Reaching for Beta*

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Abstract

Using equity mutual fund holdings and transactions, we show that managers actively tilt toward high-beta stocks when monetary policy is contractionary and short rates rise. This "reaching for beta" is persistent, elevates sector-wide net buying of high-beta stocks, and attracts fund inflows under tighter policy. It raises funds' raw but not risk-adjusted returns and induces temporary stock-level price pressure that subsequently reverts. We show that reaching for beta is consistent with fund managers counteracting investor outflows by boosting expected returns. Unlike reaching for yield in bonds, tighter policy increases risk-taking in equities, revealing a beta channel of monetary policy transmission.

Keywords: Interest Rates, Monetary Policy, Mutual Funds, Risk-shifting, High Beta Stocks

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1 Introduction

How risk-free rates and monetary policy impact investors' portfolio allocations is a central question in macroeconomics and finance. Recent research has documented that low interest rates and easy monetary policy induce different types of investors to reach for higher-yielding, often riskier, fixed-income assets to boost returns and attract inflows (e.g., Kacperczyk and Schnabl, 2013; Hanson and Stein, 2015; Becker and Ivashina, 2015; Choi and Kronlund, 2018). In this literature, higher interest rates are generally associated with less risk-taking.

In this paper, we show that equity mutual funds respond to interest rate changes in the opposite way: when short-term interest rates rise and monetary policy tightens, they actively tilt portfolios towards high market-beta stocks. As a result, higher rates lead to more risk-taking for these intermediaries. We label this novel type of risk-taking behavior *Reaching for Beta (RFB)*.

We show that RFB has important implications for fund investors and asset prices. Funds that actively reach for beta attract more inflows when monetary policy is tight and generate higher raw returns. However, they don't earn significant alphas for taking more market risk. Thus, reaching for beta does not indicate superior managerial skill. Consistently, we find that RFB is associated with immediate price pressures of high-beta stocks, which only gradually dissipate over time. Our findings reveal a beta channel of monetary policy transmission to equity markets.

We argue that this behavior is consistent with fund managers' career concerns. When short rates rise, investors reallocate toward safer outside options such as money market funds. With their compensation being closely tied to assets under management (AUM) and performance, equity fund managers respond by boosting expected returns to preserve AUM. As explicit leverage is tightly regulated for these funds, managers scale risk within their mandate by tilting their portfolios towards high-beta stocks.

Consistent with this explanation, we show that (i) the aggregate equity fund sector experiences outflows when monetary policy tightens, (ii) higher short rates lead to net purchases of high-beta stocks controlling for other characteristics, and (iii) funds facing lower flow-performance pressures reach for beta less. Alternative explanations based on central bank information effects, implicit leverage constraints, and market timing are not supported by the data. We formalize this mechanism in a parsimonious static partial equilibrium model in the Online Appendix.

We start our analysis by constructing a measure of reaching for beta (RFB) that captures how much each fund tilts its portfolio toward high-beta stocks. Our approach is similar in spirit to the reaching-for-yield measure of Choi and Kronlund (2018). In our baseline analysis, we define *total* RFB as the deviation of the value-weighted fund beta from a global benchmark fund beta which we set equal to the market beta of 1. Our results are robust to instead using (i) the fund's stated prospectus benchmark index and (ii) the fund's own lagged beta as an implicit proxy of the benchmark. We also decompose total RFB into an active component due to the managers' active portfolio reallocation and a passive component driven by price changes. Active rebalancing towards higher-beta stocks is the key driver of variation in total reaching for beta.

Armed with our RFB measures, we first assess whether fund managers tilt their portfolios toward high-beta stocks in response to a rise in risk-free Treasury yields of different maturities. It is particularly changes in short rates that prompt fund managers to adjust the beta allocation of their portfolios. We control for potential market timing and dynamic liquidity management among mutual funds in these regressions. The results suggest that RFB, especially its active component, is tightly linked to the short end of the yield curve and does not depend much on broader equity market conditions.

We then explicitly analyze the role of monetary policy for funds' beta allocation. We do so by using the monetary policy surprise measure of Nakamura and Steinsson (2018) updated by Acosta et al. (2024) as an instrument for short-term yields in a two-stage least squares (2SLS) analysis. Fund managers actively tilt their portfolios toward high-beta stocks in response to a surprise tightening of monetary policy. Using local projections in the spirit of Jordà (2005), we also show that beta-tilting increases for about one year after surprise hikes by the Federal Reserve. Hence, monetary policy leads to persistent reallocations of equity mutual fund portfolios. Unlike recent evidence for bond funds (Adrian et al., 2024), the response of RFB is symmetric regarding tightening versus easing shocks.

We complement our evidence from quarterly mutual fund holdings with two stock-level analyses that further leverage the granularity of our data. First, we investigate the share-based net purchases of the equity fund sector for individual stocks. We confirm that beta-tilting in response to higher short rates and tighter monetary policy reflects active mutual fund trading and is not captured by other stock-level risk characteristics such as the dividend yield, the book-to-market ratio, and cash-flow duration. Second, using the Abel Noser database of daily institutional trading, we study the high-frequency response of fund managers' net stock-level purchases to monetary policy shocks. Consistent with our quarterly results, we find that funds' cumulative net buying pressure for high beta stocks remains flat for about two to three months after surprise Federal Reserve rate hikes and then rises sharply and persistently.

We show that the documented behavior is consistent with managerial incentives. The aggregate equity fund sector experiences outflows when monetary policy tightens. To defend AUM by boosting expected returns, the average fund actively reaches for beta, given constraints on using explicit leverage. However, larger funds, older funds, and funds of larger families adjust their beta less strongly, consistent with prior evidence that these funds face lower flow-performance pressures (Chevalier and Ellison, 1997; Huang et al., 2007, 2011).

We rule out several alternative potential explanations for reaching for beta. First, we re-estimate our baseline regressions using the policy surprise measures by Jarociński and Karadi (2020) and Bauer and Swanson (2023), which purge "pure" monetary policy surprises from central bank information or "Fed's response to news" effects. We show that these effects do not drive our results. Second, we document that proxies for leverage constraints and the shadow-cost of leverage proposed in previous work (Frazzini and Pedersen, 2014; He et al., 2017; Boguth and Simutin, 2018; Lu and Qin, 2021) do not predict active reaching for beta. This is consistent with evidence that the use of explicit leverage via borrowing or derivatives is rare for open-end funds (Almazan et al., 2004; Koski and Pontiff, 1999; Deli and Varma, 2002). Third, we augment our baseline regressions with fund-level measures of market timing and selectivity by Kacperczyk et al. (2014) and Daniel et al. (1997). These measures do not change the relationship between monetary policy surprises and active RFB. Hence, reaching for beta is distinct from market timing and stock picking.

What are the implications of RFB for fund returns and flows? Consistent with our preferred explanation based on managerial career concerns, we first show that active RFB predicts higher raw fund returns. However, this predictability disappears once we consider returns adjusted for factor exposures via the capital asset pricing model and the Carhart (1997) four-factor model. In line with Huang et al. (2011), increased risk-taking via beta tilts boosts contemporaneous raw returns and flows but does not generate alpha. Higher returns are thus earned as compensation for higher risk, and RFB does not indicate skill-based performance. Still, we find that active RFB is associated with net fund inflows when monetary policy is contractionary: investors allocate money to funds that actively increase their portfolio beta when short rates rise.

Finally, we study the asset pricing implications of reaching for beta. We show that demand for high-beta stocks induced by active RFB is associated with systematic price pressures. In the spirit of the flow-induced trading measure by Lou (2012), we construct a "beta-induced trading" (BIT) measure of demand shocks for individual stocks by aggregating the trading related to active RFB across all funds in our sample. We show that the BIT measure positively predicts excess returns for several quarters. This is consistent with the returns of BIT-sorted portfolios. While a long-short BIT portfolio features significant excess returns in the formation quarter, even on a risk-adjusted basis, these returns fully revert in subsequent quarters. Hence, beta-induced trading does not contain fundamental information but instead reflects temporary price pressures due to uninformed trading.

Our paper contributes to several strands of the literature. There is a large body of research on the implications of interest rate changes and monetary policy for investors' portfolio choices. Prior work on "reaching for yield" in low-rate environments focuses on institutional investors' trading in fixed-income markets (e.g., Hanson and Stein, 2015; Becker and Ivashina, 2015; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018). This literature concludes that low rates lead to more risk-taking. In contrast, we document a distinct channel of risk-taking in the equity market that has the opposite sign: when rates rise, active mutual funds tilt their portfolios toward riskier high-beta stocks.[1] This channel also differs from households' reaching for income in low-rate environments (Jiang and Sun, 2020; Daniel et al., 2021). In our sample of equity mutual funds, managers' dividend tilts in response to rate changes are weak, whereas reaching-for-beta is strong and robust.

Reaching for beta is also distinct from the leverage-constraint explanation for a flattened security market line (Frazzini and Pedersen, 2014), which implies an overweight of high beta stocks when leverage is costly. Relatedly, Boguth and Simutin (2018) use aggregate mutual fund beta as a proxy for the tightness of leverage constraints and link it to the slope of the risk-return relation. In contrast, we highlight monetary policy as a key driver of managers' active demand for beta. Consistent with this distinction, standard leverage-constraint proxies do not predict active reaching for beta.

Our paper also relates to the literature on mutual fund risk-taking. A large body of

[1]We remain agnostic about the mechanisms driving the differences in risk-taking behavior between equity and bond mutual funds. It may reflect differences in investor clienteles, in how flows respond to performance in each asset class, and differences in managerial constraints (Chen and Qin, 2017, Goldstein et al., 2017, Babina et al., 2021). Exploring these differences is beyond the scope of this paper.

work links changes in fund risk to tournament-style rank-based incentives (e.g., Brown et al., 1996; Chevalier and Ellison, 1997). More recently, Han et al. (2021) document that exogenous variation in the Morningstar rating methodology induce risk-shifting toward high-beta stocks. Contractual incentives to beat benchmarks also spur risk-taking, especially for managers of sponsor-controlled retirement assets (Christoffersen and Simutin, 2017; Buffa et al., 2022). We complement these channels with one in which managerial incentives and exogenous changes in risk-free rates interact. Our results highlight that variations in monetary policy and career concerns are joint determinants of mutual fund risk-taking via the beta margin.

We further contribute to the literature on the price impact of mutual fund trading. Prior research shows that flow-induced demand temporarily pushes up the prices of stocks held by mutual funds (Frazzini and Lamont, 2008; Lou, 2012). Relatedly, performance-based risk shifting by laggard funds can generate overpricing in high-beta stocks (Han et al., 2021). We complement these works by documenting a beta channel of monetary policy transmission. Higher risk-free rates lead to industry-wide reaching for beta, and the associated trading generates contemporaneous price pressures that subsequently reverse.

Finally, our paper complements the vast literature on the effects of monetary policy on the equity market. Prior research has documented that (the anticipation of) Federal Reserve policy has sizable effects on stock prices (e.g. Bernanke and Kuttner, 2005; Lucca and Moench, 2015). Our results highlight that contractionary policy does not universally reduce risk-taking but can also increase it in the equity market. As such, central bank decisions not only directly affect the market through their previously documented discount-rate and cash-flow channels, but also indirectly and persistently via mutual funds' portfolio reallocation.

2 Variable Construction and Data

We study reaching for beta (RFB) using two complementary datasets: funds' stock *holdings* to construct and decompose RFB at the fund–quarter level, and daily *transactions* from Abel Noser (formerly known as Ancerno) to provide trade-level evidence with a more granular timing around Federal Reserve announcements. This section defines our RFB measures, describes the data sources, and provides summary statistics.

2.1 Measures of RFB

We quantify RFB using several complementary metrics at the fund–quarter level. We begin with a *total* RFB measure defined as the value-weighted deviation of the betas of a fund's stock holdings from a benchmark beta:

$$RFB_{i,t}^{Total} = \sum_{j} w_{i,j,t} \times (\beta_{j,t} - \beta_{i,t}^{\text{Bench}}) \tag{1}$$

where $w_{i,j,t}$ represents the portfolio weight of stock j in fund i at the end of quarter t, $\beta_{j,t}$ is the estimated market beta of stock j in period t, and $\beta_{i,t}^{\text{Bench}}$ is the benchmark beta of fund i. In our baseline results, we set $\beta_{i,t}^{\text{Bench}} = 1$, defining RFB as the deviation from the market portfolio. Actively managed equity funds typically target broad market exposure near one and are highly restricted with respect to taking leverage. Thus, raising portfolio β via stock selection is the natural way to reach for market risk.[2]

In practice, not all funds track a market index benchmark. We therefore also com-

[2]While the market portfolio theoretically has a beta of one, it includes all assets, not only equities, and betas estimated from historical returns can be biased. In our data, the value-weighted and equal-weighted averages of stock betas are 0.96 and 1.04, respectively, and fluctuate narrowly around one. Our results are robust to using these empirical averages as $\beta_{i,t}^{\text{Bench}}$ instead of imposing a benchmark beta that exactly equals one.

pute our RFB measures using betas with respect to two alternative choices of fund benchmark: (i) each fund's prospectus benchmark index (e.g., the Russell 2000), and (ii) each fund's average lagged beta over the previous year. Assuming that tracking errors average out over time, the latter is an implicit measure of each fund's benchmark. We provide the details on the construction of these alternative benchmarks in Online Appendix IA3. Our results, reported in Online Appendix IA4.1, are robust to using these alternative measures.

Deviations of a fund's portfolio beta from a benchmark can arise from managers' rebalancing or from changes in betas of the underlying holdings (and/or the benchmark). To separate these sources, we decompose quarter-to-quarter change in $RFB^{Total}_{i,t}$ as follows:

$$
\begin{aligned}
\Delta RFB^{Total}_{i,t} &= \sum_j \left(\Delta w_{i,j,t} \times (\beta_{j,t} - \beta^{\text{Bench}}_{i,t})\right) \\
&= \underbrace{\sum_j \left(\Delta w_{i,j,t} \times (\beta_{j,t-1} - \beta^{\text{Bench}}_{i,t-1})\right)}_{\Delta RFB^{Active}_{i,t}} \\
&\quad + \underbrace{\sum_j \left(w_{i,j,t-1} \times \Delta(\beta_{j,t} - \beta^{\text{Bench}}_{i,t})\right)}_{\Delta RFB^{BetaShift}_{i,t}} \\
&\quad + \underbrace{\sum_j \left(\Delta w_{i,j,t} \times \Delta(\beta_{j,t} - \beta^{\text{Bench}}_{i,t})\right)}_{\Delta RFB^{Interaction}_{i,t}}
\end{aligned}
$$

$$
\Delta RFB^{Total}_{i,t} = \Delta RFB^{Active}_{i,t} + \Delta RFB^{BetaShift}_{i,t} + \Delta RFB^{Interaction}_{i,t} \qquad (2)
$$

The first term, ΔRFB^{Active}, captures changes in portfolio weights evaluated at lagged betas relative to the benchmark. A higher ΔRFB^{Active} indicates *active* rebalancing toward high-beta stocks. The second, $\Delta RFB^{BetaShift}$, captures shifts in relative stock betas holding portfolio composition fixed at $t-1$. The third, $\Delta RFB^{Interaction}$, is the interaction of the two, reflecting contemporaneous co-movement of weights and relative betas within the quarter. Because our interest is in managerial risk-taking, we focus primarily on the active RFB measure $\Delta RFB_{i,t}^{Active}$ in our analysis.

To calculate our RFB measures, we need to estimate the benchmark beta of each stock in the fund's portfolio at the end of each quarter t. To estimate a stock's beta, we regress its monthly excess return on the contemporaneous benchmark excess return and the lagged benchmark excess return, following the methodology of Liu et al. (2018) and Han et al. (2021). The regression is specified as follows:

$$R_{j,t} - R_{f,t} = \alpha_{j,t} + \beta_j^1 R_{Bench,t} + \beta_j^2 R_{Bench,t-1} + \varepsilon_{j,t}, \quad (3)$$

where $R_{j,t}$ is the return on stock j in month t, $R_{f,t}$ is the risk-free rate, and $R_{Bench,t}$ is the excess return of the benchmark index. Our baseline results are based on the aggregate market portfolio as each fund's benchmark. We obtain the excess return on the Center for Research in Security Prices (CRSP) value-weighted market portfolio from Kenneth French's data library. Each stock's beta is then computed as the sum of the two beta estimates: $\hat{\beta}_j = \hat{\beta}_j^1 + \hat{\beta}_j^2$. We use a 36-month rolling window with at least 24 months of data to compute the betas at the end of each quarter.

2.2 Monetary Policy Shocks and Macro Controls

To capture variations in risk-free interest rates along the term structure, we obtain the yields on the 3-month Treasury bill as well as the 2- and 10-year Treasury notes from the Federal Reserve Economic Data (FRED) database. We measure surprise changes in Federal Reserve policy following the common practice of using high-frequency data pioneered by Kuttner (2001) and Gürkaynak et al. (2005). Specifically, we use the monetary surprise series of Nakamura and Steinsson (2018) (NS), extended in time by Acosta et al. (2024). This series captures the common variation in changes of a set of short-dated interest rate futures observed over 30-minute windows around scheduled Federal Open Market Committee (FOMC) announcements. As such, it combines news about the target rate as well as the likely path of policy in the medium term.

As a robustness check, we also employ high-frequency measures of target and path shocks separately following Gürkaynak et al. (2005). FOMC meetings occur roughly every six to eight weeks, so many quarters cover two subsequent FOMC meetings. We compute the quarterly monetary policy surprise by summing surprises across the scheduled FOMC announcements within each quarter. Our sample spans the period 1995-2020.

2.3 Fund and Stock Holdings Data

We obtain mutual fund holdings data from the CRSP Survivor-Bias Free U.S. Mutual Fund Database. We supplement these data with Morningstar Direct (MS) for prospectus benchmarks and additional classification fields. Our analysis focuses on actively managed domestic equity funds. Following Kacperczyk et al. (2008) and Akbas and Genc (2020), we exclude balanced, fixed income, money market, sector, and international funds from our sample based on the fund-style classifications provided by CRSP and MS. We further remove index funds, target date funds, variable annuities, and exchange-traded funds (ETFs) from the remaining sample. We conduct our analysis at the fund level, aggregating data across the share classes of the same fund to obtain fund-level characteristics. Finally, we eliminate funds with less than $5 million in assets under management and fund age below one year to address incubation bias (Evans, 2010). Further details on sample selection are provided in Online Appendix IA2.

The dataset covers various fund characteristics that we use as controls in our empirical analysis, including fund flows, returns, total net assets (TNA), turnover, age, and expense ratio. We measure the growth rate of assets of a fund due to new investments as:

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + Ret_{i,t})}{TNA_{i,t-1}} \tag{4}$$

where $Ret_{i,t}$ is the quarterly return of the fund i in quarter t, and $TNA_{i,t}$ is the total net asset of fund i at the end of quarter t. Each quarter, we compute return volatility as the standard deviation of monthly returns over the previous 12 months. Fund turnover is calculated as the minimum of aggregate purchases or sales of securities during the month, divided by the monthly average total net assets. Fund age is the number of months since the inception of the fund's oldest share class. The expense ratio equals total operating expenses expressed as a percentage of a fund's average net assets. All continuous variables are winsorized at the 1% and 99% to mitigate the impact of outliers.

We merge our fund data with Thomson Reuters Mutual Fund Holdings (s12) using the MFLINKS file provided in WRDS. Until 2003, funds were required to disclose their holdings semi-annually, although approximately 60% of funds also reported quarterly holdings. We carry forward the most recently disclosed holding position for up to six months until the next disclosure and obtain stock-level information from CRSP Security files. Our final fund sample includes 135,211 fund-quarter observations with non-missing RFB measures from 1995Q1 to 2020Q4.

2.4 Abel Noser (Ancerno) Data

In addition to quarterly fund holdings, we also study daily equity transactions for a sample of funds obtained from Abel Noser. Abel Noser is a renowned financial firm specializing in helping institutions to optimize transaction costs and maintain regulatory compliance with entities like the SEC and FINRA. Its institutional clients include major investment managers, such as Fidelity and Putnam Investments, as well as plan sponsors like the California Public Employees' Retirement System (CalPERS) and the Commonwealth of Virginia.

Abel Noser gathers detailed, transaction-level equity trading data from its clients. This dataset includes execution details like the date, stock identifiers (CUSIP and symbol), number of shares, execution price, commissions, and whether the trade was a buy or sell. Additionally, anonymized codes for the institutions and specific funds involved in the trades are provided. This dataset has been extensively used in academic research.[3] Following Puckett and Lan (2011), we match the Abel Noser data with CRSP daily stock files using the CUSIP code and keep stocks with ordinary common shares (i.e., Shrcd code equal to 10 or 11). We aggregate the data at the stock level for each execution date, calculating key metrics such as the number of buy and sell transactions, the total number of shares traded, and the dollar volume traded for each stock. The dataset contains approximately 238 million trades, corresponding to 1.2 trillion shares and a total trading volume of $32.8 trillion, spanning from January 1999 to December 2011. These estimates are similar to those reported by Gang et al. (2018), providing a comprehensive view of institutional trading activity during this period.

2.5 Summary Statistics

In Table 1, we present the average, median, and standard deviation of RFB^{Total} and other fund characteristics over the full sample. We also report the average characteristics of funds in each of the three portfolios of funds constructed based on the 30th (Low) and 70th (High) percentiles of RFB in each quarter, as well as the difference between the High and Low portfolios. These three portfolios are well populated. The Low and High portfolios each contain an average of 390 funds per quarter, while the

[3] Gang et al. (2018) conduct a comprehensive survey of the academic literature that uses Abel Noser's data, providing detailed information about the database itself.

middle one contains 520 funds. The average portfolio beta is 1.125, a value-weighted exposure that is substantially above the market $\beta = 1$. Accordingly, the average value of RFB^{Total} among all funds is 0.125: the portfolio of the average equity mutual fund is tilted toward stocks with betas above one. This aligns with Frazzini and Pedersen (2014), who show that mutual funds tend to overweight high-beta stocks in their portfolios. However, RFB^{Total} shows considerable heterogeneity, ranging from -0.139 for the Bottom 30 percent of funds to 0.556 for the top portfolio. While some funds adopt a more conservative approach to risk-taking, others tend to reach for substantially higher betas.

Changes in RFB^{Total} are primarily driven by managers' active portfolio choices. Variation in ΔRFB^{Active} is much larger than in $\Delta RFB^{BetaShift}$ and $\Delta RFB^{Interaction}$. Specifically, funds in the High RFB bucket exhibit an economically and statistically significant 7% higher ΔRFB^{Active} than those in the Low group. In contrast, the corresponding differences for $\Delta RFB^{BetaShift}$ and $\Delta RFB^{Interaction}$ are 0.3% and 0.6%, respectively. This underscores the dominant role of active decisions in shaping fund-level RFB dynamics.

Return volatility increases with beta exposure, consistent with the notion that portfolios with higher market sensitivity exhibit greater systematic risk. Fund size is negatively associated with RFB^{Total}, echoing the result of Christoffersen and Simutin (2017) that larger funds tend to exhibit lower systematic risk exposures. Consistent with the idea that managers' portfolio choices drive RFB^{Total}, funds in the High portfolio exhibit higher turnover. Moreover, younger funds and those with higher expense ratios tend to have higher RFB^{Total}. Finally, managers of funds with higher RFB^{Total} exhibit stronger timing abilities but weaker stock-picking performance.

Table 1: Descriptive Statistics

Variable	Average	p50	SD	Low	Mid	High	High–Low	
RFB^{Total}	0.125	0.091	0.268	-0.139	0.091	0.418	0.556	[20.23]
ΔRFB^{Active}	0.023	0.012	0.077	-0.007	0.016	0.062	0.069	[9.83]
$\Delta RFB^{BetaShift}$	-0.002	-0.003	0.064	-0.007	-0.003	0.000	0.006	[0.96]
$\Delta RFB^{Interaction}$	-0.004	0.000	0.030	-0.005	-0.005	-0.002	0.003	[2.32]
Flow	0.009	-0.014	0.149	0.011	0.014	0.013	0.002	[0.39]
Return	0.024	0.033	0.099	0.026	0.027	0.028	0.001	[0.22]
Alpha	-0.001	-0.001	0.008	-0.001	-0.001	-0.002	-0.001	[-0.71]
Volatility	0.047	0.043	0.023	0.039	0.045	0.057	0.019	[7.98]
Assets ($\$M$)	1681.3	271.1	6465.8	1898.7	1785.5	1147.0	-751.7	[-5.52]
Expense Ratio	0.012	0.011	0.004	0.011	0.012	0.013	0.002	[15.63]
Turnover	0.764	0.590	0.678	0.615	0.751	0.954	0.338	[7.73]
Age	187.4	143.0	166.8	197.2	189.0	167.0	-30.2	[-8.90]
Retail	0.661	0.895	0.396	0.681	0.669	0.679	-0.002	[-0.24]
Timing	0.836	1.102	2.391	0.744	0.914	1.190	0.446	[3.12]
Selectivity	-0.058	-0.028	1.274	0.056	-0.044	-0.234	-0.290	[-2.16]
CT (Char. Timing)	0.003	-0.001	0.454	0.001	0.008	0.014	0.012	[0.59]
CS (Char. Selectivity)	0.040	0.034	0.882	0.020	0.045	0.070	0.051	[0.65]

This table reports the overall mean, median (p50), and standard deviation of RFB measures, along with other fund characteristics, for observations where RFB^{Total} is available from 1995:Q1 to 2020:Q4. It also presents the average characteristics of funds sorted into three portfolios each quarter based on the cross-sectional ranking of RFB^{Total}. The "Low" portfolio includes funds in the bottom 30th percentile of RFB^{Total}, the "Mid" portfolio includes those between the 30th and 70th percentiles, and the "High" portfolio comprises funds in the top 30th percentile. The last column reports the difference between the 'High' and 'Low' portfolios, along with the associated t-statistics (reported in brackets). "Flow" captures a fund's growth rate due to new investments, as defined in Equation (4), assuming all new capital is invested at the end of each quarter. "Return" represents the fund's quarterly performance, aggregated from monthly returns. "Volatility" is measured as the standard deviation of 12-month returns ending in quarter t. "Assets" are measured in millions and reflect the fund's total net asset value. The expense ratio indicates the proportion of a fund's average net assets consumed by operating expenses. "Turnover" is calculated as the lesser of total purchases or sales of securities during a month, divided by the monthly average net assets. "Age" denotes the number of months since the launch of the fund's oldest share class. "Retail" is the percentage of TNA of retail share classes in a fund. Timing and selectivity are market timing and selectivity measures of Kacperczyk et al. (2014). CT and CS are characteristic market timing and selectivity measures of Daniel et al. (1997). To minimize the influence of outliers, all variables are winsorized at the 1st and 99th percentiles.

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3 Reaching for Beta: Empirical Evidence

In this section, we document pervasive "reaching for beta" by mutual funds. Using quarterly holdings, we show that managers tilt toward high-beta stocks following increases in short-term Treasury yields. We then attribute this risk-shifting to monetary policy surprises in an instrumental variables setup and, finally, corroborate the mechanism with granular daily transaction data for a subset of funds.

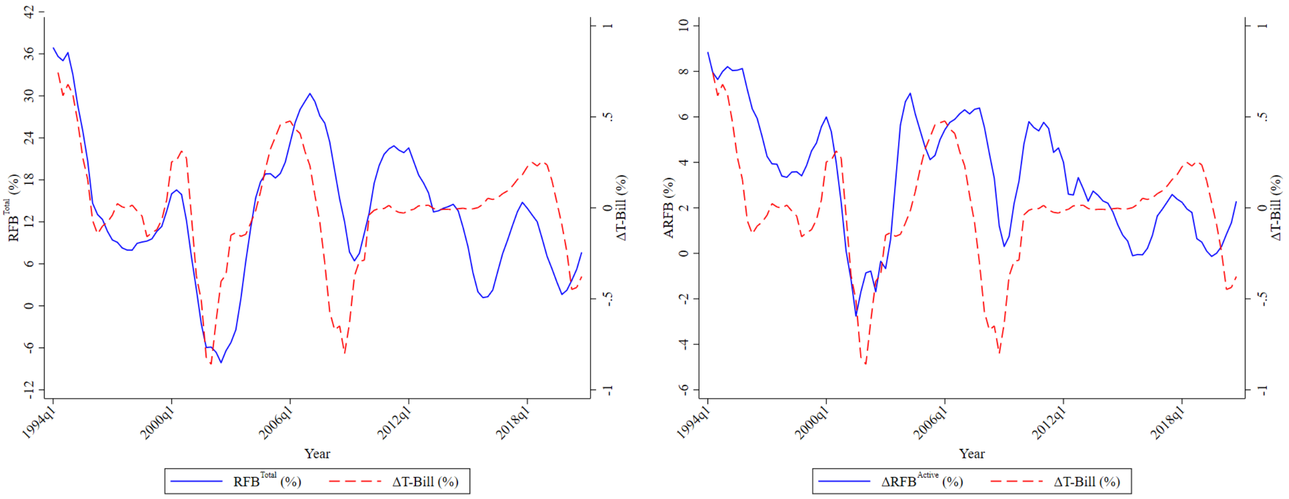
3.1 Evidence from Quarterly Holdings

3.1.1 RFB and Interest Rates

We begin by providing evidence that mutual fund managers actively engage in reaching for beta when interest rates rise. As a first step, we examine the dynamics of RFB and short-term interest rates over our sample period. Figure 1 superimposes the time series of average RFB^{Total} and ΔRFB^{Active} in equity mutual funds with the quarterly change in the 3-month T-Bill. Both charts suggest that our RFB measures co-move considerably with short rates, and elevated levels of RFB^{Total} and ΔRFB^{Active} typically coincide with periods of rising interest rates. The co-movement is somewhat attenuated in the zero lower bound period between 2008 and 2016, likely reflecting the diminished informativeness of short-term rates as a signal of the monetary policy stance during that time.

We now formally test the hypothesis that mutual fund managers tilt their portfolios toward high-beta stocks following an increase in interest rates. To disentangle the effect of interest rate changes on reaching for beta across the yield curve, our baseline analysis considers not only short-term but also medium- and long-term yields.

Figure 1: Reaching for Beta Over Time



This figure displays the time series of total reaching for beta (RFB^{Total}, left panel, solid blue line) and active reaching for beta (ΔRFB^{Active}, right panel, solid blue line), alongside quarterly changes in the 3-month T-Bill rate (dashed red line). The sample period spans 1994:Q1 to 2020:Q4. All series are expressed in percentage points. To reduce high-frequency noise and highlight medium-term dynamics, we apply a moving average filter using a backward-looking window of four lags and the current quarter.

Specifically, we estimate the following quarterly panel regressions:

$$RFB_{i,t+1} = \alpha_i + \beta\,\Delta IR_t + \gamma'\,X_{i,t} + \theta'\,Z_t + \varepsilon_{i,t+1} \tag{5}$$

where RFB represents either total reaching for beta (RFB^{Total}) or active reaching for beta (ΔRFB^{Active}) as defined in Equation (2). ΔIR represents the quarterly yield change in the 3-month Treasury bill (ΔTBILL3M), the 2-year Treasury (ΔTBOND2Y) or the 10-year Treasury note (ΔTBOND10Y), respectively. α_i captures fund fixed effects, and X_i is a vector of fund-level control variables including (log) fund age, (log) total net assets, fund's return over the quarter, CAPM alpha and return volatility over the previous 12 months, turnover ratio, expense ratio, and fund flows. We also add aggregate controls Z, including the quarterly stock market return, the VIX index, and the Pastor and Stambaugh (2003) market-liquidity factor, to account for broader market conditions and potential market timing. The coefficient β captures the sensitivity of fund beta tilts to interest rate changes. A positive and significant β would indicate

Table 2: Reaching for Beta and Interest Rate Changes

	RFB^{Total}				ΔRFB^{Active}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔTBILL3M	0.091***			0.126**	0.022***			0.036***
	(3.138)			(2.502)	(3.062)			(2.834)
ΔTBOND2Y		0.052*		−0.061		0.008		−0.023
		(1.970)		(−0.921)		(1.303)		(−1.583)
ΔTBOND10Y			0.022	0.038			−0.0004	0.008
			(0.836)	(0.867)			(−0.059)	(0.882)
Mkt Return	0.072	0.055	0.041	0.067	0.007	0.002	−0.0003	0.006
	(0.315)	(0.239)	(0.174)	(0.290)	(0.181)	(0.047)	(−0.009)	(0.145)
Vix	−0.003	−0.004**	−0.005**	−0.003	0.001***	0.001**	0.001	0.001***
	(−1.476)	(−2.098)	(−2.371)	(−1.382)	(3.037)	(2.088)	(1.645)	(3.060)
PS	−0.099	−0.129	−0.021	−0.030	0.046	0.050	0.071	0.077
	(−0.322)	(−0.388)	(−0.068)	(−0.101)	(0.717)	(0.697)	(1.043)	(1.279)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,136	130,136	130,136	130,136	129,755	129,755	129,755	129,755
Adjusted R^2	0.503	0.495	0.491	0.504	0.179	0.171	0.170	0.181

This table reports coefficient estimates from predictive panel regressions of reaching-for-beta measures on interest rate changes and controls. The sample covers the period 1995:Q1–2020:Q4. RFB is either total reaching for beta (RFB^{Total}) or active reaching for beta (ΔRFB^{Active}), as defined in Equation (2) and computed at the fund-quarter level. (ΔTBILL3M), (ΔTBOND2Y), (ΔTBOND10Y) denote quarterly changes in the yields on the 3-month Treasury bill, 2-year Treasury note, and 10-year Treasury bond, respectively. Control variables include log fund age, log total net assets, past three months of fund returns, CAPM alpha over the previous 12 months, return volatility over the previous 12 months, turnover ratio, expense ratio, and fund flows. All regressions include fund fixed effects, and standard errors are double-clustered at the fund and time levels. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

that mutual fund managers increase their exposure to higher beta stocks in response to rising interest rates – consistent with reaching for beta behavior.

Table 2 presents the results. The first four columns report estimates for RFB^{Total}, while the remaining columns focus on ΔRFB^{Active}. Changes in the 3-month T-Bill rate are highly predictive of reaching for beta in the subsequent quarter. Changes in medium-term and long-term rates also have predictive power, albeit to a smaller degree. This predictability is present for both RFB^{Total} and ΔRFB^{Active}. Importantly, these regressions include fund fixed effects and a rich set of fund-level controls, accounting for a broad range of heterogeneity across funds and also accounting for several other dimensions of funds' risk-taking.

The coefficients on interest rate changes are positive, indicating that funds *increase* the beta of their equity portfolios in response to higher rates. Specifically, a 1% increase in the 3-month T-Bill rate is associated with a 0.126 increase in RFB^{Total}, implying a roughly 11% increase in the market exposure of an average fund in our sample with a beta of 1.13. Changes in short-term rates also significantly affect ΔRFB^{Active}, indicating that funds actively reallocate their portfolios toward higher-beta stocks. Our estimates imply that a 1% increase in the T-Bill leads the average fund to reallocate approximately \$59 million – about 3.6% of its \$1.63 billion portfolio – toward higher-beta positions to increase market exposure.

Government bond yields are well known to co-move across maturities. When we include all three maturities jointly (columns (4) and (8)), only short rate changes remain statistically significant. Since the short end of the yield curve is tightly linked to monetary policy, this suggests that variations in the monetary policy stance may be particularly salient for shaping mutual funds' risk-taking. We explicitly study the role of monetary policy surprises on funds' reaching for beta in the next section.

In Online Appendix IA4.1, we verify that our results are robust to varying fund benchmarks. Specifically, we recompute the RFB measures using (i) the fund's prospectus benchmark beta and (ii) the fund's lagged beta as alternative benchmarks. Table IA1 shows that the coefficient estimates on RFB^{Total} and ΔRFB^{Active} are closely comparable in magnitude and statistical significance to the baseline results shown in Table 2. Hence, while the unit-beta benchmark is theoretically well-motivated and maps cleanly to market exposure, our conclusions are robust to other economically meaningful benchmark definitions.

Importantly, our finding of reaching for beta stands in stark contrast to another form of risk-taking in response to changes in interest rates documented in the prior literature: reaching for yield. As documented by Choi and Kronlund (2018), bond mutual funds *increase* their exposure to higher-yielding riskier fixed-income assets when short-term interest rates are low. While understanding the reasons for this contrasting behavior of equity and bond mutual funds is beyond the scope of our paper, differences regarding their flow-performance relationships and investor clienteles are likely drivers (Chen and Qin, 2017; Goldstein et al., 2017). In a stock-level analysis based on quarterly fund transactions, we also show in Section 3.1.3 that RFB is complementary to other types of investor behavior that have been documented in the prior literature, such as reaching for income/dividend (Daniel et al., 2021; Jiang and Sun, 2020).

In equilibrium, some investors must accommodate mutual funds' increased demand for high-beta stocks. A natural counterpart is the set of less constrained leveraged intermediaries (e.g., hedge funds, broker-dealers) whose balance sheet size strongly depends on financing costs. When policy rates rise, margin and prime-broker funding rates rise too, thereby increasing the effective cost of leverage and tightening funding constraints. Theory and prior evidence suggest that these intermediaries respond by de-leveraging and reducing their risky asset exposures (e.g., Adrian and Shin, 2008; Brunnermeier and Pedersen, 2009).

3.1.2 RFB and Monetary Policy

The previous section documents that managers actively tilt their portfolios toward high-beta stocks following an increase in short-term interest rates. Because short rates and equity prices may both respond to common shocks, endogeneity remains a concern even when we use one-quarter lagged interest rate changes in Regression (5).

We address this by studying the response of ΔRFB^{Active} to exogenous variations in short-term interest rates. Specifically, we employ the high-frequency measure of monetary policy surprises of Nakamura and Steinsson (2018) (NS), updated by Acosta et al. (2024), as an instrument for changes in the Treasury bill yield. The monetary policy surprise is the first principal component of several interest rate futures with maturities up to one year in 30-minute windows around scheduled FOMC announcements. It thus captures news about both the target rate and the near-term expected path of policy rates communicated by the FOMC.

Formally, we conduct a two-stage least squares (2SLS) instrumental variable analysis. The first stage is a time-series regression:

$$\Delta TBILL3M_t = \delta_0 + \delta_1 NS_t + \varepsilon_t \tag{6}$$

where $\Delta TBILL3M$ is the change in three-month T-Bill yield, and NS is the monetary policy surprise in quarter t. In the second stage, we replace the observed T-Bill with its fitted value from Equation (6):

$$\Delta RFB^{Active}_{i,t+1} = \alpha_i + \beta\, \Delta T\widehat{BILL3}M_t + \gamma_1' X_{i,t} + \gamma_2' Z_t + \varepsilon_{i,t+1}, \tag{7}$$

where X and Z are the fund level and aggregate controls from the baseline, and α_i denotes fund fixed effects.

Table 3 provides the results. Column (1) restates the baseline finding from Table 2: increases in short rates predict higher ΔRFB^{Active}. Column (2) complements this result by regressing $\Delta RFB^{Active}_{t+1}$ directly on NS_t. The highly significant and positive coefficient indicates that a surprise tightening of monetary policy induces active tilts toward higher beta stocks. The next two columns report the 2SLS estimation. The first-stage regression in Column (3) shows that tighter policy leads to an increase in short-term Treasury rates. The highly significant F-statistic indicates that the monetary policy surprise is a strong instrument for quarterly T-Bill changes. The second-stage regression in Column (4) shows that the instrumented short rate change significantly raises active RFB. Hence, policy-induced movements in short-term rates result in active beta tilts.

Taken together, these results document a novel monetary-policy transmission chan-

Table 3: RFB and Interest Rates: Evidence from IV and High-Frequency Monetary Policy Shocks

	ΔRFB^{Active}		ΔTBILL3M	ΔRFB^{Active}
	Interest Rates	Pure MP Shock	IV - 1st Stage	IV - 2nd Stage
	(1)	(2)	(3)	(4)
ΔTBILL3M	0.022***			
	(3.062)			
NS		0.145***	3.912***	
		(3.156)	(5.460)	
$\Delta \widehat{TBILL}3M\_NS$				0.037***
				(3.156)
Fund FE	Yes	Yes		Yes
Controls	Yes	Yes		Yes
Observations	129,755	129,755	104	129,755
Adjusted R^2	0.179	0.177	0.219	0.177
F Statistic			29.814*** (df = 1; 102)	

This table presents coefficient estimates from predictive panel regressions and two-stage least squares (2SLS) specifications. The sample covers the period 1995:Q1–2020:Q4. Columns (1) and (2) report baseline predictive regressions of active reaching for beta (ΔRFB^{Active}) on changes in short-term interest rates and monetary policy shocks (NS). Columns (3) and (4) show the first-stage and second-stage results of the corresponding 2SLS regressions, where NS is used as an instrument for changes in the 3-month Treasury bill yield. Control variables in the panel regressions include log fund age, log total net assets, past three months of fund returns, CAPM alpha over the previous 12 months, return volatility over the previous 12 months, turnover ratio, expense ratio, and fund flows. All panel regressions include fund fixed effects, and standard errors are double-clustered at the fund and time levels. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively

nel that operates on the beta margin: when policy tightens, managers raise market exposure via stock selection. Thus, monetary policy affects equity markets not only through immediate price effects (e.g., Bernanke and Kuttner, 2005) but also through fund managers' active reallocation of fund portfolios.

In Online Appendix IA4.2, we verify robustness to alternative high-frequency monetary policy surprises, separating between news about the target rate and the policy path following Gürkaynak et al. (2022). We also show that the active RFB response is symmetric. Fund managers increase their beta exposure in response to positive changes in short-term rates and contractionary policy surprises and reduce their portfolio betas in response to negative changes in short rates and expansionary policy surprises.

Monetary policy shocks have recently been shown to have persistent effects on government bond markets and flows into and out of bond funds (e.g., Brooks et al., 2020; Adrian et al., 2024). Motivated by these findings, we examine the persistence of reaching for beta in response to monetary policy. We use the high-frequency monetary policy surprise as a measure of interest rate changes in panel local projections in the spirit of Jordà (2005):

$$\Delta RFB_{i,t+h}^{Active} = \alpha_i + \beta_h NS_t + \gamma_1' X_{i,t} + \gamma_2' Z_t + \varepsilon_{i,t+h}, \tag{8}$$

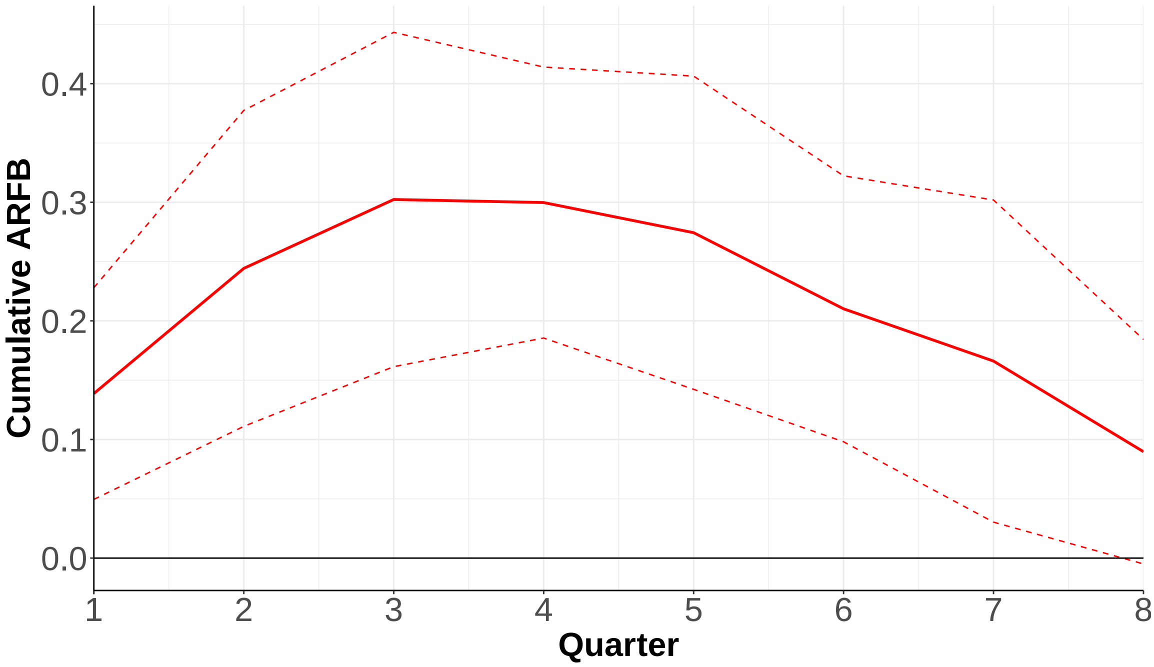
where NS_t is the Nakamura-Steinsson monetary policy surprise, h is the forecast horizon, X_i and Z represent sets of fund–level and aggregate control variables, and α_i denotes fund fixed effects. We estimate the regression for horizons from one to eight quarters and plot the sum of the coefficients $\sum_{h=1}^{n} \beta_h$ as the cumulative active reaching for beta n quarters into the future following a 100 bps monetary policy surprise.

Figure 2 shows that mutual funds tilt their portfolios significantly and persistently toward higher beta stocks for up to one year following an *exogenous* increase in short-term interest rates. Subsequently, the effect gradually reverses and is no longer statistically significant after six quarters. These results highlight that fund managers adjust market exposure slowly but persistently in response to changes in monetary policy.

3.1.3 Evidence from Quarterly Mutual Fund Transactions

So far, we have shown that our *fund-level* RFB metrics respond strongly and significantly to monetary policy-induced changes in short-term rates. Since the RFB measures capture deviations of portfolio beta from a benchmark, they represent an easy-to-interpret summary of active market-risk tilts.

Figure 2: Dynamics of Active Reaching for Beta



This figure displays the dynamics of active reaching for beta (ΔRFB^{Active}) in response to a 100 bps monetary policy shock. On the *y*-axis, we report the sum of coefficients estimated from the local projection specification (8) for the forecast horizons from one to the respective quarter on the *x*-axis. Dashed lines indicate 90% confidence bands.

To strengthen our evidence on reaching for beta, we add a complementary *stock-level* analysis based on share-based net purchases by fund managers. This analysis (i) validates that the beta exposure shifts reflect active trading, further alleviating the concern that weight-based measures may be mechanically affected by within-quarter price movements, and (ii) allows us to control for stock characteristics correlated with beta (e.g., dividend yield, valuation, cash-flow duration), thereby isolating a beta-driven trading response to rate and policy shocks.

Specifically, we follow Lakonishok et al. (1992) and compute the net purchase of stock j in quarter t as:

$$NetPurchase_{j,t} = \frac{Buy_{j,t} - Sell_{j,t}}{Buy_{j,t} + Sell_{j,t}}, \tag{9}$$

where $Buy_{j,t}$ and $Sell_{j,t}$ are the total share increases and decreases of stock j by all equity fund managers in our sample from the end of quarter $t-1$ to the end of quarter t. The difference between $Buy_{j,t}$ and $Sell_{j,t}$ is normalized by the total trading activity to obtain a scale-free measure comparable across stocks. We then estimate the following stock-quarter panel regression:

$$NetPurchase_{j,t+1} = \beta \, \text{HighBeta}_{j,t} \times IR_t + \gamma X_{j,t} + \alpha_j + \alpha_t + \varepsilon_{j,t}, \tag{10}$$

where $\text{HighBeta}_{j,t}$ equals 1 if stock j is in the top beta quintile in quarter t, and 0 otherwise. IR_t represents either the quarterly change in the 3-month T-Bill ($\Delta TBILL3M_t$) or the Nakamura–Steinsson monetary policy surprise (NS_t). $X_{j,t}$ includes stock-level controls: past quarterly returns, CAPM alpha over the previous 12 months, log market capitalization, log firm age, Amihud's quarterly illiquidity, dividend yield, book-to-market (BM) ratio, and cash-flow duration from Gonçalves (2021).[4] We include stock (α_j) and time (α_t) fixed effects to absorb unobserved heterogeneity in both dimensions and two-way cluster standard errors by stock and time. A positive and significant coefficient on $\text{HighBeta}_{j,t} \times IR_t$ indicates increased net buying of high-beta stocks relative to low-beta stocks by mutual funds following rate changes or monetary policy shocks.

Table 4 presents the results. Column (1) shows that net purchases of high-beta stocks rise after increases in short-term rates, consistent with the fund-level RFB evidence. Column (6) shows analogous results using monetary-policy surprises: the positive, highly significant interaction coefficient indicates that surprise tightenings induce net buying of high-beta stocks. Taken together, the stock-level tests reveal industry-wide rebalancing: following rate changes and policy shocks, the mutual fund sector increases its aggregate positions in high-beta stocks relative to low-beta stocks, reiterating that the fund-level RFB results reflect active trading rather than mechanical,

[4]Following Fama and French (1992), we use accounting data from the fiscal year ending in calendar year $t-1$ and market equity as of December $t-1$, ensuring a minimum six-month gap between accounting data and CRSP returns. Cash flow duration is available at https://andreigoncalves.com/.

Table 4: Mutual Fund Purchases and Monetary Shocks

	$NetBuy_{t+1}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔTBILL3M × High Beta	0.051***	0.049***	0.041***	0.051***	0.039***					
	(4.223)	(3.995)	(3.503)	(4.202)	(3.316)					
ΔTBILL3M × Div. Yield		−0.467**			−0.355					
		(−2.085)			(−1.502)					
ΔTBILL3M × Duration			0.041***		0.044***					
			(4.360)		(4.961)					
ΔTBILL3M × BM				−0.007	0.013					
				(−0.419)	(0.730)					
NS× High Beta						0.247***	0.228***	0.194**	0.247***	0.183**
						(2.898)	(2.660)	(2.549)	(2.916)	(2.306)
NS× Div. Yield							−3.482*			−2.870
							(−1.777)			(−1.465)
NS× Duration								0.227**		0.205***
								(2.149)		(2.723)
NS× BM									−0.142	−0.046
									(−0.859)	(−0.313)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196,551	196,551	196,551	196,551	196,551	196,551	196,551	196,551	196,551	196,551
R-squared	0.1450	0.1451	0.1453	0.1450	0.1454	0.1449	0.1450	0.1451	0.1450	0.1451

This table reports coefficient estimates from predictive panel regressions of net purchases on interactions between stock characteristics and interest rate changes. The sample covers the period 1995:Q1–2020:Q4. Columns (1)-(3) use the quarterly change in the 3-month Treasury Bill yield ($\Delta TBILL3M$), while Columns (4)-(6) use the monetary policy surprise measure of Nakamura and Steinsson (NS). High Beta is a dummy equal to one if stock j falls in the top quintile of market beta in a given quarter. Control variables include past three months of stock returns, CAPM alpha over the previous 12 months, return volatility over the previous 12 months, log market capitalization, log firm age, Amihud's quarterly illiquidity measure, dividend yield, book-to-market ratio, and cash flow duration. Regressions include stock and/or time fixed effects as indicated. Standard errors are clustered at both the stock and time levels. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

price-driven changes in portfolio weights.

A remaining concern is that high-beta stocks may differ from low-beta stocks along other dimensions. Thus, differential trading could reflect preferences unrelated to market beta. For example, Daniel et al. (2021) document that retail investors reach for income in low-rate environments by buying stocks with high dividend yields, which tend to have low betas. In a similar vein, short rate and monetary policy changes likely coincide with time-varying business-cycle expectations. As a result, fund managers might buy high-beta stocks when rates are rising because of growth or cash-flow characteristics rather than their market-risk exposure.

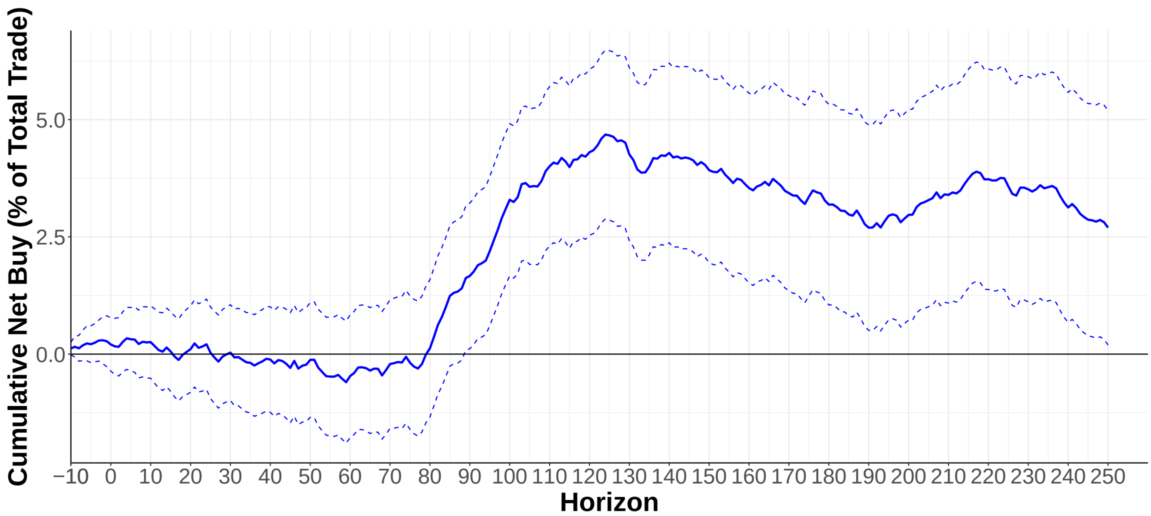
To address these points, we augment the above regression with interactions between the interest rate change and the dividend yield, book-to-market, and cash-flow duration. This allows us to explicitly control for other characteristics that may co-move with beta at the stock level. Columns (2)-(4) add these interactions individually with the change in the 3-month T-Bill; Column (5) includes all three interactions jointly. Columns (7)-(10) repeat the exercise, interacting with the monetary policy surprise. Across all specifications, the coefficient on $\text{HighBeta}_{j,t} \times IR_t$ remains positive and significant. This highlights that fund managers adjust their exposure to high-beta stocks in response to short rate changes over and above the effects these changes may also have on dividends, valuation, and cash flow. Thus, the trading response is beta-driven, not a by-product of dividend, book-to-market, or duration characteristics.

3.2 Evidence from Daily Mutual Fund Transactions

In Section 3.1.2, using quarterly holdings data, we have documented a gradual and persistent shift toward higher-beta stocks following tighter monetary policy. In this section, we zoom in on the high-frequency response of fund managers to monetary policy shocks using the Abel Noser database of daily institutional trading. Relative to our baseline holdings data, the Abel Noser data covers fewer funds and spans the subsample 1999-2011. Its daily granularity, however, allows us to provide sharper evidence on reaching for beta and to characterize the timing of these effects more precisely.

Using daily transactions from Abel Noser, we calculate the net ratio ($NetPurchase$) for stock j on day t as in Equation (9) above, again following Lakonishok et al. (1992). Now, $Buy_{j,t}$ and $Sell_{j,t}$ measure the total buying and selling of stock j on day t by all funds in the Abel Noser sample. We then explore whether surprise tightenings of monetary policy are associated with increased net buying of high-beta stocks using the

Figure 3: Dynamics of daily net purchases in response to monetary policy



This figure displays the dynamics of net purchases ($NetPurchase$) responses to a 100 bps monetary policy surprise conditional on stock beta. The y-axis reports the sum of coefficients estimated from the local projection specification (11) for forecast horizons from 10 days prior to 250 days after an FOMC announcement day. Dashed lines show 90% confidence bands.

local projections method of Jordà (2005):

$$NetPurchase_{j,t+h} = \alpha_j + \theta_h \, \beta_{j,t}^{Stock} \times NS_t + \gamma_1' X_{j,t} + \gamma_2' Z_t + \gamma_3 \sum_{k=t+1}^{t+h} NS_k + \varepsilon_{j,t+h}, \quad (11)$$

where NS is the monetary policy surprise measure of Nakamura and Steinsson (2018) on FOMC announcement day t, h is the horizon, and α_j are stock fixed effects. X_j includes additional stock-level control variables such as stock beta, return, book-to-market ratio, (log) market capitalization, and Amihud's liquidity ratio. Z represents a set of aggregate control variables (value-weighted CRSP return, VIX, and the federal funds rate). To account for potential mild serial correlation in the policy shock series, we include the sum of *future* NS shocks $\sum_{k=t+1}^{t+h} NS_k$ up to date $t+h$. Standard errors are clustered by day. We estimate the regression for horizons h running from 10 days before to 250 days after an FOMC announcement day. Motivated by the pre-FOMC announcement drift documented in Lucca and Moench (2015), we begin before the announcement to account for potential anticipatory trading.

Figure 3 plots the sum of the coefficients $\sum_{h=1}^{H} \theta_h$. This measures the cumulative net buying pressure of high beta stocks up to H days following a 100 bps monetary policy surprise. Two patterns emerge. First, there is no significant net buying ahead of the FOMC announcement. Second, the cumulative buying pressure for high beta stocks remains flat for about 80 trading days after the FOMC announcement and then rises sharply and persistently. This delayed yet sustained response is consistent with our quarterly results: funds actively increase their beta exposure for several quarters after a surprise tightening. Hence, fund managers appear to take some time to process the monetary policy decision and then systematically reallocate toward higher-beta stocks. The persistence in the response is also consistent with the evidence in Brooks et al. (2020) and Adrian et al. (2024) for bond funds.

4 Dissecting the Mechanism

In this section, we shed light on the economic underpinnings of our empirical evidence on reaching for beta. We start by discussing our proposed mechanism based on fund managers' career concerns and show that it is consistent with the data. Then we provide evidence that potential alternative explanations, including a central bank information effect, funds' leverage constraints, and market-timing activity by funds, are not supported by the data.

4.1 RFB as a Result of Career Concerns

As delegated asset managers, equity mutual fund managers' incentives are shaped by agency frictions, career concerns, and the sensitivity of investor flows to performance (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Chevalier and Ellison, 1999). These incentives can rationalize reaching for beta. When risk-free rates rise – raising the payoffs on low-risk alternatives such as money market funds – equity funds face elevated outflow risk. Because managers' compensation is closely tied to assets under management (AUM) and performance-based bonuses (Ibert et al., 2018; Ma et al., 2019; Del Guercio et al., 2022; Cen et al., 2023), they have strong incentives to defend AUM and boost returns by taking more risk via active portfolio rebalancing (Huang et al., 2011). Since explicit leverage is tightly regulated for open-end funds, managers can scale risk within their mandate mainly by using "implicit leverage" – i.e., overweighting riskier high-beta stocks.[5]

We formalize this conceptual framework in Online Appendix IA1 by sketching a simple static partial equilibrium model. In the model, households allocate wealth between a money market fund that invests in a risk-free asset and an equity mutual fund that mixes high- and low-beta stocks. Crucially, investor allocations to the equity fund depend on the expected return spread relative to the risk-free alternative. When the risk-free rate rises, the spread narrows, potentially shifting flows away from equity funds. Since the equity fund manager chooses an optimal portfolio composition to maximize expected return and AUM (i.e., investor flows), in equilibrium, she tilts the portfolio towards high-beta stocks. The resulting increase in portfolio beta raises expected returns and partially offsets the increase in the risk-free rate.

The empirical evidence in Section 3 is consistent with this explanation. Funds' RFB strongly co-moves with the risk-free rate, and managers actively increase portfolio betas following higher interest rates and tighter monetary policy. Although our stylized framework does not formulate all potential interactions between stock returns and interest rates or monetary policy (e.g., general equilibrium effects, intertemporal effects, etc.), it delivers additional testable implications that we take to the data.

First, the mechanism presumes that higher short rates and contractionary policy elevate outflow risk from equity funds. We test this prediction using a time-series

[5]For open-end funds, the Investment Company Act §.18(f)(1) requires 300% asset coverage for bank borrowings and restricts senior securities. SEC Rule 18f–4 imposes VaR-based limits and governance for derivatives. Empirically, borrowing and margin usage are rare (Almazan et al., 2004), and while derivatives are used, exposures are far from universal and typically modest in portfolio weight (e.g., Koski and Pontiff, 1999; Deli and Varma, 2002; Kaniel and Wang, 2025).

Table 5: Aggregate Flows and Monetary Policy

	Agg. Flows	Δ Agg. Flows
NS	-0.091**	-0.107***
	(-2.44)	(-2.73)
R_{Equity}	0.027	0.028
	(-1.25)	(-1.26)
VIX	0.002	0.007
	(-0.06)	(-0.29)
PS	0.052	0.047
	(-0.58)	(-0.49)
Lag Agg.Flows	0.636***	
	(-4.11)	
Observations	103	103
R-squared	0.4686	0.1215

This table presents results from a time-series regression of aggregate net flows into equity funds on the monetary policy surprise (NS), controlling for the value-weighted average equity fund return, the VIX, and stock market liquidity (Pastor and Stambaugh, 2003). The sample covers the period 1995:Q1–2020:Q4. The first column estimates the regression in levels, also controlling for lagged aggregate flows. The second column estimates the regression in first differences of aggregate flows. t-statistics are reported in parentheses; *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

regression of aggregate equity mutual fund flows on the monetary-policy surprise in the same quarter. Table 5 shows that aggregate net fund flows to the equity fund sector correlate negatively with the monetary policy surprise, consistent with the premise.

Second, our conceptual framework implies that the elasticity of assets under management to fund performance is a key determinant of how aggressively a fund increases its portfolio beta when interest rates rise. We therefore expect that reaching for beta is more pronounced among funds that face stronger flow pressure and thus incentives to boost returns when monetary policy is tight.

A natural source of heterogeneity regarding flow pressures comes from fund and fund-family size. Huang et al. (2011) find *less* risk-taking in large funds and funds affiliated with prominent management companies. Large fund families (such as Vanguard or Fidelity) benefit from brand recognition, retirement-platform defaults, and broad distribution, so even average performance can attract assets (Huang et al., 2007). Small family funds lack these cushions and rely more heavily on recent performance to attract and retain assets. Moreover, the marginal value of AUM is likely higher in small families due to pre-breakpoint fee rates and a higher fixed-cost share, making each incremental dollar more valuable. In light of these considerations, we expect active RFB to be negatively related to fund size and family size.

Fund age is another characteristic that can generate differential allocation pressure and thus differences in RFB behavior. Chevalier and Ellison (1997) show that younger funds, which lack an established performance record, are more vulnerable to outflows when returns are not sufficiently strong. These funds should therefore also face stronger incentives to take additional risk to attract inflows, particularly during periods of industry-wide redemptions. Accordingly, we also expect reaching for beta to be negatively correlated with fund age.

We test these implications by investigating how the response of ΔRFB^{Active} to monetary policy shocks varies with fund size, family size, and age. Specifically, we re-estimate our regression (8) and interact the monetary policy surprise with each characteristic in turn. Table 6 reports the results. As before, the monetary-surprise coefficient is positive and highly significant in all specifications. Moreover, each interaction term is negative and statistically significant. Larger funds, older funds, and funds in larger families adjust portfolio beta *less* strongly following policy shocks, providing direct support for a career-concerns channel behind reaching for beta.

Our conceptual framework further implies that funds increase their beta in response to higher short rates to counteract outflows into risk-free alternative investments. In Section 5.1, we show that funds which engage more strongly in reaching-for-beta attract higher net flows and achieve higher returns when monetary policy is tightened, consistent with our proposed explanation based on career concerns.

Table 6: ΔRFB^{Active} and Fund Characteristics

	ΔRFB^{Active}		
	(5)	(6)	(7)
NS	0.243***	0.239***	0.231***
	(3.530)	(3.575)	(4.017)
log(TNA) $\times$ NS	−0.018***		
	(−2.867)		
log(Age) $\times$ NS		−0.020*	
		(−1.953)	
log(Family TNA) $\times$ NS			−0.011***
			(−2.922)
Fund FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	129,694	129,694	129,694
Adjusted R^2	0.1973	0.1970	0.1972

This table reports coefficient estimates from predictive panel regressions of active reaching for beta (ΔRFB^{Active}) on monetary policy surprises (NS) interacted with fund characteristics. The sample covers the period 1995:Q1–2020:Q4. The interaction terms are log total net assets, log fund age, and log family total net assets, considered separately across columns. Control variables include (log) fund age, (log) total net assets, past three months of fund returns, CAPM alpha, and return volatility over the previous 12 months, turnover ratio, expense ratio, fund flows, as well as macroeconomic variables such as market returns, liquidity, and the VIX. All regressions include fund fixed effects, and standard errors are two-way clustered at the fund and time levels. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

4.2 Alternative explanations

In the previous sections, we have shown that our proposed mechanism is consistent with our empirical findings. We now examine alternative mechanisms that may potentially explain reaching for beta in equity mutual funds. For each, we first describe the intuition and then present evidence indicating it does not account for our results.

4.2.1 Fed Information Effect

A recent literature argues that central bank announcements convey information not only about the path of policy rates, but also about the state of the economy (e.g. Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). As a result, some announcements may give rise to seemingly counterintuitive asset-price reactions: a surprise tightening can be followed by rising equity prices if investors infer a stronger economy than previously expected, whereas lower rates may signal deteriorating economic conditions. This "Fed information effect" presumes that the central bank has superior information about the state of the economy than market participants. An alternative explanation is the "Fed response to news" effect, where both the central bank and investors respond to the same public information (e.g., Bauer and Swanson, 2023).

If either of these effects were present, it could constitute an important omitted variable in our regressions. In particular, higher policy rates might lead to active reaching for beta not because of perceived flow pressures (our proposed mechanism), but because fund managers may seek to benefit from an improved economic outlook via increased market exposure. To assess these alternative channels, we re-estimate our baseline predictive regressions of active reaching for beta on monetary policy surprises by adding relevant control variables and by relying on policy surprise measures that decompose "pure" monetary policy and "information" or "response to news" effects.

Table 7 provides the results. The first column shows that the relation between NS shocks and ΔRFB^{Active} remains intact after we account for the information channel using contemporaneous Greenbook forecasts and revisions as additional controls.[6] Second, we directly test for an information effect using the quarterly monetary policy shock measures of Jarociński and Karadi (2020) that decompose Federal Reserve announcement surprises into pure monetary policy (MP) and central bank information (CBI) components, estimated via either a "poor man's" (pm) or a sign-restriction approach. Columns (2) and (3) in Table 7 show that the pure monetary policy (MP) shocks – purged of the information effect – remain statistically significant under both identification approaches. Finally, we employ the orthogonalized monetary policy surprise

[6]Forecast data are available until 2019 and can be found at the Philadelphia Fed: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/philadelphia-data-set.

Table 7: ΔRFB^{Active} and Fed's Information & Response to News Effects

	ΔRFB^{Active}			
	(1)	(2)	(3)	(4)
NS	0.123**			
	(2.532)			
MP_pm		0.083**		
		(2.542)		
CBI_pm		0.084		
		(1.047)		
MP_median			0.073***	
			(2.654)	
CBI_median			0.120**	
			(2.449)	
MPS_Orth				7.629*
				(1.975)
Fund FE	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes
Greenbook Controls	Yes	No	No	No
Observations	125,604	129,755	129,755	125,604
Adjusted R^2	0.186	0.180	0.181	0.180

This table reports coefficient estimates from predictive panel regressions that account for the information channel of monetary policy. The sample covers the period 1995:Q1–2020:Q4. Column (1) augments the baseline specification with contemporaneous Greenbook forecasts and revisions as controls. Columns (2) and (3) use the decomposition of Jarociński and Karadi (2020) to separate monetary policy (MP) and central bank information (CBI) shocks, employing both the "poor man's" and sign-restriction (median) versions. Column (4) reports results using an orthogonalized monetary policy shock measure. All regressions include fund fixed effects and a standard set of fund-level controls: log fund age, log total net assets, past three months of fund returns, CAPM alpha, and return volatility over the past twelve months, turnover ratio, expense ratio, and fund flows. Standard errors are clustered at both the fund and time levels. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

of Bauer and Swanson (2023) (MPS_Orth), which removes the Fed response-to-news component in our baseline specification.[7] Column (4) shows that these orthogonalized surprises still significantly predict active RFB. In sum, monetary policy shocks that are orthogonal to changing economic conditions retain strong explanatory power for our RFB measure.

[7]MPS_Orth is computed as residuals from projecting raw surprises on macro and financial variables. As in our baseline, we aggregate monthly surprises to the quarterly level by summation. Orthogonalized surprises are largely unavailable in 2020 (COVID-19 period), so we end this exercise in 2019.

4.2.2 Leverage Constraints & Cost of Leverage

The prior literature suggests that certain investors tilt their portfolios toward high-beta assets when leverage constraints tighten or the shadow cost of leverage rises (e.g., Black, 1972; Frazzini and Pedersen, 2014; Lu and Qin, 2021). Although the use of explicit leverage is highly constrained for mutual funds, we investigate whether active reaching for beta is related to such constraints. Specifically, we consider five proxies for leverage constraints or the shadow cost of leverage: the Treasury Bill–Eurodollar (TED) spread and the betting-against-beta (Bab) factor suggested by Frazzini and Pedersen (2014), the leverage constraint tightness (LCT) measure of Boguth and Simutin (2018), the intermediary capital risk factor (ICRF) of He et al. (2017), and the shadow cost of leverage measure (Ψ) of Lu and Qin, 2021. Higher values of TED spread, LCT, and Ψ and lower values of Bab and ICRF are associated with tighter leverage constraints.

To assess whether tighter borrowing constraints or higher leverage costs predict higher active RFB, we run the following quarterly panel regression:

$$\Delta RFB^{Active}_{i,t+1} = \alpha_i + \beta\, LCProxy_t + \gamma\, X_{i,t} + \theta\, Z_t + \varepsilon_{i,t+1} \tag{12}$$

where $LCProxy$ represents one of the leverage constraint proxies listed above, α_i captures fund fixed effects, and X_i and Z are the same set of fund-level and aggregate control variables as before. Table 8 shows that none of the leverage constraint proxies significantly predict active RFB by fund managers. Since most mutual fund managers can make limited use of borrowing or margin, these findings are rather unsurprising (Almazan et al., 2004). The portfolio decisions of equity mutual fund managers do not depend on variations in borrowing conditions.

Table 8: ΔRFB^{Active} and Leverage Constraints

	ΔRFB^{Active}				
	(1)	(2)	(3)	(4)	(5)
TED	−0.010				
	(−1.168)				
Bab		−0.143			
		(−1.017)			
LCT			0.044		
			(0.956)		
ICRF				−0.041	
				(−1.116)	
Ψ					−0.018
					(−1.589)
Fund FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	129,755	129,755	98,517	129,755	60,279
Adjusted R^2	0.172	0.172	0.190	0.172	0.207

This table presents coefficient estimates from predictive panel regressions examining whether active reaching for beta is related to margin requirements or leverage constraints. The sample covers the period 1995:Q1–2020:Q4. We consider five proxies for leverage constraint tightness or the shadow cost of leverage: the Treasury Bill–Eurodollar (TED) spread and the betting-against-beta factor (Bab) suggested by Frazzini and Pedersen (2014), the leverage constraint tightness (LCT) measure of Boguth and Simutin (2018), the intermediary capital risk factor (ICRF) of He et al. (2017), and the shadow cost of leverage measure (Ψ) of Lu and Qin, 2021. Higher values of the TED spread, LCT, and Ψ, and lower values of Bab and ICRF, indicate tighter leverage constraints. All regressions include fund fixed effects and a standard set of fund-level controls: log fund age, log total net assets, past three months of fund returns, CAPM alpha, and return volatility over the past twelve months, turnover ratio, expense ratio, and fund flows. Standard errors are clustered at both fund and time levels. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

4.2.3 Market Timing

A third alternative explanation is that our findings reflect funds' market timing rather than reaching for beta. Market timing involves managers adjusting their market exposure in anticipation of market movements – for example, increasing beta when the expected market risk premium is high and decreasing it when it is low. Past research shows that FOMC announcements create return patterns that could be exploited for tactical timing. Specifically, surprise policy changes cause large market moves on the announcement day: an unexpected 25 bp hike is associated with a roughly 1% decline

Table 9: ΔRFB^{Active} and Market Timing

	ΔRFB^{Active}					
	(1)	(2)	(3)	(4)	(5)	(6)
NS	0.152***	0.151***	0.149***	0.132***	0.132***	0.130***
	(4.426)	(4.359)	(4.264)	(2.793)	(2.787)	(2.707)
Timing	0.564***	0.564***	0.565***			
	(5.102)	(5.251)	(5.198)			
Timing x NS		0.904	0.876			
		(0.972)	(0.958)			
Selectivity			0.145			
			(1.162)			
Selectivity x NS			1.602			
			(1.280)			
CT				0.224	0.207	0.208
				(1.192)	(1.078)	(1.075)
CT x NS					−2.461	−2.627
					(−0.925)	(−1.010)
CS						−0.088
						(−0.751)
CS x NS						1.478
						(0.946)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,075	129,075	129,075	115,656	115,656	115,656
Adjusted R^2	0.195	0.195	0.196	0.179	0.179	0.180

This table presents coefficient estimates from predictive panel regressions of active reaching for beta (ΔRFB^{Active}) on monetary policy surprises (NS) and interactions with fund skill and characteristic-based measures. The sample covers the period 1995:Q1–2020:Q4. Timing and selectivity measures are constructed following Kacperczyk et al. (2014), while characteristic timing (CT) and characteristic selectivity (CS) measures follow Daniel et al. (1997). All regressions include fund fixed effects and a standard set of fund-level controls: log fund age, log total net assets, past three months of fund returns, CAPM alpha, and return volatility over the past twelve months, turnover ratio, expense ratio, and fund flows. Standard errors are clustered at both fund and time levels. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

in the stock market (Bernanke and Kuttner, 2005). These announcement-day returns are proportional to market betas: high-beta stocks move more than low-beta stocks. Moreover, the equity market response to *tightening* surprises is largely reversed in the days after the announcement (Boguth et al., 2023). If managers trade on these regularities – e.g., temporarily adding cheaper high-beta stock or trimming low-beta positions after surprise hikes – our patterns could, in principle, be consistent with timing.

However, a body of evidence from our analyses weighs against a timing interpretation. First, using local projections, we find that the response of ΔRFB^{Active} to a positive monetary surprise is gradual and persists for multiple quarters (see Figure 2). Consistent with this, our results from daily transactions in Section 3.2 show slow portfolio reallocation after policy shocks. Such gradual and persistent portfolio changes are inconsistent with short-lived tactical timing concentrated around announcement dates.

Second, we augment the panel regression relating ΔRFB^{Active} to monetary surprises (see Table 3) with the fund-level timing measures of Daniel et al. (1997) and Kacperczyk et al. (2014).[8] We first implement all measures at the monthly frequency and then compute the quarterly value as the simple average of the three monthly scores within quarter t. As shown in Table 9, the timing measures do not alter the relation between ΔRFB^{Active} and the monetary surprise: the coefficient remains positive and statistically significant – if anything, larger in magnitude – while the interactions between monetary surprises and our timing proxies are insignificant. Taken together, these facts are difficult to reconcile with market-timing skill.

5 Implications of Reaching for Beta

We have shown that equity mutual funds reach for beta following tighter monetary policy and that this behavior aligns with incentive-based rather than alternative explanations. This section examines the consequences for fund performance and flows, and then studies stock-level price effects of RFB-induced trading.

[8]Following Daniel et al. (1997), we compute characteristic timing (CT) and characteristic selectivity (CS) by comparing fund holdings to characteristic-matched benchmarks (size, book-to-market, momentum). CT captures returns from changing characteristic weights interacted with subsequent benchmark returns, while CS captures stock-selection returns relative to those benchmarks. Following Kacperczyk et al. (2014), we compute *Timing* as the sum of each position's overweight across holdings relative to the market times the systematic component of its next-month return, and *Selectivity* as the sum of each overweight times the idiosyncratic component of its next-month return, where the systematic part is given by $\beta \times R_{m,t+1}$ and where β is estimated each month from a 12-month rolling regression of excess stock returns on the market. Accordingly, the idiosyncratic part is given by the stock's next-month excess return minus the systematic part.

5.1 Implications for Fund Returns and Flows

How does reaching for beta affect fund performance and investor flows? Section 5.1.1 shows that ΔRFB^{Active} predicts higher *raw* but not *risk-adjusted* returns. Section 5.1.2 shows that funds with higher ΔRFB^{Active} attract more inflows *during* monetary tightenings, even after controlling for past performance.

5.1.1 Does Active RFB result in higher returns?

In an influential paper, Huang et al. (2011) document that mutual funds' risk-shifting varies over time and that it can reflect either managerial skill or agency costs. Skilled risk-taking should generate persistent positive abnormal returns (alphas), whereas risk-taking induced by agency frictions may increase raw returns without creating risk-adjusted value or even result in lower returns. In this paper, we identify a specific form of risk-taking behavior, reaching for beta. In line with our preferred explanation based on career concerns, fund managers would reach for beta to attract net flows and boost headline returns, which, in turn, positively impact their compensation. According to this interpretation, active RFB primarily reflects agency-driven risk shifting. Hence, return differences should disappear after appropriate risk adjustment. In contrast, if active RFB were to reflect managerial skill, we should observe persistent alphas. We now test these competing interpretations.

First, we conduct panel regressions of quarterly raw and risk-adjusted fund returns on lagged active RFB (ΔRFB^{Active}). As before, we control for fund characteristics that could be correlated with fund returns (log size, log age, expense ratio, and turnover ratio) and include specifications with fund and style-time fixed effects.

Table 10 reports the results. Columns (1) - (3) show that higher active reaching for beta predicts higher raw returns. For example, the coefficient in Column (3) implies that a one-standard-deviation increase in ΔRFB^{Active} is associated with about 13 bps

Table 10: Active Reaching for Beta and Fund Returns: Panel Evidence

	$FundReturn_{t+1}$						
	Raw			CAPM		FF4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔRFB^{Active}	0.072**	0.092***	0.013*	0.009	0.009	−0.0001	0.001
	(2.240)	(2.933)	(1.841)	(0.922)	(1.152)	(−0.011)	(0.297)
Fund FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Style x Time FE	No	No	Yes	No	Yes	No	Yes
Observations	130,661	130,661	130,658	125,005	125,002	125,005	125,002
Adjusted R^2	0.031	0.039	0.876	0.024	0.291	0.019	0.147

This table reports results from the regressions of future quarterly fund returns on the active reaching for the beta measure. The sample covers the period 1995:Q1–2020:Q4. ΔRFB^{Active} is defined in Equation (2). All regressions include log fund age, log total net assets, past three months of fund returns, return volatility over the past twelve months, turnover ratio, expense ratio, and fund flows. Regressions include fund-fixed effects and style-time fixed effects as indicated. Standard errors are clustered at both fund and time levels. t-stats are reported in parentheses; *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

higher quarterly returns ($\approx$ 52 bps annualized). Hence, reaching for beta allows fund managers to enhance returns. However, this relation disappears once we control for risk. Columns (4) - (7) use risk-adjusted returns accounting for market risk (CAPM) and the Fama-French three factors plus momentum (FF4), respectively. The results show that ΔRFB^{Active} is not associated with higher future risk-adjusted returns. Crucially, as evidenced in Columns (4) and (5), the predictability already disappears once the market factor is accounted for, suggesting that funds with high ΔRFB^{Active} generate superior raw returns primarily by loading on market risk.

To reinforce this point, we sort all funds each quarter into quintiles by ΔRFB^{Active} and form equal and value-weighted portfolios. Table 11 reports the excess returns and factor alphas (estimated with respect to CAPM and FF4) for these portfolios. Fund excess returns rise monotonically with ΔRFB^{Active} for both equal- and value-weighted portfolios. The high-minus-low (H–L) portfolio earns a positive quarterly return of 0.49% (significant at the 10% level), indicating outperformance of high ΔRFB^{Active} funds in terms of raw returns. Controlling for market exposure substantially reduces performance, particularly for the H–L portfolio, which strongly loads on the market factor. This confirms that RFB-induced higher fund returns reflect increased market risk rather than superior stock-picking ability, consistent with the agency-based risk-shifting interpretation of Huang et al. (2011).

5.1.2 Does Active RFB attract more fund flows?

The previous section shows that reaching for beta does not raise risk-adjusted performance. Nonetheless, managers may still have incentives to pursue higher raw returns in response to changes in risk-free rates if their clients do not properly account for risk when allocating funds. Consistent with such an interpretation, the previous literature finds that many retail investors fail to fully account for risk in their decision-making processes (Guercio and Reuter, 2014).

In this section, we analyze whether fund flows respond to beta-tilting behavior. We first test whether higher total reaching-for-beta (RFB^{Total}) predicts future quarterly flows, and whether that response depends on the monetary policy stance by interacting RFB^{Total} with NS. Because RFB^{Total} combines manager-initiated beta tilts and passive beta changes, we also decompose total RFB and regress fund flows on all three components ΔRFB^{Active}, $\Delta RFB^{BetaShift}$, and $\Delta RFB^{Interaction}$, each also interacted with NS. This design allows us to assess whether investors reward managers' *active* reaching for beta under tighter policy conditions. As before, our regressions include fund and style–time fixed effects and a host of fund controls which could correlate with flows (log age, log TNA, past three months' returns, CAPM alpha, return volatility over the prior twelve months, turnover, expense ratio, and lagged flows). Standard errors are clustered by fund and time.

The results are presented in Table 12. Columns (1)-(3) use RFB^{Total} while Columns (4)-(6) use the three components of changes in RFB. Column (1) shows that flows are unresponsive to RFB^{Total} unconditionally, suggesting that investors do not gen-

Table 11: Active Reaching for Beta and Fund Returns: Portfolio Sorts

(a) Equal Weighted ΔRFB^{Active} Sorted Portfolios

	Low	P2	P3	P4	High	H-L
Excess Return	2.51	2.64	2.77	2.85	2.95	0.44
	(3.42)	(3.72)	(3.88)	(3.98)	(3.86)	(1.78)
CAPM α	0.22	0.35	0.41	0.37	0.25	0.03
	(0.87)	(1.33)	(1.30)	(1.09)	(0.67)	(0.10)
FF4 α	0.17	0.30	0.36	0.34	0.28	0.11
	(1.12)	(2.03)	(2.04)	(1.67)	(1.14)	(0.63)
β^{MKT}	0.94	0.94	0.95	0.98	1.02	0.09
	(71.48)	(62.06)	(64.90)	(61.42)	(41.19)	(4.16)
β^{HML}	0.10	0.09	0.07	0.02	-0.12	-0.22
	(1.80)	(1.98)	(1.52)	(0.33)	(-2.67)	(-3.76)
β^{SMB}	0.10	0.10	0.14	0.24	0.41	0.31
	(3.93)	(3.88)	(6.31)	(8.59)	(8.43)	(7.00)
β^{Mom}	0.00	0.01	0.01	0.02	0.01	0.01
	(0.11)	(0.64)	(0.76)	(0.77)	(0.37)	(0.51)

(b) Value Weighted ΔRFB^{Active} Sorted Portfolios

	Low	P2	P3	P4	High	H-L
Excess Return	2.41	2.60	2.74	2.79	2.91	0.49
	(2.99)	(3.54)	(3.78)	(3.67)	(3.45)	(1.90)
CAPM α	0.15	0.39	0.50	0.34	0.23	0.08
	(1.10)	(1.75)	(2.07)	(1.41)	(0.96)	(0.34)
FF4 α	0.13	0.34	0.45	0.36	0.28	0.15
	(0.99)	(2.14)	(2.70)	(1.69)	(1.26)	(0.70)
β^{MKT}	0.96	0.93	0.93	0.99	1.05	0.10
	(57.88)	(60.18)	(56.24)	(40.27)	(38.05)	(3.69)
β^{HML}	0.06	0.07	0.06	-0.05	-0.16	-0.23
	(1.21)	(1.28)	(1.26)	(-1.66)	(-4.20)	(-3.28)
β^{SMB}	-0.05	-0.02	0.03	0.14	0.22	0.26
	(-1.20)	(-0.67)	(1.00)	(4.43)	(4.22)	(5.23)
β^{Mom}	0.00	0.02	0.02	0.00	0.02	0.02
	(-0.44)	(0.92)	(0.93)	(-0.07)	(0.47)	(0.76)

This table reports alphas and betas for quarterly portfolios sorted by the active reaching-for-beta measure (ΔRFB^{Active}). Each quarter, we form equal-weighted (Panel A) and value-weighted (Panel B) portfolios by sorting funds into quintiles of ΔRFB^{Active} and tracking their subsequent risk-adjusted returns. Columns "Low" through “High” present results for the five quintiles; column "H–L" is a long-short portfolio that is long the highest-ΔRFB^{Active} quintile and short the lowest. We report the average quarterly excess return and alphas from the CAPM and the Carhart four-factor model (FF4). For each panel, we also report FF4 factor loadings. t-statistics (in parentheses) are based on Newey–West standard errors with optimal lags.

Table 12: Reaching for Beta and Fund Flows

	$Flow_{t+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RFB^{Total}	0.002	0.002	0.011**				
	(0.409)	(0.497)	(2.389)				
RFB^{Total} x NS		0.293***	0.304***				
		(2.943)	(3.119)				
ΔRFB^{Active}				0.003	0.014*	0.006	0.017**
				(0.364)	(1.896)	(0.755)	(2.381)
$\Delta RFB^{BetaShift}$				0.013	0.014	0.016	0.018
				(0.684)	(0.784)	(0.830)	(0.970)
$\Delta RFB^{Interaction}$				−0.010	−0.017	−0.017	−0.024
				(−0.335)	(−0.600)	(−0.550)	(−0.865)
ΔRFB^{Active} x NS						0.416***	0.469***
						(2.833)	(2.839)
$\Delta RFB^{BetaShift}$ x NS						0.439*	0.538**
						(1.713)	(2.026)
$\Delta RFB^{Interaction}$ x NS						0.007	0.028
						(0.019)	(0.076)
Style x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,878	130,878	130,878	130,485	130,485	130,485	130,485
Adjusted R^2	0.183	0.184	0.220	0.183	0.219	0.183	0.219

This table presents coefficient estimates from panel regressions of future quarterly fund flows on four measures of reaching for beta (RFB^{Total}, ΔRFB^{Active}, $\Delta RFB^{BetaShift}$, and $\Delta RFB^{Interaction}$), defined in Equation (2), interacted with the monetary policy surprise measure of Nakamura and Steinsson (2018). The sample covers the period 1995:Q1–2020:Q4. Control variables include log fund age, log total net assets, past three months of fund returns, CAPM alpha and return volatility over the past twelve months, turnover ratio, expense ratio, and fund flows. All regressions include fund fixed effects and style-time fixed effects, as indicated. Standard errors are clustered at both fund and time levels. t-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

erally reward higher market risk. However, Columns (2)–(3) reveal that the coefficient on $RFB^{Total} \times NS$ is positive and significant: during tightening episodes, a higher

RFB^{Total} is associated with larger net flows. Economically, a one-standard-deviation increase in RFB^{Total} corresponds to roughly a 9.6% increase in quarterly flows, about one standard deviation of flows in our sample. Hence, investors tend to favor higher-beta funds when monetary policy tightens.

Turning to the components in Columns (4)–(6), we see that funds which *actively* reach for beta attract higher flows, especially under tighter policy. These results are economically meaningful: a one-standard-deviation increase in ΔRFB^{Active} is associated with nearly a 4% increase in quarterly net flows. We also note that some specifications show a significant – albeit weaker – association between $\Delta RFB^{BetaShift}$ and flows. In sum, our results show that active RFB raises raw performance and draws net flows in tightening states, even though risk-adjusted performance does not improve.

5.2 Asset-Pricing Implications

Systematic mutual fund tilts towards higher market beta likely generate correlated demand for high-beta stocks. If this demand is not based on information about stock fundamentals, it should move prices contemporaneously but not permanently, creating transitory price pressure. Here, we test this asset pricing implication of RFB. We first construct a holdings-based measure of *beta-induced trading* (BIT), in the spirit of the flow-induced trading measure of Lou (2012), and then examine price dynamics following BIT innovations.

We define beta-induced trading (BIT) for each stock j in each quarter t as:

$$BIT_{j,t} = \frac{\sum_i shares_{i,j,t-1} \times \Delta RFB_{i,t}^{Active}}{\sum_i shares_{i,j,t-1}} \tag{13}$$

where $\Delta RFB_{i,t}^{Active}$ is the active reaching for beta of fund i in quarter t as defined in Equation (2), and $shares_{i,j,t-1}$ is the number of shares of stock j held by mutual fund i

at the end of the previous quarter. Intuitively, $BIT_{j,t}$ captures the mutual fund trading pressure on stock j induced by active RFB in our mutual fund universe. By construction, BIT isolates trading linked to funds' active reaching-for-beta and is not designed to capture managers' stock-specific fundamental information.

Using the BIT measure, we test whether active RFB affects stock prices through beta-induced trading. First, we estimate predictive stock-level panel regressions for horizons $h = 0, \ldots, 8$:

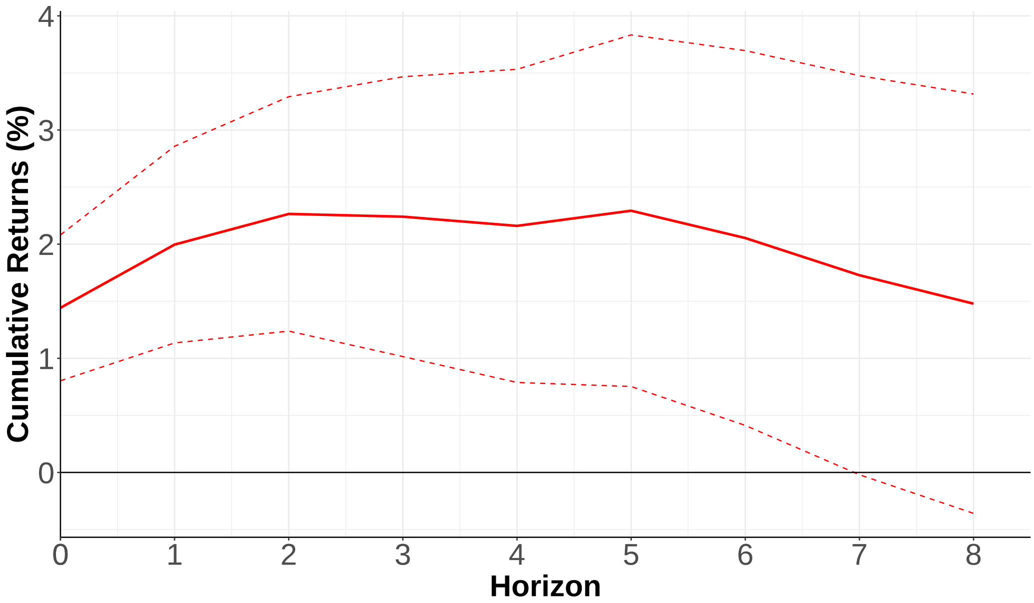
$$ExRet_{j,t+h} = \alpha_j + \beta_h BIT_{j,t} + \gamma' X_{j,t} + \varepsilon_{j,t+h}, \tag{14}$$

where $ExRet_{j,t+h}$ represents stock j's quarterly excess return, α_j are stock fixed effects, and $X_{j,t}$ represents a vector of stock-level controls including the book-to-market ratio, market capitalization, idiosyncratic volatility, and Amihud's illiquidity measure. Standard errors are clustered by quarter. We standardize BIT over the entire sample so that coefficients reflect units of stock-level return response per one standard deviation of BIT. We estimate the regression for horizons h running from 0 to 8.

Figure 4 plots the cumulative response of stock returns $\sum_{h=0}^{n} \beta_h$. It shows economically and statistically significant price pressure on stocks associated with active reaching for beta. A one standard-deviation BIT raises excess returns by about 1.5% ($\approx$ 6% annualized) in the same quarter. Cumulative returns increase to roughly 2.3% ($\approx$ 9% annualized) over the next two quarters, and then gradually reverse over the following six quarters. The immediate impact and subsequent reversal are consistent with demand-driven price pressure from beta-induced trading that moves prices away from fundamentals on impact and dissipates only gradually thereafter.

In the spirit of Lou (2012), we also form portfolios sorted on BIT to examine return spreads associated with beta-induced trading. Each quarter, we sort stocks into quintiles based on BIT and track their corresponding quarterly returns in the formation and subsequent quarters, reporting both equal-weighted and value-weighted results

Figure 4: Beta-induced trading (BIT) and the Dynamics of Excess Returns



This figure displays the dynamics of excess stock returns in response to beta-induced trading (BIT). On the y-axis, we report the sum of coefficients estimated from the predictive regressions (14) for forecast horizons from one to eight quarters. We standardize BIT over the entire sample such that the coefficients reflect standard deviations relative to the sample mean. Dashed lines indicate 90% confidence bands.

for various holding periods. Table 13 provides the results. In the formation quarter, the equal-weighted high-minus-low (H-L) portfolio shown in Panel A earns 1.22% ($t = 5.29$), consistent with the contemporaneous impact in Figure 4. Controlling for the market and risk factors diminishes the returns of both High and Low legs but leaves the H-L spread largely intact. Panel B also shows a sizable spread for value-weighted portfolios. Overall, these results suggest a strong contemporaneous price effect of beta-induced trading by mutual funds, in line with Figure 4.

Table 13: Portfolio Sorts by BIT and Excess Returns

(a) Equal-Weighted Portfolios

	Excess Return	CAPMα	FF4α	Excess Return	CAPMα	FF4α	Excess Return	CAPMα	FF4α	Excess Return	CAPMα	FF4α
Quintile	Quarter 0 (Formation Qtr.)			Quarter 1-2			Quarter 3-4			Quarter 5-8		
Low	0.17	-0.79	-0.68	1.29	-0.29	-0.23	1.57	0.08	0.08	3.23	0.19	-0.44
High	1.40	0.54	0.64	1.90	-0.05	0.05	1.69	-0.07	-0.08	3.57	0.12	-0.37
H-L	1.22	1.32	1.32	0.60	0.24	0.27	0.12	-0.15	-0.16	0.34	-0.07	0.07
	(5.29)	(5.20)	(5.21)	(2.09)	(0.70)	(0.86)	(0.29)	(-0.29)	(-0.35)	(0.60)	(-0.10)	(0.11)

(b) Value-Weighted Portfolios

	Excess Return	CAPMα	FF4α	Excess Return	CAPMα	FF4α	Excess Return	CAPMα	FF4α	Excess Return	CAPMα	FF4α
Quintile	Quarter 0 (Formation Qtr.)			Quarter 1-2			Quarter 3-4			Quarter 5-8		
Low	0.04	-0.78	-0.68	1.36	0.11	0.30	1.61	0.57	0.55	2.94	0.05	-0.22
High	1.61	0.43	0.30	2.28	0.03	0.49	0.86	-1.10	-0.82	2.30	-1.28	-1.34
H-L	1.51	1.31	1.46	0.29	-0.33	0.11	-0.59	-1.31	-0.72	-0.83	-1.99	-1.46
	(3.36)	(2.86)	(2.82)	(0.56)	(-0.54)	(0.17)	(-0.75)	(-1.43)	(-1.04)	(-0.87)	(-1.84)	(-1.88)

This table reports returns for quarterly portfolios sorted by beta-induced trading (BIT). Each quarter, funds are sorted into BIT quintiles and used to form equal-weighted (Panel A) and value-weighted (Panel B) portfolios. Portfolios are rebalanced each quarter and held for two years (eight quarters). Quarter 0 is the formation quarter. Columns "Low" and "High" report the first and fifth quintiles; "H-L" is a long-short portfolio that is long the highest-BIT quintile and short the lowest. We report average quarterly excess returns and alphas from the CAPM and the Carhart four-factor (FF4) model. t-statistics (in parentheses) are based on Newey–West standard errors with optimal lags.

After the formation period, the effect reverses, especially for risk-adjusted returns. For equal-weighted portfolios, the H-L excess returns remain positive and significant in Quarters 1 and 2 but lose significance thereafter. For value-weighted portfolios, post-formation excess returns are not significant. Moreover, risk-adjusted H-L spreads become indistinguishable from zero over the four quarters following formation in both panels. After two years, risk-adjusted H–L returns for value-weighted portfolios are negative and borderline significant, implying that the initial gains fully reverse.

In summary, our findings indicate that the beta-induced demand causes sizable but transitory price pressure: prices move on impact, yet the return premium dissipates over a two-year horizon. These return dynamics align with the persistence of active RFB (Figure 2) and suggest that BIT captures non-informational demand pressure.

6 Conclusion

In this paper, we have documented that higher short-term interest rates and tighter monetary policy induce an active shift of equity mutual fund managers toward high-beta stocks. This *Reaching for Beta* (RFB) is persistent and increases the net buying pressure of high beta stocks for about one year. RFB is beta-driven and not a by-product of other stock characteristics such as dividends, book-to-market ratios, or duration.

We argue that RFB is consistent with equity fund managers' career concerns. When short rates rise, investors reallocate some of their wealth into risk-free investments. Since fund managers' compensation is closely tied to assets under management and performance, they have strong incentives to counteract outflows and boost returns. Being tightly constrained in their ability to take leverage, managers raise expected returns by overweighting riskier high-beta stocks. Consistent with this explanation, the equity fund sector overall faces outflows when the Fed hikes rates. We also show that tighter policy leads to more active RFB, but that this effect is smaller for funds which face lower flow-return pressures because they are larger, older or from a large fund family. Finally, we document that funds that reach for beta more strongly see net inflows in times of tighter monetary policy. Alternative explanations based on central bank information effects, leverage constraints, and market-timing are not supported by the data.

We show that RFB has important fund performance and asset pricing implications. Funds that tilt more heavily towards high-beta stocks increase their raw, but not their risk-adjusted returns. Moreover, stock-specific demand related to reaching for beta generates systematic and persistent price pressures that take several months to dissipate. This suggests that beta-induced demand does not reflect fundamental information but instead causes price swings via uninformed trading.

Our findings are in stark contrast to reaching for yield, the tendency of bond mutual funds and other fixed-income investors to increase their risk-taking in response to low interest rates and accommodative monetary policy. Reaching for beta has the opposite implication. Equity mutual fund managers tilt their portfolios towards riskier stocks precisely when short-term interest rates rise and monetary policy is restrictive. Hence, we document that central bank decisions affect the stock market not only by moving prices directly but also indirectly via the portfolio decisions of mutual fund managers. While studying the drivers behind the stark contrast in investment behavior of equity and bond mutual funds is beyond the scope of this paper, differences in flow-return relationships and investor clienteles are likely candidates.

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Online Appendix

for

Reaching for Beta

IA1 Career Concerns & RFB: A Conceptual Framework

To motivate our empirical analysis, we provide a conceptual framework for understanding fund managers' career concerns and their portfolio allocation towards high-beta stocks (i.e., reaching for beta). We argue that equity mutual fund managers face unique incentives shaped by career concerns, agency issues, and convex fund flow-performance relations (e.g., Chevalier and Ellison, 1997, Sirri and Tufano, 1998, Chevalier and Ellison, 1999, Guerrieri and Kondor, 2012). As such, they seek to enhance returns by taking more risk via active portfolio rebalancing as the rise in interest rates intensifies the threat of outflows due to the rise in potential income from low-risk investments. Here, we sketch a simple static partial equilibrium model that formalizes our intuition.

IA1.1 Investment Universe

We start by describing a stylized investment environment in which a representative equity mutual fund and a representative money market fund operate to cater to a continuum of investors.

Investors: Investors allocate their wealth W between the *Money Market Fund (MMF)*, which invest in short-term risk-free assets with a risk-free rate of return r_f, or the *Equity Mutual Funds (EMF)*, which invest in stocks with an expected rate of return $\mathbf{E}[R_p]$. As such, investors choose a portfolio with a fraction α of her wealth in equity mutual funds and the remaining in money market mutual funds to maximize their expected return on wealth

$$\max_{\alpha} \mathbf{E}[R_W] = \alpha \, \mathbf{E}[R_p] + (1 - \alpha) \, r_f \tag{IA1}$$

We suppose that investors adjust their share of risky investment α based on a function g defined on the spread between expected return on risky (EMF) and risk-free (MMF) investment such that $\alpha = g(\mathbf{E}[R_p] - r_f)$. Without loss of generality, we assume g is a concave function of the return spread, i.e., $g' > 0$ and $g'' < 0$. In words, we assume that investors allocate more wealth to the EMF when the EMF's expected return increases relative to r_f, but at a decreasing rate. Such a concave function is consistent with a broad class of preferences, including log utility and mean-variance preferences.

Money Market Funds (MMFs) MMFs invest all wealth in short-term treasuries, yielding r_f. It absorbs any funds not invested in the EMF, such that the total assets held by MMFs are given by $W(1 - \alpha)$

Equity Mutual Funds (EMFs): EMFs invest in a mixture of *low-beta (β_L)* and *high-beta (β_H)* stocks. Suppose w represents the weight on high-beta assets, and λ represents the benchmark expected risk premium. Without loss of generality, we assume a positive equity risk premium $\lambda > 0$, which can also be affected by short-term interest rates (and hence monetary policy). Then, portfolio beta and the expected portfolio return of the EMF are defined as $\beta_P = w\beta_H + (1 - w)\beta_L$ and $\mathbf{E}[R_P] = \beta_P\lambda$, respectively. The EMF's assets under management (AUM) are determined by investor allocations based on function g such that $AUM = W\alpha = W\, g(\beta_P\lambda - r_f)$.

IA1.2 Fund Manager's Optimization Problem & Equilibrium

The EMF manager maximizes an objective function (e.g., her compensation) that balances three key concerns, expected return, assets under management, and tracking error, as follows:

$$\Pi(w) = \beta_P\lambda + \eta g(\beta_P\lambda - r_f) - \frac{k}{2}(\beta_P - \beta^*)^2 \tag{IA2}$$

where $\eta > 0$ captures the sensitivity of manager compensation to investor flows, and $k > 0$ penalizes deviations from a benchmark beta β^*. Taking the first-order condition (FOC) of EMF manager's objective function $\Pi(w)$ with respect to the high-beta share w implies:

$$\frac{d\Pi}{dw} = (\beta_H - \beta_L)\left[\lambda + \eta g'(\beta_P \lambda - r_f)\lambda - k(\beta_P - \beta^*)\right] = 0. \tag{IA3}$$

Since $\beta_H > \beta_L$, the equilibrium portfolio beta should satisfy after rearranging:

$$\beta_P - \beta^* = \frac{\lambda}{k}\left[1 + \eta g'(\beta_P \lambda - r_f)\right] \tag{IA4}$$

IA1.3 Comparative Statics: Effect of an increase in r_f

Now, we analyze how funds change their portfolio beta β_P in response to an increase in r_f. Formally, differentiating the equilibrium condition on both left and right sides of Equation (IA4), and then observing the conditions $g'' < 0$, $\lambda > 0$, $k > 0$, $\eta > 0$ result in the following inequality:

$$\frac{d\beta_P}{dr_f} = \frac{-\lambda \eta g''}{k - \lambda^2 \eta g''} > 0 \tag{IA5}$$

In words, as $g' > 0$, investors would reallocate flows out from the EMF into the MMF when the interest rates rise. In equilibrium, the EMF manager should respond by increasing their expected return $\mathbf{E}[R_P]$, which they achieve by increasing their portfolio beta β_P by tilting their assets towards high-beta stocks.

Our stylized framework implies that the elasticity of the AUM to the expected return differential relative to the risk-free rate (η) is an important ingredient in scaling how much a fund increases its portfolio beta when interest rates rise. As such, one should expect a stronger effect for funds with more flow pressure to boost returns in responding to flow-performance sensitivity. For example, large funds and high-profile funds with prominent family affiliation (e.g, Vanguard) are less sensitive to the flow-performance relationship (e.g., Sirri and Tufano, 1998), hence their manager feel less pressure being protected by brand reputation and default investor allocations. Similarly, smaller funds and young funds with short track records are more vulnerable to outflows when performance is weak (e.g., Chevalier and Ellison, 1997, Huang et al., 2007), hence their managers are more likely to feel pressure to take higher risks to boost inflows during industry-wide outflows. Guided by this literature, our empirical investigation in Table 6 of the main text aims to empirically test this implication of our stylized framework.

IA2 Fund Sample Selection

The CRSP Mutual Fund Database provides comprehensive coverage of the entire universe of domestic funds for our sample period, spanning from 1995 to 2020. As our focus is on U.S. equity funds, we begin by filtering on fund-style classification codes, closely following Kacperczyk et al. (2008) and Akbas and Genc (2020). Over the sample period, CRSP offers classification codes from three different sources: Weisenberger (until 1993), Strategic Insight (from 1993 to 1998), and Lipper (after 1998). We first identify funds with Lipper codes EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE. If Lipper is unavailable, we use Strategic Insight objectives AGG, GMC, GRI, GRO, ING, and SCG. If Lipper and Strategic Insight codes are missing, we rely on Wiesenberger objective codes G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG. When a style code is missing in a given year, we impute it from adjacent years when available. Funds with codes missing for their entire reporting history are excluded.

We match the CRSP fund universe to Morningstar Direct using ISINs (primary key), supplemented by a merge on ticker and name when necessary. We retain only funds that are classified as U.S. equity in both sources. Specifically, we require the fund to map to one of Morningstar's nine U.S. equity style-box categories and a CRSP equity style code as defined above. To ensure equity focus, we further drop funds whose time-series average share of assets in common stocks (CRSP "per_com") is below 80%.

Next, we remove index funds, target-date funds, exchange–traded products (ETFs/ETNs), and variable annuities. Index funds are flagged using CRSP and Morningstar indicators and a case-insensitive name screen for INDEX, IDX, INDX, S&P, BARRA, DOW JONES, DOW 30, RUSSELL 1000/2000/3000. Enhanced index funds are retained. ETFs/ETNs are identified primarily via the CRSP et_flag. When this flag is missing, we classify ETFs/ETNs if the fund name contains any of the following case-insensitive strings: EXCHANGE TRADED NOTE, EXCHANGE-TRADED NOTE, ISHARES, SPDR, HOLDRS, STREETTRACKS, " ETF ". We identify Target–date funds using Lipper classes: MATA, MATB,..., MATM; if unavailable, we use Morningstar target–date categories and a name search for vintage years (2005, 2010,..., 2060, plus intermediate years such as 2012, 2014,..., 2059). We remove variable annuities using the CRSP variable-annuity flag (and the corresponding Morningstar indicator when available). Funds flagged in any of these categories are dropped.

Mutual funds often have multiple share classes with different fee structures but share the same underlying portfolio. To capture fund-level characteristics, we aggregate data across all fund share classes. Specifically, a fund's total net assets (TNA) are calculated as the sum of the TNAs of its share classes. Fund age is determined based on the share class with the earliest inception date within each fund. For other time-varying quantitative variables, we compute fund-level observations using a value-weighted average, with weights determined by the lagged TNAs of the individual share classes. We use the data from the largest share class for qualitative characteristics such as the fund's name and objectives. Finally, we eliminate funds that are less than $5M and with fund age less than one year to account for potential incubation bias (Evans, 2010).

IA3 RFB measures with Alternative Benchmarks

We study the "reaching-for-beta" behavior by constructing an RFB measure that captures the value-weighted average deviation of a fund's stock beta from a benchmark fund beta. In our baseline results, we use the benchmark fund beta as the market portfolio beta, which is equal to one. This benchmark, while theoretically well-motivated, may not fully capture the nuanced realities of fund management. For example, some fund managers may choose to invest primarily within the universe of their own benchmark, other than the market portfolio, while complying with tracking error limits and controlling risk relative to those fund-specific benchmarks.

To alleviate concerns over the benchmark measure in our baseline analysis, we compute two other RFB measures using two alternative benchmark fund betas and conduct robustness checks with those alternative RFB measures. In the first alternative, we consider the beta of each fund's *prospectus benchmark index* (e.g., the Russell 2000) as a relevant benchmark index for a given fund. Below, Subsection IA3.1 provides details on how we choose a relevant benchmark and then construct the fund beta for a particular fund in this approach.

In the second alternative, we examine each fund's *lagged fund beta* as a natural reference point, hence the relevant benchmark beta. This approach recognizes that a fund's historical risk profile can serve as an internal benchmark for assessing changes in market beta exposure.

Using these alternative fund benchmark betas, we compute our two alternative measures of reaching for beta (RFB^{Total}) by replacing the benchmark beta with the two alternative fund benchmark betas in our baseline equation (1). As in Section 2.1, we also decompose changes in RFB^{Total} into active and passive components as described in Equation 2.

IA3.1 Constructing Prospectus Benchmark Index Beta

We compute RFB using funds' prospectus benchmarks by collecting each fund's benchmark information from Morningstar Direct, following the approach of Cremers et al. (2022). Although Morningstar Direct does not provide a historical time series of benchmarks for each fund, it does offer a snapshot of the most recent benchmark. Nevertheless, Mullally and Rossi (2024) documents that benchmark changes are relatively infrequent, occurring in 6.85% of all fund-year observations when benchmark information is collected from fund prospectuses on an annual basis.

In our sample, we find that 90% of equity mutual funds report one of the 18 Russell or 15 S&P equity indices as their sole benchmarks. The Russell indices include the Russell 1000, 2000, 2500, 3000, Microcap, and Midcap, along with their respective growth and value variations. The S&P indices include the S&P 400, 500, 600, 1000, and 1500, as well as their corresponding growth and value variations. This percentage is very similar to the findings of Mullally and Rossi (2024) and Cremers et al. (2022).[9] Occasionally, some funds report a custom index as a weighted average of multiple indices (e.g., 80% Russell 3000 + 20% MSCI EAFE). In such cases, if the custom index includes one of the major indices listed above as its dominant component, we treat it as the fund's primary prospectus benchmark.

For the remaining funds that report a rarely-used stock index (e.g., MSCI US Small & Mid Cap 2200, Wilshire 5000 Total Market) or for which the benchmark is unavailable in Morningstar, we proceed in two steps. First, we assign a benchmark based on the index with the lowest Active Share among the major benchmarks listed above.[10] As a final step, we cross-reference Table A1 of Mullally and Rossi, 2024 and assign the fund to the most commonly used benchmark in its 3x3 style category. For example, if

[9] Using Table A1 of Mullally and Rossi, 2024, we find that 89% of funds report one of the 33 Russell and S&P indices in their sample. Cremers et al. (2022) report that 93% of funds in their sample report major Russell or S&P indices as the benchmarks they follow.

[10] The lowest Active Share identifies the benchmark whose holdings most closely resemble the fund's portfolio. Data on Active Share and benchmark lists is available at https://activeshare.nd.edu.

a fund is classified as large value, we assign the Russell 1000 Value Index as its benchmark. None of our results change if we skip these steps and instead drop funds whose prospectus benchmarks are not among the 33 major indices tracked by Morningstar.

Once we determine the relevant benchmark for each fund, we obtain the monthly return series of those benchmarks (i.e., Russell and S&P indices) and estimate their betas by running the regression specified in equation 3 in Section 2.1.

IA4 Robustness Checks

This section provides the robustness checks on the main results of the paper.

IA4.1 Robustness Checks with Alternative Benchmark Measures

Here, we explore the robustness of our baseline evidence regarding our choice of benchmark fund beta in constructing our RFB measures. In Section IA3, we describe two approaches to using alternative benchmark betas, namely *fund's prospectus benchmark beta* and *lagged fund beta*, as benchmark fund beta on Equation (1) and (2). Armed with those new alternative measures, we replicate our baseline analysis on the impact of interest rates on reaching for beta in Section 3.1.1, and the impact of monetary policy on reaching for beta in Section 3.1.2.

Tables IA1 and IA2 provide robustness checks using the alternative RFB measures for interest rates and monetary policy, respectively. The results on alternative RFB measures, more so on our main variable of interest ΔRFB^{Active}, are quite comparable not only in terms of significance levels but also of magnitudes to our baseline results in the main text. As such, other results that use RFB measures in the main text (such as our evidence on fund flows &returns, BIT, etc.) are also robust to using these alternative RFB measures instead. Those additional results are unreported but available upon request. Overall, we conclude that our main results are not driven by a particular selection of the fund benchmark in constructing RFB measures.

Table IA1: RFB and Interest Rates: Alternative Benchmarks

(a) Prospectus Fund Benchmark Beta

	RFB^{Total}				ΔRFB^{Active}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔTBILL3M	0.066***			0.098**	0.020***			0.034***
	(2.677)			(2.419)	(2.981)			(2.741)
ΔTBOND2Y		0.035		−0.056		0.007		−0.021
		(1.645)		(−1.005)		(1.192)		(−1.527)
ΔTBOND10Y			0.014	0.033			−0.001	0.007
			(0.713)	(0.853)			(−0.133)	(0.794)
Mkt Return	0.020	0.005	−0.004	0.016	−0.002	−0.008	−0.010	−0.003
	(0.134)	(0.036)	(−0.028)	(0.105)	(−0.064)	(−0.214)	(−0.261)	(−0.086)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128,364	128,364	128,364	128,364	127,842	127,842	127,842	127,842
Adjusted R^2	0.402	0.395	0.393	0.403	0.113	0.105	0.104	0.116

(b) Lagged Fund Beta Benchmark

	RFB^{Total}				ΔRFB^{Active}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔTBILL3M	0.038***			0.052**	0.018***			0.032***
	(3.298)			(2.112)	(2.922)			(2.965)
ΔTBOND2Y		0.023**		−0.027		0.007		−0.023*
		(2.044)		(−0.914)		(1.219)		(−1.848)
ΔTBOND10Y			0.012	0.020			0.002	0.011
			(1.068)	(1.165)			(0.273)	(1.165)
Mkt Return	0.011	0.004	−0.002	0.008	0.027	0.023	0.021	0.026
	(0.116)	(0.044)	(−0.024)	(0.087)	(0.712)	(0.595)	(0.539)	(0.669)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,769	129,769	129,769	129,769	129,270	129,270	129,270	129,270
Adjusted R^2	0.127	0.121	0.119	0.128	0.061	0.055	0.054	0.063

This table reports the coefficient estimates from the predictive panel regressions:

$$RFB_{i,t+1} = \alpha_f + \beta IR_t + \gamma X_{i,t} + \theta Z_t + \varepsilon_{t+1} \quad \text{(IA6)}$$

where RFB is either total reaching for beta (RFB^{Total}) or active reaching for beta (ΔRFB^{Active}). RFB^{Total} and ΔRFB^{Active} are defined in Equation 2 and computed at the fund-quarter level using either fund's prospectus benchmark index beta (Panel A) or the fund's lagged fund beta (Panel B) as benchmark beta. IR represents the quarterly change in the yield on the 3-month Treasury bill (ΔTBILL3M), the 2-year Treasury note (ΔTBOND2Y) and the 10-year Treasury note (ΔTBOND10Y), respectively. X represents (log) fund age, (log) total net assets, the past three months of fund returns, the standard deviation over the past twelve months of fund returns, turnover ratio, expense ratio, and fund flows as control variables. All regressions include fund-fixed effects, and standard errors are clustered at both fund and time levels. t-stats are reported in parentheses; *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table IA2: 2SLS IV and Monetary Policy Shocks: Alternative Benchmarks

(a) Prospectus Fund Benchmark Beta

	ΔRFB^{Active}		ΔTBILL3M	ΔRFB^{Active}
	Interest Rates	Pure MP Shock	IV - 1st Stage	IV - 2nd Stage
	(1)	(2)	(3)	(4)
ΔTBILL3M	0.020***			
	(2.981)			
NS		0.154***	4.375***	
		(3.674)	(5.656)	
$\Delta T\widehat{BILL}3M\_NS$				0.035***
				(3.674)
Fund FE	Yes	Yes		Yes
Controls	Yes	Yes		Yes
Observations	127,842	127,842	117	127,842
Adjusted R^2	0.113	0.113	0.211	0.113
F Statistic			31.994*** (df = 1; 115)	

(b) Lagged Fund Beta Benchmark

	ΔRFB^{Active}		ΔTBILL3M	ΔRFB^{Active}
	Interest Rates	Pure MP Shock	IV - 1st Stage	IV - 2nd Stage
	(1)	(2)	(3)	(4)
ΔTBILL3M	0.018***			
	(2.922)			
NS		0.130***	4.375***	
		(2.735)	(5.656)	
$\Delta T\widehat{BILL}3M\_NS$				0.030***
				(2.735)
Fund FE	Yes	Yes		Yes
Controls	Yes	Yes		Yes
Observations	129,270	129,270	117	129,270
Adjusted R^2	0.061	0.060	0.211	0.060
F Statistic			31.994*** (df = 1; 115)	

This table presents the coefficient estimates from the predictive panel regressions described in Equation (5) in Columns 1 and 2, and the results of 2SLS regressions described in Equations (6) and (7) in Columns 3 and 4. $DeltaRFB^{Active}$ is defined in Equation 2 and computed at the fund-quarter level using either the fund's prospectus benchmark index beta (Panel A) or the fund's lagged fund beta (Panel B) as benchmark beta. For further details on the 2SLS estimation, see the main text. All panel regressions include fund fixed effects and a set of control variables such as (log) fund age, (log) total net assets, past three months of fund returns, standard deviation of past twelve quarterly fund returns, turnover ratio, expense ratio, and fund flows. In panel regressions, standard errors are clustered at both fund and time levels. t-stats are reported in parentheses; *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

IA4.2 Robustness Checks for the Monetary Policy Measures

Alternative instruments of monetary policy shocks Table IA3 reports the robustness checks concerning the measure of monetary policy shocks from Nakamura and Steinsson (2018) used in panel regressions and the two-stage least square (2SLS) instrumental variable analysis in Section 3.1.2. As alternative measures, we employ Target and Path measures of Gürkaynak et al. (2005) constructed by Gürkaynak et al. (2022). In a nutshell, Target shock is related to the change in policy rate, whereas Path shock is related to forward guidance. As in Section 3.1.2, we include both shocks as an instrument to the change in three-month Treasury bill yields in the first-stage time-series regression of 2SLS, and then regress the active RFB on the predicted change in three-month Treasury bill yields in the second stage. We thank all authors for graciously providing their data.

Our main results hold with the alternative instruments of monetary policy shocks. The first-stage regression results in Column (3) are qualitatively very similar to the results in Table 3, indicating that monetary policy surprises of Gürkaynak et al. (2005) are also strong instruments for TBill changes with highly significant F-statistics. As such, Column (4) Tbill yields due to tighter monetary policy predict significantly higher active RFB as in the main text. Column (2) provides the results of the regression of active RFB on both Target and Path shocks. Interestingly, active RFB responses are driven by Path shocks, that is, the forward guidance that captures revisions to expectations of policy rate, rather than Target shocks, that is, the surprises to policy action. Since the monetary policy surprises of Nakamura and Steinsson (2018) blends both effects in one measure, it appears to work as a more powerful instrument of Tbill yields as seen in higher F-statistics in Table 3.

Expansionary vs. Contractionary Impact Table IA4 further reports the robustness checks on whether positive or negative changes in interest rates or monetary policy

Table IA3: Alternative instruments of monetary policy shocks

	ΔRFB^{Active}			ΔRFB^{Active}
		IV - 1st Stage	IV - 2nd Stage	Pure MP Shocks
	(1)	(2)	(3)	(4)
ΔTBILL3M	0.022***			
	(3.062)			
$Target$		0.078*	1.801***	
		(1.698)	(2.682)	
$Path$		0.037***	1.316***	
		(2.701)	(5.264)	
$\Delta \widehat{TBILL3M\_GSS}$				0.032***
				(3.401)
Fund FE	Yes		Yes	Yes
Controls	Yes		Yes	Yes
Observations	129,755	129,755	117	129,755
Adjusted R^2	0.179	0.177	0.222	0.177
F Statistic			17.570*** (df = 2; 114)	

This table presents the coefficient estimates from the predictive panel regressions described in Equation 5 (Columns 1 and 2) and the results of 2SLS regressions described in Equations 6 and 7 (Columns 3 and 4). For further details on 2SLS estimation, see the main text. All panel regressions include fund fixed effects and a set of control variables such as (log) fund age, (log) total net assets, past three months of fund returns, standard deviation of past 12 months of fund returns, turnover ratio, expense ratio, and fund flows. In panel regressions, standard errors are clustered at both fund and time levels. t-stats are reported in parentheses; *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

drive the results. We assess expansionary and contractionary effects by using separate measures of positive and negative changes in interest rates and monetary policy shocks in our baseline regressions. The results show that the predictability of active RFB is driven by both expansionary and contractionary changes for both Tbill yields (ΔTBILL3M) and monetary policy surprises of Nakamura and Steinsson (2018) (NS).

Table IA4: Expansionary vs. Contractionary Monetary Policy Shocks

	$\Delta RFB^{Active}_{t+1}$			
ΔTBILL3M+	0.032**			
	(2.555)			
ΔTBILL3M-		0.023**		
		(2.518)		
NS+			0.203**	
			(2.034)	
NS-				0.179***
				(3.248)
Fund FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	129,755	129,755	129,755	129,755
Adjusted R^2	0.174	0.177	0.173	0.176

This table presents the coefficient estimates from the predictive panel regressions described in Equation 5 by using positive and negative changes in the short-term interest rates (ΔTBILL3M) and monetary policy surprises of Nakamura-Steinsson (NS). For further details, see the main text. All panel regressions include fund fixed effects and a set of control variables such as (log) fund age, (log) total net assets, past three months of fund returns, standard deviation of past 12 months of fund returns, turnover ratio, expense ratio, and fund flows. In panel regressions, standard errors are clustered at both fund and time levels. t-stats are reported in parentheses; *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.