Reaching for Beta

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Abstract

Using data on equity mutual fund portfolio allocations and transactions, we show that a rise in short-term interest rates via contractionary monetary policy leads fund managers to tilt their portfolios towards stocks with higher market exposure. This *Reaching for Beta* is persistent and increases the net buying pressure of high beta stocks. Funds that actively reach for beta experience more inflows when monetary policy is restrictive, while they deliver higher raw returns but no significant alpha after controlling for market and other risk factors. Funds' demand for high beta stocks induces systematic price pressures, which take several months to dissipate. In contrast to reaching for yield, which associates low interest rates with risk-shifting, reaching for beta implies that tighter monetary policy increases risk-taking in the equity market.

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

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1 Introduction

How interest rates and monetary policy impact the portfolio allocation of economic agents is a key debate in macroeconomics and finance. Recent research has documented that low interest rates and easy monetary policy drive different types of investors to reach for higher-yielding and often riskier fixed-income assets to boost returns and attract more inflows (e.g., Hanson and Stein, 2015, Becker and Ivashina, 2015, Choi and Kronlund, 2018). Lower interest rates are thus associated with more risk-taking, potentially amplifying risks in financial markets.

However, not all investors should respond to interest rate dynamics similarly. Equity mutual funds, as delegated asset 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). When interest rates rise and the potential income from low-risk investments increases, equity mutual fund managers face a threat of outflows (see e.g., Jiang and Sun, 2020). As such, they have an incentive to enhance returns by taking more risk via active portfolio re-balancing (Huang, Sialm, and Zhang, 2011). Since most mutual fund managers are restricted from using explicit leverage, a key alternative to boost their returns would be to take on implicit leverage by increasing their exposure to high-beta stocks (e.g., Frazzini and Pedersen, 2014).[1]

In this paper, we document that higher interest rates indeed lead equity mutual fund managers to increase their risk-taking through portfolio reallocation towards high market-beta stocks. We label this novel mechanism *Reaching for Beta*. We show that mutual funds *actively* shift their portfolios towards stocks with higher beta in response to rising short-term interest rates and contractionary monetary policy. Our evidence is

[1]Most equity mutual funds have a limited use of borrowing, margin, and leverage. For example, Almazan, Brown, Carlson, and Chapman (2004) report that only 9.5% of funds engage in borrowing, and only 3.5% of funds trade on margin. Boguth and Simutin (2018) show that mutual funds tilt their portfolios towards stocks with higher beta due to funds' binding leverage constraints.

based on both quarterly holdings and daily transaction records of mutual funds.

Reaching for beta has important implications for fund investors and asset prices. Funds actively reaching for beta attract more inflows and produce higher raw returns. However, they don't earn significant alphas for taking higher market (i.e., beta) risk. Thus, reaching for beta does not indicate superior skill. In the stock market, reaching for beta leads to immediate price pressures of high-beta stocks, which only gradually dissipate over time.

Our findings are in stark contrast to "reaching for yield", the tendency of institutional investors to load up on risky fixed-income assets to achieve higher returns in response to low or falling interest rates (e.g., Kacperczyk and Schnabl, 2013, Becker and Ivashina, 2015, Hanson and Stein, 2015, Choi and Kronlund, 2018). Reaching for beta has the opposite implication: equity fund managers increase their risk-taking in response to higher, not lower, short-term interest rates. Reaching for beta also differs from the "reaching-for-income" behavior of households in which expansionary monetary policy increases household demand for assets with higher dividend yield, which are not necessarily riskier (e.g., Jiang and Sun, 2020 and Daniel, Garlappi, and Xiao, 2021). Our results underline that contractionary monetary policy does not universally mitigate but can also increase risk-taking in financial markets. As such, central bank decisions affect the stock market not only through their direct effect on stock prices (e.g., Bernanke and Kuttner, 2005) but also via the portfolio allocation of mutual funds.

We start our analysis by constructing a measure of reaching for beta (RFB) that captures how much each fund tilts its portfolio toward higher beta stocks. In particular, we measure total RFB as the deviation of the value-weighted fund beta from a global benchmark fund beta, which is very close to the market beta of one. Our measure is similar in spirit to the reaching-for-yield measures of Choi and Kronlund (2018). In contrast to these authors, we also decompose total RFB into an active component due to the portfolio reallocation of fund managers and a passive component driven by price changes. We show that the active RFB, not the passive beta changes, are mainly affected by monetary policy and short-term interest rates.

Armed with our RFB measures, we first conduct a panel analysis to assess whether fund managers tilt their portfolios toward high-beta stocks in response to a rise in interest rates. We investigate the impact of changes in 3-month Treasury Bill, 2-year and 10-year Treasury note yields to understand the role of the entire term structure for RFB dynamics. We find that particularly changes in short-term yields lead fund managers to adjust the beta allocation of their portfolios. Crucially, we control for potential market timing and dynamic liquidity management among mutual funds in these regressions. Overall, our findings suggest that active RFB is not primarily linked to the economic growth prospects or the risk and liquidity conditions in the stock market, but instead tightly related to the the short end of the yield curve.

Next, we analyze the role of monetary policy in driving active RFB induced by changes in short-term interest rates. To do so, we employ the monetary policy surprise measure of Nakamura and Steinsson (2018) updated by Acosta (2023) as an instrument for short-term yields in a two-stage least square (2SLS) analysis. We show that fund managers actively tilt their portfolios toward high-beta stocks in response to a surprise tightening of monetary policy. Importantly, unlike recent evidence for bond markets (Adrian, Gelos, Lamersdorf, and Moench, 2024), the response of RFB is symmetric regarding tightening versus easing shocks. We also employ local projections in the spirit of Jordà (2005) to show that a surprise monetary tightening increases active RFB up to one year ahead. Hence, monetary policy leads to persistent reallocations of equity mutual fund portfolios.

We complement our evidence from quarterly mutual fund holdings with a more granular assessment of the impact of monetary policy surprises on fund risk-taking using the daily institutional transaction data from the Ancerno database. To do so, we follow Lakonishok, Shleifer, and Vishny (1992) and compute the net purchase ratio of the funds in that sample for each stock on a given day. We then regress daily net purchase ratios on the interaction of high-frequency monetary policy surprises with stock betas for horizons up to 250 days. The results show that the net buying pressure for high beta stocks increases sharply and persistently around two months after monetary policy tightenings. The delayed impact is consistent with our quarterly evidence and indicates a slow-moving but persistent beta allocation of mutual fund portfolio holdings in response to monetary policy changes.

Having documented the role of interest rates in active RFB of mutual funds, we investigate whether active RFB results in flow-return outcomes as the fund managers desire. Via panel regressions, we first show that active RFB predicts higher raw fund returns. However, the predictability of raw returns disappears once we consider returns adjusted for factor risk exposures, e.g., via the capital asset pricing model and the Fama-French four-factor model. Hence, reaching for beta does not indicate skill-based performance for investors since the returns are earned as compensation for higher risk, particularly market risk. Still, we find that high active RFB is associated with more fund inflows when monetary policy is contractionary. Together with our evidence on fund performance, those findings indicate that investors allocate more money to funds that actively increase their portfolio beta. Although we do not observe fund managers' beliefs, it is not implausible that these inflows are one of their motives when fund managers reallocate risks. That said, we also study the RFB behavior in the cross-section of funds and show that funds universally reach for beta in response to tighter monetary policy. Hence, fund managers tilt their portfolios toward high-beta stocks regardless of their specific attributes that may cater to investors' preferences, including fund performance, fund income, and expected fund flows.

Finally, 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 induced by active RFB across all mutual funds. Using the BIT measure in predictive panel regressions over multiple horizons, we show that it positively predicts excess returns not only in the current but also in the next few quarters. We also construct BIT-sorted portfolios and track their subsequent risk-adjusted performance to assess whether this predictability reflects just increased price pressures or some deviation from fundamental stock values. We find that stocks purchased by mutual funds with high active RFB (i.e., with high BIT) significantly outperform those with low active RFB in the ranking period. Crucially, this return differential is gradually but completely reversed over time. As in flow-induced trading (e.g., Lou, 2012), BIT does not contain fundamental information but instead causes a significant but temporary price impact of uninformed trading.

Our paper contributes to the growing literature on the effects of interest rates and monetary policy on investors' portfolio choices. The literature on reaching for yield in low interest rate environments naturally focuses on the behavior of institutional investors in fixed-income markets (e.g., Hanson and Stein, 2015, Becker and Ivashina, 2015, Di Maggio and Kacperczyk, 2017, Choi and Kronlund, 2018, Barbu, Fricke, and Moench, 2021). Instead, we present novel evidence on equity fund managers reaching for beta when interest rates *rise*. Reaching for beta also differs from households' reaching-for-income documented by Jiang and Sun (2020) and Daniel, Garlappi, and Xiao (2021). Boguth and Simutin (2018) show that equity mutual funds with binding leverage constraints tilt their portfolios toward high-beta stocks to take implicit leverage. Their focus is on the link between leverage constraints (revealed by the aggregate level of fund beta) and the steepness of the risk-return relationship in the market (Black, 1972, Frazzini and Pedersen, 2014, Jylhä, 2018). In contrast, we focus on the role of interest rates and monetary policy as a determinant of fund managers' *active* demand for high-beta stocks.

Our paper is also related to the literature on mutual fund risk-taking motivated by agency issues (e.g., Brown, Harlow, and Starks, 1996, Chevalier and Ellison, 1997, Goetzmann, Ingersoll, Spiegel, and Welch, 2007, Huang, Sialm, and Zhang, 2011, Buffa, Vayanos, and Woolley, 2022). We contribute to this literature by showing that interest rates and monetary policy determine risk-shifting in mutual funds with implications for fund flows, fund performance, and asset prices. Consistent with Christoffersen and Simutin (2017), Boguth and Simutin (2018) and Hitzemann, Sokolinski, and Tai (2022), our paper highlights that constrained managers adjust the risk and corresponding expected returns of their portfolios through the trading of high-beta assets in lieu of using explicit leverage.

Our results also add to the literature on the price impact of mutual fund trading, such as Coval and Stafford (2007), Frazzini and Lamont (2008), Lou (2012). Those studies examine the pricing implications of flow-driven trades by mutual funds. In contrast, we focus on the return patterns related to beta-induced trading by fund managers. Our findings on the price pressures and gradual return reversals due to reaching for beta complement the evidence on asset price dynamics caused by the slow-moving capital of institutional investors (see Duffie, 2010 for a review). As such, our results differ from the empirical evidence linking the betting-against-beta anomaly to institutional trading (e.g., Han, Roussanov, and Ruan, 2021) since beta-induced price pressure does not seem to contain fundamental information and thus indicates a role for uninformed trading.

The paper is organized as follows. Section 2 discusses the variable construction and data used to measure RFB. In Section 3, we provide our main empirical results. In Section 4, we discuss several implications of the documented RFB behavior for fund returns and flows. In Section 5, we then provide evidence on the implications of funds' reaching for beta for the cross-section of stock returns. Section 6 concludes. Robustness along several dimensions, as well as additional results, are provided in the Online Appendix.

2 Variable Construction and Data

Our paper explores the link between interest rates and portfolio managers' tendency to reach for beta. In Section 2.1, we outline the construction of our primary variable: reaching for beta (RFB). Sections 2.2 to 2.4 detail our data sources. Specifically, Section 2.2 discusses the macroeconomic variables and high-frequency measures used to capture changes in monetary policy. We provide evidence on reaching for betas using two distinct datasets : (i) U.S mutual funds and stock holdings, (ii) institutional trading data obtained from Aber Noser Solutions. Section 2.3 and 2.4 describe the details of two datasets respectively.

2.1 Measures of RFB

We calculate various metrics to assess the extent to which each fund engages in reaching for beta (RFB). To begin, we determine the total RFB as the value-weighted average deviation of a fund's stock holdings from a benchmark index each quarter. Specifically, for fund i, stock j, and quarter t, we compute:

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

where $w_{i,j,t}$ represents the market weight of stock j in fund i at the end of quarter t, $\beta_{j,t}$ is the estimated market beta of the stock i at quarter t , and $FB_{i,t}^{Bench}$ is a benchmark beta of the fund. For our baseline results, we use the benchmark fund beta as the market beta, which is equal to one.[2]

[2]While the market portfolio theoretically has a beta of 1, it includes all assets, not just stocks, and estimating stock betas from historical data can introduce well-known biases. In our dataset, the value-weighted and equally-weighted averages of betas for all stocks in the CRSP sample are 0.96 and 1.04, respectively. These estimates fluctuate around 1 each quarter, showing minimal variation over time.

Mutual funds may reach for beta either through active portfolio choices or through changes in the past stock betas. To differentiate between active portfolio decisions and passive beta changes, we decompose the changes in RFB into three components:

$$
\begin{aligned}
\Delta RFB_{i,t}^{Total} &= \sum_j \Delta(w_{i,j,t} \times (\beta_{j,t} - FB_{i,t}^{Bench})) \\
&= \underbrace{\sum_j (\Delta w_{i,j,t}) \times (\beta_{j,t-1} - FB_{i,t-1}^{Bench})}_{\Delta RFB_{i,t}^{Active}} \\
&+ \underbrace{\sum_j (w_{i,j,t-1}) \times \Delta(\beta_{j,t} - FB_{i,t}^{Bench})}_{\Delta RFB_{i,t}^{BetaShift}} \\
&+ \underbrace{\sum_j (\Delta w_{i,j,t}) \times \Delta(\beta_{j,t} - FB_{i,t}^{Bench})}_{\Delta RFB_{i,t}^{Interaction}}
\end{aligned}
$$

$$\Delta RFB_{i,t}^{Total} = \Delta RFB_{i,t}^{Active} + \Delta RFB_{i,t}^{BetaShift} + \Delta RFB_{i,t}^{Interaction} \tag{2}$$

The first component represents active portfolio adjustments toward higher-beta stocks. The second component reflects changes in RFB driven by shifts in past stock betas, while the third component captures the interaction between portfolio changes and shifts in stock betas. Since our focus is on active fund management that adjusts portfolio composition toward higher-beta stocks, much of our analysis relies on the active RFB measure, $\Delta RFB_{i,t}^{Active}$.

To calculate our RFB measure, we require the market 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 market excess return and the lagged market excess return, following the methodology of Liu, Stambaugh, and Yuan (2018) and

As expected, our results remain robust when calculating our RFB measures using these actual beta estimates.

Han, Roussanov, and Ruan (2021). The regression is specified as follows:

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_i^1 R_{Mkt,t} + \beta_i^2 R_{Mkt,t-1} + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the return on stock i for month t, $R_{Mkt,t}$ is the market return in excess of risk-free rate obtained from Kenneth French's website. Each stock's beta is then computed as the sum of the two beta estimates: $\beta_i^{Stock} = \beta_i^1 + \beta_i^2$. We use a 36-month rolling window with at least 18 months of data to compute the betas at the end of each quarter.

2.2 Monetary Policy Shocks and Macro Variables

We gather aggregate variables, such as the yield of the 3-month Treasury bill, the yields of 2- and 10-year Treasury notes, and the VIX index from the Federal Reserve Economic Data (FRED) database. We follow the previous event-study literature on measuring the impact of monetary policy (e.g., Kuttner, 2001, Gürkaynak, Sack, and Swanson, 2004) and employ the high-frequency based measure of U.S. monetary policy shock series of Nakamura and Steinsson (2018) (NS), which is extended by Acosta (2023). As a robustness check, we also employ the high-frequency measures of monetary policy shocks from Gürkaynak, Sack, and Swanson (2004). We thank all authors for graciously providing their data. FOMC meetings are scheduled every six to eight weeks. Most quarters contain multiple FOMC meetings and, thus, monetary policy surprises. For quarters with more than one scheduled FOMC meeting, we simply add surprises for the multiple meetings. We set our sample period with respect to the availability of NS shocks between 1995-2020.

2.3 Fund and Stock Holdings Data

We use the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database to obtain information on mutual funds. Our analysis focuses on actively managed domestic equity funds. Following Kacperczyk, Sialm, and Zheng (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. We further remove index funds and target date funds 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 the Online Appendix IA1.

This dataset provides information on various fund characteristics, including fund flows, returns, total net assets (TNA), turnover, age, and expense ratio, which we use in our empirical analysis. Our mutual fund flow variable measures the growth rate of a fund due to new investments:

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

where $Ret_{i,t}$ is the quarterly return of the fund i in quarter t, $TNA_{i,t}$ is the the total net asset value of fund i at the end of quarter t. In 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 measured as the number of months since the inception of the fund's oldest share class. Finally, the expense ratio is defined as the total operating expenses expressed as a percentage of a fund's average net assets. All variables are winsorized at the 1% and 99%

to mitigate the impact of outliers in the empirical analysis.

Next, 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, though approximately 60% of funds also reported quarterly holdings. We carry forward the most recently disclosed holding position from the end of each quarter to the following months until the next reporting date. We use a six-month period as the cutoff for the portfolio holding period.For each stock position reported in the data, we obtain stock level information from CRSP Security files. Our final fund sample includes 156,401 fund-quarter observations with non-missing RFB measure 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 from Abel Noser (formerly known as Ancerno). Aber 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, transactional-level equity trading data from its clients. This data 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 data has been extensively used in academic research. Notable studies include those by Goldstein, Irvine, Kandel, and Wiener (2009), Chemmanur, He, and Gang (2009), Puckett and Lan (2011) among others. Gang, Jo, Yi, and Xie (2018) also conduct a comprehensive survey of the academic literature that uses

Abel Noser's data, providing detailed information about the database itself.

Following Puckett and Lan (2011), we match the Abel Noser data with CRSP daily stocks files using 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 $32.8 trillion, spanning from January 1999 to December 2011. These estimates are similar to those reported by Gang, Jo, Yi, and Xie (2018), providing a comprehensive view of institutional trading activity during this period.

2.5 Summary Statistics

In Table 1, we present the average RFB^{Total} and other fund characteristics for three portfolios based on the 30th (Low) and 70th (High) percentiles of RFB in quarter t, as well as the overall mean, median, and standard deviations of these variables. The three portfolios (Low, Mid, High) are well diversified. The Low and High portfolios each contain an average of 408 funds per quarter, while the Mid portfolio includes 650 funds. The average value of RFB^{Total} is 0.12, indicating that equity mutual funds, on average, hold stocks with betas slightly above the market benchmark of 1. However, RFB^{Total} shows considerable heterogeneity, ranging from -0.138 for the Low portfolio to 0.411 for the High portfolio. This suggests that some funds adopt a more conservative approach to risk-taking, while others tend to reach for higher betas. Additionally, we observe greater variation in ΔRFB^{Active} compared to $\Delta RFB^{BetaShift}$ and $\Delta RFB^{Interaction}$, implying a stronger relationship between managers' active portfolio choices and the resulting RFB^{Total}. With respect to fund characteristics, we find that smaller, younger funds, and those with higher expense ratios and turnover, tend to have higher RFB^{Total}.

	RFB^{Total}					
	Low	Mid	High	Mean	p50	SD
RFB^{Total}	-0.138	0.093	0.411	0.119	0.086	0.264
ΔRFB^{Active}	-0.008	0.021	0.074	0.028	0.015	0.083
$\Delta RFB^{BetaShift}$	-0.007	-0.003	-0.001	-0.003	-0.003	0.061
$\Delta RFB^{Interaction}$	-0.004	-0.003	-0.001	-0.003	-0.002	0.031
Flow	0.009	0.009	0.008	0.008	0.005	0.137
Return	0.023	0.024	0.028	0.025	0.026	0.098
Volatility	0.039	0.045	0.056	0.047	0.043	0.022
Assets ($\$M$)	1787.1	1720.3	1103.6	1555.6	258.3	6067.4
Expense Ratio	0.011	0.012	0.014	0.012	0.010	0.001
Turnover	0.636	0.755	0.935	0.773	0.589	0.694
Age (months)	193.1	186.7	169.1	183.3	142.0	162.0
Retail	0.661	0.651	0.662	0.657	0.897	0.401

Table 1: The three portfolios are constructed based on the ranking of RFB^{Total} for each quarter from 1995/Q1 to 2020/Q4. The "Low" portfolio consists of 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 table also presents the overall mean, median (p50), and standard deviation of RFB measures, along with other fund characteristics, for observations where RFB^{Total} is available. “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, reflecting the fund’s total net asset value. The expense ratio indicates the proportion of a fund’s average net assets consumed by operating expenses. Fund “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. Lastly, “Retail” is the percentage of TNA of retails share classes in a fund. To minimize the influence of outliers, all variables are winsorized at the 1st and 99th percentiles.

To better understand the factors influencing a fund’s tendency to reach for beta, we regress RFB^{Total} in quarter t+1 on three components of change in the RFB measure (ΔRFB^{Active}, $\Delta RFB^{BetaShift}$, and $\Delta RFB^{Interactions}$), as well as other fund characteristics measured in quarter t. The regressions include style-by-time fixed effects and/or fund fixed effects. The results, provided in Table 2, show that ΔRFB^{Active} is a strong predictor of future RFB^{Total}. Specifically, a one standard deviation increase in ΔRFB^{Active} (sd = 0.083) is associated with a 6.2% to 7.4% increase in RFB^{Total}, depending on the specification used. In contrast, a one standard deviation increase in $\Delta RFB^{BetaShift}$ leads to a 1.2% increase in RFB^{Total}, while the same increase in the interaction component results in a 3.5% rise. This suggests that managers’ active port-

	RFB^{Total}		
	(1)	(2)	(3)
ΔRFB^{Active}		0.895***	0.742***
		(22.559)	(23.278)
$\Delta RFB^{BetaShift}$		0.077	0.200***
		(1.023)	(3.359)
$\Delta RFB^{Interaction}$		0.664***	0.581***
		(6.316)	(5.780)
Retail Share	−0.001	−0.001	0.007
	(−0.299)	(−0.227)	(0.972)
Return	0.219**	0.164*	0.081
	(2.299)	(1.860)	(1.168)
Volatility	9.917***	9.224***	5.889***
	(21.621)	(20.495)	(15.696)
Size (log)	0.007***	0.007***	0.011***
	(5.777)	(6.099)	(5.686)
Age (log)	0.001	−0.001	−0.001
	(0.499)	(−0.406)	(−0.208)
Expense Ratio	4.730***	4.184***	1.405*
	(8.522)	(7.620)	(1.664)
Turnover	0.024***	0.0001	−0.004
	(4.786)	(0.017)	(−1.135)
Flow	−0.002	0.005	0.007
	(−0.316)	(0.717)	(1.203)
Style x Time FE	Yes	Yes	Yes
Fund FE	No	No	Yes
Observations	139,765	121,653	121,653
Adjusted R^2	0.567	0.622	0.730

Table 2: This table reports results from panel regressions of RFB^{Total} on three reaching for beta measures as defined in Equation 2 (ΔRFB^{Active}, $\Delta RFB^{BetaShift}$, $\Delta RFB^{Interaction}$) and fund characteristics, such as retail share, expense ratio, turnover ratio, quarterly fund flow, fund (log) size as total net assets, fund (log) age. Regressions may include style times time fixed effects and fund fixed effects. The observations are at the fund-quarter level, 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.

folio decisions are the most important contributors to reaching for beta in fund portfolios. Apart from size, expense ratio and volatility, RFB^{Total} does not appear to be significantly related to other lagged fund characteristics in the cross-section.

3 Reaching for Beta: Empirical Evidence

In this section, we present our main results documenting pervasive reaching for beta behavior by mutual fund managers. Section 3.1 relies on quarterly fund holdings. In Section 3.1.1, we first show that managers actively tilt their portfolios towards higher beta stocks in the quarters following an increase in short-term Treasury yields. Section 3.1.2 then directly attributes this risk-shifting to tighter monetary policy using two-stage instrumental variables regression. Finally, section 3.2 documents reaching for beta using granular daily transactions 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. Specifically, we 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, we investigate the impact of not only short-term but also long-term yields in our baseline analysis.

Formally, we estimate the following quarterly panel regressions:

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

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 change in 3-month Treasury bill (ΔTBILL3M), the 2-year Treasury (ΔTBOND2Y) or the 10-year Treasury yield (ΔTBOND10Y), respectively. α_f captures fund fixed effects, and X is a

	RFB^{Total}				ΔRFB^{Active}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔTBILL3M	0.122***			0.151***	0.021***			0.034**
	(3.326)			(2.766)	(2.887)			(2.364)
ΔTBOND2Y		0.086***		−0.054		0.010		−0.021
		(2.865)		(−0.764)		(1.649)		(−1.163)
ΔTBOND10Y			0.045*	0.040			0.001	0.006
			(1.841)	(1.004)			(0.124)	(0.537)
Mkt Return	0.353*	0.342	0.324	0.353*	0.084*	0.081*	0.078*	0.083*
	(1.729)	(1.625)	(1.433)	(1.698)	(1.918)	(1.828)	(1.781)	(1.927)
ΔVix	0.004**	0.003*	0.002	0.004**	0.001	0.0003	0.0001	0.0004
	(2.400)	(1.920)	(1.157)	(2.399)	(0.992)	(0.532)	(0.150)	(0.869)
PS	0.086	0.027	0.108	0.119	−0.015	−0.019	−0.008	0.001
	(0.623)	(0.195)	(0.788)	(0.881)	(−0.298)	(−0.351)	(−0.152)	(0.024)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	139,983	139,983	139,983	139,983	139,541	139,541	139,541	139,541
Adjusted R^2	0.510	0.496	0.487	0.510	0.217	0.211	0.210	0.219

Table 3: This table reports the coefficient estimates from the predictive panel regressions:

$$RFB_{i,t+1} = \alpha_f + \beta IR_t + \gamma X_{i,t} + \theta Z_t + \varepsilon_{t+1} \tag{6}$$

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. 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.

vector of fund-level control variables that include (log) fund age, (log) total net assets, fund returns and standard deviation, turnover ratio, expense ratio, and fund flows. We also add aggregate controls Z, such as quarterly stock market return, the change of VIX index, and market liquidity, to control for potential market timing and dynamic liquidity management among mutual funds. The coefficient β measures the reaching for beta of mutual fund managers following a 1% change in the respective interest rate. If high interest rates lead mutual fund managers to reach for beta, we should see a positive value for the coefficient β.

Table 3 presents the results. The first four columns provide estimates and t-statistics for total RFB, and the remaining columns for active RFB. Several remarks are in order. First, changes in the 3-month TBill are highly informative about reaching for beta in the next quarter. Changes in medium-term and long-term rates also carry predictive information, albeit to a smaller degree. This is true for both the total RFB and its active reallocation component. Second, the coefficients on interest rate changes are positive, indicating that funds *increase* the beta of their equity portfolios in response to higher rates. This is in stark contrast to other dimensions of risk-taking documented in the prior literature such as reaching-for-yield (e.g., Choi and Kronlund, 2018) or reaching-for-income/dividend (e.g., Daniel, Garlappi, and Xiao, 2021, Jiang and Sun, 2020) which are associated with investors taking on more risk in response to *lower* rates. Third, in line with the above finding that funds predominantly reach for beta by actively reallocating their portfolios towards higher-beta stocks, the active component of funds' RFB is significantly affected by short- and medium-term rates.

It is well-known that government bond yields strongly co-move across maturities. When considered jointly in columns (4) and (8), only changes in the TBill 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 might be particularly important for funds' risk-taking. Importantly, these regressions control for fund-fixed effects and a host of fund-level controls and thus account for various dimensions of fund heterogeneity.

In Online Appendix IA2.1, we also check whether interest rate changes also predict the other components of the change in total RFB, i.e.,$\Delta RFB_{i,t}^{BetaShift}$ and $\Delta RFB_{i,t}^{Interaction}$. Table IA1 indicates that both short and medium-term rates don't predict the other components of total RFB. That is, changes in interest rates seem to induce only the *active* beta tilting of mutual fund managers. Combined, these results suggest that to understand the drivers of reaching-for-beta, it is instructive to study the response of active

RFB to exogenous variation in short-term interest rates. This will be done in the next section.

3.1.2 RFB and Monetary Policy

In the previous section, we have shown that mutual fund managers actively tilt their portfolios toward high-beta stocks following an increase in short-term interest rates. Of course, both short rates and stock prices might be responding to the same market forces. Hence, notwithstanding the fact that we consider one-quarter lagged interest rate changes in Regression (5), our results might suffer from endogeneity. We address this concern by studying the response of active RFB to exogenous variations in short-term interest rates. Specifically, we employ the high-frequency measure of monetary policy shock from Nakamura and Steinsson (2018) (NS), updated through 2023 byAcosta (2023), as an instrument for change in the Treasury bill yield. This measure represents the first principal component of several interest rate futures with maturities up to one year ahead in 30 minute windows around scheduled FOMC announcements. As such, it captures both news about the target rate as well as the expected path of policy rates over the next twelve months revealed by the Federal Open Market Committee (FOMC) statement.

Formally, we conduct a two-stage least square (2SLS) instrumental variable analysis by first estimating the following first-stage time-series regression:

$$\Delta TBILL3M_t = \alpha_t + NS_t + \varepsilon_t \tag{7}$$

where $\Delta TBILL3M$ is the change in three-month Treasury bill yield in quarter t, and NS is the monetary policy surprise measure of Nakamura-Steinsson from Acosta (2023) in quarter t. Then, in the second stage, we use the predicted change in the three-month

TBill, $\Delta \widehat{TBILL3M}$, from regression (7) in the following panel regressions:

$$\Delta RFB_{i,t+1}^{Active} = \alpha_f + \beta\, \Delta \widehat{TBILL3M}_t + \gamma_1' X_{i,t} + \gamma_2' Z_t + \varepsilon_{i,t+1}, \tag{8}$$

where X and Z represent sets of fund level and aggregate control variables and α_f captures fund fixed effects as before.

Table 4 provides the results. Before presenting the results for the 2SLS regressions, we first restate our baseline finding from Table 3 in Column 1: funds actively invest in higher beta stocks in response to an increase of short-term yields. In Column 2, we complement this result by regressing active RFB directly on the monetary policy shock series. The highly significant and positive coefficient indicates that mutual funds actively tilt their portfolios toward higher beta stocks in response to a surprise tightening of monetary policy in the same quarter.

Columns 3 and 4 present the first-stage time-series and second-stage panel regressions results in our 2SLS estimation. The result from the first-stage regression shows that tighter Federal Reserve policy leads to an increase in short-term Treasury rates. The F-statistic is highly significant, indicating that the monetary policy surprise is a strong instrument for TBill changes, as expected. The result from the second-stage regression, presented in Column 4, highlights that a positive change in short-term rates due to tighter monetary policy leads to significantly higher reaching for beta. In other words, fund managers take more risk in response to tighter, not looser, monetary policy. This finding highlights that changes in the monetary policy stance affect stock markets not only through their direct effects on prices (Bernanke and Kuttner, 2005) but also through a reallocation of mutual funds' equity portfolios.

In Online Appendix IA2.2, we show that our results are robust to using alternative measures of monetary policy surprises of Gürkaynak, Sack, and Swanson (2004) constructed by Gürkaynak, Karasoy-Can, and Lee (2022). Online Appendix IA2.2 also documents that the active RFB responses are driven by both positive and negative

Interest Rates 2SLS IV and HF Monetary Policy Shocks

	ΔRFB^{Active}		ΔTBILL3M	ΔRFB^{Active}
	Interest Rates	MP Shock	IV - 1st Stage	IV - 2nd Stage
	(1)	(2)	(3)	(4)
ΔTBILL3M	0.021***			
	(2.881)			
NS		0.133**	3.833***	
		(2.625)	(5.592)	
$\Delta \widehat{TBILL}3M\_NS$				0.035**
				(2.625)
Fund FE	Yes	Yes		Yes
Controls	Yes	Yes		Yes
Observations	139,541	139,100	109	139,100
Adjusted R^2	0.217	0.214	0.219	0.214
F Statistic			31.266*** (df = 1; 107)	

Table 4: 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 (7) and (8) in Columns 3 and 4. 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.

changes in interest rates, as well as expansionary and contractionary monetary policy surprises.

Monetary policy shocks have recently been documented to have surprisingly persistent effects on government bond markets and flows in and out of bond funds (e.g., Brooks, Katz, and Lustig, 2020 and Adrian, Gelos, Lamersdorf, and Moench, 2024). In light of these findings, it is instructive to also study the persistence of reaching for beta in response to monetary policy. To this end, 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) via the following model:

$$\Delta RFB^{Active}_{i,t+h} = \alpha_f + \beta_h NS_t + \gamma_1' X_{i,t} + \gamma_2' Z_t + \varepsilon_{i,t+h+1}, \tag{9}$$

where NS is the monetary policy surprise measure of Nakamura-Steinsson in quarter

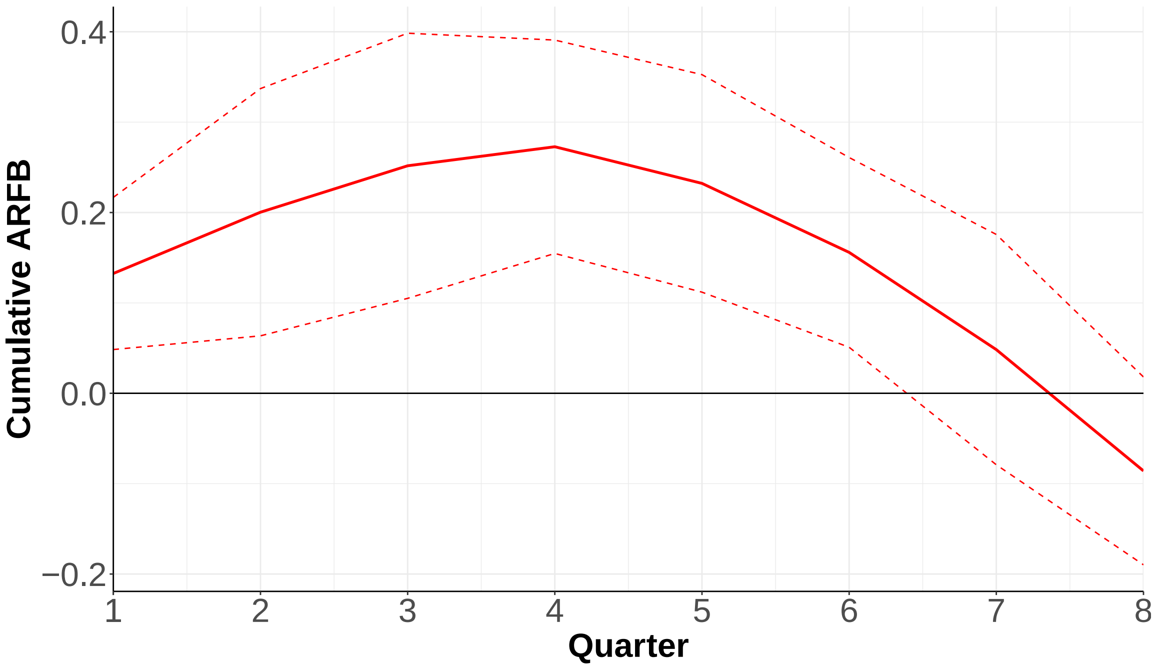

Figure 1: This figure displays the dynamics of active reaching for beta (ΔRFB^{Active}) in response to a 100 bps monetary policy shock. On the y-axis, we report the sum of coefficients estimated from the local projection specification (9) for the forecast horizons from one to the respective quarter on the x-axis. Dashed lines indicate 90% confidence bands.

t , h is the forecast horizon, X and Z represent sets of fund level and aggregate control variables and α_f captures fund fixed effects as before. We estimate the regression for horizons from one to eight quarters ahead and plot the sum of the coefficients $\sum_{h=1}^{n} \beta_h$ as the cumulative active reaching for beta up to n quarters following a 1% change in the interest rate.

Figure 1 reports the cumulative active reaching for beta of mutual funds in response to a 1% increase in the federal funds rate over different time horizons. Mutual funds tilt their portfolios significantly and persistently toward higher beta stocks following an *exogenous* increase in short-term interest rates up to one year ahead. Thereafter, reaching for beta gradually reverses. Six quarters after the shock the effect is no longer statistically significant. These results highlight that fund managers move slowly and persistently toward higher beta stocks in response to tighter monetary policy.[3]

[3]The persistence of responses is consistent with either the transmission of monetary policy being long-lived rather than transitory, or capital allocations being slow-moving (Duffie, 2010) It is plausible that both effects co-exist, but how much is an open question. We are agnostic about which effect

3.2 Evidence using Daily Transactions Data

Thus far, we have used quarterly mutual fund holdings data to establish that funds slowly but persistently tilt their portfolios toward higher beta stocks following tighter monetary policy. In this section, we zoom in onto the response of fund managers to monetary policy shocks using higher frequency data. Specifically, we rely on the Ancerno database of daily institutional trading. As compared to our baseline data on quarterly holdings of mutual funds, the Ancerno sample has limited coverage of mutual funds and is available only for the period from 2001 through 2010. However, the daily transaction data allows us not only to provide more granular evidence on reaching for beta but also to more carefully assess the timing of these effects.

Using mutual fund stock transaction data from Ancerno, we calculate the net buying pressure on each stock for a given day. Specifically, we follow Lakonishok, Shleifer, and Vishny (1992) and compute the net purchase ratio $NetPurchase$ for stock j on day t as follows:

$$NetPurchase_{j,t} = \frac{Buy_{j,t} - Sell_{j,t}}{Buy_{j,t} + Sell_{j,t}} \tag{10}$$

Here, $Buy_{j,t}$ and $Sell_{j,t}$ measure the total buying and selling of stock j on day t by all the mutual funds in the Ancerno database. Using this measure, we explore whether a tighter monetary policy is associated with increased net buying of high-beta stocks. Specifically, we implement the local projections method of Jordà (2005) using $NetPurchase$ and high-frequency monetary policy surprises as follows:

$$NetPurchase_{j,t+h} = \alpha_s + \theta_h \, \beta^{Stock}_{j,t} \times NS_t + \gamma_1' X_{j,t} + \gamma_2' Z_t + \gamma_3 \sum_{k=t+1}^{t+h} NS_k + \varepsilon_{j,t+h}, \tag{11}$$

where NS is the monetary policy surprises of Nakamura-Steinsson on FOMC day t, h

dominates, and leave the analysis of disentangling those effects for future research.

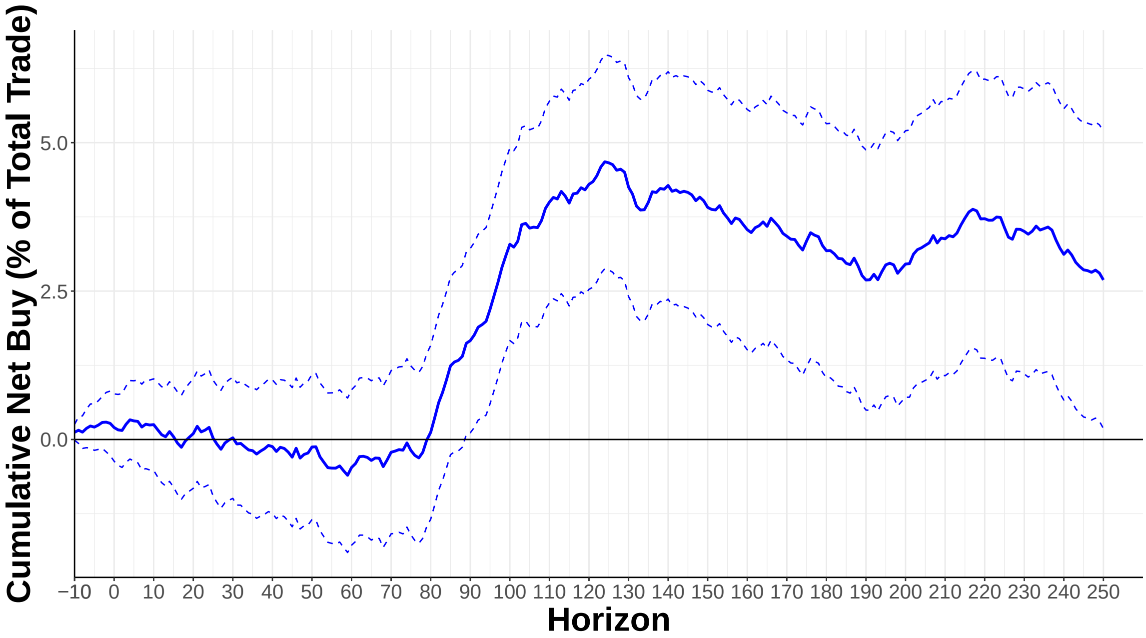

Figure 2: This figure displays the dynamics of net purchases ($NetPurchase$) responses to a 100 bps monetary policy shock conditional on stock beta. y-axis reports the sum of coefficients estimated from the local projection specification 11 for the forecast horizons from 10 days prior to FOMC date to 250 days after the FOMC date. Dashed lines indicate the 90% confidence bands.

is the future horizon. $alpha_s$ captures stock fixed effects. X includes additional stock-level control variables such as stock beta, stock return, book-to-market ratio, (log) market capitalization, and Amihud's liquidity ratio. Z represents a set of aggregate control variables such as value-weighted CRSP stock market return, VIX index, and the fed funds rate. To account for potential mild serial correlation in the policy shock series, we also control for the sum of *future* NS shocks between t and $t + h$. Standard errors are clustered at the time level.

We estimate the regression for horizons h running from 10 days *before* the FOMC meeting day to 250 days after the FOMC meeting. Inspired by the findings of a pre-FOMC announcement drift documented in Lucca and Moench (2015), we start before the announcement day to analyze if there is any trading activity prior to the FOMC meeting.

Figure 2 plots the sum of the coefficients $\sum_{h=1}^{H} \theta_h$ as the cumulative net buying pressure up to H days after a 1% monetary policy surprise. Given that the FOMC meets every six to eight weeks, our forecast horizons may include some future policy meetings. The chart shows that there is no evidence of significant buying pressure ahead of the FOMC announcement. Moreover, the cumulative net buying pressure for high beta stocks remains flat for about 80 business days or roughly two months after the FOMC announcement, before rising sharply and persistently. This is consistent with our previous evidence based on quarterly data which showed a significant response of ARFB to monetary policy surprises several quarters into the future. Hence, mutual fund managers appear to take some time to process the monetary policy decision but then respond by persistently adjusting the beta allocation of their portfolio holdings, consistent with the evidence in Brooks, Katz, and Lustig (2020) and Adrian, Gelos, Lamersdorf, and Moench (2024).

4 Implications for Fund Returns and Flows

We now study the implications of reaching for beta for funds. Section 4.1 starts by documenting that active reaching for beta is associated with higher future raw, but not risk-adjusted, returns. In Section 4.2, we then show that funds which actively reach for yield attract higher inflows in periods when monetary policy is tightened, even controlling for past returns. We also document that funds shift towards high-beta stocks in response to tighter monetary policy independently of their beta, income or expected flows.

4.1 Does Active RFB result in higher returns?

Reaching for beta as a form of risk-taking can work out as a key tactic to impact fund returns. Fund managers may aim to attract more fund flows by achieving superior returns that beat the benchmark or peer returns through taking higher risk, even if this risk is pure market risk. If higher returns don't reflect managerial skill, they may result in higher managerial compensation for fund managers, highlighting agency problems within mutual funds (Huang, Sialm, and Zhang, 2011). Here, we explore whether active reaching for beta is associated with higher fund returns, and assess whether any return differences are associated with risk or skill.

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 various specifications with fund and style-time fixed effects. Table 5 shows the results.

Columns 1 to 3 of Table 5 highlight that higher active reaching for beta predicts higher raw returns. For example, the coefficient estimate in Column 3 predicts 15 bps (60 bps for annual) higher quarterly fund returns for funds with one standard deviation higher active RFB than the average fund. At first, the results may imply the reaching for beta works out as a way of enhancing returns for mutual fund managers as desired. However, those results are for raw returns that are not adjusted for potential risk factors. Columns 4 to 7 report the results of the regressions that use returns that are adjusted for the capital asset pricing model (CAPM) or the three-factor model of Fama and French (1993) augmented by the momentum factor (FF4). The results highlight that the active reach-for-beta is not significantly associated with future risk-adjusted fund returns. Crucially, the predictability disappears once the market performance is taken into account, as shown in Columns 4 and 5. These results suggest that the funds with ΔRFB^{Active} are not generating any superior return but simply loading up on risk, particularly market risk. This is not necessarily surprising given that funds with high ΔRFB^{Active} load up on stocks with higher exposure to the market, i.e., higher beta.

To further highlight that the raw outperformance of active RFB reflects risk rather than skill, we also group funds based on their active reaching for beta and examine their fund alphas. Specifically, we sort funds into five quintiles based on ΔRFB^{Active}

[Fund Returns - Active RFB]

	$Fund\ Return_{t+1}$						
	Raw			CAPM		FF4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔRFB^{Active}	0.079**	0.103***	0.015**	0.010	0.010	0.001	0.001
	(2.414)	(3.158)	(1.997)	(1.001)	(1.236)	(0.137)	(0.284)
Fund FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Style x Time FE	No	No	Yes	No	Yes	No	Yes
Observations	140,070	140,070	140,067	133,396	133,393	133,396	133,393
Adjusted R^2	0.028	0.034	0.870	0.022	0.285	0.019	0.143

Table 5: This table reports results from the regressions of future quarterly fund returns on the active reaching for the beta measure. ΔRFB^{Active} is defined in Equation (2). The observations are at the fund-quarter level. All regressions include (log) fund age, (log) total net assets, past three months of fund return, the standard deviation of the past twelve months of fund returns, turnover ratio, expense ratio, and fund flows as control variables. Regressions may 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.

and form equal and value-weighted portfolios of funds at the end of each quarter. For each portfolio, we report the quarterly fund returns in excess of the risk-free rate, the abnormal returns (alphas) estimated using the market factor (CAPM), and the factor loadings and alphas estimated using Fama-French three-factor augmented by the momentum factor (FF4).

Table 6 shows that the raw fund outperformance is monotonically increasing in ΔRFB^{Active} for both equal- and value-weighted portfolios. Yet, the excess return on the high-minus-low portfolio is positive but statistically indistinguishable from zero (0.52%, t=1.40), indicating a weak outperformance of high RFB funds. More importantly, high ΔRFB^{Active} funds are sensitive to stock market risk due to the overweighting of higher beta stocks. Controlling for market beta dramatically reduces excess returns on the ΔRFB^{Active} portfolios, and more so for the long-short ΔRFB^{Active} portfolio. As expected, this reduction in performance is mainly a result of higher loadings on the market factor. Note that the H-L portfolio also strongly loads on the market factor, indicating that the fund outperformance reflects exposure to market risk.

In summary, the higher returns of funds that actively tilt their portfolios toward

(a) Fund Returns - Equal Weighted ARFB Portfolios

	Low	P2	P3	P4	High	H-L
Excess Return	2.48	2.65	2.77	2.90	3.00	0.52
	(3.44)	(3.67)	(3.89)	(3.97)	(3.85)	(1.89)
CAPM α	0.18	0.33	0.37	0.37	0.26	0.08
	(0.71)	(1.26)	(1.21)	(1.13)	(0.71)	(0.28)
FF4 α	0.14	0.28	0.33	0.35	0.31	0.18
	(0.93)	(1.95)	(1.91)	(1.78)	(1.17)	(0.87)
β^{MKT}	0.92	0.93	0.95	0.98	1.02	0.10
	(64.04)	(58.74)	(60.45)	(61.70)	(42.69)	(5.44)
β^{HML}	0.11	0.10	0.07	0.02	-0.12	-0.23
	(1.87)	(2.02)	(1.57)	(0.41)	(-2.83)	(-3.82)
β^{SMB}	0.09	0.09	0.13	0.24	0.40	0.30
	(3.69)	(3.78)	(6.10)	(8.00)	(8.14)	(6.77)
β^{Mom}	0.00	0.00	0.02	0.02	0.01	0.01
	(-0.03)	(0.18)	(0.74)	(0.71)	(0.32)	(0.59)

(b) Fund Returns - Value Weighted ARFB Portfolios

	Low	P2	P3	P4	High	H-L
Excess Return	2.43	2.56	2.75	2.87	2.89	0.46
	(3.12)	(3.44)	(3.77)	(3.69)	(3.39)	(1.62)
CAPM α	0.17	0.34	0.44	0.39	0.16	-0.01
	(1.25)	(1.64)	(1.81)	(1.39)	(0.62)	(-0.05)
FF4 α	0.14	0.28	0.40	0.40	0.23	0.09
	(1.15)	(1.86)	(2.22)	(1.67)	(0.96)	(0.38)
β^{MKT}	0.93	0.92	0.94	0.98	1.05	0.13
	(48.56)	(47.67)	(53.53)	(34.72)	(42.18)	(6.14)
β^{HML}	0.07	0.09	0.04	-0.03	-0.17	-0.24
	(1.36)	(1.66)	(1.16)	(-0.69)	(-3.92)	(-3.41)
β^{SMB}	-0.02	-0.01	0.01	0.14	0.22	0.24
	(-0.48)	(-0.40)	(0.52)	(4.24)	(3.80)	(4.45)
β^{Mom}	0.00	0.02	0.02	0.00	0.01	0.01
	(-0.26)	(0.86)	(0.88)	(0.11)	(0.27)	(0.44)

Table 6: This table reports alphas and betas of quarterly portfolios sorted on the active reaching for beta measure (ΔRFB^{Active}). Each quarter, we create equal-weighted (Panel A) and value-weighted (Panel B) portfolios by sorting funds into quintiles based on their ΔRFB^{Active} and track their future risk-adjusted returns. The columns labeled "Low" through "High" present results for the five ΔRFB^{Active} quintile funds. The column labeled "H-L" presents results for the portfolio that is long funds in the highest ΔRFB^{Active} quintile and short funds in the lowest ΔRFB^{Active} quintile. The table reports the average quarterly excess return (Excess return), and the abnormal returns (alphas) relative to the capital asset pricing model (CAPM), and the model with three Fama French factors and Momentum factor (FF4). In each panel, we also report the factor loadings implied by the FF4 model. t-statistics reported in parentheses are based on standard errors adjusted using Newey and West with optimal lags.

higher beta stocks can be explained by risk, particularly aggregate market risk. Therefore, the raw outperformance of those funds is not associated with superior managerial skill but rather indicates more risk-taking.

4.2 Does Active RFB attract more fund flows?

In Section 4.1, we have shown that reaching for beta does not lead to outperformance on a risk-adjusted basis. However, reaching for beta may still incentivize fund managers to pursue higher returns, especially if an average investor does not account for risk when allocating funds. In such cases, the cost of taking on additional risk may even be negligible for fund managers. The previous literature supports this view, suggesting that investors often fail to fully account for risk in their decision-making processes (Clifford, Fulkerson, Jordan, and Waldman, 2011), and some may even find risk-taking appealing.

In this section, we use panel regressions to investigate whether investor flows respond positively to shifts toward high-beta stocks. We begin by regressing future quarterly fund flows on RFB^{Total} to assess whether portfolios with higher beta tilts attract additional inflows. The primary objective is to understand how flows respond to reaching for beta under different monetary policy conditions. To do so, we interact RFB^{Total} with monetary policy shocks (NS) in our regressions.

Since reaching for beta — RFB^{Total} — may reflect fund managers' active shifts, passive beta shifts, or a combination of both, we further analyze how flows respond to the active and passive components of beta changes. Specifically, we regress quarterly future fund flows on the components of reaching for beta: ΔRFB^{Active}, $\Delta RFB^{BetaShift}$, $\Delta RFB^{Interaction}$, each of which is also interacted with the monetary policy shock series. If fund managers' active pursuit of beta in response to contractionary monetary policy attracts more flows, we would expect only the active component of RFB to predict future flows, especially under tighter monetary policy conditions.

As before, our models include various specifications with fund and style-time fixed effects, as well as fund characteristics that could correlate with future flows, such as past returns and previous flows. The results are presented in Table 7.

Columns 1 through 3 present results using RFB^{Total}, while Columns 4 through 6 examine the three components of changes in RFB. Column 1 shows that future fund flows do not respond to RFB^{Total} unconditionally, suggesting that the average investor does not prioritize systematic risk-taking in fund allocation decisions. However, these unconditional estimates obscure the conditional impact of monetary policy on fund flows through RFB.

In Columns 2 and 3, we find that investors tend to favor portfolios with higher beta funds during periods of tighter monetary policy, as indicated by the significant interaction term between RFB^{Total} and the monetary policy shock. The estimates suggest that a one standard deviation increase in RFB^{Total} raises quarterly flows by 9.6%, a magnitude nearly ten times the average fund flow, close to one standard deviation of fund flows in our sample.

Columns 4 through 6 reveal that funds actively reaching for beta attract more flows when monetary policy tightens. In contrast, flows to funds with passive beta tilts remain unresponsive to monetary policy changes. These results are also economically meaningful: a one standard deviation increase in active RFB correlates with nearly a 4% increase in quarterly fund flows.

Taken together, Tables 5 through Table 7 indicate that funds engaging in reaching-for-beta strategies achieve higher returns and attract more inflows — even though they do not outperform on a risk-adjusted basis. Fund managers benefit from increased flows when active RFB proves effective, particularly under tighter monetary policy, which helps mitigate potential outflows due to rising interest rates. Our flow results further demonstrate that reaching for beta impacts fund flows even after controlling for past returns, suggesting an additional, direct effect of active RFB beyond its influence

Active RFB and Equity Mutual Fund Flows

	$Flow_{t+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RFB^{Total}	−0.001	−0.000	0.006				
	(−0.252)	(−0.011)	(1.464)				
ΔRFB^{Active}				−0.002	0.007	−0.0001	0.009
				(−0.347)	(0.951)	(−0.020)	(1.261)
$\Delta RFB^{BetaShift}$				0.002	0.004	0.005	0.006
				(0.192)	(0.348)	(0.403)	(0.499)
$\Delta RFB^{Interaction}$				−0.029	−0.035	−0.032	−0.038
				(−1.116)	(−1.410)	(−1.192)	(−1.442)
RFB^{Total} x NS		0.352***	0.366***				
		(2.768)	(3.061)				
ΔRFB^{Active} x NS						0.460**	0.481**
						(2.196)	(2.289)
$\Delta RFB^{BetaShift}$ x NS						0.187	0.184
						(0.723)	(0.686)
$\Delta RFB^{Interaction}$ x NS						−0.081	−0.020
						(−0.209)	(−0.050)
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	140,384	139,810	139,810	139,864	139,864	139,311	139,311
Adjusted R^2	0.218	0.219	0.257	0.217	0.255	0.217	0.255

Table 7: This table reports results from panel regressions of future quarterly fund flows on the interactions of four reaching for beta measures (ΔRFB^{Total}, ΔRFB^{Active}, $\Delta RFB^{BetaShift}$, $\Delta RFB^{Interaction}$) defined in Equation (2) with the monetary policy surprise measure of Nakamura-Steinsson (NS). The observations are at the fund-quarter level. All regressions include (log) fund age, (log) total net assets, the past three months of fund returns, the standard deviation of the past twelve months of fund returns, turnover ratio, expense ratio, and fund flows as control variables. 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.

through previous performance.

Moreover, Online Appendix IA2.3 shows that funds actively reach for beta in response to monetary policy, regardless of past performance — whether they had low or high prior returns. This implies that investors may prefer high-beta-tilted portfolios for reasons unrelated to enhanced returns.[4]

The results in Table 7 raise the question of whether fund managers' motivation for reaching for beta could be attributed to a "catering mechanism." In other words, fund managers might engage in reaching for beta in advance because mutual funds attract inflows based on investors' preference for risk-taking behavior rather than enhanced returns through active RFB. To explore this channel, we examine how the ARFB response to monetary policy shocks varies across different types of funds. If investors channel their flows into funds with specific attributes associated with active RFB behavior, then funds with those characteristics would be expected to increase their active RFB to cater to these investors.

However, the results provided in Online Appendix IA2.3 suggest that this catering channel is unlikely. Figure IA1 shows that tighter monetary policy predicts higher active RFB consistently across groups of funds with varying attributes. This indicates that funds shift toward high-beta stocks in response to tighter monetary policy regardless of whether their beta, income, performance or expected flows are high or low. This uniform response in active RFB does not align with a catering mechanism.

5 Active RFB-Induced Trading and Stock Returns

In this section, we analyze whether RFB-driven mutual fund demand results in systematic price fluctuations in the stock market. To examine the return patterns associated with mutual funds' purchases toward higher beta stocks, we first construct a measure of *beta-induced trading* in the spirit of the flow-induced trading measure of Lou (2012).

[4] While our focus is on mutual fund managers' risk-taking behavior, the observed flow results among retail investors under tightening policy conditions are also new to the literature. We conjecture that these results align with the leverage demand story proposed by Frazzini and Pedersen (2014).

In particular, we define beta-induced trading (BIT) for each stock in each quarter as follows:

$$BIT_{j,t} = \frac{\sum_i shares_{i,j,t-1} \times \Delta RFB_{i,t}^{Active}}{\sum_i shares_{i,j,t-1}} \tag{12}$$

where ΔRFB^{Active} represents the active reaching for beta of fund i in quarter t as defined in Equation (2), and $shares_{i,j,t-1}$ represents the number of shares held by mutual fund i for stock j at the end of the previous quarter. Intuitively, $BIT_{j,t}$ captures the amount of mutual fund trading caused by active RFB for each stock j in quarter t in our mutual fund universe. As such, BIT doesn't reflect managers' information about fundamentals but isolates the non-discretionary trading only associated with active reaching for beta.

Using the BIT measure, we test whether active RFB substantially affects stock prices through beta-induced trading. First, we estimate the response of stock returns to stock-level BIT. Specifically, we run the following predictive panel regressions for each horizon h:

$$ExRet_{i,t+h} = \alpha_i + \beta_h BIT_{j,t} + \gamma' X_{i,t} + \varepsilon_{i,t+h}, \tag{13}$$

where Ret represents the stock returns in excess of the risk-free rate, h is the forecast horizon. α_i captures stock fixed effects, and $X_{i,t}$ represents the set of stock-level controls such as book-to-market ratio, market capitalization, idiosyncratic volatility, and Amihud's illiquidity measure. Standard errors are clustered at the quarter level. We standardize BIT over the entire sample so that coefficients reflect standard deviations relative to the sample mean. We estimate the regression for horizons from 0 (i.e., upon impact effect) to eight quarters ahead. Figure 3 plots the cumulative response of stock returns ($\sum_{h=0}^{n} \beta_h$) to a 1% change in mutual fund trading through active reaching for beta.

Figure 3 highlights a significant price pressure on stocks associated with active reaching for beta. A one-standard-deviation increase in mutual fund trading towards

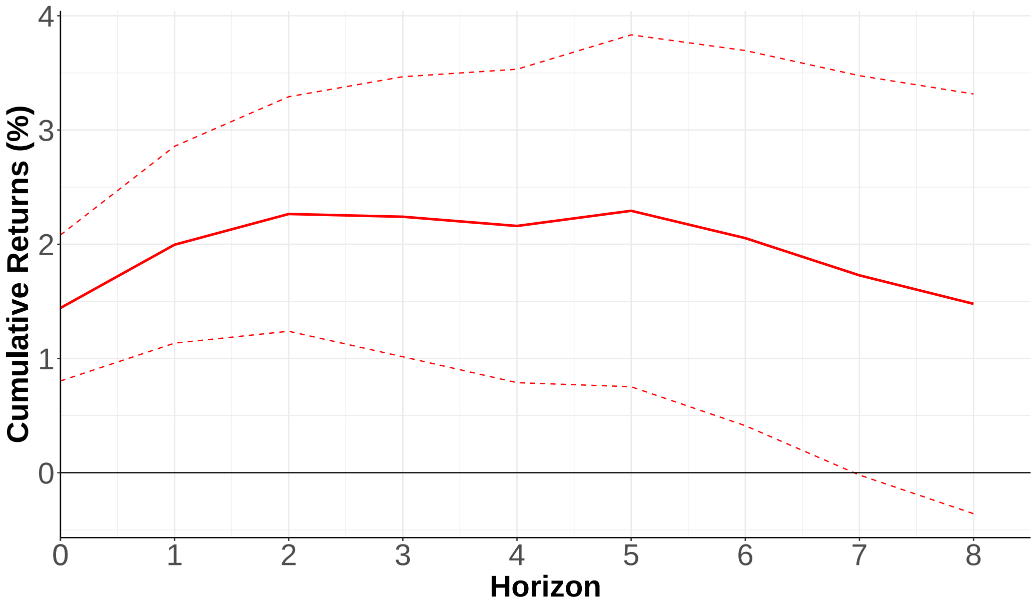

Figure 3: This figure displays the dynamics of excess stock returns in response to beta-induced trading (BIT). On the y-axis, we report the sum of coefficients estimated from the predictive regressions (13) for forecast horizons from one to eight quarters. We standardize BIT over the entire sample such that the coefficients reflect standard deviations relative to the sample mean. Dashed lines indicate 90% confidence bands.

higher beta stocks via BIT leads to price pressure of approximately 1.2% (4.8% annualized) in the same quarter. Cumulative returns increase to 1.7% (6.8% annualized) in the next 2 quarters, and then gradually reverse in the following six quarters. The on-impact effect and the gradual revision pattern suggest that beta-induced trading immediately drives stock prices away from their fundamental values, and that the effect only wanes gradually in multiple quarters.

As shown in Figure 1, active reaching for beta is persistent. Hence, stocks which receive more allocation via active reach-for-beta in the current quarter can be expected to be purchased more also in subsequent quarters. As such, the persistence of active reach-for-beta tilts the prices away from the fundamental values during a few quarters. Because BIT doesn't reflect managers' information about fundamentals, this pricing effect gradually and eventually dies out.

In the spirit of Lou (2012), we also construct portfolios sorted based on the BIT measure and examine the return spread associated with mutual funds' beta-induced trading. In particular, we sort stocks into quintiles based on BIT at the end of each quarter and track their corresponding returns in the formation and subsequent quarters. Then, we report the quarterly returns to equal-weighted and value-weighted quintile portfolios ranked by BIT for various holding periods.

Figure 8 provides the results. In Panel A, the equal-weighted high-minus-low (H-L) portfolio return is 1.22% ($t = 5.29$) in the formation quarter. Note that this result is consistent with the contemporaneous impact shown in Figure 3. Controlling for the market risk factor diminishes the returns of both high and low BIT portfolios, yet it ultimately has little impact on H-L portfolio returns. The return spread between top and bottom quintiles is also sizable for the value-weighted portfolios in Panel B. Overall, these results suggest a strong price effect of beta-induced trading in the same quarter via active reaching for beta by mutual funds, consistent with our evidence shown in Figure 3.

That said, after the formation period, this effect reverses, especially for the risk-adjusted returns. Although excess returns for the equal-weighted H-L portfolio are still positive and significant in Quarters 1 and 2 (consistent with the results in Figure 3), the positive excess returns are not significant for the value-weighted H-L portfolio after the formation period. Moreover, the risk-adjusted return spread becomes indistinguishable from zero in the four quarters following the formation period for both equal and weighted portfolios in Panel A and B. Crucially, the CAPM and FF4-adjusted return spread for value-weighted portfolios are -1.99% (t=-1.84) and -1.46% (t=-1.88) at the end of quarter 8. As such, the positive return to the H-L portfolio accumulated in the formation quarter is completely reversed by the end of year two. As mutual funds significantly tilt their portfolios toward large-cap stocks, the reversal effect is undetected for equal-weighted portfolios.

In summary, our findings indicate that BIT leads to price pressures that vanish over time. The beta-induced demand tends to cause a large price impact in the quarter in which active reaching for beta occurs. However, this return impact is reversed, especially on a risk-adjusted basis. As in Lou (2012), the reversal does not dominate the price formation immediately, but slowly builds up after portfolio formation and dissipates in two years. The gradual reversal pattern is consistent with our finding that active reaching for beta is mildly persistent (Figure 1). Nevertheless, our evidence in Figure 3 and Table 8 suggests that the price pressure fully reverts back over time eventually, suggesting that BIT does not contain fundamental information.

(a) Equal-weighted returns to portfolios ranked by BIT

	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 returns to portfolios ranked by BIT

	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)

Table 8: This table reports returns of quarterly portfolios ranked by the beta-induced trading (BIT). Each quarter, we create equal-weighted (Panel A) and value-weighted (Panel B) portfolios by sorting funds into quintiles based on BIT and tracking their future risk-adjusted returns in the following two years (8 quarters). Quarter 0 is the formation quarter. The portfolios are rebalanced every quarter and held for two years. The columns labeled "Low" and "High" present results for the first and the fifth BIT quintile portfolios. The column listed "H-L" presents results for the portfolio that is long funds in the highest BIT quintile and short funds in the lowest BIT quintile. The table reports the average quarterly excess return (Excess return), and the abnormal returns (alphas) relative to the capital asset pricing model (CAPM), and the model with three Fama French factors and Momentum factor (FF4). t -statistics reported in parentheses are based on standard errors adjusted using Newey and West with optimal lags.

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 highly persistent and increases the net buying pressure of high beta stocks for at least one year. While RFB is a universal phenomenon and does not differ much with respect to fund characteristics such as beta, performance, income, or expected fund flows, we find that funds that actively reach for beta experience more inflows when monetary policy is restrictive. Those funds also deliver higher raw returns but no significant alpha when controlling for market and other risk factors, suggesting that RFB does not reflect skill-based performance.

We also show that funds' demand for high beta stocks induces systematic price pressures, which take several months to dissipate. Specifically, we construct a beta-induced trading measure for individual stocks by aggregating the trading induced by active RFB across all mutual funds and show that it predicts excess stock returns several quarters out. Moreover, stocks purchased by mutual funds with a strong degree of active RFB deliver higher returns than stocks bought by funds with low RFB. Those results suggest that beta-induced trading does not reflect fundamental information but instead causes price swings via uninformed trading.

Our findings are in stark contrast to investor behavior, typically referred to as reaching-for-yield, which refers to the tendency of institutional or retail 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.

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Online Appendix

for

Reaching for Beta

IA1 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 the dataset using fund-style classification codes. Our selection procedure closely follows the methodologies outlined by Kacperczyk, Sialm, and Zheng (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 the following Lipper classifications: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE. If the Lipper classification is unavailable, we select funds based on Strategic Insight objectives: AGG, GMC, GRI, GRO, ING, and SCG. In cases where both Lipper and Strategic Insight codes are missing, we rely on Wiesenberger objective codes, such as G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG.

If all classification codes are absent but the "policy" variable is listed as CS (Common Stock), the fund remains in the sample. For instances where a style code is missing in a specific year, we impute the code using data from earlier or later years, if available. However, we exclude funds from the sample if classification codes are missing for the entire duration after filings.

Next, we remove index funds and target date funds from the remaining sample. For index fund classification, we rely on both the CRSP and Morningstar index fund flags. Additionally, we classify a fund as an index fund if its name contains any of the following (case-insensitive) strings: INDEX, IDX, S&P, INDX, BARRA, DOW JONES, DOW 30, RUSSELL 1000, RUSSELL 2000, or RUSSELL 3000. However, we retain enhanced index funds in the sample. To identify and remove target date funds, we use both Lipper classifications and a fund name search.

Mutual funds often have multiple share classes that feature different fee structures but share the same underlying portfolio. To capture fund-level characteristics, we aggregate data across all share classes of each fund. 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. For qualitative characteristics such as the fund's name and objectives, we use the data from the largest share class. 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).

IA2 Robustness Checks

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

IA2.1 Other Components of Reaching for Beta

Here, we explore the link between interest rates and the components of the change in total RFB other than the active RFB, i.e., i.e.,$\Delta RFB^{BetaShift}_{i,t}$ and $\Delta RFB^{Interaction}_{i,t}$. Table IA1 shows that both $\Delta RFB^{BetaShift}_{i,t}$ and $\Delta RFB^{Interaction}_{i,t}$ are not predicted by the change in short, medium-term interest rates. Taken together with the results in 3.1.1 of the main text, our findings indicate that only the active component of funds' RFB is significantly affected by short-term rates.

IA2.2 Robustness Checks for the Monetary Policy Measures

Alternative instruments of monetary policy shocks Table IA2 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, Sack, and Swanson (2004) constructed by Gürkaynak, Karasoy-Can, and Lee (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.

	$RFB^{BetaShift}_{t+1}$				$\Delta RFB^{Interaction}_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔTBILL3M	0.004			−0.007	0.002			0.011
	(0.645)			(−0.443)	(0.467)			(1.211)
ΔTBOND2Y		0.008		0.018		−0.004		−0.011
		(1.155)		(0.918)		(−0.755)		(−0.954)
ΔTBOND10Y			0.004	−0.008			−0.006*	−0.001
			(0.601)	(−0.684)			(−1.710)	(−0.174)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	139,541	139,541	139,541	139,541	139,541	139,541	139,541	139,541
Adjusted R^2	0.012	0.013	0.011	0.013	0.016	0.018	0.021	0.028

Table IA1: This table reports the coefficient estimates from the predictive panel regressions:

$$RFB_{i,t+1} = \alpha_f + \beta IR_t + \gamma X_{i,t} + \theta Z_t + \varepsilon_{t+1} \tag{IA1}$$

where RFB is either $\Delta RFB^{BetaShift}_{i,t}$ or $\Delta RFB^{Interaction}_{i,t}$. $\Delta RFB^{BetaShift}_{i,t}$ and $\Delta RFB^{Interaction}_{i,t}$ are defined in Equation 2 and computed at fund-quarter level. IR represents the changes in 3-month treasury bill yields(ΔTBILL3M), the changes in 2-year treasury bond yields ΔTBOND2Y) or the changes in 2-year treasury bond yields ΔTBOND2Y). X represents (log) fund age, (log) total net assets, past three months of fund returns and standard deviation of past 12 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.

The first-stage regression results in Column (3) are qualitatively very similar to the results in Table 4, indicating that monetary policy surprises of Gürkaynak, Sack, and Swanson (2004) 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 4.

	ΔRFB^{Active}		ΔTBILL3M	ΔRFB^{Active}
	Interest Rates	MP Shocks	IV - 1st Stage	IV - 2nd Stage
	(1)	(2)	(3)	(4)
ΔTBILL3M	0.021***			
	(2.887)			
$Target$		0.072	1.940***	
		(1.566)	(3.270)	
$Path$		0.058*	1.804***	
		(1.942)	(4.457)	
$\Delta T\widehat{BIL}L3M\_GSS$				0.034***
				(2.626)
Fund FE	Yes	Yes		Yes
Controls	Yes	Yes		Yes
Observations	139,541	139,100	109	139,100
Adjusted R^2	0.217	0.214	0.219	0.214
F Statistic			16.143*** (df = 2; 106)	

Table IA2: 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 7 and 8 (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.

Expansionary vs. Contractionary Impact Table IA3 further reports the robustness checks on whether the results are driven by positive or negative changes in interest rates or monetary policy. 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).

	ΔRFB^{Active}			
	(1)	(2)	(3)	(4)
ΔTBILL3M+	0.029**			
	(2.204)			
ΔTBILL3M-		0.025**		
		(2.547)		
NS+			0.173*	
			(1.748)	
NS-				0.182***
				(2.764)
Fund FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	139,541	139,541	139,100	139,100
Adjusted R^2	0.212	0.216	0.211	0.213

Table IA3: 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.

IA2.3 Reaching for Beta in the Cross-Section of Funds

In this section, we investigate whether the active reaching for beta responses of mutual funds differ in the cross-section of funds. In particular, we first form decile groups (ranks) of funds sorted by their characteristics, such as fund beta, fund performance (returns), fund income (dividend yield), and expected fund flows.

First, we construct each fund characteristic as follows:

Fund Beta: We calculate the fund beta for each fund as the weighted average of the individual stock betas within the fund's portfolio as below:

$$FBeta_{f,t} = \sum_{i} w_{i,t} \times \beta_{i,t} \tag{IA2}$$

where $FBeta_{f,t}$ represents the beta of fund j at the end of quarter t. Here, $w_{i,t}$ denotes the weight of stock i in the portfolio for quarter t, and $\beta_{i,t}$ is the stock's beta, estimated from rolling regressions over the prior 36 months as in the main text.

Fund Performance We use twelve-month cumulative fund returns up to the end of quarter t as a fund's performance metric. Our results are qualitatively robust to using the past three months of returns as a fund's performance.

Fund Income: We follow Daniel, Garlappi, and Xiao (2021) and compute fund income for quarter t as the total dividend distribution of the fund scaled by the net asset value at the end of that quarter.

Expected Fund Flows: We follow mutual fund literature and use a prediction model for fund flows to estimate the *expected* fund flows. Previous literature has shown that fund flows can be predicted using past returns and flows (Coval and Stafford, 2007, Lou, 2012). Following Shive and Yun (2013), we employ an out-of-sample model that incorporates returns and flows from the previous four quarters, augmenting their base predictive model:

$$\mathbb{E}_t[Flow_{i,t+1}] = \sum_{\tau=0}^{3} A_{i,\tau}, Flow_{i,t-\tau} + \sum_{\tau=0}^{3} B_{i,\tau}, FRet_{i,t-\tau} + C_{i,t}, FBeta_{i,t} \tag{IA3}$$

$$+ D_{i,t}, FBeta_{i,t}, NS_t + E_{i,t}, NS_t \tag{IA4}$$

where $\mathbb{E}_t[Flow_{i,t+1}]$ denotes expected flow for fund i in quarter $t+1$ estimated at the end of quarter t. $FRet_{i,t}$ and $Flow_{i,t}$ denote the quarterly returns and flows, respectively. Since our goal is to understand the impact of additional flows in response to high fund beta during periods of monetary policy shifts, we extend the model from (Shive and Yun, 2013) by adding fund beta ($FBeta_{i,t}$) given by equation IA2 and its interaction with Nakamura-Steinsson's monetary policy surprise measure (NS_t). The regression coefficients (A,B,C,D,E) are estimated for each fund in each quarter using OLS regressions based on past data from the previous 36 months. We compute the flows predicted from OLS regression IA3 as our expected flow measure in sorting funds accordingly.

Next, we divide our sample into deciles based on each of the variables mentioned above and conduct our baseline predictive regressions using monetary policy surprises for each decile group of funds *separately*. Specifically, we estimate the following predictive panel regression for each group g:

$$\Delta RFB^{Active}_{i(g),t+1} = \alpha_g + \beta\, \Delta NS_t + \gamma\, X_{i(g),t} + \theta\, Z_t + \varepsilon_{i(g),t+1}, \quad g = 1, 2, ..., 10. \tag{IA5}$$

where ΔRFB^{Active} represents active reaching for beta as defined in Equation 2. NS represents the monetary policy surprise measure of Nakamura-Steinsson. α_f captures fund fixed effects, and X is the set of fund-level control variables that include (log) fund age, (log) total net assets, fund returns and standard deviation, turnover ratio,

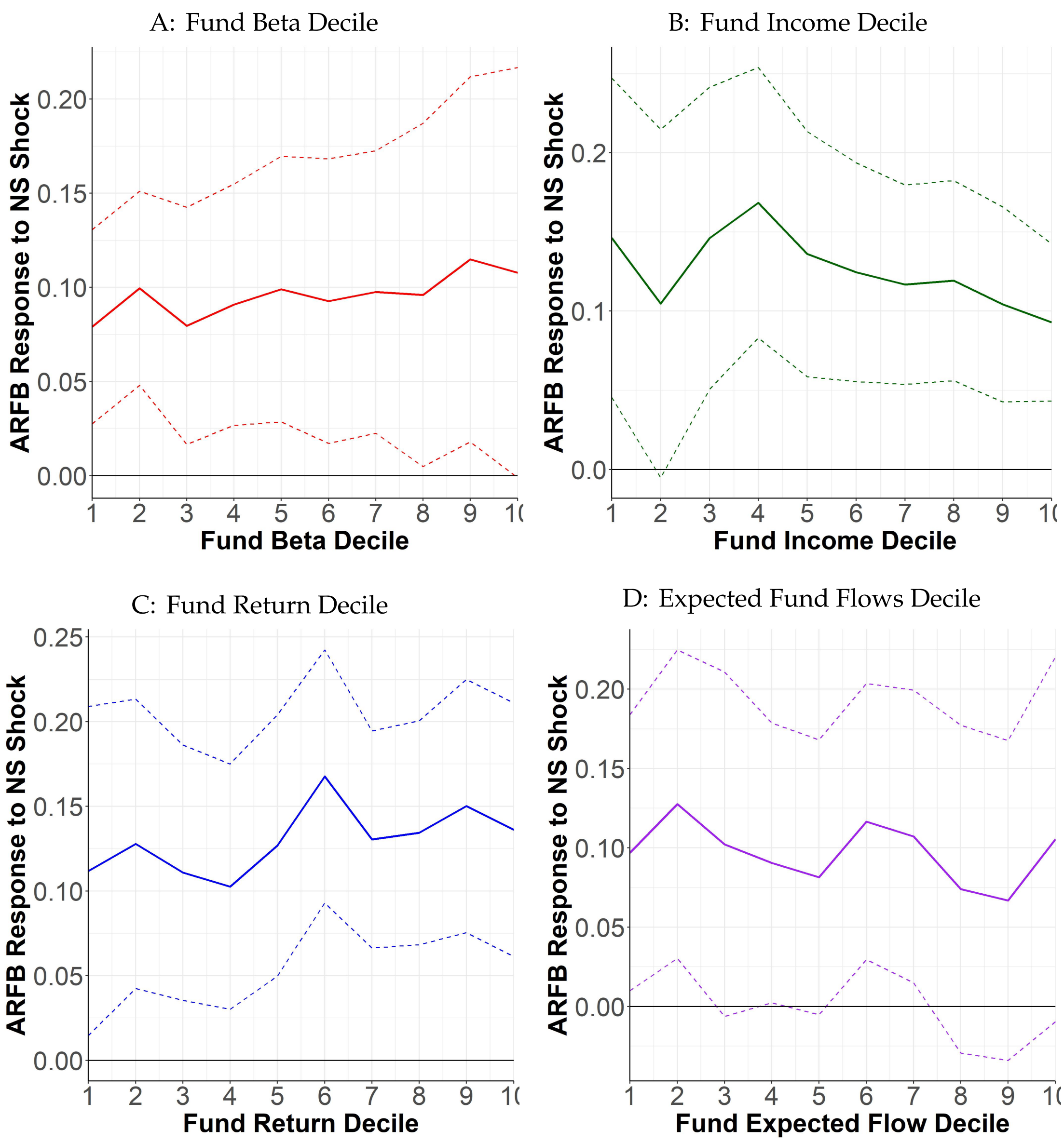

Figure IA1: This figure displays the coefficient estimated from the panel regression IA5 within each group (deciles) based on Fund Beta (Panel A), Fund Income (Panel B), Fund Return (Panel C) and Expected Fund Flow (Panel D). Dashed lines indicate the 90% confidence bands. See the text for further details.

expense ratio, and fund flows. Z represents aggregate controls including quarterly stock market return, the change of VIX index, and market liquidity. Figure IA1 displays the coefficient β in the y-axis along with the fund decile in the x-axis for each fund groupings (fund beta, fund returns, fund income and expected fund flows).

Figure IA1 suggests that tighter monetary policy predicts higher active RFB uniformly across groups of firms with different fund betas, fund income, fund performance, or fund expected flows. That is, funds tilt their portfolios toward high-beta stocks in response to tighter monetary policy regardless of their specific attributes that may cater to investors' preferences.

IA2.4 Role of Margin Requirements & Leverage Constraints

Past literature suggests that investors tilt their portfolios toward high-beta assets when leverage or margin constraints are tighter (e.g., Black, 1972, Frazzini and Pedersen, 2014). Here, we investigate whether active reaching for beta is related to higher margin requirements or tightened leverage constraints. We consider four measures that proxy either leverage constraint tightness or increased margin requirements.: the broker-dealer leverage measure from Adrian, Etula, and Muir (2014) (Δ BDLev), the change in debit balances in margin accounts at the broker-dealers from FRED: BOGZ1FL663067003Q (Δ Margin), the betting-against-beta factor from Frazzini and Pedersen (2014) (Bab), and the innovation in the intermediary capital ratio from He, Kelly, and Manela (2017) (ICR). According to their definitions, higher values of Δ BDLev and Δ Margin measures and lower values of the BAB and the ICR measures are associated with tighter margin/leverage constraints.

As before, we conduct quarterly panel regressions to assess whether tighter borrowing constraints predict higher active RFB. Specifically, we run the following panel regression: Formally, we estimate the following quarterly panel regressions:

$$\Delta RFB_{i,t+1}^{Active} = \alpha_f + \beta\, LCProxy_t + \gamma\, X_{i,t} + \theta\, Z_t + \varepsilon_{i,t+1} \tag{IA6}$$

where ΔRFB^{Active} represents active reaching for beta (ΔRFB^{Active}) as defined in Equation 2. $LCProxy$ represents one of the leverage constraint proxies listed above, α_f captures fund fixed effects, and X is the set of fund-level control variables and Z is aggregate controls as before. Table IA4 shows that none of the leverage constraint proxies predict active RFB by fund managers. All coefficients are found to be insignificant. Considering the fact that most mutual fund managers have limited use of borrowing or margin, the findings are rather unsurprising. Since mutual fund managers don't rely much on borrowing or using margin, their portfolio choices is not dependent on

	ΔRFB^{Active}			
	(1)	(2)	(3)	(4)
Δ BDLev	0.022			
	(0.403)			
Δ Margin		0.027		
		(1.285)		
Bab			−0.099	
			(−0.621)	
ICR				−0.036
				(−1.540)
Fund FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	139,541	139,541	126,870	34,114
Adjusted R^2	0.210	0.211	0.220	0.174

Table IA4: This table presents the coefficient estimates from the predictive panel regressions using alternative proxies that capture margin requirements or leverage constraints. For further details on variables, 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. 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.

changes in external borrowing conditions. Since those proxies are already poor predictor of active RFB standalone, they don't predict active RFB in a second-stage regression of 2SLS analysis in which they are instrumented by monetary policy surprises (untabulated).