016) argue that high-beta assets experience greater disagreement, leading to overpricing due to speculative demand. Cederburg and O'Doherty (2016) suggest that time-varying betas resolve the anomaly, as conditional betas covary negatively with the equity premium and positively with market volatility. Bali et al. (2017) suggest demand for lottery-like assets is responsible for the beta anomaly. Karceski (2002) proposes that mutual fund managers, anticipating return-chasing investors, tilt portfolios towards high-beta stocks, leading to their overpricing. While Karceski suggests a consistently high demand for high-beta assets, our paper demonstrates that time variation in this demand largely explains the beta anomaly. We demonstrate that high-beta asset prices are inflated primarily when demand is high, typically following market uptrends. This provides a comprehensive explanation that directly links market conditions, investor behavior, and the resulting overpricing of high-beta assets. Buffa et al. (2023) examine how tracking error (TE) constraints – limits on asset managers' deviations from benchmark indices – influence equilibrium asset prices. Their theoretical model extends the literature on delegated asset management and limits to arbitrage (e.g., Shleifer and Vishny, 1997; Frazzini and Pedersen, 2014; Basak and Pavlova, 2013) by highlighting how agency-driven risk limits such as TE-constraints, even absent leverage or short-sale restrictions, can explain important asset pricing anomalies, including the low-volatility anomaly.

Antoniou et al. (2016) propose time-varying market sentiment (Baker and Wurgler, 2006) as an explanation for the beta anomaly. Their approach, similar to ours, relies on time-varying investor capital flows into the stock market. They demonstrate that during periods of high sentiment, overconfident noise traders enter the market, preferentially buying risky assets. This behavior drives up risky asset prices, leading to lower expected returns.

Our approach differs significantly from Antoniou et al. (2016) in several key aspects. We focus on uptrend and downtrend markets isolating the effect of observable market conditions on investor behavior, fund flows, and subsequent demand pressures. This approach allows a more direct examination of how market dynamics contribute to the beta anomaly, separate from psychological factors captured by sentiment measures. Notably, our signal (market returns) differs substantially from Baker and Wurgler's sentiment index. We find a low, slightly negative correlation (-7.58%) between monthly market returns and sentiment over our sample period. Similarly, rolling averages of market returns used to determine market trends show a negative correlation (-3.60%) with rolling average sentiment.

Most importantly, our findings are explicitly connected to the concept of inelastic asset demand, where demand elasticity depends on assets' systematic risk. Our analysis demonstrates that high-beta assets experience significantly larger price impacts than low-beta stocks, not only because they receive larger flow-driven demand pressure but also because their demand is substantially less elastic.

Our study also contributes to the literature on the inelastic demands for financial assets. Wurgler and Zhuravskaya (2002) argues that the risk inherent in arbitraging between imperfect substitutes deters risk-averse arbitrageurs from flattening demand curves, verifying that stocks without close substitutes experience higher price impacts. Greenwood (2005) extends the theory to the multi-asset case, finding that a unique redefinition of the Nikkei 225 index causes large price impacts. Recently, Gabaix and Koijen (2022) proposed that capital markets are sufficiently inelastic, such that investors' flows and demand shocks significantly affect prices and expected returns.[7]

[7]The micro-foundation of downward-sloping demand curves is due to imperfectly competitive financial markets, which involve a demand submission game. Kyle (1989) pioneered the workhorse model for analyzing equilibrium in imperfectly competitive financial markets for a divisible asset, which Rostek and Weretka (2012) later extended to the multi-asset case.

Building upon these foundations, our research provides a novel contribution by demonstrating that flow-driven demand pressure accounts for the low-risk anomaly. We extend the existing literature by examining how mutual fund flows shape the demand for assets with different risk profiles and impact their returns.

A substantial body of literature has explored the impact of fund flows on equity returns. Coval and Stafford (2007) demonstrate that significant mutual fund flows, combined with funds' tendency to pass these through, notably affect equity prices. Building on this, Lou (2012) introduces the Flow-Induced Trade (FIT) measure, showing its predictive power for mutual fund returns via short-term stock return forecasts. Li (2022) further demonstrates that FIT explains considerable variation in traditional asset pricing factors like SMB and HML (Fama and MacBeth, 1973).

Our research uses the flow-induced trading (FIT) measure, introduced by Lou (2012), to explain stock return momentum and mutual fund performance persistence jointly. However, our study diverges from Lou (2012) in its primary focus: we investigate how flow-driven demand pressure exerts differential price impacts on assets with varying risk profiles, thereby contributing to the low-risk anomaly. This novel application of the FIT measure allows us to shed new light on the mechanisms underlying the well-documented but incompletely understood low-risk anomaly in asset pricing.

The paper is organized as follows. Section 2 introduces the mutual fund and other relevant data. Section 3 demonstrates aggregate mutual funds' role in flow-driven demand pressures. Section 4 examines how mutual fund flows affect the demand for assets with varying risk profiles and impact their returns. Section 5 investigates the effect of flow-driven demand pressure on the beta anomaly through time series and cross-sectional analyses. Section 6 provides a microfoundation for how arbitrageurs' limited risk-bearing capacity influences equilibrium asset returns. Section 7 concludes.

2 Mutual Fund Holdings and Other Data

Quarterly mutual fund holdings data were obtained from the CDA/Spectrum database covering the period from 1990 to 2022. This database is compiled from both mandatory SEC filings and voluntary disclosures. Although mutual funds typically file their reports at the end of a quarter, the report date, which indicates when the holdings are valid, often differs from the filing date. To calculate the number of shares held by each mutual fund at the end of the quarter, we assume that managers do not trade between the report date and the quarter-end, while adjusting for stock splits.

Mutual funds' total net assets, net monthly returns, expense ratios, and other characteristics are obtained from the Center for Research in Security Prices (CRSP) survivorship-bias-free mutual fund database. Since the study focuses on gross returns, monthly fund returns are calculated as net returns plus one-twelfth of annual fees and expenses. For mutual funds with multiple share classes reported by CRSP, we aggregate the total net assets (TNA) across all share classes to derive the TNA of the fund. We then compute the TNA-weighted average for net returns and expense ratios across all share classes. The MFLinks file is used to merge CDA/Spectrum data with the CRSP mutual fund database (Wermers, 2000).

Following prior literature as Chevalier and Ellison (1997), we compute the investment flow to fund j in period t as

$$flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1} \cdot (1 + ret_{j,t})}{TNA_{j,t-1}} \tag{1}$$

where $ret_{j,t}$ is the return of fund j in period t and $TNA_{j,t}$ is the total net assets managed by fund j at the end of period t.

We use the target fund's last net asset value (NAV) report date as an estimate of the merger date. We also assume that inflows and outflows occur at the end of each quarter and that investors reinvest their dividends and capital appreciation distributions in the same fund. Finally, initiated mutual funds have inflows equal to their initial TNA, while liquidated funds have outflows equal to their terminal TNA. All these assumptions are consistent with prior studies (e.g., Lou (2012)).

3 Mutual Funds as Conduits for Flow-driven Demand Pressure

The literature documents that funds are approximately "pass-through vehicles" that trade in roughly one-to-one fashion in response to investor flows (e.g.,Greenwood and Thesmar (2011), Lou (2012), Li (2022) and references therein). Precisely, fund managers tend to expand or liquidate their existing holdings proportionally in response to inflows or outflows as long as capital flows from retail investors are uninformative about future stock returns.

To ensure this, we first measure the split-adjusted trading in stock i by fund j in quarter t:

$$trade_{i,j,t} = \frac{shares_{i,j,t}}{shares_{i,j,t-1}} - 1 \tag{2}$$

where $shares_{i,j,t}$ represents stock $i's$ number of shares held by fund j at time t.

We then estimate a fund-level quarterly panel regression similar to Lou (2012) and Li (2022) to investigate mutual funds' trading response to fund flows,

$$trade_{i,j,t} = \gamma_1 \cdot flow_{j,t} + \eta_j + \eta_t + \epsilon_{i,j,t} \tag{3}$$

where η_j represents a fund's fixed effect, η_t time fixed effect. The regression effectively decomposes trading into a flow-dependent part (the fitted) and an information-related part (the residuals). We estimate the regression separately for outflow and inflow samples to gauge the effects of funds' trading responses on capital inflows and outflows.

Table 1 reports the estimates of the fund-level panel regression (3). As shown, mutual funds are approximately 'pass-through' vehicles. Fund managers proportionally expand or liquidate their holdings in response to capital flows. The estimate of the flow-to-trade γ_1 is approximately close to unity. The estimates are statistically robust and significantly different from zero. Standard errors of the estimates in the table are clustered by fund and month.

Table 1 also reports a small asymmetric trading response to in- and out-flows to a fund. In fact, such asymmetric responses are also reported in Lou (2012) and Li (2022); None of the estimates in Table 1 statistically significantly differ from them.

4 Mutual Funds' Demand Pressure and Beta Anomaly

4.1 Conceptual overview

Our key mechanism posits that market returns influence asset returns through two channels: traditional risk compensation and an additional effect stemming from mutual fund flows. Specifically, market fluctuations trigger fund flows, which in turn exert demand pressure on assets, particularly those heavily held by mutual funds. This flow-induced demand pressure creates a correlation between market returns and asset returns that is distinct from the standard CAPM theory, which assumes posits perfectly elastic demand curves for individual stocks. Our mechanism, along with Gabaix and Koijen (2022), demonstrates that capital markets are sufficiently inelastic (i.e., downward sloping demand curve) to generate substantial effects on asset returns from demand pressure.

The return of asset i depends on both market returns and the demand pressure triggered by market trends. We thus have

$$dr_{it} = \frac{\partial r_{it}}{\partial r_{mt}} \cdot dr_{mt} + \frac{\partial r_{it}}{\partial D_{it-1}} \cdot \frac{\partial D_{it-1}}{\partial r_{mt-1}} \cdot dr_{mt-1} + \epsilon_{it} \tag{4}$$

The first term represents the direct risk-compensation effect, controlling for the indirect demand pressure channel. This term depends on the amount of systematic risk β_i, consistent with the standard CAPM.

The second term captures the indirect effect of market fluctuations on asset i's return through the demand pressure exerted by aggregate mutual funds. It can be further decomposed into two parts: (i) the term $\partial D_{it-1}/\partial r_{mt-1}$ represents the realized demand pressure on asset i exerted by the aggregate mutual funds in response to market fluctuations and (ii) the term $\partial r_{it}/\partial D_{it-1}$ represents the price reversal after the demand pressure on asset i, keeping other factors fixed. The latter composite term $(\partial r_{it}/\partial D_{it-1}) \cdot (\partial D_{it-1}/\partial r_{mt-1})$ measures the effect of market trends on an asset's return through the demand pressure channel.

Our key findings are twofold. First, we will show that riskier assets receive larger demand pressure from mutual funds in response to changes in market conditions (i.e., $\partial D_{it-1}/\partial r_{mt-1}$ increases with β_i). Second, we demonstrate that the demand pressure has a greater price impact on riskier assets (i.e., $|\partial r_{it}/\partial D_{it-1}|$ increases with β_i). In other words, greater risk is associated with a steeper demand curve, a finding that is consistent with the evidence documented in Wurgler and Zhuravskaya (2002), Greenwood (2005), and Gromb and Vayanos (2010). These results highlight the importance of the indirect demand pressure channel in understanding the relationship between market fluctuations and asset returns, particularly for high-risk assets.

4.2 Fund flow sensitivity to funds' beta

Building on our earlier finding that aggregate mutual funds transmit investors' capital flows to their portfolio holdings, this section demonstrates that funds with higher portfolio betas experience significantly larger capital flow variations in response to market fluctuations compared to low-beta funds.

We begin by categorizing the sample funds into quintiles based on their betas. Fund-level betas are estimated using rolling window regressions of fund excess returns on market excess returns over the previous 36 months, requiring a minimum of 18 valid monthly observations.[8]

[8]We also compute fund betas as the weighted average of all constituent stock betas. Results are statistically similar.

We then estimate a fund-level monthly panel regression for each quintile:

$$flow_{j,t} = \gamma_1 \cdot r^e_{m,t} + \sum_{k=1}^{6} \gamma_{1,-k} \cdot r^e_{m,t-k} + \eta_j + \epsilon_{j,t} \quad (5)$$

where $flow_{j,t}$ represents the flow to fund j within a given quintile, r^e_{mt} the contemporaneous excess market return in month t, r^e_{mt-k} the k-month lagged market return, and and η_j represents a fund fixed effect. This analysis allows us to examine how the sensitivity of fund flows to market returns varies across different levels of fund beta, providing insights into the relationship between fund risk characteristics and investor behavior.

Table 2 presents the estimates of panel regressions (5) for each beta quintile. Panel A reports sample means, while Panel B shows the regression estimates. Standard errors are clustered by month and fund to account for potential time-series and cross-sectional dependencies.

The results show that the highest quintile fund ("High β" Column) presents economically sizeable and statistically robust responses to market fluctuations. By contrast, market fluctuations have no economically sizeable effect on the lowest quintile fund ("Low β" Column). Moreover, the flow-to-market estimate γ_1 of the lowest quintile fund appears statistically insignificant.

The results align with prior studies demonstrating that aggregate mutual fund flows closely track market returns at the daily level (Edelen and Warner (2001), Ben-Rephael et al. (2011)). Consequently, monthly flows appear to vary contemporaneously with monthly market returns, consistent with Warther (1995) and Fant (1999). This finding is crucial as it documents investors' return-chasing behavior fluctuating with market returns at the monthly horizon. We argue that this phenomenon is central to explaining the beta anomaly.

We gauge the economic significance of the model estimates as follows. In January 2022, the average asset under management (AUM) of the top 20% high-beta funds was 3.9 billion. The monthly market volatility was about 4.4%. Given a one standard deviation increase in the market return, a median AUM fund in the highest beta quintile receives an additional $12 million per month ($0.0746 \times 4.4\% \times$3.9 billion) compared to a median fund in the lowest beta quintile. With approximately 600 funds in the highest-beta quintile, this results in an influx of roughly \$7.2 billion in new capital to the highest-beta quintile funds compared to those with the lowest-beta quintile.

4.3 Differential price impact of flow-induced trading on high- and low-beta stocks

To study the effect of flow-induced trading by the entire mutual fund industry, we define flow-induced trading (FIT) for stock i in time t, following Lou (2012):

$$FIT_{i,t} = \sum_{j} \left(\frac{shares_{i,j,t-1}}{\sum_{j'} shares_{i,j',t-1}} \right) \cdot flow_{j,t} \tag{6}$$

Intuitively, $FIT_{i,t}$ measures the demand pressure on stock i exerted by the entire mutual fund industry in period t. It is also vital to note that FIT measures a flow-predicted trade, *not* actual trade.

Recall that according to the model (5), the funds tilting toward high-beta assets experience larger flows in response to market fluctuations relative to the low-beta funds. By the definition of (6), we expect that the high-beta assets' FIT measures respond economically stronger and statistically robust to market fluctuations than the low-beta assets.

To validate this, we first partition the sample stocks into quintiles based on their betas. The betas are calculated using rolling window regressions of stock excess returns on market excess returns, requiring a minimum of 18-month valid entries. We then estimate a stock-level monthly panel regression at each quintile:

$$FIT_{i,t} = \gamma_1 \cdot r^e_{m,t} + \sum_{k=1}^{6} \gamma_{1,k} \cdot r^e_{m,t-k} + \eta_i + \epsilon_{i,t} \tag{7}$$

where $FIT_{i,t}$ the aggregate mutual fund's demand pressure on stock i in month t, r^e_{mt} the contemporaneous excess market return, r^e_{mt-k} the k-lagged market return, and and η_j represents stock fixed effect.

Table 3 shows the estimates of the panel regressions (7) at each quintile. Panel A in the table reports the means of monthly flow-induced trades (FIT) partitioned into quintiles using NYSE beta-quintile cut-offs each month. Panel B reports the estimates of the regressions of monthly fund flows on the market factor and the lags of the market factor. Columns in Panel B report the estimates by beta quintile. Standard errors in both panels are clustered by stock and month.

The results strongly support the aforementioned intuition. The highest-beta assets' market-to-FIT estimate (Column "High β"; 0.048) is economically much more sizeable and statistically robust than the lowest-beta assets (Column "Low β"; 0.029). Moreover, the market-to-FIT estimate difference between the highest-beta and the lowest-beta assets is statistically significant as well (the Wald-statistics of 7.15).

We gauge the economic significance of the model estimates of (7) as follows. Given one standard deviation (5.13%) increase in the monthly contemporaneous market return, on average, the highest beta quintile stocks' FIT increases 0.1% (i.e., $(0.048 - 0.029) \times 5.13\%$) more than that of the lowest-beta quintile, which is 1.5% of one standard deviation of FIT measures.

To test the effect of market trends, we estimate the following stock-level monthly panel regression at each quintile:[9]

$$\overline{FIT}_{i,t,t-k} = \gamma_{down} \cdot \overline{r^e_{m,t,t-k}} \cdot \mathbf{1}_{downtrend} + \gamma_{up} \cdot \overline{r^e_{m,t,t-k}} \cdot \mathbf{1}_{uptrend} + \eta_i + \epsilon_{i,t} \tag{8}$$

where $\overline{FIT}_{i,t,t-k}$ the average k-lagged mutual fund's demand pressure on stock i (cumulative demand pressure on stock i), $\overline{r^e_{m,t,t-k}}$ the average k-lagged excess market return, η_i represents stock fixed effect. $\mathbf{1}_{\text{uptrend}}$ and $\mathbf{1}_{\text{downtrend}}$ are dummy variables indicating that the rolling 24-month past cumulative market returns are below or above the sample median.

Table 4 shows the estimates of rolling window panel regressions (8) at each beta quintile.

[9] The equivalent and standard specification is to use an interaction:

$$\overline{FIT}_{i,t,t-k} = \gamma_1 \cdot \overline{r^e_{m,t,t-k}} + \gamma_2 \cdot \overline{r^e_{m,t,t-k}} \cdot \mathbf{1}_{uptrend} + \eta_i + \epsilon_{i,t}$$

where the estimates $\gamma_{down} = \gamma_1$ and $\gamma_{up} = \gamma_1 + \gamma_2$. We choose the specification for expositional convenience.

Betas are calculated using the previous 36 months of returns, requiring a minimum of 18 months. The sample includes all firms for which we are able to measure FIT in a given month. The sample period is from January, 1991 through March, 2021. Standard errors are clustered by firm and month.

The results reveal distinct investor behaviors across market trends. In uptrend markets, return-chasing investors consistently allocate capital to mutual funds with high-beta assets, accumulating significant demand pressures on these securities. Conversely, in downtrend markets, investors react more conservatively and cautiously to market fluctuations. Flows to funds become both economically and statistically insignificant across all beta quintiles, rendering the demand pressures exerted by funds negligible.

We now investigate the impact of mutual funds' aggregate demand pressure on an individual stock's return using stock-level FIT. Our focus is on the differential effect of this demand pressure on high-beta versus low-beta stocks. First, we study the price impact of FIT on asset returns at the portfolio level, employing a structural vector autoregressive model (SVAR). The SVAR analyses provide insight into the joint dynamics of market returns, the demand pressure exerted by aggregate mutual funds on beta-quintile returns, and the beta-quintile returns themselves. Next, we conduct a micro-level analysis, examining the price impact of an individual stock's FIT on its return using a stock-level panel regression.

Portfolio level analysis We examine the price impact of FIT on asset returns at the portfolio level using a structural vector autoregressive (SVAR) model. The SVAR model, with four lags, captures the joint dynamics of monthly market excess returns, the beta-quintile FIT measures, and their returns.

We precisely partition the sample stocks into quintiles based on their betas. As before, the betas are calculated using rolling window regressions of stock excess returns on market excess returns, requiring a minimum of 18 months of valid entries. At each beta quintile, we define a vector $Y_t = [r_{m,t}, FIT_{p,t}, r_{p,t}]'$ where $FIT_{p,t}$ represents the average FIT of stocks in the p-th beta quintile, $r_{p,t}$ is the value-weighted average return of stocks in the p-th beta quintile, and $r_{m,t}$ the contemporaneous market excess return. We then estimate a structural vector autoregressive (SVAR) model:

$$A \cdot Y_t = b_0 + \sum_{k=1}^{4} L_k \cdot Y_{t-k} + \epsilon_t \tag{9}$$

where $\epsilon_t = [\epsilon_t^m, \epsilon_t^f, \epsilon_t^i]'$ is the stationary orthogonal structural error vector such that $\texttt{cov}(\epsilon_t) = diag(\sigma_{mt}, \sigma_{ft}, \sigma_{it})$.

The lower triangular matrix $A \in \mathbb{R}^{3\times3}$ characterizes the contemporaneous relationships among the components of the vector Y_t.[10] This lower triangular structure imposes a "causality" ordering: the current market return has an instantaneous effect on both the quintile FIT measure and the beta-quintile asset return, while the quintile FIT measure may have a contemporaneous effect on the beta-quintile return but not on the market return. The matrix L_k, on the other hand, defines the lagged relationship of components in the vector Y_{t-k}.

Table 8 reports the parameter estimates and their statistical significances of the SVAR model (9) for the lowest and highest quintile beta portfolios. Precisely, the highest beta quintile FIT's response to a change in market return, keeping all things fixed, is measured

$$\mathbb{E}\left[\frac{\partial FIT_{\beta^H,t}}{\partial r^e_{m,t}}\right] = \begin{matrix} 0.045 \\ (6.36) \end{matrix} \tag{10}$$

while the lowest beta quintile FIT's response to a change in market return, keeping all things fixed, is measured

$$\mathbb{E}\left[\frac{\partial FIT_{\beta^H,t}}{\partial r^e_{m,t}}\right] = \begin{matrix} 0.021 \\ (3.30) \end{matrix} \tag{11}$$

The numbers in parentheses represent the corresponding Z statistics, indicating that both estimates are statistically significant. The market-to-FIT response for the highest beta quintile

[10] Because the off-diagonal elements of A matrix contain the negative of the actual contemporary effects, the estimated effects are positive, as expected.

is twice as large as that for the lowest beta quintile. These results align with our findings from the panel regression model (7) (see Table 3). Specifically, FITs for high-beta quintiles exhibit stronger responses to market fluctuations compared to those for low-beta quintiles.

We now highlight the main results of the SVAR analyses: the price impacts of aggregate mutual fund demand pressure on high-beta and low-beta quintiles. Specifically, we measure the return response of the highest beta quintile to a change in its FIT, holding all other factors constant:[11]

$$\mathbb{E}\left[\frac{\partial r^e_{\beta^H,t}}{\partial FIT_{\beta^H,t}}\right] = \begin{matrix} 1.269 \\ (5.00) \end{matrix} \tag{12}$$

In contrast, we measure the return response of the lowest beta quintile to a change in its FIT under the same conditions:

$$\mathbb{E}\left[\frac{\partial r^e_{\beta^L,t}}{\partial FIT_{\beta^H,t}}\right] = \begin{matrix} 0.012 \\ (0.06) \end{matrix} \tag{13}$$

The numbers in parentheses represent the corresponding Z statistics.

As shown, the price impact of FIT on the highest beta quintile return is both economically sizeable and statistically significant. A one standard deviation increase in the highest quintile FIT (0.79%) leads to an approximate 1% increase (0.0079×1.26) in the highest quintile's monthly return, equating to roughly 12% annually. In contrast, the price impact of FIT on the lowest beta quintile return is both economically and statistically *insignificant*. Given a similar FIT distribution to the highest beta quintile, the aggregate mutual fund demand pressure (i.e., FIT) has a negligible price impact on the lowest-beta quintile asset returns, whereas the fund demand pressure has an extremely robust impact on the highest-beta quintile asset returns.[12] Consistent results are found in the micro-level analysis, which investigates the fund's demand pressure on

[11] The literature often refers to it as Kyle's Lambda (Kyle, 1985).

[12] As shown in Figure 2, the standard deviation of the lowest quintile FIT is comparable to that of the highest quintile FIT.

individual stock returns, as discussed in the following paragraph.

Figure 3 provides a more intuitive illustration of the differential price impact of aggregate mutual fund demand pressure on the highest and lowest beta quintile asset returns. Panel A shows the response function of the highest beta quintile asset returns to a unit impulse in the quintile FIT measure, while Panel B presents the corresponding response function for the lowest beta quintile. Consistent with the results from the models (12) and (13), the unit impulse demand pressure exerted by mutual funds at time 0 strongly affects the asset returns of the highest beta quintile. In contrast, the response of the lowest beta quintile asset returns is both economically and statistically insignificant over a 16-month window. Panel A of Figure 3 intriguingly demonstrates a gradual price reversal subsequent to the time-0 unit impulse: the affected highest-beta quintile return exhibits a slow decline throughout the simulated period.

Such short-term momentum and long-term reversal patterns are consistently corroborated in the subsequent micro-level analysis. Furthermore, the literature documents that these patterns are ubiquitous in the return series of many financial assets and trading strategies (e.g., see Cutler et al. (1991), Ghayur et al. (2010) and references therein).

Stock-level analysis We now proceed to examine the price impact of mutual funds' demand pressure on asset returns at a finer granularity: individual stocks. Precisely, we estimate a stock-level panel regression of returns on their contemporaneous and lagged FIT measures, as specified in model (16).

As before, we first partition the sample stocks into quintiles based on their betas, which are calculated using rolling window regressions of stock excess returns on market excess returns, with a minimum requirement of 18 months of valid entries. We first investigate the impact of mutual funds' aggregate demand pressure on an individual stock's return using stock-level FIT. Our focus is on the differential effect of this demand pressure on high-beta versus low-beta stocks. We use zero-leverage returns of each stock by subtracting market exposure from each stock i's returns:

$$r_{i,t}^{ZL} := r_{i,t}^{e} - \beta_{i,t} \cdot r_{M,t}^{e}, \tag{14}$$

where $\beta_{i,t}$ denotes stock i's beta calculated over the previous 36 months. For each stock, the zero-leverage returns $r_{i,t}^{ZL}$ are constructed to be market-neutral following Novy-Marx and Velikov (2022) and Barroso et al. (2022) who suggest a refined measure of the market-neutral returns used in Frazzini and Pedersen (2014). We then examine the relationship between market neutral returns and current and past FIT:

$$r_{i,t}^{ZL} = \omega_1 \cdot FIT_{i,t} + \sum_{k=1}^{6} \omega_{1,k} \cdot FIT_{i,t-k} + \eta_i + \zeta_t + \epsilon_{i,t}, \tag{15}$$

where η_i denotes firm fixed effect and ζ_t denotes month fixed effects.

Average market-neutral returns (Panel A) as well as the results of the regression in Equation (15) (Panel B), are reported in Table 5. Consistent with previous documentation of the beta anomaly, market-neutral returns are higher on average in the low-beta quintile than in the high-beta quintile.

However, as shown in Panel B, for each unit of contemporaneous FIT, the price sensitivity to contemporaneous FIT is highly significant. Lagged values of FIT have little statistical significance but their signs are negative for the most part. This is consistent with positive price impact of contemporaneous FIT on market-neutral returns followed by a gradual reversal of price impact. This is consistent with findings in Coval and Stafford (2007), Lou (2012) and Li (2022) of investors' demand through mutual funds, impacting the prices of stocks.

While all quintiles show a significant relationship between FIT and market-neutral returns, the point estimate for the high-beta quintile is more than double that of the low-beta quintile. The difference is statistically significant at the 1% level as shown by the Wald statistic. This shows that higher-beta stocks exhibit higher inelasticity to demand pressure than lower-beta stocks.

We then estimate the stock-level monthly panel regression specified in model (16) for each quintile:

$$r_{i,t}^{ZL} = \lambda^{+} \cdot FIT_{i,t} + \lambda^{-} \cdot \overline{FIT}_{i,t-k,t} + \eta_i + \epsilon_{i,t} \quad (16)$$

where $r_{i,t}^{ZL} := r_{it} - \beta_{it-1} r_{mt}^{e}$ represents the monthly return of stock i after controlling the market risk-premium, $FIT_{i,t}$ denotes the contemporaneous demand pressure on the stock, $\overline{FIT}_{i,t-k,t} := \frac{1}{K}\sum_{k=1}^{K} FIT_{i,t-k}$ is the cumulative demand pressures exerted by the aggregate fund on the stock over a K-month window, and η_i represents the stock fixed effect.

Table 6 presents the estimates of the panel regressions specified in model (16) for each quintile. Panel B provides the estimates and their corresponding statistical significance for each quintile. Standard errors in both panels are clustered by stock and month. Specifically, the first row of Panel B reports the estimates of λ^{+}, the FIT-to-return coefficients, which can be interpreted as the *price impact* of the aggregate fund's contemporaneous demand pressure on individual stock returns for each quintile, controlling the effect of market fluctuations.[13] Hence, $1/\lambda^{+}$ represents the *price elasticity* of demand.[14] The second row presents the estimates of λ^{-}, the average lagged FIT-to-return coefficients, which can be interpreted as the reversal effect of the fund's past demand pressure.

According to the λ^{+} estimates in Panel B, the aggregate fund's demand pressure has a significantly stronger economic impact on the highest-beta quintile asset returns compared to the lowest-beta quintile (0.34 versus 0.16). This difference is also statistically significant, as indicated by the Wald statistic of 36.98. On the other hand, the λ^{-} estimates are negative across all quintiles and are both economically and statistically significant. This suggests gradual price reversals following the contemporaneous demand pressures, with affected beta quintile returns exhibiting persistent declines over a 6-month window.

We assess the economic significance of these estimates as follows: given a one standard deviation increase in the highest-beta quintile FIT (0.0756), the monthly return of a stock in the highest-beta quintile increases by approximately 1.37% ($(0.340 - 0.159) \times 0.0756$) more

[13] The literature often refers to it as Kyle's Lambda (Kyle, 1985).

[14] See Wurgler and Zhuravskaya (2002) and Chacko et al. (2008).

than that of a stock in the lowest beta quintile. This magnitude is economically substantial.

To assess the effect of cumulative demand pressure on asset i, we estimate

$$r_{i,t}^{ZL} = \lambda_{down}^{-} \cdot \overline{FIT}_{i,t-k,t} \cdot \mathbf{1}_{downtrend} + \lambda_{up}^{-} \cdot \overline{FIT}_{i,t-k,t} \cdot \mathbf{1}_{uptrend} + \eta_i + \epsilon_{i,t} \tag{17}$$

where the dependent variable, r_{it}^{ZL} is calculated for each firm i at time t such that $r_{it}^{ZL} := r_{it}^{e} - \beta_{it-1} r_{mt}^{e}$. $\overline{FIT}_{i,t,t-k}$ the average k-lagged mutual fund's demand pressure on stock i (cumulative demand pressure on stock i), and η_i represents stock fixed effect. $\mathbf{1}_{\text{uptrend}}$ and $\mathbf{1}_{\text{downtrend}}$ are dummy variables indicating that the rolling 24-month past cumulative market returns are above or below the sample median as before.

Tabe 7 reports the estimates of the panel regressions of model (17). Regressions are run after partitioning the sample into quintiles based upon stock-level betas. We use NYSE beta-quintile cut-offs each month. Betas are calculated using the previous 36 months of returns regressed on the market factor requiring a minimum of 18 months. The regressions include firm fixed effects. Standard errors in both panels are clustered by firm and month.

The results reveal that the substantial reversal effect for high-beta assets is predominantly observed following uptrend markets. The coefficients of average lagged FIT-to-return (λ_{up}^{-}) are economically sizeable and statistically significant across all beta quintiles only after uptrend periods. In contrast, these coefficients (λ_{down}^{-}) become both economically negligible and statistically insignificant following downtrend markets. This asymmetry, coupled with our earlier finding that long-term market fluctuations significantly affect fund flows only during uptrends, provides robust evidence that uptrend markets are the primary driver of the beta anomaly.

The core findings of this section reveal that the aggregate mutual fund's demand pressure affects asset returns and, more importantly, exerts differential effects on high-beta and low-beta assets. Specifically, the fund's demand pressure has a stronger impact on the returns of high-beta stocks compared to low-beta stocks. The affected returns exhibit a gradual decline over subsequent periods.

The limited risk-bearing capacity of arbitrageurs ensures that uninformed demand pressure can cause price dislocations from fundamental values. If arbitrageurs could bear unlimited risk, they would take infinitely large positions to fully absorb demand pressure, resulting in no price impact. Demand-induced price impacts are well-documented by Greenwood (2005), Greenwood and Thesmar (2011), and Lou (2012). More recently, Gabaix and Koijen (2022) demonstrates that capital markets are sufficiently inelastic, such that high sensitivity of prices to flows has significant consequences: investors' flows and demand shocks affect prices and expected returns in a quantitatively important way.

A stronger price impact on the returns of high-beta stocks compared to low-beta stocks implies that the demand for high-beta assets is more inelastic than that for low-beta assets. In other words, greater risk is associated with a steeper demand curve. Supporting evidence is documented in Wurgler and Zhuravskaya (2002), Greenwood (2005), and Gromb and Vayanos (2010). Additionally, short sales costs also contribute to steepening the demand curve, making prices less resilient to changes in uninformed demand pressure (Greenwood, 2009).

5 Fund Flows and Asset Pricing Tests

5.1 Time series analysis

Our analysis begins with time-series tests using market-neutral portfolios, following the methodology outlined in Frazzini and Pedersen (2014) and subsequently refined by Novy-Marx and Velikov (2022) and Barroso et al. (2022). We construct five portfolios using NYSE breakpoints, based on rolling window CAPM betas estimated over the previous 36 months (requiring a minimum of 18 months of observations). These portfolios are value-weighted, with returns calculated monthly. We then compute market-neutral portfolio returns for each portfolio as follows:

$$r_{i,t}^{ZL} := r_{i,t}^{e} - \beta_{i,t} \cdot r_{m,t}^{e}, \tag{18}$$

where $\beta_{i,t}$ denotes portfolio i's beta calculated over the previous 36 months.

Panel A of Table 10 presents regressions of each market-neutral portfolio return on the market factor. The risk-adjusted returns (alphas) for each portfolio are reported in percentages. Notably, only the highest beta-quintile portfolio exhibits statistically significant risk-adjusted returns, with monthly risk-adjusted returns of -41 basis points. This translates to an economically substantial annualized risk-adjusted return exceeding 5%. As anticipated, the betas of each portfolio are statistically and economically negligible, and R-squared values are insignificant across all quintile portfolios, confirming the market-neutral construction. Consistent with existing literature, the highest-beta portfolio's risk-adjusted return is negative, both economically and statistically significant. Aligning with prior research, the low-beta portfolios show positive risk-adjusted returns, while their economic magnitude and statistical significance are modest. This pattern of returns across beta quintiles provides strong evidence for the presence and persistence of the beta anomaly in our sample period, with high-beta stocks significantly underperforming on a risk-adjusted basis.

In Panels B and C, we analyze the same portfolios after removing stocks with extreme Flow-Induced Trading (FIT) measures. This approach tests our hypothesis that flow-driven demand pressure is a primary driver of the beta anomaly. If this hypothesis holds, eliminating stocks with the most extreme FIT measures should significantly reduce or eliminate the premiums associated with extreme betas. Our methodology involves calculating the average FIT for each stock over the previous 24 months, requiring at least 18 observed monthly FIT measures. We define extreme FIT stocks as those in the highest or lowest 30% of average past FIT each month across the entire sample. These extreme FIT stocks are then removed from all portfolios. Subsequently, we recalculate the betas of the portfolios to maintain their market-neutral status. This approach allows us to isolate the effect of flow-induced trading on the beta anomaly, providing insight into whether the observed premiums are primarily driven by these cases of extreme demand pressure. By comparing the results before and after removing extreme FIT stocks, we can assess the extent to which flow-driven demand influences the beta-return relationship

Panel B of Table 10 presents an analysis of portfolio returns after excluding stocks with high average Flow-Induced Trading (FIT) over the preceding 24 months. Our earlier panel regressions demonstrated that stocks with consistently high FIT tend to become substantially overpriced, leading to predictably low subsequent returns relative to CAPM predictions. This effect was shown to be most pronounced among high-beta stocks. In this panel, we report the risk-adjusted returns of each market-neutral portfolio after removing all stocks in the top 30% of average FIT, measured over the past 24 months. This refined analysis allows us to isolate the impact of extreme positive flow-induced demand on the beta anomaly. By comparing these results to those in Panel A, we can assess the extent to which high FIT stocks contribute to the observed patterns in risk-adjusted returns across beta quintiles.

The results presented in Panel B of Table 10 support our hypothesis that flow-driven demand pressure largely accounts for the substantial negative risk-adjusted returns of the high-beta portfolio. After removing stocks with extreme positive FIT, we observe a significant reduction in the magnitude of alpha for the high-beta portfolio. Specifically, the point estimate of α decreases from -41 basis points to -9 basis points in monthly returns, equivalent to a drop from -5% to -1% annually. This represents a reduction of nearly 80% in the anomalous returns.

Moreover, the statistical significance of these risk-adjusted returns is markedly diminished. The t-statistic for the high-beta portfolio's alpha in Panel B is -0.43, rendering it statistically insignificant. This stands in stark contrast to the statistically significant alpha (t-statistic of -2.19) observed in Panel A before the removal of high FIT stocks.

In addition to the t-statistics for point estimates reported in parentheses, Panels B and C present t-statistics for the difference between the original market neutral portfolios and those with extreme FIT stocks removed. These differential t-statistics are reported in square brackets beneath the standard t-statistics. To compute these differential t-statistics, we conduct CAPM time-series regressions using long-short portfolios defined as

$$r^{ZL}_{diff} := r^{ZL}_{exFIT} - r^{ZL} \tag{19}$$

where r^{ZL}_{exFIT} denotes the portfolio with extreme FIT stocks removed.

Comparing Panels A and B, we observe that the change in risk-adjusted returns after removing extreme-FIT stocks increases monotonically with beta. The reduction in alpha is largest for the high-beta portfolio, with a statistically significant difference (t-statistic of 2.46). This aligns with our earlier panel regressions, indicating that high-beta stocks experience the largest price impact from demand. While the number of stocks in each portfolio decreases in Panels B and C due to the removal of 30% of the sample, the high-beta portfolios remain well-diversified with over 500 stocks on average. This suggests that the results are not driven merely by reduced sample size.

In Panel C, where we remove low-FIT stocks, the effects are negligible, consistent with our panel regression results. FIT accumulates most significantly in uptrend markets for both high and low-beta stocks, but due to the inelasticity of high-beta stock prices, the price impact and reversal effects are stronger for these stocks. Removing high-FIT stocks from high-beta portfolios reduces their negative unconditional returns, while removing low-FIT stocks has little effect.

Table 11 examines whether return differences between portfolios with and without high-FIT stocks are due to systematic risk exposure. We regress r^{ZL}_{diff} (i.e., the difference between returns of portfolios with and without extreme FIT stocks) on a six-factor model including the Fama-French five factors and the momentum factor.

The results show a monotonically increasing relation between risk-adjusted returns and beta. The high-beta portfolio's r^{ZL}_{diff} has a statistically significant alpha of 26 basis points per month, with no significant loadings on other risk factors. This suggests that the premium associated with r^{ZL}_{diff} cannot be attributed to these well-studied risk factors, further supporting our hypothesis that return-chasing investors' demand for high-beta stocks largely explains their low risk-adjusted returns.

5.2 Cross-sectional analysis: Fama-MacBeth regressions

A key finding of our analysis is that market trend conditions are the primary driver of the low-risk anomaly. Our cross-sectional analysis reveals that the beta anomaly manifests only following uptrend markets, while the Capital Asset Pricing Model (CAPM) holds following downtrend markets.

We examine the cross-sectional relationship between portfolio betas and expected returns using the two-pass regression analysis of Fama and MacBeth (1973). In the first pass, we estimate portfolio betas by running time-series regressions of each portfolio's excess returns on the market factor. The second pass involves cross-sectional regressions of the vector of excess returns r^e on portfolio betas $\hat{\beta}$, yielding a slope estimate $\hat{\lambda}_t$ for each month. We average these monthly slope estimates to obtain an estimate of the unconditional price of risk $\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t$:

$$\mathbb{E}[r^e] = \hat{\lambda}_0 + \hat{\lambda}\hat{\beta} \tag{20}$$

We compare the estimated price of market risk, $\hat{\lambda}$, with the market premium implied by time-series tests of the CAPM. The implied premium is calculated as the simple average of realized market excess returns, denoted by $\bar{r}^e_m$. This comparison allows us to assess whether the cross-sectionally estimated price of risk aligns with the historical market risk premium.

In the Capital Asset Pricing Model (CAPM), the Security Market Line (SML) slope equals the market risk premium. The beta anomaly is characterized as the empirical observation that the estimated slope of the SML is lower than the average market excess return: $\hat{\lambda} < \bar{r}^e_m$. This discrepancy challenges a fundamental prediction of the CAPM. We use value-weighted, beta-sorted quintile portfolios from July 1967 through December 2022, available from Kenneth French's Data Library.

Our panel regressions reveal that demand pressures on high-beta stocks accumulate during market uptrends. As a result, the expected returns of high-beta stocks are likely to be lower than CAPM predictions following uptrend markets. Based on this, we hypothesize that the discrepancy between the estimated price of market risk ($\hat{\lambda}$) and the average realized market excess return ($\bar{r}^e_m$) is most pronounced following market uptrends.

Table 9 presents the results of Fama-MacBeth regressions using both full-sample estimates of portfolio betas ($\hat{\beta}$) and 36-month rolling window estimates ($\hat{\beta}_t$). For both estimation methods, the final row of the first column shows the difference between the estimated price of risk ($\hat{\lambda}$) and the average realized market excess return ($\bar{r}^e_m$) for the entire sample period. This difference is statistically significant and negative in both cases, indicating that the security market line estimated from our cross-sectional regressions is flatter than the average market excess return. Specifically, using full-sample betas, the difference is estimated to be -50 basis points per month, while using rolling window betas yields a difference of -43 basis points per month. Both estimates are significant at the 5% level, confirming the presence of the beta anomaly in our sample.

We then examine the estimated differences between $\hat{\lambda}$ and $\bar{r}^e_m$ over two subsamples: months following market downtrends and months following market uptrends. In the final columns of both panels, we report the point estimate of $(\hat{\lambda} - \bar{r}^e_m)$ following market uptrends. In these months, we hypothesize negative values. This is overpricing builds up in high-beta stocks due to high demand in market uptrends as shown in our panel regressions. Following this overpricing, high-beta stocks tend to have negative abnormal returns, resulting in lower cross-sectional slope estimates of expected returns as a function of test asset betas. The results in the final columns of each panel confirm our intuition. The point estimates of $(\hat{\lambda} - \bar{r}^e_m)$ are almost identical, regardless of how portfolio betas are estimated (-94 bps and -95 bps). Both are economically large and statistically very significant. The results of our analysis in Table 9 are consistent with the hypothesis that the Beta Anomaly is largely driven by demand pressure stemming from retail investors' return-chasing behavior, which fluctuates with market returns.

In both panels, the difference between $\hat{\lambda}$ and $\overline{r}_m^e$ following downtrend markets is below 10 bps (-6 bps using full-sample betas and 9 bps using rolling window betas). Both estimates are statistically insignificant. This suggests that when there is less built up price distortion, cross-sectional estimates of the price of market risk are very close to average market excess returns.

6 The Model

Consider an economy with two types of traders: leverage-constrained risk-averse mutual funds (type m) and value-at-risk (VaR) constrained risk-neutral arbitrageurs (hedge funds, type h). The wealth (net worth) of the mutual fund sector is e_t^m and that of the hedge funds is e_t^h. Let type-i trader dollar demand for risky asset be a vector y_t^i.

There are n risky assets and one risk-free asset with a return of r_f in the economy. For simplicity, we assume that the risk-free asset has zero net supply and a normalizing return of $r_f = 0$. The risky assets have a positive (exogenous) net supply denoted by a vector $\overline{y}$. The excess returns of risky assets by a vector r_{t+1} with $\mathbb{E}_t[r_{t+1}] = \mu_t$. Type-$i$ trader's the next period net-worth is $e_{t+1}^i = r_{t+1}' y_t^i + e_t^i = e_t^i(r_{t+1}' x_t^i + 1)$ where a weight vector $x_t^i = y_t^i / e_t^i$.

We assume that retail investors are passive in the sense that they invest in risky assets only through mutual funds. In particular, they put more money into the mutual funds sector, thus increasing the flows to the funds.

Following Black (1972) and Frazzini and Pedersen (2014), risk-averse mutual fund trader whose risk-tolerance $1/\gamma_m$ solves

$$\max_{x_t^m} x_t^{m\prime} \mu_t - \frac{\gamma_m}{2} x_t^{m\prime} \Sigma_t x_t^m \tag{21}$$

subject to their leverage constraint

$$x_t^{m\prime} \mathbf{1} \leq \nu_t^m \tag{22}$$

where ν_t^m determines the effective leverage constraint. For instance, $\nu_t^m = 1$ reduces to Black (1972).

The leverage-constrained risk-averse mutual funds' optimal holding for risky assets is

$$x_t^m = \frac{1}{\gamma_m}\Sigma^{-1}\left(\mu_t - \psi_t^m \mathbf{1}\right) \tag{23}$$

where $1/\gamma_m$ mutual funds' risk-tolerance and λ_t^m measures the shadow price of the binding leverage constraint at time t, decreasing in the effective leverage constraint ν_t^m.

On the other hand, the risk-neutral arbitrageurs maximize

$$\max_{x_t^h} \; x_t^{h'}\mu_t \tag{24}$$

subject to the Value-at-Risk constraint

$$x_t^{h'}\Sigma_t x_t^h \leq \overline{\sigma}_t^2 \tag{25}$$

where $\overline{\sigma}_t$ is an exogenous constant reflecting the arbitrageurs' VaR policy (i.e., the maximum allowable risk in a hedge fund's position). The parameter $\overline{\sigma}_t$ is time-varying, potentially depending on the net worth of hedge fund sector e_t^h.

Notably, the arbitrageurs' Lagrangian, corresponding to their optimization, is

$$\mathcal{L}_h(x_t^h, \gamma_h) = x_t^{h'}\mu_t + \frac{\gamma_t^h}{2}\left(\overline{\sigma}_t^2 - x_t^{h'}\Sigma_t x_t^h\right) \tag{26}$$

where $\gamma_t^h/2$ is the multiplier (i.e., shadow price) to the VaR constraint. The arbitrageurs' optimal demand for risky assets is then

$$x_t^h = \frac{1}{\gamma_t^h}\Sigma_t^{-1}\mu_t \tag{27}$$

From the binding VaR constraint, we have

$$\frac{1}{\gamma_t^h} = \frac{\overline{\sigma}_t}{\sqrt{\mu_t' \Sigma_t^{-1} \mu_t}} \tag{28}$$

The inverse of the multiplier $1/\gamma_t^h$ represents the arbitrageurs' risk appetite, which can fluctuate based on their current net worth. This risk appetite naturally varies over time in response to changes in their net worth. For example, during adverse market conditions that diminish arbitrageurs' net worth, their risk-bearing capacity decreases accordingly. This dynamic relationship between market conditions, arbitrageur net worth, and risk-bearing capacity makes the arbitrageurs' risk-bearing capacity time-varying.[15]

A Wallasian auctioneer clears the financial market:

$$e_t^m x_t^m + e_t^h x_t^h = \overline{y} \tag{29}$$

Lemma 1. *The equilibrium returns satisfy*

$$\mu_t = \underbrace{\overline{\gamma}_t \, \Sigma_t \, \overline{y}}_{\textit{CAPM}} + \underbrace{\phi_t \mathbf{1}}_{\textit{Frictions}}$$

The sensitivity to the mispricing and the average amount of mispricing are

$$\frac{1}{\overline{\gamma}_t} = \left(\frac{e_t^m}{\gamma_m} + \frac{e_t^h}{\gamma_t^h} \right), \qquad \phi_t = \underbrace{\psi_t^m}_{\substack{\textit{shadow cost of} \\ \textit{MF's margin constraint}}} \cdot \left(\frac{\overbrace{(e_t^h / \gamma_t^h)}^{\textit{HF' average risk-"appetite"}}}{\underbrace{(e_t^m / \gamma_m)}_{\textit{MF's averge risk-tolerance}}} + 1 \right)^{-1}$$

where $1/\gamma_m$ represents the mutual funds' risk tolerance, $1/\gamma_t^h$ is the arbitrageurs' time-varying risk-"appetite", and ψ_t^m is the mutual funds' time-varying shadow cost of leverage constraint. The arbitrageurs' aggregate risk-"appetite" is the inverse of the shadow cost of the arbitrageurs' VaR constraint and is

[15] Lagrangian multipliers associated with VaR constraints have been first studied by Gromb and Vayanos (2002) and Danielsson et al. (2009).

proportional to their net worth at time t.

All proofs are contained in the Appendix.

Proposition 1. *The equilibrium expected excess returns of assets satisfies:*

$$\mathbb{E}_t[r_{it+1}] = \beta_{it}\lambda_t + \phi_t \tag{30}$$

where the price of risk

$$\lambda_t = \mathbb{E}_t[r_{mt+1}] - \phi_t \tag{31}$$

Corollary 1. *The equilibrium price of asset i is*

$$p_{it} = \frac{\mathbb{E}_t[p_{it+1}]}{1 + \beta_{it}\mathbb{E}_t[r_{mt+1}] + (1-\beta_{it})\phi_t} \tag{32}$$

Corollary 2. *Keeping all other things fixed, as the arbitrageurs (HFs) become well-capitalized, their aggregate risk appetite e_t^h/γ_t^h increases and the mispricing ϕ_t decreases. The expected returns on risky assets then deviate less from a standard CAPM.*

The mtual funds' optimal holding for a risky asset n is

$$x_t^m(n) = \frac{1}{\gamma_t^m}\left(\Sigma_t^{-1}(n)\mu_t - \psi_t^m \cdot \Sigma_t^{-1}(n)\mathbf{1}\right) \tag{33}$$

where $\Sigma_t^{-1}(n)$ represents the n^{th} row vector of the precision matrix Σ_t^{-1}. It is well known that (33) is difficult to estimate in a working precision because one cannot precisely estimate Σ_t^{-1}.

Following Koijen and Yogo (2019), we apply the demand-based asset pricing technique.

$$\ln\left(\frac{x_t^m(n)}{x_t^m(0)}\right) = b_{m,p}p(n) + b'_{m,\theta}\theta(n) + \epsilon_m(n) \tag{34}$$

Here $p(n)$ represents the market price of risky asset n in the mutual funds investment universe and $b_{m,p}$ is the elasticity of demand for the risky asset n. The parameter $\theta(n)$ represents asset n's K-dimensional characteristics vector, $b_{m,\theta}(k)$ and $\epsilon_m(n)$ represent a mutual funds m's strategy tilts toward k^{th} characteristic, controlling other characteristics, and mutual fund m's unobservable latent demand for the risky asset n, respectively.

Figure 1 presents the estimates of characteristics-based demand for each institution type from 1980Q1 to 2022Q3. The horizontal axis displays the cross-sectional means of the estimated coefficients on market beta, weighted by assets under management, for each institution type and quarter. Notably, the mean estimated coefficients on market beta characteristics for mutual funds are consistently positive, both economically and statistically significant, throughout almost the entire sample period. This indicates that mutual funds significantly tilt their portfolios towards high-beta assets.

7 Conclusion

We provide compelling evidence that mutual fund flows significantly explain the beta anomaly in asset pricing. Our analysis reveals that the beta anomaly manifests only following uptrend markets, while the CAPM holds following downtrend markets. Mutual funds with high-beta assets receive significantly larger capital flows than those with low-beta assets with market fluctuations during uptrend markets. This leads to greater cumulative demand pressure on high-beta assets. Due to their substantially less elastic demand than low-beta assets, high-beta assets experience more pronounced price impacts and subsequent underperformance (reversal) exclusively following uptrend markets.

Our study highlights the importance of distinguishing between uptrend and downtrend market conditions in asset pricing research. The trend-based measure we introduce captures long-term accumulating flow-driven demand pressures, more directly examining how market dynamics contribute to the beta anomaly than sentiment-based measures.

Our research contributes to the literature on inelastic demands for financial assets by providing a novel explanation for the low-risk anomaly. We demonstrate assets' demand elasticity depends on their systematic risk, and show that high-beta assets experience significantly larger price impacts than low-beta stocks, not only because they receive larger flow-driven demand pressure but also because their demand is substantially less elastic.

Future research could explore the development of predicting fund flows and their impact on asset prices, investigate the long-term persistence of the flow-induced effects on the beta anomaly and its potential connection to momentum anomaly, and examine how changes in market structure or regulatory environments might affect the relationship between fund flows and asset pricing anomalies.

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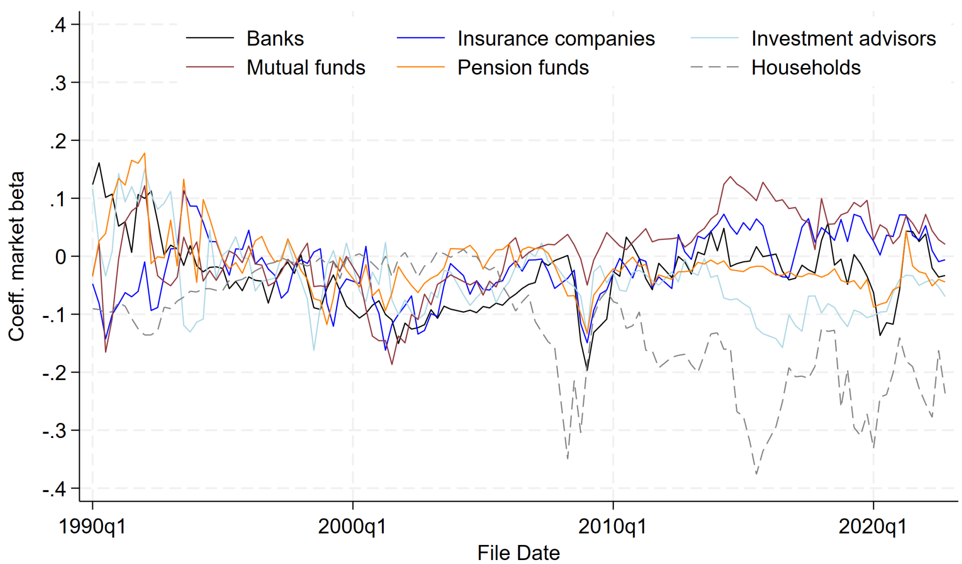
A Figures and Tables

A.1 Figures



Following Koijen and Yogo (2019), characteristics-based demand is estimated for each institution at each quarter. This figure reports the cross-sectional mean of the estimated coefficients on the market beta by institution type, weighted by assets under management. The quarterly sample period is from 1980Q1 to 2022Q3.

Figure 1: Average coefficients on the market beta characteristics by instituion type

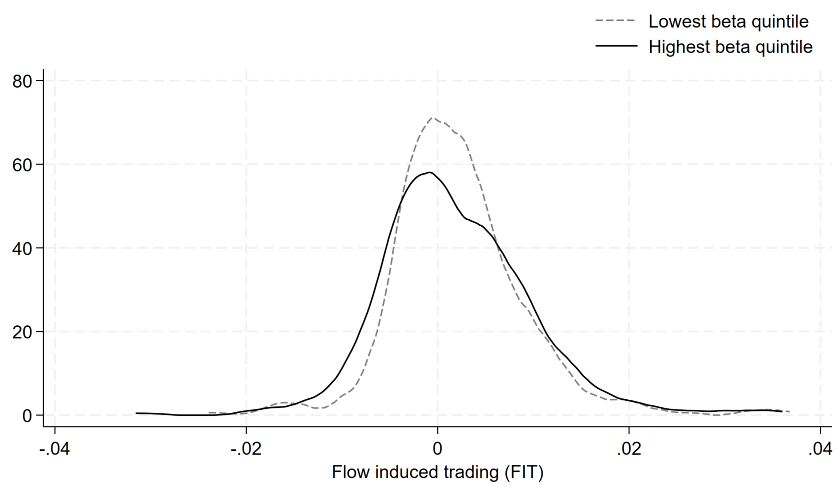
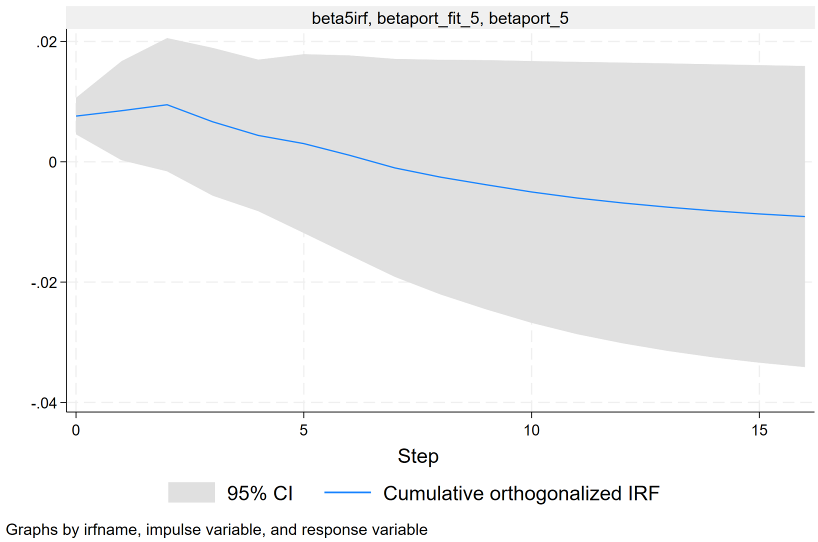
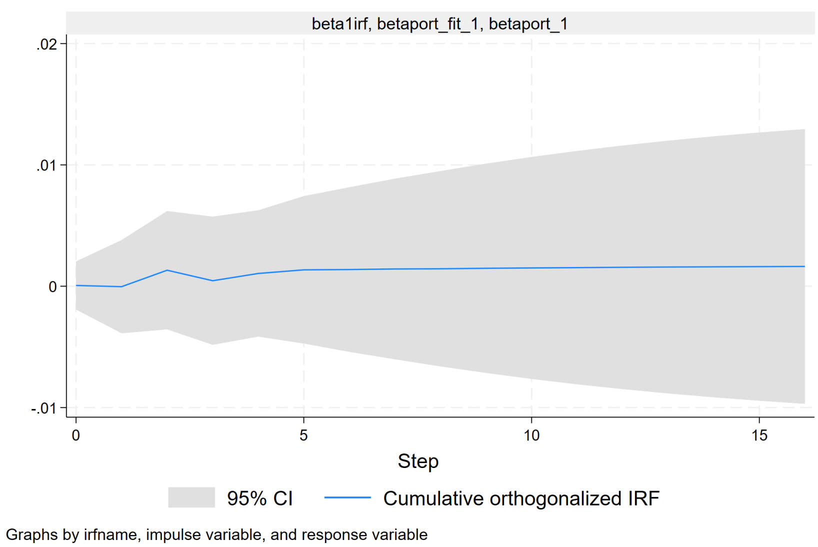


Figure 2: Flow-induced trades unconditional distributions in the highest and lowest beta quintiles



(a) Panel A: Highest-beta quintile



(b) Panel B: Lowest-beta quintile

The figure illustrates the impulse responses of monthly asset returns with respect to an instant FIT shock, estimating from the SVAR model (9). Panel A shows the impulse responses of asset returns in the highest-beta quintile. Panel B shows the impulse responses of asset returns in the lowest-beta quintile.

Figure 3: Responses of Asset Returns with FIT Impulse shock

A.2 Tables

Table 1: Funds' trade Responses to Capital Flows

This table reports panel regressions of flow to fund j on the fund j's corresponding trade in period t. Fund j's flow at time t is defined in (1) and its trade at time t is defined by (2). The panel regressions include firm and time-fixed effects. Standard errors in both panels are clustered by firm and quarter/month.

Panel A: S12 Quarterly holdings [1990Q1 - 2022Q4]

	Outflow sample $trade_{i,j,t}$	Inflow sample $trade_{i,j,t}$
$flow_{j,t}$	0.883***	1.122***
	(26.06)	(23.98)
N	17,273,547	13,912,375
Within R^2	0.011	0.119

Panel B: CRSP Monthly holdings [2008m6 - 2022m12]

	Outflow sample $trade_{i,j,t}$	Inflow sample $trade_{i,j,t}$
$flow_{j,t}$	0.891***	1.152***
	(5.83)	(56.80)
N	32,194,510	22,326,297
Within R^2	0.028	0.346

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Fund Flows by Sample Beta Quintiles

This table reports panel regressions and means of monthly fund flows partitioned into quintiles of fund-level betas. Fund-level betas are calculated using rolling window regressions of fund excess returns on market excess returns. Panel A reports means by beta quintile. Panel B reports panel regressions of monthly fund flows regressed on the market factor and lags of the market factor. Columns report regressions by beta quintile. Betas are calculated using the previous 36 months of returns (requiring a minimum of 18 months). The regressions in Panel B include fund fixed effects. Standard errors in both panels are clustered by month and fund.

Panel A: Mean Flow

	Low β	(2)	(3)	(4)	High β	Wald
Mean	0.0000730	0.00180***	−0.000145	−0.00102**	−0.00137**	4.99**
	(0.15)	(4.31)	(−0.36)	(−2.37)	(−2.21)	
N	238669	238903	238906	238882	238678	

Panel B: Flow and Mrkt-RF

	Low β	(2)	(3)	(4)	High β	Wald
Mkt-RF	0.0112	0.0247**	0.0186**	0.0371***	0.0746***	14.90***
	(1.00)	(2.54)	(2.34)	(4.29)	(5.93)	
lag_mktrf	−0.00419	−0.000699	0.00142	0.0200**	0.0277**	4.08**
	(−0.37)	(−0.08)	(0.17)	(2.26)	(2.20)	
lag2_mktrf	0.00563	0.00413	0.00307	0.0122	0.0194	0.46
	(0.61)	(0.47)	(0.38)	(1.37)	(1.43)	
lag3_mktrf	−0.0119	−0.00897	−0.00871	0.00313	0.00361	0.81
	(−1.32)	(−1.09)	(−1.22)	(0.42)	(0.32)	
lag4_mktrf	0.0182	0.0155	0.0148*	0.0223**	0.0270*	0.09
	(1.59)	(1.57)	(1.67)	(2.52)	(1.70)	
lag5_mktrf	−0.0188*	−0.00936	−0.00912	−0.00204	−0.00936	0.21
	(−1.66)	(−0.89)	(−0.97)	(−0.21)	(−0.63)	
lag6_mktrf	−0.00650	−0.00376	−0.00137	−0.000112	0.00303	0.20
	(−0.67)	(−0.41)	(−0.17)	(−0.01)	(0.24)	
N	238572	238732	238735	238726	238548	
R^2	0.0606	0.104	0.0934	0.0785	0.0520	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Market to Flow Induced Trade (FIT) response by NYSE Beta Quintiles

This table reports panel regressions and means of monthly flow-induced trades (FIT) partitioned into quintiles using NYSE beta-quintile cut offs each month. Betas are calculated using rolling window regressions of stock excess returns on market excess returns. Panel A reports means by beta quintile. Panel B reports panel regressions of monthly FIT regressed on the market factor and lags of the market factor. Columns report regressions by beta quintile. Betas are calculated using the previous 36 months of returns (requiring a minimum of 18 months). The regressions in Panel B include firm fixed effects. Standard errors in both panels are clustered by firm and month.

Panel A: Mean FIT

	Low β	(2)	(3)	(4)	High β	Wald
Mean	0.00415***	0.00339***	0.00333***	0.00326***	0.00451***	0.99
	(8.40)	(7.04)	(7.00)	(6.92)	(8.02)	
N	314434	244907	223138	227030	346039	

Panel B: FIT and Mrkt-RF

	Low β	(2)	(3)	(4)	High β	Wald
Mkt-RF	0.0289***	0.0290***	0.0326***	0.0366***	0.0483***	7.15***
	(2.97)	(2.92)	(3.41)	(3.97)	(4.85)	
lag_mktrf	0.0313***	0.0298***	0.0289***	0.0290***	0.0363***	0.21
	(3.32)	(3.23)	(3.30)	(3.21)	(2.91)	
lag2_mktrf	0.00519	0.00777	0.0109	0.0126	0.0153	1.30
	(0.57)	(0.87)	(1.28)	(1.42)	(1.37)	
lag3_mktrf	0.0108	0.00924	0.0114	0.00889	0.0205*	1.24
	(1.15)	(0.99)	(1.26)	(0.99)	(1.73)	
lag4_mktrf	0.0181*	0.0162	0.0175*	0.0168	0.0198	0.00
	(1.78)	(1.56)	(1.71)	(1.59)	(1.40)	
lag5_mktrf	−0.00255	−0.00338	−0.00216	−0.00261	0.00413	0.66
	(−0.23)	(−0.29)	(−0.19)	(−0.24)	(0.34)	
lag6_mktrf	−0.0182	−0.0158	−0.0158	−0.0160	−0.0132	0.46
	(−1.49)	(−1.37)	(−1.40)	(−1.42)	(−0.99)	
N	313882	244150	222366	226336	345622	
R^2	0.143	0.145	0.154	0.155	0.116	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Market to Flow Induced Trade (FIT) response by NYSE Beta Quintiles
(Up- and Down-trend Markets)

This table reports panel regressions of firm-level 24-month rolling average FIT on (24-month rolling avg r^e_{mt}) $\times \mathbf{1}_{\text{Downtrend Market}}$ and (24-month rolling avg r^e_{mt}) $\times \mathbf{1}_{\text{Uptrend Market}}$. We partition stocks based upon NYSE beta-quintile cut offs each month. Columns report regressions by beta quintile. $\mathbf{1}_{\text{Uptrend Market}}$ and $\mathbf{1}_{\text{Downtrend Market}}$ are dummy variables indicating that the rolling 24-month average of past market returns are below or above the sample median of 24-month rolling average market returns. Betas are calculated using the previous 36 months of returns (requiring a minimum of 18 months). The sample includes all firms for which we are able to measure FIT in a given month. The sample period is from January, 1991 through March, 2021.The regressions include firm fixed effects. Standard errors are clustered by firm and month.

24-month rolling avg FIT

	Low β	(2)	(3)	(4)	High β	Wald
(24-month rolling avg r^e_{mt}) $\times \mathbf{1}_{\text{Downtrend Market}}$	0.0726**	0.0159	−0.00633	−0.0136	−0.0190	7.59***
	(2.48)	(0.52)	(−0.22)	(−0.50)	(−0.77)	
(24-month rolling avg r^e_{mt}) $\times \mathbf{1}_{\text{Uptrend Market}}$	0.0723***	0.0643***	0.0610***	0.0486**	0.0531***	0.61
	(3.11)	(2.78)	(2.93)	(2.55)	(2.61)	
N	364566	274875	249484	254493	399044	
r2	0.456	0.429	0.450	0.463	0.433	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Price Impacts by NYSE Beta Quintiles

This table reports panel regressions and means of monthly de-levered excess returns partitioned into quintiles of stock-level betas using NYSE beta-quintile cut offs each month. Excess returns are de-levered by subtracting exposure to market returns: $R_{it}^{ZL} = R_{it}^{e} - \beta \times R_{M,t}^{e}$. Betas are calculated using rolling window regressions of stock excess returns on market excess returns. Panel A reports mean zero-leverage excess return by beta quintile. Panel B reports panel regressions of monthly zero-leverage excess returns regressed on stock-level FIT and the average lagged value of stock FIT over the previous 6 months. Columns report regressions by beta quintile. Betas are calculated using the previous 36 months of returns (requiring a minimum of 18 months). The regressions in Panel B include firm and month fixed effects. Standard errors in both panels are clustered by firm and month.

Panel A: Mean Zero-Leverage Returns

	Low β	(2)	(3)	(4)	High β	Wald
Mean	0.00910***	0.00539***	0.00324**	0.00191	−0.00391	9.87***
	(4.05)	(3.87)	(2.18)	(1.07)	(−1.06)	
N	459750	305764	272141	277292	447599	

Panel B: Zero-Leverage Excess Returns and FIT

	Low β	(2)	(3)	(4)	High β	Wald
FIT_t	0.150***	0.234***	0.278***	0.280***	0.341***	27.16***
	(6.73)	(8.36)	(7.08)	(8.48)	(8.90)	
FIT_{t-1}	−0.0167	−0.0868***	−0.0408	−0.0681	−0.0876	2.28
	(−0.62)	(−2.73)	(−1.22)	(−1.58)	(−1.61)	
FIT_{t-2}	−0.0300	−0.0561**	−0.0129	−0.0278	−0.0416	0.11
	(−1.24)	(−2.30)	(−0.52)	(−0.90)	(−1.34)	
FIT_{t-3}	0.00706	−0.00195	−0.0173	−0.00331	−0.00353	0.12
	(0.25)	(−0.09)	(−0.63)	(−0.10)	(−0.13)	
FIT_{t-4}	−0.0216	−0.00104	−0.0221	−0.0466	0.0465	4.07**
	(−0.92)	(−0.04)	(−0.94)	(−1.41)	(1.41)	
FIT_{t-5}	0.00187	0.00421	−0.0460*	−0.0186	−0.0455	2.18
	(0.09)	(0.20)	(−1.66)	(−0.61)	(−1.43)	
FIT_{t-6}	−0.0498*	−0.00540	−0.0443*	0.00536	−0.0451	0.02
	(−1.83)	(−0.21)	(−1.65)	(0.18)	(−1.28)	
N	249455	190625	174198	179614	285602	
R^2	0.111	0.118	0.115	0.113	0.106	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Price Impacts of FIT on NYSE Beta Quintiles Returns

This table reports panel regressions and means of monthly excess returns partitioned into quintiles of stock-level betas using NYSE beta-quintile cut-offs each month. Betas are calculated using rolling window regressions of stock excess returns on market excess returns. Panel ! reports panel regressions of monthly market neutral returns regressed on stock-level FIT and the average lagged value of stock FIT over the previous 6 months. We define market neutral returns as $r_{it}^{ZL} := r_{it}^{e} - \beta_{it} r_{mt}^{e}$. Columns report regressions by beta quintile. Betas are calculated using the previous 36 months of returns (requiring a minimum of 18 months). The regressions in Panel B include firm and time-fixed effects. Standard errors in both panels are clustered by firm and month.

	Low β	(2)	(3)	(4)	High β	Wald
FIT	0.159***	0.225***	0.289***	0.292***	0.340***	36.98***
	(7.02)	(8.67)	(7.76)	(8.47)	(8.13)	
avg lag FIT	-0.0811**	-0.0964**	-0.151***	-0.155***	-0.127**	32.18***
	(-2.53)	(-2.42)	(-3.27)	(-2.74)	(-2.17)	
N	309084	241612	220288	224158	341561	
R^2	0.121	0.184	0.193	0.198	0.194	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Price Impacts of FIT on NYSE Beta Quintiles Returns

This table reports panel regressions of monthly market-neutral return r_{it}^{ZL} regressed on avg 24-lag FIT $\times \mathbf{1}_{\text{Downtrend Market}}$ and 24-lag FIT $\times \mathbf{1}_{\text{Uptrend Market}}$. The dependent variable, r_{it}^{ZL} is calculated for each firm i at time t: $r_{it}^{ZL} := r_{it}^{e} - \beta_{it} r_{mt}^{e}$. Regressions are run after partitioning the sample into quintiles based upon stock-level betas. We use NYSE beta-quintile cut-offs each month. Betas are calculated using the previous 36 months of returns (requiring a minimum of 18 months) regressed on the market factor. $\mathbf{1}_{\text{Downtrend Market}}$ and $\mathbf{1}_{\text{Uptrend Market}}$ denote dummies indicating current market excess returns are below and above sample median values of rolling 24 months average market returns. The regressions include firm fixed effects. Standard errors in the panel is clustered by firm and month.

	Low β	(2)	(3)	(4)	High β	Wald
avg 24-lag FIT $\times \mathbf{1}_{\text{Downtrend Market}}$	-0.0141	-0.0116	-0.0510	-0.166**	-0.0423	0.13
	(-0.32)	(-0.19)	(-0.68)	(-2.07)	(-0.50)	
avg 24-lag FIT $\times \mathbf{1}_{\text{Uptrend Market}}$	-0.0449	-0.0778	-0.152**	-0.133	-0.282***	9.36***
	(-0.82)	(-1.39)	(-2.05)	(-1.41)	(-2.85)	
N	360367	272706	247526	252077	392886	
r2	0.107	0.106	0.101	0.102	0.0972	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Price Impacts: Structural vector autoregressive (SVAR) model

This table reports the parameter estimates of the SVAR model defined in (9). The estimates of the triangular matrix A determine the contemporaneous relationship between the components of the vector $Y_t = [r_{mt}, FIT_{it}, r_{it}]$. Panel A reports the estimates of matrix A of SVAR for the highest-beta quintile portfolio. Panel B reports those estimates for the lowest-beta quintile portfolio.

Panel A: SVAR estimates for the highest-beta quintile

Matrix A	Coeff.	Std. err.	Z-statistics
a_{21}	-0.045***	0.691	-6.36
a_{31}	-1.544***	0.042	-41.94
a_{32}	-1.269***	0.254	-5.00

Panel B: SVAR estimates for the lowes-beta quintile

Matrix A	Coeff.	Std. err.	Z-statistics
a_{21}	-0.021***	0.006	-3.30
a_{31}	-0.573***	0.023	-24.52
a_{32}	-0.012	0.184	-0.06

Table 9: Fama-MacBeth Regressions, Beta-Sorted Portfolios

This table reports results from two-pass Fama-MacBeth regressions using beta-sorted portfolios from Kenneth French's data library. For each of the five NYSE quintile sorted portfolios, we first calculate one-factor betas for each portfolio. For completeness we calculate both full sample (Panel A) and 36 month rolling window (Panel B) betas of the five portfolios. Next we regress portfolio excess returns on the betas to get slope estimates, λ, for each month. Finally, we average the slope estimates over the full sample, sub-periods. We examine sub-periods where the rolling average of past 24 months of market returns is above and below the median value of the rolling 24 month average market returns.

Panel A: Full-Sample Betas

	Full	Downtrend	Uptrend
$\widehat{\lambda}_0(\%)$	0.55	0.13	0.98
	(2.69)	(0.46)	(3.41)
$\widehat{\lambda}(\%)$	0.06	0.64	-0.55
	(0.23)	(1.59)	(-1.56)
$(\widehat{\lambda} - \bar{R}^e_M)(\%)$	-0.50	-0.06	-0.94
	(-2.45)	(-0.20)	(-3.44)
Obs	677	338	339

Panel B: Rolling-Window Betas

	Full	Downtrend	Uptrend
$\widehat{\lambda}_0(\%)$	0.47	-0.06	1.00
	(2.24)	(-0.19)	(3.37)
$\widehat{\lambda}(\%)$	0.13	0.79	-0.56
	(0.47)	(1.99)	(-1.43)
$(\widehat{\lambda} - \bar{R}^e_M)(\%)$	-0.43	0.09	-0.95
	(-2.03)	(0.30)	(-3.23)
Obs	677	338	339

Table 10: Zero-Leverage NYSE-sorted Beta Portfolio Excluding Extreme FIT

This table reports time series regressions where monthly zero-leverage portfolio excess returns are regressed on the market factor. Portfolios are formed based upon NYSE beta cutoffs using a 36 month rolling window. Each portfolio is value-weighted and contains stocks for which we have FIT measures in a given month. Zero leverage portfolio returns are calculated by $R^{ZL}_{i,t} := R^{e}_{i,t} - \beta_{it} R^{e}_{M,t}$. Panel A reports α and β for each portfolio. Panel B reports results when stocks with high past FIT are removed from each portfolio. We measure past FIT as the average FIT for each stock over the previous 24 months (requiring at least 18 months of observed FIT within the 24 month rolling window). We define a stock to have high past FIT if its average FIT over the past 24 months is in the top 30% of all observations that month. Panel C reports results when the lowest 30% of past FIT stocks are removed each month. In Panels B and C, the numbers in square brackets report t-statistics for differences between point estimates and those in Panel A. Standard errors are adjusted Newey-West with 6 month lags.

Panel A: Beta Portfolio Excess Returns

	β_L	2	3	4	β_H
$\alpha(\%)$	0.09	0.07	0.01	–0.09	–0.41
	(0.65)	(0.64)	(0.08)	(–0.74)	(-2.19)
β	–0.04	–0.01	0.00	0.01	0.04
	(–0.98)	(–0.26)	(–0.07)	(0.27)	(0.71)
$R^2(\%)$	0.83	0.06	0	0.06	0.3
N	327	327	327	327	327
Avg # stocks	828.8	611.65	548.97	559.02	880.58

Panel B: Beta Portfolios Excluding High FIT_{24m}

	β_L	2	3	4	β_H
$\alpha(\%)$	0.12	0.20	0.14	0.08	–0.09
	(0.77)	(1.51)	(0.98)	(0.51)	(–0.43)
	[0.40]	[1.97]	[1.50]	[1.82]	[2.46]
β	–0.04	–0.01	–0.01	0.01	0.05
	(–0.79)	(–0.32)	(–0.12)	(0.33)	(0.96)
	[0.23]	[–0.17]	[–0.13]	[0.13]	[0.26]
$R^2(\%)$	0.53	0.08	0.01	0.07	0.47
N	327	327	327	327	327
Avg # stocks	453.41	365.11	337.17	349.39	527.34

Panel C: Beta Portfolios Excluding Low FIT_{24m}

	β_L	2	3	4	β_H
$\alpha(\%)$	0.16	0.16	0.09	0.09	–0.36
	(1.05)	(1.18)	(0.72)	(0.55)	(–1.69)
	[0.88]	[1.13]	[0.91]	[1.63]	[0.50]
β	–0.05	–0.01	–0.01	0.04	0.06
	(–1.04)	(–0.15)	–0.29)	(0.82)	(0.97)
	[–0.25]	[0.24]	[–0.46]	[1.44]	[0.59]
$R^2(\%)$	0.80	0.02	0.05	0.50	0.51
N	327	327	327	327	327
Avg # stocks	477.75	359.62	324.93	332.74	542.94

Table 11: Time-Series Regressions of Difference: $R^{ZL}_{exFIT} - R^{ZL}$

This table presents results of time series regressions for each NYSE-β-sorted, zero-leverage portfolio's monthly returns. For each beta portfolio, $i \in \{1,2,3,4,5\}$, zero-leverage portfolio returns are defined by $R^{ZL}_{i,t} := R^{e}_{i,t} - \beta_{it} R^{e}_{M,t}$. Each column reports results of the difference between the beta-sorted portfolio with high past 24m FIT stocks removed (R^{β}_{exFIT}) and the beta-sorted portfolio without any stocks removed ($R^{\beta,ZL}$). A stock is said to have high past 24m FIT if it is in the top 30% of all stocks' average past 24m FIT over the previous 24 months. The regressions reported in the table are meant to determine whether differences in expected returns, $R^{\beta,ZL}_{exFIT} - R^{\beta,ZL}$), are due to known systematic risk exposures. Standard errors are calculated using Newey-West adjustments with 6 lags.

	Low-β	2	3	4	high-β
α(%)	0.09	0.13	0.16	0.17	0.26
	(1.27)	(2.31)	(2.03)	(2.07)	(2.69)
mrkt	–0.03	–0.01	–0.03	–0.02	0.03
	(–1.20)	(–0.83)	(–1.05)	(–0.63)	(1.01)
SMB	0.02	0.07	0.05	0.08	0.03
	(0.82)	(2.52)	(1.45)	(2.21)	(0.66)
HML	0.09	0.09	0.00	–0.10	0.02
	(2.32)	(1.94)	(0.08)	(–2.02)	(0.36)
RMW	–0.07	–0.02	0.00	0.09	0.14
	(–2.13)	(–0.66)	(0.06)	(2.20)	(1.90)
CMA	–0.1	–0.06	–0.01	0.03	0.07
	(–1.98)	(–1.25)	(–0.19)	(0.48)	(0.86)
UMD	–0.03	0.02	–0.05	–0.07	–0.06
	(–1.60)	(1.39)	(–1.85)	(–4.62)	(–1.88)
R^2(%)	5.94	7.54	3.51	7.09	7.58
Obs	327	327	327	327	327

A.3 Proofs

Proof of Proposition 1. Define the market risk premium

$$r_{mt+1} = \bar{w}' r_{t+1} \qquad \text{where } \bar{w} = \frac{\overline{y}}{\overline{y}'\mathbf{1}} \tag{35}$$

Note that

$$\mathbb{E}_t[r_{mt+1}] = \bar{w}'\mu_t \overset{in\, eqb.}{=} \bar{w}'\left(\overline{\gamma}_t \Sigma_t \bar{w} + \phi_t \mathbf{1}\right) = \bar{\gamma}_t \bar{w}' \Sigma_t \bar{w}_t + \phi_t \tag{36}$$

Note also that

$$\texttt{cov}_t(r_{t+1}, r_{mt+1}) = \texttt{cov}_t\left(r_{t+1}, r_{t+1}'\bar{w}\right) = \Sigma_t\,\bar{w}, \qquad \texttt{var}_t(r_{mt+1}) = \bar{w}'\Sigma_t\bar{w}, \tag{37}$$

Therefore, in equilibrium, we have

$$\mathbb{E}_t[r_{t+1}] \;\;=\;\; \bar{\gamma}_t\Sigma_t\bar{w} + \phi_t\mathbf{1} = \bar{\gamma}_t\bar{w}'\Sigma_t\bar{w}\cdot\frac{\Sigma_t\bar{w}}{\bar{w}'\Sigma_t\bar{w}} + \phi_t\mathbf{1} = (\mathbb{E}_t[r_{mt+1}] - \phi_t)\beta_t + \phi_t\mathbf{1} \tag{38}$$