What Can Macro-Active Bond Funds Tell Us about Monetary Policy Change?*

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Abstract

This paper focuses on actively managed bond mutual funds, whose performance is most sensitive to monetary policy shocks. We document significant and persistent FOMC-day outperformance by macro-active bond funds, which is particularly pronounced during periods of heightened macroeconomic disagreement and attention. Consistent with their forecasting ability, these funds' pre-FOMC portfolio duration adjustments can predict FOMC-day monetary policy shocks beyond the information offered by economic data and asset returns. Furthermore, we show that this macro-investing skill extends to GDP and CPI announcements and is consistently shared across various fund styles within fund families.

Keywords: Macro-Timing, Bond Funds, Macro Announcement, Monetary Policy

JEL classification: G01, G11, G12, G14, G23

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Scheduled macroeconomic announcements, such as Federal Open Market Committee (FOMC) releases, are key moments when new information gets incorporated into asset prices. These events can reshape investor expectations, influence the yield curve, and alter risk premiums.[1] While previous research has extensively examined the impact of macro announcements on asset prices, there has been less focus on how institutional investors, particularly fixed-income funds, trade around these events.

Our primary focus is on government bond funds because price movements in the Treasury market are significantly influenced by market-moving macroeconomic news.[2] Given that government bond funds primarily invest in interest rate products, it follows that macroeconomic announcement days should be the most important moments for bond fund managers to exercise their skills, if any, in effectively timing the Treasury bond market. Moreover, among various mutual fund styles, government bond funds are notably the most macro-active.[3] Their turnover rate strongly comoves with the level of monetary policy uncertainty and tends to peak during major events such as the tech bubble in 2001, the global financial crisis of 2008, and the Fed's tapering of 2015.

Given these distinct attributes, government bond funds offer a valuable lens through which we can gain insights into the perspective of investors regarding monetary policy. By delving into their performance around FOMC announcements, we ask the questions: Do institutional investors possess superior macro-investing skills? And if they do, can their proactive adjustments to duration exposure ahead of the FOMC announcements offer valuable insights into shifts in monetary policy?

Overall, we find evidence that macro-active government bond funds exhibit strong outperformance on FOMC announcement days, and such outperformance persists over time.

[1] See Savor and Wilson (2013, 2014), Lucca and Moench (2015), Cieslak, Morse, and Vissing-Jorgensen (2019), and Hu, Pan, Wang, and Zhu (2022), among others.

[2] For example, Fleming and Remolona (1999) and Balduzzi, Elton, and Green (2001) document that Treasury prices respond almost instantaneously to macroeconomic news releases. Boguth et al. (2026) show that while the prices of interest rate futures following FOMC news releases are likely driven by information, equity prices are likely driven by noise.

[3] The average annual turnover rates are 196% for government bond funds, 169% for investment-grade funds, and 78% for equity funds. Compared to corporate bond funds, government bond funds also have the advantage that they are less affected by liquidity and credit risks.

While similar patterns are observed in corporate bond and equity funds, the magnitude of outperformance is much smaller. Relative to the mixed evidence on bond fund market-timing ability in the existing literature (e.g., Chen, Ferson, and Peters (2010); Huang and Wang (2014)), our approach provides a more direct test of funds' macro-investing skill by exploiting the time-series variation in returns around major macroeconomic announcements. We further show that this FOMC-day alpha is driven largely by macro-timing. In particular, macro-active government bond funds adjust portfolio duration ahead of FOMC announcements, and these pre-announcement duration changes significantly predict subsequent monetary policy shocks beyond standard economic and financial indicators. The predictive power of these duration adjustments suggests that asset prices do not fully incorporate all available information in real time, even in a market as transparent, liquid, and competitive as the $30 trillion U.S. Treasury market.

FOMC-Day Performance: Using daily return data from U.S. government bond funds for the period from 1998 to 2021, we first document significant fund outperformance on FOMC announcement days. By applying a four-factor model that includes the first three principal components of the bond market and the aggregate risk factor of the stock market, we find that government bond funds, on average, outperform by 1.44 bps (t-stat $= 2.40$) on FOMC days, with the most active quintile funds achieving up to 4.23 bps (t-stat $= 3.63$).[4] Given that the daily return of government bond funds has a mean of 1.77 bps and a standard deviation of 29.5 bps, a magnitude of 4.23 bps is 2.4 times the daily mean and 14% of the standard deviation.[5] This FOMC-day outperformance remains robust when evaluated using funds' benchmark returns or net-fee returns, which have magnitudes of 3.47 and 3.97 bps, respectively, and is also robust across alternative factor models. In contrast, passive index funds do not exhibit such FOMC-day outperformance.

Extending the analysis to other styles of mutual funds, we find that corporate and equity

[4] Appendix Section 1 details the construction of the four-factor model and compares it with alternative factor models in the literature.

[5] The FOMC-day alpha of 4.23 bps translates to an annual cumulative alpha of 34 bps, provided that FOMC meetings are held eight times a year. This magnitude can enhance an average government bond fund's percentile ranking by 13%.

funds also tend to outperform on FOMC announcement days, albeit with a much weaker magnitude. For instance, actively managed corporate bond funds, on average, outperform by 2.12 bps (t-stat = 1.97) on FOMC announcement days. Actively managed equity funds have an FOMC-day alpha of 4.69 bps (t-stat = 1.63), which is economically trivial given their daily return volatility of 137 bps. While our primary focus is on government bond funds, which offer the most robust and clear evidence of macro-trading, we find that macro-investing skills are likely shared across styles within the same fund family. For example, a one standard deviation increase in the FOMC-day alpha of corporate bond funds within a fund family is associated with a 3.68 bps (t-stat = 12.36) increase in the same-family government fund's FOMC-day alpha.

This outperformance is distinctly linked to the FOMC news release, as no similar outperformance is observed on the days immediately before or after the announcement. To verify the unique role of the FOMC news release in driving fund performance, we conduct two placebo tests: (1) Following Hillenbrand (2025), we generate 10,000 simulated placebo FOMC paths by randomly selecting the same number of days within a month as actual FOMC meetings. We find that the probability of funds achieving a similar magnitude of outperformance on these placebo days is less than 0.03%. (2) Recognizing that FOMC-day returns are generally more volatile than non-macro days, we further conduct placebo events by matching each FOMC day with a non-macro day that exhibits very similar asset or factor return distributions. We observe no fund outperformance for these placebo announcements, which lack a monetary policy news release.

Explaining the FOMC-Day Alpha: To understand the drivers of funds' FOMC-day outperformance, we next examine its cross-sectional determinants along three key aspects: fund activeness, past performance, and the transferability of skill. First, in alignment with the notion of active fund management, we document a significant positive relationship between macro-day performance and various proxies for fund activeness, including fund turnover, idiosyncratic risk taking, and the R-squared measure derived from the factor model (Amihud and Goyenko (2013)). Among these activeness proxies, idiosyncratic volatility stands out as the strongest predictor, both economically and statistically. A one standard deviation increase in funds' idiosyncratic risk-taking predicts an increase of 1.05 bps (t-stat = 3.48) in FOMC-day alpha. In contrast, the coefficient for systematic volatility is negative and statistically insignificant, indicating that macro-day outperformance is not the result of passive risk-taking.

Such active management is further evident in their portfolio holdings. Funds with stronger FOMC-day performance tend to take on slightly higher leverage, maintain larger bond holdings, and exhibit a greater use of derivative assets. For instance, funds in the highest quintile of macro-day performance are 10% more likely to use Treasury futures and other interest rate derivatives, compared to those in the lowest quintile. In addition to utilizing a more diverse set of derivative instruments, these funds also more actively adjust portfolio maturity and duration. Notably, the best-performing quintile demonstrates a 0.2-year higher duration volatility (t-stat = 5.47) compared to their peers.

Second, we find that funds exhibit performance persistence in their macro-investing abilities. Specifically, a fund's past performance on FOMC days significantly and positively predicts its future performance. A one standard deviation increase in a fund's past FOMC-day alpha, measured over the previous 24 months, predicts a 0.61 bps (t-stat = 2.95) increase in future FOMC-day alpha.[6] Thus, contrary to existing literature (Carhart (1997), Brown and Goetzmann (1995), and Blake, Elton, and Gruber (1993)), which often reports little outperformance or performance persistence, our focus on information-intensive macroeconomic announcement days shows that funds not only outperform on FOMC days, but their past macro-day performance is a strong predictor of future success. This suggests that FOMC-day alpha reflects genuine skill in processing macro-relevant information—a transferable capability that persists over time.

Finally, if the observed outperformance is indeed due to a fund's active macro-investing ability, we would expect that a fund demonstrating predictive skill for FOMC shocks would

[6]This relationship with fund activeness and past performance is also evident in corporate and equity funds.

also show similar proficiency in anticipating other macroeconomic announcements. Our findings support this hypothesis: a fund's performance on FOMC days is significantly and positively correlated with its performance on GDP and CPI announcement days. Specifically, for government bond funds, a one standard deviation increase in FOMC-day alpha results in a 0.54 bps (t-stat=1.91) increase in GDP-day alpha and a 0.48 bps (t-stat = 2.19) increase in CPI-day alpha. Similar patterns are observed for corporate and equity funds as well.

Information on Monetary Policy: While a fund's FOMC-day performance reflects its macro-investing ability, it does not directly reveal the managers' expectations regarding FOMC outcomes. Specifically, when macro-active funds increase their duration exposure relative to less active funds ahead of an FOMC announcement, can these adjustments predict a reduction in interest rates on the announcement day? To explore this, we examine the duration changes made by government bond funds. Their liquid portfolios, which are less susceptible to stale pricing, enable us to detect their duration changes made immediately before the announcements.

We estimate fund duration using a return-based approach by regressing fund returns against yield changes. The regression coefficient captures the percentage change in fund price (returns) with respect to a one-unit change in interest rates, which is precisely the definition of modified duration. The change in duration, $\Delta Duration$, is the difference between the duration measured during the [-14, -1] window before the announcement and that measured during the [-28, -15] window. We first validate the effectiveness of this duration change measure by demonstrating that active funds adjust their duration exposure ahead of FOMC announcements, increasing duration before rate cuts and decreasing it before hikes. A back-of-the-envelope calculation indicates that the alpha predicted by duration adjustment can account for approximately 68% of the magnitude of the observed FOMC-day alpha at the fund level.

Using pre-announcement duration change to predict announcement-day yield curve movements, we find that $\Delta Duration$ contains unique and non-redundant information about upcoming monetary policy decisions. A one standard deviation increase in $\Delta Duration$

predicts a 2.41 bps (t-stat=3.85) reduction in the 2-year yield on the day of the announcement, with an R^2 of 8.2%. Consistent with the expectation that monetary policy primarily affects the shorter end of the yield curve (Hanson and Stein (2015)), the predictive power of $\Delta Duration$ is strongest at the 2-year horizon and gradually declines at longer maturities. The estimates are qualitatively similar when we replace announcement-day yield changes with high-frequency monetary policy shock measures from Nakamura and Steinsson (2018) and Gürkaynak, Sack, and Swanson (2005). Importantly, the predictive power remains robust after controlling for a broad set of established interest rate predictors, including survey-based forecasts, measures of economic activity, asset return predictors, yield-based predictors, and sentiment measures derived from central bank communications. These findings suggest that fund managers' duration adjustments reflect distinct skill in processing and interpreting macroeconomic information beyond existing public signals.

Finally, we explore the time-series variation in funds' FOMC-day outperformance and the predictability of $\Delta Duration$ over time. We show that fund managers' macro-investing ability becomes more valuable during periods when opportunities to excel are greater—such as when economists disagree strongly on the Fed's decision, when market attention to FOMC announcements is heightened, and when announcements are likely to introduce large shocks to the bond market. For instance, a one standard deviation increase in Bloomberg Fed funds rate disagreement is associated with an increase in FOMC-day alpha of 2.9 bps (t-stat=2.77) for the most actively managed funds. Meanwhile, during those periods, the predictability of $\Delta Duration$ is also much stronger.[7]

Related Literature: Our paper contributes to the literature on mutual fund trading skills, particularly market timing ability. Prior research generally finds that both bond and equity mutual funds struggle to consistently outperform the market, although there is considerable variation across funds.[8] In the context of the highly competitive government bond market,

[7]While announcements marked by high disagreement and large surprises often coincide with periods of heightened market volatility, we find that the market-level indices such as the VIX are unimportant for the macro-day outperformance.

[8]See, for example, Fama and French (2010), Blake, Elton, and Gruber (1993), Elton, Gruber, and Blake (1995), Ferson, Henry, and Kisgen (2006), Cici and Gibson (2012), Pástor, Stambaugh, and Taylor (2017), and Choi and Kronlund (2018), among others.

Huang and Wang (2014) find that bond funds exhibit neutral or even negative timing ability once public information is taken into account. However, using U.K. data, Czech et al. (2021) show that mutual fund order flow can predict gilt returns. The evidence for corporate bond funds is also mixed (Chen, Ferson, and Peters (2010)). Taken together, whether funds possess macro-timing skill remains an open question.

Traditional tests of market-timing ability typically infer skill from convexity in the relation between fund returns and common risk factors, following Treynor and Mazuy (1966). However, these approaches are subject to well-known concerns, including nonlinearities in asset returns and stale pricing (e.g., Ferson, Henry, and Kisgen (2006); Chen, Ferson, and Peters (2010); Scholes and Williams (1977)). We take a different approach by focusing on the time-series variation in fund performance. Because managers' attention to macroeconomic conditions varies over time (Fisher, Martineau, and Sheng, 2022; Kwan, Liu, and Matthies, 2026), macroeconomic announcement days—when macro-relevant information is concentrated—provide a natural setting for testing macro-investing skill. Moreover, because our analysis centers on the highly liquid and competitive U.S. Treasury market, concerns about stale pricing are less acute. Our study is the first to document a stark contrast between macro and non-macro days in bond fund performance evaluation. This time-series perspective is related to Kacperczyk et al. (2014, 2016), who show that fund-manager skill is time-varying and that market-timing ability varies over the business cycle. We further show that macro-day performance is persistent and transferable across different types of announcements, over time, and within fund families. Overall, our evidence that macro-active funds exhibit superior macro-timing skill distinguishes our paper from the existing literature and challenges the "no-skill" view of bond fund markets.

Our paper is also related to the literature on the predictability of monetary policy changes. Kuttner (2001) and Piazzesi and Swanson (2008) discuss the effectiveness of utilizing Fed funds futures to gauge expected changes in monetary policy. Additionally, Cieslak (2018), Bauer and Chernov (2024), and Bauer and Swanson (2023b) provide evidence that various macroeconomic indicators and measures from Treasury, stock, and commodity markets can effectively predict monetary policy shocks. Our findings complement this literature by demonstrating that the duration exposure of institutional investors prior to FOMC announcements contains unique information about monetary policy changes, beyond what can be deduced from macroeconomic and financial data. Our findings are consistent with those of Czech et al. (2021), who demonstrate that aggregate order flows from mutual funds in the UK are effective in forecasting gilt returns.

Finally, our paper contributes to the literature on the pricing effects of macroeconomic announcements. Savor and Wilson (2013, 2014) show that equity returns are significantly higher on macroeconomic announcement days, whereas this effect is much weaker for short-term Treasuries. Lucca and Moench (2015) find that equity prices, but not bond prices, drift upward before FOMC announcements, a result that Hu, Pan, Wang, and Zhu (2022) extend to other major macroeconomic announcements, such as GDP releases.[9] In contrast, we document significant FOMC-day outperformance for government bond funds, but much weaker effects for equity funds. This contrast highlights differences in the risk-return tradeoff between bonds and equities across fund styles. Because equity funds are less adept at trading on macroeconomic news, they require consistently higher premiums for holding equities around FOMC announcements. By contrast, bond funds actively trade on interest rate news and possess greater skill in doing so, allowing them to require lower premiums for holding Treasuries on these days.

The rest of the paper is organized as follows. Section 1 outlines the data and methodology. Section 2 discusses funds' FOMC-day performance and links it to their macro-investing abilities. Section 3 examines the predictive power of fund duration changes for FOMC-day yield curve movements and monetary policy shocks. Section 4 extends the analysis to other macroeconomic announcements and discusses the distribution of capital flows around FOMC days. Finally, Section 5 concludes the paper.

[9] Savor and Wilson (2013) document a positive premium for longer-maturity government bonds that increases monotonically with maturity. This positive bond premium is driven primarily by price movements *after* the 2 p.m. announcement and through the end of the day. In our sample, we find that the announcement-day bond premium is economically small relative to the equity premium: 30 bps (t-stat = 3.44) for equities versus 3 bps (t-stat = 1.28) for Treasuries, as reported in Appendix Table IA1.

1 Data and Methodology

1.1 Data

Data concerning scheduled FOMC and other macro announcements are collected from the Bloomberg economic calendar. We exclusively consider scheduled macroeconomic announcements in our analysis, as unscheduled announcements do not provide fund managers with the time or opportunity to adjust their portfolios proactively. We retrieve the announcement dates for the five most important U.S. macroeconomic announcements, based on the Bloomberg relevance score. The five macroeconomic series include the Federal Open Market Committee (FOMC), Gross Domestic Product (GDP), Total Nonfarm Payroll Employment (NFP), the Consumer Price Index (CPI), and the Institute for Supply Management manufacturing index (ISM). During our sample period, we have a total of 186 FOMC announcements, 279 GDP announcements, and 280 announcements each for NFP, CPI, and ISM. In cases where announcements coincide with holidays, we use the next trading day as the designated announcement day.

The data on mutual funds are obtained from the survivor-bias free Center for Research in Security Prices (CRSP) mutual fund database. The sample period spans from September 1998 to December 2021, as CRSP only started providing daily return data for funds after September 1998. Our analysis includes government bond funds (Govt), investment-grade bond funds (Corp), and equity funds. We define the investment styles of these funds using methodologies similar to those in Choi, Kronlund, and Oh (2022), Goldstein, Jiang, and Ng (2017), and Kacperczyk, Sialm, and Zheng (2008). Government bond funds are identified by a CRSP style code starting with "IG". Money market funds, identified by the CRSP style code starting with "IM", are not included. We also exclude funds specializing in inflation-protected securities (CRSP style code "IGT"), as the illiquidity of TIPS could introduce an additional risk factor to our analysis of government bond funds.[10] Corporate bond funds and equity funds are classified based on a combination of Lipper, Strategic Insight, and Wiesenberger

[10]Including TIPS funds yields qualitatively similar, and sometimes stronger, results.

objective codes.[11] As our primary focus is on actively managed mutual funds, we exclude index funds, ETF funds, and ETN funds from the sample.[12]

From CRSP, we collect funds' daily returns, total net assets (TNA), fund age, turnover ratio, monthly flows, and expense ratios. To obtain information on fund prospectus benchmarks, manager characteristics, and daily flows, we use data from Morningstar, matching each fund from CRSP with Morningstar data using the CUSIP of each fund share class. To ensure data quality, we require funds to have at least $1 million in total assets under management, be older than 12 months, and have a zero-return-day (ZRD) ratio $\leq 60\%$.[13] After applying these screening procedures, our sample includes 851 government bond fund share classes, 2,364 corporate bond fund share classes, and 3,811 equity funds.[14]

Table 1 reports the distribution of the main variables used in our analyses, summarized using fund-quarter observations for each style category. All variables except daily return are winsorized within each style category at the 1% and 99% percentiles to mitigate the impact of outliers. On average, the daily raw return for government bond funds is 1.77 bps, with a standard deviation of 29.54 bps.[15] Corporate bond funds show similar performance, with a daily raw return of 1.98 bps and a standard deviation of 25.26 bps. Consistent with the volatile nature of the equity market, equity funds have a daily return of 4.15 bps and an exceptionally high volatility of 136.55 bps, about five times higher than that of bond funds.

On FOMC announcement days, fund returns, particularly those of equity funds, are markedly higher, with returns of 4.51 bps for government bond funds, 4.66 bps for corporate

[11] Corp funds are those with (1) Lipper class of "A", "BBB", "SII", "SID", "IID", or (2) Strategic Insight objective code of "CGN", "CHQ", "CIM", "CMQ", "CPR", "CSM", or (3) Wiesenberger objective code of "CBD". Equity funds are those with (1) Lipper class of "EIEI", "G", "LCCE", "LCGE", "LCVE", "MCCE", "MCGE", "MCVE", "MLCE", "MLGE", "MLVE", "SCCE", "SCGE", "SCVE", or (2) Strategic Insight objective code of "AGG", "GMC", "GRI", "GRO", "ING", "SCG", or (3) Wiesenberger objective code of "G", "G-I", "AGG", "GCI", "GRI", "GRO", "LTG", "MCG", "SCG", or (4) Policy code of "CS".

[12] Passive funds are identified by index fund flags B, D, E, or ET flags F or N.

[13] The zero-return-day (ZRD) ratio is the fraction of days with zero returns in the last quarter. A higher ZRD indicates greater susceptibility to stale pricing issues (Choi, Kronlund, and Oh (2022)).

[14] We use individual fund share classes as our unit of observation for bond funds, following Choi, Kronlund, and Oh (2022) and Goldstein, Jiang, and Ng (2017), as funds typically issue multiple share classes with heterogeneous fee schedules and investor restrictions. Following the literature on equity mutual funds (e.g., Kacperczyk et al. (2008) and Lou (2012)), the unit of observation for equity funds is at the fund level.

[15] As our focus is on examining the macro-investing ability of fund managers, we use funds' raw returns or gross returns in our analysis.

bond funds, and 33.74 bps for equity funds. The notably higher returns for equity funds are primarily driven by the underlying asset returns, as documented in Savor and Wilson (2013, 2014) and Lucca and Moench (2015). Consistent with the literature, Appendix Table IA1 compares the performance of government bonds and the equity market on FOMC announcement days with that on non-macro days. In our sample, the FOMC-day bond premium increases monotonically with maturity, but remains statistically weak and economically small. By contrast, the equity market FOMC-day premium is 29.99 bps (t-stat = 3.44), substantially larger than the corresponding bond market premium of 3.04 bps (t-stat = 1.28). Turning to other fund characteristics, average expense ratios differ across fund types, ranging from 0.87% to 1.22%. Turnover also varies considerably: government bond funds have the highest turnover ratio at 196%, followed by corporate bond funds at 169%, and equity funds at 78%.

1.2 Fund Turnover and Monetary Policy Uncertainty

Figure 1 further shows the annual turnover rates for various fund styles on a quarterly basis from 1998 to 2021. Fund turnover ratios are calculated as the minimum of total purchases or total sales, divided by the 12-month average total net assets (TNA), with higher values indicating more active management. To relate fund activeness with monetary policy, we also plot monetary policy uncertainty on the right axis, measured by the standard deviation of changes in 2-Year Treasury yields (Hanson and Stein (2015)).[16]

In alignment with the statistics presented in Table 1, Figure 1 illustrates that government bond funds consistently exhibit higher turnover rates compared to other fund styles. Additionally, there is a positive correlation between turnover rates and monetary policy uncertainty, with the most pronounced effect observed in government bond funds. For example, during the 2001 tech bubble, the 2008 global financial crisis, and the 2015 Fed tapering, turnover for government bond funds surged by approximately 64% from pre-event levels. During these periods, corporate bond funds also experienced increased turnover, while the effects were less pronounced for equity funds. This pattern is consistent with the understanding that

[16]Throughout the paper, we use the nominal par-coupon yield curve data constructed by Gürkaynak, Sack, and Wright (2010). This data is sourced from the Federal Reserve's website: https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html.

government bond funds primarily hold interest rate-sensitive securities, making interest rate risk and monetary policy their primary concerns. In contrast, corporate and equity funds are also subject to credit and firm-specific risks, which influence their turnover dynamics differently.

Focusing more closely on government bond funds, the lower graph in Figure 1 reports (1) the turnover rates for the most active quintile of government funds, and (2) the excess turnover of active funds compared to passive funds within the same Morningstar categories.[17] The turnover of actively managed government bond funds closely comoves with the interest rate volatility, with a correlation of 51.4%. During both the 2008 financial crisis and the 2015 Fed tapering, annualized turnover for the most active government bond funds surged from a baseline average of 278% to 829% and 564% respectively. These dramatic increases—representing 2-4 standard-deviation moves from mean levels—suggest that fund managers executed substantial duration and yield curve positioning changes in response to changing policy expectations. The 2015 taper tantrum episode proves particularly important, as the turnover peak occurred during an economic expansion rather than recession. This pattern implies that monetary policy uncertainty itself—distinct from broader economic conditions—drives fund managers' trading activity.

1.3 Estimation of Fund Performance — Four-Factor Model

To evaluate fund performance and disentangle managerial skill from systematic movements in the underlying asset classes, we employ a four-factor model consisting of one equity factor and three bond factors. Prior work, including Litterman and Scheinkman (1991), Cochrane and Piazzesi (2005), and Czech et al. (2021), shows that three factors are sufficient to capture variation in the level and term structure of the yield curve. We additionally include an equity factor to account for the well-documented impact of FOMC announcements on stock prices (Savor and Wilson (2014)). The model is specified as follows:

[17] The most active quintile of funds is identified based on their last-quarter idiosyncratic volatility, which we discuss in detail in Section 2.3.

$$
\begin{aligned}
R_t - r_t^f = \alpha + \beta^{\mathrm{L}} \left(R_t^{\mathrm{Level}} - r_t^f \right) + \beta^{\mathrm{S30}} \left(R_t^{\mathrm{Slope30}} - r_t^f \right) + \beta^{\mathrm{S10}} \left(R_t^{\mathrm{Slope10}} - r_t^f \right) \\
+ \beta^{\mathrm{E}} \left(R_t^{\mathrm{Stock}} - r_t^f \right) + \varepsilon_t,
\end{aligned}
\tag{1}
$$

where R_t represents the day-t fund return and r_t^f denotes the risk-free rate of one-month Treasury bill, sourced from Kenneth French's website. The intercept, α, captures the fund's factor-adjusted performance. The stock factor, $R_t^{\mathrm{Stock}} - r_t^f$, is calculated by subtracting the risk-free rate from the CRSP value-weighted market return index (VWRETD). The bond factors, *Level*, *Slope*30 and *Slope*10, reflect returns associated with day-to-day variations in the Treasury yield curve.

To construct these bond factors, we perform principal component analysis (PCA) on the daily return indices of 2-, 5-, 10-, and 30-year Barclays U.S. Treasury bonds from September 1998 to December 2021. Unlike PCA in yield space, PCA in return space allows the resulting principal components to be interpreted directly as portfolio returns. We use the eigenvectors associated with each principal component to construct corresponding bond portfolios and normalize them so that each represents a one-dollar net long investment. The first factor, $R_t^{\mathrm{Level}} - r_t^f$, is defined as the return on the first normalized portfolio minus the risk-free rate. The portfolio weights on the 2-, 5-, 10-, and 30-year indices are 3.57%, 13.38%, 26.96%, and 56.09%, respectively, effectively mimicking a parallel shift in the yield curve.[18] Similarly, R_t^{Slope30} and R_t^{Slope10} are constructed from the returns on the second and third principal portfolios. R_t^{Slope30} primarily captures yield differences between the 30-year bond and the short end of the yield curve, with weights of 26.04%, 60.74%, 56.56%, and -43.34% on the 2-, 5-, 10-, and 30-year indices, respectively. R_t^{Slope10} focuses more on the yield spread between the 10- and 2-year bonds, with weights of 101.26%, 86.36%, -116.88%, and 29.26%.[19] Detailed discussion of the bond factor construction and their ability to explain fund returns is provided in Appendix Section 1, which also shows that this four-factor model is among the most appropriate benchmarks for evaluating government bond fund performance relative to

[18] By performing PCA in return space, longer-duration bonds receive higher weights because their prices respond more strongly to a given change in yields.

[19] Although the third principal component is often referred to as the curvature factor, we label it R_t^{Slope10} because it is more closely related to the 10- minus 2-year yield slope.

alternative specifications used in the literature.

To further assess corporate bond funds, we extend the model by incorporating the $Corp$ factor, which is calculated as the return on the Barclays US Corporate Bond Index minus the risk-free rate. The four- (five-) factor model effectively explains approximately 91% of the daily performance variation in government funds, 99% in equity funds, and 85% in corporate bond funds. As robustness checks, Appendix Section 2 further assesses fund performance using prospectus benchmark indices and alternative factor specifications that additionally include TIPS (Treasury Inflation-Protected Securities), MBS (Mortgage-Backed Securities), and agency bond factors, as well as other models used in the literature. The results are qualitatively and quantitatively similar.

2 FOMC-Day Fund Performance

In this section, we examine how funds perform specifically on days when the Federal Open Market Committee (FOMC) makes announcements. If fund managers are adept at predicting and capitalizing on news related to monetary policy, we expect them to outperform on FOMC announcement days when shocks about monetary policy are realized.

2.1 Fund Performance around FOMC Announcements

We start by estimating the FOMC-day alphas for various styles of mutual funds using Equation (1). For each fund, in each quarter t, we estimate the factor loadings by regressing daily excess returns against the four (or five) factors over a rolling 24-month window from quarter $t-8$ to $t-1$. We then compute the daily factor-adjusted excess return as the actual return minus the return predicted by the factor model ($Ret_{i,t} - \sum_k \hat{\beta}_{i,t}^k \times Factor_t^k$). Table 2 reports value-weighted average alphas across funds for each event day surrounding the FOMC announcement t (i.e., $t-1$, t, and $t+1$), and over all trading days ("All Days").

As shown in Table 2, government bond funds exhibit significantly positive alphas on FOMC announcement days. For the general category of actively managed government bond funds ("All"), the FOMC-day alpha is 1.44 bps (t-stat = 2.40). We also report the factor-adjusted excess returns for the most actively managed quintile fund portfolio ("Most Active").[20] Consistent with their macro activeness as discussed in Section 1.2, these funds deliver even stronger FOMC-day outperformance, with an alpha of 4.23 bps (t-stat = 3.63).

While an alpha of only a few basis points per day may appear modest, it is both economically meaningful and statistically significant for government bond funds, whose average daily return is 1.77 bps and whose daily return volatility is 29.5 bps. The estimated FOMC-day alpha is 2.4 times the average daily return and 14% of daily return volatility. Assuming eight FOMC meetings per year, this estimate implies an annual cumulative alpha of approximately 34 bps. For the average government bond fund in our sample, with net assets of $959 million, this corresponds to roughly $3.3 million in annual value added, or about $0.8 billion per year in aggregate across all government bond funds. This magnitude is economically significant, as it is sufficient to increase the average government bond fund's percentile ranking by approximately 13%. In contrast, we fail to identify any substantial FOMC-day outperformance for passively managed index funds ("Passive Index"). Their average alpha on FOMC days is 0.54 bps (t-stat = 0.92), which is neither statistically nor economically significant. Moreover, across all trading days, average alphas are considerably smaller: 0.48 bps for the full sample and 0.56 bps for the most active funds.

The outperformance observed on FOMC days is not contingent upon the specific factor model used and remains robust under net-of-fee returns. When estimating funds' four-factor adjusted alpha using net-fee returns, computed as raw returns net of all management expenses and fees, the most active government bond funds show a value-weighted net-of-fee alpha of 3.97 bps (t-stat = 3.41) on FOMC days, but only 0.3 bps (t-stat = 1.27) on all days (Appendix Table IA2). This indicates that the FOMC-day outperformance is not eroded by fund expenses and is not driven by high-fee funds. Furthermore, the FOMC-day outperformance remains robust when assessing fund performance relative to their prospectus benchmark index. As shown in Appendix Table IA2, the benchmark-adjusted excess return on FOMC days is 3.47

[20] Active funds are the top quintile group of funds sorted based on last-quarter factor-adjusted idiosyncratic volatility. Section 2.3 discusses the cross-sectional relationship between various proxies of fund activeness and FOMC-day performance.

bps (t-stat = 2.95) for the most active group. We further discuss in detail the robustness of FOMC-day performance under alternative factor models in Appendix Table IA3.

In line with the hypothesis that the FOMC-day alpha is closely linked to fund managers' skill in anticipating and trading on the release of monetary policy news, we find that the outperformance is exclusively concentrated on the day of the FOMC announcement (t=0), and becomes insignificant for the -1, and +1 trading days around the announcement. The upper graph of Figure 2 plots the four-factor-adjusted excess returns, as well as the benchmark-adjusted returns, for the most active government bond funds over a [-10, +10] day event window around FOMC announcements. The results show a pronounced and statistically significant daily alpha on the FOMC day ($t = 0$), which declines sharply as we move away from the FOMC day.

The lower panel of Figure 2 plots the time series of quarterly FOMC-day four-factor adjusted excess returns for the most active government bond funds, alongside two proxies for monetary policy uncertainty: the standard deviation of daily changes in 2-year Treasury yields and the macro-attention index from Fisher, Martineau, and Sheng (2022). The figure reveals a strong comovement between monetary policy uncertainty and the magnitude of FOMC-day alpha. Notably, alpha tends to peak during periods of significant monetary policy changes, such as 2006–2009 and the Fed tapering and rate lift-off around 2015–2016. These periods of elevated alpha are also characterized by higher fund turnover, as shown in Figure 1, indicating that active trading on monetary policy news is a key driver of FOMC-day outperformance.

For corporate bond funds, which derive returns from both interest rate exposure and the credit risk of underlying bonds, we observe a much weaker FOMC-day alpha of 0.79 bps (t-stat = 0.90) for "All" funds, and 2.12 bps (t-stat = 1.97) for the "Most Active" portfolio.[21] For equity funds, the FOMC-day alpha is 1.22 bps (t-stat = 1.65) for the full sample, and is

[21]The FOMC-day alpha for passive corporate bond funds is weakly positive and should be interpreted with caution. On the one hand, it may be driven by volatility, as corporate debt is affected by the option-like properties of firms' equity (Campbell and Taksler (2003)). On the other hand, the statistical significance of passive corporate bond fund alpha is weak, especially under alternative factor models that incorporate an MBS factor.

statistically insignificant for the most active group. These findings suggest that equity mutual funds are less able than bond funds to capitalize on monetary policy news. This cross-fund variation in macro-day performance is economically intuitive, reflecting the transition from macro-sensitive bond funds, which invest primarily in interest rate securities, to equity funds, which are more closely tied to firm-level fundamentals. An interesting observation is that these results differ from the contrast between bond and equity premium documented around FOMC announcements in the literature (e.g., Savor and Wilson (2013, 2014); Lucca and Moench (2015)), where the announcement premium in the equity market is much stronger than that in the bond market. One possible explanation is that equity funds are less capable of trading on macro news and therefore require a higher announcement premium, whereas the opposite is true for bond funds.

2.2 Placebo FOMC Announcements

To verify the unique impact of FOMC announcements on fund performance, we conduct two placebo tests. First, following Hillenbrand (2025), we simulate 10,000 placebo FOMC paths by randomly selecting, within each month, the same number of days as actual FOMC meetings. For each simulated path, we compute the alpha for the actively managed government bond funds, and plot the distribution of these placebo alphas. As shown in the upper panel of Figure 3, both the factor-adjusted (upper left panel) and benchmark-adjusted (upper right panel) alpha distributions are centered around zero. Importantly, only 3 out of 10,000 simulated factor-adjusted excess returns exceed the observed 4.23 bps, and only 2 out of 10,000 simulated benchmark-adjusted returns exceed the observed 3.47 bps. This indicates that the actual FOMC-day outperformance is statistically significant and unlikely to occur by chance.

Second, Treasury returns in general are much more volatile on FOMC days than non-macro days.[22] To ensure our findings are not merely a result of differing return distributions between macro and non-macro days, we conduct a validation test using placebo FOMC events derived

[22]The Bloomberg Treasury Index has a daily return standard deviation of 27.4 bps on non-macro days and 32.4 bps on FOMC days (Appendix Table IA1). Days that fall outside the [-1, +1] window of the five macro announcements are classified as non-macro days.

from non-macro days. Specifically, we pair each FOMC day with a non-macro day that has the closest bond and stock factor returns, but without any macro announcements. The lower panel of Figure 3 compares the distribution of fund factor-adjusted and benchmark-adjusted alphas on actual FOMC days versus the placebo FOMC days. The alpha distribution on FOMC days is generally more positive, with a higher mean and greater skew towards positive values, compared to placebo days. The absence of significant alpha on placebo days, despite using the same factor model, alleviates concerns that our results are due to any misspecification in the four-factor model.

2.3 Fund Activeness and Performance Persistence

To better understand the drivers of funds' FOMC-day performance, in this subsection, we further explore the cross-sectional determinants of funds' macro-investing abilities by analyzing the relationship between fund activeness and FOMC-day performance. We use several proxies to capture fund activeness. *Turnover* is the decile rank of a fund's turnover ratio, measured at the end of quarter $t-1$. As demonstrated in Section 1.2, aggregate fund turnover is highly responsive to changes in monetary policy uncertainty. Thus, we anticipate that, in the cross-section, funds with higher turnover will also demonstrate greater macro-investing activeness.

Additionally, as suggested by Amihud and Goyenko (2013), the extent to which a factor model can explain fund returns serves as an indicator of fund passiveness. Therefore, we simultaneously estimate *Idio* σ, *Sys* σ, and R^2 based on the four-factor model from Equation (1), using daily observations from quarter $t-1$. Specifically, *Sys* σ is defined as the standard deviation of the model's fitted values, *Idio* σ as the standard deviation of the residuals, and $1-R^2$ as one minus the regression's R-squared. Higher values of *Idio* σ and $1-R^2$ indicate greater fund activeness that cannot be explained by the factor model. We then assess the determinants of FOMC-day performance conditional on fund activeness using Fama-MacBeth regressions in Table 3, controlling for a range of fund characteristics including *Log(Size)*, *Log(Age)*, *Fee*, *Flow*, and the average return over the past 12 months (*Momentum*), all observed at the end of quarter $t-1$. For ease of interpretation, all independent variables are standardized to have a mean of zero and a standard deviation of one.

We observe a robust positive relationship between proxies for activeness and fund performance on FOMC announcement days for government bond funds. A one standard deviation increase in fund *Turnover*, observed at the end of quarter $t-1$, predicts a 0.19 bps (t-stat = 2.02) increase in quarter-t FOMC-day alpha. Similarly, a one standard deviation increase in *Idio* σ and $1-R^2$ predicts increases of 1.05 bps (t-stat = 3.48) and 0.33 bps (t-stat = 2.46) in FOMC-day alpha, respectively. Notably, the coefficient related to systematic volatility is negative and statistically insignificant, indicating that macro-day outperformance is not driven by passive risk-taking. Instead, it is through dynamic portfolio risk adjustments, reflected in idiosyncratic or discretionary risk-taking, that fund managers can achieve enhanced performance on FOMC announcement days.

Extending the cross-sectional analysis to other fund styles in Appendix Table IA4, we observe similar patterns. Both idiosyncratic volatility and $1-R^2$ effectively capture fund activeness and can predict the cross-sectional variation in funds' macro-day performance. For example, a one standard deviation increase in *Idio* σ predicts 0.65 bps (t-stat=2.32) and 2.91 bps (t-stat=2.90) increases in the FOMC-day performance for corporate bond and equity funds, respectively. Consistent with existing literature (e.g., Pástor et al. (2017), Kacperczyk et al. (2005)), turnover is generally a weaker predictor of fund performance on macro days across different fund types, although the sign remains consistent.

If the FOMC-day performance of funds is indeed attributed to their proficiency and activeness in macro investing, it is anticipated that this macro-investing skill would carry forward over time. In other words, funds that have previously demonstrated positive FOMC-day alpha should continue to exhibit positive FOMC-day alpha in the future. Column (4) further reports the time-series persistence of FOMC-day performance. By regressing funds' FOMC-day alpha against their past FOMC-day performance, $\alpha^{\text{Past-FOMC}}$, estimated over the past rolling 24 months, we observe strong predictability of future FOMC-day alpha based on their past FOMC-day performance. A one standard deviation increase in past FOMC-day alpha is associated with a 0.61 bps (t-stat=2.95) increase in future FOMC-day alpha. Hence, in contrast to the existing literature which often finds little outperformance and performance persistence for mutual funds, we document a distinct two-day effect: Not only do funds outperform the market on FOMC announcement days, but their past FOMC-day alpha also serves as a positive and statistically significant predictor of their forthcoming FOMC-day alpha.

Regarding control variables, we find that most fund characteristics have very limited predictive power for macro-day performance, with the exception of the past 12-month return. A one standard deviation increase in $Momentum$ results in an increase of approximately 0.5 bps in FOMC-day performance. This finding also supports the evidence of performance persistence. Further analysis in Appendix Section 3 shows that independent funds and those targeting institutional investors tend to outperform more on FOMC days. Among the various proxies, as presented in Column (5), idiosyncratic volatility stands out as the most robust predictor of FOMC-day alpha, both in terms of economic magnitude and statistical significance. Consequently, in subsequent analyses concerning monetary policy information, we focus on idiosyncratic volatility as our primary measure of fund activeness.

2.4 Interconnected Skill within Fund Family

In Section 2.1, we document the outperformance on FOMC days, which is most pronounced among government bond funds but also evident in corporate bond and equity funds. This raises the question of how FOMC-day performance is interconnected among various fund styles within the same fund family. For instance, if a PIMCO government bond fund outperforms on an FOMC day, could this imply potential outperformance for a PIMCO corporate bond fund as well? Cici et al. (2017) and Auh and Bai (2020) indicate that fund families often provide research support and encourage the sharing of insights and information among their fund managers. If FOMC-day performance is driven by a common skill shared within the family (Brown and Wu (2016)), we might expect this macro-investing expertise to be transferable across different fund styles managed by the same family.[23]

[23] If macro-investing ability is unique to individual managers, or if competition rather than collaboration prevails within fund families (Evans et al. (2020)), we might not observe such a relationship.

Table 4 presents Fama-MacBeth regression estimates that examine the relationship between the FOMC-day performance of government bond funds and other funds within the same family. The dependent variable, $Govt\ \alpha_t^{i \in A}$, represents the FOMC-day alpha of government bond fund i in quarter t, with fund i belonging to family A. Independent variables include the FOMC-day alphas of other government bond funds (excluding the focal fund i), as well as corporate bond funds and equity funds within the same fund family A.

Columns (1) to (3) reveal a significant positive relation between the FOMC-day performance of fund i and that of other funds in the same family. A one standard deviation increase in the FOMC-day alpha of family-level government bond funds, excluding the focal fund i, is associated with an increase of 3.69 bps (t-stat=13.29) in fund i's FOMC-day alpha. Similarly, a one standard deviation increase in the FOMC-day alpha of same-family corporate bond funds corresponds to an increase of 3.68 bps (t-stat=12.36) in the focal government fund i's FOMC-day alpha. This suggests that FOMC-day performance is interconnected not only among government bond funds within the same family but also extends across styles to corporate bond funds. We find no significant relationship between the FOMC-day alpha of government bond funds and that of equity funds within the same fund family, indicating a larger barrier in information transmission across major asset classes.

This within-family and cross-style transferability of macro-investing skills is unlikely to be merely mechanical. When we replace the independent variables with the past 24 months' macro-day performance of other funds in the family, as shown in columns (4) to (6), the positive relationship persists, albeit with a weaker magnitude. This suggests that the macro-investing capabilities of other funds in the same family can predict a fund's FOMC-day performance. This interconnected macro-investing ability likely arises from institutional characteristics that enable macro trading and facilitate the flow of information within the fund family.

2.5 Portfolio Holdings and Dynamic Adjustments

To shed light on how and through which instruments funds achieve superior macro-day performance, we examine the holdings of government bond funds as an illustration. We obtain detailed holdings data of government bond mutual funds from Morningstar Direct. Table 5 presents the portfolio holding characteristics for quintile groups of funds sorted based on their past 24-month FOMC-day performance ($\alpha^{\text{Past-FOMC}}$). Columns (1) to (3) report the average portfolio weights of bonds, cash, and other assets held by funds in each group, while columns (4) to (8) report the fraction of funds with interest rate derivative usage.

We find that funds with better FOMC-day performance tend to take on slightly higher leverage, hold smaller cash reserves, maintain larger bond holdings, and exhibit a greater presence of other derivative assets. Specifically, funds in the highest $\alpha^{\text{Past-FOMC}}$ quintile hold 2% more bonds (t-stat = 4.40) and 4% less cash (t-stat = 4.51) compared to those in the lowest quintile. Among various interest rate derivatives, over 30% of the best-performing funds use Treasury futures, compared to around 20% for the worst-performing group. The usage of Eurodollar futures, Fed funds futures, interest rate swaps, and currency derivatives is also significantly higher for the best-performing group, with extra usage rates ranging from 4% to 13%. This suggests that fund managers not only take larger positions in bonds but also actively use derivatives to manage portfolio risk exposure, consistent with the findings of Choi et al. (2026).[24]

In addition to using a more diverse set of instruments, we find that funds also actively adjust portfolio maturity and duration to achieve the macro-day performance. To capture the time-series variation in portfolio maturity, we compute the value-weighted Treasury maturity for each fund on a quarterly basis. The standard deviation (STD) of maturity is calculated for each fund each quarter, representing the time-series volatility of maturity over the past 24 months. A higher STD indicates a higher frequency of adjustments, suggesting that the fund is more actively managing its bond maturity profile to respond to changing market

[24] As the information on notional amount and long and short positions of derivatives is reported with very low quality, following Deli and Varma (2002) and Chen (2011), we focus on the proportion of funds that invest in derivative assets.

conditions.

To better capture the full portfolio duration exposure—particularly in light of the substantial use of derivatives by these funds (Choi et al. (2026); Barth et al. (2024))—we utilize a return-based approach. This approach enables us to efficiently and timely measure the combined impact of all fund holdings, including cash, bonds, and derivatives. Specifically, for each fund, duration is estimated quarterly by the sensitivity of fund returns ($Ret_{i,t}$) to yield curve changes (Δy_t). Here, Δy_t is defined as the average yield change across 2-, 5-, 10-, 15-, and 20-year Treasury yields. The regression specification is as follows:

$$Ret_{i,t} = a_i + b_i \times \Delta y_t + \varepsilon_{i,t}. \tag{2}$$

The negative value of the coefficient b_i captures the fund's return (percentage price change) with respect to a 1% change in yield. This is precisely the definition of modified duration, which measures the sensitivity of a bond's price to changes in interest rates. Given that government bond fund returns are less prone to the issue of stale pricing, this regression framework provides a method to infer portfolio duration in a timely manner, even without access to high-frequency holdings data. Similar to maturity, the time-series standard deviation of fund duration is calculated to capture the active duration adjustment behavior of funds, with a higher standard deviation indicating more active adjustments.

From columns (9) to (12), we observe that government bond funds hold Treasuries with an average maturity of around eight years, consistent with the findings of Huang and Wang (2014), and their portfolio duration averages around four years. The best-performing funds have higher duration and higher maturity, and significantly higher standard deviations of duration and maturity compared to the worst-performing funds. For instance, the average value of duration and the time-series volatility of duration are one year (t-stat=4.31) and 0.2 years (t-stat=5.47) larger for the top-performing funds relative to the bottom-performing funds. Collectively, these findings suggest that government bond mutual funds actively manage their duration exposure by adjusting bond maturities and utilizing a diverse range of interest rate derivatives. This active management is likely the key contributor to the gains realized on FOMC announcement days.

3 Information on Monetary Policy Change

In this section, we explore whether the ex-ante duration adjustments made by actively managed government bond funds contain predictive information about upcoming FOMC policy decisions. We focus on government bond funds because previous results indicate that they are the most active group capable of successfully trading on monetary policy. Additionally, their liquid return profiles enable us to detect high-frequency duration changes leading up to the announcements.

3.1 Fund Duration Change

To infer fund managers' expectations regarding the FOMC outcome, we examine the changes in their portfolio duration just before the FOMC announcement. We anticipate that managers will increase their duration exposure in anticipation of a rate cut and decrease it in anticipation of a rate hike. We use Equation (2) from Section 2.5 to measure funds' duration exposure. To capture the adjustments made immediately prior to the FOMC announcement, we construct $\Delta Duration^i_{t-1}$ as the difference between the duration estimated in the window [-14, -1] before the announcement and the duration estimated in the window [-28, -15] before the announcement:

$$\Delta Duration^i_{t-1} = Duration^i_{[t-14,\,t-1]} - Duration^i_{[t-28,\,t-15]}, \tag{3}$$

where $t = 0$ is the FOMC announcement day. We estimate duration using a 14-day window because the Beige Book, which provides the Federal Reserve's information on economic conditions, is typically released around two weeks before each FOMC meeting. Consequently, this half-month period leading up to the FOMC announcement is a critical window for institutions to adjust their positions in anticipation of monetary policy decisions.[25]

Since duration is estimated using daily fund returns rather than being directly constructed

[25] To prevent the duration measure from being influenced by pre-FOMC announcement drift, in Appendix Table IA5, we estimate duration by skipping the one day immediately before the announcement. The results remain robust.

from portfolio holdings, we first verify that $\Delta Duration^i_{t-1}$ effectively captures managers' actual duration adjustment behavior. We do this by linking the estimated duration change to the funds' performance on FOMC announcement days. If our $\Delta Duration^i_{t-1}$ accurately reflects the manager's portfolio adjustments, and given that actively managed funds tend to outperform on FOMC days, we expect $\Delta Duration^i_{t-1}$ to be greater than zero when rates decrease and less than zero when rates increase.

In Panel A of Table 6, we report the average $\Delta Duration_{t-1}$ for quintile groups of funds sorted based on their last-quarter activeness. We categorize all FOMC events into two groups: those with a yield increase ($\Delta y^{\text{FOMC}}_t > 0$) and those with a yield decrease ($\Delta y^{\text{FOMC}}_t < 0$) on announcement days. We then report the value-weighted duration change for quintile groups of funds sorted by their level of activeness. Focusing on the most actively managed government bond funds, we observe a significant decrease in duration ($\Delta Duration_{t-1} = -0.33$) before FOMC-day yield increases, and an increase in duration ($\Delta Duration_{t-1} = 0.19$) before yield decreases. The difference between these two is -0.53, with a t-statistic of 3.03. In contrast, for passively managed (inactive) funds, we do not observe such active duration adjustments before the announcement. The difference in $\Delta Duration_{t-1}$ before positive and negative monetary policy shocks is an insignificant 0.01, with a t-statistic of 0.22. This suggests that more active funds are better at anticipating and adjusting duration exposure to expected FOMC outcomes than their passive counterparts, and our $\Delta Duration_{t-1}$ measure successfully captures it.

Furthermore, the upper graph of Figure 4 reports funds' FOMC-day alpha, conditional on whether the funds' pre-announcement $\Delta Duration^i_{t-1}$ aligns with the announcement monetary policy shock. We classify funds into three distinct categories based on their varying levels of activeness and the alignment of $\Delta Duration^i_{t-1}$ with the announcement-day yield change Δy^{FOMC}_t. Notably, active funds that make accurate predictions—where $-\Delta Duration^i_{t-1}$ and Δy^{FOMC}_t share the same sign—can generate a substantial FOMC-day alpha of 3.17 bps (t-stat=3.20). In contrast, active funds with opposing positions show performance akin to inactive funds, resulting in an FOMC-day alpha of about 1.25 bps (t-stat=1.17). As a back-of-envelope calculation, we estimate the duration-implied FOMC-day alpha for actively managed bond funds by multiplying each fund's duration change by the average yield change on FOMC days ($\hat{\alpha} = \Delta Duration_{t-1}^{i} \times \Delta y_t^{\text{FOMC}}$). We find that the alpha predicted by duration adjustment can explain around 68% of the magnitude of the actual alpha. Taken together, these pieces of evidence suggest that $\Delta Duration_{t-1}$, despite being computed based on daily returns, is quite effective in capturing managers' pre-announcement portfolio adjustment behaviors.

3.2 Predicting Monetary Policy Change

After confirming the reliability of $\Delta Duration_{t-1}$, we next examine the ability of changes in duration to forecast yield curve movement (or monetary policy shock) on FOMC announcement days using the following regression model:

$$\Delta y_t^k (\text{or } MPS_t) = a + b \times \Delta Duration_{t-1} + \varepsilon_t, \tag{4}$$

where Δy_t^k is the change in k-year Treasury yield on announcement day t, with k ranging from 2 years to 20 years. We also include the monetary policy shock measure, MPS from Nakamura and Steinsson (2018), and the $Target$ and $Path$ factors from Gürkaynak, Sack, and Swanson (2005), as dependent variables.[26] Using high-frequency data, Nakamura and Steinsson (2018) show that unexpected changes in interest rates in a 30-minute window surrounding FOMC announcements more effectively capture news pertaining to monetary policy. In a similar vein, Gürkaynak, Sack, and Swanson (2005) show that unanticipated changes in the federal funds rate (target factor) capture only a small fraction of the monetary policy news, while large variations in long-term yield are captured by the path factor associated with FOMC statements. The independent variable is $\Delta Duration_{t-1}$, calculated as the value-weighted average of duration changes within the respective quintile group, scaled by the standard deviation of duration changes. The coefficient estimates of b along with the regressions' R^2

[26] The MPS measure is derived from the principal component of unanticipated changes over 30-minute windows in five interest rates: the federal funds rate immediately following the FOMC meeting, the anticipated federal funds rate following the subsequent FOMC meeting, and projected 3-month eurodollar interest rates at horizons of two, three, and four quarters. We thank Miguel Acosta for providing the data.

are reported in Panel B of Table 6.

Focusing on the most active quintile, we find that changes in the duration of macro-active funds significantly and negatively predict yield curve movements on announcement days. The estimated effect is sizable relative to the typical variation in short rates around FOMC announcements. A one-standard-deviation increase in $\Delta Duration_{t-1}$ predicts a 2.41 bps decline in the 2-year yield on the day of the announcement (t-stat = 3.85), which represents 54% of the average absolute change in the 2-year yield on announcement days. The explanatory power of 8.2% is also notable because announcement-day yield changes are high-frequency asset-price responses to new macroeconomic information and are therefore inherently difficult to forecast. For instance, Bauer and Swanson (2023b) examine a range of monetary policy predictors with explanatory power between 2% and 9%, while Czech et al. (2021) show that mutual fund order flow predicts monthly yield changes with an R^2 of 1.9%.[27] Against this benchmark, the predictive content of fund duration changes is not only statistically significant but also economically important.

The lower graph of Figure 4 presents a graphical illustration of the relation, where we observe a clear negative relation between the change in the 2-year yield on the day of the announcement and the fund duration change, and this effect is not influenced by significant outliers. The opacity of the dots corresponds to the magnitude of FOMC-day alpha for the funds. Notably, the darker green dots are positioned at both the upper left and lower right ends of the graph, signifying occasions when fund managers accurately predicted the correct direction. In contrast, for inactive funds, which fail to outperform on FOMC days, their changes in duration lack the ability to predict variations in the yield on announcement days. This contrast also suggests that the predictability of $\Delta Duration_{t-1}$ is unlikely to be mechanically driven by the yield change itself.

Moreover, consistent with the expectation that monetary policy primarily affects the shorter end of the yield curve, the predictive power of duration change is strongest at the

[27] Short-horizon yield changes and returns are well known to be more difficult to predict than their longer-horizon counterparts (e.g., Fama and French (1988), Campbell et al. (1998), Gargano et al. (2019)).

2-year horizon (Hanson and Stein (2015)). This predictive ability gradually diminishes to -1.88 bps with an R^2 of 3.7% at the 10-year horizon, and -1.07 bps with an R^2 of 1.5% at the 20-year horizon.[28] When replacing the announcement-day yield change with the high-frequency monetary policy news measures, our findings remain consistent. A one standard deviation increase in $\Delta Duration_{t-1}$ predicts a 27.4% (t-stat=2.59) standard deviation reduction in MPS, a 19.1% (t-stat=1.62) standard deviation reduction in the $Target$ factor, and a 20% (t-stat=2.03) standard deviation reduction in the $Path$ factor.

3.3 Controlling for Other MPS Predictors

By examining the changes in fund managers' duration using publicly available fund return data, we show that active government bond fund managers either possess insightful information or have the ability to anticipate monetary policy decisions that might surprise the broader market. Bauer and Swanson (2023b) and Bauer and Swanson (2023a) show that the Fed's monetary policy decisions are influenced by the arrival of public news, with monetary policy surprises being correlated with macroeconomic and financial data available before the FOMC announcement. This raises the question: are fund managers' duration adjustments also responding to the same public information? Moreover, can these duration adjustments enhance forecasting accuracy when integrated with economists' forecasts and signals from the equity, commodity, and Treasury markets?

Table 7 addresses these questions by comparing the predictive content of fund duration changes with a broad set of alternative predictors of FOMC-day yield curve movements. Specifically, we consider five classes of predictors: survey-based expectations, macroeconomic indicators, asset-price-based variables, yield-based predictors, and communication-based measures of monetary policy. To facilitate comparisons across specifications, all predictors are standardized. As a result, the estimated coefficients can be interpreted as the effect of a one-standard-deviation increase in each predictor, allowing a direct assessment of their

[28]In untabulated results, we also investigate the ability of manager duration change to predict yield curve movements within a [-2, +2] trading-day window surrounding the announcement. The results reveal that $\Delta Duration_{t-1}$ solely predicts yield changes on the FOMC announcement day (t=0), rather than the yield changes on t =-2, -1, 1, 2 around the announcement.

relative economic importance.

We begin with survey-based forecasts from Bloomberg and Blue Chip. *Bloomberg* is defined as the Bloomberg economists' forecast of the Fed funds rate relative to its latest value, and *BlueChip* as the change from the previous month in the Blue Chip forecast for the upcoming FOMC quarter. Both variables positively predict the monetary policy shock (MPS) and the FOMC-day change in the 2-year yield, although the estimates are only weakly significant. In contrast, the coefficient on $\Delta Duration_{t-1}$ remains statistically significant and economically similar to that in Table 6. This is not surprising, since economists' forecasts mainly capture anticipated rate moves that are likely already incorporated into prices before the announcement.

Next, to control for aggregate macroeconomic conditions, we include *Employment*, defined as the percentage change in nonfarm payroll employment over the previous year, following Cieslak (2018). The sign is economically intuitive: stronger employment growth predicts larger announcement-day increases in Treasury yields, consistent with the notion that an overheated economy raises the likelihood of policy tightening. Yet controlling for this macroeconomic indicator leaves the predictive content of fund duration essentially unchanged. In particular, the coefficient on $\Delta Duration_{t-1}$ remains -2.41 bps with a t-stat of 3.86, indicating that fund managers' timing ability is not simply a response to well-known employment news.

We then consider asset return predictors. Following Bauer and Swanson (2023b), we include past three-month returns on the equity and commodity markets. Both variables positively predict announcement-day increases in yields, but their economic and statistical significance is smaller than that of duration changes. A one-standard-deviation increase in $S\&P500_{\text{3M}}$ and $Commodity_{\text{3M}}$ predicts increases of 0.80 bps (t-stat = 1.46) and 0.90 bps (t-stat = 2.11), respectively, in the 2-year yield. By comparison, after controlling for these asset market signals, a one-standard-deviation increase in $\Delta Duration_{t-1}$ predicts roughly a 2.3 bps decrease in the 2-year yield.

We next assess whether fund duration changes simply proxy for information already embedded in the yield curve and related fixed-income instruments. Following Swanson (2024), we control for three-month changes in the Baa–Treasury spread, the 2-year Treasury yield, and the slope of the yield curve. We also include the Cochrane and Piazzesi (2005) γ factor, the forward-spot spread from Fama and Bliss (1987), as well as the Fed funds futures rate and the 2-year inflation swap rate. Several of these variables—the Baa–Treasury spread, the yield curve slope, Fed funds futures, and inflation swap rates—significantly predict the monetary policy shock, but not the FOMC-day yield change. Even so, $\Delta Duration_{t-1}$ remains economically and statistically significant in both specifications. For example, a one-standard-deviation increase in the 2-year inflation swap rate predicts a 0.13 increase in MPS (t-stat = 1.73), whereas, in the same regression, fund duration change predicts a 0.24 decrease (t-stat = 2.41), close to the baseline estimate of a 0.27 decrease (t-stat = 2.59).

Finally, we consider central bank communication-based measures of monetary policy. Following Neuhierl and Weber (2019), we construct *Speech Sentiment*, which captures whether speeches by FOMC members between two meetings contain relatively more dovish than hawkish language. We also include *Text Sentiment* and *Conference Tone* from Gorodnichenko et al. (2023), which measure, respectively, the sentiment in FOMC statements, remarks, and Q&A sessions, and the vocal tone in Fed Chairs' press conference responses.[29] Although prior work shows that these sentiment measures matter for stock markets, they have limited predictive power for FOMC-day yield changes in our setting. The only exception is textual sentiment in FOMC statements, which predicts the monetary policy shock with a coefficient of -0.15 (t-stat = 2.20). In all specifications, the predictive power of fund duration remains economically and statistically robust.

Overall, fund duration consistently emerges as the most economically powerful predictor across specifications. The evidence suggests that fund managers' portfolio adjustments are not merely passive responses to public information, but instead play a meaningful role in price discovery around monetary policy events. Moreover, because the fund-duration measure can be constructed in real time and front-end Treasury markets are highly liquid with low transaction costs, a strategy that exploits this signal ahead of announcement days could

[29] *Text Sentiment* and *Conference Tone* are available for a smaller sample because FOMC press conferences have been held only since 2011.

generate economically meaningful returns.

3.4 Dynamic Performance and Predictability Over Time

Section 1.2 highlights that the macro-activeness of funds varies significantly over time, likely due to fluctuations in monetary policy uncertainty. In this section, we examine the factors influencing funds' performance on FOMC days and whether these variations also affect the predictive power of duration changes in relation to monetary policy shocks. If funds' outperformance on FOMC days is linked to their macro-investing abilities, we expect them to perform better during periods with greater investment opportunities and pronounced information asymmetry between the funds and the public. Such conditions often arise when macroeconomic announcements have the potential to trigger significant bond market shocks or when there is considerable disagreement regarding the Fed's decisions.

We use the standard deviation of daily changes in the 2-year Treasury yield ($\sigma(\Delta y^{2\text{YR}})$) over the past month to proxy monetary policy uncertainty.[30] To measure attention to FOMC announcements, we use the monetary macro-attention index (MAI) from Fisher, Martineau, and Sheng (2022). Disagreement about monetary policy is measured using Bloomberg and Blue Chip forecasts. *Bloomberg Disagreement* is calculated as the difference between the 75th and 25th percentiles of the latest economist forecasts on the target Fed funds rate. *Blue Chip Disagreement* is measured as the difference between the top 10 and bottom 10 forecasts on the current-quarter Fed funds rate.[31] To measure FOMC announcement surprise, we use the 1-day change in the spot-month Fed funds futures rate (*Surprise*) from Kuttner (2001) on the announcement day. For ease of comparison, all the above variables are standardized to have a mean of zero and a standard deviation of one.

Table 8 shows that government bond funds' FOMC-day outperformance is significantly larger when the announcement is associated with higher attention and disagreement. For the most active quintile of funds, a one standard deviation increase in last month's $\sigma(\Delta y^{2\text{YR}})$

[30]As Figure 1 shows a strong downward trend in turnover, possibly related to the level of interest rates over time, we detrend $\sigma(\Delta y^{2\text{YR}})$ and use its decile rank in the analysis.

[31]The Blue Chip surveys are conducted monthly, usually within the first three business days of each month, to gather economists' views on changes in the quarterly Fed funds rate.

and *MAI* predicts a 2.59 bps (t-stat=2.01) and a 3.64 bps (t-stat=2.99) increase in the funds' four-factor adjusted FOMC-day excess return the next month, respectively. For macro disagreement, the corresponding economic and statistical significance are of similar magnitudes: 2.87 bps (t-stat=2.77) for Bloomberg disagreement and 4.30 bps (t-stat=3.34) for Blue Chip disagreement.

In addition to macro attention and disagreement, we observe stronger FOMC-day performance when the announcement surprise is of greater magnitude.[32] Specifically, a one standard deviation increase in the magnitude of macro surprise (i.e., the absolute value of the surprise) is associated with a 2.18 bps (t-stat=1.72) increase in FOMC-day alpha. Interestingly, and perhaps unsurprisingly, the direction of the macro surprise does not significantly affect FOMC-day performance, which suggests that government bond funds can achieve outperformance with both positive and negative news and are not constrained by the direction of the announcement outcome.

Finally, in the last two columns, we introduce proxies for the risks associated with the FOMC announcement, namely the *VIX* and the *Pre-FOMC Drift*. The *Pre-FOMC Drift* measures the stock market returns from the previous day's close at 4 pm to 5 minutes before the FOMC release. According to Hu, Pan, Wang, and Zhu (2022), the *Pre-FOMC Drift* reflects the accumulation of heightened uncertainty regarding the magnitude of the news' impact on the market. We find that neither of these risk proxies can explain the variation in government bond funds' FOMC-day performance. The coefficient on *VIX* is 0.76 bps (t-stat=0.51), and the coefficient on the *Pre-FOMC Drift* is 2.21 bps (t-stat=1.24).[33] This evidence further supports the notion that the FOMC-day outperformance of government bond mutual funds is uniquely tied to their ability to successfully time the announcement outcome, rather than being driven by market risks or uncertainties.

Given the time-series variation in funds' FOMC-day performance, we further investigate whether the predictive capability of fund duration changes over time in a similar pattern.

[32]One caveat is that these surprise measures are based on the announcement-day yield change and thus are not intended for predictive purposes.

[33]Replacing VIX with Treasury VIX still fails to significantly explain macro-day alpha.

Specifically, we explore whether changes in fund managers' duration carry greater information during periods marked by intensified attention and uncertainty regarding the Fed's decision. To test this hypothesis, Table 9 reports the time-varying forecasting power of fund duration change. We include the last-month standard deviation of 2-year Treasury yield change ($\sigma(\Delta y^{2\mathrm{YR}})$), the monetary macro attention index (MAI), the Blue Chip disagreement (*BC Disp*) from Table 8, and their interactions with duration change in the baseline forecasting model of Equation (4).[34]

Table 9 consistently shows negative coefficient estimates for the interaction terms across various specifications. This indicates that the forecasting power of duration changes is enhanced when the market is more focused on FOMC announcements or when these announcements are accompanied by significant uncertainty. Specifically, a one standard deviation increase in the rank of $\sigma(\Delta y^{2\mathrm{YR}})$ boosts the predictive capacity of duration changes on FOMC-day 2-year yield changes by 1.63 bps (t-stat=2.37). Similarly, a one standard deviation increase in the macro attention index amplifies the predictive magnitude on the MPS (Nakamura and Steinsson (2018)) by 0.29 standard deviations (t-stat=2.68). These findings suggest that fund managers' adjustments in duration offer valuable and dynamic insights, aligning with their time-varying performance on FOMC days.

4 Other Discussions

In this section, we extend our analysis to study fund performance in relation to other macroeconomic announcements, including GDP, Nonfarm Payrolls (NFP), Consumer Price Index (CPI), and ISM releases. Furthermore, we analyze the distribution of capital flows around FOMC announcement days.

4.1 Relation to Other Macro Announcements

In our primary analysis, we examine the macro-investing capabilities of government bond funds, particularly in the context of FOMC announcements. We explore how institutional investors trade on monetary policy news and how their adjustments in portfolio duration

[34]We do not include FOMC-day surprises, VIX, and other measures in Table 8 to avoid look-ahead bias.

can serve as a predictive tool for such news. Beyond FOMC announcements, these macro-investing skills may also enable funds to achieve superior performance during other significant macroeconomic events, such as employment, GDP, and inflation announcements, which are pivotal to monetary policy decisions. If the FOMC-day alpha we have identified indeed reflects genuine macro-investing skill, it is reasonable to expect these capabilities to extend across various macroeconomic announcements.

Table 10 illustrates the relationship between funds' performance on FOMC days and their performance on other macroeconomic announcement days, including Gross Domestic Product (GDP), Nonfarm Payrolls (NFP), the Consumer Price Index (CPI), and the Institute for Supply Management manufacturing index (ISM). We regress funds' factor-adjusted average excess returns on other macro-announcement days in quarter t (α_t^{GDP}, α_t^{NFP}, α_t^{CPI}, α_t^{ISM}) against their contemporaneous FOMC-day alpha (α_t^{FOMC}). We observe a significantly positive relationship across different macro announcements. A one standard deviation increase in FOMC-day alpha is associated with a 0.54 bps increase (t-stat = 1.91) in GDP-day alpha for government bond funds, 0.49 bps (t-stat = 2.02) for corporate bond funds, and 2.99 bps (t-stat = 3.01) for equity funds. Similar results are found for CPI and ISM announcements. Collectively, these findings suggest that a fund's performance on FOMC days correlates with its success on other macroeconomic announcement days, indicating that the FOMC-day alpha captures genuine skill in processing macro-relevant information—a transferable capability that extends across different types of announcements.

Despite this interconnected skill across various announcements, the unconditional evidence of outperformance on other macro announcements is mixed. Appendix Table IA6 reports the unconditional performance of various fund styles on other macroeconomic announcement days, showing varied results. One exception is the GDP announcements, which demonstrate an outperformance of around 4-6 basis points. However, since approximately 25% of GDP announcements occur at the turn of the month, excluding the last and first trading days of a month reveals that this outperformance largely disappears.[35]

[35] FOMC announcements are less influenced by the turn-of-the-month effect because they are scheduled on various calendar days.

4.2 Implications for Overall Fund Performance

To assess whether the macro-investing skill revealed on FOMC announcement days translates into performance over horizons that matter to investors, we examine whether two ex ante indicators—fund activeness and past FOMC-day alpha—predict net-of-fee performance in the subsequent quarter. Panel A of Table IA7 reports Fama-MacBeth regressions in which the dependent variable is a fund's factor-adjusted net-of-fee alpha in quarter t. For government bond funds, a one standard deviation increase in *Idio* σ, measured in quarter $t-1$, predicts a 5.6 bps (t-stat = 2.06) increase in quarter-t fund alpha. Past FOMC-day performance also contains information about subsequent performance: a one standard deviation increase in $\alpha^{\text{Past-FOMC}}$ predicts increases of 2.8 bps (t-stat = 1.83) and 2.2 bps (t-stat = 1.84) in next-quarter alpha for government and corporate bond funds, respectively. These estimates are marginally significant, mainly because fund performance reflect many sources of information apart from macro information. In contrast, neither measure significantly predicts subsequent alpha for equity funds, consistent with previous finding that equity funds are less capable in macro trading.

Panel B presents complementary evidence from dependent portfolio sorts. Within the group of government bond funds with high past FOMC-day alpha, active funds earn an average daily alpha of 0.47 bps, compared with 0.08 bps for inactive funds. The resulting Active-minus-Inactive spread of 0.39 bps per day corresponds to approximately 98 bps per year. For corporate bond funds, the corresponding alpha spread is 0.23 bps per day, or approximately 58 bps per year.[36] Moreover, active-minus-inactive spreads are concentrated among funds that have previously demonstrated superior FOMC-day performance. In the low-$\alpha^{\text{Past-FOMC}}$ groups, by comparison, the active-minus-inactive alpha spreads are only 0.10 bps for government bond funds and zero for corporate bond funds. Though the alpha (return) spreads from portfolio sorts are only marginal significant, they overall provide consistent evidence that macro-investing skill identified around FOMC announcements is informative

[36]Annualized magnitudes are calculated by multiplying average daily basis-point estimates by 252 trading days.

about bond funds' broader future performance.

Figure IA1 illustrates the long-run economic relevance of these findings from an investor's perspective. We compare cumulative net-of-fee excess returns for all funds with those for active funds, defined as funds in the highest *Idio* σ quintile and the high-$\alpha^{\text{Past-FOMC}}$ group. For both government and corporate bond funds, the active group earns substantially higher cumulative returns when performance is measured over all trading days. To assess the contribution of FOMC-related periods, the figure also separately cumulates returns earned during the four-day event window $-1, +2$ surrounding each FOMC announcement. Although these windows comprise only 32 trading days per year, the cumulative event-window return of active government bond funds reaches approximately 61%, a magnitude comparable to the all-day cumulative return of the full sample of government bond funds. Thus, returns earned around FOMC announcements constitute an economically meaningful component of long-run fund performance.

4.3 Capital Flows

To investigate whether investors are aware of fund managers' macro-investing skills and whether FOMC-day performance is influenced by flow-induced trading pressure of Lou (2012), Appendix Table IA8 presents the distribution of capital flows surrounding FOMC announcements. We obtain daily fund flow data from Morningstar Direct and construct dummy variables for the two days before and after each FOMC announcement. To control for potential confounding factors and seasonal effects, we include controls for factor returns, turn-of-month and turn-of-year dummies, the VIX, and the TED rate.

The regression results indicate an absence of abnormal flows around FOMC announcement days. The coefficient estimates for the time dummies are generally insignificant, a pattern that holds not only for the broader sample of actively managed government bond funds but also for the most and least active quintiles. In summary, while government bond funds demonstrate superior macro-investing abilities around FOMC announcements, investors do not appear to adjust their capital allocation behavior in response to these events.

5 Conclusions

In this paper, we examine whether actively managed mutual fund managers possess skill in processing macroeconomic information and whether their management of interest-rate exposure ahead of FOMC announcements contains information about subsequent monetary policy shocks.

We find that government bond funds actively adjust their interest-rate exposure in anticipation of monetary policy changes and earn significant alpha on FOMC announcement days. By contrast, they exhibit no significant outperformance on non-macro days, when opportunities to exploit macroeconomic information are more limited. This concentration of outperformance around information-intensive events is consistent with the time-varying nature of managerial attention and skill documented by Kacperczyk et al. (2016) and Fisher, Martineau, and Sheng (2022). The identified macro-investing skill is persistent, shared across fund styles within the same family, and closely related to measures of fund activeness, including idiosyncratic volatility and turnover. Moreover, we also find suggestive evidence that returns earned around FOMC announcements are relevant to longer-horizon fund performance.

Our evidence further points to managers' ability to forecast the content of macroeconomic announcements as an important source of this informational advantage. Duration adjustments made by macro-active funds immediately before FOMC announcements predict announcement-day changes in the yield curve, even after controlling for established measures of monetary policy expectations and other economic and financial indicators. These portfolio adjustments therefore reveal information about prospective monetary policy changes that is not fully captured by conventional predictors. Caballero and Simsek (2022) argue that market participants may hold heterogeneous views about appropriate interest-rate policy and that the Federal Reserve could benefit from considering these dispersed market assessments. By extracting fund managers' expectations from their portfolio-duration choices, our analysis provides a new source of information for both policymakers and market participants.

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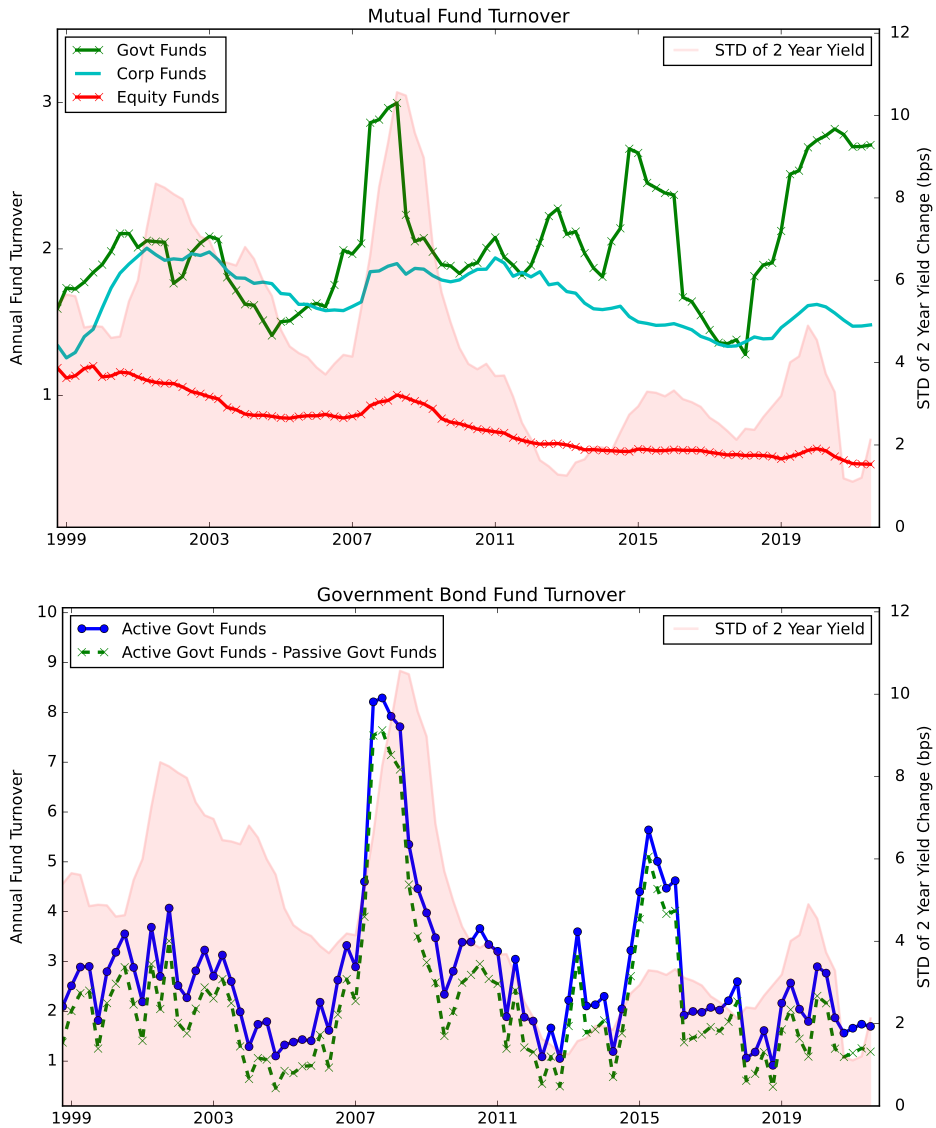
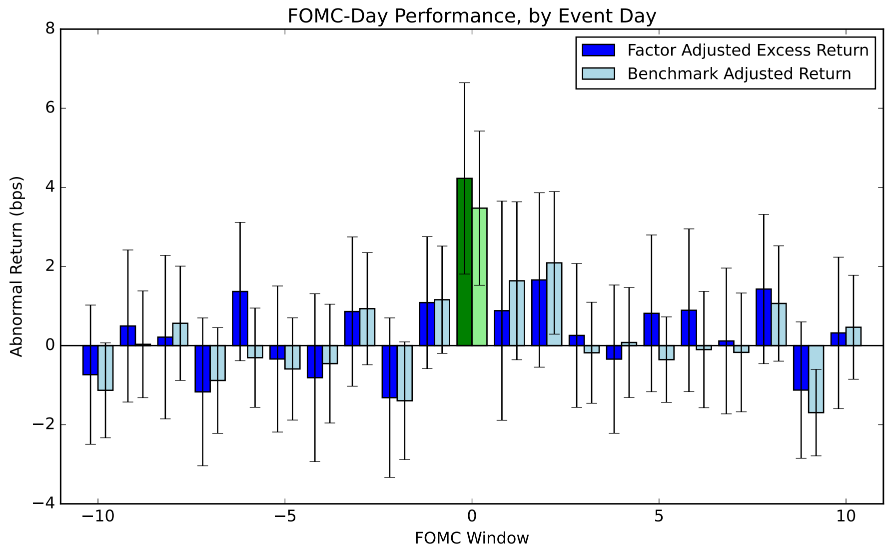
Figure 1

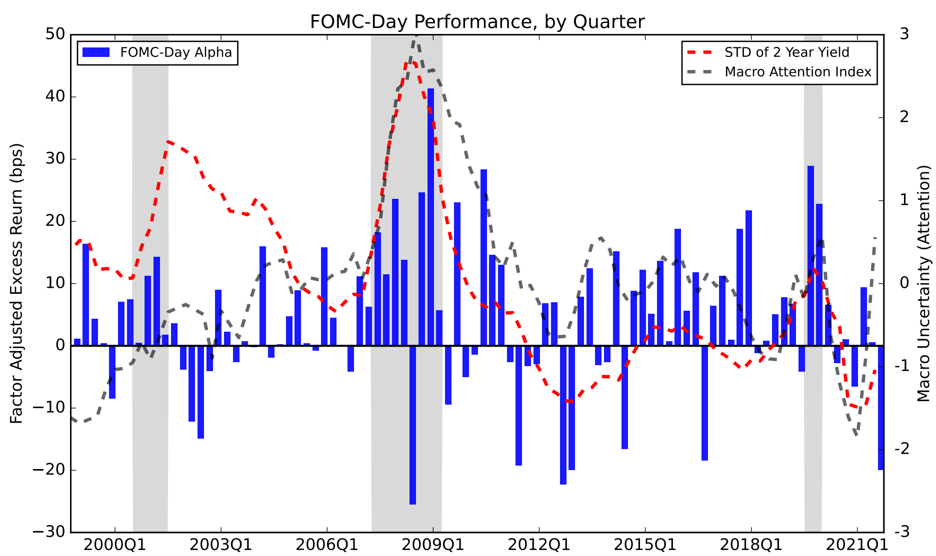
Turnover for Different Styles of Mutual Funds



Notes – The upper graph displays the annual turnover rates for three categories of mutual funds: government bond funds (Govt), investment-grade bond funds (Corp), and equity funds. The turnover rates are calculated as the minimum value between total sales and total purchases, divided by the average total net assets (TNA) over a 12-month period. The lower graph shows (1) the turnover rates for the most active quintile of government bond funds, and (2) the excess turnover of active funds relative to passive funds within the same Morningstar categories. The right axis (pink shaded area) displays the standard deviation of daily changes in the 2-year Treasury yield, estimated using a 12-month rolling window. The grey shaded areas indicate the NBER recession periods. The sample period is from 1998 to 2021.

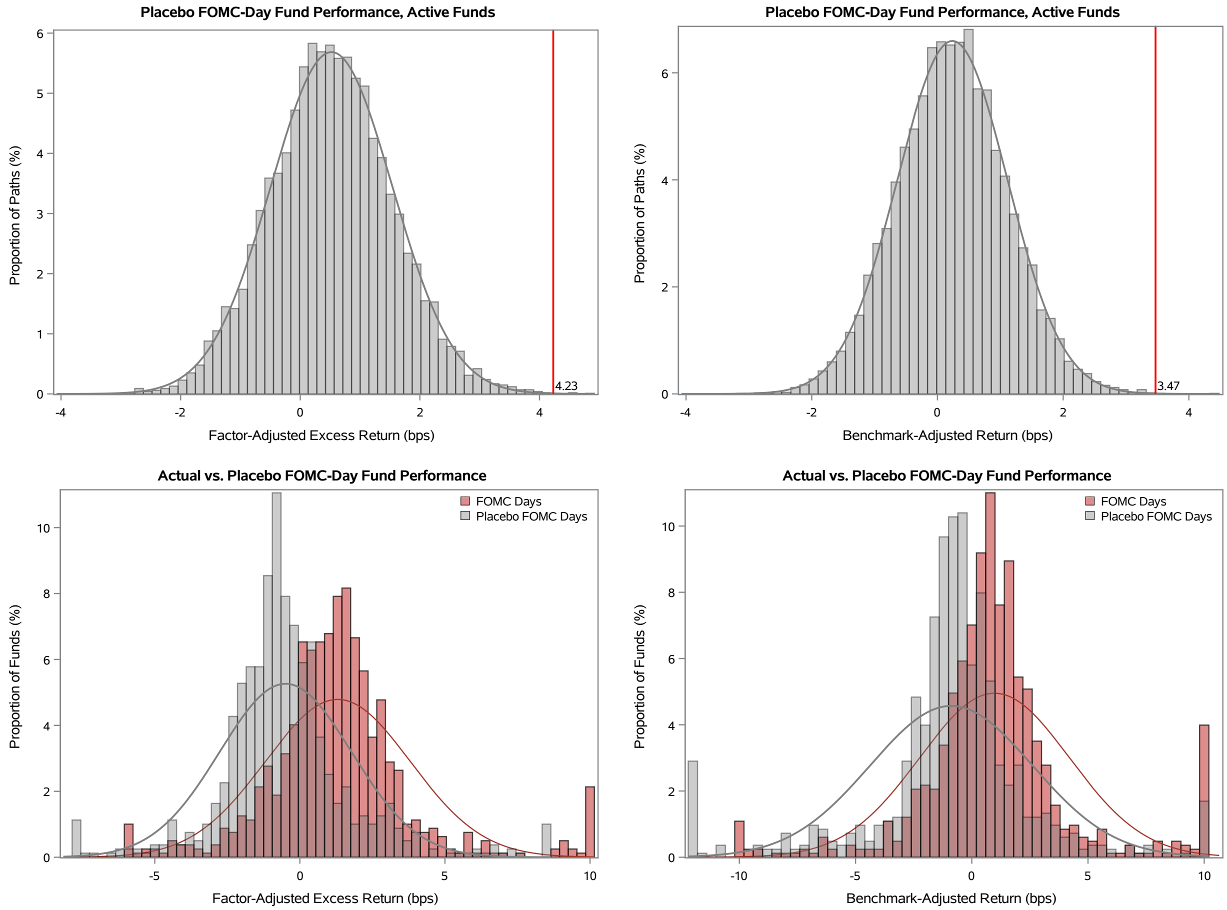
Figure 2
FOMC-Day Fund Performance





Notes – The upper graph illustrates the abnormal returns of actively managed mutual funds for each day within the [-10, 10] window surrounding an FOMC announcement. Day 0 corresponds to the day of the FOMC announcement. For each event day, we plot both the four-factor-adjusted excess returns and the benchmark-adjusted returns for the most actively managed government bond funds. The black line represents the 95% confidence interval. The lower graph presents the four-factor-adjusted FOMC-day excess returns, averaged quarter by quarter, for the period from 1998 to 2021. The red dotted line (right axis) represents the volatility of the 2-year Treasury yield, calculated as the standard deviation of daily changes in the 2-year yield over the past 12 months. The grey dotted line (right axis) represents the 12-month moving average of the monetary macro attention index (MAI) from Fisher, Martineau, and Sheng (2022). Both the standard deviation of the 2-year yield and the MAI are standardized, with means of zero and standard deviations of one.

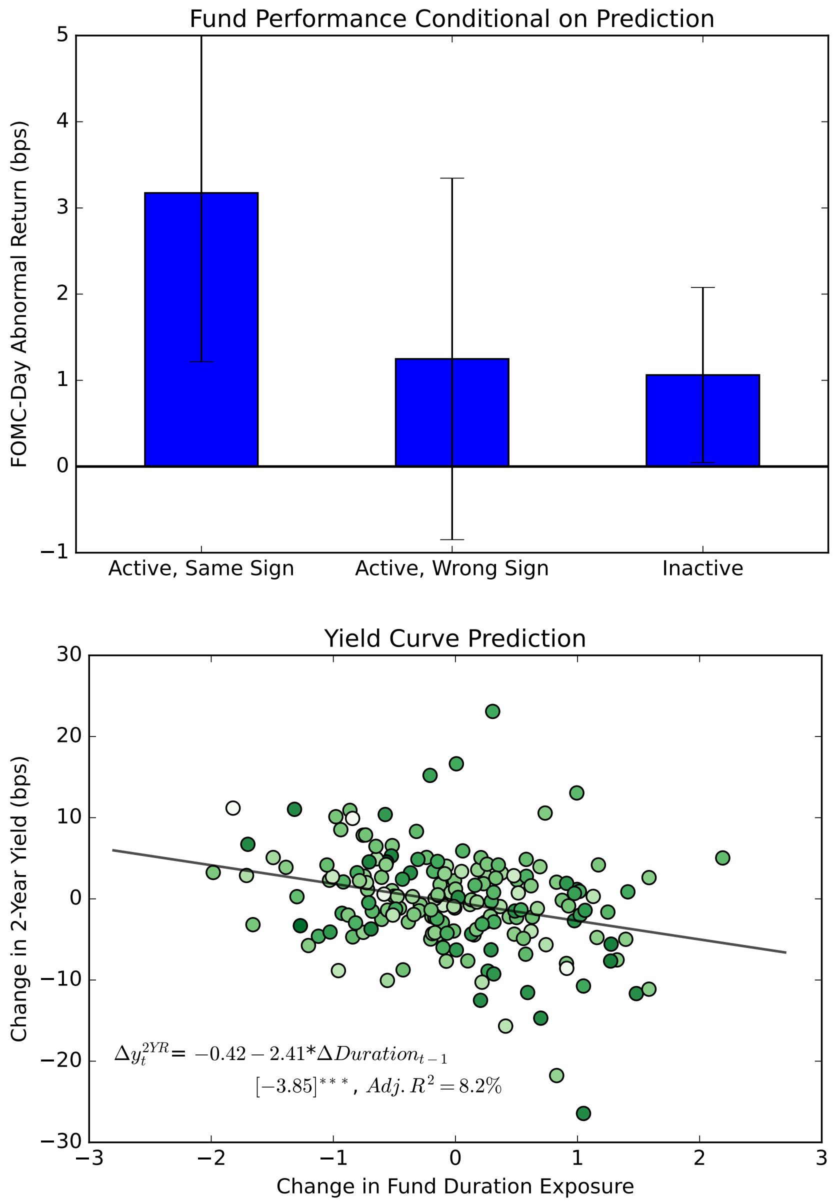
Figure 3
Placebo FOMC Days



Notes – The upper panels display the distribution of the most active funds' factor- (or benchmark-) adjusted returns under the first placebo test. Following Hillenbrand (2025), we simulate 10,000 placebo FOMC paths, where each placebo path is generated by randomly selecting the same number of days within a month as actual FOMC meetings. The actual FOMC-day performance, 4.23 bps (factor-adjusted) and 3.47 bps (benchmark-adjusted), is shown as a reference. The lower panels present the distributions of fund alpha under the second placebo test. Each placebo day is selected by matching an FOMC day to a non-macro day that exhibits the closest four-factor returns. We then plot the distribution of individual fund performance on FOMC days and on placebo FOMC days. The lower left graph plots the four-factor-adjusted daily excess return, and the lower right graph shows the distribution of average benchmark-adjusted returns across funds on FOMC days and on placebo FOMC days, respectively.

Figure 4

Fund Duration Change and Monetary Policy Shocks



Notes – The upper graph presents the distribution of funds' FOMC-day alpha, conditional on changes in their pre-announcement duration. The change in fund duration exposure ($\Delta Duration^i_{t-1}$) is computed as the duration measured within the window [-14, -1] prior to the announcement, relative to the window of [-28, -15] preceding the announcement. Duration is estimated by the sensitivity of fund returns to yield curve changes, using the regression model $Ret_{i,t} = a + b_i \times \Delta y_t + \varepsilon_t$, where the negative value of the coefficient b_i captures the Duration. Funds are considered to have made correct predictions if they increase their duration exposure (i.e., $\Delta Duration^i_{t-1}>0$) when yield decreases ($\Delta y_t^{\text{FOMC}} < 0$) on the announcement day. For instance, the label "Active, Same Sign" refers to funds that are in the top quintile for idiosyncratic volatility in the previous quarter and have successfully anticipated the direction of the Treasury yield change, as inferred from $\Delta Duration^i_{t-1}$. The lower graph illustrates the predictability of changes in pre-announcement duration exposure of actively managed government bond funds in relation to changes in the 2-year Treasury yield on announcement days. The darker the green dots, the more positive the FOMC-day fund alpha.

Table 1
Summary Statistics

	Govt Funds		Corp Funds		Equity Funds	
	Mean	STD	Mean	STD	Mean	STD
Daily Return	1.77	29.54	1.98	25.26	4.15	136.55
FOMC Return	4.51	31.53	4.66	29.02	33.74	134.21
Log(Size)	4.05	1.92	4.31	2.19	5.35	1.98
Log(Age)	4.46	0.95	4.26	1.05	4.63	1.00
Fee	0.97	0.47	0.87	0.42	1.22	0.43
Flow	0.07	6.73	0.53	6.51	0.07	5.40
Turnover	1.96	2.50	1.69	1.70	0.78	0.71
Idio σ	9.13	5.08	8.70	5.02	41.70	27.71
Sys σ	20.39	14.04	19.22	9.88	108.16	63.53
R^2	0.77	0.18	0.79	0.16	0.83	0.17

Notes – This table reports the mean and standard deviation of fund returns and fund characteristics for government bond funds (Govt), investment-grade bond funds (Corp), and equity funds. *Daily Return* is fund daily raw return in bps. *FOMC Return* is fund daily raw return on FOMC announcement days in bps. *Log(Size)* is the natural logarithm of a fund's total net assets in millions of dollars. *Log(Age)* is the natural logarithm of the number of months since a fund's inception. *Fee* is a fund's annual expense ratio in percent. *Flow* is the last-month fund flow in percent, estimated as $\frac{TNA_t - TNA_{t-1}(1+Ret_t)}{TNA_{t-1}}$. *Turnover* is the annualized turnover ratio, computed as the minimum of aggregated purchases or sales, scaled by the 12-month average TNA. Idiosyncratic volatility (*Idio* σ), systematic volatility (*Sys* σ) and R^2 are estimated simultaneously using daily observations in the last quarter under the four (five) factor model. The sample period is from September 1998 to December 2021.

Table 2
Mutual Fund Performance around FOMC Announcement Days

Fund Style	Type	Variable	-1	FOMC	+1	All Days
Govt Funds	All	α	-0.44	1.44	0.90	0.48
		t-stat	(-1.27)	(2.40)	(1.56)	(5.54)
	Most Active	α	1.09	4.23	0.88	0.56
		t-stat	(1.32)	(3.63)	(0.67)	(2.37)
	Passive Index	α	-0.23	0.54	0.69	0.29
		t-stat	(-0.87)	(0.92)	(1.22)	(3.16)
Corp Funds	All	α	-0.69	0.79	0.67	0.42
		t-stat	(-1.34)	(0.90)	(1.12)	(3.87)
	Most Active	α	-0.48	2.12	0.69	0.67
		t-stat	(-0.70)	(1.97)	(0.78)	(4.14)
	Passive Index	α	-0.58	1.39	0.48	0.28
		t-stat	(-1.30)	(1.92)	(0.67)	(2.51)
Equity Funds	All	α	-0.74	1.22	1.90	0.28
		t-stat	(-1.05)	(1.65)	(2.58)	(1.99)
	Most Active	α	-3.72	4.69	4.23	-0.24
		t-stat	(-1.15)	(1.63)	(1.25)	(-0.41)
	Passive Index	α	0.61	-1.01	0.80	-0.00
		t-stat	(0.76)	(-1.66)	(1.10)	(-0.03)

Notes –This table presents the performance of government bond funds (Govt), investment-grade bond funds (Corp), and equity funds around FOMC announcement days. To evaluate fund performance, we apply the four-factor model (Equation (1)) to government bond and equity funds, and the extended five-factor model to corporate bond funds. For each fund, factor-adjusted daily excess returns are estimated quarterly using risk loadings derived from the prior 24-month window. For each event day surrounding the FOMC announcement t (i.e., $t{-}1$, t, and $t{+}1$), as well as for the full sample of days ("All Days"), the table reports the value-weighted average alpha across funds. "Most Active" refers to the most actively managed funds, identified based on their last-quarter idiosyncratic volatility. Passively managed index funds are included for comparison. Alphas are estimated for the value-weighted portfolios directly. The standard errors are adjusted for heteroskedasticity. The t-stats are in parentheses.

Table 3
Fund Activeness and Performance Persistence

	Dep. Var. = FOMC-Day Performance, α_t^{FOMC}				
	(1)	(2)	(3)	(4)	(5)
Turnover	0.193				0.154
	(2.02)				(1.82)
Idio σ		1.051			0.997
		(3.48)			(3.31)
Sys σ		−0.272			−0.384
		(−0.84)			(−1.06)
1-R^2			0.328		−0.088
			(2.46)		(−0.64)
$\alpha^{\text{Past-FOMC}}$				0.608	0.369
				(2.95)	(1.98)
Log(Size)	0.084	0.072	0.106	0.074	0.054
	(1.08)	(0.96)	(1.41)	(0.92)	(0.75)
Log(Age)	−0.094	−0.057	−0.083	−0.032	−0.017
	(−1.00)	(−0.71)	(−0.91)	(−0.29)	(−0.20)
Fee	−0.039	−0.012	0.020	−0.039	−0.036
	(−0.30)	(−0.10)	(0.16)	(−0.30)	(−0.32)
Flow	−0.019	−0.030	−0.014	−0.016	−0.016
	(−0.29)	(−0.45)	(−0.22)	(−0.25)	(−0.24)
Momentum	0.561	0.527	0.684	0.516	0.619
	(1.66)	(1.22)	(2.29)	(1.53)	(1.37)
Intercept	1.084	1.371	0.926	0.957	1.178
	(2.04)	(2.09)	(1.80)	(1.95)	(1.88)
Observations	27,074	27,013	27,013	27,071	27,013
R-squared	10.9%	19.4%	12.2%	13.9%	25.6%
Number of groups	91	91	91	91	91

Notes – This table presents the Fama-MacBeth regression estimates on the determinants of government bond funds' FOMC-day alpha conditional on their activeness and past performance. The dependent variable is a fund's quarter-t FOMC-day factor-adjusted average excess return. *Turnover* is the decile rank of a fund's turnover ratio, measured at the end of quarter $t-1$. *Idio* σ, *Sys* σ, and R^2 are estimated simultaneously using daily observations from quarter $t-1$, where *Sys* σ is the standard deviation of the fitted values from the four-factor model, *Idio* σ is the standard deviation of the residuals, and R^2 is the regression R-squared. $\alpha^{\text{Past-FOMC}}$ denotes the average factor-adjusted excess returns on FOMC days over the past 24 months from quarter $t-8$ to $t-1$. We control for fund-level characteristics, including *Log(Size)*, *Log(Age)*, *Fee*, *Flow*, and the average return over the past 12 months (*Momentum*), all observed at the end of quarter $t-1$. For ease of interpretation, all the independent variables are standardized with means of zero and standard deviations of one. The standard errors are Newey-West adjusted with three lags. The t-stats are in parentheses.

Table 4
Interconnected Macro-Skill within the Same Fund Family

	Y= *Govt* $\alpha_t^{i \in A}$						
	(1)	(2)	(3)		(4)	(5)	(6)
Govt α_t^{A-i}	3.690			*Govt* α_{t-1}^{A-i}	0.615		
	(13.29)				(2.13)		
Corp α_t^{A}		3.684		*Corp* α_{t-1}^{A}		0.509	
		(12.36)				(1.71)	
Equity α_t^{A}			−0.239	*Equity* α_{t-1}^{A}			0.300
			(−1.31)				(1.60)
Log(Size)	−0.021	0.083	0.075	*Log(Size)*	−0.038	0.067	0.076
	(−0.24)	(1.17)	(0.90)		(−0.38)	(0.90)	(0.97)
Log(Age)	−0.003	−0.080	−0.092	*Log(Age)*	−0.018	−0.076	−0.105
	(−0.03)	(−0.74)	(−0.90)		(−0.16)	(−0.68)	(−1.06)
Fee	−0.076	0.017	−0.044	*Fee*	−0.092	−0.016	−0.038
	(−0.56)	(0.14)	(−0.32)		(−0.64)	(−0.13)	(−0.28)
Flow	0.003	−0.029	−0.027	*Flow*	0.007	−0.016	−0.027
	(0.05)	(−0.43)	(−0.41)		(0.10)	(−0.22)	(−0.40)
Momentum	0.633	0.250	0.478	*Momentum*	0.476	0.438	0.586
	(1.58)	(0.67)	(1.45)		(1.10)	(1.22)	(1.82)
Intercept	0.816	0.276	1.088	*Intercept*	0.791	0.944	1.319
	(2.32)	(0.76)	(2.03)		(1.54)	(1.83)	(2.41)
Observations	19,186	23,268	26,070	Observations	19,185	23,266	26,070
R-squared	30.1%	24.6%	12.1%	R-squared	17.8%	14.8%	11.4%
# of groups	91	91	91	# of groups	91	91	91

Notes – This table presents the Fama-MacBeth regression estimates on the relationship between the FOMC-day performance of government bond funds and that of other funds within the same family. The dependent variable is the government fund i's FOMC-day factor-adjusted average excess return in quarter t (*Govt* $\alpha_t^{i \in A}$), where fund i belongs to fund family A. In columns (1) to (3), the independent variables, *Govt* α_t^{A-i}, is the quarter-t FOMC-day alphas of other government bond funds in fund family A, excluding the focal fund i itself. Similarly, *Corp* α_t^{A} and *Equity* α_t^{A} are the FOMC-day alphas of investment-grade and equity funds within the same family A in quarter t, respectively. In columns (4) to (6), we replace the quarter-t family fund performance with their average FOMC-day performance over the past 24 months observed by the end of quarter $t-1$ (*Govt* α_{t-1}^{A-i}, *Corp* α_{t-1}^{A}, and *Equity* α_{t-1}^{A}). We control for fund-level characteristics, including *Log(Size)*, *Log(Age)*, *Fee*, *Flow*, and the average return over the past 12 months (*Momentum*), all observed at the end of quarter $t-1$. For ease of interpretation, all the independent variables are standardized with means of zero and standard deviations of one. The standard errors are Newey-West adjusted with three lags. The t-statistics are in parentheses.

Table 5
Portfolio Holdings

	Portfolio Weight			Funds with Derivative Ownership					Bond Maturity		Duration	
$\alpha^{\text{Past-FOMC}}$	Bonds	Cash	Other	TNote Futures	Tbond Futures	IR Futures	IR Swap	Currency Derivatives	Mean	STD	Mean	STD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Loser	95.7%	1.9%	2.4%	22.3%	15.2%	6.6%	8.7%	3.7%	8.2	1.2	4.1	0.6
2	97.3%	1.7%	0.8%	23.8%	14.2%	6.5%	9.8%	3.7%	7.1	1.2	3.6	0.5
3	96.5%	1.5%	2.0%	25.5%	14.7%	4.1%	10.0%	4.1%	6.7	1.2	3.6	0.5
4	96.3%	1.3%	2.3%	29.7%	18.6%	6.3%	13.0%	4.1%	7.6	1.3	3.8	0.5
Winner	97.7%	−2.1%	4.5%	33.6%	25.9%	10.4%	21.6%	8.9%	9.5	1.5	5.2	0.8
Winner-Loser	2.0%	−4.0%	2.2%	11.3%	10.7%	3.8%	12.9%	5.2%	1.3	0.2	1.0	0.2
t-stat	(4.40)	(−4.51)	(2.45)	(6.43)	(6.40)	(4.06)	(6.43)	(5.52)	(3.56)	(5.29)	(4.31)	(5.47)

Notes – This table reports the portfolio holding characteristics for quintile groups of government bond funds, sorted based on their past 24-month FOMC-day performance ($\alpha^{\text{Past-FOMC}}$). Columns (1) to (3) report the average weights of bonds, cash, and other assets held by funds in each group. Columns (4) to (8) report the fraction of funds with derivative ownership, where TNote Futures include 2-, 3-, 5-, 7-, and 10-year Treasury futures, TBond Futures include 20- and 30-year Treasury futures, and IR Futures include Eurodollar futures and Fed funds futures. Columns (9) and (10) present the average value-weighted maturity of Treasury bonds held by a fund, as well as the time-series standard deviation of this maturity for each fund, estimated using the past 24 months. Similarly, columns (11) and (12) report the mean and standard deviation of portfolio duration. Duration is estimated for each fund each quarter by the sensitivity of fund return to yield curve change, using the regression specification $Ret_{i,t} = a_i + b_i \times \Delta y_t + \varepsilon_t$, where the negative value of the coefficient b_i captures fund duration. We calculate these statistics for each fund quarter, and then report the statistics averaged within each quintile group and over time. The last two rows provide the difference between the top and bottom quintile groups, with t-statistics in parentheses. The sample period is from Q4 1998 to Q4 2021.

Table 6
Fund Duration Change and Monetary Policy Shocks

Panel A: Pre-Announcement Fund Duration Change

	Yield Increase		Yield Decrease		Difference	
	$\Delta Duration$	t-stat	$\Delta Duration$	t-stat	$\Delta Duration$	t-stat
Most Active	−0.33	(2.53)	0.19	(1.73)	−0.53	(3.03)
4	−0.08	(0.99)	0.08	(1.17)	−0.16	(1.51)
3	−0.04	(0.49)	0.08	(1.45)	−0.12	(1.28)
2	−0.03	(0.51)	0.06	(1.36)	−0.09	(1.24)
Least Active	0.01	(0.19)	−0.00	(0.12)	0.01	(0.22)

Panel B: Predicting Monetary Policy Shocks Using $\Delta Duration$

		Δy^{2YR}	Δy^{5YR}	Δy^{10YR}	Δy^{15YR}	Δy^{20YR}	MPS	$Target$	$Path$
Most Active	Coeff.	−2.412	−2.467	−1.875	−1.401	−1.074	−0.274	−0.191	−0.200
	t-stat	(−3.85)	(−3.11)	(−2.45)	(−2.13)	(−1.82)	(−2.59)	(−1.62)	(−2.03)
	Adj.R^2	8.2%	5.8%	3.7%	2.5%	1.5%	4.1%	1.7%	1.9%
4	Coeff.	−0.998	−0.665	−0.119	0.201	0.410	−0.228	−0.127	−0.189
	t-stat	(−1.97)	(−1.35)	(−0.27)	(0.49)	(1.02)	(−2.19)	(−0.99)	(−2.26)
	Adj.R^2	1.4%	0.1%	−0.5%	−0.5%	−0.1%	3.6%	0.7%	2.3%
3	Coeff.	−1.030	−0.801	−0.211	0.139	0.325	−0.207	−0.089	−0.190
	t-stat	(−1.79)	(−1.45)	(−0.45)	(0.33)	(0.80)	(−1.90)	(−0.74)	(−2.18)
	Adj.R^2	1.3%	0.2%	−0.5%	−0.5%	−0.3%	2.5%	0.0%	2.0%
2	Coeff.	−0.851	−1.002	−0.470	−0.054	0.192	−0.158	−0.041	−0.165
	t-stat	(−1.36)	(−1.42)	(−0.77)	(−0.10)	(0.38)	(−1.40)	(−0.31)	(−1.97)
	Adj. R^2	0.5%	0.4%	−0.3%	−0.5%	−0.5%	0.9%	−0.5%	1.0%
Least Active	Coeff.	−0.296	0.116	0.381	0.601	0.742	−0.146	−0.218	−0.020
	t-stat	(−0.44)	(0.14)	(0.50)	(0.88)	(1.16)	(−1.00)	(−1.35)	(−0.18)
	Adj.R^2	−0.4%	−0.5%	−0.4%	−0.1%	0.2%	0.4%	1.6%	−0.5%

Notes – Panel A reports the change in fund duration prior to FOMC announcements. Duration is estimated by the return-yield relationship specified in the regression model: $Ret_{i,t} = a + b_i \times \Delta Yield_t + \epsilon_t$, where the negative value of the coefficient b_i captures the Duration. The pre-announcement duration change, $\Delta Duration^i_{t-1}$, is computed as the difference in duration measured within the window [-14, -1] prior to the announcement, relative to the window of [-28, -15] days preceding the announcement. We categorize all FOMC events into two groups: those with a yield increase ($\Delta y^{\text{FOMC}}_t > 0$) and those with a yield decrease ($\Delta y^{\text{FOMC}}_t < 0$) on announcement days. We then report the value-weighted duration change for quintile groups of funds sorted by their level of activeness. Panel B reports the predictive power of $\Delta Duration_{t-1}$ for monetary policy shocks. We use the standardized $\Delta Duration_{t-1}$ for each quintile group of funds to predict the FOMC-day changes in Treasury yields (2-20 years) using the model:

$$\Delta y^k_t (\text{or}\, MPS_t) = a + b \times \Delta Duration_{t-1} + \varepsilon_t.$$

We also report the coefficient estimates using high-frequency monetary policy shocks (MPS) from Nakamura and Steinsson (2018), as well as the target and path factors from Gürkaynak, Sack, and Swanson (2005), as additional dependent variables. The standard errors are adjusted for heteroskedasticity, and the t-statistics are provided in parentheses.

Table 7
Controlling for Other Monetary Policy Predictors

			Y=FOMC-Day $\Delta y^{2\mathrm{YR}}$			Y=*MPS*		
X=		Nobs	ΔDuration	*X*	Adj.R^2	ΔDuration	*X*	Adj.R^2
Survey	*Bloomberg*	185	**−2.414**	0.349	8.0%	**−0.276**	**0.293**	13.0%
			(**−3.87**)	(0.66)		(**−2.82**)	(**3.31**)	
	BlueChip	161	**−2.452**	0.160	7.6%	**−0.309**	0.145	7.0%
			(**−3.63**)	(0.56)		(**−2.82**)	(1.26)	
Economic Activity	*Employment*	185	**−2.407**	**0.668**	8.9%	**−0.273**	**0.133**	5.5%
			(**−3.86**)	(**2.02**)		(**−2.60**)	(**2.37**)	
Asset Return	$S\&P500_{3\mathrm{M}}$	185	**−2.255**	0.795	9.3%	**−0.221**	**0.273**	11.5%
			(**−3.65**)	(1.46)		(**−2.24**)	(**2.64**)	
	$Commodity_{3\mathrm{M}}$	185	**−2.429**	**0.895**	9.8%	**−0.279**	**0.245**	10.1%
			(**−3.90**)	(**2.11**)		(**−2.77**)	(**2.46**)	
Yield Related	$BaaSpread_{3\mathrm{M}}$	185	**−2.430**	−0.968	10.2%	**−0.278**	**−0.212**	8.5%
			(**−3.98**)	(−1.60)		(**−2.70**)	(**−2.25**)	
	$\Delta y^{2\mathrm{YR}}_{3\mathrm{M}}$	185	**−2.413**	−0.034	7.7%	**−0.264**	**0.201**	8.0%
			(**−3.82**)	(−0.05)		(**−2.61**)	(**1.83**)	
	$Slope_{3\mathrm{M}}$	185	**−2.416**	−0.246	7.8%	**−0.279**	**−0.217**	8.7%
			(**−3.85**)	(−0.37)		(**−2.68**)	(**−2.24**)	
	γ	185	**−2.413**	−0.126	7.7%	**−0.275**	−0.098	4.6%
			(**−3.83**)	(−0.32)		(**−2.59**)	(−1.46)	
	$Forward^{2\mathrm{YR}}$	185	**−2.504**	−0.499	8.3%	**−0.289**	−0.079	4.3%
			(**−3.95**)	(−1.02)		(**−2.75**)	(−1.08)	
	FFFuture	185	**−2.400**	0.203	7.8%	**−0.260**	**0.251**	10.5%
			(**−3.84**)	(0.25)		(**−2.65**)	(**2.25**)	
	$ISwap^{2\mathrm{YR}}$	137	**−2.357**	−0.071	9.5%	**−0.244**	**0.130**	7.8%
			(**−3.41**)	(−0.11)		(**−2.41**)	(**1.73**)	
Central Bank	*Speech Sentiment*	185	**−2.415**	−0.418	8.1%	**−0.275**	−0.055	3.9%
			(**−3.83**)	(−0.95)		(**−2.59**)	(−1.05)	
	Text Sentiment	68	**−2.445**	−0.641	14.8%	**−0.188**	**−0.152**	10.1%
			(**−3.25**)	(−1.53)		(**−2.00**)	(**−2.20**)	
	Conference Tone	37	**−2.792**	−0.685	25.3%	**−0.245**	−0.072	12.3%
			(**−3.41**)	(−1.15)		(**−2.27**)	(−0.90)	

Notes – This table reports the forecasting power of changes in fund duration for FOMC-day yield changes and *MPS* from Nakamura and Steinsson (2018), while controlling for other monetary policy predictors. $\Delta Duration$ is the value-weighted pre-announcement change in duration for the most active quintile of funds, scaled by the standard deviation of duration changes. *Bloomberg* and *BlueChip* capture economists' forecasts of changes in the federal funds rate. *Employment* is the percentage change in nonfarm payroll employment over the past year (Cieslak (2018)). Following Bauer and Swanson (2023b), $S\&P500_{3\mathrm{M}}$ and $Commodity_{3\mathrm{M}}$ represent the returns in the equity and commodity markets, respectively, over the previous three months. Following Swanson (2024), $BaaSpread_{3\mathrm{M}}$, $\Delta y^{2\mathrm{YR}}_{3\mathrm{M}}$, and $Slope_{3\mathrm{M}}$ are the changes over the previous three months in the Baa–Treasury spread, the 2-year Treasury yield, and the slope of the yield curve, respectively. γ is a tent-shaped linear function of forward rates for the previous month, constructed following Cochrane and Piazzesi (2005). $Forward^{2\mathrm{YR}}$ is the 2-year forward–spot spread for the previous month, constructed following Fama and Bliss (1987). *FFFuture* and $ISwap^{2\mathrm{YR}}$ denote the one-month changes in the federal funds futures rate and the 2-year inflation swap rate, respectively. *Speech Sentiment* measures whether speeches by FOMC members from the previous FOMC meeting to the current one contain more dovish than hawkish terms (Neuhierl and Weber (2019)). *Text Sentiment* and *Conference Tone* are from Gorodnichenko et al. (2023) and capture, respectively, the textual sentiment in FOMC statements, remarks, and Q&A sessions, and the vocal emotions embedded in the answers given by Fed Chairs during press conferences. Higher values indicate more dovish communication or a more positive vocal tone. All independent variables are measured using values observed just before the FOMC announcement and are standardized to have mean zero and unit standard deviation. Standard errors are adjusted for heteroskedasticity, and t-statistics are reported in parentheses.

Table 8

Impact of Announcement Uncertainty and Surprises on Fund Performance

		$\sigma(\Delta y^{2\text{YR}})$	*MAI*	*Disagreement* *Bloomberg*	*Disagreement* *BlueChip*	*Surprise*	|*Surprise*|	*VIX*	*Pre-FOMC Drift*
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All	β^{TM}	0.737	1.714	1.161	2.559	−0.366	1.066	−0.186	0.464
	t-stat	(1.30)	(2.83)	(3.03)	(3.62)	(−0.62)	(2.15)	(−0.32)	(0.61)
Most Active	β^{TM}	2.591	3.644	2.868	4.301	−1.610	2.178	0.760	2.205
	t-stat	(2.01)	(2.99)	(2.77)	(3.34)	(−1.19)	(1.72)	(0.51)	(1.24)
Least Active	β^{TM}	−0.553	0.300	−0.063	0.328	−0.310	−0.187	−0.446	0.106
	t-stat	(−1.15)	(0.68)	(−0.13)	(0.55)	(−0.56)	(−0.33)	(−0.82)	(0.16)

Notes – This table reports the impact of announcement uncertainty and surprise on the FOMC-day performance of funds. We regress funds' FOMC-day returns against measures of announcement disagreement, surprise, and risk, while controlling for the four-factor returns on announcement days:

$$Ret_t^{\text{FOMC}} - r_t^f = \alpha + \beta^{\text{TM}} \times AnnProxy_t + \sum_k \beta^k \times Factor_t^k + \varepsilon_t.$$

The coefficients, β^{TM}, on the announcement measure *AnnProxy* are reported. For *AnnProxy*, we include the following variables: $\sigma(\Delta y^{2\text{YR}})$, which is the decile rank of the standard deviation of daily changes in the 2-year Treasury yield over the past month, adjusted for the downward trend; *MAI*, which is the last-month monetary macro attention index in Fisher, Martineau, and Sheng (2022); *Bloomberg Disagreement*, constructed as the difference between the 75th and 25th percentiles of the latest economist forecasts for the Fed funds rate; *BlueChip Disagreement*, which measures the difference between the top 10 and bottom 10 most recent forecasts on the current-quarter Fed funds rate; *Surprise*, derived from the 1-day change in the spot-month future rate following the methodology of Kuttner (2001); and |*Surprise*|, representing the absolute value of the announcement-day surprise. To account for the risk associated with announcements, we also include the *VIX* index and the *Pre-FOMC Drift* of Hu, Pan, Wang, and Zhu (2022). We report the regression estimates separately for value-weighted returns of all government bond mutual funds in our sample ("All"), as well as for the most and least actively managed funds, categorized based on their last-quarter idiosyncratic volatility. For ease of interpretation, all independent variables are standardized to have a mean of zero and a standard deviation of one. The t-statistics are in parentheses.

Table 9
Time-Varying Predictability of Fund Duration Changes

	$\Delta y^{2\text{YR}}$			*MPS*		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ*Duration*	-2.148	-2.366	-2.478	-0.225	-0.271	-0.305
	(-3.82)	(-3.78)	(-3.68)	(-2.48)	(-2.75)	(-2.98)
Δ*Duration* $\times$ $\sigma(\Delta y^{2\text{YR}})$	-1.627			-0.256		
	(-2.37)			(-2.21)		
Δ*Duration* $\times$ *MAI*		-0.946			-0.294	
		(-1.81)			(-2.68)	
Δ*Duration* $\times$ *BC Disp*			-0.734			-0.299
			(-1.11)			(-2.24)
$\sigma(\Delta y^{2\text{YR}})$	-0.841			-0.256		
	(-1.73)			(-3.40)		
MAI		0.122			-0.096	
		(0.29)			(-1.45)	
BC Disp			0.188			-0.146
			(0.30)			(-1.51)
Observations	185	185	162	185	185	162
Adj.R^2	12.2%	8.3%	7.9%	13.0%	8.7%	13.6%

Notes – This table reports the forecasting power of fund duration changes on monetary policy shocks, conditioned on pre-announcement monetary policy uncertainty. We use the decile rank of the standard deviation of changes in the 2-year Treasury yield, calculated using daily observations from the previous month ($\sigma(\Delta y^{2\text{YR}})$), the last month monetary macro attention index (*MAI*) from Fisher, Martineau, and Sheng (2022), and the latest Blue Chip disagreement on the current-quarter Fed funds rate (*BC Disp*) to capture monetary policy uncertainty. These variables, along with their interactions with duration change, are included in the model. All independent variables are standardized to have means of zero and standard deviations of one. Standard errors are adjusted for heteroskedasticity, and t-statistics are shown in parentheses.

Table 10
Interconnected Macro-day Performance

	Govt Funds				Corp Funds				Equity Funds			
	α_t^{GDP}	α_t^{NFP}	α_t^{CPI}	α_t^{ISM}	α_t^{GDP}	α_t^{NFP}	α_t^{CPI}	α_t^{ISM}	α_t^{GDP}	α_t^{NFP}	α_t^{CPI}	α_t^{ISM}
α_t^{FOMC}	0.542	0.083	0.482	0.379	0.492	0.056	0.348	0.258	2.991	0.757	1.810	1.526
	(1.91)	(0.56)	(2.19)	(2.68)	(2.02)	(0.41)	(1.83)	(2.31)	(3.01)	(0.95)	(2.24)	(1.90)
Idio σ	1.180	−0.104	−0.652	0.383	1.678	−0.480	−0.830	−0.271	1.600	1.187	−0.141	−0.504
	(4.89)	(−0.52)	(−3.50)	(1.31)	(5.60)	(−4.09)	(−6.19)	(−2.04)	(2.07)	(1.39)	(−0.20)	(−0.45)
Log(Size)	0.033	0.067	0.076	0.139	0.049	0.029	−0.081	0.008	0.290	0.241	0.009	−0.346
	(0.52)	(1.50)	(1.52)	(1.90)	(0.92)	(0.69)	(−2.34)	(0.17)	(1.75)	(1.86)	(0.05)	(−1.43)
Log(Age)	0.099	−0.175	−0.137	−0.175	0.14	−0.106	0.094	−0.063	−0.101	−0.229	0.065	0.719
	(0.80)	(−2.58)	(−2.41)	(−2.03)	(1.65)	(−2.35)	(2.38)	(−1.13)	(−0.58)	(−1.25)	(0.29)	(3.34)
Fee	−0.163	0.108	0.272	0.167	−0.091	0.044	−0.004	0.051	0.191	0.129	−0.073	−0.159
	(−2.14)	(2.07)	(4.75)	(2.29)	(−1.90)	(1.81)	(−0.12)	(1.68)	(1.15)	(0.87)	(−0.57)	(−0.76)
Flow	0.015	0.066	0.021	−0.007	0.033	−0.041	0.014	0.028	0.043	0.322	0.029	0.126
	(0.29)	(1.73)	(0.62)	(−0.15)	(0.84)	(−1.20)	(0.45)	(0.81)	(0.37)	(2.76)	(0.23)	(0.92)
Momentum	0.266	0.431	0.061	0.056	−0.035	0.798	0.464	0.179	0.612	1.102	3.174	1.814
	(0.82)	(1.65)	(0.20)	(0.25)	(−0.16)	(4.23)	(2.75)	(1.07)	(0.35)	(0.59)	(1.57)	(0.66)
Observations	27,011	27,009	27,010	27,010	83,207	83,206	83,207	83,205	183,548	183,549	183,556	183,554
R-squared	23.0%	20.6%	23.9%	20.8%	18.1%	10.5%	14.3%	9.8%	22.7%	19.6%	23.5%	20.8%
Number of groups	91	91	91	91	91	91	91	91	91	91	91	91

Notes – This table presents Fama-MacBeth regression results examining the interconnected macro-day performance. The dependent variables are the factor-adjusted average excess returns on other macro announcements in quarter t (α_t^{GDP}, α_t^{NFP}, α_t^{CPI}, α_t^{ISM}). The independent variables include fund's FOMC-day factor-adjusted average excess return in quarter t (α_t^{FOMC}) and fund-level characteristics. For ease of interpretation, all the independent variables are standardized with means of zero and standard deviations of one. The standard errors are Newey-West adjusted with three lags. The t-stats are in parentheses.

Internet Appendix for
"What Can Macro-Active Bond Funds Tell Us About Monetary Policy Change?"

This appendix provides supplemental materials for the paper titled "What Can Macro-Active Bond Funds Tell Us About Monetary Policy Change?" Section 1 describes the methodology for constructing bond factors, assesses the effectiveness of the factor model in explaining variations in bond and fund returns, and compares it with alternative factor models. Section 2 presents additional robustness tests of funds' FOMC-day alpha. Section 3 explores other characteristics related to funds' FOMC-day performance.

Contents

1. The Four-Factor Model

1.1. Bond Factor Constructions

Litterman and Scheinkman (1991) provide evidence that three factors – representing the level, slope, and curvature of the yield curve – can effectively capture its shape and day-to-day fluctuations. We construct these three government bond factor portfolios using principal component analysis (PCA) based on the return indices of the 2-, 5-, 10-, and 30-year Barclays U.S. Treasury bonds. Unlike the traditional approach of performing PCA in the yield space, we conduct our analysis in the return space, enabling the resulting factors to directly serve as actual portfolio returns. Our PCA analysis utilizes Treasury return indices from September 1998 to December 2019. Panel A presents the eigenvectors for each principal component, which are essentially linear combinations of the 2-, 5-, 10-, and 30-year bond indices, with the coefficients determined by the corresponding eigenvectors.

$$\begin{cases} PC1_t = D_1 \times R_t^{2Y} + D_2 \times R_t^{5Y} + D_3 \times R_t^{10Y} + D_4 \times R_t^{30Y} \\ PC2_t = G_1 \times R_t^{2Y} + G_2 \times R_t^{5Y} + G_3 \times R_t^{10Y} + G_4 \times R_t^{30Y} \\ PC3_t = F_1 \times R_t^{2Y} + F_2 \times R_t^{5Y} + F_3 \times R_t^{10Y} + F_4 \times R_t^{30Y}, \end{cases} \tag{A1}$$

where $D^T = (D_1, D_2, D_3, D_4)^T$, $G^T = (G_1, G_2, G_3, G_4)^T$ and $F^T = (F_1, F_2, F_3, F_4)^T$ represent the eigenvectors for the three principal components (PCs) as reported in Panel A. For example, the first principal component assigns weights of 0.056, 0.210, 0.423, and 0.880 to the 2-, 5-, 10-, and 30-year bond indices, respectively. In line with the findings of Litterman and Scheinkman (1991), these three principal components effectively capture the variations in bond returns: the first principal component accounts for 95.43% of the variations, while the second and third principal components explain an additional 4.18% and 0.32%, respectively. Importantly, since all three bond factors are orthogonal by construction, the combination of all three PCs collectively explains 99.93% of the variations in the returns of the 2-, 5-, 10-, and 30-year Barclays U.S. Treasury indices.

Panel A. Eigenvectors for the Three PCs			
	$PC1$	$PC2$	$PC3$
2 Year	0.056	0.268	−0.564
5 Year	0.210	0.625	−0.481
10 Year	0.423	0.582	0.651
30 Year	0.880	−0.446	−0.163
Eigenvalue/Total	95.43%	4.18%	0.32%

Panel B. Bond Factors' Portfolio Weights			
	Level	*Slope*30	*Slope*10
2 Year	3.57%	26.04%	101.26%
5 Year	13.38%	60.74%	86.36%
10 Year	26.96%	56.56%	−116.88%
30 Year	56.09%	−43.34%	29.26%

The principal components (PCs), however, cannot be directly taken as portfolio returns in the bond market, since the eigenvectors do not sum up to one. To address this, we perform the following transformation to normalize each principal component, ensuring that the resulting portfolio can be interpreted as a net long position of a dollar investment.

$$\begin{cases} R_t^{\text{Level}} = PC1_t / \sum_{i=1}^4 D_i \\ R_t^{\text{Slope30}} = PC2_t / \sum_{i=1}^4 G_i \\ R_t^{\text{Slope10}} = PC3_t / \sum_{i=1}^4 F_i. \end{cases} \tag{A2}$$

Panel B reports the portfolio weights after normalization. The normalized first principal component (PC1) portfolio is labeled as *Level* (R_t^{Level}), reflecting its role in capturing the overall level of interest rate movements on bond returns. The respective portfolio weights for the 2-, 5-, 10-, and 30-year bond index returns are 3.57%, 13.38%, 26.96%, and 56.09%. Longer-duration bonds are assigned higher weights due to the duration effect: for the same unit change in yields, long-duration bonds experience greater returns. As shown in Panel C, when regressing changes in daily yields across various maturities on the level portfolio return, a 10 bps increase in R_t^{Level} corresponds to a decrease of 0.48 bps, 0.72 bps, 0.81 bps, and 0.72 bps in the 2-, 5-, 10-, and 30-year yields, respectively, which effectively replicates a parallel shift of the yield curve.

We refer to the normalized second and third principal components as *Slope*30 (R_t^{Slope30}) and *Slope*10 (R_t^{Slope10}), rather than the traditional slope and curvature factors, because of their distinct weight distributions across various bond maturities. Specifically, the R_t^{Slope30} portfolio assigns weights of 26.04%, 60.74%, 56.56%, and -43.34% to the 2-, 5-, 10-, and 30-year bond indices, respectively. Meanwhile, the R_t^{Slope10} portfolio allocates weights of 101.26%, 86.36%, -116.88%, and 29.26% to the same indices. In essence, *Slope*30 reflects a positive influence from short-maturity bonds and a negative influence from 30-year bonds, while *Slope*10 is characterized by a pronounced negative exposure to 10-year maturity bonds.

	Panel C. Bond Factors and Yield Curve Change				
	2 Year	5 Year	10 Year	30 Year	10-2 Year
Level	−0.048	−0.072	−0.081	−0.072	−0.032
	(−113.82)	(−182.31)	(−161.26)	(−97.38)	(−58.20)
*Slope*30	−0.144	−0.136	−0.067	0.029	0.077
	(−97.65)	(−99.23)	(−41.17)	(12.13)	(40.43)
*Slope*10	−0.137	−0.037	0.050	−0.007	0.187
	(−36.55)	(−11.03)	(14.40)	(−1.49)	(38.33)
Intercept	0.131	0.126	0.072	0.054	−0.059
	(6.88)	(7.79)	(4.06)	(1.80)	(−2.80)
Observations	5,825	5,825	5,825	5,825	5,825
Adj.R^2	91.4%	95.6%	94.5%	82.1%	81.9%

When mapping the return space into the yield space, we consistently observe significant relationships between both *Slope*30 and *Slope*10 and changes in the yield curve slope, as indicated by the difference between the 10-year and 2-year yields. Specifically, a 10 bps increase in R_t^{Slope30} results in a 0.29 bps increase in the 30-year yield, accompanied by decreases in the 2-, 5-, and 10-year yields. Likewise, the same 10 bps increase in R_t^{Slope10} corresponds to a 0.50 bps increase in the 10-year yield and decreases in the 2- and 5-year yields. Therefore, even though the third principal component is often regarded in academic literature and by practitioners as the curvature factor, we interpret the second and third principal components as both reflecting slope variations, with *Slope*30 capturing more of the 30-year slope and *Slope*10 capturing more of the 10-year slope.

Finally, Panel D illustrates the effectiveness of the factor models in capturing the risk-taking behavior of government bond funds, equity funds and corporate bond funds on both FOMC days and all days. We utilize the four-factor model for government bond funds and equity funds. For Corp funds, we extend the model by adding the *Corp* factor, which is the return on the Barclays US Corporate Bond Index minus the risk-free rate. Panel D reveals that the four-factor model accounts for approximately 91% of the variations in government bond fund returns and 99% in equity fund returns. For corporate bond funds, the extended five-factor model effectively explains around 85% of the variations in daily fund returns.

Panel D. Fund Performance and Factor Models						
	FOMC Days			All Days		
	Govt	Equity	Corp	Govt	Equity	Corp
Level	0.289	−0.004	−0.048	0.293	−0.008	0.076
	(29.97)	(−0.36)	(−0.72)	(117.62)	(−2.96)	(7.30)
*Slope*30	0.346	−0.019	0.149	0.313	−0.007	0.177
	(15.20)	(−0.78)	(4.31)	(45.34)	(−0.82)	(15.11)
*Slope*10	0.141	0.093	0.171	0.066	0.030	0.041
	(3.48)	(1.83)	(2.89)	(4.21)	(1.83)	(1.78)
Stock	0.005	0.970	0.006	0.007	0.975	0.016
	(0.90)	(130.12)	(0.67)	(4.71)	(487.55)	(7.81)
Corp			0.709			0.457
			(4.89)			(21.95)
Intercept	1.782	1.382	1.272	0.443	0.231	0.430
	(3.35)	(1.89)	(1.67)	(4.83)	(1.63)	(3.70)
Observations	185	185	185	5,807	5,807	5,807
Adj. R^2	91.9%	99.3%	84.9%	89.8%	99.2%	84.9%

1.2. Comparison with Alternative Factor Models

We evaluate fund performance using a four-factor model. The first three factors are bond factors constructed from the principal components of Treasury returns, as described above. The fourth factor, *Stock*, is included to capture the well-documented effect of FOMC announcements on equity markets (Savor and Wilson (2014)), which may also influence mutual fund returns around announcement days. Because the literature does not adopt a single standard specification for bond fund performance evaluation, it is important to compare our four-factor model with alternative models employed in prior studies.

Appendix Table IA9 summarizes the main factor models used in prior research on government and corporate bond mutual funds. For government bond funds, Khorana (1996) and Huang and Wang (2014) use a one-factor model based on aggregate Treasury returns, labeled either as a Treasury or term factor. Similar to our approach, Czech et al. (2021) use three factors—level, slope, and curvature—to capture bond market movements.

Factor models used for corporate bond funds are more varied. One strand combines equity and bond market factors, such as the five-factor *MKT+SMB+HML+Term+Def* specification in Fama and French (1993) and Bessembinder et al. (2008). Other studies use more market-segment-specific return factors, such as the *Stock+Term+Def* model in Choi and Kronlund

(2018), the *HY+IG* model in Aragon et al. (2019), the *Treasury+IG+HY+MBS* model in Jones and Mo (2021), and the *Stock+Bond+Def+Option* specification used in several studies of corporate bond mutual funds.

This diversity in the literature motivates a direct comparison between our baseline four-factor model and existing alternatives. Appendix Table IA10 presents the performance of various models in evaluating both passive government bond benchmark indices and individual mutual funds. Following Cremers, Petajisto, and Zitzewitz (2013) and Ahmed, Bu, and Tsvetanov (2019), a well-specified benchmark should explain a large share of the variation in passive benchmark returns while leaving little abnormal performance unexplained, which corresponds to higher adjusted R^2 and lower absolute alpha. Panel A reports this comparison using 69 government bond benchmark indices spanning a range of maturities and index providers. For each model, we regress daily index returns on the corresponding factors and report the cross-index mean and standard deviation of adjusted R^2 and absolute alpha. Among the government bond factor models, our baseline specification performs best: it produces the highest average adjusted R^2, 81.6%, and an average daily absolute alpha of 0.23 bps. One-factor models perform substantially worse. For example, the *Term* model explains only 54.7% of the variation in benchmark returns.

We then extend the analysis to individual fund returns. The results are broadly consistent with those for the benchmark indices. Our baseline model explains 67.3% of the average variation in fund returns, compared with 56.1% for the *Term* model. The evidence on absolute alpha is less clear-cut, however. Unlike passive indices, mutual funds reflect active and discretionary portfolio choices, so even a well-specified factor model need not produce an alpha close to zero.

Finally, because some government bond funds may also hold corporate bonds, we compare our baseline specification with several commonly used corporate bond factor models. As reported in Panel B of Appendix Table IA10, these models generally have less explanatory power for government bond indices than our baseline model. For example, the *Stock+Bond+Def+Option* model yields an adjusted R^2 of 75.8%, well below the 81.6% achieved by our baseline specification. In terms of absolute alpha, the corporate bond models produce values ranging from 0.16 to 0.57 bps, while the 0.23 bps generated by our baseline model also ranks among the lowest. Taken together, these results suggest that models designed for corporate bond funds do not fully capture the primary sources of variation in government bond returns. Our four-factor model therefore appears to provide a particularly appropriate benchmark for evaluating government bond fund performance.

2. Additional Robustness Tests

2.1. Net-Fee Fund Returns

In our primary analysis, we focus on fund gross returns to evaluate the funds' macro-investing skills. To assess whether the FOMC-day outperformance remains robust after accounting for fees and expenses, we calculate alpha using net-fee returns. These returns are computed as fund raw returns net of all management expenses and 12b-1 fees, excluding front- and back-end load fees. As illustrated in the left panel of Appendix Table IA2, investors continue to earn significant alphas on FOMC days. The most active government bond funds achieve a value-weighted net-fee alpha of 3.97 bps (t-stat = 3.41). This confirms that fund outperformance on FOMC days persists after fees and is not dominated by high-fee funds.

2.2. Benchmark-Adjusted Fund Returns

To assess the robustness of funds' outperformance on FOMC days, we analyze funds' benchmark-adjusted returns as an alternative. Information on funds' prospectus benchmarks is collected from Morningstar Direct. As presented in the right panel of Appendix Table IA2, results based on benchmark-adjusted returns largely align with the main findings, indicating that government bond funds significantly outperform on FOMC days. The most active funds achieve a value-weighted benchmark-adjusted return of 3.47 bps, with a t-statistic of 2.95. Furthermore, Figure 2 and Figure 3 illustrate that the benchmark-adjusted outperformance, akin to the factor-adjusted return, is concentrated exclusively on the day of the FOMC announcement. This outperformance is absent in placebo FOMC paths that occur within the same month or have similar underlying factor return distributions but lack an actual news release.

2.3. Alternative Factor Models

To further examine the robustness of our alpha estimates, we estimate government bond funds' FOMC-day alpha under a broad set of alternative factor model specifications, using the value-weighted portfolios of "All" funds, the "Most Active" funds, and the "Least Active" funds, respectively. As reported in Appendix Table IA3, the estimated FOMC-day alpha remains consistently positive and significant across a wide range of factor models for the overall sample and for the most active funds, while remaining statistically insignificant for the least active funds.

Row (a) reports results using the baseline four-factor model, and row (b) reports FOMC-day alpha estimates using equal-weighted fund returns. In rows (c)–(e), we replace the baseline factors with alternative government bond factor models summarized in Appendix Table IA9: the *Treasury* factor following Khorana (1996) and Czech et al. (2021), the *Term* factor following Huang and Wang (2014), and the *Treasury*, *Slope*,*Curvature* factors following Czech et al. (2021), respectively. Row (f) replaces the baseline bond factors with excess returns on the 2-year, 10-year, and 30-year Barclays Treasury indices. Across these alternative government bond factor models, the estimated FOMC-day alpha remains highly robust. For all government bond funds, the estimated alpha ranges from 1.64 bps to 2.24 bps. For the most active funds, it ranges from 3.15 bps to 4.23 bps. In contrast, for the least active funds, the corresponding estimates remain small and statistically insignificant.

Rows (g) through (j) augment the baseline specification with additional fixed-income sector factors. Rows (g), (h), and (i) introduce an MBS factor, a $TIPS$ factor, and an *Agency* factor to our baseline specification, respectively, considering that government bond funds may also invest in mortgage-backed securities, inflation-protected securities, and agency bonds. Row (j) further incorporates all three additional factors to form a seven-factor model for estimating fund alpha. These additions reduce the estimated alpha somewhat, but do not alter the qualitative conclusion. The estimated FOMC-day alpha for all funds remains positive, ranging from 1.03 bps to 1.51 bps, while the corresponding estimates for the most active funds remain between 3.09 bps and 3.97 bps and continue to be statistically significant.

Finally, rows (k) through (p) estimate fund alpha using factor models employed in the corporate bond fund literature. These include the two versions of the *MKT+SMB+HML+Term+Def* model, as well as the *Stock+Term+Def*, *HY+IG*, *Treasury+IG+HY+MBS*, and *Stock+Bond+Def+Option* specifications. Although these models are designed primarily for corporate bond funds rather than government bond funds, the estimated FOMC-day alpha remains qualitatively similar. For all government bond funds, the estimated alpha ranges from 0.83 bps to 2.36 bps, and for the most active funds it ranges from 2.77 bps to 4.92 bps.

Overall, the results in Appendix Table IA3 show that our main finding is not driven by a particular choice of factor model. Whether we use alternative government bond factor models, augment the baseline model with additional sector-specific bond factors, or adopt factor models from the corporate bond fund literature, we continue to find positive and significant FOMC-day alpha for government bond funds, especially among the most active funds.

2.4. Alternative Activeness Measures

In our analysis of information on monetary policy, we use funds' last quarter idiosyncratic volatility as a proxy for their activeness. This choice is based on the observation that idiosyncratic volatility is the strongest predictor of FOMC-day alpha among various activeness proxies, as demonstrated in Table 3. To further validate the robustness of our activeness measure, we construct two alternative measures of fund activeness.

Firstly, we construct a benchmark-adjusted activeness measure. We estimate *Idio* σ by regressing fund excess returns on benchmark index excess returns using daily observations from quarter $t-1$, where *Idio* σ is the standard deviation of the residuals. In Panel A of Appendix Table IA11, we categorize government bond funds into quintile groups based on this alternative activeness measure, then examine the relationship of their duration changes and FOMC outcomes. The results are consistent with Table 6. Duration adjustments by the most active quintile group significantly predict 2-year yield reduction on FOMC days with an R^2 of 7%, while those of less active funds remain uninformative.

Secondly, we construct a PCA-based activeness measure. We conduct a principal component analysis (PCA) to capture the combined effect of multiple activeness indicators. Specifically, each quarter, we perform a PCA on fund *Turnover*, *Idio* σ, and $1-R^2$, then use the first principal component as an alternative measure of fund activeness. The results remain consistent that duration changes in macro-active funds significantly and negatively predict shifts in the yield curve on announcement days.

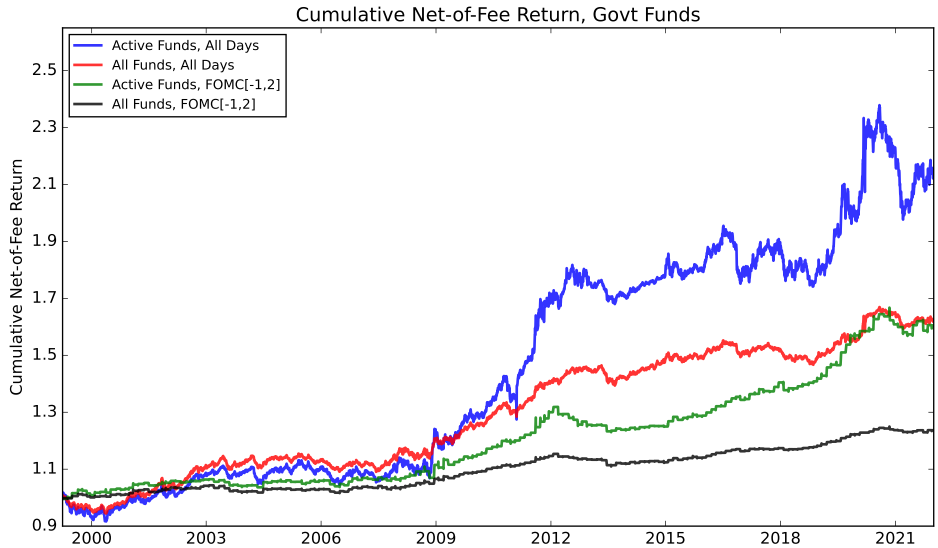
3. Other Fund and Family Characteristics

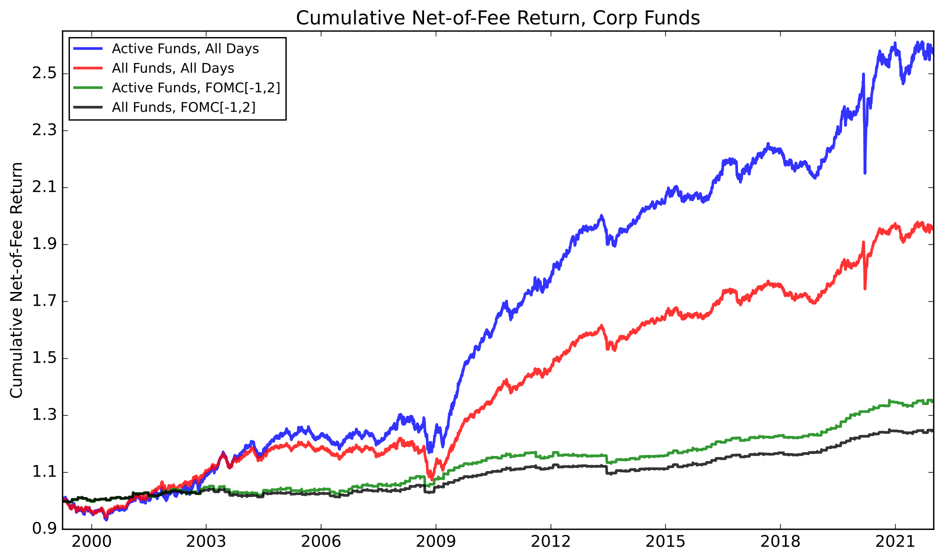
Appendix Table IA12 examines the explanatory power of additional fund- and family-specific attributes in relation to their performance on FOMC announcement days. Specifically, we include variables such as fund duration as defined in Table 5 (*Duration*), family size (*Log(FamilySize)*), an *Independent* dummy (set to 1 if the fund operates independently and is not affiliated with any insurance company, broker, commercial bank, or investment banks), an *Institutional* dummy (set to 1 if the fund's share class is aimed at institutional investors), a *Teammanage* dummy (set to 1 if the fund is managed by multiple managers), and the manager's experience (*Log(Manager Experience)*), measured from the time they entered the fund industry.

Our analysis shows that independent funds and those targeting institutional investors tend to perform better on FOMC announcement days. Specifically, independent funds and those with institutional share classes exhibit additional alpha outperformance of 0.39 bps (t-stat = 2.15) and 0.25 bps (t-stat = 2.63), respectively, on these days. These findings are consistent with previous studies (e.g., Evans and Fahlenbrach (2012), Hao and Yan (2012), Di Maggio and Kacperczyk (2017), and Choi and Kronlund (2018)), which emphasize the strong governance structures and the propensity for risk-taking among institutional and independent funds.

Figure IA1

Cumulative Net-of-Fee Returns





Notes – The figures plot cumulative net-of-fee returns for government bond funds and investment-grade corporate bond funds. The blue and red lines cumulate returns over all trading days, while the green and black lines cumulate returns earned during FOMC event windows [-1,+2]. Results are reported for the full sample of funds and for active funds, respectively. At the end of each quarter, funds are first sorted into quintiles based on *Idio* σ and then, within each quintile, divided into two groups based on $\alpha^{\text{Past-FOMC}}$. Active funds are defined as those in the highest *Idio* σ quintile and the high-$\alpha^{\text{Past-FOMC}}$ group.

Table IA1

Market Returns on FOMC vs. Non-Macro Days

		FOMC			Non-Macro			Difference	
		Mean	t-stat	STD	Mean	t-stat	STD	Mean	t-stat
Bloomberg	Treasury	3.04	1.28	32.36	0.36	0.67	27.35	2.68	1.27
	2 Year	0.75	0.93	11.04	0.13	0.80	8.48	0.62	0.94
	5 Year	2.83	1.13	34.05	0.23	0.49	24.21	2.60	1.37
	10 Year	4.26	1.02	57.12	0.26	0.30	43.84	4.00	1.18
	30 Year	5.49	0.77	97.38	0.73	0.42	88.23	4.76	0.71
CRSP	2 Year	1.04	1.19	11.91	0.17	1.01	8.92	0.86	1.24
	5 Year	4.14	1.62	34.95	0.43	0.89	24.88	3.71	1.90
	10 Year	5.54	1.32	57.18	0.34	0.41	42.96	5.20	1.56
	30 Year	10.62	1.36	106.29	0.24	0.14	88.89	10.39	1.52
	Stock	29.99	3.44	118.96	2.12	0.92	118.77	27.87	3.09

Notes – This table reports the distribution of bond and stock market returns on FOMC days and non-macro days. *Treasury* is the return on the Barclays U.S. Treasury Index in excess of the risk-free rate. Bloomberg *2 Year*, *5 Year*, *10 Year*, and *30 Year* are the excess returns computed as the difference between the Barclays Treasury 2-year, 5-year, 10-year, and 30-year index returns and the risk-free rate. CRSP *2 Year*, *5 Year*, *10 Year*, and *30 Year* are the excess returns on CRSP fixed-maturity Treasury portfolios with maturities of 2, 5, 10, and 30 years, respectively. *Stock* is the excess return on the CRSP value-weighted equity market index.

Table IA2

FOMC-Day Alpha under Alternative Specifications

			Factor-Adjusted Net-Fee Returns				Benchmark-Adjusted Returns			
Fund Style	Type	Variable	-1	FOMC	+1	All Days	-1	FOMC	+1	All Days
Govt Funds	All	α	−0.68	1.19	0.66	0.24	−0.47	1.38	0.79	0.15
		t-stat	(−1.98)	(1.99)	(1.14)	(2.74)	(−1.53)	(3.02)	(1.75)	(1.97)
	Most Active	α	0.82	3.97	0.62	0.30	1.16	3.47	1.64	0.27
		t-stat	(1.00)	(3.41)	(0.47)	(1.27)	(1.41)	(2.95)	(1.36)	(1.33)
	Passive Index	α	−0.32	0.44	0.60	0.20	0.11	0.66	0.67	0.08
		t-stat	(−1.22)	(0.76)	(1.06)	(2.16)	(0.21)	(0.89)	(0.92)	(0.71)
Corp Funds	All	α	−0.92	0.55	0.44	0.19	−1.10	1.14	0.33	0.28
		t-stat	(−1.79)	(0.64)	(0.73)	(1.76)	(−1.83)	(1.53)	(0.51)	(2.57)
	Most Active	α	−0.71	1.89	0.46	0.44	−0.68	2.41	0.44	0.62
		t-stat	(−1.04)	(1.76)	(0.52)	(2.70)	(−0.87)	(2.18)	(0.48)	(4.09)
	Passive Index	α	−0.67	1.30	0.39	0.19	−0.59	0.43	0.24	0.02
		t-stat	(−1.49)	(1.80)	(0.55)	(1.74)	(−1.51)	(0.76)	(0.43)	(0.20)
Equity Funds	All	α	−1.11	0.85	1.54	−0.08	−2.88	0.74	−1.15	0.05
		t-stat	(−1.56)	(1.16)	(2.08)	(−0.59)	(−2.15)	(0.54)	(−0.66)	(0.21)
	Most Active	α	−4.17	4.24	3.78	−0.69	−6.00	5.17	1.85	0.06
		t-stat	(−1.30)	(1.47)	(1.11)	(−1.18)	(−2.20)	(2.08)	(0.61)	(0.12)
	Passive Index	α	0.52	−1.10	0.71	−0.09	−1.88	−0.37	−0.98	−0.53
		t-stat	(0.65)	(−1.81)	(0.97)	(−0.64)	(−1.72)	(−0.40)	(−0.83)	(−1.30)

Notes – This table presents the factor-adjusted net-fee returns and benchmark-adjusted returns for government bond funds (Govt), investment-grade bond funds (Corp), and equity funds around FOMC announcement days. The factor-adjusted net-fee returns are computed using net-fee returns following the same methodology as in Table 2. These returns are funds' raw returns net of all management expenses and 12b-1 fees, excluding front- and back-end load fees. For the benchmark-adjusted returns, each fund's prospectus benchmark is obtained from Morningstar, with the benchmark index returns collected from Morningstar and supplemented by Bloomberg. The t-stats are in parentheses.

Table IA3
FOMC-Day Alpha under Alternative Factor Models

	All		Most Active		Least Active	
	α	t-stat	α	t-stat	α	t-stat
Government Bond Factor Models						
(a) Our Four-Factor Model (Baseline)	1.78	(3.35)	4.23	(3.63)	0.25	(0.60)
(b) Equal-weighted Return	1.63	(3.38)	3.22	(3.98)	0.38	(1.17)
(c) Treasury	1.64	(2.90)	3.38	(2.78)	0.34	(0.61)
(d) Term	2.24	(2.27)	4.11	(3.02)	0.83	(0.92)
(e) Treasury+Slope+Curvature	1.64	(3.07)	3.15	(3.00)	0.42	(0.82)
(f) 2Yr+10Yr+30Yr+Stock	1.84	(3.38)	4.23	(3.64)	0.33	(0.74)
(g) Baseline+MBS	1.47	(3.04)	3.89	(3.31)	−0.08	(−0.23)
(h) Baseline+TIPS	1.51	(2.81)	3.54	(3.09)	0.23	(0.51)
(i) Baseline+Agency	1.50	(2.95)	3.97	(3.36)	0.07	(0.18)
(j) Baseline+MBS+TIPS+Agency	1.03	(2.32)	3.09	(2.76)	−0.20	(−0.57)
Corporate Bond Factor Models						
(k) MKT+SMB+HML+Term+Def (V1)	1.57	(1.52)	3.61	(2.46)	0.09	(0.10)
(l) MKT+SMB+HML+Term+Def (V2)	2.36	(1.91)	4.92	(2.75)	0.65	(0.64)
(m) Stock+Term+Def	1.17	(1.68)	3.18	(2.53)	−0.11	(−0.19)
(n) HY+IG	1.43	(2.18)	2.98	(2.42)	0.17	(0.26)
(o) Treasury+IG+HY+MBS	1.10	(2.32)	2.93	(2.50)	−0.28	(−0.71)
(p) Stock+Bond+Def+Option	0.83	(1.72)	2.77	(2.19)	−0.47	(−1.08)

Notes – This table reports government bond funds' FOMC-day fund performance under alternative factor specifications. In row (a), we estimate fund alpha using the baseline four-factor model. In row (b), fund alpha is estimated using equal-weighted fund returns. In rows (c)–(e), we replace the baseline factors with alternative constructions: the *Treasury* factor following Khorana (1996) and Czech et al. (2021), the *Term* factor following Huang and Wang (2014), and the *Treasury*, *Slope*,*Curvature* factors following Czech et al. (2021), respectively. In row (f), we substitute the three bond factors with the 2-year, 10-year, and 30-year bond factors, defined as the difference between the Barclays Treasury 2-year, 10-year, and 30-year index returns and the risk-free rate. In rows (g), (h) and (i), we incorporate the *MBS* factor, *TIPS* factor and *Agency* factor, respectively, into our baseline specification. In row (j), we estimate fund alpha using a seven-factor model, which includes the *MBS*, *TIPS* and *Agency* factors in addition to the baseline specifications. In rows (k)–(p), we estimate fund alpha using the corporate bond factor models described in Table IA9. We report alphas estimated for value-weighted portfolios of all actively-managed government bond funds ("All"), the "Most Active" and the "Least Active" funds, respectively. The t-stats are in parentheses.

Table IA4

Fund Activeness and Performance Persistence – Other Funds

	Dep. Var. = FOMC-Day Performance α_t^{FOMC}									
	Corp Funds					Equity Funds				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Turnover	0.075				0.057	0.471				0.465
	(0.78)				(0.65)	(1.14)				(1.59)
Idio σ		0.651			0.754		2.905			2.128
		(2.32)			(2.67)		(2.90)			(1.15)
Sys σ		−0.208			−0.393		−5.647			−3.524
		(−1.34)			(−1.88)		(−1.59)			(−0.78)
1-R^2			0.254		−0.214			2.754		−0.006
			(1.81)		(−1.63)			(3.02)		(−0.00)
$\alpha^{\text{Past-FOMC}}$				0.514	0.394				2.414	2.521
				(2.52)	(2.12)				(2.62)	(3.07)
Log(Size)	0.034	0.005	0.006	0.010	0.005	0.083	0.231	0.229	0.008	0.190
	(0.44)	(0.07)	(0.07)	(0.13)	(0.08)	(0.38)	(1.17)	(1.07)	(0.04)	(0.97)
Log(Age)	−0.001	0.047	0.065	0.004	0.011	0.139	−0.199	−0.165	0.054	−0.254
	(−0.01)	(0.69)	(0.95)	(0.07)	(0.17)	(0.49)	(−0.59)	(−0.53)	(0.20)	(−0.90)
Fee	0.037	0.062	0.051	0.050	0.064	0.890	0.275	0.379	0.778	0.195
	(0.63)	(1.18)	(0.85)	(0.93)	(1.42)	(2.00)	(1.14)	(1.04)	(1.88)	(0.94)
Flow	0.077	0.067	0.092	0.072	0.050	0.048	−0.035	0.002	−0.077	−0.078
	(1.51)	(1.39)	(1.72)	(1.48)	(1.26)	(0.28)	(−0.25)	(0.01)	(−0.47)	(−0.57)
Momentum	0.318	0.294	0.551	0.082	0.122	3.185	3.017	2.707	3.160	2.345
	(1.52)	(1.06)	(2.01)	(0.34)	(0.39)	(1.23)	(1.27)	(1.05)	(1.42)	(1.16)
Intercept	0.732	0.686	0.561	0.542	0.524	−0.341	−4.494	−0.153	−1.053	−3.633
	(1.22)	(1.26)	(0.92)	(0.97)	(0.98)	(−0.16)	(−1.69)	(−0.07)	(−0.57)	(−1.36)
Observations	83,312	83,208	83,208	83,308	83,208	183,727	183,558	183,558	183,715	183,558
R-squared	5.5%	10.1%	6.3%	7.8%	14.8%	10.5%	20.2%	12.9%	14.3%	25.1%
Number of groups	91	91	91	91	91	91	91	91	91	91

Notes – This table presents the Fama-MacBeth regression estimates on the determinants of FOMC-day alpha for investment-grade bond funds (Corp), and equity funds conditional on their activeness and past performance. The dependent variable is a fund's quarter-t FOMC-day factor-adjusted average excess return. *Turnover* is the decile rank of a fund's turnover ratio, measured at the end of quarter $t-1$. *Idio* σ, *Sys* σ, and R^2 are estimated simultaneously using daily observations from quarter $t-1$, where *Sys* σ is the standard deviation of the fitted values from the four- (or five-) factor model, *Idio* σ is the standard deviation of the residuals, and R^2 is the regression R-squared. $\alpha^{\text{Past-FOMC}}$ denotes the average factor-adjusted excess returns on FOMC days over the past 24 months from quarter $t-8$ to $t-1$. We control for fund-level characteristics, including *Log(Size)*, *Log(Age)*, *Fee*, *Flow*, and *Momentum*, all observed at the end of quarter $t-1$. For ease of interpretation, all the independent variables are standardized with means of zero and standard deviations of one. The standard errors are Newey-West adjusted with three lags. The t-stats are in parentheses.

Table IA5

Fund Duration Change and Monetary Policy Shocks – Exclude the Day before FOMC

Panel A: Pre-Announcement Fund Duration Change

	Yield Increase		Yield Decrease		Difference	
	$\Delta Duration$	t-stat	$\Delta Duration$	t-stat	$\Delta Duration$	t-stat
Most Active	−0.34	(2.54)	0.21	(1.80)	−0.55	(3.09)
4	−0.09	(1.14)	0.10	(1.43)	−0.19	(1.81)
3	−0.05	(0.62)	0.10	(1.69)	−0.15	(1.54)
2	−0.03	(0.42)	0.08	(1.66)	−0.10	(1.35)
Least Active	0.01	(0.31)	0.00	(0.01)	0.01	(0.22)

Panel B: Predicting Monetary Policy Shocks Using $\Delta Duration$

		$\Delta y^{2\text{YR}}$	$\Delta y^{5\text{YR}}$	$\Delta y^{10\text{YR}}$	$\Delta y^{15\text{YR}}$	$\Delta y^{20\text{YR}}$	*MPS*	*Target*	*Path*
Most Active	Coeff.	−2.273	−2.391	−1.888	−1.459	−1.160	−0.248	−0.166	−0.187
	t-stat	(−3.72)	(−3.10)	(−2.53)	(−2.26)	(−1.99)	(−2.40)	(−1.49)	(−1.97)
	Adj.R^2	7.6%	5.7%	4.0%	2.9%	2.0%	3.4%	1.2%	1.7%
4	Coeff.	−1.096	−0.788	−0.228	0.106	0.320	−0.228	−0.119	−0.195
	t-stat	(−2.19)	(−1.62)	(−0.52)	(0.25)	(0.77)	(−2.17)	(−0.92)	(−2.32)
	Adj.R^2	1.8%	0.3%	−0.5%	−0.5%	−0.3%	3.6%	0.5%	2.4%
3	Coeff.	−1.107	−0.851	−0.244	0.092	0.264	−0.197	−0.092	−0.176
	t-stat	(−2.00)	(−1.58)	(−0.53)	(0.22)	(0.65)	(−1.85)	(−0.77)	(−2.07)
	Adj.R^2	1.6%	0.4%	−0.5%	−0.5%	−0.4%	2.3%	0.1%	1.7%
2	Coeff.	−0.890	−1.018	−0.469	−0.055	0.178	−0.146	−0.045	−0.147
	t-stat	(−1.49)	(−1.51)	(−0.80)	(−0.10)	(0.36)	(−1.34)	(−0.34)	(−1.85)
	Adj. R^2	0.6%	0.5%	−0.3%	−0.5%	−0.5%	0.7%	−0.4%	0.7%
Least Active	Coeff.	−0.456	0.032	0.442	0.714	0.867	−0.161	−0.238	−0.024
	t-stat	(−0.70)	(0.04)	(0.64)	(1.12)	(1.43)	(−1.13)	(−1.50)	(−0.22)
	Adj.R^2	−0.3%	−0.5%	−0.4%	0.1%	0.5%	0.7%	2.1%	−0.5%

Notes – Panel A reports the change in fund duration prior to FOMC announcements. Duration is estimated by the return-yield relationship specified in the regression model: $Ret_{i,t} = a + b_i \times \Delta Yield_t + \epsilon_t$, where the negative value of the coefficient b_i captures the Duration. We exclude the day before FOMC announcement to measure the pre-announcement duration change, $\Delta Duration^i_{t-1}$, which is computed as the difference in duration measured within the window [-14, -2] prior to the announcement, relative to the window of [-28, -15] days preceding the announcement. We categorize all FOMC events into two groups: those with a yield increase ($\Delta y_t^{\text{FOMC}} > 0$) and those with a yield decrease ($\Delta y_t^{\text{FOMC}} < 0$) on announcement days. We then report the value-weighted duration change for quintile groups of funds sorted by their level of activeness. Panel B reports the predictive power of $\Delta Duration_{t-1}$ for monetary policy shocks. We use the standardized $\Delta Duration_{t-1}$ for each quintile group of funds to predict the FOMC-day changes in Treasury yields (2-20 years) using the model:

$$\Delta y_t^k (\text{or } MPS_t) = a + b \times \Delta Duration_{t-1} + \varepsilon_t.$$

We also report the coefficient estimates using high-frequency monetary policy shocks (*MPS*) from Nakamura and Steinsson (2018), as well as the target and path factors from Gürkaynak, Sack, and Swanson (2005), as additional dependent variables. The standard errors are adjusted for heteroskedasticity, and the t-statistics are provided in parentheses.

Table IA6

Mutual Fund Performance on other Macro Announcement Days

	Govt Funds			Corp Funds			Equity Funds		
	All	Most Active	Passive Index	All	Most Active	Passive Index	All	Most Active	Passive Index
FOMC	1.44	4.23	0.54	0.79	2.12	1.39	1.22	4.69	−1.01
	(2.40)	(3.63)	(0.92)	(0.90)	(1.97)	(1.92)	(1.65)	(1.63)	(−1.66)
GDP	3.78	4.76	3.49	5.03	6.44	4.55	2.01	4.10	−0.57
	(7.78)	(5.13)	(4.42)	(7.74)	(7.47)	(6.00)	(3.07)	(1.43)	(−1.10)
GDP (ex. TOM)	0.62	0.58	−0.27	0.55	1.02	−0.29	1.84	2.37	−0.00
	(1.94)	(0.63)	(−0.77)	(1.41)	(1.57)	(−0.66)	(2.42)	(0.71)	(−0.00)
NFP	−0.00	−0.12	−0.48	0.35	0.23	−0.52	0.10	1.31	−1.22
	(−0.01)	(−0.13)	(−1.09)	(0.80)	(0.39)	(−1.08)	(0.19)	(0.50)	(−2.29)
CPI	−0.94	−1.46	−0.73	−1.65	−1.51	−1.01	0.71	−3.01	0.15
	(−2.65)	(−1.64)	(−2.02)	(−3.10)	(−2.30)	(−2.69)	(1.26)	(−1.17)	(0.25)
ISM	0.76	1.18	0.54	0.20	0.14	0.24	−0.25	−1.72	0.50
	(2.42)	(1.34)	(1.60)	(0.55)	(0.24)	(0.68)	(−0.37)	(−0.46)	(0.63)

Notes – This table presents the factor-adjusted excess returns for various styles of mutual funds on days when macroeconomic announcements are made. The announcements considered include those from the Federal Open Market Committee (FOMC), Gross Domestic Product (GDP), Nonfarm Payrolls (NFP), Consumer Price Index (CPI), and the Institute for Supply Management manufacturing index (ISM). Since approximately 25% of GDP announcements coincide with the turn of the month, "GDP (ex. TOM)" represents fund performance on GDP announcement days that fall outside the last and first trading days of a month. We estimate the factor-adjusted daily excess returns for each fund in each quarter by utilizing risk loadings derived from the preceding 24 months. "All" is the value-weighted average of fund alphas for each event, then averaged across events over time. "Most Active" and "Passive Index" are the alphas for the value-weighted portfolio consisting of the most actively managed funds and passively-managed index funds, respectively.

Table IA7
Future Performance of Macro-Active Funds

Panel A. Predicting Next-Quarter Fund Alpha

	Govt Funds		Corp Funds		Equity Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
Idio σ	5.630		3.300		6.086	
	(2.06)		(1.46)		(0.32)	
$\alpha^{\text{Past-FOMC}}$		2.794		2.227		7.130
		(1.83)		(1.84)		(0.54)
Controls	Y	Y	Y	Y	Y	Y
Observations	27,013	27,071	83,208	83,308	183,558	183,715
R-squared	25.0%	20.9%	16.3%	13.6%	17.7%	16.0%
Number of groups	91	91	91	91	91	91

Panel B. Portfolio Sorts

	Govt Funds				Corp Funds			
	Low $\alpha^{\text{Past-FOMC}}$		High $\alpha^{\text{Past-FOMC}}$		Low $\alpha^{\text{Past-FOMC}}$		High $\alpha^{\text{Past-FOMC}}$	
Idio σ	Return	Alpha	Return	Alpha	Return	Alpha	Return	Alpha
Inactive	0.60	0.12	0.65	0.08	0.85	0.05	0.86	0.17
2	0.72	0.08	0.80	0.16	0.94	0.09	0.92	0.03
3	0.89	0.25	0.79	0.20	0.99	0.07	1.10	0.10
4	0.79	0.15	0.79	0.13	1.17	0.19	1.25	0.17
Active	1.09	0.22	1.44	0.47	1.31	0.05	1.71	0.39
Difference	0.49	0.10	0.79	0.39	0.46	0.00	0.86	0.23
t-stat	(1.62)	(0.72)	(1.72)	(1.56)	(2.47)	(0.00)	(4.46)	(1.64)

Notes – This table examines whether fund activeness and past FOMC-day performance predict subsequent fund performance. Panel A presents Fama-MacBeth regression estimates, where the dependent variable is a fund's factor-adjusted net-of-fee alpha in quarter t. *Idio σ* is the standard deviation of the residuals from the factor model, estimated using daily observations from quarter $t-1$. $\alpha^{\text{Past-FOMC}}$ denotes the fund's average factor-adjusted excess return on FOMC announcement days over the preceding 24 months, from quarter $t-8$ through quarter $t-1$. All specifications control for *Log(Size)*, *Log(Age)*, *Fee*, *Flow*, and *Momentum*, measured at the end of quarter $t-1$. For ease of interpretation, all independent variables are standardized to have a mean of zero and a standard deviation of one. Newey-West standard errors are computed using three lags. Panel B presents results from dependent double sorts for government bond funds and investment-grade corporate bond funds. At the end of each quarter, funds are first sorted into quintiles based on *Idio σ* and then, within each quintile, divided into two groups based on $\alpha^{\text{Past-FOMC}}$. The table reports the value-weighted average daily net-of-fee excess returns and factor-adjusted net-of-fee alphas in quarter t, measured in basis points. The t-statistics are reported in parentheses.

Table IA8
Fund Flows around FOMC Announcements

	All		Most Active		Least Active	
	(1)	(2)	(3)	(4)	(5)	(6)
$D(t=-2)$	−0.856	−0.594	−1.250	−0.924	−1.986	−1.813
	(−1.06)	(−0.74)	(−1.01)	(−0.78)	(−1.50)	(−1.35)
$D(t=-1)$	−1.083	−0.799	0.639	0.952	−0.418	−0.307
	(−1.53)	(−1.19)	(0.73)	(1.12)	(−0.34)	(−0.26)
$D(t=0)$	−0.356	−0.096	−1.273	−1.004	−1.873	−1.804
	(−0.58)	(−0.16)	(−1.06)	(−0.88)	(−1.80)	(−1.79)
$D(t=1)$	−0.475	−0.104	−0.488	−0.116	−0.677	−0.249
	(−0.59)	(−0.14)	(−0.60)	(−0.15)	(−0.57)	(−0.21)
$D(t=2)$	−0.311	−0.418	0.656	0.320	−0.493	−0.319
	(−0.43)	(−0.63)	(0.67)	(0.35)	(−0.37)	(−0.24)
Level		−0.007		−0.006		−0.003
		(−2.53)		(−1.69)		(−0.80)
*Slope*30		0.005		0.004		0.012
		(0.50)		(0.40)		(0.83)
*Slope*10		0.015		0.011		0.017
		(0.93)		(0.58)		(0.70)
Stock		0.004		0.004		0.007
		(1.82)		(2.09)		(2.60)
TOM		2.218		3.802		0.187
		(3.59)		(5.44)		(0.20)
TOY		−1.651		−2.062		−0.721
		(−4.60)		(−3.71)		(−1.17)
VIX		0.371		0.353		0.406
		(13.89)		(11.67)		(11.00)
TED		−0.030		−0.035		−0.037
		(−4.33)		(−4.61)		(−4.06)
Intercept	−0.210	−6.527	−1.562	−7.436	0.318	−6.443
	(−1.35)	(−15.11)	(−7.39)	(−14.85)	(1.23)	(−10.64)
Observations	3,365	3,365	3,365	3,365	3,365	3,365
Adj.R^2	−0.1%	15.2%	0.0%	7.8%	0.0%	5.8%

Notes – The table reports the distribution of flows to government bond funds around FOMC announcements. We regress value-weighted government bond fund daily flows on FOMC announcement event-day dummies. The dummy variable, denoted as $D(t=i)$, takes the value one for the ith trading day around the FOMC announcement and zero otherwise, with t=0 representing the announcement day. In columns (2), (4) and (6), we include control variables for the factor returns on the same day (*Level*, *Slope*30, *Slope*10, and *Stock* factors), turn-of-month (TOM) and turn-of-year (TOY) dummies, VIX (CBOE Volatility Index), and TED rate (TED spread). The TOM dummy takes a value of one if the day falls within the [-1, +1] trading days at the turn of the month, and the TOY dummy equals one if the month is January or December, and zero otherwise. The TED spread is calculated as the difference between the three-month LIBOR and the three-month Treasury bill rate.

Table IA9

Bond Factor Models in the Literature

Factor Model	Paper	Construction
Government Bond Factor Models		
Treasury	Khorana (1996); Czech et al. (2021)	*Treasury* is the return on the Barclays US Treasury Index in excess of the risk-free rate.
Term	Huang and Wang (2014)	*Term* is the return on the Barclays US Long-Term Government Bond Index in excess of the risk-free rate.
Treasury+Slope+Curvature	Czech et al. (2021)	*Treasury* is the return on the Barclays US Treasury Index in excess of the risk-free rate; *Slope* is the difference between the returns on CRSP 20-year Treasury Index and CRSP 1-year Treasury Index; *Curvature* is the average return of the CRSP 20-year Treasury Index and CRSP 1-year Treasury Index, minus that of the CRSP 10-year Treasury Index.
Corporate Bond Factor Models		
MKT+SMB+HML+Term+Def (V1)	Fama and French (1993)	*MKT*, *SMB*, and *HML* are obtained from Kenneth French's data library; *Term* is the excess return on the Barclays US Long-Term Government Bond Index; *Def* is the difference between the returns on Barclays US Long-Term Corporate Bond Index and Barclays US Long-Term Government Bond Index.
MKT+SMB+HML+Term+Def (V2)	Bessembinder et al. (2008)	*MKT*, *SMB*, and *HML* are obtained from Kenneth French's data library; *Term* is the slope of the Treasury yield curve, defined as the difference between the returns on Barclays US 30-year Treasury Index and Barclays US 2-year Treasury Index; *Def* is the difference between the returns on Barclays US Long-Term Corporate Bond Index and Barclays US Long-Term Treasury Index.
Stock+Term+Def	Choi and Kronlund (2018)	*Stock* is the excess return on the CRSP value-weighted equity market index. *Term* is the difference between the returns on Barclays US 30-year Treasury Index and Barclays US 2-year Treasury Index; *Def* is the excess return on the Barclays US Corporate Bond Index.
HY+IG	Aragon et al. (2019)	*HY* is the difference between the returns on Barclays US High Yield Index and Barclays US Corporate Bond Index; *IG* is the excess return on the Barclays US Corporate Bond Index.
Treasury+IG+HY+MBS	Jones and Mo (2021)	*Treasury* is the excess return on the Barclays US Treasury Index. *IG* is the excess return on the Barclays US Corporate Bond Index. *HY* is the excess return on the Barclays US High Yield Index; *MBS* is the excess return on the Barclays US MBS Index.
Stock+Bond+Def+Option	Elton et al. (1995), Bessembinder et al. (2008), Cici and Gibson (2012), Amihud and Goyenko (2013), Chen and Qin (2017), Ma et al. (2019), Wang et al. (2020), Anand et al. (2021)	*Stock* is the excess return on the CRSP value-weighted equity market index; *Bond* is the excess return on the Barclays US Aggregate Bond Index; *Def* is the difference between the returns on Barclays US High Yield Index and Barclays US Intermediate Government Bond Index; *Option* is the difference between the returns on Barclays US GNMA Index and Barclays US Intermediate Government Bond Index.

Notes –This table summarizes the factor models used in the literature to evaluate the performance of government and corporate bond mutual funds.

Table IA10
Comparison of Factor Models' Explanatory Power

Panel A. Comparison with Other Government Bond Factor Models

		Adjusted R^2		Absolute α	
Model	N Obs.	Mean	STD	Mean	STD
Evaluating Benchmark Indices					
Our Four-Factor Model (Baseline)	69	81.6%	24.7%	0.23	0.22
Treasury+Slope+Curvature	69	74.3%	26.5%	0.31	0.58
Treasury	69	70.2%	27.5%	0.31	0.59
Term	69	54.7%	27.4%	0.42	0.55
Evaluating Individual Funds					
Our Four-Factor Model (Baseline)	851	67.3%	20.7%	0.57	0.93
Treasury+Slope+Curvature	851	66.4%	22.0%	0.49	0.71
Treasury	851	63.8%	22.6%	0.50	0.74
Term	851	56.1%	23.0%	0.65	0.79

Panel B. Comparison with Corporate Bond Factor Models

		Adjusted R^2		Absolute α	
Model	N Obs.	Mean	STD	Mean	STD
Evaluating Benchmark Indices					
Stock+Bond+Def+Option	69	75.8%	26.1%	0.16	0.12
Treasury+IG+HY+MBS	69	75.1%	27.5%	0.13	0.29
Stock+Term+Def	69	62.3%	25.4%	0.23	0.14
HY+IG	69	60.9%	24.8%	0.33	0.29
MKT+SMB+HML+Term+Def (V1)	69	58.0%	27.2%	0.36	0.19
MKT+SMB+HML+Term+Def (V2)	69	49.0%	26.0%	0.57	0.26
Evaluating Individual Funds					
Stock+Bond+Def+Option	851	68.0%	21.6%	0.37	0.59
Treasury+IG+HY+MBS	851	68.4%	22.1%	0.32	0.73
Stock+Term+Def	851	58.8%	20.2%	0.53	0.93
HY+IG	851	57.9%	19.8%	0.52	0.80
MKT+SMB+HML+Term+Def (V1)	759	57.7%	21.8%	0.78	0.69
MKT+SMB+HML+Term+Def (V2)	759	48.8%	20.4%	1.13	0.84

Notes – This table evaluates how well different factor models explain returns on government bond indices and individual funds. Panel A compares the baseline four-factor model with alternative government bond factor models. To assess each model's ability to explain benchmark index returns, we regress daily index returns on the factors included in that model and report the mean and standard deviation, across indices, of the adjusted R^2 and the absolute value of α. To evaluate explanatory power for individual government bond funds, we run the same regressions at the fund level and report the corresponding mean and standard deviation, across funds, of the adjusted R^2 and the absolute value of α. Using the same methodology, Panel B reports the explanatory power of corporate bond factor models.

Table IA11

Fund Duration Change and Monetary Policy Shocks – Alternative Activeness Measures

Panel A: Benchmark-Adjusted Activeness									
		Δy^{2YR}	Δy^{5YR}	Δy^{10YR}	Δy^{15YR}	Δy^{20YR}	*MPS*	*Target*	*Path*
Most Active	Coeff.	−2.306	−2.408	−1.915	−1.469	−1.148	−0.269	−0.188	−0.197
	t-stat	(−3.53)	(−2.75)	(−2.28)	(−2.07)	(−1.82)	(−2.54)	(−1.63)	(−2.05)
	Adj.R^2	7.0%	5.2%	3.7%	2.7%	1.7%	3.7%	1.5%	1.7%
Least Active	Coeff.	−0.719	−0.285	0.034	0.312	0.513	−0.211	−0.291	−0.045
	t-stat	(−1.06)	(−0.33)	(0.04)	(0.43)	(0.78)	(−1.42)	(−1.60)	(−0.41)
	Adj.R^2	0.1%	−0.5%	−0.5%	−0.4%	−0.2%	1.6%	3.5%	−0.4%

Panel B: PCA-Based Activeness									
		Δy^{2YR}	Δy^{5YR}	Δy^{10YR}	Δy^{15YR}	Δy^{20YR}	*MPS*	*Target*	*Path*
Most Active	Coeff.	−2.182	−2.005	−1.369	−0.952	−0.681	−0.309	−0.184	−0.253
	t-stat	(−3.73)	(−2.82)	(−2.00)	(−1.58)	(−1.23)	(−2.79)	(−1.48)	(−2.45)
	Adj.R^2	6.3%	3.5%	1.6%	0.8%	0.3%	5.1%	1.4%	3.2%
Least Active	Coeff.	−0.793	−0.694	−0.304	0.001	0.193	−0.151	−0.131	−0.088
	t-stat	(−1.41)	(−1.07)	(−0.53)	(0.00)	(0.40)	(−1.46)	(−1.07)	(−1.08)
	Adj.R^2	0.5%	0.0%	−0.4%	−0.5%	−0.5%	1.0%	0.6%	0.0%

Notes – This table examines the relationship between fund duration change and FOMC outcomes across different quintiles of government bond funds, categorized based on their last-quarter activeness. In Panel A, we construct a benchmark-adjusted activeness. We estimate *Idio* σ using daily observations from quarter $t-1$ by regressing fund excess returns on benchmark index excess returns, where *Idio* σ is the standard deviation of the residuals. In Panel B, we construct a PCA-based activeness by performing principal component analysis (PCA) on *Turnover*, *Idio* σ, and $1 - R^2$ each quarter, and take the first principal component as a proxy for fund activeness. Based on these measures, we calculate the value-weighted change in duration for each quintile group of funds. We then report the predictive power of $\Delta Duration_{t-1}$ for monetary policy shocks. We use the standardized $\Delta Duration_{t-1}$ for each quintile group of funds to predict the FOMC-day changes in Treasury yields (2-20 years) using the model:

$$\Delta y_t^k (\text{or } MPS_t) = a + b \times \Delta Duration_{t-1} + \varepsilon_t.$$

We also report the coefficient estimates using high-frequency monetary policy shocks (*MPS*) from Nakamura and Steinsson (2018), as well as the target and path factors from Gürkaynak, Sack, and Swanson (2005), as additional dependent variables. The standard errors are adjusted for heteroskedasticity, and the t-statistics are provided in parentheses.

Table IA12
Conditional on Additional Fund Characteristics

	Dep. Var. = FOMC-Day Performance α_t^{FOMC}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Idio σ	1.039	0.996	0.911	0.989	1.020	0.974	0.977
	(3.52)	(3.24)	(2.98)	(3.12)	(3.18)	(3.10)	(3.45)
Duration	0.219						0.345
	(0.71)						(1.18)
Log(FamilySize)		0.152					0.148
		(1.19)					(1.32)
Independent			0.387				0.329
			(2.15)				(1.84)
Institutional				0.253			0.314
				(2.63)			(3.00)
Teammanage					−0.099		−0.068
					(−0.50)		(−0.40)
Manager Experience						−0.115	−0.090
						(−1.09)	(−0.93)
Log(Size)	0.067	0.032	0.101	0.095	0.062	0.082	−0.003
	(0.89)	(0.44)	(1.43)	(1.25)	(0.81)	(1.15)	(−0.06)
Log(Age)	−0.049	−0.023	−0.082	−0.074	−0.038	−0.047	0.028
	(−0.61)	(−0.28)	(−0.96)	(−0.83)	(−0.42)	(−0.51)	(0.37)
Fee	−0.018	−0.020	0.012	0.039	0.005	0.009	0.010
	(−0.15)	(−0.16)	(0.10)	(0.31)	(0.04)	(0.07)	(0.09)
Flow	−0.036	−0.018	−0.026	−0.011	−0.009	−0.027	−0.071
	(−0.54)	(−0.26)	(−0.40)	(−0.17)	(−0.13)	(−0.38)	(−1.13)
Momentum	0.520	0.304	0.443	0.382	0.271	0.257	0.537
	(1.12)	(0.81)	(1.04)	(0.98)	(0.73)	(0.70)	(1.18)
Intercept	1.388	1.491	1.389	1.614	1.691	1.658	0.855
	(2.15)	(2.65)	(2.31)	(2.62)	(2.77)	(2.75)	(1.45)
Observations	27,013	27,005	26,760	26,771	26,436	26,384	26,146
R-squared	19.7%	18.0%	17.5%	16.3%	17.4%	17.5%	25.7%
Number of groups	91	91	91	91	91	91	91

Notes – This table reports the Fama-MacBeth regression estimates for the determinants of government bond funds' performance on FOMC days, while accounting for additional fund-level and family-level characteristics. Specifically, we include variables such as fund duration as defined in Table 5 (*Duration*), the logarithm of family size (*Log(FamilySize)*), an *Independent* dummy (set to 1 if the fund operates independently and is unaffiliated with any insurance company, broker, commercial bank, or investment bank), an *Institutional* dummy (set to 1 if the fund's share class is aimed at institutional investors), a *Teammanage* dummy (set to 1 if the fund is managed by multiple managers), and the logarithm of months since the manager entered the fund industry (*Log(Manager Experience)*). For ease of interpretation, all the continuous independent variables are standardized with means of zero and standard deviations of one. The standard errors are Newey-West adjusted with three lags. The t-statistics are in parentheses.