LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Essays in Asset Pricing and Monetary Policy

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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I confirm that Chapter 2 is jointly co-authored with Anna Cieslak, Stephen Hansen and Michael McMahon, and I contributed 25% of this work.

I confirm that Chapter 3 is jointly co-authored with Riccardo Sabbatucci and Andrea Tamoni, and I contributed 33% of this work.

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Abstract

In this thesis, I explore the economic mechanisms by which financial institutions shape asset returns. Additionally, I study the impact of uncertainty on the decision-making processes of the Federal Open Market Committee (FOMC).

The first chapter documents that major equity anomalies earn more than half of their annual risk-adjusted returns during the week before scheduled Federal Open Market Committee (FOMC) announcements. These risk-adjusted returns are primarily driven by equity duration. The duration-driven returns (i) increase with monetary policy uncertainty, (ii) are procyclical, co-moving with the market expectation of federal funds rate changes, and (iii) are reversed after FOMC announcements. I rationalize these findings within a model of temporary price pressure generated by institutional investors facing leverage and tracking-error constraints. Empirical evidence from institutional holdings and trading is consistent with the model's mechanism.

The second chapter (with Anna Cieslak, Stephen Hansen and Michael McMahon) studies how uncertainty affects decision-making by the Federal Open Market Committee (FOMC). We distinguish between the notion of Fed-managed uncertainty vis-á-vis uncertainty that emanates from within the economy and which the Fed takes as given. A simple theoretical framework illustrates how Fed-managed uncertainty introduces a wedge between the standard Taylor-type policy rule and the optimal decision. Using private Fed deliberations, we quantify the types of uncertainty the FOMC perceives and their effects on its policy stance. The FOMC's expressed inflation uncertainty strongly predicts a more hawkish policy stance that is not explained either by the Fed's macroeconomic forecasts or by public uncertainty proxies. We rationalize these results with a model of inflation tail risks and argue that the effect of uncertainty on the FOMC's decisions reflects policymakers' concern with maintaining credibility for the inflation anchor.

In the third chapter (with Riccardo Sabbatucci and Andrea Tamoni), we estimate a demand system linking 401(k) plans ownership of individual stocks and funds to their demand for equities, and quantify the effect of 401(k) stock holdings on investor behavior. We introduce a new variable, stock-level 401(k) ownership, and find it to be a key determinant of investor demand, with a one standard deviation increase in 401(k) ownership leading to 11-19% increase in stock demand. We also estimate the equilibrium price impact of a change in stock-level 401(k) ownership to be positive and increasing over time, consistent with the shift from active to passive investing. Lastly, we document that funds managing a larger fraction of 401(k) assets tilt their portfolios toward winners, high beta and long duration stocks, and they hold less cash.

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Chapter 1

Duration-Driven Returns and Institutional Constraints

Song Xiao[1]

1.1 Introduction

A vast literature in finance is devoted to documenting and understanding market anomalies. Some explanations are risk-based, others are behavioral, and others rely on frictions.[2] In this paper, I contribute to the literature on market anomalies by empirically documenting that major equity anomalies earn more than half of their annual risk-adjusted returns during the week before scheduled Federal Open Market Committee (FOMC) announcements.[3] These risk-adjusted returns can be rationalized as temporary price pressure generated by institutional investors facing leverage and tracking-error constraints, highlighting the crucial role of market frictions. My results also indicate that flows by institutional investors cause asset returns to be predictable even when the flows themselves are predictable.

I consider long-short equity strategies that bet on anomalies such as risk, profitability, value, investment, payout, and volatility. Betting on these anomalies within the 5-day pre-FOMC-announcement window yields an average annual CAPM alpha of 4.57% with a *t*-

[1]Any errors or omissions are my responsibility. I am deeply indebted to Dimitri Vayanos and Dong Lou for advice and guidance. I also thank Anna Cieslak, Andrea Tamoni, Riccardo Sabbatucci, Christopher Polk, Peter Kondor, Walker Ray, Cynthia Balloch, Jane Chen, Ran Shi, Shiyang Huang and Jiantao Huang for helpful comments.

[2]See, for example Fama and French (2015a) and Hou, Xue, and Zhang (2014) for risk-based factor models, and Barber and Odean (2013) for a survey of the literature on behavioral explanations, and Gromb and Vayanos (2010) for a survey of frictions and limits to arbitrage.

[3]There are eight scheduled FOMC meetings in a year, and the risk-adjusted returns accumulated over the corresponding eight weeks exceed half of the annual risk-adjusted returns for major equity anomalies.

statistic of 4.50. This constitutes, on average, 55% of the annual CAPM alpha of these anomalies. Adjusting for well-known risk factors such as market, size, value, and momentum, has limited impact on the long-short returns. These long-short risk-adjusted returns reverse after FOMC announcements.

Crucially, I show these risk-adjusted returns are primarily driven by equity duration. All of the above anomalies take long positions in firms with short duration and short positions in firms with long duration, where duration is measured following Gormsen and Lazarus (2022). The long-short risk-adjusted returns increase with the duration spreads between the short and long legs of equity portfolios. When controlling for the equity-duration factor, which goes long the short-duration firms and short the long-duration firms, the long-short risk-adjusted returns pre-FOMC announcements decrease by 60% on average across anomalies.

I rationalize my empirical findings within a model of institutional investors facing leverage and tracking-error constraints. Institutional investors such as mutual funds, are prohibited from borrowing or can borrow only to a limited extent. These investors are also constrained in how much they can deviate from their benchmark indices, thereby limiting their risk-taking capacity. A common constraint is a bound on the tracking error, which is defined as the standard deviation of the difference between the return of a fund and the return of its benchmark index (e.g., Roll, 1992). Leverage constraints induce investors to deviate from their benchmark indices by overweighting long-duration assets and underweighting short-duration assets (e.g., Black, 1972; Frazzini and Pedersen, 2014b). However, tracking-error constraints limit these deviations. Importantly, the latter effect is time-varying. During times of heightened monetary policy uncertainty, such as the week before FOMC announcements, tracking-error rises, forcing investors to bring their positions closer to their benchmark indices by selling long-duration assets and buying short-duration assets. While the trading is anticipated, I demonstrate that it induces price pressure and return predictability due to order-flow uncertainty (Vayanos and Woolley, 2013).

Empirical evidence from institutional holdings and trading is consistent with the mechanism in my model. I find that financial institutions, such as mutual funds, indeed bring their positions closer to the benchmark indices during the week before scheduled FOMC announcements. On average, throughout the year, actively managed equity mutual funds overweight long-duration stocks and underweight short-duration stocks in their portfolios. They reduce their active weights, however, in the week prior to FOMC announcements by selling long-duration stocks and buying short-duration stocks.

Besides explaining my main empirical findings, my model also generates additional predictions. First, an increase in monetary policy uncertainty intensifies price pressure, leading to lower risk-adjusted returns on long-duration assets and higher risk-adjusted returns on short-duration assets. Second, following the resolution of uncertainty after FOMC announcements, the model predicts an immediate return reversal.

I empirically test my model's predictions using two methodologies: a portfolio approach and a stock-level panel regression approach. In the first approach, I sort stocks into deciles on duration, using breakpoints based on NYSE firms. I show that, in line with my model, the long-duration decile underperforms with a daily risk-adjusted return of -5.23 bps (t =-2.04) during the 5-day pre-FOMC-announcement window compared to other days while the short-duration decile outperforms with a daily risk-adjusted return of 3.08 bps (significant at the 10% level). Additionally, I find that a one standard deviation increase in monetary policy uncertainty leads to a 6.82 bps (t=2.10) decrease in risk-adjusted returns for the long-duration decile, while it leads to a 4.00 bps (t=2.04) increase in risk-adjusted returns for the short-duration decile, an observation consistent with my model's prediction. Lastly, my empirical results indicate that the long-duration decile exhibits 12.90 bps (t=3.23) higher risk-adjusted returns in the 3-day window after FOMC announcements compared to other days, whereas the short-duration decile yields 5.32 bps (t=2.17) lower risk-adjusted returns post-FOMC announcements than on other days. These findings thus suggest that, consistent with the model's prediction, duration-driven returns are reversed after FOMC announcements.

In the second approach, I regress daily risk-adjusted stock returns on a long-duration indicator which is equal to one if a stock is in the long-duration decile and zero in the short-duration decile. The regression results suggest that long-duration stocks on average exhibit a daily risk-adjusted return that is 10 bps (t=3.62) lower than short-duration stocks during the week before FOMC announcements. Incorporating additional controls, such as stock size, industry effects, and FOMC meeting fixed effects, does not drive out the main result. Furthermore, consistent with the model's implications, regression results reveal that long-duration stocks underperform pre-FOMC announcements especially (i) when monetary policy uncertainty is high, (ii) when the market anticipates a monetary policy tightening, and (iii) among stocks with high liquidity cost. Monetary policy tightening creates volatility in financial markets, especially for long-duration stocks. Hence, the selling pressure on long-duration stocks is stronger due to tighter tracking-error constraints. Moreover, the selling pressure is expected to have a larger price impact on less liquid stocks.

To further substantiate the economic mechanism, I show that tracking-error constraints are likely to bind in the 5-day pre-FOMC-announcement window during which uncertainty builds. The realized stock market volatility is elevated in the window, leading to a notable increase in portfolio volatilities and tracking-error variances. Additionally, realized Treasury yield volatility also rises in the window. Long-duration stocks, which are sensitive to interest rates changes, exhibit higher realized volatilities in the week before FOMC announcements.

The elevated volatilities of long-duration stocks further exacerbate the tightness of tracking-error constraints, as equity mutual funds overweight long-duration stocks in their portfolios. I also document that the duration-driven returns pre-FOMC announcements increase with the realized volatility of the S&P 500 index and realized Treasury yield volatility, which serve as proxies for the tightness of tracking-error constraints.

Based on Morningstar mutual fund holdings, I find that equity mutual funds overweight long-duration stocks and the active weights on long-duration stocks move closely with the Treasury security-based funding liquidity which is widely considered as a measure of the leverage-constraint tightness, an observation that corroborates my economic interpretations.[4] Furthermore, institutional trading in Ancerno data reveals that equity mutual funds indeed move close to the benchmark indices during the week before FOMC announcements. I find equity mutual funds sell long-duration stocks pre-FOMC announcements, particularly among funds with high tracking errors. This is due to the fact that high-tracking-error funds deviate more from benchmark indices by allocating higher portfolio weights on long-duration stocks. Furthermore, the sale of long-duration stocks prior to FOMC announcements cannot be explained by mutual fund flows. I show that equity mutual funds, on average, sell the long-duration portfolio by approximately 8 bps (of AUM) per day in the pre-FOMC-announcement window, implying that they reduce 16%–20% of their active weights on long-duration stocks in the trading week before FOMC announcements. Conversely, these mutual funds appear to increase their holdings in the short-duration portfolio by 2 bps (of AUM) per day during the week before FOMC announcements.

I conclude the paper by conducting a series of robustness checks. First, I show that the duration-driven returns are not explained by outliers and time-varying betas around FOMC announcements, and that they remain robust to alternative measures of duration and monetary policy uncertainty. Second, I construct double-sorted portfolios based on duration and mutual fund active weights to examine how portfolio risk-adjusted returns pre-FOMC announcements vary in mutual fund active weights, independent of duration. My findings indicate that exclusively long-duration stocks overweighted by mutual funds underperform, while short-duration stocks, particularly those underweighted by mutual funds, tend to outperform. Lastly, I demonstrate that duration-driven returns are significant during high monetary policy uncertainty days, but not for other macroeconomic announcements. This evidence further corroborates the economic mechanism, suggesting that heightened monetary policy uncertainty tightens the tracking-error constraints, inducing shifts in investors' demand for long-duration assets and short-duration assets.

[4] The Treasury security-based funding liquidity is grounded in the theory proposed by Gromb and Vayanos (2002) that arbitrage violations should be more frequent if arbitrageurs are leverage constrained, see Fontaine and Garcia (2011).

This paper complements existing literature on the effects of FOMC announcements. Lucca and Moench (2015) find large average equity excess returns before FOMC announcements. Cieslak, Morse, and Vissing-Jorgensen (2019) document a biweekly pattern in stock market excess returns over the FOMC cycle. In contrast, this paper investigates the risk-adjusted returns of major equity anomalies. Unlike Ozdagli and Velikov (2020) and Ai, Han, Pan, and Xu (2022), who explore the cross-sectional excess returns in response to monetary policy shocks, I link the cross-sectional return heterogeneity to equity duration and mainly focus on the abnormal risk-adjusted returns before FOMC announcements. Additionally, Neuhierl and Weber (2017) document sizable stock market drifts pre- and post-FOMC announcements with signs depending on the direction of monetary policy surprises. This paper demonstrates large duration-driven returns during the week before scheduled FOMC announcements and return reversals post-FOMC announcements, regardless of monetary policy surprises.

This paper is related to the emerging literature linking equity duration to asset prices (e.g., Dechow, Sloan, and Soliman, 2004; Lettau and Wachter, 2007, 2011; Weber, 2018a; Gonçalves, 2021; Gormsen and Lazarus, 2022). These works document a downward-sloping term structure of equity returns. Weber (2018a) attributes the downward-sloping term structure of equity returns to mispricing. This paper extends Weber (2018a) by showing that the mispricing is particularly pronounced pre-FOMC announcements and increases with monetary policy uncertainty. Most recently, the findings of Gormsen and Lazarus (2022), which suggest that long-duration stocks tend to be high-beta, high-investment, low-profitability, low-payout, and growth stocks, are consistent with my findings of significant duration-driven returns on major equity anomalies before FOMC announcements.

The notion that demand shocks can push asset prices away from fundamental values is highlighted in the literature on the limits of arbitrage, surveyed in Gromb and Vayanos (2010). Prior research (e.g., Shleifer, 1986; Chen, Noronha, and Singal, 2004; Boyer, 2011) has established that index additions and deletions, even in mechanically constructed indices, can have strong effects on stock prices. These index effects seem to be driven by shifts in the demand of institutional investors that passively hold an index or are benchmarked against an index. Research in this area is currently evolving into a broader agenda that focuses on the role of financial institutions and agency frictions in shaping asset prices. One important strand of research studies that flow-induced buying and selling pressure can have large price effects (e.g., Coval and Stafford, 2007; Lou, 2012; Anton and Polk, 2014). Other research underscores that the presence of agency frictions has the potential to explain "market anomalies". For instance, Buffa, Vayanos, and Woolley (2022a) model agency frictions in asset management and provide an explanation for risk-return inversion.

This paper extends the literature by documenting that tight institutional constraints can generate demand shocks, thereby amplifying anomalies.

This paper also contributes to the growing literature on asset management and asset pricing (e.g., Cuoco and Kaniel, 2011; Basak and Pavlova, 2013; Pavlova and Sikorskaya, 2022). The closest paper to mine is Lines (2016), which documents that increasing volatility between quarters puts downward price pressure on overweight stocks and upward price pressure on underweight stocks. My paper distinguishes itself by focusing on major equity anomalies and duration-driven returns around FOMC announcements. Furthermore, I link equity duration to mutual fund holdings and provide empirical evidence from institutional trading.

The remainder of the paper proceeds as follows. Section 1.2 introduces the model. Section 3.2 describes the data used in my empirical analysis. In Section 1.4, I document my main empirical findings about the duration-driven returns and their properties. Section 1.5 provides supporting evidence, and Section 1.6 concludes.

1.2 Theoretical Framework

In this section, I introduce a model that studies the combined effects of leverage constraints and tracking-error constraints faced by institutional investors.[5] On the one hand, leverage-constrained investors deviate from their benchmark indices by overweighting long-duration assets and underweighting short-duration assets, but on the other hand, tracking-error constraints impose a bound on the extent to which investors can deviate from their benchmarks. During times of heightened monetary policy uncertainty, such as the week before FOMC announcemnts, tight tracking-error constraints force investors to bring their positions closer to the benchmark indices, thereby inducing selling pressure on long-duration assets and buying pressure on short-duration assets.

1.2.1 The Model Setup

There are three periods, $t = 0, 1, 2$. The financial market consists of N risky assets paying dividends $D_{t,i}$, $i = 1, ..., N$ in periods $t = 1, 2$, and a riskless asset with an interest rate

[5]These are two realistic constraints confronted by mutual funds. For example, Frazzini and Pedersen (2014b) and Boguth and Simutin (2018) demonstrate that active mutual funds face leverage constraints, and the tightness of those leverage constraints predicts stock returns. Buffa, Vayanos, and Woolley (2022a) presents evidence that mutual funds face tight tracking-error constraints. He and Xiong (2013) argue that tracking-error constraints act as a cost-efficient monitoring device on asset managers.

normalized to zero. Dividends of risky assets follow

$$D_{t,i} = \bar{D}_i + \beta_i Z_t + \epsilon_i \,, \tag{1.1}$$

where $\bar{D}_i \geq 0$ is a constant for asset i. $\epsilon_i \sim N(0, \eta^2)$ is an idiosyncratic shock, which is assumed to be independent across assets. $Z_t = Z\mathbb{1}_{t=2}$, where Z is a common shock in period 2, captures the shock to dividends due to the interest rate shock.[6] Investors are uncertain about the monetary policy decision at $t = 2$ when making portfolio decisions at $t = 0$ and $t = 1$. More specifically, I assume that investors in period 1 learn that the shock to dividends is normally distributed with mean μ and variance σ^2 and is independent of ϵ. Investors in period 0, however, lack knowledge of the exact value of μ. Instead, they have a belief on μ as $\mu \sim N(0, \sigma_\mu^2)$. Throughout the paper, it is assumed that σ and η are common knowledge to investors in all periods and that $\sigma_\mu^2 \ll \sigma^2$. Thus, σ serves as a proxy for the monetary policy uncertainty. Period 1 corresponds to the pre-FOMC-announcement window in which market participates are highly uncertain about the future stance of monetary policy. Period 2 refers to the FOMC announcement day on which the interest rate decision is made. β_i, which is interpreted as asset duration, measures the sensitivity of asset dividends to the changes in interest rates. I assume $\beta_i > 0$ for all assets.

Risky assets are in supply of $\theta \equiv (\theta_1, ..., \theta_N)'$ shares. The price of risky assets $S_t \equiv (S_{t,1}, ..., S_{t,N})$ in period t will be determined endogenously in the model. There is a benchmark portfolio in the economy which is used to evaluate the performance of investors universally, that is, the market index. I denote by $\phi_{b,i}$ the number of shares of risky asset i in the benchmark portfolio, and by $\phi_b \equiv (\phi_{b,1}, ..., \phi_{b,N})'$ the vector of shares of risky assets. The share supply θ_i of asset i can be different from $\phi_{b,i}$ due to the unmodeled noise traders' demand. Moreover, I assume θ and ϕ_b are constant over all periods.

In each period, there is a continuum of investors with measure one. They are of two types: *unconstrained investors* and *constrained investors*. Unconstrained investors, who can invest in all assets without any constraints, are in measure $1 - x \in (0, 1)$. They demand risky assets in periods 0 and 1 to maximize the constant absolute risk aversion (CARA) utility over terminal wealth in period 2. Constrained investors, however, are overlapping generations that are born each time period with the complementary measure x, and live for two periods. They have a CARA preference over terminal wealth. Most crucially, constrained investors in each generation are confronted with both leverage and tracking-error constraints when they make portfolio decisions. I denote unconstrained investors by the subscript u and constrained investors by the subscript c. All types of investors have the same coefficient of

[6] The dividend paid at $t = 2$ can be considered as the present value of all future cash flows of an asset. Thus, changes in interest rates affect the present value.

absolute risk aversion γ.

Specifically, unconstrained investors demand the number of shares in risky assets $\phi_{0,u}$ and $\phi_{1,u}$ to maximize their utility

$$-\mathbb{E}_0\left(e^{-\gamma W_{2,u}}\right) \tag{1.2}$$

subject to the budget constraints

$$W_{t+1,u} = W_{t,u} + \phi'_{t,u}\left(D_{t+1} + S_{t+1} - S_t\right), \tag{1.3}$$

where $t = 0, 1$. $W_{t,u}$ is the wealth of unconstrained investors in period t. $\phi_{t,u}$ denotes the number of shares invested in risky assets by unconstrained investors in period t. $D_{t+1} + S_{t+1} - S_t$ is the share returns of risky assets as the interest rate of the riskless asset has been normalized to zero. The capital gains for investors' portfolio are equal to the number of shares times the share returns.

On the other hand, constrained investors born in period t choose a portfolio $\phi_{t,c}$ to maximize their utility

$$-\mathbb{E}_t\left(e^{-\gamma W_{t+1,c}}\right) \tag{1.4}$$

subject to the budget constraint (1.5), the leverage constraint (1.6), and the tracking-error constraint (1.7).

$$W_{t+1,c} = W_{t,c} + \phi'_{t,c}\left(D_{t+1} + S_{t+1} - S_t\right) \tag{1.5}$$

$$L\phi'_{t,c}S_t \leq W_{t,c} \tag{1.6}$$

$$(\phi_{t,c} - \phi_b)'\Sigma_t(\phi_{t,c} - \phi_b) \leq \tau \tag{1.7}$$

The leverage constraint (1.6) requires that the dollar amount $\phi'_{t,c}S_t$ invested in risky assets multiplied by a constant leverage factor L must be less than or equal to investors' initial wealth. For instance, when $L = 1$, investors are simply not allowed to use leverage; On the other hand, investors with $L > 1$ are required to retain some of their wealth in cash, while those with $L < 1$ can use leverage but are subjected to margin constraints. The tracking-error constraint (1.7) is in the spirit of Buffa, Vayanos, and Woolley (2022a). It imposes a limit on the variance of the portfolio payoff compared to the benchmark portfolio. $\phi_{t,c} - \phi_b$ is the active shares of the constrained investors' portfolio compared to the benchmark. $\Sigma_t \equiv \mathbb{V}ar_t(D_{t+1} + S_{t+1})$ represents the variance-covariance matrix of asset payoffs. τ is the bound on the tracking variance. If $\tau = 0$, constrained investors must hold the benchmark portfolio. On the other hand, if $\tau = \infty$, the tracking-error constraint is never binding and their optimal portfolio allocations are exclusively determined by the tightness of the leverage constraint.

1.2.2 Portfolio Choice and Equilibrium Prices

Constrained investors of generation t demand the number of shares in risky assets determined by

$$\phi_{t,c} = \frac{1}{\gamma + 2\lambda_t}\Sigma_t^{-1}\left[\mathbb{E}_t(D_{t+1} + S_{t+1}) - (1+\varphi_t)S_t\right] + \frac{2\lambda_t}{\gamma + 2\lambda_t}\phi_b\,, \tag{1.8}$$

where $\varphi_t \geq 0$ is the Lagrange multiplier on the leverage constraint and $\lambda_t \geq 0$ is the Lagrange multiplier on the tracking-error constraint.

The optimal portfolio of constrained investors is a weighted average of a leverage-constrained portfolio and the benchmark portfolio. When neither the leverage constraint nor the tracking-error constraint is binding (i.e., $\varphi_t = 0$ and $\lambda_t = 0$), constrained investors simply hold a standard mean-variance portfolio. If the leverage constraint is binding but the tracking-error constraint is not (i.e., $\varphi_t > 0$ and $\lambda_t = 0$), the optimal portfolio for constrained investors reduces to a leverage-constrained portfolio as in Frazzini and Pedersen (2014b). However, if the tracking-error constraint is binding (i.e., $\lambda_t > 0$), investors must tilt their positions toward the benchmark portfolio. In other words, the tightness of the tracking-error constraint imposes a limit on how much constrained investors can deviate from the benchmark portfolio. Consequently, changes in the tightness of the tracking-error constraint induce shifts in investors' demand for risky assets.

In contrast, the optimal demand of *unconstrained investors* is given by

$$\phi_{1,u} = \frac{1}{\gamma}\Sigma_1^{-1}[\mathbb{E}_1(D_2) - S_1] \tag{1.9}$$

$$\phi_{0,u} = \frac{1}{\gamma}\left(\eta^2 I + \left(\frac{a_1}{1-a_1}\right)^2 \Sigma_x(I + \Sigma_1^{-1}\Sigma_x)^{-1}\right)^{-1}\left(2\bar{D} - K - S_0 - \frac{a_1}{1-a_1}\Sigma_x(I + \Sigma_1^{-1}\Sigma_x)^{-1}\Sigma_1^{-1}K\right) \tag{1.10}$$

where $a_1 = \frac{\gamma+2\lambda_1-2\lambda_1 x}{\gamma+2\lambda_1-2\lambda_1 x+x\varphi_1\gamma}$, $b_1 = \frac{\gamma(\gamma+2\lambda_1)}{\gamma+2\lambda_1-2\lambda_1 x+x\varphi_1\gamma}$, $\Sigma_x = (1-a_1)^2\beta\beta'\sigma_\mu^2$, and $K = (1-a_1)\bar{D} + b_1\Sigma_1\left(\theta - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_b\right)$.[7]

In equilibrium, assets market clearing requires that the aggregate demand equals the asset supply in all periods:

$$(1-x)\phi_{t,u} + x\phi_{t,c} = \theta \tag{1.11}$$

[7] All proofs are in the Appendix 1.A.2.

Proposition 1.1. *The equilibrium asset prices are determined by*

$$\begin{aligned}S_1 &= a_1\mathbb{E}_1(D_2) - b_1\Sigma_1\left(\theta - \frac{2\lambda_1 x}{\gamma + 2\lambda_1}\phi_b\right)\\ S_0 &= (a_0 I + b_0 k_1 \beta\beta')\mathbb{E}_0(D_1 + S_1) - \eta^2 b_0 \Sigma_s\left(\theta - \frac{2\lambda_0 x}{\gamma + 2\lambda_0}\phi_b\right) - k_2\beta\beta' K\end{aligned} \tag{1.12}$$

where $\Sigma_s = I + \sigma_s^2\beta\beta'$*,* a_t*,* b_t*,* σ_s^2*,* k_1*, and* k_2 *are positive constants.*

Equations (1.12) illustrate that asset prices are increasing in expected future payoffs. Conversely, an increase in asset supply is associated with a decrease in asset prices. Furthermore, this proposition elucidates the index effect, which indicates that the addition of an asset to the benchmark index or an increase in the benchmark shares results in a rise in asset prices. The index effect arises in the model only if the tracking-error constraint is binding such that constrained investors have inelastic demand for assets in the benchmark index.

Substituting the price equations (1.12) into equation (1.8), we can find the optimal allocation of constrained investors in period 0 and the following result.

Proposition 1.2. *Assume that the leverage constraint is binding in period 0, that is,* $\varphi_0 > 0$*, and* σ_μ^2 *is small. Then, constrained investors tilt their portfolio toward long-duration assets, that is,* $\partial\phi_{0,c}^i/\partial\beta_i > 0$*.*

This proposition demonstrates that the leverage constraint creates an incentive to overweight long-duration assets. The economic intuition is essentially the same as in Frazzini and Pedersen (2014b), where leverage-constrained investors opt to overweight risky (high beta) assets. Long-duration assets are viewed as risky in the model as they are affected the most by the change in interest rates. In fact, Gormsen and Lazarus (2022) empirically show that high-beta stocks are likely to be long-duration stocks as firms with long cash-flow duration are more exposed to the discount-rate shocks which account for much of the variation in market returns, causing them to co-move more with the market and thus have high betas. In Section 1.5.1, I establish that, consistent with the predictions, active equity mutual funds collectively overweight long-duration stocks and underweight short-duration stocks in their holdings.

Subsequently, I characterize how uncertainty about the future stance of monetary policy impacts asset prices and expected risk-adjusted returns. I denote by $\alpha_{t,i}$ the expected risk-adjusted return of asset i in period t, where the return is adjusted by the market risk. For instance, $\alpha_{1,i}$ is the constant in the regression of the asset's return $e_i'(D_1 + S_1 - S_0)$ on the market index return $\phi_b'(D_1 + S_1 - S_0)$ in period 1:

$$e_i'(D_1 + S_1 - S_0) = \alpha_{1,i} + \beta_{1,i}^{MKT}\phi_b'(D_1 + S_1 - S_0) + \xi_i\,,$$

where e_i is a $n \times 1$ vector with a 1 in row i and zeros elsewhere. The regression yields

$$\begin{aligned}\beta_{1,i}^{MKT} &= \frac{\phi_b'\Sigma_0 e_i}{\phi_b'\Sigma_0\phi_b} \\ \alpha_{1,i} &= e_i'\mathbb{E}(D_1 + S_1 - S_0) - \frac{\phi_b'\Sigma_0 e_i}{\phi_b'\Sigma_0\phi_b}\phi_b'\mathbb{E}(D_1 + S_1 - S_0).\end{aligned}$$

Since period 2 corresponds to the FOMC announcement day, I interpret $\alpha_{1,i}$ and $\alpha_{2,i}$ as, respectively, the pre-and post-FOMC risk-adjusted returns.

Proposition 1.3. *Suppose $\lambda_1 > 0$; that is, the tracking-error constraint is binding in period 1. We find that*

- *$\partial\alpha_{1,i}/\partial\sigma^2 > 0$ if $\phi_{1,c}^i - \phi_{b,i} < N_{1,i}$ and $\partial\alpha_{1,i}/\partial\sigma^2 < 0$ if $\phi_{1,c}^i - \phi_{b,i} > N_{1,i}$, where $N_{1,i}$ is an asset-specific constant. Hence, pre-FOMC risk-adjusted returns of underweight (overweight) assets increase (decrease) in monetary policy uncertainty.*

- *$\partial\alpha_{2,i}/\partial\sigma^2 > 0$ if $\phi_{1,c}^i - \phi_{b,i} > N_{2,i}$ and $\partial\alpha_{2,i}/\partial\sigma^2 < 0$ if $\phi_{1,c}^i - \phi_{b,i} < N_{2,i}$, where $N_{2,i}$ is an asset-specific constant. Hence, post-FOMC risk-adjusted returns of underweight (overweight) assets decrease (increase) in monetary policy uncertainty, indicating post-announcement return reversals.*

The first part of the proposition establishes that in the presence of tight tracking-error constraints, rising monetary policy uncertainty leads to an increase in expected risk-adjusted returns of underweight assets pre-FOMC announcements. Conversely, the pre-FOMC risk-adjusted returns of overweight assets decrease in monetary policy uncertainty. This is due to two facts. Firstly, the binding tracking-error constraint brings the position of constrained investors closer to the benchmark. As indicated by equation (1.8), the demand for benchmark assets by constrained investors is increasing in the tightness of the tracking-error constraint. Moreover, the tracking-error constraint becomes tighter when monetary policy uncertainty rises.[8] As a result, the rising monetary policy uncertainty puts selling pressure on overweight assets and buying pressure on underweight assets, which further leads to underpricing for overweight assets and overpricing for underweight assets in period 1.

Secondly, although the temporary demand shock stemming from constrained investors causes overweight assets to be underpriced, the decrease in risk-adjusted returns of overweight

[8]See the formal proof that $\partial\lambda_1/\partial\sigma^2 > 0$ by Lemma 2 in the Appendix.

assets in period 1 is yet puzzling, and vice-versa for underweight assets. Why is the well-anticipated demand shock not fully reflected into the price in period 0? The economic intuition is that unconstrained investors prefer to guarantee an attractive return rather than expose themselves to the risk that underpricing may cease to exist—the so-called "bird in the hand" effect in Vayanos and Woolley (2013). To be more precise, the temporary demand shock in period 1 induces underpricing for overweight assets and offers an attractive return in period 2. However, due to the uncertainty on the direction of monetary policy, the selling pressure on overweight assets may not materialize, in which case the underpricing would cease to exist. For instance, constrained investors, when anticipating accommodative monetary policy, may even demand more of assets they already overweight due to an increase in D_i, as indicated by (1.8). Therefore, unconstrained investors in the model prefer to buy assets in period 0 to guarantee an attractive return in period 2, which effectively prevents the price in period 0 from dropping to a level that fully reflects constrained investors' demand shock.

The second part of Proposition 1.3 illustrates that the price distortions due to the tight tracking-error constraint are temporary. Once uncertainty has been resolved on the FOMC announcement day, asset prices will revert to their fundamental values. The model thus predicts return reversals post-FOMC announcements, giving rise to higher risk-adjusted returns for overweight assets and lower risk-adjusted returns for underweight assets.

Combining the results with Proposition 1.2, the model demonstrates that the high uncertainty about the future stance of monetary policy at $t = 2$ can induce price distortions in the cross section in period 1 by generating temporary demand shocks. Tight tracking-error constraints creates selling pressure on long-duration assets and buying pressure on short-duration assets. Consequently, higher levels of monetary policy uncertainty imply higher duration-driven returns pre-FOMC announcements.

1.3 Data

1.3.1 Mutual Fund Data

Mutual fund holdings and fund characteristics, such as fund domicile, category, investment type, the primary prospectus benchmark, and total net assets (TNA), are obtained from Morningstar Direct. There is a rising trend in adopting the Morningstar mutual fund database in academic research due to its exceptional quality.[9] Since the focus of this paper is

[9] Morningstar provides exhaustive mutual fund holdings compared to other mutual fund holding databases, such as CRSP and Thomson Reuters Mutual Funds Holding (s12). For example, Schwarz and Potter (2016) find that CRSP misses many SEC-mandated portfolios available in SEC filings. Berk and van Binsbergen (2015) identify several shortcomings in the CRSP mutual fund data and instead opt to use Morningstar data. This choice has been increasingly adopted in current academic literature, such as Pástor, Stambaugh,

on the price pressure stemming from benchmarking incentives, I include all actively managed domestic equity mutual funds in the sample.

Specifically, I require the fund domicile to be the United States. To ensure the sample only includes equity mutual funds, I closely follow the approach in Pástor, Stambaugh, and Taylor (2015) to exclude bond funds, money market funds, target retirement funds, funds of funds, industry funds, real estate funds and other non-equity funds by using the CRSP objective code and the Morningstar category variable. Additionally, I exclude funds identified by CRSP or Morningstar as index funds and any funds with “index” in their names. I also exclude exchange-traded funds (ETFs) identified by the ETF flag in Morningstar. Lastly, I require the ratio of equity holdings to total net assets to fall within the range of 0.6 to 2. The lower bound is necessary to filter out non-equity mutual funds, while the upper bound serves to eliminate possible data errors.

After applying these screening procedures, my sample includes 4256 actively managed domestic equity mutual funds from 1988 to 2021. For active mutual funds with multiple share classes in Morningstar, the total net assets of the fund are calculated by aggregating the TNA across all share classes. For net returns and expense ratios, I compute the TNA-weighted average across all share classes. For other fund characteristics, such as the primary prospectus benchmark, I use the data from the share class with the largest total net assets. Figure 1.A.1 illustrates the number of active mutual funds in each year, along with their benchmarks, and summary statistics of fund total net assets and equity holdings. There is an increasing trend in both the number of funds and average fund size. A large majority of funds benchmark against the S&P 500 index. In addition, the fraction of the U.S. equity market held by mutual funds in my sample steadily increases from less than 2% before 1990 to 11% since 2006, similar to estimates presented in the literature.

1.3.2 Institutional Trading Data

The Abel Noser (also known as Ancerno) data is a proprietary dataset of institutional equity trading. It contains institutional trading transactions from mutual funds, hedge funds, and pension funds between January 1999 and September 2011. It provides detailed information regarding each transaction, including trade date, stock traded (CUSIP), trade direction (buy or sell), shares traded, and the execution price. Prior literature has documented that institutions in Ancerno dataset cover 8% of CRSP trading volume and 10% of institutional trading volume (e.g., Puckett and Yan, 2011). Moreover, the dataset is free of survivorship and backfill biases.

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and Taylor (2015) and Dou, Kogan, and Wu (2020).

While the Ancerno data includes several variables to identify institutional clients, identities of individual funds are concealed.[10] As a result, it is challenging to merge Ancerno institutional trading with Morningstar mutual fund characteristics, such as total net assets, tracking errors, and fund flows. To overcome this problem and examine mutual fund trading around FOMC announcements, I begin by isolating mutual funds as managers that are not hedge funds or pension funds. Specifically, I distinguish investment managers (namely, mutual funds and hedge funds) within the Ancerno data using the "clienttype" variable. "clienttype" identifies the type of institutional clients, for instance, pension funds (*clienttype*= 1), investment managers (*clienttype*= 2). I then use Form ADV to filter out hedge funds from investment managers following the methodology introduced by Jame (2018). Next, I reverse engineer and uncover mutual fund identities by comparing the transaction data in Ancerno with Morningstar mutual fund holdings. To be more specific, I implement a non-trivial algorithm to identify mutual funds in the Ancerno dataset by matching the changes in the stock holdings indicated by the transaction data with the changes in the holdings reported in Morningstar following the approached outlined in Agarwal, Tang, and Yang (2012). I further merge the matched data with Morningstar mutual fund characteristics and keep only active equity mutual funds for analysis. To ensure accuracy, I manually validate each match by comparing fund names from Morningstar with client manager names provided by Ancerno. The detailed matching procedures can be found in the Appendix 1.A.3.

I end up with a dataset comprising 394 actively managed domestic equity mutual funds, which belong to 89 fund-managing firms with 4.4 funds in each managing firm on average. The quantity of mutual funds matched within my sample is akin to the research conducted by Binsbergen, Han, Ruan, and Xing (2022), wherein they identified 331 active equity mutual funds through a similar matching process of Ancerno data with mutual fund holdings in Thomson Reuters. The slightly greater number of matches in my sample could be attributed to the superior quality of Morningstar mutual fund holdings data.

1.3.3 Other Data

Stock returns and characteristics: Daily stock returns, dividends, and shares are obtained from the Center for Research in Security Prices (CRSP) database. I supplement the CRSP daily data with stock characteristics from Compustat and the Open Source Asset Pricing shared by Chen and Zimmermann (2022). Throughout this paper, the equity-duration mea-

[10]Variables identifying institutional clients include, for example, *managercode*, *clienttype*, and *clientmgrcode*. *managercode* is used to identify the asset management firm, such as Fidelity or State Street. *clienttype* identifies the type of institutional clients. *clientmgrcode* identifies funds; however, it may change over time for the same fund and is not very reliable.

sure follows the method developed in Gormsen and Lazarus (2022). Other equity-duration measures are also employed as robustness checks, such as those from Weber (2018a). I construct duration-sorted portfolios by sorting stocks into deciles based on equity duration using NYSE breakpoints. Portfolios are value-weighted and rebalanced at the end of each calendar month. The long-duration portfolio is the highest 10% tail while the short-duration portfolio is the lowest 10% tail.

High-frequency stock prices: I construct a high-frequency stock price dataset with 5-minute sampling frequency from January 1994 to December 2022 for common stocks (i.e., share codes 10 and 11) that trade on the NYSE, AMEX, and NASDAQ (i.e., exchange codes 1, 2, and 3). The high-frequency prices are obtained from the "TAQ Monthly" (pre-2015) and "TAQ Daily" (post-2015). The data was cleaned following the procedures in Barndorff-Nielsen, Hansen, Lunde, and Shephard (2009) and Aleti and Bollerslev (2022). Then, I calculate 5-minute stock returns using the high-frequency stock prices. I next compute 5-minute value-weighted returns for duration-sorted portfolios and estimate their daily realized volatilities. Further details about TAQ data cleaning and high-frequency volatility estimation can be found in Appendix 1.A.4. I also supplement the realized 5-minute stock volatilities with 5-minute realized volatility of the S&P 500 index from the Oxford-Man Institute's realized library.

Realized bond yield volatilities: Realized bond yield volatilities are estimated by using high-frequency data on the pricing of U.S. 10-year Treasury bonds from January 1997 through December 2018, which was gathered by splicing historical observations from two platforms: GovPX (pre-2000) and BrokerTec (post-2000) following the approach of Cieslak and Povala (2016).[11] Yield volatility is estimated with 10-minute sampling frequency and is reported in basis points per annum. I select 10-year Treasury bonds for two reasons. On one hand, equity duration is relatively long, making it appropriate to consider long-term bond yield volatility in this context. On the other hand, 10-year Treasury bonds are much more liquid than other long-term Treasury bonds, such as 30-year Treasury bonds (e.g., Fleming and Mizrach, 2008).

Uncertainty indices: As a proxy for market uncertainty about monetary policy, I acquire the Merrill Lynch Option Volatility Estimate (MOVE) index from Bloomberg. The MOVE index is a weighted average of basis point volatility for one-month Treasury options across bond maturities, measuring market uncertainty about medium- or long-term interest rates.

[11] I deeply thank Anna Cieslak for kindly sharing her data and codes.

1.4 Duration-Driven Returns

This section presents my main empirical findings that more than half of the risk-adjusted returns of major equity anomalies accrue during the week before scheduled Federal Open Market Committee (FOMC) announcements. Crucially, I show these risk-adjusted returns are primarily driven by equity duration. All of these anomalies take long positions in firms with short duration and short positions in firms with long duration. In addition, I document that the duration-driven risk-adjusted returns, in line with my model predictions, (i) increase with monetary policy uncertainty; (iii) are procyclical, comoving with the market expectation of federal funds rate changes; and (iii) are reversed after FOMC announcements.

1.4.1 Anomalies around FOMC Announcements

I empirically document that a broad set of long-short strategies betting on major equity anomalies in the 5-day pre-FOMC-announcement window exhibit economically and statistically significant risk-adjusted returns, which are subsequently reversed after FOMC announcements. Table 1.1 presents a catalog of these anomalies in detail, including their long-short legs. These anomalies originate from a diverse set of categories, including risk, profitability, value, investment, payout and volatility. Table 1.2 reports the summary statistics for daily risk-adjusted returns of each long-short equity strategy for the 5-day pre-FOMC-announcement window (Panel A), FOMC announcement days (Panel B), and the full sample (Panel C).

Table 1.1: Anomaly Long-Short Trading Strategies.

This table presents the details of anomaly long-short strategies that are particularly profitable in the pre-FOMC-announcement window, that is, the five trading days before each scheduled FOMC announcement. There are eight scheduled FOMC meetings in a year. Therefore, the long-short strategies apply to 40 days a year.

Anomaly Names	**Category**	**Literature**	**Long Leg**	**Short Leg**
CAPM Beta	Risk	Fama and MacBeth (1973)	Low beta	High beta
Operating Profitability	Profitability	Fama and French (2006)	High profit	Low profit
EPS Forecast	Profitability	Cen, Wei, and Zhang (2006)	High forecast	Low forecast
Return on Equity	Profitability	Haugen and Baker (1996)	High ROE	Low ROE
Fundamental-to-Market	Value	Gonçalves and Leonard (2023)	Value	Growth
Net Operating Assets	Investment	Hirshleifer, Hou, Teoh, and Zhang (2004)	Low investment	High investment
Net Payout Yield	Payout	Boudoukh, Michaely, Richardson, and Roberts (2007)	High yield	Low yield
Idiosyncratic Volatility	Volatility	Ang, Hodrick, Xing, and Zhang (2006)	Low ivol	High ivol
Firm Age	Other	Zhang (2006)	Old	Young
Duration	Duration	Gormsen and Lazarus (2022)	Short duration	Long duration

Table 1.2: Anomaly Long-Short Returns.

This table reports summary statistics of anomaly long-short returns for the 5-day pre-FOMC-announcement window (Panel A), FOMC announcement days (Panel B), and the full sample (Panel C), respectively. The long and short legs are value-weighted portfolios of the lowest or highest 10% tail of stocks sorted by anomaly characteristics elaborated in Table 1.1. All numbers are expressed in daily basis points (bps) except for Sharpe ratios (SR), which are annualized, taking into account the annual frequency of days in the pre-FOMC-announcement window (40/252) and FOMC announcement days (8/252). "Excess Return" represents the mean daily portfolio returns in excess of the risk-free rate. "CAPM Alpha" and "FF3F Alpha" are the mean daily CAPM alphas and Fama-French 3-factor alphas estimated from a rolling-window regression using daily portfolio returns from the previous 252 trading days. "Dur-2F Alpha" is the daily alpha adjusted by the market risk and the duration risk factor. "Dur-3F Alpha" denotes risk-adjusted returns which are adjusted by the market risk, small minus big (SMB), and the duration risk factors. "SR" denotes the annualized Sharpe ratio. The data sample is from January 1, 1994, to December 31, 2022. $t-$statistics are reported in parentheses.

Anomaly	**Excess Return**	**CAPM Alpha**	**FF3F Alpha**	**Dur-2F Alpha**	**Dur-3F Alpha**	**SR**
	Panel A: 5-Day Pre-FOMC Announcement ($n = 1,160$)					
CAPM Beta	15.43	17.65	9.88	6.45	6.43	0.52
	(2.74)	(3.82)	(2.69)	(2.25)	(2.35)	
Operating Profitability	11.72	11.85	8.10	6.45	6.09	0.81
	(4.29)	(4.43)	(3.77)	(3.00)	(3.12)	
EPS Forecasts	14.67	14.84	8.40	8.92	8.92	0.73
	(3.89)	(4.24)	(3.14)	(3.10)	(3.49)	
Return on Equity	9.09	9.57	5.88	5.74	5.46	0.72
	(3.79)	(4.18)	(3.12)	(2.97)	(3.01)	
Value	9.59	10.05	9.00	8.38	8.99	0.55
	(2.78)	(3.18)	(2.88)	(2.81)	(3.13)	
Net Payout Yield	13.27	14.40	11.36	7.62	7.43	0.76
	(4.02)	(4.69)	(4.54)	(2.96)	(3.08)	
Idiosyncratic Volatility	16.84	17.41	10.57	8.92	8.66	0.69
	(3.67)	(4.18)	(3.31)	(2.80)	(2.93)	
Firm Age	4.05	5.15	3.46	1.45	1.16	0.35
	(1.83)	(2.33)	(1.86)	(0.81)	(0.68)	
Duration	9.18	9.17	4.57	-1.04	-1.14	0.45
	(2.41)	(2.74)	(1.79)	(-0.61)	(-0.68)	
Average	11.68	11.43	7.43	4.91	4.75	0.75
	(4.06)	(4.50)	(3.96)	(3.35)	(3.58)	
	Panel B: FOMC Announcement Days ($n = 232$)					
CAPM Beta	-38.84	-17.39	-15.44	-4.40	-3.03	-0.56
	(-2.96)	(-1.89)	(-1.88)	(-0.68)	(-0.48)	
Operating Profitability	-11.76	-7.06	-1.71	-2.65	-2.98	-0.35
	(-1.86)	(-1.17)	(-0.32)	(-0.50)	(-0.60)	
EPS Forecasts	-10.93	-0.92	9.69	6.81	6.23	-0.26
	(-1.36)	(-0.14)	(1.54)	(1.14)	(1.04)	
Return on Equity	-6.51	-1.08	4.21	2.42	3.32	-0.23
	(-1.23)	(-0.22)	(0.92)	(0.53)	(0.77)	
Value	-3.64	2.23	-2.19	7.95	6.15	-0.07
	(-0.34)	(0.22)	(-0.22)	(0.81)	(0.65)	
Net Payout Yield	-6.62	0.75	2.59	10.09	10.41	-0.17
	(-0.90)	(0.11)	(0.43)	(1.84)	(1.95)	
Idiosyncratic Volatility	-30.86	-15.87	-8.49	-6.05	-5.29	-0.48
	(-2.54)	(-1.56)	(-1.03)	(-0.68)	(-0.64)	
Firm Age	-12.03	-9.10	-6.94	-3.19	-4.62	-0.52
	(-2.77)	(-2.22)	(-1.94)	(-0.85)	(-1.27)	
Duration	-32.26	-17.40	-17.08	-4.63	-8.03	-0.71
	(-3.84)	(-2.69)	(-2.94)	(-1.17)	(-2.05)	
Average	-19.74	-8.75	-5.81	0.14	0.01	-0.53
	(-2.86)	(-1.75)	(-1.47)	(0.04)	(0.00)	
	Panel C: Full Sample ($n = 7,308$)					
CAPM Beta	-1.75	2.52	1.47	1.10	1.60	-0.14
	(-0.72)	(1.43)	(1.04)	(0.97)	(1.49)	
Operating Profitability	1.22	2.42	2.90	1.48	1.88	0.21
	(1.10)	(2.35)	(3.44)	(1.76)	(2.41)	
EPS Forecasts	2.87	4.74	4.70	3.76	4.30	0.34
	(1.79)	(3.30)	(4.20)	(3.18)	(3.92)	
Return on Equity	1.05	2.23	2.45	1.82	2.14	0.20
	(1.07)	(2.44)	(3.19)	(2.34)	(2.88)	
Value	2.83	4.29	3.28	4.16	3.58	0.39
	(1.98)	(3.31)	(2.60)	(3.38)	(3.02)	
Net Payout Yield	2.56	4.44	4.23	2.64	2.76	0.35
	(1.87)	(3.46)	(3.96)	(2.56)	(2.81)	
Idiosyncratic Volatility	2.64	4.86	4.60	3.32	3.98	0.25
	(1.32)	(2.84)	(3.25)	(2.37)	(3.00)	
Firm Age	-0.74	0.53	0.50	-0.31	-0.32	-0.15
	(-0.80)	(0.59)	(0.65)	(-0.42)	(-0.44)	
Duration	-0.26	2.18	1.34	0.12	-0.06	-0.03
	(-0.16)	(1.64)	(1.16)	(0.17)	(-0.09)	
Average	1.57	3.31	2.92	2.10	2.28	0.23
	(1.25)	(3.28)	(3.73)	(3.62)	(4.29)	

Several noteworthy observations step into the limelight. First, summary statistics for the 5-day pre-FOMC-announcement window, detailed in Panel A of Table 1.2, reveal that the long-short daily CAPM risk-adjusted returns are not only statistically significant for anomalies in my sample, but also economically meaningful. For instance, the average daily CAPM alpha from betting on beta is 17.65 bps (t=3.82) in the 5-day pre-FOMC-announcement window, far larger than 2.52 bps in the full sample. Similarly, the daily CAPM alpha from betting on operating profitability is on average 11.85 bps (t=4.43) with a Sharpe ratio of 0.81 pre-FOMC announcements, five times larger than the average daily CAPM alpha in the full sample. In fact, as illustrated by the bottom row in Panel A, betting on anomalies in my sample merely for the 5-day pre-FOMC-announcement window yields on average a significant annual excess return of 4.67% (11.68×40=467.2 bps). Adjusting for well-known risk factors has limited impact on these long-short returns. The average daily CAPM alpha across anomalies pre-FOMC announcements is 11.43 bps (t=4.50). The Fama-French 3-factor alpha also remains large and statistically significant at 7.43 bps (t=3.96).

Second, the long leg of anomalies exhibits positive abnormal risk-adjusted returns while the short leg exhibits negative abnormal risk-adjusted returns pre-FOMC announcements. Moreover, the long-short risk-adjusted returns pre-FOMC announcements are primarily driven by the short leg. Table 1.A.2 presents the summary statistics for daily risk-adjusted returns of anomaly long-short legs. For example, it can be seen that the high-beta portfolio on the short leg of the beta anomaly exhibits an average daily CAPM alpha of -16.83 bps (t=-4.82) prior to FOMC announcements. Similarly, the mean daily CAPM alpha of the low-profitability portfolio, also on the short leg, has been -9.36 bps (t=-4.49) in the pre-FOMC-announcement window. Across anomalies in my sample, the average daily CAPM alpha of the short leg pre-FOMC announcements is -9.26 bps (t=-4.58), whereas the long leg on average exhibits a positive daily CAPM alpha of 2.17 bps (t=2.73). These estimates imply that the short leg accounts for 81% of risk-adjusted returns in the pre-FOMC-announcement window.

Third, the substantial long-short risk-adjusted returns documented above subsequently reverse after FOMC announcements. Panel B of Table 1.2 shows that, in contrast to the positive risk-adjusted returns pre-FOMC announcements, the average long-short CAPM risk-adjusted returns across anomalies on FOMC announcement days have been -8.75 bps (significant at the 10% level).

Another interesting observation from Panel A of Table 1.2 is that the large long-short risk-adjusted returns pre-FOMC announcements declined substantially when controlling for the equity-duration risk factor. The duration factor, constructed using the approach in Gormsen and Lazarus (2022), goes long the short-duration stocks and short the long-duration stocks. Take the beta anomaly as an example: the inclusion of the duration factor (in the Dur-2F Alpha column) led to a notable decrease in the CAPM adjusted returns before FOMC announcements, specifically declining from 17.65 bps to 6.45 bps. It is worth noting that, on average, the duration factor itself accounts for approximately 60% of CAPM alphas in the 5-day pre-FOMC-announcement window across anomalies in my sample. In contrast, the size factor has little impact on the pre-FOMC announcement returns, as indicated by the duration three-factor model (including market, duration, and size). Additionally, long-short risk-adjusted returns of these anomalies on FOMC announcement days are not statistically different from zero when adjusting for the duration risk factor.

In fact, the anomalies presented in Table 1.1 consistently bet on equity duration. Specifically, all of these anomalies take long positions in firms with short duration and short positions in firms with long duration. I adopt the notion of equity duration from Gormsen and Lazarus (2022), who use the expected long-term growth rate as a proxy for cash-flow duration. They claim that high beta, low profit, high investment, low payout, and low book-to-market imply long cash-flow duration. Therefore, risk premia on major equity factors can be explained by one single factor—the duration factor. Intuitively, high investment and low payout ratios naturally imply high growth rate and thus long cash-flow duration. Analogously, low-profit firms should have large future profits relative to today, therefore low profit implies long duration. In my sample period post-1994, growth firms have higher growth rate than value firms, resulting in longer duration.[12] Additionally, long-duration stocks are likely to be high-beta stocks as firms with long cash-flow duration are more exposed to the discount-rate shocks which account for much of the variation in aggregate prices, causing them to co-move more with the market and thus have high betas.

[12]See, for example, Chen (2017) and Gormsen and Lazarus (2022).

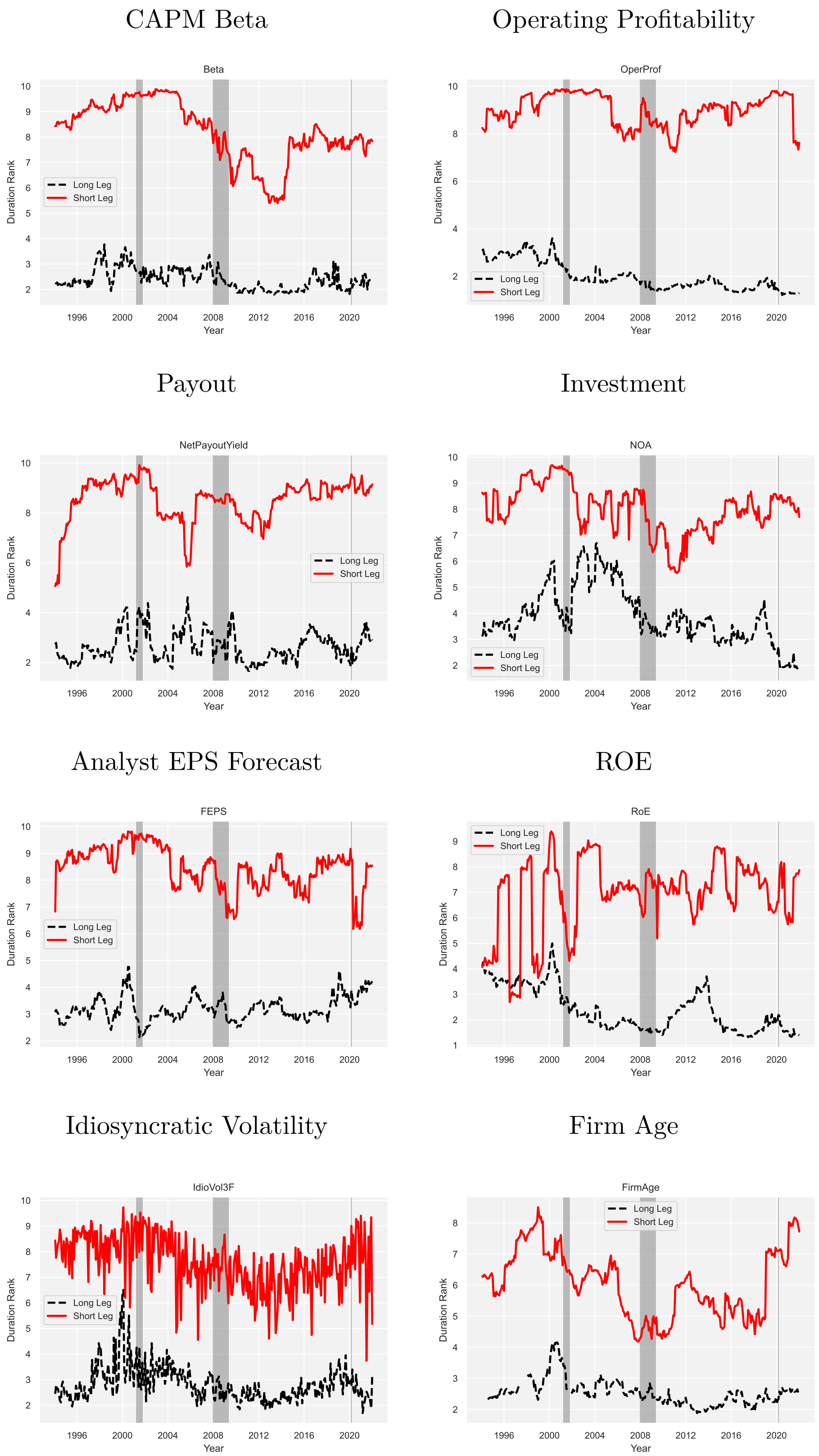
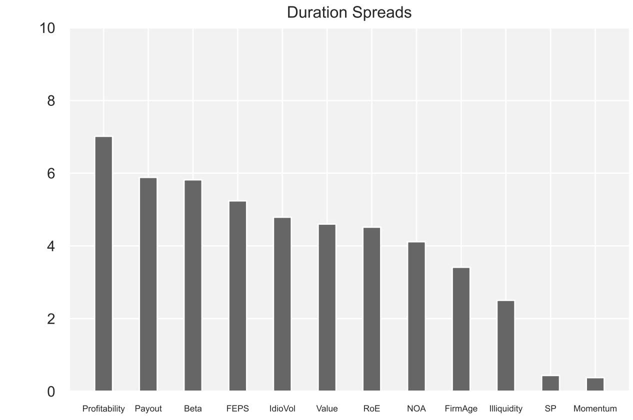
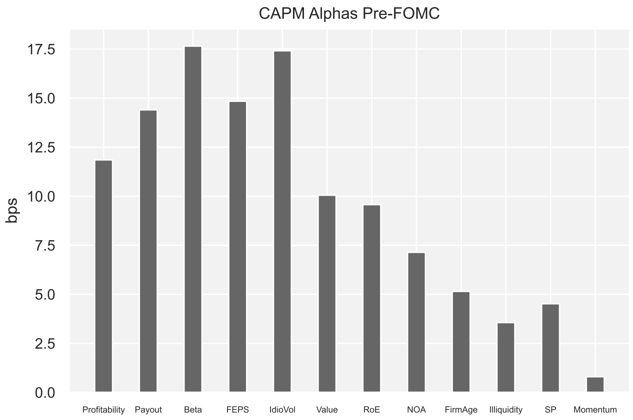


Figure 1.1: Duration Spreads Between the Long Leg and the Short Leg of Anomalies. This figure illustrates the duration rank for portfolios on the long leg and the short leg, respectively, for each anomaly. Portfolio duration rank is calculated as the value-weighted average of stock duration decile, which takes time-varying values from 1 to 10 based on the rank of stock duration defined by Gormsen and Lazarus (2022). Specifically, I sort stocks in the universe into 10 deciles at the end of each month. Stocks in the k^{th} decile take the value k as their duration rank.

Panel A: Duration Spreads of Anomalies



Panel B: Risk-adjusted Returns Pre-FOMC



Panel C: t-Statistics

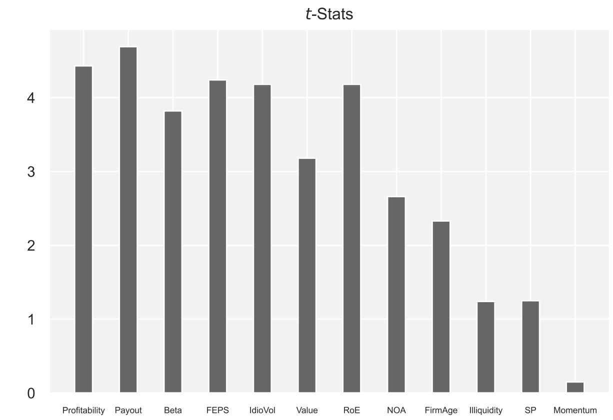


Figure 1.2: Anomalies' Risk-adjusted Returns and Duration Spreads.
This figure shows the anomalies' duration spreads between the short leg and the long leg (Panel A), daily long-short CAPM alphas pre-FOMC announcements (Panel B) and t-statistics associated with long-short CAPM alphas pre-announcements (Panel C). Returns are expressed in daily basis points (bps). The duration spread is the duration rank of portfolios on the short leg minus the duration rank of portfolios on the long leg. Portfolio duration rank is calculated as the value-weighted average of stock duration decile, which takes values from 1 to 10 based on the rank of stock duration defined by Gormsen and Lazarus (2022).

Figure 1.1 confirms the intuition by showing the duration rank of portfolios on the long and short legs for the anomalies listed in Table 1.1. Portfolio duration rank is computed as the value-weighted average of the duration ranks of stocks in the portfolio. Specifically, in each month, I sort all stocks in the universe into deciles based on duration. Stocks in decile k are assigned a duration rank of k. It is estimated that the realized duration varies from 15 years for the short-duration portfolio (decile 1) to 59 years for the long-duration portfolio (decile 10). As shown in the figure, anomaly portfolios on the short leg (red solid lines) have longer duration compared to those on the long leg (black dashed lines). In addition to equity risk factors like beta, profitability, payout, and investment, as established by Gormsen and Lazarus (2022), other anomalies such as idiosyncratic volatility and firm age also seem to exhibit large duration spreads. More precisely, young firms and stocks with high idiosyncratic volatility are revealed to have longer cash-flow duration than old firms and stocks with low idiosyncratic volatility.

Notably, anomalies with relatively small duration spreads between the short and long legs do not appear to exhibit significant returns before FOMC announcements. Panel A of Figure 1.2 demonstrates the duration spreads between the short leg and the long leg for anomalies in my sample. The duration spreads are calculated as the difference in duration ranks between portfolios on the short leg and those on the long leg. As depicted in the plot, anomalies such as momentum and sales-to-price have narrow duration spreads.[13] Panel B and Panel C show the daily long-short CAPM risk-adjusted returns in the 5-day pre-FOMC-announcement window and their corresponding t-statistics for each anomaly. It is shown that anomalies with low duration spreads such as momentum and sales-to-price do not seem to show statistically significant risk-adjusted returns before FOMC announcements. Furthermore, it appears that risk-adjusted returns and t-statistics are likely to decline as duration spreads decrease.

[13] Figure 1.A.2 confirms the result by showing duration ranks of their long and short legs.

1.4.2 Duration-Driven Returns around FOMC Announcements

To establish that equity duration drives the common return pattern observed in various anomalies around FOMC announcements, I conduct the following panel regressions:

$$R_{t,k}^{(h,H)} = \beta_S + \beta_{LMS} D_{t,k}^l + \gamma_0 X_{t,k} + \gamma_1 D_{t,k}^l X_{t,k} + \epsilon_{t,k} \tag{1.13}$$

where $R_{t,k}^{(h,H)}$ is the daily risk-adjusted stock return for firm k on date t. (h, H) indicates the time window around FOMC announcements within which the date t falls. For instance, $R_{t,k}^{(-5,-1)}$ represents the daily risk-adjusted stock returns for firm k during the 5-day period prior to FOMC announcements. $R_{t,k}^{(0,2)}$ denotes the daily risk-adjusted returns within the 3-day window immediately after FOMC announcements. Risk-adjusted returns are stock returns adjusted by the market risk where the market beta of a stock is estimated using a 60-month rolling-window regression of monthly stock excess returns over the 1-month Treasury-bill rate on market excess returns, with at least 20 months of non-missing observations. $D_{t,k}^l$ is an indicator equal to one if firm k is in the long-duration decile (decile 10) on date t or zero in the short-duration decile (decile 1). β_{LMS} measures the return to long-duration stocks relative to short-duration stocks in the time window (h, H). $X_{t,k}$ is a set of control variables—for example, size and liquidity cost. The sample consists exclusively of stocks sorted into either the long-duration decile (decile 10) or the short-duration decile (decile 1). All regressions include FOMC meeting fixed effects and firm-industry fixed effects.[14] Standard errors are double clustered by firm and date.

The regression results are presented in Table 1.3, where dependent variables are daily risk-adjusted stock returns. Column (1) reveals a negative and statistically significant coefficient on the long-duration indicator suggesting that long-duration stocks on average yield 10.06 bps (t=3.62) lower daily risk-adjusted returns in the 5-day pre-FOMC-announcement window than do short-duration stocks. Furthermore, the underperformance of long-duration stocks pre-FOMC announcements is significant across all stock sizes, as indicated by column (2). The coefficient on the interaction term between the long-duration indicator and size is insignificant, where size represents the market capitalization of stocks. Figure 1.A.3 plots

[14] Firm industries are classified by the Fama-French 10 industry codes.

Table 1.3: Duration-Driven Returns Panel Regressions.

This table reports the estimates of the stock-day panel regressions: $R_{t,k}^{(h,H)} = \beta_S + \beta_{LMS} D_{t,k}^l + \gamma_0 X_{t,k} + \gamma_1 D_{t,k}^l X_{t,k} + \epsilon_{t,k}$. The dependent variable $R_{t,k}^{(h,H)}$ is either daily excess returns (Panel A) or daily abnormal returns (Panel B) of stock k on date t for days in time window $(-5,-1)$, the 5-day pre-FOMC-announcement window, or $(0,2)$, the 3-day post-FOMC-announcement window. The daily abnormal returns are adjusted by the CAPM model where the CAPM beta of a stock is estimated using a 60-month rolling-window regression of monthly stock excess returns over the 1-month Treasury-bill rate on market excess returns, with at least 20 months of non-missing observations. $D_{t,k}^l$ is an indicator equal to one if the duration of stock k falls within the highest 10% tail and zero otherwise. $X_{t,k}$ is a set of control variables. Specifically, $Size_{t,k}$ represents the quintile of stocks' market capitalization taking values from 1 to 5. $Liqcost_{t,k}$ is the daily stock CRSP bid-ask spread as described in Chung and Zhang (2014). $Hike_t$ is an indicator equal to one when the market expects a minimum 25 bps (0.25%) rate increase at the upcoming FOMC meeting and zero otherwise. The market expectation of interest rate changes is measured from federal funds futures following Kuttner (2001). MPU_t^{high} is an indicator equal to one if the monetary policy uncertainty on date t is larger than the median of monetary policy uncertainty in the sample. I use the standardized Merrill Lynch Option Volatility Estimate (MOVE) as a proxy for monetary policy uncertainty. GSS_t and NS_t are the target factor in Gurkaynak, Sack, and Swanson (2004) and policy news shock in Nakamura and Steinsson (2018), respectively. Regressions include stock-industry fixed effects and FOMC meeting fixed effects. Standard errors are double clustered by stock and date. The sample period is from 1994 to 2022. *p<0.1; **p<0.05; ***p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	$R_{t,k}^{(-5,-1)}$	$R_{t,k}^{(-5,-1)}$	$R_{t,k}^{(-5,-1)}$	$R_{t,k}^{(-5,-1)}$	$R_{t,k}^{(-5,-1)}$	$R_{t,k}^{(0,2)}$
$D_{t,k}^l$	-10.06***	-10.09**	-6.84**	-7.44**	-0.59	8.85*
	(-3.62)	(-2.22)	(-2.37)	(-2.57)	(-0.17)	(1.76)
$Size_{t,k}$		-0.85				
		(-1.07)				
$D_{t,k}^l \times Size_{t,k}$		-0.47				
		(-0.39)				
$Liqcost_{t,k}$			-0.06			
			(-0.04)			
$D_{t,k}^l \times Liqcost_{t,k}$			-3.42**			
			(-2.02)			
$D_{t,k}^l \times Hike_t$				-24.66**	-25.54*	
				(-2.01)	(-1.95)	
MPU_t^{high}					3.49	
					(0.29)	
$D_{t,k}^l \times \text{MPU}_t^{high}$					-15.41**	
					(-2.41)	
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Meeting FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	378,336	378,336	378,336	378,336	378,336	227,610

the risk-adjusted returns of portfolios double-sorted by duration and size around FOMC announcements. It shows that long-duration stocks exhibit negative CAPM risk-adjusted returns regardless of size, whereas short-duration stocks exhibit positive risk-adjusted returns across various sizes portfolios.

Column (3) shows that the coefficient on the interaction term between the long-duration indicator and liquidity cost is -3.42 (t = -2.02), where the stock liquidity cost refers to the daily CRSP bid-ask spread. The result suggests that long-duration stocks yield negative risk-adjusted returns pre-FOMC announcements, especially for those with higher liquidity costs. In columns (4) and (5), I introduce additional controls, namely Hike_t and MPU_t^{high}. Hike_t is an indicator that equals one when the market expects a minimum of a 25-basis-point rate increase at the upcoming FOMC meeting. The market expectation of interest rate changes is measured from federal funds futures, following the methodology of Kuttner (2001). MPU_t^{high} is an indicator that equals one when the monetary policy uncertainty exceeds the median level of monetary policy uncertainty in the sample. I use the standardized Merrill Lynch Option Volatility Estimate (MOVE) as a proxy for monetary policy uncertainty. The result in column (4) reveals that the coefficient on the interaction term between the long-duration indicator and Hike is -24.66, indicating that long-duration stocks perform worse when the market expects at least a 25-basis-point increase in the federal fund rate. Surprisingly, once controlling MPU_t^{high} in column (5), Hike_t becomes less significant. Moreover, the long-duration indicator loses its statistical significance. The coefficient on the interaction term between the long-duration indicator and MPU^{high} is -15.41 (t = -2.41). These results indicate that monetary policy uncertainty drives the underperformance of long-duration stocks and that monetary policy tightening is likely to induce greater monetary policy uncertainty as the statistical significance on Hike_t can be partially absorbed by MPU^{high}.

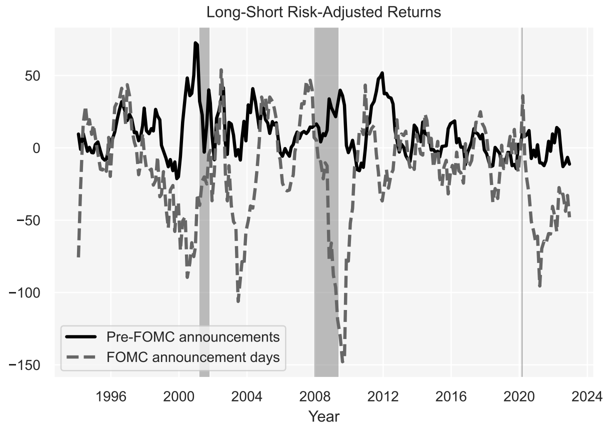
Next, I investigate duration-driven returns post-FOMC announcements, as documented in column (6). The key finding is that, in line with the return reversal observed across anomalies, the coefficient on the long-duration indicator becomes positive and significant (at the 10% level) in the 3-day post-FOMC-announcement window. The long-duration stocks exhibit a daily risk-adjusted return that is 8.85 bps higher than that of short-duration stocks post-FOMC announcements.

In sum, I document that a long-short duration strategy with long-duration stocks on the short leg exhibits significant risk-adjusted returns pre-FOMC announcements. These long-short risk-adjusted returns subsequently reverse in the 3-day window post-FOMC announcements. Furthermore, I show additionally long-duration stocks underperform pre-FOMC announcements particularly (i) during periods of high monetary policy uncertainty, (ii) when the market anticipates an increase in the federal funds rate, and (iii) among stocks with high liquidity cost. These empirical findings are consistent with my model's predictions. Monetary policy tightening creates volatility in financial markets, especially for long-duration stocks. Hence, the selling pressure on long-duration stocks is stronger due to tighter tracking-error constraints. Moreover, the selling pressure is expected to have a larger price impact on less liquid stocks.

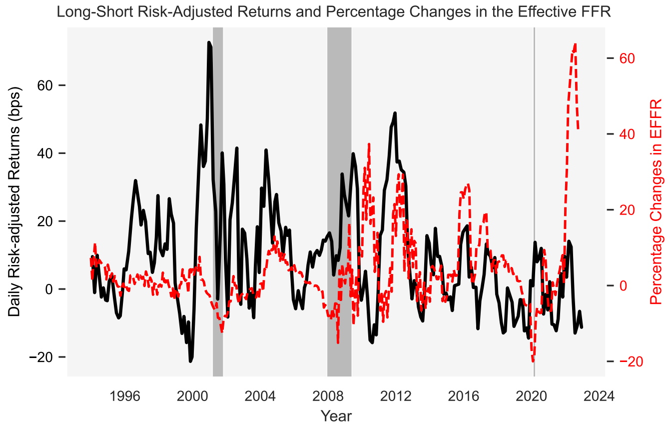
Figure 1.3 plots the risk-adjusted returns to long-short duration portfolios over time. The top panel reveals the fact that during the 5-day pre-FOMC announcement period, betting on duration generally exhibits positive alphas. This trend, however, is observed to reverse on FOMC announcement days, as indicated by the apparent negative correlation of risk-adjusted returns between pre-FOMC and FOMC announcement days. The middle panel illustrates that long-short alphas in the 5-day pre-FOMC-announcement window are procyclical, comoving with the changes in the effective federal funds rate. Long-short alphas in the pre-FOMC window are high when the Fed is about to implement a tightening monetary policy. Lastly, as demonstrated by the bottom panel, the risk-adjusted returns pre-FOMC announcements increase with market-based monetary policy uncertainty, an observation consistent with my model's prediction.

Motivated by earlier findings that indicate equity duration as the key driver of the large abnormal risk-adjusted returns pre-FOMC announcements, which are then followed by return reversals, I sort stocks into deciles based on their cash-flow duration, as defined by Gormsen and Lazarus (2022). Portfolios are value-weighted and rebalanced at the end of each calendar month, using breakpoints based on NYSE firms. Figure 1.4 depicts the average cumulative returns and risk-adjusted returns for duration-sorted portfolios around FOMC announcements. Panel A reveals that, on average, the cumulative return from betting on duration in the 5-day pre-FOMC-announcement window has been 45 bps, outperforming the

Panel A: Long-short alpha pre-FOMC v.s. FOMC announcement days



Panel B: Long-short alpha pre-FOMC v.s. changes in the effective FFR



Panel C: Long-short alpha pre-FOMC v.s. MPU

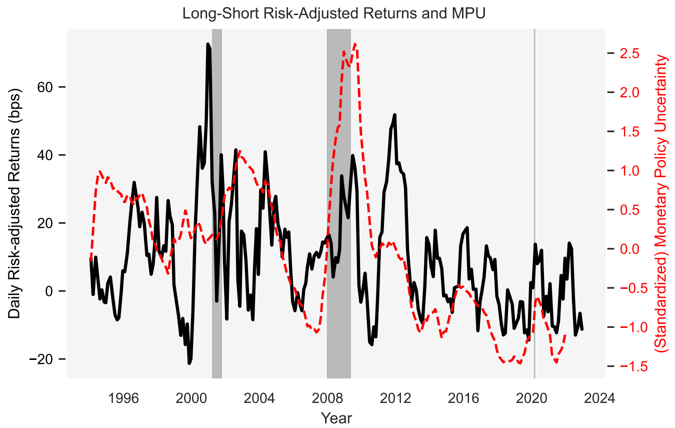


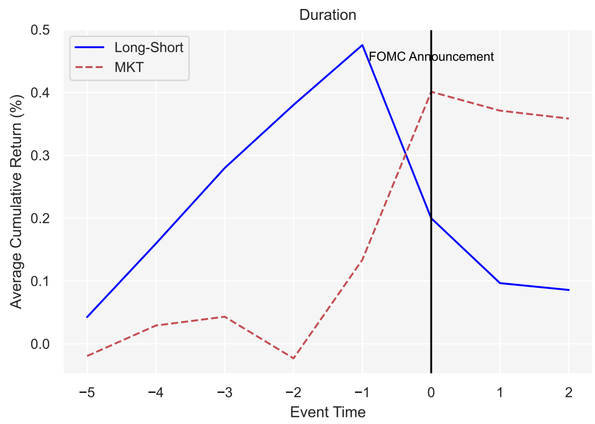
Figure 1.3: Time-series properties of long-short duration risk-adjusted returns. This figure presents the time-series CAPM alphas generated from betting against equity duration around FOMC announcements. In panel A, the black-real line shows the daily CAPM alphas of long-short portfolios in the pre-FOMC announcement window while the gray-dash line illustrates the daily CAPM alphas of long-short portfolios on FOMC announcement days. Panel B shows the long-short CAPM alphas before FOMC announcements and the changes in the effective Federal Funds Rate (FFR) between meetings (red line). Panel C demonstrates the co-movement between the long-short CAPM alphas pre-FOMC announcements and the standardized monetary policy uncertainty. All time-series are smoothed averages over the last 8 FOMC meetings.

market by 40 bps. The large long-short returns pre-FOMC announcements are primarily driven by the long-duration portfolio as illustrated in Panel B. The long-duration portfolio, which is on the short leg, exhibits negative cumulative holding period returns before FOMC announcements. Panel C confirms the similar pattern in risk-adjusted returns, where the average cumulative CAPM alpha for the long-duration portfolio is approximately -30 bps in the 5-day pre-FOMC-announcement window, while the short-duration portfolio's cumulative alpha is 15 bps. Notably, risk-adjusted returns are nearly reversed in the 3-day window after FOMC announcements.

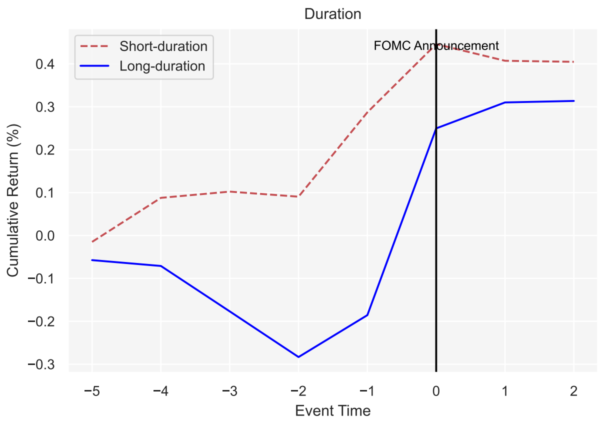
Table 1.2 presents the summary statistics for daily excess returns and risk-adjusted returns on duration-sorted portfolios. In Panel A, it is observed that betting on duration leads to an average daily excess return of 9.18 bps (t=2.41) pre-FOMC announcements. The annualized Sharpe ratio in the pre-FOMC-announcement window is 0.45. Even after controlling for the market risk, the risk-adjusted returns to long-short duration portfolios remain significant at 9.17 bps with a t-statistic of 2.74. Furthermore, Panel A of Table 1.A.2 reveals that the long-duration portfolio underperforms, exhibiting a negative alpha, while the short-duration portfolio outperforms, showing a positive alpha in the 5-day pre-FOMC-announcement window. Additionally, Panel B of Table 1.2 illustrates that the substantial duration-driven returns pre-FOMC announcements are subsequently reversed on FOMC announcement days, generating a CAPM risk-adjusted return of -17.40 bps (t = 2.69). In particular, on FOMC announcement days, the long-duration portfolio yields a positive risk-adjusted return of 12.38 bps, whereas the short-duration portfolio exhibits a negative risk-adjusted return of -5.02 bps.

To validate my findings and investigate the potential determinants of duration-driven returns around FOMC announcements, I conduct time-series regressions using portfolio returns. Specifically, as a benchmark regression, I regress duration-sorted portfolio returns on a pre-FOMC indicator which takes the value of one in the 5-day pre-FOMC-announcement

Panel A: Long-short cumulative returns



Panel B: Cumulative returns for long short legs



Panel C: Cumulative CAPM alphas

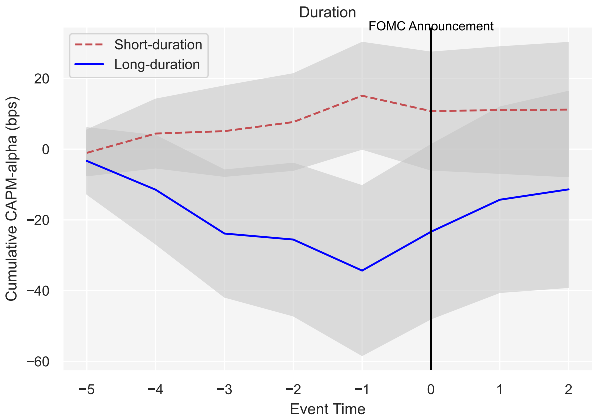


Figure 1.4: Duration-sorted Portfolio Returns around FOMC Announcements.
This figure shows the average cumulative returns and CAPM alphas of duration-sorted portfolios around FOMC announcements. The top panel shows the average long-short cumulative returns from a long position in short-duration portfolio and a short position in long-duration portfolio. The middle panel shows the average cumulative holding period returns of the long-duration portfolio and the short-duration portfolio, respectively. The bottom panel shows the average cumulative CAPM alphas of the long-duration portfolio and the short-duration portfolio. The shaded areas represent 95% confidence intervals. The long-duration portfolio is the highest 10% tail of stocks sorted by duration defined in Gormsen and Lazarus (2022). The short-duration portfolio is the lowest 10% tail. The data sample is from January 1, 1994 to December 31, 2021, in which there are 224 scheduled FOMC announcements.

window and zero otherwise.[15]

$$R_t = \beta_0 + \beta_1 \times D_t^{preFOMC} + \epsilon_t \tag{1.14}$$

where R_t represents the daily portfolio returns. β_0 measures the mean daily return of a portfolio on days falling outside the pre-FOMC-announcement window, while β_1 measures the difference between the mean returns earned in the pre-FOMC-announcement window and outside the window.

Panel A of Table 1.4 presents the regression results. Columns (1) and (3) demonstrate that a long-short strategy betting on duration generates higher returns in the 5-day pre-FOMC-announcement window compared to other days. Specifically, the daily return to long-short portfolios in the 5-day pre-FOMC-announcement window is 11.22 bps higher (t=2.55) compared to other days. In addition, the daily CAPM alpha for long-short portfolios in the 5-day pre-FOMC-announcement window is also higher by 8.31 bps (t=2.26) when compared to other days. In column (5), it can be seen that the coefficient on the pre-FOMC indicator for the short-duration portfolio is positive (3.08 bps) and significant at the 10% level, indicating that the short-duration portfolio outperforms pre-announcements. Conversely, column (7) shows that the long-duration portfolio underperforms by 5.23 bps (t=2.04) during the 5-day pre-FOMC-announcement window compared to other days.

Next, I test my model prediction that the significant duration-driven risk-adjusted returns pre-FOMC announcements are in response to the presence of monetary policy uncertainty. Specifically, I regress portfolio returns on the pre-FOMC indicator interacted with the monetary policy uncertainty, which is proxied by the standardized MOVE index. The MOVE index, which measures uncertainty about medium- or long-term interest rates, is suitable for analyzing the effect of monetary policy uncertainty on duration-sorted portfolios as these

[15]The results presented in Table 1.4 are based on cash-flow duration following the approach outlined in Gormsen and Lazarus (2022). The main results remain unchanged when alternative measures of duration are used. For example, Table 1.A.3 reports the results of time-series regressions for duration-sorted portfolios, where duration is defined following the methodology in Weber (2018a).

Table 1.4: Duration-Driven Returns Time-Series Regressions.

This table reports results of time-series regressions of duration-sorted portfolios. The long-short strategy has the long-duration portfolio on the short leg and the short-duration portfolio on the long leg. The long-duration portfolio is a value-weighted portfolio of the highest 10% tail of stocks sorted by duration, as defined in Gormsen and Lazarus (2022), while the short-duration portfolio is the lowest 10% tail. The dependent variable is the daily portfolio return or CAPM alpha. The daily portfolio CAPM alpha is estimated from a rolling-window regression using daily portfolio returns from the last 252 trading days. "Pre-FOMC" is an indicator equal to one on the five trading days before FOMC announcements and zero otherwise. "MPU" is the standardized Merrill Lynch Option Volatility Estimate (MOVE), which serves as a proxy for monetary policy uncertainty. "Post-FOMC" is an indicator equal to one in the 3-day window after FOMC announcements and zero otherwise. GSS is the target factor in Gurkaynak, Sack, and Swanson (2004). $\text{MPU}^{high}_{preFOMC}$ is an indicator equal to one if monetary policy uncertainty in the pre-announcement window falls within the top 25% of monetary policy uncertainty observed in the entire sample. The data sample is from January 1, 1994, to December 31, 2022. Newey-West adjusted $t-$statistics are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	Panel A: 5-Day Pre-FOMC Announcement Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Long-Short Returns		Long-Short Alphas		Long-Leg Alphas		Short-Leg Alphas	
Intercept	1.18	-1.21	0.86	0.84	0.35	0.32	-0.51	-0.52
	(-0.62)	(-0.64)	(0.58)	(0.56)	(0.51)	(0.47)	(-0.49)	(-0.49)
Pre-FOMC	11.22**	10.87**	8.31**	8.05**	3.08*	3.01*	-5.23**	-5.04**
	(2.55)	(2.51)	(2.26)	(2.23)	(1.87)	(1.85)	(-2.04)	(-1.99)
MPU		0.01		-1.79		-0.96		0.83
		(0.01)		(-0.95)		(-1.22)		(0.57)
Pre-FOMC × MPU		12.03**		10.82**		4.00**		-6.82**
		(2.39)		(2.41)		(2.04)		(-2.1)
Adj.R^2	0.07%	0.17%	0.06%	0.16%	0.03%	0.09%	0.04%	0.12%

	Panel B: FOMC Announcement Day Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Long-Short Returns		Long-Short Alphas		Long-Leg Alphas		Short-Leg Alphas	
Intercept	10.04**	10.04**	9.17***	9.17***	3.43**	3.43**	-5.74**	-5.74**
	(2.54)	(2.54)	(2.73)	(2.73)	(2.29)	(2.29)	(-2.46)	(-2.46)
Post-FOMC	-22.88***	-17.78**	-18.23***	-13.99**	-5.32**	-3.84	12.90***	10.14**
	(-3.33)	(-2.54)	(-3.24)	(-2.41)	(-2.17)	(-1.49)	(3.23)	(2.49)
Post-FOMC × GSS		13.81*		-2.60		2.37		4.97
		(1.70)		(-0.41)		(0.73)		(0.99)
Post-FOMC × $\text{MPU}^{high}_{preFOMC}$		-35.86**		-29.82**		-10.40*		19.41*
		(-1.96)		(-2.16)		(-1.83)		(1.78)
Adj.R^2	0.61%	1.00%	0.53%	0.73%	0.20%	0.32%	0.54%	0.71%

portfolios have relatively long duration varying from 15 years to 59 years.[16]

$$R_t = \beta_0 + \beta_1 \times D_t^{preFOMC} + \beta_2 \times MPU_t + \beta_3 \times D_t^{preFOMC} \times MPU_t + \epsilon_t \tag{1.15}$$

[16]The results remain robust to other market-based monetary policy uncertainty measures, such as Treasury Implied Volatility (TIV) in Choi, Mueller, and Vedolin (2017).

In this regression, the primary interest is in the coefficient β_3, which quantifies the additional return that can be attained pre-FOMC announcements relative to other days as monetary policy uncertainty increases.

Columns (2) and (4) in Panel A of Table 1.4 demonstrate that both the long-short returns and risk-adjusted returns increase with monetary policy uncertainty, as illustrated by the positive coefficients on the interaction terms. Column (8) provides further insight into this relationship, revealing that the coefficient associated with the interaction term is -6.82 (t=-2.10) for the long-duration portfolio, suggesting that the underperformance of the long-duration portfolio is more pronounced as monetary policy uncertainty rises. Specifically, a one standard deviation increase in monetary policy uncertainty leads to a 6.82 bps decrease in CAPM risk-adjusted returns for the long-duration portfolio. In contrast, the coefficient on the interaction term for the short-duration portfolio in column (6) is 4.00 (t=2.04), implying that the short-duration portfolio tends to outperform more when monetary policy uncertainty increases. Note that monetary policy uncertainty, per se, does not appear to have an effect on risk-adjusted returns of portfolios outside the 5-day pre-FOMC-announcement window, as indicated by the insignificance of β_2.

Finally, according to Proposition 3, my model predicts return reversals post-FOMC announcements once monetary policy uncertainty has been resolved. To test this prediction, I regress duration-sorted portfolio returns on a post-FOMC indicator that is equal to one during the 3-day post-FOMC-announcement window and zero otherwise. Panel B of Table 1.4 reports the results. The estimated coefficients for long-short duration returns and alphas are both found to be negative and statistically significant. Specifically, the results in column (1) indicate that the long-short strategy exhibits 22.88 bps (t=3.33) lower daily returns in the post-FOMC-announcement window compared to returns on other days. Similarly, column (3) shows that the long-short risk-adjusted returns underperform by an average of 17.78 bps (t=2.54) post-FOMC announcements. Further insights are provided in columns (5) and (7). The long-duration portfolio demonstrates 12.90 bps (t=3.23) higher CAPM alphas after FOMC announcements compared to other days, whereas the short-duration portfolio shows 5.32 bps (t=1.91) lower risk-adjusted returns post-FOMC announcements than on other days. These findings suggest the presence of return reversals post-FOMC announcements, wherein the long-duration portfolio exhibits positive alphas while the short-duration portfolio exhibits negative alphas.

Column (2) in Panel B of Table 1.4 shows that the coefficient on the interaction term between the post-FOMC indicator and the monetary policy path factor of Gurkaynak, Sack, and Swanson (2004) is positive and significant for the long-short portfolio returns. This aligns with the findings in Table 1.3, where it was found that a tightening monetary policy surprise leads to the underperformance of long-duration stocks compared to short-duration stocks post-FOMC announcements. However, monetary policy shocks do not have any significant effects on risk-adjusted returns as indicated by column (4), indicating that the reversal of risk-adjusted returns post-FOMC announcements are not driven by unexpected monetary policy changes. Instead, the interaction term between the post-FOMC indicator and $\text{MPU}^{high}_{preFOMC}$, which is an indicator equal to one if monetary policy uncertainty in the pre-FOMC-announcement window falls within the top 25% of monetary policy uncertainty observed in the entire sample, is statistically significant across all portfolios. This result suggests that return reversals are stronger when the monetary policy uncertainty prior to FOMC announcements is higher. These findings further confirm that an increase in uncertainty regarding monetary policy before Fed announcements leads to the underperformance of long-duration stocks and the outperformance of short-duration stocks in the 5-day pre-FOMC-announcement window. This pattern is then followed by a stronger return reversal after FOMC announcements.

1.4.3 Robustness

I conclude this section by running several robustness checks. First, I show that the duration-driven returns are not explained by outliers and time-varying stock betas around FOMC announcements, and that they remain robust to alternative measures for equity duration and market-based monetary policy uncertainty. Second, I construct double-sorted portfolios based on duration and mutual fund active weights to examine how portfolio risk-adjusted returns pre-FOMC announcements vary in mutual fund active weights, independent of duration. My findings indicate that only long-duration stocks that are overweighted by mutual funds underperform before FOMC announcements, an observation that is consistent with my economic interpretation. Conversely, short-duration stocks tend to outperform, especially those stocks that mutual funds underweight in their portfolios. Lastly, I check whether other macroeconomic announcements lead to similarly large abnormal risk-adjusted returns as those documented for FOMC announcements.

Panel A in Figure 1.3 shows the CAPM risk-adjusted returns to long-short duration portfolios over time. It can be clearly seen that the long-short risk-adjusted returns pre-FOMC announcements are not driven by outliers in the sample. A potential concern with these risk-adjusted portfolio returns is that CAPM betas, estimated by a rolling-window regression using daily portfolio returns from the last 252 trading days, could be biased around FOMC announcements. To directly address this concern, I estimate the daily betas of individual stocks prior to FOMC announcements. Specifically, I obtain the intraday 25-minute returns for each individual stock and the S&P 500 index (SPDR with ticker SPY) from the TAQ database. I then compute daily realized betas as the ratio of a stock's covariance with the index to the variance of the index over a given day, following the approach in Patton and Verardo (2012). Table 1.A.4 presents the stock-level panel regressions using daily CAPM risk-adjusted returns pre-FOMC announcements where daily market betas are estimated from the high-frequency sample. As expected, the estimated coefficients on the long-duration indicator are all negative and significant. This suggests that the variation in beta cannot explain the negative abnormal risk-adjusted returns on long-duration stocks prior to FOMC announcements.

Next, I verify that the positive relationship between duration-driven returns and monetary policy uncertainty pre-FOMC announcements previously documented is invariant to our measures of uncertainty and equity duration. Table 1.A.3 presents the estimated coefficients from rerunning regression (1.15) using an alternative measure of equity duration from Weber (2018a) and other market-based monetary policy uncertainty measures, such as the Treasury Implied Volatility (TIV) in Choi, Mueller, and Vedolin (2017). As the table indicates, similar to the results in Panel A of Table 1.4, the estimated coefficients on the interaction term between the pre-FOMC indicator and monetary policy uncertainty are positive and significant.

To test the model's implication that there is downward price pressure on long-duration stocks that mutual funds overweight and upward price pressure on short-duration stocks that are underweighted, I construct double-sorted portfolios based on duration and mutual fund active weights. Specifically, I sort all common stocks traded on the NYSE, AMEX, and NASDAQ at the end of each calendar month into quintiles based on duration. I intersect these quintiles with a sort on mutual fund active weights, which are computed based on aggregate active equity mutual fund holdings from Morningstar using the S&P 500 index as the benchmark. The "underweight" portfolios only include stocks with negative active weights while "overweight" portfolios include stocks with positive active weights.[17] Table 1.A.5 reports average daily CAPM risk-adjusted returns in the 5-day pre-FOMC-announcement window for double-sorted portfolios. It is noted that long-duration stocks that mutual funds overweight exclusively exhibit negative CAPM alphas before FOMC announcements. In contrast, short-duration stocks tend to outperform, exhibiting positive CAPM alphas prior to FOMC announcements, particularly those stocks that mutual funds underweight in their portfolios. These findings are consistent with the economic interpretation that duration-driven returns pre-FOMC announcements are price pressures stemming from benchmarking incentives.

Lastly, I consider whether other macroeconomic announcements are able to generate similarly large duration-driven returns as those earned prior to FOMC announcement days. I extend the analysis to three major U.S. macroeconomic news releases: the Consumer Price Index (CPI), the Gross Domestic Product (GDP), and the Producer Price Index (PPI), all published by the Bureau of Labor Statistics. Table 1.A.6 reports the averages of long-short duration returns around each macroeconomic announcement. As the table illustrates, there are no statistically significant returns on long-short duration-sorted portfolios for any of these announcements. This result indicates that interest rate announcements by the Federal Reserve have a distinct impact on the duration-driven returns that is not shared by other macroeconomic announcements. In fact, betting on duration during the highest 20% of days ranked by monetary policy uncertainty (even excluding days in the 5-day window before FOMC announcements) results in an average daily CAPM risk-adjusted return of 5.9 basis points, which is statistically significant at the 10% level. This additional evidence provides

[17] The number of stocks in the long-duration-overweight portfolio and long-duration-underweight portfolio are 2716 and 63, respectively. This is consistent with my empirical findings that mutual funds collectively overweight long-duration stocks in their portfolios.

further support for the economic mechanism, indicating that the Federal Reserve effectively changes the duration risk around FOMC announcements. As a result, it triggers prominent demand shocks in the cross-section of stocks due to the constrained risk-taking capacity of mutual funds.

1.5 Suggestive Evidence

The model outlined in Section 1.2 posits that institutional frictions act to amplify cross-sectional mispricing when monetary policy uncertainty rises. Leverage constraints induce investors to deviate from their benchmark indices by overweighting long-duration assets and underweighting short-duration assets. However, tracking-error constraints limit these deviations. Crucially, the latter effect is time-varying. During times of heightened monetary policy uncertainty, such as the week before FOMC announcements, tracking-error rises, forcing investors to bring their positions closer to their benchmark indices by selling long-duration assets and buying short-duration assets. This, as a result, generates temporary downward price pressure on long-duration stocks and upward price pressure on short-duration stocks.

In this section, I first use Morningstar mutual fund holdings to show that, in line with Proposition 2, active equity mutual funds collectively overweight long-duration stocks and underweight short-duration stocks in their portfolios. Secondly, I provide empirical evidence suggesting that tracking-error constraints are likely to bind in the 5-day pre-FOMC-announcement window due to the elevated realized bond market volatility and stock market volatility. Lastly, I present supporting evidence from Ancerno institutional trading data showing that active equity mutual funds bring their positions closer to their benchmark indices in the week prior to FOMC announcements by selling long-duration stocks and buying short-duration stocks.

1.5.1 Mutual Fund Holdings

One of the key predictions of my model is that leverage constraints induce investors to overweight long-duration assets in their portfolios. To test this prediction, I compute active weights of domestic equity mutual funds on duration-sorted portfolios based on Morningstar mutual fund holdings. The empirical findings corroborate the prediction showing that active domestic equity mutual funds overweight long-duration stocks and underweight short-duration stocks in portfolio holdings. Furthermore, I investigate the relation between the leverage-constraint tightness and the active weights of equity mutual funds on the long-duration portfolio. The result uncovers that active weights of equity mutual funds on the long-duration portfolio move closely with the leverage-constraint tightness, which is proxied by the Treasury security-based funding liquidity.

To start with, I compute the active weights of aggregate active equity mutual funds on an individual stock n at quarter-end t, $\mathrm{AW}_t(n)$, as

$$\mathrm{AW}_t(n) = \frac{\sum_{i=1}^{N} \mathrm{TNA}_{i,t} \times [w_{i,t}(n) - w_{i,t}^{B}(n)]}{\sum_{i=1}^{N} \mathrm{TNA}_{i,t}},$$

where $\mathrm{TNA}_{i,t}$ is the total net assets of mutual fund i as of quarter-end t, $w_{i,t}(n)$ is the portfolio weight of mutual fund i on stock n at quarter-end t, and $w_{i,t}^{B}(n)$ represents the portfolio weight on stock n held in the benchmark index of fund i at quarter-end t; the sum is taken over all active domestic equity mutual funds. Detailed information regarding my sample of active equity mutual funds is presented in Section 1.3.1. Mutual fund benchmarks are the primary prospectus benchmark provided by Morningstar. In cases where the primary prospectus benchmark is not provided, I use the S&P 500 index as the benchmark index. The S&P 500 index is widely considered as the most common benchmark for equity mutual funds, with more than 60% of mutual fund assets being managed against this benchmark. Additionally, other value-weighted indexes, such as the Russell 1000 and Russell 3000, exhibit similar weights of the largest 500 stocks as compared to the S&P 500 index.

Next, I compute active weights on a portfolio as follows:

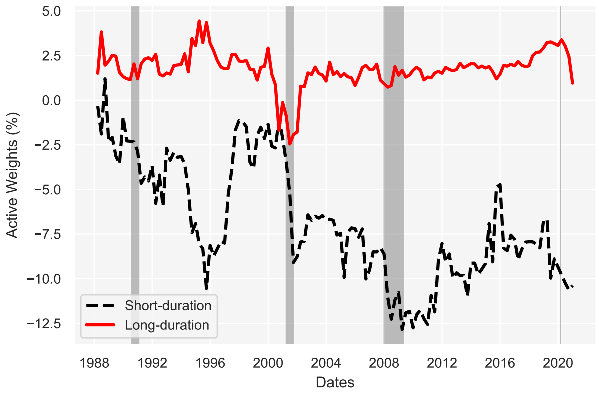
$$\mathrm{AW}_{p,t} = \sum_{n \in p_t} \mathrm{AW}_t(n)\,, \tag{1.16}$$

where the summation is taken over all stocks that are present in portfolio p at the end of quarter t. In the following empirical analysis, I consider only the long-duration and short-duration portfolios where portfolios are sorted by equity duration following the approach in Gormsen and Lazarus (2022) and are rebalanced at the end of each calendar month. The long-duration portfolio is the highest 10% tail while the short-duration portfolio is the lowest 10% tail. My main results still hold for quintile portfolios sorted by equity duration.

Panel A of Figure 1.5 depicts active weights of aggregate equity mutual funds on long-duration and short-duration portfolios. It is clearly demonstrated that equity mutual funds *overweight* the long-duration portfolio by about 1%–2%, compared to their benchmark indices. Conversely, the active weights on the short-duration portfolio are negative over time, indicating that equity mutual funds *underweight* short-duration stocks in their portfolios. The result that equity mutual funds overweight long-duration stocks and underweight short-duration stocks is, in fact, consistent with the findings by Lettau, Ludvigson, and Manoel (2018) [hereafter LLM]. LLM document that actively managed mutual funds, ETFs, and hedge funds are strongly tilted towards stocks with low book-to-market ratio, low profitability, and high investment growth rather than stocks with a high book-to-market ratio, high profitability, and low investment growth. On the other hand, existing literature, such as Frazzini and Pedersen (2014b) and Boguth and Simutin (2018), has extensively established that mutual funds overweight high-beta stocks in their portfolios. As Gormsen and Lazarus (2022) claim, high beta, low profit, high investment, and low book-to-market imply long cash-low duration.

Recall from Section 1.2 that, according to Proposition 2, constrained investors tend to overweight long-duration assets in their portfolios due to leverage constraints. The economic intuition is similar to the rationale presented in Frazzini and Pedersen (2014b), where mutual funds that are limited in their ability to use leverage opt to overweight high-beta stocks, which tend to have long duration. Panel B of Figure 1.5 presents the active weights of equity mutual funds on the long-duration portfolio (shown as the red solid line) and the Treasury security-based funding liquidity measure (illustrated by the gray dashed line). The Treasury security-based funding liquidity, as measured by Fontaine and Garcia (2011), is closely connected to measures of funding conditions and diminishes when the supply of funds to financial intermediaries is ample. This idea is grounded in the theory proposed by Gromb and Vayanos (2002) that arbitrage violations should be more frequent if arbitrageurs are leverage constrained. Boguth and Simutin (2018) demonstrate that their measure of leverage-constraint tightness is positively correlated with the Treasury security-based funding

Panel A: Active weights of equity mutual funds on duration-sorted portfolios



Panel B: Active weights on the long-duration portfolio and funding liquidity

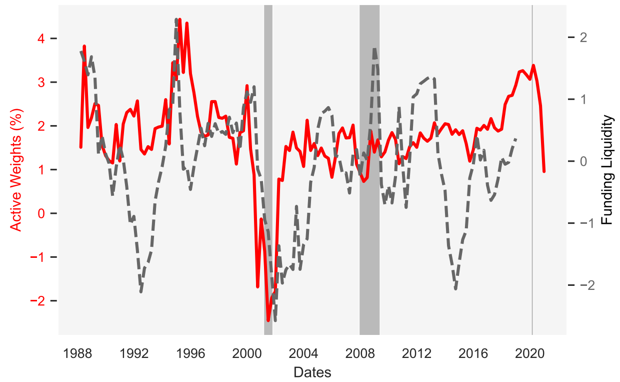


Figure 1.5: Active weights on duration-sorted portfolios and the Treasury security-based funding liquidity.

Panel A presents the active weights of aggregate domestic active equity mutual funds on long-duration and short-duration portfolios. Portfolios are sorted by the equity duration defined in Gormsen and Lazarus (2022) and are rebalanced at the end of each calendar month. The long-duration portfolio is the highest 10% tail while the short-duration portfolio is the lowest 10% tail. Active weights are calculated based on the primary prospectus benchmark of mutual funds provided by Morningstar. In cases where the primary prospectus benchmark is not provided, I use S&P 500 index as the benchmark index. Panel B depicts the active weights on the long-duration portfolio (the red-real line) and the Treasury security-based funding liquidity measure (the gray-dash line) in Fontaine and Garcia (2011). The funding liquidity is closely connected to measures of funding conditions. Specifically, when the supply of funds to financial intermediaries is ample, the value of funding liquidity decreases.

liquidity. Hence, the comovement observed between the active weights on the long-duration portfolio and the value of funding liquidity vindicates the idea that leverage constraints create an incentive for mutual funds to overweight long-duration stocks in their holdings.

Interestingly, the negative active weights on the long-duration portfolio during the recession in 2001 and the near zero active weights during the recession in 2008 have two important implications. Firstly, it is inferred that mutual funds lacked the incentive to sell long-duration stocks prior to FOMC announcements in these two recessions, as they did not, in aggregate, overweight long-duration stocks, implying an absence of selling pressure on the long-duration stocks during these economic downturns. Secondly, the presence of positive active weights on long-duration stocks prior to recessions implies that mutual funds must have sold off these assets prior to these downturns, thus exerting selling pressure on long-duration stocks prior to recessions. These two predictions are consistent with the empirical evidence that long-short risk-adjusted returns are particularly high prior to recessions and low during economic downturns, as depicted in Figure 1.3.

1.5.2 Realized Volatilities

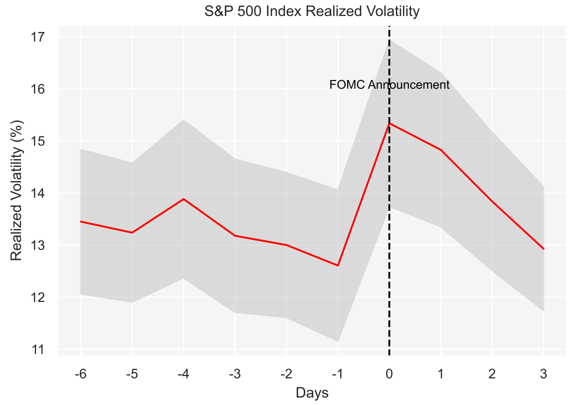
I next present empirical evidence suggesting that tracking-error constraints are likely to be binding before FOMC announcements. The 5-day pre-FOMC-announcement window, referred to as the "accumulation period" by Hu, Pan, Wang, and Zhu (2022), is the period during which uncertainty builds up. In particular, the realized stock market volatility is elevated in that window. Consequently, the rise in stock market volatility leads to a notable increase in portfolio volatilities and tracking-error variance. Moreover, the realized bond yield volatility also notably escalates in the 5-day pre-FOMC-announcement window. As a result, long-duration stocks, which are highly sensitive to changes in interest rates, exhibit high realized volatility prior to FOMC announcements. The elevated realized volatility of long-duration stocks pre-FOMC announcements further exacerbates the tightness of tracking-error constraints as equity mutual funds overweight long-duration stocks in their portfolios.

Figure 1.6 depicts the averages of realized volatility of the S&P 500 index (Panel A), realized 10-year Treasury bond yield volatility (Panel B), and realized volatilities of duration-sorted portfolios (Panel C) around FOMC announcements. The realized volatility of the S&P 500 index is the 5-minute realized volatility obtained from the Oxford-Man Institute's realized library. The sample covers the period from January 3, 2000, to June 28, 2022, totaling 5635 trading days. Realized yield volatility is estimated by using high-frequency data on the pricing of U.S. 10-year Treasury bonds from January 1997 through December 2018 by splicing historical observations from two platforms: GovPX (pre-2000) and BrokerTec (post-2000) following the procedure of Cieslak and Povala (2016). Yield volatility is estimated with 10-minute sampling frequency and is reported in basis points per annum. I select 10-year Treasury bonds for two reasons. On one hand, equity duration is relatively long, making it appropriate to consider long-term bond yield volatility in this context. On the other hand, 10-year Treasury bonds are much more liquid than other long-term Treasury bonds, such as 30-year Treasury bonds (e.g., Fleming and Mizrach, 2008). Realized volatilities of duration-sorted portfolios are calculated by utilizing high-frequency stock prices from the TAQ data with 5-minute sampling frequency following the same approach as Barndorff-Nielsen, Hansen, Lunde, and Shephard (2009) and Aleti and Bollerslev (2022). Further details about TAQ data cleaning and high-frequency volatility estimation can be found in Appendix 1.A.4.

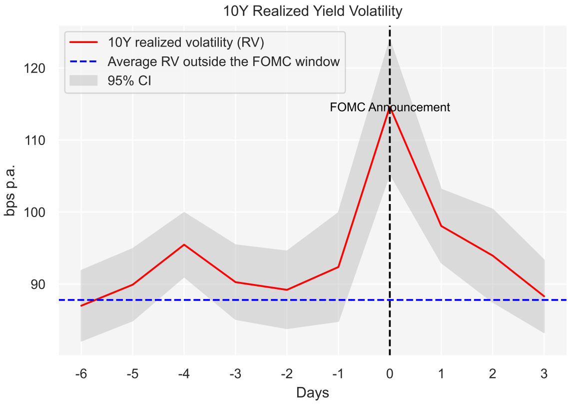
Panel A of Figure 1.6 illustrates that the realized volatility of the S&P 500 index is heightened during the five-day window before FOMC announcements, with a notable increase four days before announcements. Nevertheless, the realized volatility is low on the day right before FOMC announcements and then surges to peak on FOMC announcement days, which is consistent with the findings by Lucca and Moench (2015). Panel B demonstrates that the realized bond yield volatility is notably elevated in the 5-day pre-FOMC-announcement window in comparison to the average of other days. Specifically, the realized yield volatility ramps up from its overall average level five days before the FOMC announcements and reaches the peak on announcement days. As indicated by Panel C, the long-duration portfolio also exhibits higher realized volatility pre-FOMC announcements, following the pattern of realized yield volatility. Given the findings by Gormsen and Lazarus (2022) that the realized equity duration varies from 15 years for the short-duration portfolio to 59 years for the long-duration portfolio, the long-duration portfolio is inherently sensitive to changes in interest rates, resulting in higher volatility pre-FOMC announcements.

The empirical evidence on realized volatilities together suggest that tracking-error constraints are likely to bind before FOMC announcements. As a result, tight tracking-error constraints force investors (e.g., mutual funds) to bring their positions closer to the benchmark indices. Hence, they induce selling-price pressure on long-duration stocks and buying-

Panel A: Realized volatilities of S&P 500 index



Panel B: Realized yield volatilities



Panel C: Realized volatilities of duration-sorted portfolios

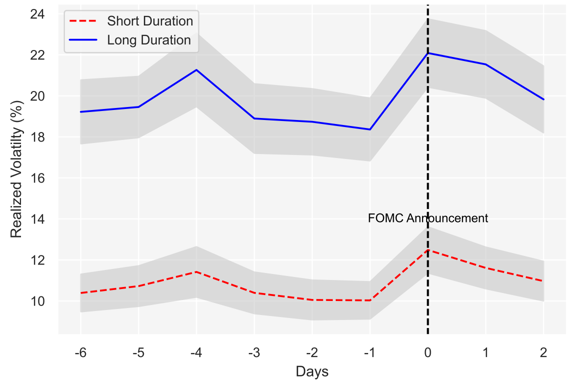


Figure 1.6: Realized volatilities.

This figure plots the averages of realized 10-year bond yield volatility (top left), realized volatilities of duration-sorted portfolios (top right), realized S&P 500 index volatility (bottom left) and VIX index (bottom right) around FOMC announcements. Yield volatility is estimated with 10-minute sampling frequency following Cieslak and Povala (2016) and is reported in basis points per annum. Realized S&P 500 index volatility is the 5-minute realized volatility downloaded from Oxford-Man Institute's realized library. Realized volatilities of duration-sorted portfolios are calculated by utilizing high-frequency stock prices from the TAQ data with 5-minute sampling frequency. Realized volatilities for stock market returns are in percentage per annum.

price pressure on short-duration stocks as mutual funds overweight long-duration stocks and underweight short-duration stocks in their portfolios. It is natural to expect that abnormal risk-adjusted returns on long-short duration portfolios pre-FOMC announcements are increasing with the tightness of tracking-error constraints.

Regression results in Table 1.5 confirm the prediction. Specifically, I conduct time-series regressions using the realized volatility of the S&P 500 index (in Panel A) and the realized 10-year Treasury yield volatility (in Panel B) as simple proxies for the tightness of tracking-error constraints. Higher volatility pre-FOMC announcements implies tighter constraints. The dependent variable is abnormal risk-adjusted returns on duration-sorted portfolios, namely the daily CAPM alphas. "Pre-FOMC" is an indicator equal to one during the five trading days before FOMC announcements and zero otherwise. Positive (significant at the 5% level) coefficients on interaction terms between the pre-FOMC indicator and realized volatility measures in column (2) demonstrate that long-short abnormal risk-adjusted returns increase with the tightness of tracking-error constraints. Columns (4) and (6) jointly imply that binding tracking-error constraints induce positive alpha on the short-duration portfolio and negative alpha on the long-duration portfolio, as indicated by the regression coefficients on the pre-FOMC indicator. Furthermore, it is noted that the regression coefficients on the interaction term are positive for the short-duration portfolio but negative for the long-duration portfolio, indicating that the price pressure induced by tracking-error constraints is larger when constraints become tighter.

1.5.3 Ancerno Mutual Funds Trading

The Ancerno data is a proprietary dataset of institutional equity trading, containing trading transactions from mutual funds, hedge funds, and pension funds. Although an abundance of transaction details are provided in the dataset, identities of individual funds are concealed. As a result, it is challenging to merge Ancerno institutional trading with Morningstar mutual fund characteristics, such as total net assets, tracking errors, and portfolio holdings. To overcome this problem, I implement a non-trivial algorithm to identify mutual funds in the Ancerno dataset by matching the changes in the stock holdings implied by the transaction data with the changes in the holdings reported in Morningstar. Section 3.2 provides detailed

Table 1.5: Duration-Driven Returns and Realized Volatilities.

This table reports results of time-series regressions of duration-sorted portfolios. The long-short strategy has the long-duration portfolio on the short leg and the short-duration portfolio on the long leg. The long-duration portfolio is a value-weighted portfolio of the highest 10% tail of stocks sorted by duration, as defined in Gormsen and Lazarus (2022), while the short-duration portfolio is the lowest 10% tail. The dependent variable is the daily CAPM alpha, which is estimated from a rolling-window regression using daily portfolio returns from the last 252 trading days. "Pre-FOMC" is an indicator equal to one on the five trading days before FOMC announcements and zero otherwise. "SPX-RV" is the standardized daily 5-minute realized volatility of the S&P 500 index. "RV-10Y" is the standardized daily realized 10-year bond yield volatility, which is estimated with 10-minute sampling frequency following Cieslak and Povala (2016). The sample periods are January 3, 2000, to June 28, 2022, for Panel A and January 1, 1997, to March 1, 2018, for Panel B due to data availability. Newey-West adjusted $t-$statistics are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	Panel A: Realized Stock Market Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
	Long-Short Alphas		Long-Leg Alphas		Short-Leg Alphas	
Intercept	0.35	0.34	0.44	0.43	0.09	0.09
	(0.2)	(0.2)	(0.55)	(0.55)	(0.07)	(0.07)
Pre-FOMC	10.71**	10.67**	3.95**	3.94**	-6.76**	-6.73**
	(2.46)	(2.48)	(2.04)	(2.05)	(-2.25)	(-2.26)
SP500-RV		-3.92		-1.64		2.28
		(-1.13)		(-1.06)		(0.95)
Pre-FOMC × SP500-RV		14.23**		5.24*		-8.99*
		(1.98)		(1.67)		(-1.94)
	Panel B: Realized Bond Yield Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
	Long-Short Alphas		Long-Leg Alphas		Short-Leg Alphas	
Intercept	0.86	0.14	0.35	-0.26	-0.51	-0.4
	(0.58)	(0.08)	(0.51)	(-0.31)	(-0.49)	(-0.36)
Pre-FOMC	8.31**	12.15***	3.08*	3.89*	-5.23**	-8.26***
	(2.26)	(2.85)	(1.87)	(1.91)	(-2.04)	(-2.97)
RV-10Y		-7.34***		-3.01***		4.34***
		(-3.81)		(-3.23)		(3.12)
Pre-FOMC × RV-10Y		11.07**		3.84*		-7.23**
		(2.49)		(1.83)		(-2.38)

information regarding the matching procedures. In the end, a total of 394 actively managed equity mutual funds are properly matched.

To ensure that my findings can be generalized to a large sample of actively managed equity mutual funds, Table 1.A.1 represents the summary statistics of the 394 mutual funds matched in Ancerno (Panel A) and the summary statistics of all actively managed equity mutual funds in the Morningstar database (Panel B). The characteristics of funds, such as turnover, expenses, equity ratio, and cash holdings are similar across the two datasets. The main difference is that these 394 funds are, on average, larger than the equity mutual funds in the Morningstar database. It is noteworthy that Ancerno's clients are more likely to be large funds than small funds, as documented by Puckett and Yan (2011).

Combining Morningstar mutual fund holdings with Ancerno institutional trading data, I construct funds' daily portfolio holdings prior to FOMC announcements and establish two empirical facts consistent with my model predictions. Firstly, active equity mutual funds, as identified in Ancerno data, overweight long-duration stocks and concurrently underweight short-duration stocks one trading week prior to FOMC announcements. Secondly, it is observed that matched equity mutual funds sell long-duration stocks and buy short-duration stocks in the 5-day window pre-FOMC announcements, moving closer to their benchmark indices.

To construct daily portfolio holdings of matched mutual funds around FOMC announcements, I find the nearest date on which the holdings are reported in Morningstar for each day around FOMC announcements. I then generate daily holdings on the basis of the holdings reported and combine them with transactions. Based on the daily holdings constructed, I compute fund active weights on individual stocks based on their benchmarks. Figure 1.7 shows the distributions of TNA-weighted active weights of matched equity mutual funds on duration-sorted portfolios one trading week prior to FOMC announcements. For instance, the top row ("Decile 1") shows the distribution of TNA-weighted active weights on the short-duration portfolio over FOMC meetings from January 1999 to September 2011. Mutual fund active weights are computed as portfolio weights minus the benchmark weights one trading week prior to FOMC announcements (i.e., active weights on day $t-6$ where t represents the FOMC announcement day). Mutual fund benchmarks are the primary prospectus benchmark provided by Morningstar. The bottom row ("Decile 10") shows the distribution of TNA-weighted active weights on the long-duration portfolio. The figure demonstrates that active equity mutual funds matched in the trading data overweight long-duration stocks and underweight short-duration stocks one trading week prior to FOMC announcements. In particular, these funds on average overweight the long-duration portfolio (decile 10) by 2.5% and underweight the short-duration portfolio (decile 1) by 8% in the data sample. This result echoes the findings in Section 1.5.1 where it is shown that aggregate equity mutual funds overweight the long-duration portfolio by 2% and underweight the short-duration portfolio by 7.5% on average over the same period.

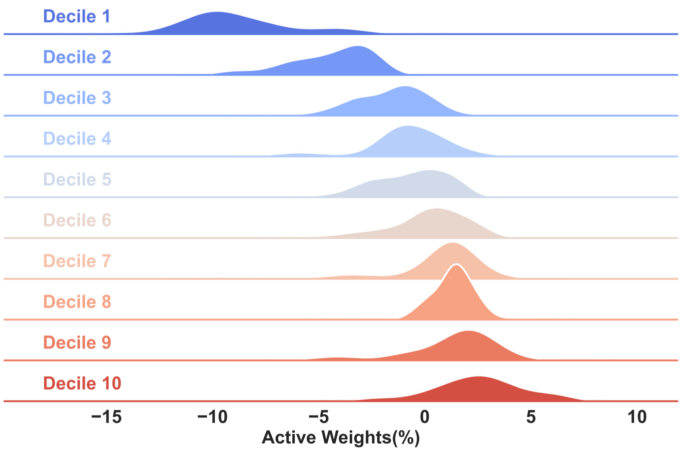


Figure 1.7: Distribution of TNA-weighted active weights on duration-sorted portfolios. The figure shows the distributions of TNA-weighted active weights of equity mutual funds matched from Ancerno trading data on different duration-sorted portfolios one trading week prior to FOMC announcements (i.e., on days $t-6$ where $t=0$ represents the FOMC announcement day). Active weights are calculated based on the fund specific benchmark index from Morningstar. Each row in the figure shows the distribution of active weights on the corresponding duration-sorted decile over years 1999-2011. Decile 1 represents the short-duration portfolio while decile 10 represents the long-duration portfolio.

Next, I examine whether mutual funds move close to their benchmarks through selling long-duration stocks and buying short-duration stocks prior to FOMC announcements. For this purpose, I compute the daily portfolio weight change in stocks for each mutual fund in my sample. Specifically, the change in stock n's weight held by fund i due to trading on day t is stock n's weight on day t minus stock n's no-trade weight:

$$\Delta w_{i,t}(n) = w_{i,t}(n) - \hat{w}_{i,t}(n).$$

Stock n's no-trade weight is

$$\hat{w}_{i,t}(n) = \frac{w_{i,t-1}(n)(1+r_{t,n})}{\sum_{k=1}^{N} w_{i,t-1}(k)(1+r_{t,k})},$$

where $w_{i,t-1}(n)$ is stock n's weight held by fund i on day $t-1$ and $r_{t,n}$ is stock n's return on day t.

I then estimate the following panel regression:

$$\Delta w_{i,t}(n) = \beta_0 + \beta_1 D_t(n) + \beta_2 TE_{i,t} + \beta_3 D_t(n) TE_{i,t} + \beta_4 Flow_{i,t} + \epsilon_{i,t}(n)\,, \tag{1.17}$$

where the dependent variable represents the weight changes in stock holdings due to trading. $D_t(n)$ is an indicator equal to one if the duration of stock n falls within the highest 10% tail and zero otherwise. The sample includes only trades on long-duration stocks (decile 10) and short-duration stocks (decile 1) in the 5-day pre-FOMC-announcement window from 1999 to 2011. $\text{TE}_{i,t}$ is an indicator equal to one if the tracking error of fund i is above 5%. The tracking error is computed using daily fund returns over benchmark returns in a one-year lookback window. $\text{Flow}_{i,t}$ represents daily mutual fund flows estimated by daily fund TNA from Morningstar and daily fund returns from CRSP. Specifically, I calculate flows in fund i at time t as

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t})}{TNA_{i,t-1}}.$$

$\text{TNA}_{i,t}$ represents total net assets and $R_{i,t}$ is the fund return. In the regression, β_0 measures the average trades on short-duration stocks in the 5-day pre-FOMC announcements window. β_1 measures the trades on long-duration stocks relative to short-duration stocks.

Table 1.6 shows the results from panel regressions where I report two-way (funds and time) clustered standard errors. Across various specifications, the coefficient on the long-duration indicator, $D_t(n)$, is negative and statistically significant, indicating that mutual funds matched in the Ancerno data sell long-duration stocks pre-FOMC announcements. As seen in column (3), the coefficient on the interaction term between the long-duration indicator and the tracking-error indicator is negative (significant at 10% level). This suggests that mutual funds with high tracking errors tend to sell more long-duration stocks compared to their low-tracking-error counterparts. This is due to the fact that high-tracking-error funds allocate higher portfolio weights on long-duration stocks. When controlling for active weights in the regression, as shown in column (4), the interaction term becomes insignificant. This implies that mutual funds adjust their positions closer to their benchmarks prior to

FOMC announcements by actively trading against their active weights. This evidence is consistent with my model predictions, which posit that mutual funds that are bounded by tracking errors would bring their positions to the benchmark when the tracking-error constraint tightens. Moreover, the result in column (5) rules out the flow-based explanation, that is, that high monetary policy uncertainty triggers mutual fund outflows which prompt the sale of long-duration stocks prior to FOMC announcements.

Table 1.6: Ancerno Mutual Fund Trading.

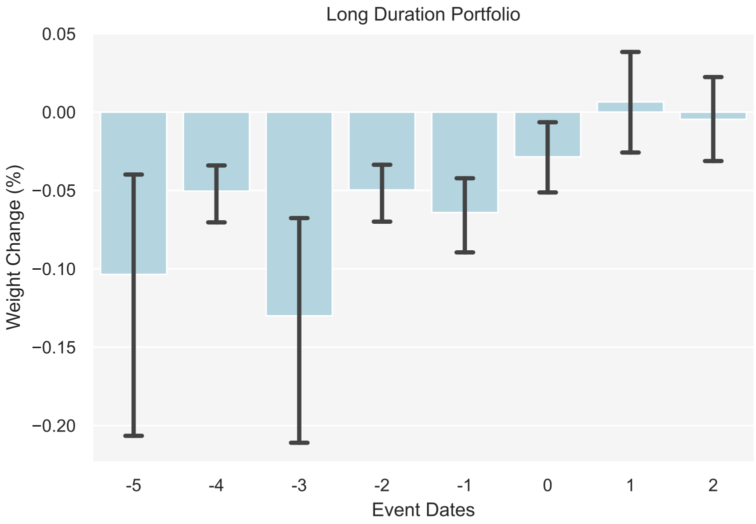
This table reports estimates of the panel regression specified in Eq.(1.17). The dependent variable $\Delta w_{i,t}(n)$ is the change in stock n's weight of fund i due to trading on day t. $D_t(n)$ is an indicator equal to one if the duration of stock n falls within the highest 10% tail and zero otherwise. $\mathrm{TE}_{i,t}$ is an indicator equal to one if the tracking error of fund i is above 5% where tracking error is computed using daily fund returns over benchmarks in a one-year lookback window. $\mathrm{AW}_{i,t-1}(n)$ is the active weight on stock n by fund i on day $t-1$. Mutual fund flows, $\mathrm{Flow}_{i,t}$, are estimated using daily fund TNA from Morningstar and daily fund returns from CRSP. The sample includes only trades on long-duration stocks (decile 10) and short-duration stocks (decile 1) in the 5-day pre-FOMC-announcement window from 1999 to 2011. Regressions include fund fixed effects and time fixed effects. Standard errors are double clustered by fund and time. *p<0.1; **p<0.05; ***p<0.01.

	(1)	(2)	(3)	(4)	(5)
Constant	0.001*	0.001	0.000	0.003	0.001
	(1.64)	(0.90)	(0.05)	(1.16)	(0.18)
$D_t(n)$	-0.009***	-0.010***	-0.006**	-0.004*	-0.006*
	(-4.11)	(-3.71)	(-2.38)	(-1.73)	(-1.86)
$\mathrm{TE}_{i,t}$			0.004	0.000	0.000
			(0.81)	(0.74)	(1.23)
$D_t(n)\times$ $\mathrm{TE}_{i,t}$			-0.008*	0.000	-0.000
			(-1.68)	(0.00)	(-0.01)
$\mathrm{AW}_{i,t-1}(n)$				-0.261***	-0.152***
				(-4.66)	(-3.23)
$\mathrm{Flow}_{i,t}$					0.238
					(0.87)
Fund FEs	No	Yes	Yes	Yes	Yes
Time FEs	No	Yes	Yes	Yes	Yes

Figure 1.8 confirms the results by illustrating the average weight changes on the long-duration portfolio and the short-duration portfolio across equity mutual funds around FOMC announcements. It reveals that equity mutual funds, on average, sell long-duration stocks by

approximately 8 basis points per day in the pre-FOMC-announcement window. As depicted in Figure 1.7, these mutual funds overweight long-duration stocks by approximately 2%–2.5%. This suggests that, in the trading week prior to FOMC announcements, mutual funds in the Ancerno data tend to reduce 16%–20% of their active weights on long-duration stocks. On the other hand, it is observed that these mutual funds buy short-duration stocks prior to FOMC announcements, albeit with a relatively small weight change of 2 basis points per day. The limited trades on short-duration stocks are consistent with the limited price pressure. Consequently, the return of the long-short duration strategy is primarily driven by the short leg, which comprises long-duration stocks.

Panel A: Mutual funds trading on long-duration stocks



Panel B: Mutual funds trading on short-duration stocks

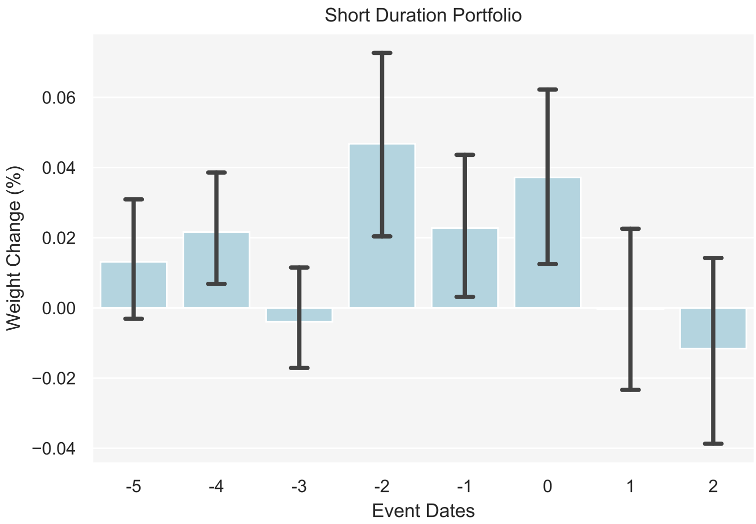


Figure 1.8: Mutual funds trading on duration-sorted stocks.
This figure presents mutual funds trading on long-duration stocks (Panel A) and short-duration stocks (Panel B) around FOMC announcements. Date 0 denotes the FOMC announcement day. Weight change in the plots is the average weight change on duration-sorted portfolios across equity mutual funds matched in Ancerno. The data sample is from January 1999 to September 2011.

1.6 Conclusions

In this paper, I document that a broad set of long-short strategies betting on major equity anomalies in the 5-day pre-FOMC-announcement window exhibit significant risk-adjusted returns. These risk-adjusted returns are primarily driven by duration. A trading strategy that is short long-duration stocks and long short-duration stocks merely in the 5-day pre-FOMC-announcement window yields statistically and economically large risk-adjusted returns. Moreover, I find that these risk-adjusted returns (i) increase with monetary policy uncertainty, (ii) are procyclical, co-moving with the market expectation of federal funds rate changes, and (iii) are reversed after FOMC announcements.

I interpret the large pre-FOMC abnormal risk-adjusted returns as temporary price pressure within a model of institutional investors who face leverage and tracking-error constraints. On one hand, institutional investors who are leverage constrained overweight long-duration stocks and underweight short-duration stocks in their portfolios. On the other hand, increasing uncertainty in the pre-FOMC-announcement window tightens the tracking-error constraint, inducing institutional investors to optimally move close to their benchmarks. This, as a result, induces temporary downward price pressure on long-duration stocks and upward price pressure on short-duration stocks. I also show that, corroborating the theory, equity mutual funds overweight long-duration stocks and underweight short-duration stocks in their holdings. Furthermore, the realized stock market volatility and the realized Treasury yield volatility are elevated in the 5-day pre-FOMC-announcement window, suggesting the tightness of tracking-error constraints. Lastly, I provide empirical evidence from institutional trading data indicating that mutual funds indeed bring their positions closer to the benchmark indices by selling long-duration stocks and buying short-duration stocks prior to FOMC announcements, supporting the economic mechanism in my model.

Appendices

1.A.1 Additional Tables and Figures

Table 1.A.1: Summary Statistics of Mutual Funds.

Panel A of this table reports the summary statistics of 394 mutual funds matched in the Ancerno data from 1999 to 2011. Panel B reports the summary statistics of 3,874 actively managed domestic equity mutual funds in the Morningstar data from 1999 to 2011. Active domestic equity mutual funds in my sample are selected following the procedure outlined in Section 1.3.1. Fund TNAs (in million dollars) are aggregated across all share classes. Fund equity ratio is the ratio of equity holdings to total net assets. Turnover represents the annual turnover reported in Morningstar, which is computed by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing by the average TNA of the fund. Expenses is annual net expense ratio, which is the total net expenses divided by the fund's average net assets. Cash holding represents cash holding as a percentage of fund TNAs as reported in Morningstar.

Panel A: Summary statistics of matched mutual funds in Ancerno data				
	25th	Median	Mean	75th
Fund TNAs ($ millions)	146.8	498.1	2537.1	1713.3
Equity Ratio	77.7%	85.7%	82.4%	90.9%
Turnover	45%	74%	91%	117%
Expenses	0.91%	1.14%	1.18%	1.45%
Cash Holding	0.68%	2.27%	3.45%	4.56%
Panel B: Summary statistics of active domestic mutual funds in Morningstar				
	25th	Median	Mean	75th
Fund TNAs ($ millions)	36.2	153.1	986.6	592.9
Equity Ratio	79.3%	86.5%	83.9%	91.6%
Turnover	38%	71%	106%	120%
Expenses	1.00%	1.25%	1.32%	1.54%
Cash Holding	0.65%	2.27%	3.99%	4.81%

Table 1.A.2: Anomaly Long Leg and Short Leg Returns.

This table reports summary statistics of anomaly long leg and short leg returns for the 5-day pre-FOMC-announcement window (Panel A), FOMC announcement days (Panel B), and the full sample (Panel C), respectively. The long and short legs are value-weighted portfolios of the lowest or highest 10% tail of stocks sorted by anomaly characteristics elaborated in Table 1.1. All numbers are expressed in daily basis points (bps) except for Sharpe ratios (SR), which are annualized, taking into account the annual frequency of days in the pre-FOMC-announcement window (40/252) and FOMC announcement days (8/252).

	Short Leg						Long Leg					
Anomaly	**Excess Return**	**CAPM Alpha**	**FF3F Alpha**	**Dur-2F Alpha**	**Dur-3F Alpha**	**SR**	**Excess Return**	**CAPM Alpha**	**FF3F Alpha**	**Dur-2F Alpha**	**Dur-3F Alpha**	**SR**
	5-Day Pre-FOMC Announcement ($n = 1,160$)											
CAPM Beta	-14.42	-16.83	-10.58	-8.36	-8.31	-0.42	1.89	0.83	-0.70	-1.91	-1.89	0.15
	(-2.23)	(-4.82)	(-3.93)	(-3.56)	(-3.78)		(0.78)	(0.51)	(-0.47)	(-1.55)	(-1.53)	
Operating Profitability	-7.28	-9.36	-5.92	-5.23	-4.88	-0.32	5.31	2.50	2.18	1.22	1.20	0.28
	(-1.7)	(-4.49)	(-3.45)	(-2.91)	(-2.98)		(1.50)	(2.14)	(1.99)	(1.21)	(1.21)	
EPS Forecasts	-10.77	-12.84	-8.37	-8.10	-8.16	-0.36	4.77	2.00	0.03	0.81	0.75	0.25
	(-1.91)	(-4.35)	(-3.49)	(-3.31)	(-3.65)		(1.34)	(2.02)	(0.04)	(0.97)	(0.99)	
Return on Equity	-5.48	-7.87	-4.67	-4.65	-4.31	-0.23	4.48	1.70	1.21	1.09	1.15	0.24
	(-1.24)	(-4.28)	(-2.98)	(-2.94)	(-2.85)		(1.25)	(1.79)	(1.42)	(1.20)	(1.30)	
Value	-7.63	-8.79	-5.59	-5.48	-5.49	-0.31	2.90	1.26	3.42	2.90	3.50	0.16
	(-1.55)	(-3.55)	(-2.33)	(-2.47)	(-2.48)		(0.79)	(0.60)	(1.86)	(1.41)	(1.94)	
Net Payout Yield	-9.91	-12.66	-11.04	-7.66	-7.73	-0.37	4.23	1.73	0.32	-0.04	-0.31	0.23
	(-1.95)	(-4.65)	(-4.86)	(-3.22)	(-3.50)		(1.22)	(1.27)	(0.27)	(-0.03)	(-0.24)	
Idiosyncratic Volatility	-12.73	-14.50	-9.11	-7.91	-7.71	-0.41	4.98	2.90	1.46	1.01	0.95	0.36
	(-2.18)	(-3.79)	(-3.02)	(-2.59)	(-2.72)		(1.9)	(3.33)	(1.85)	(1.32)	(1.24)	
Firm Age	-0.17	-2.89	-2.54	-1.63	-1.51	-0.01	4.75	2.26	0.91	-0.18	-0.35	0.28
	(-0.04)	(-1.88)	(-1.81)	(-1.13)	(-1.07)		(1.46)	(1.79)	(0.89)	(-0.18)	(-0.36)	
Duration	-5.33	-5.74	-2.60	0.93	0.99	-0.19	4.71	3.43	1.96	-0.11	-0.15	0.28
	(-1.04)	(-2.47)	(-1.28)	(0.62)	(0.67)		(1.49)	(2.25)	(1.45)	(-0.11)	(-0.15)	
Mean	-9.05	-9.26	-6.04	-4.34	-4.14	-0.35	3.48	2.17	1.40	0.57	0.61	0.21
	(-1.89)	(-4.58)	(-3.99)	(-3.2)	(-3.36)		(1.14)	(2.73)	(2.02)	(1.06)	(1.15)	
	FOMC Announcement Days ($n = 232$)											
CAPM Beta	48.09	11.35	8.76	0.98	-1.04	0.57	10.11	-6.04	-6.68	-3.43	-4.07	0.33
	(3.03)	(1.49)	(1.4)	(0.18)	(-0.2)		(1.75)	(-1.75)	(-1.83)	(-1.06)	(-1.23)	
Operating Profitability	31.49	3.36	0.30	0.43	0.39	0.56	20.61	-3.70	-1.41	-2.22	-2.59	0.54
	(2.98)	(0.67)	(0.07)	(0.09)	(0.09)		(2.86)	(-1.37)	(-0.57)	(-0.92)	(-1.06)	
EPS Forecasts	36.18	2.03	-6.78	-5.34	-4.74	0.51	26.12	1.11	2.91	1.47	1.48	0.63
	(2.72)	(0.35)	(-1.18)	(-0.99)	(-0.87)		(3.36)	(0.58)	(1.74)	(0.9)	(0.93)	
Return on Equity	30.77	1.73	-2.31	-1.26	-2.22	0.56	25.13	0.65	1.90	1.16	1.10	0.62
	(2.97)	(0.4)	(-0.57)	(-0.31)	(-0.59)		(3.28)	(0.3)	(0.98)	(0.56)	(0.51)	
Value	24.5	-7.57	-4.68	-13.36	-11.84	0.36	21.79	-5.34	-6.87	-5.4	-5.69	0.49
	(1.81)	(-0.8)	(-0.51)	(-1.52)	(-1.37)		(2.48)	(-1.28)	(-1.91)	(-1.33)	(-1.53)	
Net Payout Yield	26.53	-1.00	-2.85	-9.85	-10.87	0.45	20.78	-0.25	-0.26	0.24	-0.45	0.57
	(2.37)	(-0.17)	(-0.55)	(-2.0)	(-2.22)		(3.02)	(-0.09)	(-0.09)	(0.09)	(-0.16)	
Idiosyncratic Volatility	47.54	14.38	6.52	5.43	4.31	0.58	17.55	-1.49	-1.97	-0.62	-0.97	0.56
	(3.07)	(1.48)	(0.8)	(0.62)	(0.54)		(2.99)	(-0.78)	(-1.16)	(-0.35)	(-0.57)	
Firm Age	27.56	3.02	2.46	-0.38	-0.06	0.62	16.4	-6.08	-4.48	-3.57	-4.68	0.46
	(3.26)	(0.98)	(0.92)	(-0.12)	(-0.02)		(2.44)	(-2.36)	(-1.95)	(-1.60)	(-2.10)	
Duration	46.3	12.38	12.95	3.24	5.78	0.73	14.91	-5.02	-4.13	-1.39	-2.26	0.45
	(3.92)	(2.61)	(2.89)	(0.93)	(1.64)		(2.44)	(-1.61)	(-1.55)	(-0.6)	(-0.95)	
Mean	38.24	5.45	2.74	-1.86	-2.35	0.6	19.36	-3.3	-3.07	-1.71	-2.34	0.55
	(3.25)	(1.33)	(0.85)	(-0.63)	(-0.92)		(2.94)	(-2.17)	(-2.19)	(-1.47)	(-1.97)	
	Full Sample ($n = 7,308$)											
CAPM Beta	2.90	-2.68	-2.03	-1.73	-2.22	0.20	2.02	-0.15	-0.56	-0.63	-0.62	0.42
	(1.06)	(-1.94)	(-1.85)	(-1.82)	(-2.49)		(2.22)	(-0.26)	(-1.0)	(-1.34)	(-1.3)	
Operating Profitability	2.46	-1.73	-2.08	-1.08	-1.60	0.26	4.55	0.69	0.83	0.4	0.28	0.64
	(1.39)	(-2.13)	(-3.04)	(-1.5)	(-2.43)		(3.41)	(1.48)	(1.94)	(0.99)	(0.69)	
EPS Forecasts	0.73	-4.23	-4.5	-3.38	-3.79	0.06	4.47	0.51	0.2	0.38	0.51	0.62
	(0.31)	(-3.46)	(-4.45)	(-3.28)	(-3.9)		(3.28)	(1.36)	(0.69)	(1.21)	(1.75)	
Return on Equity	2.89	-1.34	-1.56	-1.04	-1.36	0.3	4.81	0.89	0.89	0.79	0.77	0.66
	(1.6)	(-1.78)	(-2.38)	(-1.56)	(-2.15)		(3.47)	(2.43)	(2.79)	(2.28)	(2.25)	
Value	2.09	-1.88	-1.12	-1.45	-1.44	0.19	5.86	2.41	2.16	2.71	2.14	0.74
	(0.96)	(-1.77)	(-1.09)	(-1.5)	(-1.51)		(3.75)	(2.96)	(3.04)	(3.41)	(3.04)	
Net Payout Yield	1.43	-3.3	-3.55	-2.03	-2.17	0.13	4.87	1.14	0.68	0.62	0.59	0.69
	(0.71)	(-2.87)	(-3.67)	(-2.07)	(-2.38)		(3.68)	(2.11)	(1.43)	(1.26)	(1.21)	
Idiosyncratic Volatility	-0.21	-4.65	-4.88	-3.56	-4.20	-0.02	3.31	0.21	-0.28	-0.23	-0.22	0.61
	(-0.08)	(-2.95)	(-3.64)	(-2.65)	(-3.3)		(3.22)	(0.59)	(-0.84)	(-0.73)	(-0.68)	
Firm Age	3.21	-0.77	-0.98	-0.36	-0.37	0.40	3.34	-0.24	-0.48	-0.67	-0.69	0.51
	(2.1)	(-1.18)	(-1.64)	(-0.6)	(-0.63)		(2.68)	(-0.48)	(-1.17)	(-1.73)	(-1.81)	
Duration	3.2	-1.34	-0.66	0.06	0.22	0.28	3.8	0.84	0.68	0.18	0.16	0.6
	(1.49)	(-1.42)	(-0.79)	(0.1)	(0.38)		(3.25)	(1.38)	(1.26)	(0.41)	(0.38)	
Mean	1.45	-2.58	-2.41	-1.70	-1.93	0.13	3.88	0.73	0.52	0.4	0.35	0.62
	(0.72)	(-3.18)	(-3.77)	(-3.18)	(-4.00)		(3.32)	(2.38)	(1.94)	(1.9)	(1.64)	

Table 1.A.3: Duration-Driven Returns Time-Series Regressions.

This table reports results of time-series regressions for duration-sorted portfolios. The long-short strategy has the long-duration portfolio on the short leg and the short-duration portfolio on the long leg. The long-duration portfolio is a value-weighted portfolio of the highest 10% tail of stocks sorted by duration, as defined in Weber (2018a), while the short-duration portfolio is the lowest 10% tail. The dependent variable is the daily long-short returns or CAPM alphas. The daily CAPM alphas are estimated from a rolling-window regression using daily portfolio returns from the previous 252 trading days. "*Pre*-FOMC" is an indicator equal to one on the five trading days before FOMC announcements and zero otherwise. "MOVE" is the standardized Merrill Lynch Option Volatility Estimate, which serves as a proxy for monetary policy uncertainty. "TIV" is the standardized Treasury Implied Volatility extracted from one-month options on 10-year Treasury futures. The data sample is from January 1, 1994, to December 31, 2021. Newey-West adjusted $t-$statistics are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Merrill Lynch Option Volatility Estimate (MOVE)

	(1)	(2)	(3)	(4)
	Long-Short Returns		Long-Short Alphas	
Intercept	2.03	2.01	1.93	1.93
	(1.35)	(1.33)	(1.39)	(1.39)
Pre-FOMC	10.89***	10.65***	11.68***	11.45***
	(2.99)	(2.95)	(3.30)	(3.27)
MOVE		-1.39		-0.69
		(-0.82)		(-0.43)
Pre-FOMC×MOVE		9.68**		7.95*
		(2.37)		(1.89)

Panel B: Treasury Implied Volatility (TIV)

	(1)	(2)	(3)	(4)
	Long-Short Returns		Long-Short Alphas	
Intercept	2.03	1.87	1.93	2.33
	(1.35)	(1.18)	(1.39)	(1.63)
Pre-FOMC	10.89***	12.75***	11.68***	11.87***
	(2.99)	(3.40)	(3.30)	(3.36)
TIV		-3.12*		-2.53
		(-1.83)		(-1.53)
Pre-FOMC×TIV		10.55**		9.81**
		(2.36)		(2.22)

Table 1.A.4: Duration-Driven Returns Panel Regressions.

This table reports the estimates of the stock-day panel regressions: $R^{(h,H)}_{t,k} = \beta_S + \beta_{LMS} D^l_{t,k} + \gamma_0 X_{t,k} + \gamma_1 D^l_{t,k} X_{t,k} + \epsilon_{t,k}$. The dependent variable $R^{(-5,-1)}_{t,k}$ is daily CAPM risk-adjusted returns of stock k on date t for days in the 5-day pre-FOMC-announcement window where daily market betas are estimated from the high-frequency sample following the approach in Patton and Verardo (2012). $D^l_{t,k}$ is an indicator equal to one if the duration of stock k falls within the highest 10% tail and zero otherwise. $X_{t,k}$ is a set of control variables. Specifically, $Size_{t,k}$ represents the quintile of stocks' market capitalization taking values from 1 to 5. $Liqcost_{t,k}$ is the daily stock CRSP bid-ask spread as described in Chung and Zhang (2014). Regressions include stock-industry fixed effects and FOMC meeting fixed effects. Standard errors are double clustered by stock and date. The sample period is from 1994 to 2022. *p<0.1; **p<0.05; ***p<0.01.

	(1)	(2)	(3)
	$R^{(-5,-1)}_{t,k}$	$R^{(-5,-1)}_{t,k}$	$R^{(-5,-1)}_{t,k}$
$D^l_{t,k}$	-8.04***	-7.82**	-5.64**
	(-3.88)	(-2.32)	(-2.58)
$Size_{t,k}$		-1.02	
		(-0.07)	
$D^l_{t,k}\times$ $Size_{t,k}$		-0.28	
		(-0.04)	
$Liqcost_{t,k}$			-0.08
			(-0.25)
$D^l_{t,k}\times$ $Liqcost_{t,k}$			-2.23**
			(-2.02)
Industry FEs	Yes	Yes	Yes
Meeting FEs	Yes	Yes	Yes
N	306,728	306,728	306,728

Table 1.A.5: CAPM Alphas of Portfolios sorted on Duration and Mutual Fund Active Weights

This table reports daily CAPM risk-adjusted returns in the 5-day pre-FOMC-announcement window for ten portfolios sorted on duration (Dur) and mutual fund active weights. I sort all common stocks traded on the NYSE, AMEX, and NASDAQ at the end of each calendar month into quintiles based on duration. I intersect these quintiles with a sort on mutual fund active weights, which are computed based on aggregate active equity mutual fund holdings from Morningstar using the S&P 500 index as the benchmark. The "underweight" portfolios only include stocks with negative active weights while the "overweight" portfolios only include stocks with positive active weights. Equity duration is measured following the approach developed by Gormsen and Lazarus (2022). $t-$statistics are reported in parentheses. The sample covers November 1, 1994, to December 30, 2021.

	Short Dur	D2	D3	D4	Long Dur
Underweight	4.76	7.75	-5.97	2.09	-2.35
	(2.70)	(2.76)	(-1.26)	(0.35)	(-0.34)
Overweight	2.79	-0.04	0.11	-3.78	-7.64
	(2.26)	(-0.03)	(0.08)	(-2.32)	(-3.51)

Table 1.A.6: Long-short Duration Returns for Other Macroeconomic Announcements.

This table reports excess returns and CAPM risk-adjusted alphas of long-short duration portfolios on announcement days and five days prior to announcements for CPI, GDP, and PPI. The long-short strategy has the long-duration portfolio on the short leg and the short-duration portfolio on the long leg. The long-duration portfolio is a value-weighted portfolio of the highest 10% tail of stocks sorted by duration defined in Gormsen and Lazarus (2022) while the short-duration portfolio is the lowest 10% tail. $t-$statistics are reported in parentheses. The sample covers November 1, 1994, to June 29, 2022.

	Consumer Price Index		Gross Domestic Product		Producer Price Index	
	Excess Return	CAPM Alpha	Excess Return	CAPM Alpha	Excess Return	CAPM Alpha
Pre-Announcement	2.98	4.61	2.8	2.33	-0.26	0.13
	(0.82)	(1.63)	(0.77)	(0.75)	(-0.16)	(0.03)
Announcement	-6.08	-8.46	-16.2	-7.49	-0.82	5.68
	(-0.84)	(-1.32)	(-2.19)	(-1.18)	(-0.08)	(0.71)

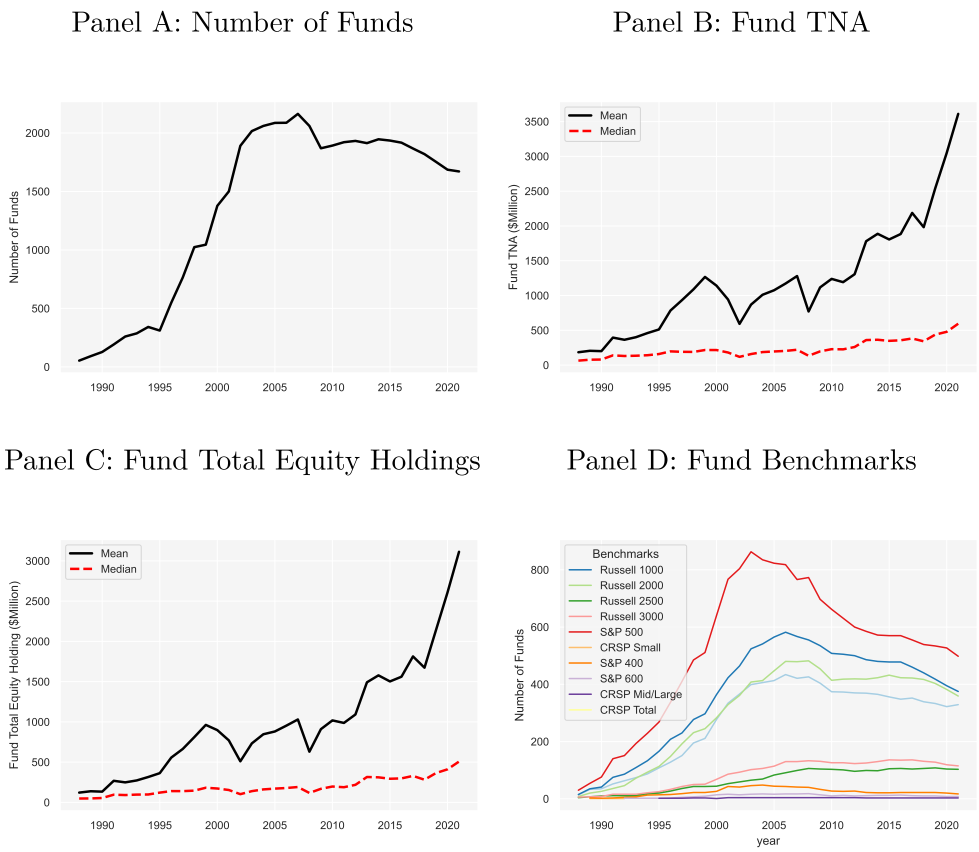


Figure 1.A.1: Mutual Funds Sample.

This figure plots the number of actively managed mutual funds in my sample (Panel A), the mean and median of fund TNA (Panel B), the mean and median of fund total equity holdings (Panel C) and the number of funds benchmarking against different indices.

Sales-to-price　　　　Momentum

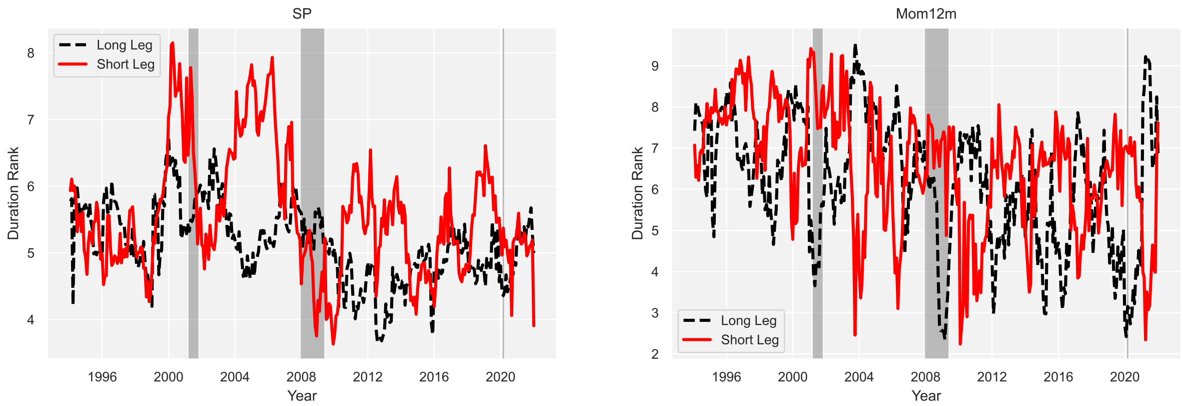
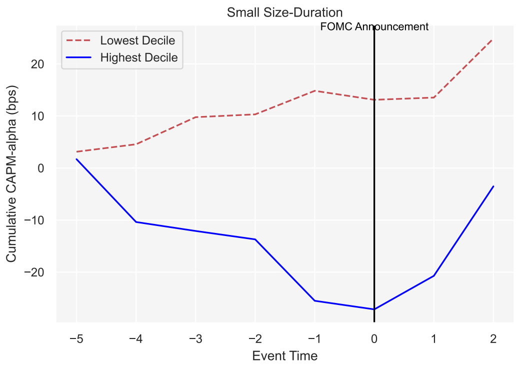
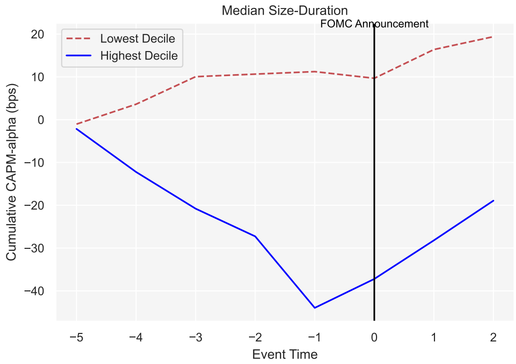


Figure 1.A.2: Duration Spreads Between the Long Leg and the Short Leg of Anomalies. This figure illustrates the duration rank for portfolios on the long leg and short leg, respectively, for sells-to-price ratio and momentum. Portfolio duration rank is calculated as the value-weighted average of stock duration decile, which takes time-varying values from 1 to 10 based on the rank of stock duration defined by Gormsen and Lazarus (2022). Specifically, I sort stocks in the universe into 10 deciles at the end of each month. Stocks in the k^{th} decile take the value k as their duration rank.

Panel A: Small size



Panel B: Mid size



Panel C: Large size

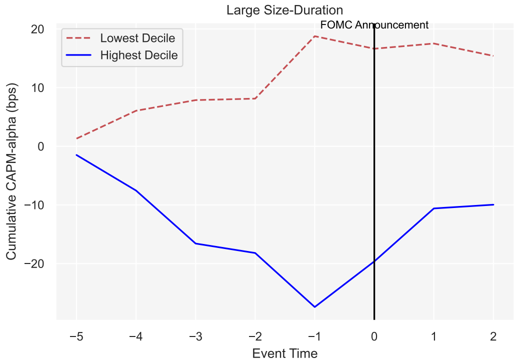


Figure 1.A.3: Risk-Adjusted Returns of Portfolios Double-Sorted by Duration and Size. This figure shows the average cumulative CAPM alphas of portfolios double-sorted by duration and size around FOMC announcements. The portfolio breakpoints are based on NYSE firms. Portfolios are value-weighted and rebalanced at the end of each calendar month. Each panel shows the average cumulative CAPM alphas of the long-duration portfolio and the short-duration portfolio within different size groups. The long-duration portfolio is the highest 10% tail of stocks sorted by duration within each size group. The short-duration portfolio is the lowest 10% tail.

1.A.2 Proof of Propositions

Before formally proving Proposition 1, I recall a useful lemma in Vayanos and Wang (2012).

Lemma 1.A.1. *Let x be an $n \times 1$ normal vector with mean zero and covariance matrix Σ_x, A a scalar, B an $n \times 1$ vector, C an $n \times n$ symmetric matrix, I the $n \times n$ identity matrix, and $|M|$ the determinant of a matrix M. Then,*

$$\mathbb{E}_x \exp\left\{-\alpha\left[A + B'x + \frac{1}{2}x'Cx\right]\right\} = \exp\left\{-\alpha\left[A - \frac{1}{2}\alpha B'\Sigma_x(I + \alpha C\Sigma_x)^{-1}B\right]\right\}\frac{1}{\sqrt{|I + \alpha C\Sigma_x|}} \tag{1}$$

Proof of Proposition 1: Unconstrained investors' wealth $W_{2,u}$ in period 2 is

$$W_{2,u} = W_{1,u} + \phi'_{1,u}(D_2 - S_1)\,,$$

where $\phi_{1,u}$ denotes unconstrained investors' asset allocations in period 1. In period 1, investors maximize

$$-\,\mathbb{E}_1\exp\left[-\gamma(W_{1,u} + \phi'_{1,u}(D_2 - S_1))\right] \tag{2}$$

with respect to $\phi_{1,u}$. The solution yields the optimal demand for risky assets as

$$\phi_{1,u} = \frac{1}{\gamma}\Sigma_1^{-1}[\mathbb{E}_1(D_2) - S_1]\,, \tag{3}$$

where $\Sigma_1 = \mathbb{V}ar_1(D_2) = \beta\beta'\sigma^2 + I\eta^2$.

On the other hand, constrained investors' demand $\phi_{1,c}$ in period 1 is

$$\phi_{1,c} = \frac{1}{\gamma + 2\lambda_1}\Sigma_1^{-1}\left[\mathbb{E}_1(D_2) - (1 + \varphi_1)S_1\right] + \frac{2\lambda_1}{\gamma + 2\lambda_1}\phi_b\,. \tag{4}$$

The market-clearing condition in period 1 is

$$(1 - x)\phi_{1,u} + x\phi_{1,c} = \theta\,.$$

Therefore, we find that the equilibrium prices in period 1 are

$$S_1 = a_1\mathbb{E}_1(D_2) - b_1\Sigma_1\left(\theta - \frac{2\lambda_1 x}{\gamma + 2\lambda_1}\phi_b\right)\,, \tag{5}$$

where $a_1 = \frac{\gamma+2\lambda_1-2\lambda_1 x}{\gamma+2\lambda_1-2\lambda_1 x+x\varphi_1\gamma} > 0$ and $b_1 = \frac{\gamma(\gamma+2\lambda_1)}{\gamma+2\lambda_1-2\lambda_1 x+x\varphi_1\gamma} > 0$.

Substituting equation (3) into equation (2), we have the value function of unconstrained investors as

$$V_1(W_{1,u}) = -\exp\left[-\left(\gamma W_{1,u} + \frac{1}{2}(\mathbb{E}_1(D_2) - S_1)'\Sigma_1^{-1}(\mathbb{E}_1(D_2) - S_1)\right)\right]. \tag{6}$$

In period 0, unconstrained investors maximize the expectation of the value function specified in (6). Their wealth in period 1 is given by

$$W_{1,u} = W_{0,u} + \phi_{0,u}'(D_1 + S_1 - S_0)\,,$$

where $\phi_{0,u}$ denotes the asset allocations in period 0. Substituting it into equation (6), we find that unconstrained investors maximize

$$-\mathbb{E}_0\left[\exp(-\gamma\phi_{0,u}'D_1)\right]\mathbb{E}_0\left[\exp\left(-(A + B'x + \frac{1}{2}x'Cx)\right)\right], \tag{7}$$

where

$$\begin{aligned}
x &\equiv \mathbb{E}_1(D_2) - S_1 - K \\
K &\equiv (1-a_1)\bar{D} + b_1\Sigma_1\left(\theta - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_b\right) \\
A &\equiv \gamma W_{0,u} + \gamma\phi_0'(\bar{D} - K - S_0) + \frac{1}{2}K'\Sigma_1^{-1}K \\
B &\equiv \gamma\frac{a_1}{1-a_1}\phi_0 + \Sigma_1^{-1}K \\
C &\equiv \Sigma_1^{-1}
\end{aligned}$$

Equation (7) comes from the fact that D_1 is independent of μ. Moreover, since $\mathbb{E}_1(D_2) = \bar{D} + \beta\mu$, where μ is normally distributed with $\mathbb{E}_0(\mu) = 0$ and $\mathbb{V}ar_0(\mu) = \sigma_\mu^2$, we have that x is also normally distributed with $\mathbb{E}_0(x) = 0$ and $\mathbb{V}ar_0(x) \equiv \Sigma_x = (1-a_1)^2\beta\beta'\sigma_\mu^2$. By Lemma 1, we find that (7) is equal to

$$-\exp\left[-\left(\gamma\phi_{0,u}'\bar{D} - \frac{\gamma^2}{2}\phi_{0,u}'\phi_{0,u}\eta^2 + A - \frac{1}{2}B'\Sigma_x(I + C\Sigma_x)^{-1}B\right)\right]\frac{1}{\sqrt{|I + C\Sigma_x|}}. \tag{8}$$

The first-order condition yields that

$$\phi_{0,u} = \frac{1}{\gamma}\left(\eta^2 I + \left(\frac{a_1}{1-a_1}\right)^2 \Sigma_x (I + C\Sigma_x)^{-1}\right)^{-1}\left(2\bar{D} - K - S_0 - \frac{a_1}{1-a_1}\Sigma_x(I + C\Sigma_x)^{-1}\Sigma_1^{-1}K\right). \tag{9}$$

In addition, we have the demand for risky assets by constrained investors in period 0 as

$$\phi_{0,c} = \frac{1}{\gamma + 2\lambda_0}\Sigma_0^{-1}\left[\mathbb{E}_0(D_1 + S_1) - (1+\varphi_0)S_0\right] + \frac{2\lambda_0}{\gamma + 2\lambda_0}\phi_b\,, \tag{10}$$

where $\Sigma_0 \equiv \mathbb{V}ar_0(D_1 + S_1) = a_1^2\beta\beta'\sigma_\mu^2 + I\eta^2$.

The market-clearing condition in period 0 is

$$(1-x)\phi_{0,u} + x\phi_{0,c} = \theta\,. \tag{11}$$

Substituting (9) and (10) into (11), we find that the equilibrium price in period 0 is

$$S_0 = (a_0 I + b_0 k_1 \beta\beta')\mathbb{E}_0(D_1 + S_1) - \eta^2 b_0 \Sigma_s\left(\theta - \frac{2\lambda_0 x}{\gamma + 2\lambda_0}\phi_b\right) - k_2\beta\beta' K\,, \tag{12}$$

where

$$\begin{aligned}
a_0 &= \frac{\gamma + 2\lambda_0 - 2\lambda_0 x}{\gamma + 2\lambda_0 - 2\lambda_0 x + x\varphi_0\gamma} > 0\\
b_0 &= \frac{\gamma(\gamma + 2\lambda_0)}{\gamma + 2\lambda_0 - 2\lambda_0 x + x\varphi_0\gamma} > 0\\
k_1 &= \frac{(1-x)x\varphi_0}{\gamma(\gamma + 2\lambda_0)y}\left(\frac{a_1^2\sigma_\mu^2}{\eta^2 + a_1^2\sigma_\mu^2\beta'\beta} - \frac{\bar{\sigma}^2}{\eta^2 + \bar{\sigma}^2\beta'\beta}\right) > 0\\
k_2 &= \frac{\eta^2\bar{\sigma}^2(1-x)(1-a_1)}{\gamma a_1 y(\eta^2 + \bar{\sigma}^2\beta'\beta)(\eta^2 + \sigma^2\beta'\beta)}\\
y &= \frac{1-x}{\gamma}\frac{\eta^2}{\eta^2 + \bar{\sigma}^2\beta'\beta} + \frac{x(1+\varphi_0)}{\gamma + 2\lambda_0}\frac{\eta^2}{\eta^2 + a_1^2\sigma_\mu^2\beta'\beta}\\
\Sigma_s &= I + \sigma_s^2\beta\beta'\\
\sigma_s^2 &= \frac{1}{y}\left(\frac{1-x}{\gamma}\frac{\bar{\sigma}^2}{\eta^2 + \bar{\sigma}^2\beta'\beta} + \frac{x(1+\varphi_0)}{\gamma + 2\lambda_0}\frac{a_1^2\sigma_\mu^2}{\eta^2 + a_1^2\sigma_\mu^2\beta'\beta}\right)\\
\bar{\sigma}^2 &= \frac{a_1^2\sigma_\mu^2(\eta^2 + \sigma^2\beta'\beta)}{\eta^2 + \sigma^2\beta'\beta + (1-a_1)^2\sigma_\mu^2\beta'\beta}\\
K &= (1-a_1)\bar{D} + b_1\Sigma_1\left(\theta - \frac{2\lambda_1 x}{\gamma + 2\lambda_1}\phi_b\right)
\end{aligned}$$

To derive the price equation (12), we use the Sherman-Morrison formula repeatedly to calculate the inverse of matrices. For instance, we have

$$\Sigma_0^{-1} = \frac{1}{\eta^2}\left(I - \frac{a_1^2\sigma_\mu^2\beta\beta'}{\eta^2 + a_1^2\sigma_\mu^2\beta'\beta}\right)$$
$$\Sigma_1^{-1} = \frac{1}{\eta^2}\left(I - \frac{\sigma^2\beta\beta'}{\eta^2 + \sigma^2\beta'\beta}\right)$$
$$(I + C\Sigma_x)^{-1} = I - \frac{(1-a_1)^2\sigma_\mu^2\beta\beta'}{\eta^2 + \sigma^2\beta'\beta + (1-a_1)^2\sigma_\mu^2\beta'\beta}$$

□

Proof of Proposition 2: Inserting the equilibrium price (12) into (10) yields constrained investors' asset allocations in period 0:

$$\begin{aligned}\phi_{0,c} = {} & \frac{2\lambda_0}{\gamma+2\lambda_0}\phi_b + \frac{1-(1+\varphi_0)a_0}{\gamma+2\lambda_0}\Sigma_0^{-1}\mathbb{E}_0(D_1+S_1) - \frac{(1+\varphi_0)b_0k_1}{\gamma+2\lambda_0}\Sigma_0^{-1}\beta\beta'\mathbb{E}_0(D_1+S_1)\\ & + \frac{(1+\varphi_0)\eta^2 b_0}{\gamma+2\lambda_0}\Sigma_0^{-1}\Sigma_s\left(\theta - \frac{2\lambda_0 x}{\gamma+2\lambda_0}\phi_b\right) + \frac{(1+\varphi_0)k_2}{\gamma+2\lambda_0}\Sigma_0^{-1}\beta\beta' K\,.\end{aligned}$$

Additionally, we have the price $S_{1,i}$ for asset i in period 1 from (5):

$$S_{1,i} = a_1(\beta_i\mu + \bar{D}_i) - b_1\sigma^2\beta_i\beta'\left(\theta - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_b\right) - b_1\eta^2\left(\theta_i - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_{b,i}\right).$$

Hence, the expectation of $S_{1,i}$ in period 0 is

$$\mathbb{E}_0(S_{1,i}) = a_1\bar{D}_i - b_1\sigma^2\beta_i\beta'\left(\theta - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_b\right) - b_1\eta^2\left(\theta_i - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_{b,i}\right).$$

It follows that

$$\begin{aligned}\frac{\partial\phi_{0,c}(i)}{\partial\beta_i} = {} & \frac{(1+\varphi_0)a_0 - 1}{(\gamma+2\lambda_0)\eta^2}b_1\sigma^2\beta'\left(\theta - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_b\right) + \frac{(1+\varphi_0)a_0-1}{(\gamma+2\lambda_0)\eta^2}\frac{a_1^2\sigma_\mu^2}{\eta^2 + a_1^2\sigma_\mu^2\beta'\beta}\beta'\mathbb{E}_0(D_1+S_1)\\ & - \frac{(1+\varphi_0)b_0k_1}{\gamma+2\lambda_0}\frac{1}{\eta^2 + a_1^2\sigma_\mu^2\beta'\beta}\beta'\mathbb{E}_0(D_1+S_1)\\ & + \frac{(1+\varphi_0)b_0}{\gamma+2\lambda_0}\frac{\sigma_s^2\eta^2 - a_1^2\sigma_\mu^2}{\eta^2 + a_1^2\sigma_\mu^2\beta'\beta}\beta'\left(\theta - \frac{2\lambda_0 x}{\gamma+2\lambda_0}\phi_b\right)\\ & + \frac{(1+\varphi_0)k_2}{\gamma+2\lambda_0}\frac{1}{\eta^2 + a_1^2\sigma_\mu^2\beta'\beta}\beta' K\,.\end{aligned}$$

It is noted that $a_0 = \frac{\gamma+2\lambda_0-2\lambda_0 x}{\gamma+2\lambda_0-2\lambda_0 x+x\varphi_0\gamma}$, $\lambda_0 \geq 0$, and $x \in (0,1)$. Hence, if $\varphi_0 > 0$, we have

$$\frac{(1+\varphi_0)a_0 - 1}{(\gamma+2\lambda_0)\eta^2} = \frac{1}{(\gamma+2\lambda_0)\eta^2}\left((1+\varphi_0)\frac{\gamma+2\lambda_0-2\lambda_0 x}{\gamma+2\lambda_0-2\lambda_0 x+x\varphi_0\gamma} - 1\right) > 0\,.$$

This is because the term $(1+\varphi_0)\frac{\gamma+2\lambda_0-2\lambda_0 x}{\gamma+2\lambda_0-2\lambda_0 x+x\varphi_0\gamma} - 1$ is monotonically increasing in φ_0 and is equal to zero when $\varphi_0 = 0$.

In addition, when σ_μ^2 is small ($\sigma_\mu^2 \to 0$), we have $k_1 \to 0$, $k_2 \to 0$, and $\sigma_s^2 \to 0$. Therefore, when $\varphi_0 > 0$ and σ_μ^2 is small, we have

$$\lim_{\sigma_\mu^2 \to 0} \frac{\partial \phi_{0,c}(i)}{\partial \beta_i} = \frac{(1+\varphi_0)a_0 - 1}{(\gamma+2\lambda_0)\eta^2} b_1 \sigma^2 \beta' \left(\theta - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_b\right) > 0.$$

□

Lemma 1.A.2. *Suppose the tracking-error constraint is binding in period 1, that is $\lambda_1 > 0$. We have $\partial\lambda_1/\partial\sigma^2 > 0$.*

Proof: The binding tracking-error constraint implies that

$$(\phi_{1,c} - \phi_b)'\Sigma_1(\phi_{1,c} - \phi_b) = \tau\,.$$

Substituting (5) into (4), we find that

$$\phi_{1,c} - \phi_b = \frac{1-(1+\varphi_1)a_1}{\gamma+2\lambda_1}\Sigma_1^{-1}(\beta\mu + \bar{D}) + \frac{(1+\varphi_1)b_1}{\gamma+2\lambda_1}\left(\theta - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_b\right) - \frac{\gamma}{\gamma+2\lambda_1}\phi_b\,.$$

We denote $F(\sigma^2, \lambda_1) \equiv (\phi_{1,c} - \phi_b)'\Sigma_1(\phi_{1,c} - \phi_b) - \tau$, and the derivative of the implicit function $F(\sigma^2, \lambda_1) = 0$ is given by

$$\frac{\partial\lambda_1}{\partial\sigma^2} = -\frac{F_{\sigma^2}}{F_{\lambda_1}}\,.$$

It is easy to verify that $F_{\sigma^2} > 0$ and $F_{\lambda_1} < 0$. Therefore, we have

$$\frac{\partial\lambda_1}{\partial\sigma^2} > 0.$$

□

Proof of Proposition 3: The risk-adjusted return (alpha) of asset i is defined as the asset's expected return adjusted by the expected return of the benchmark (market) index. Specifically, alpha between periods 0 and 1 is the constant in the regression of the asset's return $e_i'(D_1 + S_1 - S_0)$ on the market index return $\phi_b'(D_1 + S_1 - S_0)$:

$$e_i'(D_1 + S_1 - S_0) = \alpha_{1,i} + \beta_{1,i}^{MKT} \phi_b'(D_1 + S_1 - S_0) + \xi_i \, .$$

where e_i is a $n \times 1$ vector with a 1 in row i and zeros elsewhere. The regression yields

$$\begin{aligned}
\beta_{1,i}^{MKT} &= \frac{\phi_b'\Sigma_0 e_i}{\phi_b'\Sigma_0\phi_b} \\
\alpha_{1,i} &= e_i'\mathbb{E}(D_1 + S_1 - S_0) - \frac{\phi_b'\Sigma_0 e_i}{\phi_b'\Sigma_0\phi_b}\phi_b'\mathbb{E}(D_1 + S_1 - S_0)
\end{aligned}$$

Hence, we have

$$\frac{\partial \alpha_{1,i}}{\partial \sigma^2} = e_i' \frac{\partial}{\partial \sigma^2}\mathbb{E}(D_1 + S_1 - S_0) - \frac{\phi_b'\Sigma_0 e_i}{\phi_b'\Sigma_0\phi_b}\phi_b' \frac{\partial}{\partial \sigma^2}\mathbb{E}(D_1 + S_1 - S_0) \, . \tag{13}$$

Inserting price equations (5) and (12) into (13), we find that

$$\begin{aligned}
\frac{\partial \alpha_{1,i}}{\partial \sigma^2} = &-(1-a_0)\left(\frac{\partial b_1}{\partial \sigma^2}\eta^2\left(\theta_i - \frac{2\lambda_1 x}{\gamma + 2\lambda_1}\phi_{b,i}\right)\right) \\
&+ (1-a_0)\left(\frac{\partial a_1}{\partial \sigma^2}\bar{D}_i - (\frac{\partial b_1}{\partial \sigma^2}\sigma^2 + b_1)\beta_i\beta'\left(\theta - \frac{2\lambda_1 x}{\gamma + 2\lambda_1}\phi_b\right)\right) \\
&+ (1-a_0)\frac{2\gamma x}{(\gamma + 2\lambda_1)^2}\frac{\partial \lambda_1}{\partial \sigma^2}\left(b_1\eta^2\phi_{b,i} + b_1\sigma^2\beta_i\beta'\phi_b\right) \\
&- 2b_0\frac{\partial k_1}{\partial \sigma^2}\beta_i\beta'\bar{D} + b_0\frac{\partial k_1}{\partial \sigma^2}\beta_i\beta' K + \eta^2 b_0\frac{\partial \sigma_s^2}{\partial \sigma^2}\beta_i\beta'\left(\theta - \frac{2\lambda_0 x}{\gamma + 2\lambda_0}\phi_b\right) \\
&+ \frac{\partial k_2}{\partial \sigma^2}\beta_i\beta' K + (b_0 k_1\beta_i + k_2\beta_i)\beta'\frac{\partial K}{\partial \sigma^2} - \frac{\phi_b'\Sigma_0 e_i}{\phi_b'\Sigma_0\phi_b}\phi_b'\frac{\partial}{\partial \sigma^2}\mathbb{E}(D_1 + S_1 - S_0) \, .
\end{aligned} \tag{14}$$

We denote $\frac{\partial \alpha_{1,i}}{\partial \sigma^2} = -(1-a_0)\left(\frac{\partial b_1}{\partial \sigma^2}\eta^2\left(\theta_i - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_{b,i}\right)\right) + M_{1,i}$ for ease of notation, where $M_{1,i}$ represents the rest terms in (14). Since $b_1 = \frac{\gamma(\gamma+2\lambda_1)}{\gamma+2\lambda_1-2\lambda_1 x + x\varphi_1\gamma}$ and $\frac{\partial \lambda_1}{\partial \sigma^2} > 0$, we have $\frac{\partial b_1}{\partial \sigma^2} > 0$. Additionally, $1 - a_0 > 0$. Therefore, we find that $\frac{\partial \alpha_{1,i}}{\partial \sigma^2} < 0$ if

$$\left(\theta_i - \frac{2\lambda_1 x}{\gamma + 2\lambda_1}\phi_{b,i}\right) > \frac{M_{1,i}}{(1-a_0)\eta^2\frac{\partial b_1}{\partial \sigma^2}} \, . \tag{15}$$

Moreover, by (5) and (4) we know that

$$\phi_{1,c} - \phi_b = \frac{1-(1+\varphi_1)a_1}{\gamma+2\lambda_1}\Sigma_1^{-1}(\beta\mu+\bar{D}) + \frac{(1+\varphi_1)b_1}{\gamma+2\lambda_1}\left(\theta - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_b\right) - \frac{\gamma}{\gamma+2\lambda_1}\phi_b\,,$$

which implies that

$$\left(\theta_i - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_{b,i}\right) = \frac{\gamma+2\lambda_1}{(1+\varphi_1)b_1}\left(\phi_{1,c}^i - \phi_{b,i}\right) + \frac{\gamma}{(1+\varphi_1)b_1}\phi_{b,i} - \frac{1-(1+\varphi_1)a_1}{(1+\varphi_1)\eta^2 b_1}\left(\beta_i\mu + \bar{D}_i - \beta_i\frac{\sigma^2\beta'(\beta\mu+\bar{D}}{\eta^2+\beta'\beta\sigma^2} \right. \tag{16}$$

Substituting (16) into (15), we find that

$$\frac{\partial\alpha_{1,i}}{\partial\sigma^2} < 0 \quad \text{if} \quad \left(\phi_{1,c}^i - \phi_{b,i}\right) > N_{1,i}\,,$$

where $N_{1,i} = \frac{(1+\varphi_1)b_1}{\gamma+2\lambda_1}\left(\frac{M_{1,i}}{(1-a_0)\eta^2\frac{\partial b_1}{\partial\sigma^2}} - \frac{\gamma}{(1+\varphi_1)b_1}\phi_{b,i} + \frac{1-(1+\varphi_1)a_1}{(1+\varphi_1)\eta^2 b_1}\left(\beta_i\mu + \bar{D}_i - \beta_i\frac{\sigma^2\beta'(\beta\mu+\bar{D})}{\eta^2+\beta'\beta\sigma^2}\right)\right)$.

Similarly,

$$\frac{\partial\alpha_{1,i}}{\partial\sigma^2} > 0 \quad \text{if} \quad \left(\phi_{1,c}^i - \phi_{b,i}\right) < N_{1,i}\,.$$

For the second part of the proposition, it is noticed that

$$e_i'(D_2 - S_1) = \alpha_{2,i} + \beta_{2,i}^{MKT}\phi_b'(D_2 - S_1) + \xi_i\,.$$

We find that

$$\alpha_{2,i} = e_i'\mathbb{E}(D_2 - S_1) - \frac{\phi_b'\Sigma e_i}{\phi_b'\Sigma\phi_b}\phi_b'\mathbb{E}(D_2 - S_1)\,,$$

where Σ is the unconditional variance-covariance matrix of $D_2 - S_1$. Thus,

$$\begin{aligned}\frac{\partial\alpha_{2,i}}{\partial\sigma^2} = {} & \frac{\partial b_1}{\partial\sigma^2}\eta^2\left(\theta_i - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_{b,i}\right) + \left(\frac{\partial b_1}{\partial\sigma^2}\sigma^2 + b_1\right)\beta_i\beta'\left(\theta - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_b\right) \\ & - \frac{2\gamma x}{(\gamma+2\lambda_1)^2}\frac{\partial\lambda_1}{\partial\sigma^2}\left(b_1\eta^2\phi_{b,i} + b_1\sigma^2\beta_i\beta'\phi_b\right) - \frac{\phi_b'\Sigma e_i}{\phi_b'\Sigma\phi_b}\phi_b'\frac{\partial\mathbb{E}(D_2 - S_1)}{\partial\sigma^2}\,.\end{aligned} \tag{17}$$

We denote $\frac{\partial\alpha_{2,i}}{\partial\sigma^2} = \frac{\partial b_1}{\partial\sigma^2}\eta^2\left(\theta_i - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_{b,i}\right) + M_{2,i}$, where $M_{2,i}$ represents the rest of the terms in (17). Hence, we have $\frac{\partial\alpha_{2,i}}{\partial\sigma^2} > 0$ if

$$\left(\theta_i - \frac{2\lambda_1 x}{\gamma+2\lambda_1}\phi_{b,i}\right) > -\frac{M_{2,i}}{\eta^2\frac{\partial b_1}{\partial\sigma^2}}\,. \tag{18}$$

Substituting (16) into (18), we find that

$$\frac{\partial \alpha_{2,i}}{\partial \sigma^2} > 0 \quad \text{if} \quad \left(\phi^i_{1,c} - \phi_{b,i}\right) > N_{2,i}\,,$$

where $N_{2,i} = \frac{(1+\varphi_1)b_1}{\gamma+2\lambda_1}\left(-\frac{M_{2,i}}{\eta^2\frac{\partial b_1}{\partial \sigma^2}} - \frac{\gamma}{(1+\varphi_1)b_1}\phi_{b,i} + \frac{1-(1+\varphi_1)a_1}{(1+\varphi_1)\eta^2 b_1}\left(\beta_i\mu + \bar{D}_i - \beta_i\frac{\sigma^2\beta'(\beta\mu+\bar{D})}{\eta^2+\beta'\beta\sigma^2}\right)\right)$.

Similarly,

$$\frac{\partial \alpha_{2,i}}{\partial \sigma^2} < 0 \quad \text{if} \quad \left(\phi^i_{1,c} - \phi_{b,i}\right) < N_{2,i}\,.$$

□

Proof of Proposition 4: The expected return per share of asset i between periods 0 and 1 is given by

$$\mathbb{E}_1(R_{1,i}) = \mathbb{E}_1(D_1 + S_1 - S_0)\,.$$

Inserting (5) and (12) into the expected return, we find that

$$\frac{\partial \mathbb{E}_1(R_{1,i})}{\partial \mu} = \frac{\gamma + 2\lambda_1 - 2\lambda_1 x}{\gamma + 2\lambda_1 - 2\lambda_1 x + x\varphi_1\gamma}\beta_i > 0$$

and

$$\frac{\partial^2 \mathbb{E}_1(R_{1,i})}{\partial \beta_i \partial \mu} = \frac{\gamma + 2\lambda_1 - 2\lambda_1 x}{\gamma + 2\lambda_1 - 2\lambda_1 x + x\varphi_1\gamma} > 0\,.$$

□

1.A.3 Matching Abel Noser Data with Morningstar Mutual Fund Holdings

The Abel Noser institutional trading data does not disclose the actual identities of mutual funds, making it challenging to merge that data with Morningstar mutual fund characteristics, such as total net assets, tracking errors, and fund flows. To address this problem and investigate mutual fund trading around FOMC announcements, I implement a non-trivial algorithm to match mutual funds in the Abel Noser data to Morningstar mutual fund holdings over the period from January 1999 to September 2011. The matching procedure closely follows the approach outlined in Agarwal, Tang, and Yang (2012), but with the unique aspect of taking advantage of Morningstar mutual fund holdings due to their exceptional data quality.

For each reporting period, which refers to the period between two consecutive reporting dates (typically one month or one quarter), of an equity mutual fund labeled as X, I calculate the share split-adjusted changes in holdings based on Morningstar mutual fund holdings. I also accumulate, for each Abel Noser mutual fund Y (as identified by "clientmgrcode"), all trades with shares adjusted for splits and distributions by fund Y in each individual stock over the reporting period. Then, I compare the change in holdings by funds X and Y for each individual stock. If the changes in holdings for a specific stock match precisely between X and Y, then I call this stock a matched stock between funds X and Y for that reporting period. I call a period a matched period between X and Y if it satisfies three criteria: (i) there exist a minimum of five matched stocks, (ii) the ratio of the number of matched stocks to the number of stocks within the changes in X's holdings is at least 10%, and (iii) the ratio of the number of matched stocks to the number of stocks traded by an Abel Noser fund Y is also at least 10%. I consider X and Y a likely match if there is at least one matched period between them. For each Abel Noser fund Y, in cases where there are multiple likely matches between Y and various equity mutual funds, I choose the best match based on criteria (i) to (iii). This entails prioritizing the number of matched periods first, followed by the ratio of the number of matched stocks to the number of stocks within the changes in X's holdings, and finally the ratio of matched stocks to the total stocks traded by Abel Noser fund Y if there is a tie.

I further merge the matched data with Morningstar mutual fund characteristics and keep only active equity mutual funds for analysis. To ensure accuracy, I manually validate each match by comparing fund names from Morningstar with client manager names provided by Ancerno.

1.A.4 TAQ

I construct a high-frequency stock price dataset with 5-minute sampling frequency from January 1994 to December 2022 for common stocks (i.e., share codes 10 and 11) that trade on the NYSE, NASDAQ, and NYSEMKT (i.e., exchange codes 1, 2, and 3). The high-frequency prices are obtained from the "TAQ Monthly" (pre-2015) and "TAQ Daily" (post-2015). The data was cleaned following the procedures in Aleti and Bollerslev (2022). Specifically, the following criteria are applied to trades for each stock: (i) occurred between 09:30:00 and 16:00:00; (ii) with positive prices and size; (iii) belonging to the exchange with the highest volume for that stock; (iv) with condition codes E, F, or blank; (v) with transaction prices between the CRSP ask-high and bid-low for the day; and (vi) with fewer than 5 immediate reversals within a 50-sample moving window. Next, using the cleaned trades, 5-minute prices are generated, resulting in a total of 79 prices per day. The price for 9:30:00 is calculated using the first trade in the 09:30:00–09:35:00 time slot, while for all other prices, the last trade within each time slot is used. Finally, I merge low-frequency CRSP prices with the high-frequency 5-minute TAQ prices as in Aït-Sahalia, Kalnina, and Xiu (2020) to effectively manage the overnight returns accounting for dividends, share splits, and delisting.

Subsequently, it is straightforward to compute the intradaily 5-minute returns for each individual stock. Next, based on the duration-sorted portfolios, I compute 5-minute value-weighted returns for the long-duration portfolio (decile 10) and the short-duration portfolio (decile 1). The high-frequency value weights are constructed in the same way as in Aït-Sahalia, Kalnina, and Xiu (2020). Specifically, I calculate the daily market capitalization for each stock using the daily close price from CRSP. Then, with the previous days' closing market capitalization, I use the high-frequency return data to produce a sequence of high-frequency market caps. Lastly, I construct the value weights by lagging the market caps by one unit of time (i.e., 5-minute). Once 5-minute value-weighted portfolio returns are constructed, I compute the realized variance as $RV_{t+1} = \sum_{j=1}^{n} r_{t+j/n}^2$.

Chapter 2

Policymakers' Uncertainty

Anna Cieslak Stephen Hansen Michael McMahon Song Xiao[1]

2.1 Introduction

Alan Greenspan famously said, "(...) uncertainty is not just a pervasive feature of the monetary policy landscape; it is the defining characteristic of that landscape" (Greenspan, 2004). Yet, despite the ubiquitous emphasis on uncertainty in central bankers' speeches and statements, we know little about how policymakers' uncertainty perceptions and, more broadly, their beliefs about higher-order moments of economic outcomes affect policy decisions. In this paper, we evaluate how uncertainty affects policymaking in the context of the Federal Open Market Committee (FOMC).

In a frequently-quoted result, Brainard (1967) postulated that policymakers should adopt

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a more conservative stance when faced with uncertainty about policy transmission. However, the effect of uncertainty on monetary policy has since been shown to be model-specific. Depending on the assumptions about the structure of the economy and policymakers' preferences, uncertainty can induce a more or less aggressive optimal policy response or no response at all.[2]

To lay out the channels through which uncertainty can impact policymaking at the Fed, we use a simple theoretical framework delineating between two notions of uncertainty. The first, which we refer to as Fed-managed uncertainty, is uncertainty about the variables that the Fed targets (such as output and inflation) that is influenced by the policy choice itself. The second type, which we generically label as economic uncertainty, emanates from uncertainty in the economy or financial markets, but importantly, it is exogenous to policy.

We provide new empirical results on how the different uncertainty types affect the Fed's behavior. Fed-managed uncertainty is one reason why policymakers may deviate from the standard Taylor-type policy prescriptions. While many existing models of monetary policy under uncertainty implicitly capture Fed-managed uncertainty, the ambiguous predictions from this literature are easy to illustrate in our framework, leaving mixed guidance for what to expect empirically. We first document that policymakers' perceptions of increased *inflation uncertainty* in particular predict a significantly more hawkish policy stance, beyond what traditional policy rules would indicate, and in contrast to Brainard (1967) conservatism. To rationalize this finding, we then argue that a prominent source of Fed-managed uncertainty relates to the FOMC's concern about inflation tail risk, i.e., unlikely but costly outcomes, whose probability depends on policy choice. Narrative evidence suggests that Fed-managed uncertainty of this kind has been a hallmark of the Fed's decision-making since the late 1980s and that policymakers are especially worried about the risk of losing credibility if they do not take a strong enough stance on inflation.

The challenges to understanding the relationship between uncertainty and policymak-

[2]The models characterizing optimal rules under uncertainty can be broadly divided into two strands, see, e.g., Blinder (1999), Rudebusch (2001), Walsh (2003), and Bernanke (2007) for discussion of this literature. Following Brainard (1967), one strand considers Bayesian policymakers facing parameter uncertainty, e.g., Söderström (2002), Kimura and Kurozumi (2007), highlighting the non-robustness of the conservatism result. The other strand derives from the literature on model uncertainty considering a robust-control policymaker (e.g., Hansen and Sargent, 2001; Giannoni, 2007; Onatski and Stock, 2002; Levin and Williams, 2003).

ing pertain to both measuring policymakers' perceptions of uncertainty and disentangling their effect from other confounders, most importantly, the first-moment beliefs about the state of the economy. The critical aspect of our analysis stems from inferring policymakers' beliefs directly from their internal private deliberations. By analyzing the transcripts of the scheduled FOMC meetings, containing nearly verbatim statements by individual FOMC members and the Fed staff between 1987 and 2015, we obtain a granular view of the Fed's policy process.

We develop three types of text-based measures to capture otherwise hard-to-quantify dimensions of policymaking. First, and most important for our analysis, we generate textual indices of policymakers' uncertainty—PMU, for short—distinguishing their perceived uncertainty about inflation and the real economy, as our main indices. Additionally, we also measure uncertainty about financial markets and models, and a residual unclassified uncertainty. For a precise attribution, we develop algorithms that match uncertainty phrases, obtained via word embeddings, with topic-specific phrases at a sentence level. Second, we construct proxies of policymakers' sentiments reflecting their directional views on the real economy and inflation. Finally, to analyze the effects of these perceptions on policy, we develop a new textual gauge of the policy stance based on the balance of hawkish and dovish language of the FOMC members: the hawk-dove (HD) score. The textual approach enables us to elicit a broad notion of policy stance encompassing forward-looking views beyond the current policy rate and is consistently available over the entire 1987–2015 sample, including the zero-lower-bound episode.[3]

To derive the above measures, we exploit the typical structure of the FOMC meetings. The meetings during our sample are comprised of two main rounds of deliberations, each serving different objectives. In the first round, which we refer to as the economy round, policymakers discuss economic and financial market developments and the baseline outlook. This step lays the foundation for the second round—the policy round—which contains discussions about the appropriate policy choice and during which the policy decision takes place.

[3]We document that the hawk-dove score based on internal FOMC deliberations is a highly significant predictor of the federal funds rate (FFR) target. Importantly, its predictive power for the FFR is not subsumed by the Greenbook forecasts that are usually included in estimated Taylor rules, which implies that the policy stance derived from the text reflects in large part deviations from the standard policy rule.

We thus study how uncertainty and sentiment that manifest in the economy round affect the FOMC's stance communicated in the policy round. The statements in the transcripts are individually attributed, allowing us to study the decision-making not only at the level of the entire committee, but also its individual members, and to delineate the differences between the FOMC and the staff.

Our core empirical finding is that policymakers' perception of higher inflation uncertainty in the economy round—higher inflation PMU—predicts a more hawkish (tighter) policy stance in the meeting. This result remains robust to controlling for various plausible confounding factors, including the Greenbook forecasts and public uncertainty measures such as the VIX or economic policy uncertainty index of Baker, Bloom, and Davis (2016). The magnitude is economically large: A one standard deviation increase in FOMC members' inflation PMU predicts a 0.18 standard deviation more hawkish policy stance expressed in the FOMC's language, in the most restrictive specification with a host of controls. Inflation PMU is also quantitatively important for the Fed's actual policy choice. Its effect on the federal funds rate (FFR) accumulates with horizon reaching 31 basis points at eight meetings ahead, or roughly 1.5 times the size of a typical interest rate increase, per one-standard-deviation increase in the FOMC's inflation PMU. A similar result continues to hold for the sample extended through the zero-lower-bound period using a shadow rate. The magnitude of the cumulative impact of inflation PMU exceeds that of the Greenbook/Tealbook economic forecasts, typically viewed as key determinants of policy action.

Importantly, the effect of policymakers' inflation uncertainty is distinct from that of their perceived uncertainty about the real economy. Contrary to inflation PMU, we find that an increased real-economy PMU in the economy round predicts an easier policy stance, and it is largely driven out by controlling for Greenbook macroeconomic forecasts and measures of public uncertainty. This suggests that real-economy PMU describes uncertainty that policymakers take as given by the economic environment, and respond to it via its effect on the expected economic conditions. This interpretation of the real-economy PMU is consistent with models studying economic uncertainty outside the Fed (Bloom, 2009; Basu and Bundick, 2017), where increased uncertainty acts as a negative demand shock and operates through reduced economic growth forecasts. The different ways in which inflation PMU and real-economy PMU are linked to policy stance highlight the need to distinguish the implications of economic uncertainty versus Fed-managed uncertainty.

The directional and independent effect of inflation PMU on policy stance leads us to revisit several candidate interpretations of Fed-managed uncertainty in setting policy. In particular, we argue that the Brainard (1967)-style parameter uncertainty is unlikely to explain our results. Indeed, while models of this kind predict that uncertainty can induce a more conservative (or more activist) behavior relative to a certainty-equivalence benchmark, they do not imply a clear directional effect of uncertainty on policy that we find. To rationalize the empirical findings, we propose an alternative channel building on the idea of inflation scares (e.g., Goodfriend, 1993), whereby policymakers are concerned about low-probability high inflation outcomes that could arise from their policy choices. We develop a stylized model, in which the effect of Fed-managed uncertainty on policy stems from the policymakers' perceptions of policy-dependent inflation tail risk. The tail risk idea rationalizes why higher PMU induces a more hawkish policy stance. Consistent with the model predictions, we show that inflation PMU tends to comove positively with current beliefs of rising inflation, and the effect of inflation PMU on policy stance emerges most strongly when expected inflation exceeds the target.

Consistent with credibility concerns introducing a wedge between the objective and policymakers' perceived uncertainty, we document that the FOMC members' inflation PMU is distinct from that of the Fed staff, and the PMU's impact on policy stance is entirely driven by the views of the FOMC members. Given that neither PMU nor directional inflation sentiment significantly predicts future inflation outcomes, policymakers' inflation beliefs in the meeting are an expression of concern that does not materialize in the sample we study. We present narrative evidence from the transcripts' language consistent with the credibility channel.

A vast body of research attempts to describe how the Fed behaves and what explains the policy stances it adopts. We derive several novel implications from our analysis for understanding the Fed's monetary policy setting. Most importantly, our findings shed light on the factors shaping the Fed's forward-looking policy stances that are not explained by the typical covariates included in policy rules. While deviations from standard linear policy rules are frequently detected empirically and are associated with the Fed's direction, their underlying sources remain debated. By drawing directly on the Fed's internal deliberations, we establish the Fed's inflation uncertainty perceptions as one prominent reason for why such deviations occur. To the extent that policymakers' perceptions of inflation uncertainty are time-varying and fluctuate with inflation conditions, our findings provide a micro-foundation for the time-variation of the Fed's reaction function and suggest endogeneity in the monetary policy shocks arising from such Fed's perceptions. More broadly, the FOMC's concerns about their perceived ability to control inflation, which have come to the fore of policy discussions again recently, are generally not captured empirically or theoretically by standard monetary reaction functions. Our results suggest that the FOMC members' desire to maintain credibility for inflation control has been an economically important driver of their decisions.

We draw on multiple strands of empirical and theoretical literature. Rather than providing a stand-alone literature review, we discuss the connections between our and related work throughout the paper. The rest of the paper is structured as follows. Section 2.2 introduces a conceptual framework through which we summarize the channels in the literature linking uncertainty and monetary policy. Section 2.3 discusses the data and the measurement. Section 2.4 empirically analyzes the relationship between uncertainty and policy stance. Section 2.5 interprets the results within an inflation tail risk model, and provides narrative evidence linking the Fed's uncertainty perceptions with credibility concerns. Section 2.6 concludes.

2.2 Uncertainty and Optimal Monetary Policy

To clarify the impact of uncertainty on monetary policy, we introduce a simple static framework describing the policymaker's decision problem which is to choose a policy stance r_t. We use this framework to summarize the leading uncertainty channels in the literature and to guide our empirical analysis.

We assume that the policymaker has a standard quadratic loss function over deviations of inflation from the target and the output gap

$$L(\pi_t, y_t) = (\pi_t - \pi^*)^2 + \lambda(y_t - y^*)^2 \tag{2.1}$$

where π_t is period t inflation, π^* is the inflation target, y_t is period t output, and y^* is medium-term potential output. $\lambda > 0$ is the weight placed on output relative to inflation. While the typical policy choice focuses on setting the nominal interest rate, we view r_t more broadly as subsuming a range of instruments the policymaker uses to achieve her goals, including asset purchases and forward guidance, in addition to the nominal interest rates. Thus, a tighter policy stance could reflect higher nominal interest rates, quantitative tightening, or a credible change in the communicated interest rate outlook.

The expected loss function takes the mean-variance form

$$E\left[L(\pi_t, y_t)\right] = \left(\overline{\Pi}_t(r_t) - \pi^*\right)^2 + V_{\pi,t}(r_t) + \lambda\left(\overline{Y}_t(r_t) - y^*\right)^2 + \lambda V_{y,t}(r_t) \tag{2.2}$$

where $\overline{\Pi}_t(r_t)$ and $\overline{Y}_t(r_t)$ are the expected values of inflation and output, respectively. It is standard to assume that both expectations are decreasing in r_t. The variances of inflation and output are, respectively, $V_{\pi,t}(r_t)$ and $V_{y,t}(r_t)$. Although not standard in the literature, these may also depend on r_t as specified below. The optimal policy choice $\hat{r}_t$ is characterized by the first-order condition

$$2\overline{\Pi}_t'(\hat{r}_t)\left(\overline{\Pi}_t(\hat{r}_t) - \pi^*\right) + V_{\pi,t}'(\hat{r}_t) = -2\lambda\overline{Y}_t'(\hat{r}_t)\left(\overline{Y}_t(\hat{r}_t) - y^*\right) - \lambda V_{y,t}'(\hat{r}_t) \tag{2.3}$$

where LHS (RHS) is the marginal inflation loss (output gain) from tightening policy. This general rule can be used to explore the different ways uncertainty may, or may not, influence optimal policy.

2.2.1 Theoretical impacts of uncertainty

1. Certainty Equivalence. We refer to certainty equivalence as a situation in which uncertainty is irrelevant to decision-making. The central bank reacts to its assessment of the economy in the same way, no matter if uncertainty about economic outcomes is high or low. Suppose that inflation and output are not subject to uncertainty and relate to r_t deterministically via the relationships $\pi_t = \overline{\Pi}_t(r_t)$ and $y_t = \overline{Y}_t(r_t)$, respectively. The policy rule (2.3) then simplifies to

$$2\overline{\Pi}_t'(\hat{r}_t)\left(\overline{\Pi}_t(\hat{r}_t) - \pi^*\right) = -2\lambda\overline{Y}_t'(\hat{r}_t)\left(\overline{Y}_t(\hat{r}_t) - y^*\right) \tag{2.4}$$

The same decision rule emerges when inflation and output are subject to some baseline uncertainty, but this uncertainty is not related to the policy choice, i.e., $V'_{\pi,t}(r_t) = V'_{y,t}(r_t) = 0$ for all r_t. As such, certainty equivalence obtains when uncertainty in the economic environment is exogenous to the policy itself.

This situation arises in classic monetary models in which the policymaker's losses are quadratic as in (2.1), and shocks affecting π_t and y_t are additive, symmetrically distributed, and independent of the policy choice (see, e.g., Blinder, 1999 for discussion of this literature). Notably, the standard Taylor rule, prescribing no role for uncertainty in policy decisions, can be derived under such conditions. In our setting, this can be captured by positing that $\overline{\Pi}_t(\hat{r}_t) = \overline{\pi}_t - ar_t$ and $\overline{Y}_t(\hat{r}_t) = \overline{y}_t - br_t$, where $\overline{\pi}_t$ and $\overline{y}_t$ are pre-determined variables reflecting inflation and output forecasts, respectively. In this case, (2.4) simplifies to

$$\hat{r}_t = \frac{a}{c}\left(\overline{\pi}_t - \pi^*\right) + \frac{b}{c}\left(\overline{y}_t - y^*\right) \text{ where } c = a^2 + \lambda b^2. \tag{2.5}$$

In a typical Taylor-rule estimation, a proxy for $\hat{r}_t$ is regressed on forecast variables, whose time-series variation is used to estimate reaction coefficients and monetary policy shocks.

2. Uncertainty as a Negative Demand Shock. A recent literature focuses on how uncertainty impacts economic agents outside the central bank. While specific theoretical mechanisms differ, greater uncertainty about the real economy tends to act similarly to a negative demand shock, which causes a drop in employment and output (e.g., Bloom, 2009; Basu and Bundick, 2017; Leduc and Liu, 2016).[4] An increase in this type of uncertainty is associated with a loosening of monetary policy, even though uncertainty shocks in these models are exogenous to policy.

To capture this, suppose the economy faces a given level of economic uncertainty ζ_t that is exogenous to Fed policy so that $V'_{\pi,t}(r_t) = V'_{y,t}(r_t) = 0$ for all r_t. In the literature cited above, expected output becomes $\overline{Y}_t(r_t, \zeta_t)$ where $\overline{Y}_t$ is decreasing in ζ_t but $\frac{\partial^2 \overline{Y}_t(r_t,\zeta_t)}{\partial r_t \partial \zeta_t} = 0$ so that changes in uncertainty do not impact the transmission of monetary policy. In the linear

[4] See also empirical evidence of Jurado, Ludvigson, and Ng (2015) and Kumar, Gorodnichenko, and Coibion (2023) documenting the effects of uncertainty on the macroeconomy.

case, the optimal policy in (2.5) becomes

$$\hat{r}_t = \frac{a}{c}\left(\overline{\pi}_t - \pi^*\right) + \frac{b}{c}\left(\overline{y}_t(\zeta_t) - y^*\right) \text{ where } c = a^2 + \lambda b^2.$$

where $\overline{y}_t'(\zeta_t) < 0$. The only impact on $\hat{r}_t$ of variation in uncertainty comes via changes in expected output. In this formulation, this case collapses back to certainty equivalence. The only difference is that the process that determines expected output is now linked to the process governing macroeconomic uncertainty. But once one controls for $\overline{y}_t$ there is no remaining shift in $\hat{r}_t$ from shifts in ζ_t.

3. Policy-managed Uncertainty. The remaining case occurs when the variance of inflation or output *does* depend on the policy choice. For simplicity, and due to our empirical findings outlined below, we here consider the situation where r_t affects the variance of inflation but equivalent arguments apply when it also affects output volatility. The decision rule (2.3) now becomes

$$2\overline{\Pi}_t'(\hat{r}_t)\left(\overline{\Pi}_t(\hat{r}_t) - \pi^*\right) + V_{\pi,t}'(\hat{r}_t) = -2\lambda\overline{Y}_t'(\hat{r}_t)\left(\overline{Y}_t(\hat{r}_t) - y^*\right). \quad (2.6)$$

Expected economic conditions are no longer sufficient to pin down optimal policy: compared to (2.4), (2.6) now has an additional term $V_{\pi,t}'(\hat{r}_t)$ which captures the effect of policy on inflation volatility. Since volatility is endogenous to r_t we refer to this situation as "Policy-managed uncertainty". In principle, policy-managed uncertainty can either increase or decrease the marginal inflation loss. When inflation volatility rises in r_t ($V_{\pi,t}'(r_t) > 0$) then policy-managed uncertainty lowers the incentive to choose higher r_t. The opposite is true when $V_{\pi,t}'(r_t) < 0$. We now specify how these effects arise in two particular settings: model parameter uncertainty and inflation tail risks.

Model parameter uncertainty. Suppose that $\pi_t = \overline{\pi}_t - a_t r_t$, where $\overline{\pi}_t$ is the pre-determined inflation forecast and a_t describes how policy transmits to inflation. a_t is a random variable with mean $\overline{a}$ and variance $\sigma_{a,t}^2$, where the latter captures parameter uncertainty. The mean and variance of inflation become $\overline{\Pi}_t(r_t) = \overline{\pi}_t - \overline{a}r_t$ and $V_{\pi,t}(r_t) = r_t^2\sigma_{a,t}^2$. We have here normalized $r_t = 0$ to be the neutral policy stance in the sense that $\hat{r}_t = 0$ when the predetermined forecasts are at target, i.e. $\overline{\pi}_t = \pi^*$ and $\overline{y}_t = y^*$. Moreover, inflation uncertainty is minimized by choosing the neutral policy as in the original Brainard model.

Plugging into the decision rule (2.6) yields

$$\overline{\Pi}_t'(\hat{r}_t)\left(\overline{\Pi}_t(\hat{r}_t)-\pi^*\right)+\underbrace{\sigma_{a,t}^2\hat{r}_t}_{\gtrless 0 \Longleftrightarrow \hat{r}_t \gtrless 0}=-\lambda\overline{Y}_t'(\hat{r}_t)\left(\overline{Y}_t(\hat{r}_t)-y^*\right)$$

where we have substituted in for $V_{\pi,t}'(\hat{r}_t)$. Policy-managed inflation uncertainty shifts the marginal inflation loss associated with tighter policy, but the direction of the shift depends on whether policy is above or below its neutral level. When $\hat{r}_t > 0$ the marginal loss increases which provides an incentive to choose lower rates, whereas if $\hat{r}_t < 0$ there is an incentive to choose higher rates. Moreover, by directly solving for optimal policy, we obtain

$$\hat{r}_t=\frac{\overline{a}}{\overline{a}^2+\lambda b^2+\sigma_{a,t}^2}\left(\overline{\pi}_t-\pi^*\right)+\frac{\lambda\overline{b}}{\overline{a}^2+\lambda b^2+\sigma_{a,t}^2}\left(\overline{y}_t-y^*\right) \tag{2.7}$$

from which it follows that

$$\hat{r}_t \gtrless 0 \Longleftrightarrow \overline{a}\left(\overline{\pi}_t-\pi^*\right)+b\lambda\left(\overline{y}_t-y^*\right)\gtrless 0.$$

In the absence of parameter uncertainty, the policymaker wishes to raise policy above its neutral value in response to inflation and output forecasts' being above target. The same is true with parameter uncertainty, but now this policy response also induces a cost in the form of increased inflation variance which dampens the response compared to certainty equivalence. A similar logic applies when inflation and output forecasts are below target. The policymaker now wishes to shift r_t below its neutral level, but this again generates increased inflation variance and so the overall response is less than under certainty equivalence. The key point is that an increase in exogenous uncertainty $\sigma_{a,t}^2$ has no clear directional impact on the marginal inflation loss.

Inflation tail risks. Our interpretation of inflation tail risks is motivated by the idea of "inflation scares" from Goodfriend (1993).[5] A policy that is not sufficiently hawkish raises the chance that the central bank loses its credibility, which in turn leads to a large

[5] See also Goodfriend and King (2005), Orphanides and Williams (2005), King and Lu (2022). Orphanides and Williams (2022) discuss how Goodfriend's insight has influenced policymakers' thinking in the decades following his 1993 paper, covering a major part of our sample.

inflation realization. A tighter monetary policy reduces the chance of losing the nominal anchor. Throughout, we maintain the standard assumption of a quadratic loss function as in equation (2.2). Even if policymakers' preferences are symmetric, they may nevertheless have motives to act on inflation uncertainty. Maintaining credibility to avoid costly scenarios in which inflation expectations become unanchored is one such motive.

To formalize this, let $p_t(r_t)$ be the probability of their being an abormally large inflation realization in period t. We make the following assumptions:

Assumption 2.1. ***Inflation tail risk***

1. *$0 \leq p_t(r_t) < 0.5$ for all r_t.*

2. *$p'(r_t) < 0$ for all r_t.*

3. *$p'(r_t)$ is continuous and bounded.*

The first assumption implies that the high-inflation state is the rarer event, consistent with the notion of tail risks. The second assumption stipulates that inflation tail risk declines when the policy becomes more hawkish. The third assumption is technical and ensures the loss function is well-behaved in r_t.

Conditional on the tail risk being realized, inflation is drawn from $P_{2,t}$; otherwise, it is drawn from $P_{1,t}$. The distributions share the same variance $s^2_{\pi,t}$ so that neither distribution is inherently more uncertain than another. Instead, they differ in their expected values. Under $P_{1,t}$ expected inflation is $\overline{\pi}_t - ar_t$ whereas under $P_{2,t}$ it is $\overline{\pi}_t - ar_t + \Delta_t$. Here a is fixed and known so there is no parameter uncertainty. Expected output remains $\overline{Y}_t(r_t)$.

As above, the mean and variance of macroeconomic outcomes are the key moments for determining policy choice, and the next result states these for the two-state mixture distribution of inflation outcomes.

Lemma 2.1. *In the presence of tail risks, expected inflation and inflation variance are*

1. *$\overline{\Pi}_t(r_t) = \overline{\pi}_t - a_\pi r_t + p_t(r_t)\Delta_t$*

2. *$V_{\pi,t}(r_t) = s^2_{\pi,t} + p_t(r_t)[1 - p_t(r_t)]\Delta^2_t$.*

The variance of inflation is given by the common baseline inflation uncertainty $s^2_{\pi,t}$ in both states plus a component due to uncertainty in the realization of the tail risk event. Using this result, one can plug into the policy rule (2.6) to obtain the decision rule

$$\overline{\Pi}'_t(\hat{r}_t)\left(\overline{\Pi}_t(\hat{r}_t) - \pi^*\right) + \underbrace{p'_t(\hat{r}_t)}_{<0}\underbrace{(1 - 2p_t(\hat{r}_t))}_{>0}\Delta_t^2 = -\lambda\overline{Y}'_t(\hat{r}_t)\left(\overline{Y}_t(\hat{r}_t) - y^*\right) \tag{2.8}$$

where the stated signs arise from Assumption 2.1. Unlike the model with parameter uncertainty, the effect of policy-managed uncertainty in the tail-risks model is unambiguous: it reduces the marginal inflation loss and so incentivizes higher rates. The reason is that increasing rates lowers the tail risk probability which, when small, reduces the variance of inflation. Of course, under alternative assumptions on the dependence of the tail risk probability on policy, the sign of the effect could flip—for example, the policymaker might worry about negative tail risks. We maintain the assumptions we do in order to stay close to the literature cited above.

2.2.2 Mapping to empirics

The above arguments establish that uncertainty matters for policy choices when it affects the marginal loss arising from the impact of policy on the variance of economic conditions. However, there is no clear mapping into an empirical strategy for detecting the presence of policy-managed uncertainty nor for discriminating among models. As mentioned above, in a typical Taylor-rule estimation, a measure of policy stance is regressed on pre-determined inflation and output forecasts whose time-series variation identifies reaction function coefficients. Our empirical strategy is to instead build measures for *pre-determined uncertainty* and examine whether their time series variation induces variation in the policy stance after conditioning on a rich set of first-moment controls. This essentially extends the Taylor rule from only considering pre-determined expected values of economic conditions to also considering pre-determined variances of economic conditions.

When different models produce different predictions on how variation in pre-determined uncertainty maps into variation in policy, this empirical strategy can distinguish them. For example, under certainty equivalence (whether with or without uncertainty shocks operating through expected output), there should be no impact of uncertainty on policy.

Moreover, from the parameter uncertainty model above, one can immediately obtain the following comparative static from (2.7):

Proposition 2.2. $\frac{\partial \hat{r}_t}{\partial \sigma^2_{a,t}} \gtrless 0 \Longleftrightarrow \overline{a}\left(\overline{\pi}_t - \pi^*\right) + b\lambda\left(\overline{y}_t - y^*\right) \gtrless 0.$

Ex-ante, there is no clear directional prediction on the policy stance from changes in pre-determined uncertainty. On the other hand, there is a conditional prediction: when expected inflation and output are below) above their targets values, an increase in uncertainty generates looser (tighter) policy.

Finally, in the tail risks model, there are two sources of pre-determined uncertainty that shift the marginal inflation loss. The first is shifts in the tail-risk $p_t(r_t)$. We capture this by decomposing $p_t(r_t) = p_{t,0} + p_{t,1}(r_t)$ where $p_{t,0}$ is the pre-determined part of the tail risk. The second is the size of the inflation jump Δ_t in the tail event. Moreover, upper-tail inflation risks are typically only relevant when forecast inflation is near or above target. The following result provides comparative statics over this range:[6]

Proposition 2.3. *There exists a constant $K < \pi^*$ such that* $\frac{\partial \hat{r}_t}{\partial p_{t,0}}, \frac{\partial \hat{r}_t}{\partial \Delta_t} > 0 \;\forall\; \overline{\pi}_t \in [K, \infty)$.

This states that over the range of inflation forecasts where upper-tail inflation risks are expected to operate, the impact of an increase in pre-determined uncertainty on policy unambiguously increase the hawkishness of the policy stance.

Of course, this empirical strategy relies on obtaining convincing measures of pre-determined uncertainty, a challenge we confront in the next section.

2.3 Measuring Policymakers' Uncertainty and Policy Stance with Text

Bringing the above comparative statics predictions to data requires empirical proxies for several objects. Most basically, we require measures of uncertainty about economic conditions. One potential source is asset prices or surveys of financial market participants, but

[6] Proving these comparative statics is not as straightforward as signing the $V'_{\pi,t}(r_t)$ term which indeed we know is negative from (2.8). This is because shifts in $p_{t,0}$ and Δ_t also shift the marginal impact of policy on expected inflation.

in our framework it is *policymakers'* perceptions of uncertainty that matter rather than external agents'. These do not necessarily align, for example due to different subjective expectations or because market participants condition on the Fed's expected policy path which potentially already internalizes the effects of policy-managed uncertainty. To the best of our knowledge, no structured survey exists regarding FOMC members' views on uncertainty over a long sample period.[7] For these reasons, we instead develop textual measures of policymakers' perceptions of uncertainty (**PMU**) about different economic variables using their deliberations in the FOMC meeting transcripts. As we explain below, the structure of each FOMC meeting in our sample allows us to isolate views on uncertainty that are pre-determined with respect to each meeting's policy choice which is vital for testing the predictions.

Next, we require a measure of policy stance. The announced policy rate is problematic for several reasons. Fed observers have noted that many meetings' formal decision is agreed in advance and that a primary purpose of FOMC deliberations is to shape views on appropriate *future* actions (e.g., Meyer, 2004). Furthermore, public communication is an increasingly important policy tool and, thus, a subject of extensive FOMC discussion in our sample, which is not necessarily reflected by the current policy rate. Finally, the last years of our sample coincide with the zero lower bound (ZLB) on the policy rate, necessitating an alternative approach that consistently reflects the FOMC's views before and during the ZLB period. To address these challenges, we again use the FOMC's language in the transcripts to construct a novel text-based policy stance proxy, which we label as the hawk-dove score (**HD**).

The focus on private FOMC deliberations (as opposed to the Fed's public communication via statements and speeches) is the key aspect of our analysis, providing a window into the decision-making process at the Fed.[8] Below, we first review the FOMC transcript corpus

[7]Beginning in 2007, the FOMC's views on uncertainty about forecasts for inflation, output, and employment, respectively, are recorded in the Summary of Economic Projections (SEP) conducted every other meeting. In some reports these are attributed to specific individuals but in others not. Also, since one function of the SEP is to communicate the FOMC's views to the public, members' stated beliefs play a signaling role which may prevent fully truthful communication.

[8]Meade (2005) pioneers the use of transcripts to analyze the FOMC voting behavior. More recently, Hansen, McMahon, and Prat (2018) study how transparency affects policymakers' deliberations. Shapiro and Wilson (2022) exploit the transcripts to estimate the Fed's loss function, approximating losses via the negative sentiment in the meeting's language. A separate literature explores the Fed's public communication. Lucca and Trebbi (2009), Apel and Blix Grimaldi (2012), Handlan (2020), among others, use central bank

that forms the basis of our constructions, followed by a description and validation of our core measures. Appendix 2.A.2 and 2.A.3 contain further details.

2.3.1 Transcript data and FOMC meeting structure

The main textual source we draw from is the nearly verbatim transcripts of Federal Open Market Committee (FOMC) meetings, available online.[9] These transcripts contain a fully attributed, statement-by-statement account of meetings with minimal editing, for example, to remove the names of specific banks with which the Fed conducts open market operations. The sample period we consider consists of the 227 meetings from August 1987 (the first meeting of Alan Greenspan's chairmanship) through December 2015 (the last meeting for which a transcript was available at the time of data processing). Regular FOMC meetings occur eight times per year. The typical composition of the FOMC consists of 19 members, of which twelve are regional Fed Presidents, and seven are Governors. During our sample, a total of 75 unique FOMC members appear in the transcripts in at least one meeting. A number of Fed staff economists also participate in the meetings.

During this period, FOMC meetings had a regular structure which we exploit in our measurement strategy. The first core part of each meeting is the *economy round*, which makes up 43% of the total sentences in the transcripts. The Fed staff economists first present their forecasts of economic activity (contained in Greenbooks/Tealbooks) along with supporting contextual information. Each FOMC member in turn presents his or her views on economic developments, which can differ from the views of the staff. These developments can be discussed in the context of alternative interest rate paths, but FOMC members do not advocate for particular policy choices at this stage. Importantly, both staff and member statements are prepared in advance and there is limited interaction between participants.

The second core part of the meeting is the *policy round*, which accounts for 24% of all

communication to measure the implied policy stance. Istrefi (2019) and Bordo and Istrefi (2023) study individual FOMC member policy preferences based on narrative records in the public media. Malmendier, Nagel, and Yan (2021) analyze individual FOMC member policy preferences based on their public speeches.

[9]See `https://www.federalreserve.gov/monetarypolicy/fomc_historical.htm`. Only a small part of the May 1988 meeting was transcribed, so we treat it as a missing observation. The FOMC also conducts occasional special meetings convened via conference call during times of macroeconomic turbulence. Since the format of these calls is somewhat irregular, we only consider regular meetings in our analysis.

sentences.[10] This round begins with the staff laying out different policy alternatives, after which FOMC members debate on which alternative to adopt before proceeding to a final vote. This section also includes a discussion of the public statement released along with the policy announcement.

To test our comparative statics results, it is important that PMU measures constructed at meeting t reflect uncertainty perceived *before* the policy stance at meeting t is adopted, i.e., before the policy stance feeds back onto the uncertainty perceptions. The structure of FOMC meetings, with the economy round separated from and preceding the policy round, allows us build such measures. We use only economy round text to build PMU and only policy round text to build HD. By constructing PMU from the economy round before the FOMC members discuss policy stance, we interpret it as uncertainty that policymakers perceive when they enter the meeting, and not the uncertainty they expect to prevail after their policy choice.[11]

Below, we primarily focus on constructing measures at the meeting level. However, the structure of the transcripts allows us to consider more granular data by attributing each statement to individual meeting participants, which we exploit in part of the analysis. In Section 2.4, we distinguish between statements made by FOMC staff vs. by FOMC members, and between statements made by individual FOMC members.

[10] The remainder of the transcripts, which we do not use, is largely made up of staff discussion of financial market conditions and discussion of special topics in monetary policy. The sectioning of meetings is done manually by us. One outlier in the meeting structure is the September 2009 meeting, for which the economy and policy rounds were merged into one round. In this case, we manually classify sentences as either belonging to the economy round or the policy round. For further details on the structure of FOMC meetings and the composition of the committee, see Hansen, McMahon, and Prat (2018).

[11] To take a concrete example, suppose that prior to a meeting, a negative demand shock hits the economy, which increases the chance of a recession occurring. In response to this shock, the Fed wishes to lower interest rates, which in turn reduces the recessionary risk. In this case, the PMU should be high, given the baseline setting at the start of the meeting (the arrival of the negative shock) rather than low (which would reflect a diminished uncertainty after the accommodative action). The timing of deliberations within the FOMC meeting largely rules out a reverse causation whereby policy decision drives PMU within meeting t, rather than vice versa. This is plausible even if the policy choice at meeting t is largely agreed upon before the meeting, as some Fed observers have argued. In this case, the economy round would focus on the prevailing conditions that justify whatever policy choice is to follow rather than an assessment of how the economy will look in future periods after the policy action has been implemented.

2.3.2 Core empirical measures

2.3.2.1 Policymakers' uncertainty (PMU)

Our measurement of topic-specific uncertainty is based on the local co-occurrence of terms denoting uncertainty and terms denoting the topic of interest.[12] To obtain the uncertainty terms, we begin with the four seed terms 'uncertain', 'uncertainty', 'risk', and 'risks'.[13] We then use a word embedding model—specifically the Continuous Bag-of-Words model (Mikolov, Chen, Corrado, and Dean, 2013)—applied to FOMC transcripts to generate an expanded set of terms.[14] A word embedding model represents each unique term in a corpus as a relatively low-dimensional vector in a vector space. Words whose vectors lie close together in the vector space share similar meanings.

In general, the neighbors are synonyms of the seeds, such as 'unclear' and 'unsure,' or terms reflecting worries and concerns, such as 'threat', 'fear', and 'wary.' The nearest neighbors can also contain generic terms not obviously related to uncertainty. We therefore further organize the lists using our domain expertise, and after removing irrelevant terms, we obtain 78 terms in total.[15] We provide fifty nearest neighbors for each of the seed words in Appendix Tables 2.A.1 and 2.A.2.

Our topic-specific PMU indices cover four dimensions of uncertainty that one would expect to be relevant for policymaking, as motivated by the framework in Section 2.2: (i) inflation and (ii) real economy, as both are standard inputs into monetary policymakers' loss functions; (iii) financial markets, as market uncertainty might spill over into the real economy; and (iv) model uncertainty, in line with the theoretical literature on the role of parameter and model uncertainty in optimal policy. The term lists we use to measure topics

[12]The use of local co-occurrence patterns to build text-based proxies for economic phenomena has been pioneered by Mikael and Blix (2014) in the monetary policy context and by Hassan, Hollander, van Lent, and Tahoun (2019) to measure specific types of uncertainty in a corporate context. Our innovation is to apply these ideas to analyze the impact of perceived risk and uncertainty on policy stances.

[13]The motivation for the seeds is that 'risk' and 'risks' capture objective uncertainty, while 'uncertain' and 'uncertainty' capture Knightian uncertainty. Combining both in the discussion of economic uncertainty is common. For example, Bloom (2014) writes: "I'll refer to a single concept of uncertainty, but it will typically be a stand-in for a mixture of risk and uncertainty."

[14]This approach follows recent studies such as Hanley and Hoberg (2019), Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2020), Davis, Hansen, and Seminario-Amez (2020), and Bloom, Hassan, Kalyani, Lerner, and Tahoun (2021). See Ash and Hansen (2023) for additional details.

[15]The separate lists contain substantial overlap, which is another reason for the reduction to 78 terms.

come from our judgment[16] and are reported in Appendix Tables 2.A.3 through 2.A.11.

An uncertainty word in the economy round is assigned to topic k if it occurs in a sentence that also contains a topic-k keyword, or if a topic-k keyword appears in an immediately surrounding sentence. Meeting-level PMU for topic k is then the number of topic-k uncertainty words expressed as a fraction of total words spoken in the economy round overall. We denote the four meeting-level indices by $InfPMU_t$ for inflation PMU, $EcoPMU_t$ for the real-economy PMU, $MktPMU_t$ for financial markets PMU, and $ModPMU_t$ for model PMU, which can be interpreted as the intensity with which policymakers discuss topic-specific uncertainty. With uncertainty mentions that cannot be classified into a specific topic, we form a residual category, $OthPMU_t$, for other PMU. Appendix 2.A.3.1 provides full details of the construction of the topic-specific PMU indices. Appendix Figure 2.A.1 presents the distribution of terms in topic-k uncertainty sentences, establishing that the presence of one of our topic keywords in a sentence is a good indicator of its overall topical focus.

Table 2.1 presents summary statistics for each PMU index. The economic uncertainty topic is most common, followed by inflation and financial market uncertainty, respectively. Model uncertainty makes up a small fraction of discussions. For this reason, we focus the empirical analysis on the other three PMU indices. These have substantial independent variation that cannot be captured by a single common factor. The pairwise correlations between the three main indices are 0.07 for $InfPMU_t$ and $EcoPMU_t$, 0.12 for $InfPMU_t$ and $MktPMU_t$, and 0.38 for $EcoPMU_t$ and $MktPMU_t$.

Figure 2.1 plots the PMU time series. To highlight their features over time, we graph both unsmoothed series and their moving averages over the past eight meetings; in the empirical analysis, we rely on the unsmoothed series. In contrast to the countercyclical behavior which is usually expected from uncertainty indicators (Bloom, 2014), $InfPMU_t$ is strongly procyclical: it rises following each of three recessions in the sample and most quickly during the 2000s-era expansion. While $EcoPMU_t$ rises at the onsets of the bursting of the dot-com bubble and the Global Financial Crisis (GFC), its variation is also not purely

[16]The reason we use a purely manual rather than partially automated approach as for the uncertainty list is that the topical terms are largely made up of phrases, and sequence embeddings are substantially more complex to build than single word embeddings.

Table 2.1: Descriptive Statistics for PMU.

The table reports summary statistics for the topic-specific PMU indices. All indices are obtained from the economy round of the FOMC meeting and represent the share of uncertainty-related mentions (by topic) relative to the total number of words in the economy round of the meeting. The sample period is 1987:08–2015:12, covering 227 meetings. Panel A expresses the summary statistics for PMU in percentages (e.g., the number 0.302 for the mean inflation PMU implies that on average uncertainty-related mentions constitute 0.302% of all words in the economy round). Column "AR(1)" reports the first-order autoregressive coefficient (at the meeting frequency). Panel B reports the pairwise correlations between topic-specific PMU indices.

A. Summary statistics for PMU indices

	N	Mean	SD	P10	P50	P90	AR1
$InfPMU_t$	227	0.302	0.153	0.131	0.276	0.529	0.550
$EcoPMU_t$	227	0.388	0.138	0.226	0.386	0.566	0.463
$MktPMU_t$	227	0.222	0.149	0.071	0.180	0.426	0.571
$ModPMU_t$	227	0.066	0.044	0.018	0.061	0.119	0.107
$OthPMU_t$	227	0.282	0.135	0.128	0.260	0.456	0.481

B. Correlations of topic-specific PMU indices

	InfPMU	*EcoPMU*	*MktPMU*	*ModPMU*
EcoPMU	0.074			
MktPMU	0.122	0.375		
ModPMU	0.222	0.113	0.096	
OthPMU	-0.335	0.132	0.161	-0.209

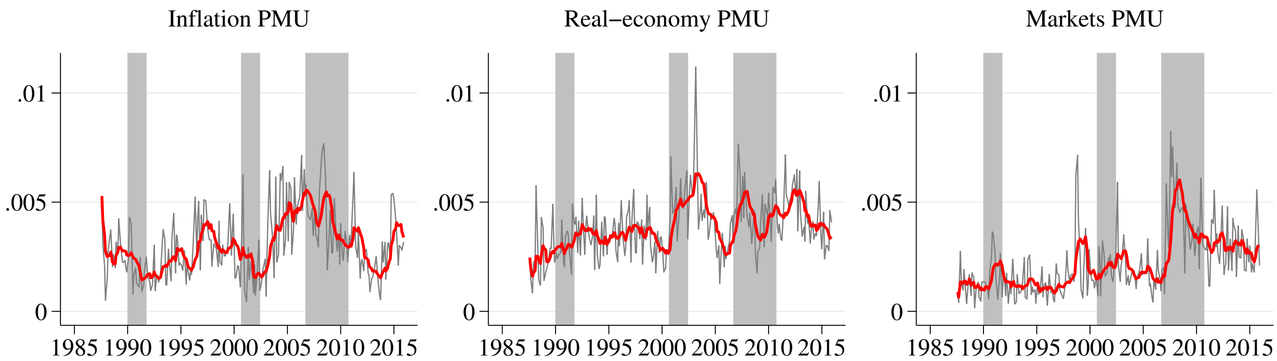


Figure 2.1: Topic-specific PMU Time Series.
This figure displays the time series of the topic-specific PMU measures during the sample period 1987:08–2015:12. The grey curves represent the raw time series. The red curves are moving averages over the last eight meetings. The y-axis is expressed as the fraction of total economy round words contained in topic-k uncertainty sentences. NBER recessions are shaded.

countercyclical.[17] Finally, $MktPMU_t$ is most elevated at the height of the GFC, a major

[17]Its highest reading occurs during the March 18, 2003 meeting, driven by the uncertainty about the timing and extent of the Iraq war and about the underlying economic conditions. In another major episode, $EcoPMU_t$ becomes elevated in the first half of 2007 before the start of the official NBER-dated recession.

market turmoil. The substantial independent variation in the topic-specific PMU suggests that the FOMC shifts its discussions depending on which sources of uncertainty are most salient, given the underlying evolution of the economy.

2.3.2.2 FOMC's policy stance: The Hawk-dove score (HD)

To construct a text-based policy stance measure, we start by identifying sentences that express views on policy in the policy round of the meeting. We define rules to flag sentences that pertain to monetary policy specifically rather than other types of policy (see Appendix 2.A.3.3 for details). Within this set, we then count the number of words that suggest a policy tightening ($Hawk_t'$) and a policy easing ($Dove_t'$). For meetings beginning in 2009, we additionally consider as policy sentences those that contain keywords related to asset purchases and count the number of words within them that suggest a reduction ($Hawk_t''$) and an increase ($Dove_t''$) in those purchases.

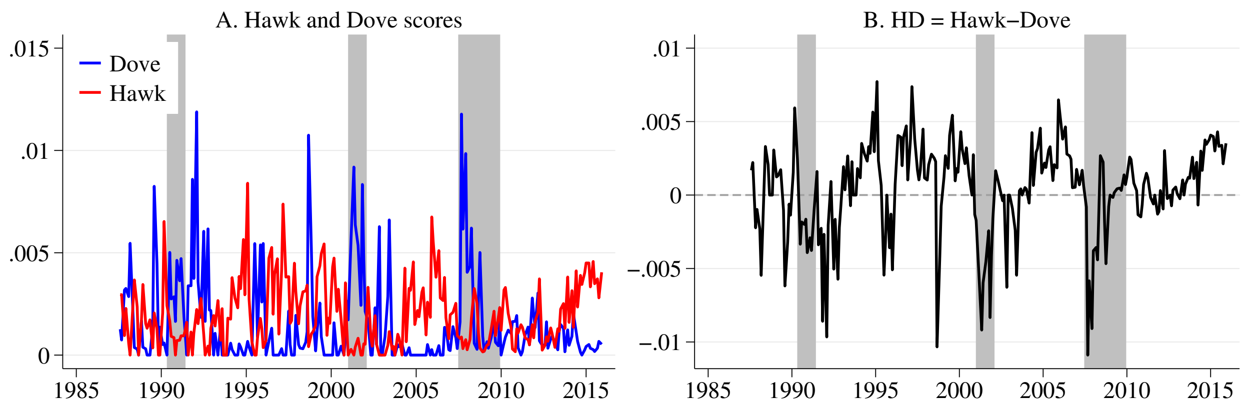


Figure 2.2: Time Series of Textual Measures of Policy Stance.
The figure presents textual measures of policy preferences derived from the statements of FOMC members during the policy round of the FOMC meetings. The construction of the measures is described in Appendix 2.A.3.3.

To each meeting, we assign $Hawk_t$ and $Dove_t$ scores measuring the intensity of hawkish and dovish views expressed in that meeting. The $Hawk_t$ score equals the sum $Hawk_t' + Hawk_t''$, scaled by the total number of words spoken in the policy round, and analogously for the $Dove_t$

The transcripts of the March 21, 2007 meeting highlight rising concerns about the growth outlook and heightened forecast uncertainty that are not yet associated with a direct downgrade of the economic forecasts. The uncertainty actually declines during the height of the financial crisis, even as policymakers continue to express negative sentiment about the real economy.

score. The overall policy stance for meeting t is the difference between the directional scores:

$$HD_t = Hawk_t - Dove_t. \tag{2.9}$$

Figure 2.2 presents the time series of the $Hawk_t$, $Dove_t$ and HD_t scores. The dynamics of these variables display intuitive properties, with $Dove_t$ becoming elevated around recessions and in periods of financial turmoil, and $Hawk_t$ increasing in expansions. Importantly, the text-derived policy stance shows substantial variation in the post-2008 sample when short-term nominal interest rates are constrained at zero.

2.3.2.3 Other control variables

Numerous factors beyond perceived uncertainty drive policymaking and are important to account for in assessing the relationship between PMU and HD. Here, we enumerate the main variables we include as controls.

Greenbook forecasts. To capture economic expectations influencing policy, we follow the literature relying on the Greenbook (now Tealbook) forecasts prepared by the Fed staff before the scheduled FOMC meetings. Greenbook forecasts are specified for quarterly forecast horizons. We denote a forecast formed at meeting t about variable Z as $F_t(Z_q)$, where subscript q indicates the target forecast horizon (in quarters) relative to the calendar quarter in which meeting t takes place, e.g., $q = 0$ meaning the current quarter of meeting t, and $q = 4$ meaning four quarters ahead from meeting t. In our main specifications, we use a four-quarter ahead CPI inflation forecast ($F_t(\pi_4)$), to reflect the more persistent inflation components that the Fed focuses on, and the current quarter real GDP growth forecast (nowcast, $F_t(g_0)$) as in Coibion and Gorodnichenko (2012). We also add forecast revisions between meetings ($FR_t(\pi_3), FR_t(g_1)$), following Romer and Romer (2004) to account for changes in forecasts in addition to levels. We calculate the forecast revision as $FR_t(Z_q) = F_t(Z_q) - F_{t-1}(Z_q)$ ensuring that the target forecast horizon at t and $t-1$ refers to the same calendar quarter.

Trend inflation. Both interest rates and inflation expectations feature a pronounced common trend (e.g., Kozicki and Tinsley, 2001; Rudebusch and Wu, 2008). To control for these slow-moving dynamics, we construct a measure of the perceived long-run inflation target or the so-called trend inflation, denoted τ_t, as the discounted moving average of past core inflation, following Cieslak and Povala (2015) and motivated by Sargent (1999) (see also Bianchi, Lettau, and Ludvigson (2022), Pflueger (2023) for a related approach). Including trend inflation in our policy regressions allows us to capture the effect that deviations of expected inflation from the target have on policy.

Sentiment. To the extent that Greenbooks contain the Fed staff's forecasts, they may not fully capture the FOMC's views on the economy. Additionally, it is likely that Greenbooks report modal forecasts.[18] These can differ from policymakers' mean beliefs if outcome distributions are skewed, and/or if FOMC and staff disagree on the modal forecast. We therefore augment our controls with text-based alsentiment indices as additional proxies for economic forecasts.[19]

To measure topic-specific sentiment, we estimate the frequency of topic-specific terms preceded or followed by direction words that indicate positive or negative sentiment, respectively. The topics generally overlap with those used for the topic-specific uncertainty. In analogy to the PMU indices, we measure meeting-level sentiment from the economy round and scale the topic-specific sentiment count by the number of total words in that round. For some applications, we further disaggregate the sentiment to distinguish between the staff versus FOMC and between the individual FOMC members. Importantly, to avoid a mechanical relationship with PMU, the sentiment construction excludes sentences used to obtain the PMU indices. We label the mentions of falling inflation in meeting t as negative inflation sentiment ($InfNeg_t$), mentions of weakening economic activity as negative sentiment about the real economy ($EcoNeg_t$), and mentions of deteriorating financial conditions as negative market sentiment ($MktNeg_t$). We reverse those relations for the positive sentiment ($InfPos_t$, $EcoPos_t$, and $MktPos_t$). As a proxy for the overall sentiment, we then define balance measures as the difference between the positive and negative sentiment, e.g., for inflation $InfSent_t = InfPos_t - InfNeg_t$. Increases in the balance indicate a positive tilt in views

[18] While there is uncertainty whether Greenbook forecasts in our sample reflect means or modes, Bernanke (2016) describes the more recent FOMC's Summary Economic Projections (SEP) as "SEP projections are explicitly of the 'most likely' or modal outcomes rather than the range of possible scenarios." Likewise, the New York Fed forecast "is referred to as the 'modal' forecast in that it is intended to be the most likely of a wide range of potential outcomes" (Alessi, Ghysels, Onorante, Peach, and Potter, 2014).

[19] Several authors show that text-based sentiments obtained from the Fed documents correlate with the Fed's policy action (Ochs, 2021; Aruoba and Drechsel, 2023) and improve forecasting (Sharpe, Sinha, and Hollrah, 2022).

about a given variable. Appendix 2.A.3.2 provides details of the sentiment construction.

Public uncertainty indices. In addition, we consider proxies based on information available to the public, which aim to reflect the uncertainty the public perceives about general economic policy and, more specifically, the Fed's policy actions and/or their consequences. We include (i) the economic policy uncertainty index (EPU) from Baker, Bloom, and Davis (2016) based on the frequency of newspaper articles that mention both uncertainty and economic policy, (ii) the monetary policy uncertainty (MPU) newspaper-based index specific to the US monetary policy from Husted, Rogers, and Sun (2020), (iii) the option-implied volatility index (VXO) following Bloom (2009), and (iv) dispersion of forecasts about CPI inflation and real GDP growth from the Blue Chip Financial Forecast survey.[20]

We find that our PMU indices are generally weakly related to public uncertainty (see Appendix Table 2.A.12). Consistent with the procyclical dynamics visible in the left panel of Figure 2.1, inflation PMU is, in fact, negatively correlated with the EPU index, the VXO, and survey growth dispersion, all of which are strongly countercyclical (e.g., Bloom, 2014). This fact reinforces the idea that inflation PMU, in particular, captures a distinct dimension of policymakers' beliefs not subsumed by existing proxies.

2.3.3 Validation

2.3.3.1 Uncertainty, sentiment, and economic outcomes

The aim of PMU indices is to gauge policymakers' perceptions of the second moments of economic outcomes. The Greenbook forecast and text-based sentiment should instead capture directional beliefs on the evolution of economic conditions. To validate that we can distinguish between those concepts, we present a series of predictive regressions. Specifically, we regress inflation and real GDP growth observed at meeting $t + h$ on meeting t Greenbook forecasts, PMU, and sentiments indices. For consistent timing of the meetings

[20]Bauer, Lakdawala, and Mueller (2022) and De Pooter, Favara, Modugno, and Wu (2021) study market-perceived monetary policy uncertainty over the FOMC cycle using implied volatility of short-term interest rate derivatives. Using the Bauer, Lakdawala, and Mueller (2022) measure, we find that inflation and real-economy PMU are weakly correlated with market-based interest rate volatility (with correlations not exceeding 0.1 in absolute value). Since interest-rate implied volatility series are available starting from 1990, we do not include them in our main specification. We verify that including this measure does not materially change our conclusions about the link between PMU and policy stance.

and macroeconomic outcomes, we use future Greenbook nowcasts as the dependent variables and estimate regressions for $h = 1, \ldots, 8$, i.e., up to eight meetings ahead.

Table 2.2 presents the forecasting results. While the PMU does not predict future outcomes, contemporaneous Greenbook forecasts and sentiment do, with longer-lasting effects for the Greenbook forecast (sentiment measures) on inflation (growth). As such, our text-based proxies indeed organize language in a conceptually distinct way. The finding that PMU lacks predictive power is not sensitive to controls we include and is confirmed in univariate predictive regressions (see Appendix Table 2.A.13). These results do not imply that economic conditions that the policymakers perceive can solely be described by the first and second moments. They do, however, suggest that PMU is not a simple reflection of directional beliefs. Instead, such beliefs (via means or skews) appear to be encoded in the text-based measure of expressed sentiment.

2.3.3.2 Hawk-dove score and policy actions

To validate the hawk-dove score, HD, as a measure of policy stance, we analyze its relationship with the policy rate, FFR, adopted by the FOMC in meeting t. In Panel A of Table 2.3, we first project HD_t on typical variables included in policy rules. Column (1) serves as a benchmark to describe the systematic policy component reflected in language. The explanatory variables include the Greenbook forecasts and forecast revisions for inflation and real GDP growth, as well as the trend inflation variable τ_t to account for slow adjustment in the inflation target over our sample. Most loadings in column (1) are highly significant and have expected signs: higher expected growth and higher expected deviation of inflation from the target predict a more hawkish tilt in the policy language. However, with $\bar{R}^2$ of 29%, the regression leaves more than two-thirds of the variation in the policy language unexplained by the macro forecasts.

Columns (2)–(4) focus on explaining changes in the FFR target from $t-1$ to t with the policy stance language in meeting t. Although our textual proxies are available until 2015:12, we estimate these regressions through 2008:12, given that the FFR is at the zero-lower bounds thereafter. To account for policy inertia, we include two lags of the FFR, following Coibion and Gorodnichenko (2012). The estimates indicate a high explanatory

Table 2.2: Predicting Macro Variables with Textual Measures of Uncertainty and Sentiment.

The table reports predictive regressions of inflation and real GDP growth by textual PMU and sentiment indices derived from the economy round of the FOMC meeting transcripts. The regressions are estimated at the FOMC meeting frequency with the forecast horizon ranging from the next meeting ($h = 1$) up to eight meetings ahead ($h = 8$). To make sure that the timing of the depend variable is consistent with the timing of the meetings, we use Greenbook nowcasts at future meetings as the dependent variable. The regression is $F_{t+h}(\pi_0) = \beta_0 + \beta_1 InfPMU_t + \beta_2 InfPos_t + \beta_3 InfNeg_t + \beta_4 \overline{F}_t(\pi) + \varepsilon_{t+h}$, where $F_{t+h}(\pi_0)$ is the CPI inflation nowcast at meeting $t+h$, and $\overline{F}_t(\pi)$ is the average forecast (across horizons) given at meeting t. We estimate analogous regressions for the real GDP growth. The coefficients are standardized. HAC standard errors to account for the overlap are reported in parentheses. The sample period is 1987:08–2015:12.

A. Dependent variable: Greenbook CPI inflation nowcast h meetings ahead, $F_{t+h}(\pi_0)$

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
$InfPMU_t$	0.039	-0.038	-0.042	0.011	-0.107	-0.070	0.038	0.044
	(0.62)	(-0.48)	(-0.38)	(0.08)	(-0.69)	(-0.42)	(0.27)	(0.45)
$InfNeg_t$	-0.260***	-0.164*	0.012	0.093	0.086	0.010	-0.058	-0.025
	(-3.49)	(-1.87)	(0.18)	(1.30)	(1.04)	(0.17)	(-0.98)	(-0.39)
$InfPos_t$	0.173***	0.144***	0.025	-0.131	-0.100	-0.120	-0.169*	-0.138
	(3.81)	(2.67)	(0.38)	(-1.32)	(-0.97)	(-1.42)	(-1.80)	(-1.47)
$\overline{F}_t(\pi)$	0.560***	0.457***	0.378***	0.351***	0.319***	0.321***	0.337***	0.335***
	(8.46)	(6.91)	(4.30)	(3.39)	(2.82)	(2.90)	(3.73)	(4.01)
$\bar{R}^2$	0.50	0.30	0.13	0.11	0.11	0.11	0.12	0.10
N	226	225	224	223	222	221	220	219

B. Dependent variable: Greenbook real GDP growth nowcast h meetings ahead, $F_{t+h}(g_0)$

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
$EcoPMU_t$	-0.081	-0.058	0.032	0.069	0.029	-0.001	0.087	0.113
	(-1.60)	(-1.15)	(0.69)	(1.03)	(0.36)	(-0.02)	(1.01)	(1.23)
$EcoNeg_t$	-0.150***	-0.163**	-0.220***	-0.275***	-0.313***	-0.226**	-0.238**	-0.237**
	(-2.92)	(-2.40)	(-2.65)	(-3.00)	(-4.29)	(-2.28)	(-2.05)	(-2.32)
$EcoPos_t$	0.116**	0.127**	0.147**	0.149*	0.151*	0.193**	0.203**	0.190**
	(2.39)	(2.17)	(2.07)	(1.68)	(1.72)	(2.25)	(2.30)	(2.14)
$\overline{F}_t(g)$	0.623***	0.553***	0.401***	0.287***	0.227**	0.174	0.112	0.075
	(7.20)	(5.78)	(5.03)	(3.20)	(2.12)	(1.31)	(0.80)	(0.51)
$\bar{R}^2$	0.56	0.48	0.35	0.28	0.26	0.19	0.16	0.13
N	226	225	224	223	222	221	220	219

content of policy language for the FFR target. In column (3), a one-standard-deviation increase in HD_t is associated with a 14 basis point increase in the FFR, with a t-statistic of 6.8. Given the results in column (1), the significance of HD_t could simply reflect the policy rule as opposed to the deviation from the rule. However, column (4) shows that this is not the case: HD_t remains an economically and statistically significant predictor of FFR with a full set of controls.

The FOMC's policy stance measured in language is likely to reflect broader forward-looking views on policy, as opposed to just the contemporaneous action. To evaluate this idea, Panel B of Table 2.3 presents predictive regressions using the same controls as column (4) of Panel A but with the dependent variable $FFR_{t+h} - FFR_t$, i.e., the cumulative change in FFR from meeting t through $t+h$. The information contained in HD_t about future policy is notably larger than its impact on the contemporaneous action: a one-standard-deviation increase in HD_t is associated with more than 25-basis-point cumulative increase in the FFR over the following four and five meetings. HD_t remains significant at the five percent level up to six meetings ahead, suggesting that it encapsulates how the FOMC positions itself in meeting t for future policy actions.

2.4 Uncertainty and Policy Stance

We now use the empirical measures constructed in section 2.3 to establish that cross-meeting variation in inflation PMU, $InfPMU_t$, is associated with a significantly more hawkish stance, as revealed by the hawk-dove score, HD_t. This result survives a host of controls, including directional beliefs on inflation and public uncertainty proxies. Finally, we quantify the impact of $InfPMU_t$ on the policy rate and find that it induces a large cumulative response.

2.4.1 Baseline empirical model and interpretation

Our baseline regression model takes the form

$$HD_t = \alpha + \beta_1' \mathbf{PMU}_t + \beta_2' \mathbf{Controls}_t + \varepsilon_t, \tag{2.10}$$

Table 2.3: Validity of HD as A Measure of Policy Stance.

This table reports results on the relationship between the textual *HD* score derived from the policy round of FOMC meeting transcripts and the target Fed Funds Rate adopted by the FOMC. Panel A, column (1) reports estimates from a regression of *HD* on Greenbook controls (forecasts $F_t(\cdot)$ and forecast updates $FR_t(\cdot)$), and the perceived inflation target τ_t. The sample period for column (1) is 1987:08–2015:12. The dependent variable in columns (2)–(4) is $FFR_t - FFR_{t-1}$ where FFR_t is the target rate adopted by the FOMC in meeting t. The sample period for columns (2)–(4) is 1987:08–2008:12, which excludes the zero-lower-bound episode. The dependent variable in Panel B is $FFR_{t+h} - FFR_t$ for $h = 1$ through $h = 8$, and each regression includes the same controls as in column (4) of Panel A. HAC t-statistics with eight lags are reported in parentheses in both Panels. All regressions are estimated at the frequency of FOMC meetings. The *HD* variable is standardized, and FFR_t is expressed in percent.

A. HD and changes to the Fed Funds Rate target: contemporaneous effect

	(1)	(2)	(3)	(4)
	HD_t	ΔFFR_t	ΔFFR_t	ΔFFR_t
HD_t			0.14***	0.096***
			(6.83)	(5.30)
$F_t(\pi_4)$	0.62***	0.23***		0.18***
	(3.64)	(3.79)		(2.97)
$F_t(g_0)$	0.38***	0.18***		0.15***
	(2.99)	(6.60)		(5.75)
τ_t	-0.70***	-0.13***		-0.078**
	(-3.81)	(-3.30)		(-2.06)
$FR_t(\pi_3)$	0.073	0.015		0.0067
	(1.43)	(0.86)		(0.39)
$FR_t(g_1)$	0.15***	0.039**		0.026
	(2.79)	(2.30)		(1.32)
L.FFR_t		0.087	0.26***	-0.013
		(1.14)	(3.18)	(-0.15)
L2.FFR_t		-0.13*	-0.27***	-0.024
		(-1.84)	(-3.40)	(-0.29)
Constant	0.00	0.14**	0.0088	0.11**
	(0.00)	(2.54)	(0.20)	(2.23)
$\bar{R}^2$	0.29	0.52	0.45	0.59
N	227	169	169	169

B. HD and changes to the Fed Funds Rate target: future effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
HD_t	0.087***	0.14***	0.20***	0.27***	0.28***	0.24**	0.22*	0.25*
	(4.10)	(3.18)	(2.62)	(2.84)	(2.88)	(2.46)	(1.88)	(1.83)
GB controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.43	0.41	0.43	0.46	0.51	0.52	0.53	0.53
$\Delta\bar{R}^2$	0.033	0.026	0.028	0.034	0.026	0.010	0.0045	0.0064
N	169	168	167	166	165	164	163	162

where $\mathbf{PMU}_t$ is the vector of PMU indices computed just using FOMC members[21] and HD_t is the hawk-dove policy stance which we take as a proxy for $\hat{r}_t$ in section 2.2.

In effect, this is an extended forward-looking Taylor rule. In the existing literature (e.g., Romer and Romer, 2004; Coibion and Gorodnichenko, 2012), such rules are estimated by regressing the FOMC's policy stance on Greenbook forecast variables. The typical assumption is that these forecasts are pre-determined relative to the current decision.[22] The linear dependence of policy on forecasts of economic conditions emerges from the policymaker minimizing a quadratic loss function as in equation (2.5). In this classic setting, beliefs on first moments of economic conditions are all that matter for policy because policy only acts to shift the mean of economic conditions.

We instead extend the model to allow beliefs on *second* moments of economic conditions to also influence the policy decision. As discussed in section 2.3.1, the $\mathbf{PMU}_t$ measures are plausibly pre-determined with respect to the policy stance: we use economy-round language to build PMU which is both prepared in advance of FOMC meetings and revealed prior to the policy round, from which we build the HD stance measure. β_1 thus captures how an increase in pre-determined uncertainty impacts the policy stance which links closely to the comparative statics predictions in section 2.2.2 via the estimated sign of β_1. In Section 2.5 we return to this and differentiate between alternative models of policy-managed uncertainty.

An important final point is that β_1 is estimated using the relationship between cross-meeting variation in uncertainty perceptions and policy stance. If uncertainty impacts policymaking in a fixed way over time, our empirical strategy will not reveal it.

2.4.2 Baseline results

Table 2.4 presents initial results. We begin with the least restrictive specification and gradually add controls for additional covariates. As a starting point, columns (1) and (2) project *HD* on the inflation and real-economy PMU and sentiment, respectively, without any controls. The PMUs in column (1) are highly significant and jointly explain 15% of the HD's

[21]We use just FOMC member language to form our baseline PMU measures for regression analysis since it is policymakers' perceptions that are most relevant for their later decisions. In Section 2.5 we discuss further the distinction between FOMC member and staff PMU language.

[22]See, e.g., Reifschneider, Stockton, and Wilcox (1997) for the discussion of assumptions in the Greenbook forecasts.

variance. Notably, inflation and real-economy PMU predict policy stance with opposite signs. A one-sigma increase in *InfPMU* is associated with a 0.34-sigma increase in *HD* (t-statistic = 3.39), indicating a more hawkish stance; in contrast, a one-sigma increase in *EcoPMU* is associated with a 0.24-sigma decrease in *HD* (t-statistic = -3.97). Column (2) shows that the text-based sentiment is also strongly predictive of policy stance. The coefficients have the expected signs: sentiments indicating rising inflation or a stronger real economy anticipate a more hawkish policy round of the meeting.

Table 2.4: Predicting FOMC Policy Stance *HD* with PMU at the Meeting-level.

The table reports regressions of the policy stance score *HD* on topic-specific PMU indices computed using just FOMC members' language. The controls include textual sentiment measures, GB forecasts, and proxies for public perceived uncertainty described in Section 2.3.2.3. The *HD* variable is derived from the statements of FOMC members in the policy round of the FOMC meeting, while the PMU and sentiment indices are based on the statements by the FOMC members in the economy round of the meeting. All regressions are estimated at the FOMC meeting frequency. The coefficients are standardized. HAC t-statistics with eight lags are reported in parentheses. The sample period is 1987:08–2015:12.

Dependent variable: Meeting-level HD_t policy stance score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$InfPMU_t$ (FOMC)	0.336***		0.284***	0.310***	0.180***	0.186***	0.182**
	(3.40)		(4.07)	(4.57)	(2.84)	(3.06)	(2.57)
$EcoPMU_t$ (FOMC)	-0.215***		-0.110**	-0.073	-0.093	-0.083	-0.075
	(-3.60)		(-2.53)	(-1.46)	(-1.48)	(-1.28)	(-1.21)
$MktPMU_t$ (FOMC)				-0.126			-0.171*
				(-1.33)			(-1.76)
$InfSent_t$ (FOMC)		0.206***	0.105	0.099	0.088	0.109*	0.079
		(2.67)	(1.52)	(1.37)	(1.56)	(1.85)	(1.32)
$EcoSent_t$ (FOMC)		0.501***	0.485***	0.432***	0.399***	0.386***	0.329***
		(5.74)	(5.78)	(5.25)	(4.51)	(3.51)	(3.85)
$MktSent_t$ (FOMC)				0.046			0.044
				(0.65)			(0.66)
GB controls	No	No	No	No	Yes	Yes	Yes
Public uncertainty	No	No	No	No	No	Yes	No
Other PMUs	No	No	No	No	No	No	Yes
$\bar{R}^2$	0.14	0.31	0.38	0.40	0.43	0.44	0.46
N	227	227	227	227	227	227	227

Importantly for subsequent interpretation, column (3) shows that the predictive content of uncertainty for policy stance is not subsumed by variation in sentiment. In fact, inflation *PMU* drives out the significance of inflation sentiment. In contrast, uncertainty and sentiment about the real economy contain largely independent information. Views of a stronger economy captured by a heightened *EcoSent* predict hawkishness, while increased uncertainty about the economy captured by *EcoPMU* predicts a more dovish stance.

Controlling for financial markets *PMU* and sentiment (*MktPMU* and *MktSent*) in column (4) weakens somewhat the economic and statistical significance of the real-economy PMU, but not that of inflation. The financial markets-based measures are themselves insignificant, echoing Cieslak and Vissing-Jorgensen (2021) that the Fed reacts to financial markets only to the extent that they affect the Fed's beliefs about the real economy. Therefore, in the subsequent analysis, we do not focus on the financial markets *PMU*.

Columns (5) through (7) augment the specification to account for various potential confounders, as detailed in Section 2.3.2.3. Column (5) includes, in addition to text-based sentiment, the Greenbook forecasts and the trend inflation (as used in Table 2.3). Even with these variables, inflation PMU maintains a material effect on the policy stance: Compared to the specification in column (3), the coefficient on inflation PMU is reduced by about a third (from 0.28 to 0.18 standard deviation units) but remains significant at the 1% level. Instead, the real-economy PMU becomes only marginally significant, suggesting that it can be largely absorbed by Greenbook forecasts and sentiment.

Column (6) introduces measures of public perceptions of policy and macroeconomic uncertainty, with the aim to account for the broad demand-shock channel of uncertainty described in Section 2.2. Considering an extensive set of proxies from the literature, we find that none of them drives out inflation PMU, while the importance of the real-economy PMU is further diminished.

Finally, for robustness, column (7) exploits the full suite of PMU indices, including the model PMU and the unclassified PMU category. Inflation PMU is only marginally affected and remains significant at the 5% level. It is thus unlikely that our main macro PMU indices omit a key aspect of policymakers' uncertainty regarding the policy-relevant outcomes.

2.4.3 Member-level regressions

One consideration in interpreting the meeting-level results is that they could arise from a disagreement among FOMC members as opposed to the common perceptions of the committee as a whole. We thus turn to estimating the language-based reaction functions at the individual FOMC-member level, exploiting the granularity of our textual data. The results show that it is the common perception of uncertainty on the FOMC that affects the policy stance.

Table 2.5: Uncertainty of FOMC Members: Individual Member-level Regressions.

The table reports regressions of individual FOMC member's i policy stance at meeting t, HD_{it}, on individual PMU indices at that meeting (denoted with "(ind)"). Column (4) controls for aggregate PMU indices (denoted with "(agg)") calculated at the meeting level. Standard errors are double-clustered at the meeting and member level.

Dependent variable: Individual meeting-level HD_{it} policy stance score

	(1)	(2)	(3)	(4)	(5)	(6)
$InfPMU_{it}$ (ind)	0.12***	0.12***	0.00014	-0.011	0.11**	-0.0097
	(2.86)	(2.82)	(0.00)	(-0.30)	(2.62)	(-0.25)
$EcoPMU_{it}$ (ind)	-0.074	-0.058	0.018	0.012	-0.041	0.011
	(-1.65)	(-1.43)	(0.45)	(0.30)	(-1.03)	(0.29)
$InfPMU_t$ (agg)			0.93***			
			(4.97)			
$EcoPMU_t$ (agg)			-0.74***			
			(-3.63)			
$MktPMU_{it}$ (ind)					-0.16***	0.011
					(-2.70)	(0.25)
$ModPMU_{it}$ (ind)					-0.071	-0.15
					(-0.64)	(-1.38)
$OthPMU_{it}$ (ind)					-0.19***	-0.11**
					(-4.20)	(-2.40)
Sentiment	No	Yes	Yes	Yes	Yes	Yes
Meeting FE	No	No	No	Yes	No	Yes
Member FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.028	0.048	0.070	0.26	0.059	0.26
N	3925	3925	3925	3925	3925	3925

In Table 2.5, the dependent variable is the policy stance of member i in meeting t, HD_{it} (using the policy-round statements), and the explanatory variables are the corresponding PMU and sentiment scores of that member (using their economy-round statements). The goal is to study how a policymaker's own expression of uncertainty predicts their individual policy stance. All regressions include member fixed effects, and so the estimates represent the within-individual reaction functions. Column (1) shows that, similar to the meeting-level results, also within-member inflation PMU is associated with more hawkishness, while the real-economy PMU with more dovishness (although this latter effect is weak). The impact of inflation uncertainty on policy stance is not driven by the member-specific sentiment (column (2)).

To distinguish between the common FOMC's perceptions vis-á-vis member heterogeneity, column (3) additionally includes aggregate meeting-level PMU indices, and column (4) includes time-fixed effects. Both specifications render the member-level PMU insignificant, indicating that the explanatory power of uncertainty for policy stance stems from the time-series variation common to members rather than from the cross-sectional dispersion of views across members.

Finally, the last two columns include the full set of individual-level PMU indices, including financial markets, model, and the unclassified other PMU, without and with meeting fixed effects in columns (5) and (6), respectively. Individual member policy views are sensitive to the financial market uncertainty, with increased $MktPMU_{it}$ associated with an easier stance, supporting the demand-shock interpretation of market uncertainty. However, this effect reflects common rather than member-specific variation and is subsumed by the meeting fixed effects in column (6). Model PMU ($ModPMU_{it}$) is not significant at the individual level, suggesting that model misspecification is not a primary concern of policymakers driving our results. The residual uncertainty component ($OthPMU_{it}$) predicts an easier policy stance even with time-fixed effects, indicating that idiosyncratic uncertainty perceptions do influence individual policy views, but their effect on the overall policy stance of the committee is weak, given results in Table 2.4 column (7).

2.4.4 Uncertainty and the target rate

The results so far relate inflation PMU to a textual measure policy stance, HD, which we show to encapsulate forward-looking FOMC's views beyond the current policy action. We now quantify the extent to which PMU affects the FOMC's actual policy choices.

To this end, we regress changes in the policy rate between meetings t and $t + h$ for $h = 1, \ldots, 8$ on time-t PMU indices and controls. We focus specifically on the dynamic effects of the FOMC members' PMU, as motivated by Table 2.7. The controls include variables from column (5) of Table 2.4, and additionally, the EPU index Baker, Bloom, and Davis (2016) to account for the demand channel of uncertainty, and two lags of the policy rate to account for its inertia. We present the estimates for the FFR target using the 1987:08–2008:12 sample as well as for the shadow rate constructed by Wu and Xia (2016) using the 1987:08–2015:12 sample, to account for the zero-lower bound period.

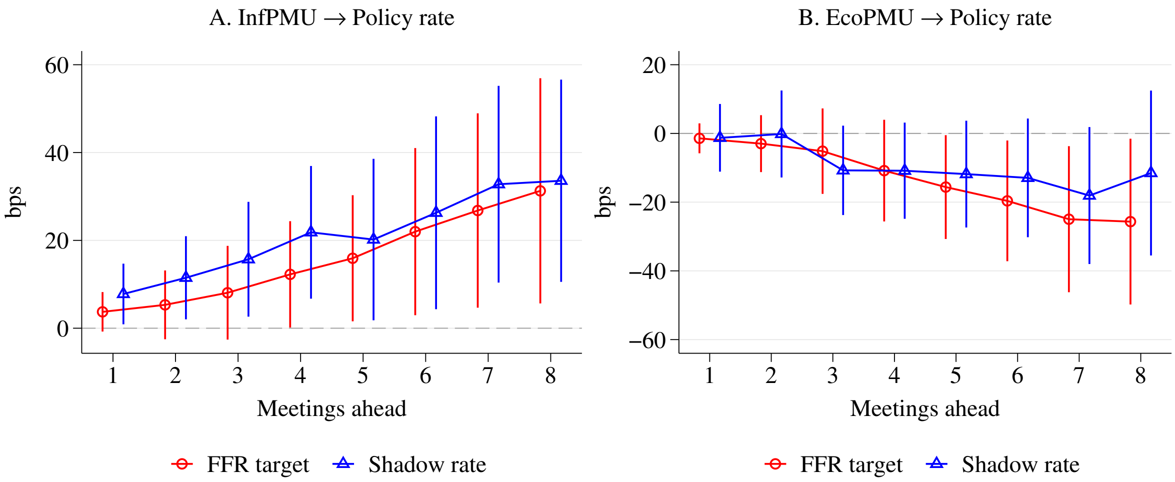


Figure 2.3: Cumulative Effects of PMU on the Policy Rate.
The figure presents the response of the policy rate (in basis points) to a one-standard deviation change in the PMU. Two measures of the policy rate are considered: the FFR target (circles) and the shadow rate of Wu and Xia (2016) (triangles). The coefficients are obtained from regressing cumulative changes in policy rate ($\Delta FFR_{t+h} = FFR_{t+h} - FFR_t$ and analogously for the shadow rate), on the PMU indices, and controls including GB forecasts, trend inflation τ_t, two lags of policy rate (t and $t-1$), the BBD EPU index and inflation and real-economy sentiment ($InfSent_t$, $EcoSent_t$). The textual measures are obtained from statements of FOMC members in the economy round of the meeting. The spikes mark the 95% confidence intervals obtained with HAC standard errors. The maximum sample for the eight-meeting-ahead forecast is 1987:08–2008:12 using the FFR target and 1987:08–2015:12 using the shadow rate.

Figure 2.3 presents the effect of a one-standard-deviation change in the inflation and real-economy PMU on the cumulative change in the policy rate up to eight meetings ahead. We superimpose the estimates for the FFR target in the pre-zero lower bound period (marked as circles) and the shadow rate in the full sample (marked as triangles). The effect of uncertainty accumulates with the horizon. At eight meetings ahead, inflation PMU induces a 31 basis point FFR target increase. In economic terms, this magnitude is the largest among the covariates we consider and is slightly larger than that of a one-standard-deviation increase in the real GDP growth nowcast (which equals 28 basis points at eight meetings ahead).

The extended analysis with the shadow rate confirms a large cumulative impact of inflation PMU (34 basis points at the eight-meeting horizon). In contrast, the longer-run effect of the real-economy PMU is less robust, with statistical and economic magnitudes weakening further in the full sample.

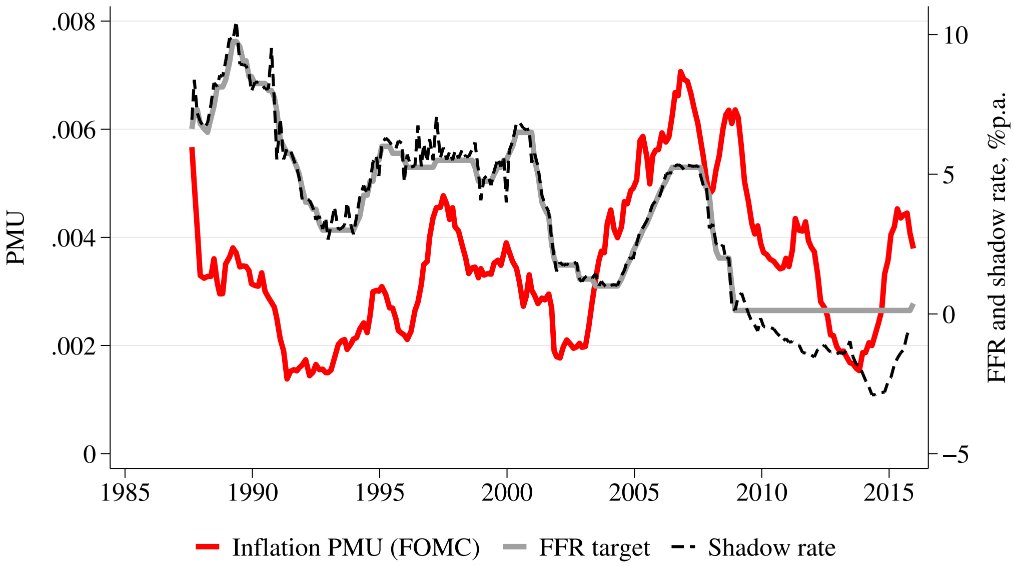


Figure 2.4: Inflation PMU and Policy Rate.
The figure superimposes the inflation PMU of FOMC members measured in the economy round of the meeting against the policy rate: FFR target and the shadow rate from Wu and Xia (2016). The PMU is smoothed over the last eight meetings.

One might be concerned that the effects of inflation PMU are due to a particular episode in our sample. Therefore, to visualize the predictive content of inflation PMU for future policy, Figure 2.4 superimposes the FFR target and the shadow rate against the FOMC members' inflation PMU (smoothed over the last eight meetings). The figure illustrates a systematic relationship whereby policy tightenings (easings) tend to be preceded by rising (declining) policymakers' perceptions of inflation uncertainty.

2.5 Interpreting Uncertainty Effects as Tail Risk Concerns

The framework from Section 2.2 helps assess which channels could explain the empirical relationship between policymakers' uncertainty and their policy stance. A first insight is that we find empirical support for the demand channel of uncertainty. Column (1) of Table 2.4 indicates that the FOMC adopts a softer policy stance in the face of higher uncertainty about the real economy, which aligns with its accommodating a negative demand shock. However, under this perspective, this effect should come entirely from the Fed responding to a downgrade in growth outlook caused by an uncertainty shock exogenous to its policy. The theory discussed in Section 2.2 predicts that once one controls for the growth outlook and public uncertainty, there should be no remaining effect of real-economy PMU on the policy stance, just as we find in column (6).

In contrast, inflation PMU consistently predicts a more hawkish policy stance, with its explanatory power not subsumed by any of the controls in Table 2.4.[23] To the best of our knowledge, we are the first to document that perceived inflation uncertainty explains FOMC policymaking beyond expected inflation (and other first-moment controls).[24] While this is suggestive of policy-managed uncertainty as outlined in section 2.2, propositions 2.2 (which relates to parameter uncertainty) and 2.3 (which relates to tail risks) provide a more direct link to our regression results. In the remainder of this section, we first argue that the empirical findings are more consistent with the comparative statics predictions of the tail risk model. We then provide further supporting evidence for this interpretation.

2.5.1 Comparative statics predictions: parameter uncertainty vs tail risks

Under the model parameter uncertainty perspective, one could view time-series variation in *InfPMU* as arising from time-series variation in $\sigma^2_{a,t}$, i.e. uncertainty in the responsiveness of inflation to monetary policy. According to proposition 2.2, though, there is no clear

[23]To the extent that controlling for sentiment may also capture policymakers' perceptions of higher-order moments, the estimated effect of PMU on HD represents a lower bound on the actual impact of perceived uncertainty on stance.

[24]Relatedly, Evans, Fisher, Gourio, and Krane (2015) study how uncertainty affects policymaking. They identify uncertainty mentions in the FOMC minutes, but do not separately consider uncertainty types. Based on reading the minutes, they human-code the directional effect of uncertainty on policy and assign an indicator variable (plus or minus one) to meetings where the effect is present, and zero otherwise. They find that this measure predicts the current FFR action beyond macro forecasts. Instead, the frequency of uncertainty mentions (ignoring the directional effect) shows a much weaker link to the policy rate. Our results, especially the opposite effects of *InfPMU* and *EcoPMU* on policy stance, highlight the need to isolate the different types of uncertainty.

directional prediction on how policy should respond to this form of increased uncertainty. To generate an overall positive sign, one would need to argue that on average FOMC meetings have above-target inflation and output forecasts. In this regime, $\frac{\partial \hat{r}_t}{\partial \sigma^2_{a,t}} > 0$ which in our regression model translates into the *InfPMU* coefficient's being positive.

Under the inflation tail risk perspective, time-series variation in *InfPMU* arises from time-series variation in exogenous components of tail risk ($p_{t,0}$ or Δ_t). According to proposition 2.3, an increase in these variables leads to more hawkish policy whenever the inflation forecast is above a critical value that itself lies below the inflation target. For even lower values of the inflation forecast, it is natural to assume that inflation tail risks do not operate strongly if at all. Hence, one obtains a prediction that an increase in *InfPMU* should increase hawkishness.

To sharpen the distinction between the two models, we next repeat the baseline regression in column (6) of Table 2.4 but split the sample based on expected economic conditions. The first split is based on whether expected inflation is relatively high or low. To focus on the cyclical variation in expected inflation, we orthogonalize the four-quarters-ahead inflation forecast $F_t(\pi_4)$ with respect to the trend inflation, τ_t, and extract the residual, which we denote with $F_t(\pi_4)^{\perp}$. We then split the sample based on whether $F_t(\pi_4)^{\perp}$ is negative (column (2)) or positive (column (3)). Column (4) presents results for the full sample but where we interact a subsample indicator with *InfPMU* to more clearly test for a differential response of policy to *InfPMU*. Columns (5)-(7) conduct a similar exercise but for real GDP growth (see Table notes for further details). Table 2.6 presents the results.

Consider first the split on inflation forecasts. We observe that the impact of $InfPMU_t$ on policy is in fact only significant for the high-inflation subsample. The point estimate is nearly 50% higher than in the full sample, and four times as high as in the low-inflation subsample. The significant interaction term in column (4) further shows a significantly more hawkish response in the high-inflation subsample. According to the parameter uncertainty model, the impact of increased uncertainty on policy stance should be positive (negative) when economic conditions are above (below) their target values. The positive and significant coefficient on $InfPMU_t$ in column (3) is consistent with this. However, there is no symmetric negative coefficient on $InfPMU_t$ in column (2). In this sense, we do not observe evidence that an increase in uncertainty shifts policy towards an uncertainty minimizing neutral rate, which

Table 2.6: Policy Impact of Policymakers' Uncertainty by Expected Economic Conditions.

The table reports regressions of meeting-level policy stance, HD_t on inflation PMU and sentiment, conditioning on the level of inflation expectations and real GDP growth. Column (1) presents the baseline estimate from Table 2.4, column (6). Columns (2)–(4) condition on the level of Greenbook four-quarter ahead CPI inflation forecasts. Column (2) runs the baseline regression on observations when $F_t(\pi_4)$ is below trend ("Low"), and column (3) runs it when $F_t(\pi_4)$ is above trend ("High"). To test the difference in coefficients, column (4) estimates the regression with an interaction of $InfPMU_t$ with a dummy variable equal to one when $F_t(\pi_4)$ is above trend. We define low (high) inflation environment when the residual from regressing $F_t(\pi_4)$ on trend inflation τ_t is negative (positive). Column (5) presents analogous results but splits the sample based on whether nowcast of real GDP growth, $F_t(g_0)$ is above or below the sample mean (2.1%). The text-based measures of PMU are constructed from statements of FOMC members in the economy round of the meeting. Coefficients are standardized. HAC t-statistics are reported in parentheses.

Dependent variable: Meeting-level policy stance score, HD_t

		Split by CPI inflation			Split by RGDP growth		
	(1) All	(2) Low	(3) High	(4) Interact	(5) Low	(6) High	(7) Interact
$InfPMU_t$ (FOMC)	0.186***	0.070	0.269***	0.094	0.191*	0.116	0.230***
	(3.06)	(1.01)	(3.57)	(1.56)	(1.85)	(1.37)	(2.80)
$EcoPMU_t$ (FOMC)	-0.083	-0.078	-0.053	-0.084	-0.164*	-0.054	-0.081
	(-1.28)	(-0.80)	(-0.55)	(-1.32)	(-1.83)	(-0.49)	(-1.27)
$InfPMU_t$(FOMC) $\times$ $1_{\pi\,\text{high}}$				0.225**			
				(2.59)			
$InfPMU_t$(FOMC) $\times$ $1_{g\,\text{high}}$							-0.120
							(-1.08)
GB controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sentiment (FOMC)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Public uncertainty	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.44	0.32	0.54	0.45	0.44	0.28	0.44
N	227	122	105	227	106	121	227

is one of the key insights of the parameter uncertainty literature. Similarly, this evidence is also not consistent with an increase in uncertainty increasing activism (e.g. Söderström, 2002) since that would also manifest as oppositely signed $InfPMU_t$ coefficients across columns (2) and (3) (albeit with signs flipped compared to our formulation). In constrast, the tail risks model shows that the effect of increased inflation uncertainty on policy is positive when inflation forecasts are relatively high. When inflation forecasts are low, one expects little to no effect which is consistent with these findings.

Turning now to the split on real GDP, note that proposition 2.2 shows that the degree to which an increase in inflation uncertainty shifts policy depends not just on the inflation forecast but also the output forecast since it is the linear combination of deviations of inflation from target and of output from target that determines the directional effect of uncertainty. However, whereas we observe a different impact of $InfPMU_t$ on policy stance across the inflation forecast split, the effect across the real GDP split is roughly symmetric with no significant interaction term in column (7). This shows that the policy impact of $InfPMU_t$ are specific to policymakers' inflation concerns and not related to business cycle variation *per se*. Again, this is consistent with the tail risks model and proposition 2.3.

Overall, then, the relationship between $InfPMU_t$ and HD_t exhibits several properties that are seemingly not consistent with model parameter uncertainty but are consistent with inflation tail risks. Importantly, this does not rule out the empirical relevance of model parameter uncertainty because our results do not speak to the existence of a fixed level of parameter uncertainty the FOMC faces. But they do strongly suggest that the *time series* variation in $InfPMU_t$ is unlikely to be driven by time-varying parameter uncertainty.

2.5.2 FOMC members vs. staff

The analysis so far exploits variation in the PMU indices derived from FOMC members' language since it is their perception of tail risks which should drive policy stance. In constrast, staff language in the economy round is meant to explain and contextualize the forecasting scenarios underlying the quantitative Greenbook forecasts. As such, one would expect the staff's uncertainty language to be mainly relevant to forming economic expectations and thus subsumed by our controls. On the other hand, the FOMC members' language should reflect a broader view of the economy, incorporating any higher-order moments relevant to their decision-making, and specifically policy-managed uncertainty considerations.

To explore this distinction, we construct PMU and sentiment indices for the staff and the FOMC separately, again using just the economy round of the FOMC transcripts. We apply the same algorithm as for the meeting-level measures but treat the staff and FOMC texts at each meeting as separate corpora.

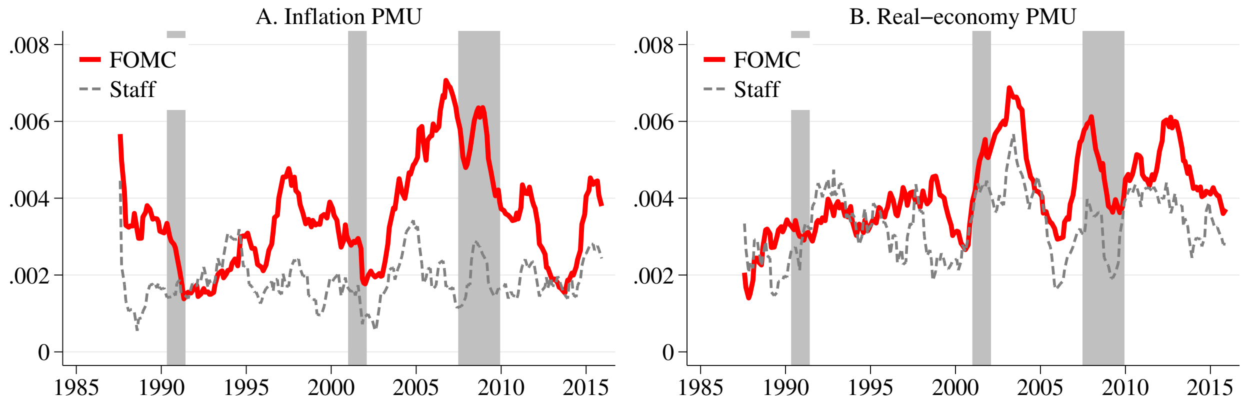


Figure 2.5: PMU of FOMC Members vs. Staff.
This figure presents inflation and economy PMU indices constructed separately for FOMC members and the staff. Each uncertainty index is scaled relative to the overall length of the statements made by FOMC members or staff, respectively, in the economy round of the meeting. The series are smoothed averages over the last eight FOMC meetings.

Figure 2.5 disaggregates the meeting-level PMU indices from Figure 2.1 by FOMC members and the staff. Both groups' real-economy PMUs show a similar cyclical variation. Instead, the FOMC's inflation PMU rises much faster during expansions than the staff's and remains persistently elevated.

Under the hypothesis that the staff's inflation PMU depicts general uncertainty around inflation forecasts at each meeting but not policy-managed uncertainty, it should not influence the FOMC's policy stance once Greenbook forecasts and sentiment are accounted for. The uncertainty relevant to the policy decisions should instead be encapsulated in FOMC's PMU. Table 2.7 tests this idea by regressing the policy stance *HD* on staff- and FOMC-specific PMU indices and the controls from Table 2.4, column (5). The results confirm that the effect of inflation uncertainty on policy stems primarily from the FOMC members' views. On a stand-alone basis, the staff's inflation PMU is marginally significant and is

Table 2.7: Uncertainty of FOMC Members vs. Staff.

The table reports regressions of meeting-level HD_t variable on uncertainty indices of staff and FOMC members. We control for sentiment (*InfSent* and *EcoSent*) specific to FOMC members (column (1)), staff (column (2)), and members and staff (column (3)). HAC t-statistics are reported in parentheses.

Dependent variable: Meeting-level HD_t policy stance score

	(1)	(2)	(3)
$InfPMU_t$ (FOMC)	0.180***		0.183***
	(2.84)		(3.18)
$EcoPMU_t$ (FOMC)	-0.093		-0.087
	(-1.48)		(-1.36)
$InfPMU_t$ (Staff)		0.109*	0.011
		(1.81)	(0.23)
$EcoPMU_t$ (Staff)		-0.137*	-0.038
		(-1.93)	(-0.65)
GB controls	Yes	Yes	Yes
Sentiment	Yes	Yes	Yes
$\bar{R}^2$	0.43	0.33	0.43
N	227	227	227

entirely driven out by the members' PMU in a joint specification.

2.5.3 Inflation PMU and inflation sentiment

The tail risk model in section 2.2 introduces a close link between expected inflation and inflation uncertainty. By Lemma 2.1, both the mean and variance of inflation are increasing in the objects that generate tail risk, i.e., Δ_t and $p_t(r_t)$. This leads to the immediate prediction that inflation PMU should be positively correlated with measures of expected inflation if the former indeed captures tail risk concerns.

To illustrate this prediction in the data, Figure 2.6 plots FOMC members' inflation PMU against two proxies for expected inflation. In Panel A, we use the same $F_t(\pi_4)^{\perp}$ measure as described above which de-trends the four-quarter-ahead Greenbook inflation forecast. In Panel B, we consider inflation sentiment $InfSent_t$ as an alternative proxy for policymakers' inflation beliefs.

A positive relationship with inflation PMU is evident for both expected inflation measures. The correlation is 0.31 for $F_t(\pi_4)^{\perp}$ and 0.30 for sentiment (based on unmoothed series).

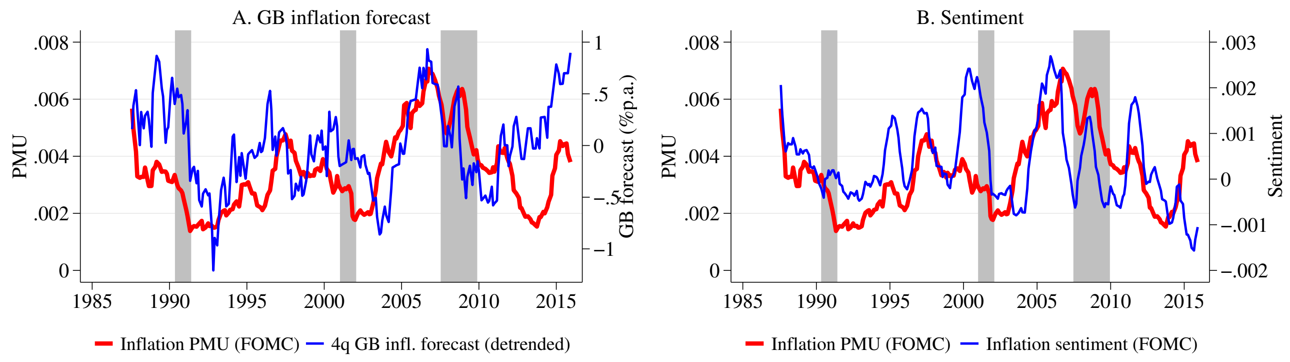


Figure 2.6: Inflation PMU and Expected Inflation.
Panel A superimposes inflation PMU against $F_t(\pi_4)^\perp$, which proxies for the deviation of expected inflation from the target. $F_t(\pi_4)^\perp$ is constructed by orthogonalizing the four-quarter Greenbook CPI inflation forecast residualized with respect to the trend inflation, τ_t. Panel B superimposes inflation PMU against inflation sentiment, constructed from FOMC members' statements. Increasing inflation sentiment indicates the balance of views toward rising inflation. The text-based series are smoothed averages over the last eight FOMC meetings.

Further decomposing inflation sentiment into separate positive and negative components, we find that the co-movement with PMU is driven primarily by the positive sentiment, i.e., the language associated with increasing inflation (as shown in Appendix Figure 2.A.2).[25] This evidence aligns with the prediction that inflation PMU increases with beliefs about rising inflation, as implied by the tail risks model.

2.5.4 Effect of PMU over the interest rate cycle

As we have emphasized above, a key prediction of the model parameter uncertainty model is that an increase in $InfPos_t$ has no clear directional effect as it shifts policy towards a neutral rate which may be above or below the current policy depending on expected economic conditions. An alternative interpretation of the model is that an increase in $InfPos_t$ induces gradualism whereby the FOMC slows the pace of interest rate adjustments. On the other hand, the model in Söderström (2002) would predict that an increase in $InfPos_t$ would induce activism and accelerate adjustments.

To test this alternative view of the impact of $InfPos_t$ on policy stance, we split the sample into meetings where the FOMC exhibited a tilt, respectively, towards lowering, raising rates,

[25] Appendix Table 2.A.14 reports regressions of expected inflation and sentiment on inflation PMU, showing that the relationship is economically and statistically significant. The loading of $InfPMU_t$ on positive sentiment ($InfPos_t$) is about twice as strong as that on negative sentiment ($InfNeg_t$).

or neither. We then repeat our baseline estimates separately for these subsets of meetings. We consider two separate but related measures of policy tilt:

1. *The interest rate cycle measure.* We define a period as part of a cutting (hiking) cycle if (i) the meeting involves a cut (hike) in interest rates, or (ii) the last move, within the previous eight meetings, was a cut (hike). Once eight meetings have passed, we assume that the cutting cycle is over even if rates have not yet started to rise; the periods between cutting and hiking cycles form the "neither" subsample.

2. *The Blue/Tealbook measure.* Tealbooks (formerly Bluebooks) contain alternative policy options prepared by the Fed staff before an FOMC meeting. Alternative B is the central policy scenario as viewed by the staff. Using alternative policy options, we define a meeting as having a cutting (hiking) tilt when either (i) the staff's proposed Alternative B involves a cut (hike) or (ii) where Alternative B assumes no change but the staff propose more cut (hike) alternatives than hike (cut) alternatives. The remaining meetings form the "neither" subsample.

The following matrix presents expected signs of the loadings of HD_t on $InfPMU_t$ under uncertainty-induced conservatism or activism, depending on the policy tilt:

	Cutting tilt	Hiking tilt
Conservatism	(+)	(−)
Activism	(−)	(+)

Table 2.8 presents the results. Column (1) repeats the baseline estimates from Table 2.4; columns (2)–(4) split the sample based on approach 1, and columns (5)–(7) based on approach 2. The results show that the predictive power of inflation PMU for policy stance stems from precisely those periods when there is no tendency to cut or hike interest rates (columns (4) and (7)). To the extent that inflation PMU only drives more hawkishness when there is no apparent bias towards raising or lowering rates, these findings are inconsistent with either conservatism or activism. Indeed, when the policy exhibits a cutting policy tilt (columns (2) and (5)), conservatism would imply a positive loading of *HD* on *InfPMU* (as higher uncertainty attenuates the desire to cut), whereas activism would imply a negative loading on *InfPMU* (as higher uncertainty strengthens the desire to cut). When the policy

exhibits a hawkish tilt (columns (3) and (6)), the loadings should be reversed. These predictions are not born out in the data. Repeating the regressions without the baseline controls or adding public uncertainty measures gives similar findings.

Table 2.8: Relationship Between PMU and Policy Stance HD Conditional on Policy Tilt.

The table reports the estimates of the relationship between PMU and policy stance conditional on policy tilt, defined by recent interest rate moves (columns (2)–(4)) or by Blue/Tealbook alternative strategies (columns (5)–(7)). Column (1) reports the baseline specification corresponding to column (5) in Table 2.4. The sample period is 1987:08–2015:12. All variables are scaled by their standard deviations. HAC t-statistics with eight lags are reported in parentheses. The regressions are estimated at the frequency of the FOMC meetings.

Dependent variable: Meeting-level HD_t policy stance score

	Baseline	Approach 1: Int. rate cycle			Approach 2: Blue/Tealbook		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Cut	Hike	Neither	Cut	Hike	Neither
$InfPMU_t$ (FOMC)	0.180***	0.122	0.017	0.368***	0.085	0.010	0.322***
	(2.84)	(1.45)	(0.09)	(3.41)	(0.59)	(0.07)	(4.29)
$EcoPMU_t$ (FOMC)	-0.093	-0.104	0.073	-0.066	0.152	0.046	-0.215**
	(-1.48)	(-0.89)	(0.49)	(-0.49)	(1.19)	(0.50)	(-2.16)
GB controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sentiment (FOMC)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.43	0.32	0.13	0.33	0.052	0.23	0.31
N	227	98	67	62	44	70	119

2.5.5 Narrative evidence

Goodfriend (1993) emphasized the importance of "the acquisition and maintenance of credibility for [Fed's] commitment to low inflation" during the Volcker and the early Greenspan Fed. Building on Goodfriend (1993) inflation scares idea, fluctuations in the PMU could thus be interpreted as reflecting the time-varying FOMC's concern about maintaining credibility.[26] To assess the plausibility of the tail-risk credibility channel, we use narrative evidence from the FOMC transcripts. Below, we highlight representative episodes of how credibility

[26]One source of potential credibility loss is that the market worries the FOMC will deviate to loose policy to boost output as in Barro and Gordon (1983). A credibility loss could also result from the FOMC's misjudgement of the neutral rate, r^*. With the true r^* being higher than policymakers assumed, their policy would become too easy and overstimulate the economy, opening a positive output gap. The probability of such a policy mistake, as well as the associated PMU, and the associated credibility concern, are plausibly time-varying.

matters in policy decisions. Appendix 2.A.5 contains a systematic chronological discussion of this issue throughout our sample.

Figure 2.4 suggests that policymakers' perceptions of inflation uncertainty fluctuate significantly and can remain persistently elevated for an extended time. Two episodes that feature rapidly rising inflation PMU are the mid-to-late 1990s and 2004 until the global financial crisis. In the second half of the 1990s, when inflation remained relatively low and stable, transcripts show the FOMC members nonetheless worried about their credibility. The rapid increase in inflation PMU in mid-2004 was accompanied by concerns about rising inflation (e.g., the May 2004 meeting). Even more recently, after a brief focus on deflation during the global financial crisis, by 2012, the FOMC quite quickly returned to worrying about the inflationary impact of the unconventional policies they pursued.

Janet Yellen's statements illustrate policymakers' thinking about inflation uncertainty and credibility. Indeed, Yellen regularly expressed credibility concerns. In the September 1996 meeting, she said *"...the risk of an increase in inflation has definitely risen, and I would characterize the economy as operating in an inflationary danger zone"* and this warranted a small policy response because *"a failure to shift policy just modestly in response to shifting inflationary risks could undermine the assumptions on which the markets' own stabilizing responses are based."*

In November 2005, she was more sanguine about the risks but wary of the need to protect credibility: *"Overall, I judge our credibility to be very much intact. Of course, our credibility going forward does depend on continued vigilance. The economy now appears to be close to full employment, with a good deal of momentum. And annual core inflation, at least as judged by the core PCE measure, remains near the upper end of my comfort zone and, arguably, inflation risks are tilted somewhat to the upside. So with respect to policy, I support at a minimum the removal of any remaining policy accommodation...So a few more increases, including one today, seem to me likely to be required."*

Ben Bernanke, in the May 2004 meeting, worried about adverse inflation movements: *"From a risk-management perspective, as we begin to raise rates we should weigh the risk of significantly impeding the labor market recovery against the risk of having to scramble to adjust to unexpectedly adverse inflation developments."* He too paid attention to credibility concerns. In March 2006, he summarized the deliberations of the policy round as: *"I took from the group some sense of at least a slight upside risk to inflation, reflecting the increasing resource utilization; the fact that inflation is somewhat on the high side of what many people describe as their comfort zone; and the fact that, if inflation does rise, there will be costs to bringing it back down and maintaining our credibility."*

Other FOMC members also focused on credibility. President Melzer (St. Louis) spoke of credibility risks in 1997: *"My reading of the economy supports the conclusion that we are at risk of losing the hard-won credibility of our commitment to hold inflation at 3 percent."* In that same year, President Guynn (Atlanta) thought that, with the economy around full employment, the FOMC had *"a unique opportunity with little downside risk to lean a bit more against the expected upward creep in inflation that most of us are forecasting and, in doing so, to underscore our resolve and credibility in the minds of financial market participants, business decisionmakers, and the general public."*

Vice Chair, Ferguson, said in December 1999 that the FOMC *"should not be afraid to act in a well-modulated fashion in order to maintain our hard fought victory over inflation and also our credibility."* In March 2005, towards the end of his term, he was still focused on the FOMC's credibility and how policy actions could affect it: *"given the stage of the cycle, the skew in the general risk assessment that I outlined, and the need to manage market expectations, I think we should use our statement to signal our awareness that inflation pressures may have picked up. The incoming data are indicative of that. If we are wrong on the upside risks, both we and the market will adjust. On the other hand, if we fail to reflect the existence of these upside risks, we could easily be perceived as being behind the curve, with negative consequences in terms of inflation dynamics and, potentially, our own credibility."*

2.6 Conclusions

We contribute to the literature by quantifying otherwise hard-to-measure factors driving monetary policymaking from the transcripts of the FOMC deliberations during the 1987–2015 sample. We develop textual measures for the policymakers' perceptions of different types of uncertainty, directional views on the path of the economy, as well as forward-looking policy stances. We show that uncertainty perceptions drive a wedge between the actual decision-making of the FOMC and standard policy rules estimated using the Fed's economic forecasts from Greenbooks.

Our main new results pertain to the effects of inflation uncertainty. Heightened inflation uncertainty leads to more hawkish views of the entire committee and individual members and predicts a tighter policy path up to eight meetings ahead. The economic magnitude of the uncertainty effect on the policy path is comparable to that of the real GDP growth. The FOMC's expressed uncertainty about inflation relevant to their decision-making is distinct from the public perceptions of uncertainty, objective measures of macroeconomic volatility, and also the uncertainty discussed by the Fed staff. We rationalize these findings with a model of upper inflation tail risks, which are endogenous to policy decisions. Narrative evidence links FOMC's inflation uncertainty perceptions to their concerns about maintaining credibility for fighting inflation.

The issue of central bank efforts to maintain credibility is timely. Chair Powell (2022), in opening remarks at the 2022 Jackson Hole Symposium, spoke forcefully about the Fed's determination to control inflation. The concern with credibility is also warranted. Credibility allows the FOMC to better manage economic expectations, as "achieving through word and deed" well-anchored inflation expectations can lead to better policy outcomes (Bernanke, 2022). Our results suggest that policymakers' inflation uncertainty has reflected their continued vigilance for inflation over the past three decades, shaping policy deliberations and choices in a way not captured by standard reaction function estimates. Understanding the implications of that vigilance for macroeconomic and financial stability is an important next step for future research.

Appendices

2.A.1 Proofs for Tail Risks Model

2.A.1.1 Proof of Lemma 2.1

Proof. The expression for expected inflation is immediate from the structure of the distribution described in (**??**).

To compute the variance, let $\overline{\pi}_L$ ($\overline{\pi}_H$) be expected inflation in the low-inflation (high-inflation) state; for now we surpress the dependence on r_t. We have (where again we surpress the dependence of p_t on r_t)

$$\mathbb{E}\left[\,\pi_t^2\,\right] = p_t\left[s_{\pi,t}^2 + \overline{\pi}_H^2\right] + (1-p_t)\left[s_{\pi,t}^2 + \overline{\pi}_L^2\right]$$

and

$$\left(\mathbb{E}\left[\,\pi_t\,\right]\right)^2 = \left(p_t\overline{\pi}_H + (1-p_t)\overline{\pi}_L\right)^2$$

and so

$$\begin{gathered}\mathrm{Var}(\pi_t) = p_t\left[s_{\pi,t}^2 + \overline{\pi}_H^2\right] + (1-p_t)\left[s_{\pi,t}^2 + \overline{\pi}_L^2\right] - \left(p_t\overline{\pi}_H + (1-p_t)\overline{\pi}_L\right)^2 = \\ s_{\pi,t}^2 + p_t\overline{\pi}_H^2 + (1-p_t)\overline{\pi}_L^2 - \left(p_t\overline{\pi}_H + (1-p_t)\overline{\pi}_L\right)^2 = \\ s_{\pi,t}^2 + p_t(1-p_t)\overline{\pi}_H^2 + p_t(1-p_t)\overline{\pi}_L^2 - 2p_t(1-p_t)\overline{\pi}_H\overline{\pi}_L = \\ s_{\pi,t}^2 + p_t(1-p_t)(\overline{\pi}_H - \overline{\pi}_L)^2 = s_{\pi,t}^2 + p_t(1-p_t)\Delta^2\end{gathered}$$

□

2.A.1.2 Proof of Proposition 2.3

Proof. First note that (2.3), i.e. the equation that implicitly defines optimal policy $\hat{r}_{0,t}$ under fixed tail risks, has a unique solution. $\overline{\Pi}'_{t,F}(r_t)\left[\overline{\Pi}_{t,F}(r_t) - \pi^*\right]$ and $\overline{Y}'_t(r_t)\left[\overline{Y}(r_t) - y^*\right]$ are strictly increasing and continuous in r_t; limit to $-\infty$ as $r_t \to -\infty$; and limit to ∞ as $r_t \to \infty$. These properties jointly imply (**??**) has a unique solution.

We now show that the optimal policy with policy-dependent tail risks $\hat{r}_{1,t}$ must lie strictly above $\hat{r}_{0,t}$. We first show that (2.3) has no solution $r_t \leq \hat{r}_{0,t}$. On this range

$$\begin{gathered}
\overline{\Pi}_t'(r_t)\left[\overline{\Pi}_t(r_t)-\pi^*\right]+\left(\sigma_{\pi,t}^2\right)'(r_t)= \\
\left[\overline{\Pi}_{t,F}'(r_t)+p'(r_t)\Delta_t\right]\left[\overline{\Pi}_t(r_t)-\pi^*\right]+\left(\sigma_{\pi,t}^2\right)'(r_t)= \\
\left[\overline{\Pi}_{t,F}'(r_t)+p'(r_t)\Delta_t\right]\left[\overline{\pi}_t-a_\pi r_t+p_t(r_t)\Delta-\pi^*\right]+\left(\sigma_{\pi,t}^2\right)'(r_t)< \\
\left[\overline{\Pi}_{t,F}'(r_t)+p'(r_t)\Delta_t\right]\left[\overline{\pi}_t-a_\pi r_t+p_t(r_t)\Delta_t-\pi^*\right]\leq \\
\left[\overline{\Pi}_{t,F}'(r_t)+p'(r_t)\Delta_t\right]\left[\overline{\pi}_t-a_\pi r_t+p_{0,t}\Delta_t-\pi^*\right]< \\
\overline{\Pi}_{t,F}'(r_t)\left[\overline{\pi}_t-a_\pi r_t+p_{0,t}\Delta_t-\pi^*\right]\leq-\lambda\overline{Y}_t'(r_t)\left[\overline{Y}_t(r_t)-y^*\right]
\end{gathered}$$

The first two equalities arise from the assumed structure of the model. The first inequality holds because the variance of inflation is strictly decreasing in r_t by Lemma 2.1. The second holds because $p_t(\hat{r}_{0,t}) = p_{0,t}$ by assumption and so $p_t(r_t) \geq p_{0,t}$ for all $r_t \leq \hat{r}_{0,t}$. The third holds because $\overline{\pi}_t - a_\pi r_t + p_{0,t}\Delta - \pi^* > 0$ and $p'(r_t) < 0$. The final inequality holds due to the properties of the functions in expression (2.3) discussed above.

On the other hand, a solution to (2.3) must exist because the LHS (RHS) limits to ∞ ($-\infty$) as $r_t \to \infty$ and to $-\infty$ (∞) as $r_t \to -\infty$. Moreover, both the LHS and RHS are continuous in r_t. But by the above any solution is strictly above $\hat{r}_{0,t}$. □

2.A.2 Dictionaries for Risk, Uncertainty, Topics, and Sentiment

Table 2.A.1: Nearest Neighbors of Risk and Risks in FOMC Word Embeddings.

This table shows the fifty nearest neighbors to the terms ‘risk’ and ‘risks’ for a word embedding model estimated from the economy round of the FOMC transcripts. For each neighbor term, we report the cosine similarity in the word embedding space and the count of the term in the economy round. We remove certain terms from our final dictionary if they are too generic (struck through).

risk			**risks**		
Term	Similarity	Count in Econ Discussion	Term	Similarity	Count in Econ Discussion
risks	0.691266	3183	downside risk*	0.737511	1118
downside risk*	0.59828	1118	upside risk*	0.704978	585
threat	0.594511	135	risk	0.691266	3236
upside risk*	0.522107	585	threat	0.52743	135
danger	0.502593	121	skewed	0.501801	101
probability	0.484233	524	uncertainties	0.48339	505
possibility	0.475492	1010	~~downside~~	0.449301	707
likelihood	0.469565	224	~~tilted~~	0.448698	119
vulnerability	0.439843	72	danger	0.445836	121
dangers	0.406005	28	dangers	0.439822	28
~~headwind~~	0.402709	38	fatter	0.434411	14
chances	0.386979	65	~~outcomes~~	0.420205	291
fragility	0.374305	106	probability	0.412639	524
~~risktaking~~	0.373512	50	skew	0.40086	29
~~challenges~~	0.348706	174	~~challenges~~	0.395508	174
~~prospect~~	0.347213	242	~~juncture~~	0.393311	114
~~unwelcome~~	0.345361	42	modal	0.391584	131
sensitivity	0.343196	82	~~headwinds~~	0.385167	288
probabilities	0.342825	87	vulnerabilities	0.378889	59
~~breakout~~	0.34249	39	probabilities	0.375555	87
uncertainty	0.341431	2317	concerns	0.374206	628
~~consequences~~	0.339106	367	~~breakout~~	0.372844	39
concern* that	0.33652	678	possibilities	0.369255	98
odds	0.332704	190	uncertainty	0.362784	2317
fatter	0.331849	14	vulnerability	0.355743	72
concern	0.326579	1047	~~directive~~	0.355738	29
potentially	0.322536	275	tensions	0.35208	51
concerns	0.318465	628	~~crosscurrents~~	0.350524	49
tension	0.313301	101	odds	0.343869	190
~~spiral~~	0.312127	69	threats	0.33815	36
possibly	0.309975	290	fragility	0.337531	106
~~costly~~	0.309472	63	~~symmetric~~	0.336238	57
~~challenge~~	0.307298	179	~~asymmetry~~	0.333936	25
~~urgency~~	0.303853	28	~~skews~~	0.33296	14
~~instability~~	0.303578	91	~~urgency~~	0.3309	28
unease	0.303215	25	skewness	0.330203	7
vulnerabilities	0.302247	59	tension	0.325514	101
fear	0.299544	194	~~headwind~~	0.323167	38
skewness	0.298903	7	~~vigilant~~	0.319233	55
~~trap~~	0.297911	58	~~drags~~	0.31894	75
~~overshoot~~	0.296446	53	~~costpush~~	0.318601	4
~~problem~~	0.295296	1221	possibility	0.318443	1010
skew	0.29475	29	~~balanced~~	0.317706	646
worries	0.294228	132	tails	0.31724	28
threats	0.294017	36	~~challenge~~	0.316888	179
~~repercussions~~	0.289451	23	likelihood	0.315145	224
skewed	0.287008	101	imponderables	0.31498	10
volatility	0.284335	360	~~considerations~~	0.311688	184
doubts	0.283668	65	~~consequences~~	0.306922	367
~~juncture~~	0.283524	114	~~leaning~~	0.305052	38

Table 2.A.2: Nearest Neighbors of Uncertain and Uncertainty in FOMC Word Embeddings.

This table shows the fifty nearest neighbors to the terms ‘uncertain’ and ‘uncertainty’ for a word embedding model estimated from the economy round of the FOMC transcripts. For each neighbor term, we report the cosine similarity in the word embedding space and the count of the term in the economy round. We remove certain terms from our final dictionary if they are too generic (struck through). An exclamation mark preceding a term indicates it is only associated with the dictionary when it is negated, i.e., when it is immediately preceded by a negation phrase, which is one of {‘less’, ‘no’,‘not’, ‘little’, ‘don’t’, ‘doesn’t’, ‘hasn’t’, ‘haven’t’, ‘won’t’, ‘shouldn’t’, ‘didn’t’}.

uncertain			**uncertainty**		
Term	Similarity	Count in Econ Discussion	Term	Similarity	Count in Econ Discussion
!confident	0.460385	367	uncertainties	0.65845	505
fragile	0.455998	157	anxiety	0.515023	70
!sanguine	0.442406	101	angst	0.433309	24
murky	0.43732	24	skepticism	0.430759	68
unclear	0.436552	57	tension	0.427094	101
wary	0.428437	41	uncertain	0.426752	399
uncertainty	0.426752	2317	~~caution~~	0.423748	445
unsure	0.423955	14	downside risk*	0.418226	1118
~~poor~~	0.411094	194	~~challenges~~	0.414084	174
~~dependent~~	0.406995	119	pessimism	0.411988	179
apprehensive	0.404002	11	fragility	0.401378	106
vulnerable	0.401095	203	gloom	0.380074	65
stressed	0.397458	53	~~conflict~~	0.370107	47
~~challenging~~	0.391555	71	risks	0.362784	3183
~~bullish~~	0.38583	65	volatility	0.359692	360
bleak	0.385454	52	concerns	0.359599	628
skeptical	0.384238	169	!clarity	0.352539	89
~~attuned~~	0.383523	15	sensitivity	0.348326	82
uncertainties	0.383365	505	unease	0.347682	25
~~vigilant~~	0.382641	55	~~publicity~~	0.346734	31
~~cautious~~	0.378045	537	fog	0.343423	20
grim	0.376893	34	~~headwinds~~	0.341591	288
~~jury~~	0.376789	20	risk	0.341431	3236
agnostic	0.375537	31	~~surrounding~~	0.340727	163
!optimistic	0.372549	1249	worries	0.337692	132
~~muted~~	0.365712	87	!certainty	0.332492	91
unsettled	0.362423	22	doubts	0.328778	65
concern* about	0.361507	1634	concern	0.327687	1047
~~buoyant~~	0.360631	70	optimism	0.32465	498
~~disruptive~~	0.359961	50	~~pain~~	0.323275	31
~~depend~~	0.359918	198	ambiguity	0.322258	18
skittish	0.35904	18	error	0.320998	234
jittery	0.358658	11	skittishness	0.319675	9
precarious	0.357391	22	nervousness	0.319648	31
fog	0.357145	20	unknown	0.316516	32
fluid	0.357016	12	tensions	0.314929	51
!convinced	0.354622	173	imponderables	0.314825	10
pessimistic	0.354016	430	upside risk*	0.313048	585
!upbeat	0.352921	217	~~debate~~	0.312722	168
~~destabilizing~~	0.35242	22	~~awareness~~	0.312388	26
precise	0.352262	81	~~uncertaintyin~~	0.310427	3
uncomfortable	0.348358	102	~~disagreement~~	0.304366	57
~~assessing~~	0.345848	110	~~admits~~	0.302832	3
~~damaging~~	0.342869	39	~~science~~	0.29633	31
~~satisfactory~~	0.339921	66	~~apprehension~~	0.292553	16
anxious	0.33839	40	~~headwind~~	0.290777	38
~~worried~~	0.337316	410	~~instability~~	0.290598	91
ambiguous	0.335987	32	~~troubles~~	0.288294	35
problematic	0.33498	78	~~questions~~	0.288182	698
daunting	0.332674	19	~~worry~~	0.286513	402

Table 2.A.3: Noun Phrases and Direction Words Related to Inflation and Wages.

The first column displays the phrases we associate with inflation and wage discussion in the FOMC transcripts. The second to fifth columns relate to the construction of inflation sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously.

Nouns	Match w/ direction words		Direction words	
	Negative	Positive	Group 1	Group 2
commodity price*	1	2	abated	acceler*
consumer energy price*	1	2	adjust* downward	adjust* upward
consumer food price*	1	2	contract*	advanc*
consumer price index*	1	2	cool*	bolster*
consumer price index* cpi	1	2	deceler*	boost*
consumer price inflation	1	2	declin*	elevat*
consumer price*	1	2	decreas*	expand*
core consumer price inflation	1	2	down	fast*
core consumer price*	1	2	downturn	gain*
core cpi	1	2	downward	go* up
core cpi inflation	1	2	downward adjust*	heighten*
core inflation	1	2	downward revision	high*
core pce inflation	1	2	drop*	increas*
core pce price inflation	1	2	eas*	mov* higher
core pce price*	1	2	fall*	mov* up
core price inflation	1	2	fell	mov* upward
core producer price*	1	2	go* down	pick* up
cost basic material*	1	2	limit*	rais*
cost* goods and services	1	2	low*	rallied
cost* health care	1	2	moderate*	rally*
cost* labor	1	2	moderati*	rebound*
cost* living	1	2	mov* down	recoup*
cost* us goods and services	1	2	mov* downward	revis* up*
crude oil price*	1	2	mov* lower	rise*
disinflation*	2	1	pullback	rising
disinflation* pressure*	2	1	reduc*	rose
employment cost index*	1	2	revis* down*	run up
energy prices	1	2	slow*	runup
headline inflation	1	2	slow* down	stop decline
health care cost*	1	2	soft*	strength*
inflation*	1	2	stagnate*	strong*
inflation compensation	2	1	stall*	tick* up
inflation expectation*	1	2	subdu*	up
inflation level	1	2	tick* down	upward
inflation outlook	1	2	tight*	upward adjust*
inflation rate	1	2	weak*	upward revision
inflation wage*	1	2	weigh* on	went up
labor compensation	1	2	went down	
labor cost pressure*	1	2		
labor cost*	1	2		
long* run inflation expectation*	1	2		
long* term inflation expectation*	1	2		
manufacturing price*	1	2		
material price*	1	2		
near* term inflation expectation*	1	2		
oil price*	1	2		
pce price index*	1	2		
pressure* inflation	1	2		
pressure* wages	1	2		
price index*	1	2		
price inflation	1	2		
price level stability	2	1		
price stability	2	1		
prices of durable goods	1	2		
prices of durables	1	2		
prices of manufacturing	1	2		
prices of material*	1	2		
producer price ind*	1	2		
producer price*	1	2		
real oil price*	1	2		
unit labor cost*	1	2		
wage gains	1	2		
wage inflation	1	2		
wage pressure*	1	2		
wage price pressure*	1	2		
wages	1	2		
inflation* pressure*	1	2		
price pressure*	1	2		
deflation* force*	2	1		
deflation* pressure	2	1		
deflation*	2	1		
prices of durable goods	1	2		
prices of durables	1	2		
prices of manufacturing	1	2		
prices of material*	1	2		

Table 2.A.4: Noun Phrases and Direction Words Related to Economic Growth (1).

The first column displays a subset the phrases we associate with economic growth discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of growth sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
aggregate demand	2	1	*adjust* downward*	*acceler**
aggregate inventory sales ratio	1	2	*adverse*	*adjust* upward*
aggregate spending	2	1	*contract**	*advanc**
building activity	2	1	*cool**	*better*
business activity	2	1	*cut**	*bolster**
business capital spending	2	1	*deceler**	*boost**
business confidence	2	1	*declin**	*elevat**
business demand capital equipment	2	1	*decreas**	*encourag**
business equipment investment	2	1	*deteriorat**	*expand**
business equipment spending	2	1	*disappoint**	*fast**
business equipment spending	2	1	*down*	*favor**
business equipment spending and industrial production	2	1	*downturn*	*gain**
business expansion	2	1	*downward*	*go* up*
business expenditure*	2	1	*downward adjust**	*heighten**
business fixed investment	2	1	*downward revision*	*high**
business fixed investment and household spending	2	1	*drag**	*improv**
business inventory investment	2	1	*drop**	*increas**
business investment	2	1	*eas**	*mov* higher*
business investment spending	2	1	*fall**	*mov* up*
business outlay*	2	1	*fell*	*mov* upward*
business outlays capital equipment	2	1	*go* down*	*pick* up*
business output	2	1	*held down*	*rais**
business purchas*	2	1	*hold down*	*rallied*
business purchases of transporation equipment	2	1	*increas* at slow* rate*	*rally**
business sector	2	1	*limit**	*rebound**
business sentiment	2	1	*low**	*recoup**
business spending	2	1	*moderate**	*revis* up**
business spending capital equipment	2	1	*moderati**	*rise**
business spending of transporation equipment	2	1	*mov* down*	*rising*
capacity utilization	2	1	*mov* downward*	*rose*
capital investment	2	1	*mov* lower*	*run up*
capital spending	2	1	*pressur**	*runup*
capital spending plan*	2	1	*pullback*	*stop decline*
civilian unemployment rate	1	2	*reduc**	*strength**
claim* unemployment insurance	1	2	*revis* down**	*strong**
construction activity	2	1	*slow**	*tick* up*
consumer confidence	2	1	*slow* down*	*tight**
consumer sector	2	1	*soft**	*up*
consumer sentiment	2	1	*stagnat**	*upward*
consumer spending	2	1	*stall**	*upward adjust**
consumption	2	1	*strain**	*upward revision*
consumption spending	2	1	*stress**	*went up*
current account deficit			*subdu**	
current account surplus			*take* toll on*	
disposable income	2	1	*tension**	
domestic components of spending	2	1	*tick* down*	
domestic demand	2	1	*took toll on*	
domestic economy	2	1	*weak**	
domestic final demand	2	1	*weigh* down*	
domestic spending	2	1	*weigh* on*	
domestic spending components	2	1	*went down*	
durable equipment	2	1	*worse**	
economic activity	2	1		
economic development*	2	1		
economic expansion	2	1		
economic growth	2	1		
economic outlook	2	1		
economic performance	2	1		
economic recovery	2	1		
economic situation	2	1		
employment	2	1		
employment growth	2	1		
employment rate	2	1		
excess capacity	1	2		
factory output	2	1		

Table 2.A.5: Noun Phrases and Direction Words Related to Economic Growth (2).

The first column displays a subset the phrases we associate with economic growth discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of growth sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
final demand	2	1	*adjust* downward*	*acceler**
gdp growth	2	1	*adverse*	*adjust* upward*
global economic growth	2	1	*contract**	*advanc**
gross domestic product	2	1	*cool**	*better*
high tech equipment investment	2	1	*cut**	*bolster**
high tech equipment spending	2	1	*deceler**	*boost**
household spending and business fixed investment	2	1	*declin**	*elevat**
household* spending	2	1	*decreas**	*encourag**
housing activity	2	1	*deteriorat**	*expand**
housing construction	2	1	*disappoint**	*fast**
housing demand	2	1	*down*	*favor**
income growth	2	1	*downturn*	*gain**
industrial production	2	1	*downward*	*go* up*
inventories	2	1	*downward adjust**	*heighten**
inventory accumulation	1	2	*downward revision*	*high**
inventory investment	2	1	*drag**	*improv**
inventory liquidation	2	1	*drop**	*increas**
inventory sales ratio	1	2	*eas**	*mov* higher*
investment condition*	2	1	*fall**	*mov* up*
investment demand	2	1	*fell*	*mov* upward*
investment high tech equipment	2	1	*go* down*	*pick* up*
investment manufacturing	2	1	*held down*	*rais**
investment situation	2	1	*hold down*	*rallied*
investment spending	2	1	*increas* at slow* rate*	*rally**
job growth	2	1	*limit**	*rebound**
labor demand	2	1	*low**	*recoup**
labor force participation	2	1	*moderate**	*revis* up**
labor market*	2	1	*moderati**	*rise**
labor market condition*	2	1	*mov* down*	*rising*
labor market indicator*	2	1	*mov* downward*	*rose*
labor market slack	1	2	*mov* lower*	*run up*
labor productivity	2	1	*pressur**	*runup*
manufacturing activity	2	1	*pullback*	*stop decline*
manufacturing capacity utilization	2	1	*reduc**	*strength**
manufacturing output	2	1	*revis* down**	*strong**
manufacturing production	2	1	*slow**	*tick* up*
manufacturing sector	2	1	*slow* down*	*tight**
motor vehicle assembl*	2	1	*soft**	*up*
motor vehicle production	2	1	*stagnat**	*upward*
motor vehicle purchas*	2	1	*stall**	*upward adjust**
motor vehicle sales	2	1	*strain**	*upward revision*
motor vehicle sector	2	1	*stress**	*went up*
new construction	2	1	*subdu**	
new home sales	2	1	*take* toll on*	
new orders	2	1	*tension**	
nominal gdp	2	1	*tick* down*	
nonfarm business sector	2	1	*took toll on*	
nonfarm payroll employment	2	1	*weak**	
nonresidential construction	2	1	*weigh* down*	
nonresidential construction activity	2	1	*weigh* on*	
orders and shipments of nondefense capital goods	2	1	*went down*	
orders of nondefense capital goods	2	1	*worse**	
outlays business equipment	2	1		
outlays high tech equipment	2	1		
outlays transporation equipment	2	1		
outlook economic activity	2	1		
output gap				
output growth	2	1		
payroll employment	2	1		
pce	2	1		
personal consumption expenditure*	2	1		
personal income	2	1		
potential output	2	1		
potential output	2	1		
private expenditures business equipment	2	1		

Table 2.A.6: Noun Phrases and Direction Words Related to Economic Growth (3).

The first column displays a subset the phrases we associate with economic growth discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of growth sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the ‘Positive’ column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
private nonfarm employment	2	1	adjust* downward	acceler*
private nonfarm payroll employment	2	1	adverse	adjust* upward
private sector investment	2	1	contract*	advanc*
private spending	2	1	cool*	better
productivity	2	1	cut*	bolster*
productivity growth	2	1	deceler*	boost*
purchas* of motor vehicle*	2	1	declin*	elevat*
real activity	2	1	decreas*	encourag*
real business spending	2	1	deteriorat*	expand*
real consumer spending	2	1	disappoint*	fast*
real disposable income	2	1	down	favor*
real disposable personal income	2	1	downturn	gain*
real gdp	2	1	downward	go* up
real gdp growth	2	1	downward adjust*	heighten*
real gnp	2	1	downward revision	high*
real personal consumption expenditure*	2	1	drag*	improv*
real spending	2	1	drop*	increas*
residential construction	2	1	eas*	mov* higher
residential construction activity	2	1	fall*	mov* up
residential investment	2	1	fell	mov* upward
resource use	2	1	go* down	pick* up
resource utilization	2	1	held down	rais*
retail trade	2	1	hold down	rallied
shipments of nondefense capital goods	2	1	increas* at slow* rate	rally*
spending and production	2	1	limit*	rebound*
spending business equipment	2	1	low*	recoup*
spending high tech equipment	2	1	moderate*	revis* up*
spending nonresidential structures	2	1	moderati*	rise*
spending transporation equipment	2	1	mov* down	rising
structural productivity	2	1	mov* downward	rose
total industrial production	2	1	mov* lower	run up
total nonfarm payroll employment	2	1	pressur*	runup
unemployment	1	2	pullback	stop decline
unemployment insurance claim*	1	2	reduc*	strength*
unemployment level	1	2	revis* down*	strong*
unemployment rate	1	2	slow*	tick* up
us economic activity	2	1	slow* down	tight*
us economy	2	1	soft*	up
outlook economy	2	1	stagnat*	upward
inventory level*	1	2	stall*	upward adjust*
fiscal			strain*	upward revision
deficit			stress*	went up
surplus			subdu*	
			take* toll on	
			tension*	
			tick* down	
			took toll on	
			weak*	
			weigh* down	
			weigh* on	
			went down	
			worse*	

Table 2.A.7: Noun Phrases Related to Financial Markets (1).

The first column displays a subset the phrases we associate with financial market discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of market sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the ‘Positive’ column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
aaa spread*	1	2	adjust* downward	acceler*
baa spread*	1	2	contract*	adjust* upward
corporate bond spread*	1	2	cool*	advanc*
corporate spread*	1	2	deceler*	adverse
cost of bank credit	1	2	declin*	bolster*
cost of bond financ*	1	2	decreas*	boost*
cost of capital	1	2	down	deteriorat*
cost of credit	1	2	downturn	edge* up*
cost of equity	1	2	downward	elevat*
cost of external capital	1	2	downward adjust*	expand*
cost of funding	1	2	drop*	fast*
cost of raising capital	1	2	eas*	gain*
cost of raising capital through equity	1	2	edge* down	go* up
credit cost*	1	2	encourag*	heighten*
credit default swap*	1	2	fall*	high*
credit risk spread*	1	2	favor*	increas*
credit spread*	1	2	fell	mov* higher
debt securities spread*	1	2	go* down	mov* up
equity risk prem*	1	2	improv*	mov* upward
expected real return equit*	1	2	limit*	pick* up
expected return equit*	1	2	low*	pressure*
financing cost	1	2	moderate*	rais*
funding cost	1	2	moderati*	rebound*
risk prem*	1	2	mov* down	recoup*
risk spread*	1	2	mov* downward	revis* up*
risk spread* corporate bonds*	1	2	mov* lower	rise*
spread* corporate bond*	1	2	narrow*	rising
spread* investment grade bond*	1	2	pullback	rose
spread* speculative grade bond*	1	2	reduc*	run up
			revis* down*	runup
			slow*	stop decline
			soft*	strain*
			subdu*	strength*
			take* toll on	stress*
			tick* down	strong*
			took toll on	tension*
			weak*	tick* up
			weigh* on	up
			went down	upward
				upward adjust*
				went up
				widen*
				worse*

Table 2.A.8: Noun Phrases Related to Financial Markets (2).

The first column displays a subset the phrases we associate with financial market discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of market sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
appetite* risk taking	2	1	_adjust* downward_	_acceler*_
appetite* risk*	2	1	_adverse_	_adjust* upward_
appetite* risk* asset*	2	1	_contract*_	_advanc*_
appetite* risk* investment*	2	1	_cool*_	_bolster*_
appetite* taking risk*	2	1	_deceler*_	_boost*_
condition* credit market*	2	1	_declin*_	_eas*_
condition* financial market*	2	1	_decreas*_	_elevat*_
credit condition*	2	1	_deteriorat*_	_encourag*_
credit growth	2	1	_down_	_expand*_
credit market*	2	1	_downturn_	_fast*_
credit market condition*	2	1	_downward_	_favor*_
credit market demand	2	1	_downward adjust*_	_gain*_
development financial market*	2	1	_downward revision_	_go* up_
financial condition*	2	1	_drop*_	_high*_
financial development*	2	1	_fall*_	_improv*_
financial instabilit*	1	2	_fell_	_increas*_
financial market condition*	2	1	_go* down_	_loos*_
financial market confidence	2	1	_limit*_	_mov* higher_
financial market development*	2	1	_low*_	_mov* up_
financial market index*	2	1	_moderate*_	_mov* upward_
financial market indic*	2	1	_moderati*_	_normaliz*_
financial market pressure*	1	2	_mov* down_	_pick* up_
financial market price*	2	1	_mov* downward_	_rais*_
financial market sentiment	2	1	_mov* lower_	_rallied_
financial market*	2	1	_pressure*_	_rally*_
financial situation	2	1	_pullback_	_rebound*_
financial stability	2	1	_reduc*_	_recoup*_
investor* appetite*	2	1	_restrictive_	_revis* up*_
investor* appetite* risk*	2	1	_revis* down*_	_rise*_
investor* confidence	2	1	_slow*_	_rising_
investor* risk appetite*	2	1	_soft*_	_rose_
investor* sentiment	2	1	_stagnate*_	_run up_
investor* sentiment toward risk*	2	1	_stall*_	_runup_
investor* sentiment toward risk* asset*	2	1	_strain*_	_stop decline_
liquidity	2	1	_stress*_	_strength*_
pressure* financial market	1	2	_subdu*_	_strong*_
risk appetite*	2	1	_take a toll on_	_tick* up_
bank credit	2	1	_tension*_	_up_
bank lending	2	1	_tick* down_	_upward_
banking supervision			_tight*_	_upward adjust*_
banking system	2	1	_took toll on_	_upward revision_
consumer credit	2	1	_turbulent_	_went up_
credit availability	2	1	_weak*_	
credit quality	2	1	_weigh* on_	
domestic credit	2	1	_went down_	
domestic nonfinancial debt	2	1	_worsen*_	
financial outlook	2	1		
financial system	2	1		
foreign exchange				
foreign exchange market*				
foreign exchange valu*				
household balance sheet*	2	1		
market exchange rate*				
market liquidity	2	1		
mortgage refinancing activity	2	1		
non market exchange rate*				
nonfinancial debt	2	1		
private credit	2	1		
private credit market*	2	1		
seasonal borrowing	2	1		
total domestic non financial debt	2	1		
total domestic nonfinancial debt	2	1		
us dollar				

Table 2.A.9: Noun Phrases Related to Financial Markets (3).

The first column displays a subset the phrases we associate with financial market discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of market sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
aaa yield*	1	2	adjust* downward	acceler*
baa yield*	1	2	contract*	adjust* upward
bond yield*	1	2	cool*	advanc*
corporate bond yield*	1	2	deceler*	bolster*
corporate debt yield*	1	2	declin*	boost*
corporate yield*	1	2	decreas*	elevat*
debt yield*	1	2	down	encourag*
high grade corporate bond* yield*	1	2	downturn	expand*
interest rate*	1	2	downward	fast*
investment grade and speculative grade corporate bond* yield*	1	2	downward adjust*	gain*
investment grade corporate bond yield*	1	2	downward movement	go* up
long* term interest rate*	1	2	downward revision	heighten*
long* term rate*	1	2	drop*	high*
mortgage interest rate*	1	2	fall*	increas*
real long* term interest rate*	1	2	fell	mov* higher
real long* term rate*	1	2	go* down	mov* up
speculative grade corporate bond* yield*	1	2	limit*	mov* upward
yield* agency mortgage backed securities mbs	1	2	low*	pick* up
yield* corporate bond*	1	2	moderate*	rais*
yield* corporate bonds and agency mbs	1	2	moderati*	rallied
yield* mortgage backed securities	1	2	mov* down	rally*
yield* private sector debt securities	1	2	mov* downward	rebound*
comparable maturity treasury securities			mov* lower	recoup*
discount rate*	1	2	pullback	revis* up
long* term treasury securities			reduc*	revision upward
nominal treasury securities			revis* down	rise*
real interest rate*	1	2	slow*	rising
short* term interest rate*	1	2	soft*	rose
us government securities			stagnate*	run up
			stall*	runup
			subdu*	stop decline
			take* toll on	strength*
			tick* down	strong*
			tight*	tick* up
			took toll on	up
			weak*	upward
			weigh* on	upward adjust*
			went down	upward movement
				upward revision
				went up

Table 2.A.10: Noun Phrases Related to Financial Markets (4).

The first column displays a subset the phrases we associate with financial market discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of market sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
asset index*	2	1	*adjust* downward*	*acceler**
asset indic*	2	1	*adverse*	*adjust* upward*
asset market*	2	1	*burst**	*advanc**
asset price index*	2	1	*contract**	*bolster**
asset price indic*	2	1	*cool**	*boost**
asset price*	2	1	*deceler**	*edge* up*
asset valu*	2	1	*declin**	*elevat**
equities	2	1	*decreas**	*encourag**
equity and home price*	2	1	*deteriorat**	*expand**
equity and home valu*	2	1	*down*	*fast**
equity and house price*	2	1	*downturn*	*favor**
equity and housing price*	2	1	*downward*	*gain**
equity index*	2	1	*downward adjust**	*go* up*
equity indic*	2	1	*downward movement*	*high**
equity market index*	2	1	*downward revision*	*improv**
equity market indic*	2	1	*drop**	*increas**
equity market price*	2	1	*eas**	*mov* high**
equity market valu*	2	1	*edge* down*	*mov* up*
equity market*	2	1	*fall**	*mov* upward*
equity price index*	2	1	*fell*	*pick* up*
equity price indic*	2	1	*go* down*	*rais**
equity price measure*	2	1	*limit**	*rallied*
equity price*	2	1	*low**	*rally**
equity valu*	2	1	*moderate**	*rebound**
equaity wealth	2	1	*moderati**	*recoup**
financial wealth	2	1	*mov* down*	*revis* up**
home and equity price*	2	1	*mov* downward*	*rise**
house and equity price*	2	1	*mov* lower*	*rising*
household wealth	2	1	*plummet**	*rose*
household* net worth	2	1	*pressure**	*run up*
housing and equity price*	2	1	*pull* back*	*runup*
price* of risk* asset*	2	1	*pullback*	*stop decline*
ratio of wealth to income	2	1	*reduc**	*strength**
risk* asset price*	2	1	*revis* down**	*strong**
s p 500 index	2	1	*slow**	*tick* up*
stock index*	2	1	*slow* down*	*up*
stock indic*	2	1	*soft**	*upward*
stock market index*	2	1	*stagnate**	*upward adjust**
stock market price*	2	1	*stall**	*upward movement*
stock market wealth	2	1	*strain**	*upward revision*
stock market*	2	1	*stress**	*went up*
stock price indic*	2	1	*subdu**	
stock price*	2	1	*take* toll on*	
stock prices index*	2	1	*tension**	
stock val*	2	1	*tick* down*	
us stock market price*	2	1	*tight**	
wealth effect*	2	1	*took toll on*	
wealth to income ratio	2	1	*tumbl**	
			*weak**	
			weigh on*	
			went down	
			*worse**	

Table 2.A.11: Noun Phrases Related to Model.

The table contains phrases we associate with model discussion in the FOMC transcripts.

parameter*
model*
measurement*
forecast error*
relationship*
error band*
nairu
trend
confidence interval*
uncertainty band*
confidence band*

Figure 2.A.1: Distribution of Phrases in Topic-Specific PMU Indices.
The figure presents the distribution of terms within topic-specific uncertainty sentences. The size of the term is approximately proportional to its frequency. All topic-specific PMU indices are obtained from the economy round of the FOMC meetings. The sample period is 1987:08–2015:12.

2.A.3 Algorithms for Uncertainty, Sentiment, and Policy Stance Construction

In this section, we describe in detail how we construct text-based measures of uncertainty, sentiment, and policy stance. The first step is to preprocess the transcripts by breaking each statement by each speaker into separate sentences using a standard sentence tokenizer. This yields 559,709 total sentences, which form the basic units of linguistic analysis for the algorithms we propose below.

2.A.3.1 Uncertainty construction

The construction of the uncertainty indices begins with the estimation of a word embedding model. Specifically, we use the Continuous Bag-of-Words (CBOW) model (Mikolov, Chen, Corrado, and Dean, 2013) estimated on the set of FOMC sentences contained in the economy round to obtain a vector representation of each unique term. We preprocess each sentence following standard steps of tokenization and stop word removal. We also replace a limited number of bigrams with a single term, e.g., 'downside risk' and 'upside risk.' We remove all sentences that do not contain at least five terms from the estimation corpus. The embedding model is estimated with 200-dimensional embedding vectors and a window size of five, which are typical defaults in the natural language processing literature. See **?** for more background on word embedding models.

Tables 2.A.1 and 2.A.2 contain the fifty nearest neighbors for the terms 'risk', 'risks', 'uncertain', and 'uncertainty'. The similarity measure for computing nearest neighbors is cosine similarity, which is the cosine of the angle formed by two vectors in a vector space.[27] As described in the main text, we then manually prune the neighbors to arrive at our final set of uncertainty words.

Let $u_{t,s}$ be the count of uncertainty terms in sentence s. That is, the number of instances of any of the non-struck-through terms in tables 2.A.1 and 2.A.2 that appear in sentence s. For each topic (inflation and wages, economic growth, financial markets, model), we

[27] So, if two vectors point in the same direction, and have a zero angle between them, the cosine similarity is 1. If they point in opposite directions, and have an angle of 180 degrees, the cosine similarity is -1. Mathematically, the formula is the dot product of two vectors normalized to have unit length.

construct topic-specific uncertainty counts using the following procedure. For each sentence in each FOMC meeting:

1. Increase the topic k uncertainty count by $u_{t,s}$ if sentence s contains any term in the list associated with topic k. Thus, if a term from more than one topic set appears in sentence s, $u_{t,s}$ can be assigned to more than one topic.

2. If no term from any set of topic words appears in sentence s, assign $u_{t,s}$ to topic k if a topic-k term appears in sentence $s-1$ or sentence $s+1$ (whenever these sentences are uttered by the same speaker of sentence s).

3. If no topic k term appears in sentences $s-1$, s, or $s+1$ then leave $u_{t,s}$ unassigned.

We then normalize the topic-specific counts by the total number of terms in the economy round of the meeting. We denote policymakers' perceived inflation uncertainty in meeting t as $InfPMU_t$; real economic uncertainty as $EcoPMU_t$; financial market uncertainty as $MktPMU_t$; and uncertainty about models as $ModPMU_t$.

2.A.3.2 Sentiment construction

Here we describe the construction of sentiment for topic k (which corresponds to economic growth, inflation and wages, and financial markets). The algorithm follows closely that in **?** which use a similar approach to build a stock market sentiment index. Here we expand this to additional topics.

Sentiment is built exclusively using economy round language. We first remove any sentence in the economy round that either contains an uncertainty flag word, i.e. a term in the 'Term' columns of tables 2.A.1 or 2.A.2 that is not struck through, as well as sentences that immediately precede or follow such sentences. This ensures that sentiment is constructed using a different set of input words than the uncertainty measures, which avoids a mechanical relationship between the two.

The next step is to break all remaining sentences in the economy round into sub-sentences based on the presence of words in {'and', 'because', 'but',' if', 'or', 'so','that', 'when', 'where', 'while', 'although', 'however', 'though', 'whereas', 'despite'}. Let $\mathbf{p}_{t,s}$ be the sth phrase in meeting t generated by this rule.

As described in the tables above, each topic is associated with a set of nouns. Let $g_{k,m}$ be the mth noun associated with topic k. This noun will be associated with a set of positive words $\text{Pos}_{k,m}$ and a set of negative words $\text{Neg}_{k,m}$ according to the group definitions in the tables. The positive and negative sentiment measures in meeting t begin with the tabulations

$$\tilde{S}^{+}_{t,k} = \sum_{s}\sum_{m}\sum_{n} \mathbb{1}(w_{t,s,n} = g_{k,m}) \left[\mathbb{1}(w_{t,s,n-1} \in \text{Pos}_{k,m}) + \mathbb{1}(w_{t,s,n+1} \in \text{Pos}_{k,m})\right]$$
$$\tilde{S}^{-}_{t,k} = \sum_{s}\sum_{m}\sum_{n} \mathbb{1}(w_{t,s,n} = g_{k,m}) \left[\mathbb{1}\left(w_{t,s,n-1} \in \text{Neg}_{k,m}\right) + \mathbb{1}\left(w_{t,s,n+1} \in \text{Neg}_{k,m}\right)\right]$$

That is, we count the number of times topic-k words are immediately preceded or followed by (word-specific) positive and negative terms.[28] To obtain our final sentiment measure, we scale these counts by the number of total tokens in the economy round.

2.A.3.3 Preference construction

We now describe the algorithm for constructing the measures of hawkishness and dovishness used in the main text to capture policy preferences. For all meetings, we measure generic monetary policy preferences using the procedure detailed below. For meetings conducted in 2009 and onwards, we additionally measure preferences over the size of asset purchases as part of the Fed's quantitative easing program. The sentences we consider consist of those in the policy round since that is the section of the meeting pertaining to the articulation of preferences.

2.A.3.3.1 Generic monetary policy preferences

First, we exclude from the policy round any sentence in which the term 'increase' appears along with any of {cpi, inflation, yield*, treasury} to ensure we do not include language describing the direction of non-policy-related market prices and interest rates. We classify each remaining sentence as pertaining to monetary policy:

1. If it contains any phrase in the set {federal funds rate, funds rate, target rate, policy rate, interest rate, taylor rule, alternative a, alternative b, alternative c, directive,

[28] Since in preprocessing we remove stop words, adjacency in this definition can include separation by stop words.

language, statement, symmetry, asymmetry, hawkish, dovish},

2. OR if 'policy' is in the sentence and NOT any phrase in the set {fiscal policy, supervisory policy, public policy, budget policy, tax policy, housing policy, regulatory policy, ecb policy, economic policy, government policy, inventory policy, health care policy, macro policy, macroeconomic policy, spending policy, legislation, law, regulation}.

3. OR if 'basis point' is found in the sentence AND any phrase in the set {[cut*, hik*, eas*, tight*, action*, moving, move, firming, recommendation, reduction, increase]}.

We define $Hawk'_t$ to be the count of terms in {tight*, hike*, increas*, hawkish, taper, liftoff} in policy sentences; and $Dove'_t$ to be the count of terms in {ease*, easing*, cut*, dovish, reduc*, decrea*} in policy sentences. Here we account for negation, and if any of the hawk (dove) terms is immediately preceded by one of {'less', 'no','not', 'little', 'don't', 'doesn't', 'hasn't', 'haven't', 'won't', 'shouldn't', 'didn't'}, it is counted as belonging to dove (hawk) set.

2.A.3.3.2 Quantitative easing preferences

We define policy round sentences beginning in 2009 as relating to quantitative easing whenever they contain the term 'purchase*' immediately preceded by a phrase in {mortgage backed securities, mbs, asset, treasur*, agency debt}.

We then define $Hawk''_t$ to be the count of terms in {reduc*, taper, stop, purchas*} within the set of QE sentences; and $Dove''_t$ to be the count of terms in {more, additional, further} within the set of QE sentences. We again account for negation.

2.A.3.3.3 Overall preference measure

Let NP_t be the overall number of terms in the policy round in meeting t. Our hawk measure is

$$Hawk_t = \begin{cases} \frac{Hawk'_t}{\text{NP}_t} & \text{if meeting } t \text{ occurs prior to 2009} \\ \frac{Hawk'_t + Hawk''_t}{\text{NP}_t} & \text{if meeting } t \text{ occurs during or after 2009} \end{cases}$$

and $Dove_t$ is defined analogously.

2.A.4 Additional Tables and Figures

2.A.4.1 Material for Section 2.3

Table 2.A.12: PMU vs. measures of public perceptions of uncertainty.

The table projects proxies for public uncertainty on the PMU indices. BBD EPU is the economic policy uncertainty index from Baker, Bloom, and Davis (2016); HRS MPU is the monetary policy uncertainty index from Husted, Rogers, and Sun (2020); VXO is the implied volatility measure from S&P500 options; inflation and growth dispersion are calculated as the mean absolute deviation of forecasts for CPI inflation and real GDP growth across individuals in the Blue Chip Financial Forecast survey. We report the first principal component of forecast dispersions across horizons from the current quarter up to four quarters ahead. The sample period is 1987:08–2015:12. All variables are scaled by their standard deviations. HAC t-statistics with eight lags are reported in parentheses. The regressions are estimated at the frequency of the FOMC meetings.

	(1) BBD EPU	(2) HRS MPU	(3) VXO	(4) Infl disp	(5) Growth disp
$InfPMU_t$	-0.397***	-0.062	-0.169*	0.057	-0.172
	(-5.83)	(-0.86)	(-1.91)	(0.68)	(-1.55)
$EcoPMU_t$	0.211*	0.276*	-0.037	-0.325***	-0.200
	(1.75)	(1.93)	(-0.22)	(-2.61)	(-1.65)
$MktPMU_t$	0.183*	0.097	0.323**	0.326**	0.007
	(1.66)	(1.02)	(2.53)	(2.36)	(0.06)
$\bar{R}^2$	0.22	0.093	0.10	0.13	0.061
N	227	227	227	227	227

Table 2.A.13: Predicting Macro Variables with PMU.

The top panel reports estimates of predictive regressions for period-$t+h$ inflation using period-t inflation PMU as a predictor. The regression is estimated at the FOMC meeting frequency with the forecast horizon ranging from the next meeting ($h = 1$) up to eight meetings ahead ($h = 8$). To ensure the timing of the dependent variable is consistent with the timing of the meetings, we use Greenbook nowcasts at future meetings as the dependent variable. The regression is $E_{t+h,0q}(\pi) = \beta_0 + \beta_1 \mathit{InfPMU}_t + \varepsilon_{t+h}$. The bottom table reports analogous estimates for predictive regressions of real GDP growth. The coefficients are standardized. HAC standard errors to account for the overlap are reported in parentheses. The sample period is 1987:08–2015:12.

A. Dependent variable: Greenbook CPI inflation nowcast h meetings ahead, $F_{t+h}(\pi_0)$

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
InfPMU_t	0.029	-0.035	-0.063	-0.083	-0.181	-0.173	-0.109	-0.073
	(0.33)	(-0.38)	(-0.63)	(-0.63)	(-1.27)	(-1.16)	(-0.91)	(-0.87)
$\bar{R}^2$	-0.0036	-0.0033	-0.00051	0.0024	0.028	0.025	0.0073	0.00081
N	226	225	224	223	222	221	220	219

B. Dependent variable: Greenbook real GDP growth nowcast h meetings ahead, $F_{t+h}(g_0)$

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
EcoPMU_t	-0.073	-0.059	-0.002	0.008	-0.050	-0.056	0.023	0.047
	(-0.92)	(-0.76)	(-0.03)	(0.09)	(-0.50)	(-0.52)	(0.21)	(0.39)
$\bar{R}^2$	0.00088	-0.00093	-0.0045	-0.0045	-0.0021	-0.0015	-0.0041	-0.0024
N	226	225	224	223	222	221	220	219

2.A.4.2 Material for Section 2.4

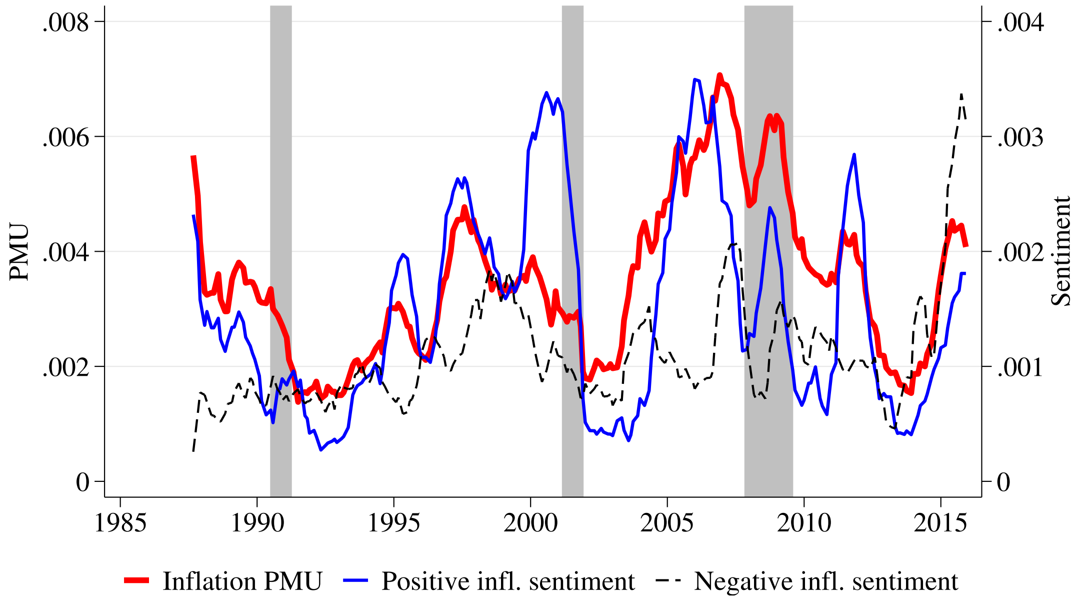


Figure 2.A.2: Inflation PMU and Inflation Sentiment (FOMC Members).
The figure presents inflation PMU superimposed against positive and negative inflation sentiment. Positive (negative) sentiment indicates views of rising (declining) inflation. The series are smoothed averages over the last eight FOMC meetings and are measured from statements of FOMC members.

Table 2.A.14: Expected Inflation and Inflation PMU.

The table documents the contemporaneous relationship (regressions) of expected inflation, inflation sentiment, and inflation PMU. $F_t(\pi_4)$ is Greenbook four-quarter ahead inflation forecast. τ_t is trend inflation constructed as in Section 2.3 of the paper. Sentiment and PMU indices are obtained from the text of FOMC members' statements in the economy round of the meeting. The coefficients are standardized. HAC standard errors with eight lags are reported in parentheses. The sample period is 1987:08–2015:12.

	(1) $F_t(\pi_4)$	(2) $InfSent_t$	(3) $InfPMU_t$
$InfPMU_t$	0.130***	0.302***	
	(3.00)	(2.77)	
$InfPos_t$			0.537***
			(4.90)
$InfNeg_t$			0.235***
			(3.85)
Trend inflation, τ_t	0.958***		
	(15.19)		
$\bar{R}^2$	0.86	0.087	0.35
N	227	227	227

2.A.5 Narrative Assessment of the Role of Credibility Concerns

As described in the text, this appendix provides a more complete narrative account of the evolving concerns for credibility in the FOMC policy deliberations. For this, we split the evolution of inflation concerns into four separate sub-samples: (i) the Mid-1990s, (ii) Post-Y2K recession, (iii) Recovery to GFC, and (iv) Post-GFC Concerns.

The issue also came up during the February 2005 special topic on "Price Objectives for Monetary Policy" there was lots of discussion of whether the Fed should adopt an explicit inflation target and lots of discussion of credibility. For example, Santomero (Philadelphia) emphasised the importance of the Fed's inflation fighting credibility and argued that this would be further enhanced by being explicit about the numerical definition of the inflation goals. "I also believe that moving to a regime of this type would increase flexibility and enhance our ability to achieve our other economic objectives. It is only because we had achieved a good deal of credibility over the years that we were able to lower the fed funds rate to 1 percent recently without igniting fears of inflation. And I would argue that this flexibility was important in contributing to the shallowness of the last recession."

2.A.5.1 Mid-1990s

In the second half of 1996, there were growing fears that a tight labor market would generate inflationary pressure. Yellen (San Francisco) noted in September 1996, "The probability of an increase in inflation is clearly higher when labor market slack is lower. For that reason, I conclude that the risk of an increase in inflation has definitely risen, and I would characterize the economy as operating in an inflationary danger zone." Discussing her policy view for that meeting, she said "My concern is that a failure to shift policy just modestly in response to shifting inflationary risks could undermine the assumptions on which the markets' own stabilizing responses are based."

In November, the risk of a pick up in inflation had not been borne out in the data but some members remained concerned. Meyer (Board) spoke of the on-going challenge that "trend growth at the prevailing unemployment rate will ultimately prove to be inconsistent with stable inflation going forward." Broadus (Richmond) argued for a credibility-enhancing surprise: "The projections do not show any further progress toward our basic longer-term price stability goal. And if that were the actual outcome over the next couple of years, the credibility of our longer-term strategy could be reduced, at least to some degree. For all these reasons, Mr. Chairman, I would still favor a 1/4 point increase in the funds rate today. Any tightening now obviously would surprise the markets. I recognize that that could have near-term consequences, but I think it could well help us over the longer run."

By the meeting in December, these worries has disappated further; Yellen said "So, I still feel that we need to avoid complacency about the potential for inflationary pressures to emerge from the labor market down the road. But while I think we cannot rule out the possibility that this long expansion is about to end with a period of stagflation and that that is a significant risk over the term of this forecast, that outcome is by no means a certainty. Capacity utilization, as a number of you have mentioned, is not strained at this point." Though some, such as Melzer (St Louis), were still concerned about the risk of lost credibility: "Economic forecasters have often interpreted our policy as a 3 percent cap on CPI inflation. Events in 1996 put us at considerable risk of losing credibility for even that modest goal.In my view, we should reaffirm our commitment to resist inflation above 3 percent."

The fears continue for some members into the first half of 1997. McDonough (New York) expresses concerns that he and the NY Fed staff have. Melzer continues to argue for credibility building measures; "My reading of the economy supports the conclusion that we are at risk of losing the hard-won credibility of our commitment to hold inflation at 3 percent." Guynn (Atlanta) said in May 1997 that "With the economy having gotten to a point where it must be near full employment, if not beyond it, we have a unique opportunity with little downside risk to lean a bit more against the expected upward creep in inflation that most of us are forecasting and, in doing so, to underscore our resolve and credibility in the minds of financial market participants, business decisionmakers, and the general public."

There was only a single 25bps rate increase in March 1997 and these concerns persisted until the demand-dampening effects of the Asian Financial Crisis in 1997, and the LTCM Collapse and Russian Default prompted some cuts in interest rates in late 1998. These concerns prompted monetary easing to calm markets and preemptively offset any negative impulses from the slowing global demand.

The effects were, however, relatively mild and once the economy had weathered the initial effects, thoughts returned to the tight labour markets and the risk of inflation. In March 1999, Broaddus emphasised the importance of the Fed's credibility, alongside growing productivity, in helping to sustain robust final domestic demand growth: "the high credibility of our low inflation strategy... supports the increases in real income and allows labor markets to operate at much lower unemployment levels without generating the potentially inflationary wage increases that have been typical historically. As I see it, maintaining this credibility is the key to what we can do to help sustain the expansion. In order to do that, I think we need to be sure we interpret the risks in the outlook as accurately as we can."

This is the reason that he sees it is time to switch out of support mode and begin to signal the Fed's anti-inflation tendency even if only in language and emphasis on the upside inflation risks. "What worries me the most, ironically, is that our high credibility may in some sense be permitting us to delay confronting this inflation risk. But if things ever begin to go in the other direction, I think they could unravel very quickly. So, as I said at the last meeting, I think it is time for us to get back in the ball game. In my view, a step toward an asymmetric directive would be a good way to do that."

Ferguson (Board) was similarly concerned about the Fed's credibility. In December of 1999 he outlined his concerns to his colleagues: "In the longer run, obviously, as others have indicated, we don't want to lose our ongoing battle with inflation expectations and inflation, or risk any damage to our own credibility... We should continue to recognize the benign effects of productivity improvements on unit cost structures, but we also should not be afraid to act in a well-modulated fashion in order to maintain our hard fought victory over inflation and also our credibility."

Ultimately, inflation never took off. Broaddus, in May 1999, recognised that his fears had not been realised when he said: "I know I have been crying wolf around this table for a long time and my fears have not been realized, but we have to take each day as it comes, I guess. So, wolf!" This prompted laughter around the FOMC table. Of course, it is the credibility that he, and others, were so concerned about retaining that means they may have ultimately appeared wrong in their projection.

2.A.5.2 Post-Y2K recession

A (small) recession started in 2001, and the terrorist attacks on September 11 2001 further added to concerns about the US economy and the financial system. In this period, the FOMC were little concerned about the inflation risks and downside risks started to dominate. In fact, FOMC members began to push the *use* of their credibility in allowing them to switch into support mode. This includes members like Broaddus who had so often argued for the need to take a Hawkish stance to build credibility; in August 2001 he argues: "And, of course, now I think we do have considerable credibility. And with the downside risks still quite substantial, as you and others have mentioned, I think we need to take advantage of that credibility. To say the same thing a bit differently: Unlike the situation in a number of earlier postwar episodes, we don't need a recession to contain inflation or inflation expectations at this point." Similarly Parry (San Francisco), in December 2001, argues "With inflation well in hand and Federal Reserve credibility in good shape, I believe we have the flexibility to respond to these risks."

2.A.5.3 Recovery to GFC

Though the formal recession had ended by the end of 2001, the trough in the interest rate cycle didn't come until 2003 (the FOMC last cut by 25bps at its June 2003 meeting). But even as the FOMC was still cutting, concerns about inflation started to build. In the March 2003 FOMC meeting, Parry says: "As we all know, there are many risks to such an inflation forecast. In particular, we are uncertain about how much and how fast energy prices will pass through to other prices, about how much demand will increase from the economies abroad, and about whether stock prices or productivity growth will surge or fall. However, despite all the possible scenarios that could be constructed, the underlying tightness of labor markets and the recent extraordinary growth in demand imply a very high risk that core inflation will rise at a faster pace this year and next." In the policy go-around, he indicates his desire to signal the FOMC's toughness on inflation – "I also think it is important to reinforce to the public that we are focusing on the heightened inflation risks for the future."

However, at that time most members did not see this risk as unduly concerning; as Hoenig said – "I am not convinced, however, that we need to be tightening aggressively. I think the gradual pace of tightening that we have followed is wise."

It wasn't until the middle of 2004 that inflation uncertainty was combined with a clear directional element to the worries; the May 2004 FOMC meeting is when the *InfPMU* is starting to pick up strongly accompanied by concerns of rising inflation. The discussion centers on shifting balance of risks on inflation. Geithner (NY Fed) says "We need to be more attentive now to the risk that a sustained increase in prices could materialize at an earlier point than had seemed likely, and we can afford, of course, to be less concerned with the risk of an unwelcome fall in the rate of inflation. The risks of being late compared with the risks of moving too early are now more symmetric. We need to adjust our statement accordingly, to position us to be ready to act soon if the numbers confirm the recent trend toward stronger employment growth." Bernanke (Chair) thinks about what this means for the risk-management approach to monetary policy: "From a risk-management perspective, as we begin to raise rates we should weigh the risk of significantly impeding the labor market recovery against the risk of having to scramble to adjust to unexpectedly adverse inflation developments."

By June, some members felt more convinced that that the FOMC needed to start raising rates. McTeer (Dallas) was explicit in his views: "As I indicated at our May meeting, I believe that the inflation risks are unambiguously on the upside and that we are behind the curve." Even Geithner seemed to be coming around to this view: "Developments since our last meeting support a reasonable degree of confidence in the strength of the expansion and somewhat more concern about the outlook for inflation.... We are somewhat more concerned about the inflation outlook...We face some risk that a modest increase in inflation expectationseven after the recent moderation of those expectations will feed through to higher compensation growth." The FOMC duly began a hiking cycle which took rates from 1% to 5.25% in June 2006.

Though over this period inflation remains contained, the concerns about it and the risk to the FOMC's credibility of getting it wrong is regularly expressed. Ferguson, in March 2005, says: "I find the baseline outlook to be credible and reasonable. But it is surrounded by a range of risks that I believe, as do others, are primarily on the upside... The economy is growing well and needs less and less stimulus; therefore, continuing to remove our accommodative policy at a measured pace seems to me reasonable." On the approach to deal with risks, he favours signalling the committee's concerns: "given the stage of the cycle, the skew in the general risk assessment that I outlined, and the need to manage market expectations, I think we should use our statement to signal our awareness that inflation pressures may have picked up. The incoming data are indicative of that. If we are wrong on the upside risks, both we and the market will adjust. On the other hand, if we fail to reflect the existence of these upside risks, we could easily be perceived as being behind the curve, with negative consequences in terms of inflation dynamics and, potentially, our own credibility."

Even the members of committee that were optimistic that inflation remained well in check expressed the importance of credibility. Yellen in November 2005 said: "So I see no indication of the '70s style wage-price spiral in the offing. Overall, I judge our credibility to be very much intact. Of course, our credibility going forward does depend on continued vigilance. The economy now appears to be close to full employment, with a good deal of momentum. And annual core inflation, at least as judged by the core PCE measure, remains near the upper end of my comfort zone and, arguably, inflation risks are tilted somewhat to the upside. So with respect to policy, I support at a minimum the removal of any remaining policy accommodation...So a few more increases, including one today, seem to me likely to be required."

Yellen also went on to support the use of stronger language than proposed with the Alternative B Bluebook option was also used to signal this stance: "In implementing monetary policy, it seems to me that actions matter, but so do words, and I wanted to briefly open up the question of the statement. I think for today the words of alternative B should suffice, but Vincent has repeatedly suggested, and a number of you have emphasized, that we need to consider how to modify the statement language." She pushed for langauge closer to the Alternative C statement as "It eliminates the balance of risk statement and the policy accommodation language; and it substitutes a new forward-looking policy statement for the 'measured pace' phrasing."

In March 2006, despite the significant tightening already completed, concerns remained about the upside to inflation. Bernanke summed up the committee discussion saying: “I took from the group some sense of at least a slight upside risk to inflation, reflecting the increasing resource utilization; the fact that inflation is somewhat on the high side of what many people describe as their comfort zone; and the fact that, if inflation does rise, there will be costs to bringing it back down and maintaining our credibility.” While he goes on to state that he is “not at all alarmist about inflation”, he argued that “it is very important for us to maintain our credibility on inflation and it would be somewhat expensive to bring that additional inflation back down. So my bottom line on inflation is that there is a very modest upside risk. Again, I think it’s not a large risk but one that we probably should pay attention to.”

2.A.5.4 Post-GFC Concerns

Inflation was not the main concern during the GFC period of 2008-2011. But by 2012, FOMC members again started to worry. In March 2012, Kocherlakota expressed the minority view that it was time to start worrying about inflation picking up again. “Indeed, my own outlook, like President George’s, is that our accommodative policy will lead average PCE inflation to rise above 2 percent over the next two years. I’m less sanguine than she is that inflation will stabilize at that level, because that depends on policy choices, and we would have to make choices to make that happen.”

In the same meeting, others acknowledged this risk but also expressed concerns about a downside risk (“I’m concerned that we could be misled yet again by hopeful signs early in the year followed by tepid growth later, and that a premature move toward policy firming could end up driving inflation further below our objective and retard what is already a long-delayed return to maximum employment.”, Yellen) and an asymmetry in the ease of policy addressing the two risks (“How do we balance these risks? As Governor Yellen mentioned, I think theres an asymmetric nature to the upside and downside risks.We know what to do if inflation threatens to move persistently above target.”, Raskin).

In August 2012, the debate concerns more stimulus. As Powell (Board) argues: “On the list of potential costs, I would include inflation, the difficulty of exit, the risk of creating expectations we cant meet, the prospect of capital losses, market function, and the grab bag of stability issues." Though others, such as Tarullo, dismiss this: "As I've listened, not just today but over the course of the last couple of years, I think I hear three kinds of costs that people are concerned, rightly, about: inflation, market functioning, and credibility of us as a central bank. On inflation, with all due respect to those who have made the argument, I must say that I do find the arguments a little conclusory. That is, the specter of runaway inflation sometime out in the indefinite future, as I've heard it, doesn't seem to me backed by an enormous amount of linear analysis that gets us from here to there and where are the real problems. And I have to say, I've tested this proposition on a fairly wide variety of non-Fed, mostly, but not exclusively, academic, economists, and even those who are on the hawkish side tend to be not too concerned about that particular prospect. They are more concerned about the other two things."[29]

These debates continue as the Fed continues its accommodative stance. And the lack of inflation means that the concers gradually diminish. By October 2014, the FOMC's concern is to bring inflation back up to target.

[29]"And lastly, on credibility, where I depart, I think, a little bit from what some of those who are inclined in my policy direction have said. I don't think I would want us to be saying that we will "do what it takes" because it isn't clear to me ultimately that we can do what it takes to solve the rather substantial economic problems that we face right now. My suggestion would be that we communicate an intention to "do what we can" and that we will continue to do what we can, with the appropriate set of costs and benefits being taken into account at each step of the way. Mr. Chairman, am I missing any wording issues that we're supposed to address here?"

Chapter 3

Stock Demand and Price Impact of 401(k) Plans

Riccardo Sabbatucci   Andrea Tamoni   Song Xiao[1]

3.1 Introduction

What drives fluctuations in the valuation of different asset classes? A recent and influential strand of the literature has tried to answer this question adopting a demand-based framework, following the seminal work of Koijen and Yogo (2019). Demand-based explanations linked to the role of investors' heterogeneity have been recently proposed to explain variation in domestic equities (Koijen and Yogo, 2019), corporate bonds (Bretscher, Schmid, Sen, and Sharma, 2021), and exchange rates (Koijen and Yogo, 2020), and to analyze the shift from active to passive investing (Haddad, Huebner, and Loualiche, 2022), green investments (Koijen, Richmond, and Yogo, 2022), and the portfolios of high-net worth individuals (Gabaix, Koijen, Mainardi, Oh, and Yogo, 2022). A key element of the demand-based asset pricing framework is the role of the latent demand, defined as the investor-specific demand not explicitly captured by well-known stock and investor characteristics.

In this paper, we shed light on this important component. More precisely, using a

[1]Sabbatucci: Stockholm School of Economics and the Wharton School of the University of Pennsylvania; Tamoni: Rutgers Business School; Xiao: London School of Economics. We are grateful to Zhi Da, Itzhak Ben-David, Ralph Koijen, Lukas Schmid (discussant), Clemens Sialm, Stanislav Sokolinski, and David Solomon for valuable suggestions. We also received helpful comments from conference and seminar participants at the AFA 2024, University of Notre Dame (Mendoza), University of Miami (Herbert), and Rutgers Business School.

demand-based framework, we study the impact that 401(k) pension plans have on investors' demand for stocks, and introduce a novel variable that appears to be a key determinant of investors' allocation decisions: *stock-level 401(k) ownership*. We then present two channels through which 401(k) ownership might drive investors' demand for specific stocks, and test their relevance.

The first channel through which 401(k) plans could affect the demand of individual stocks is related to the magnitude of stock-level 401(k) ownership. The fraction of an individual stock cumulatively owned by 401(k) plans can be seen as an additional stock characteristic, similarly to book-to-market or momentum. Fund managers and other types of investors might take into account the information conveyed by this additional stock characteristic when evaluating how many shares of a specific stock to purchase. For example, it might be that active funds prefer to deviate from their respective benchmarks by investing in stocks with more stable and long-term investors, like pension funds. Thus, we hypothesize that the quantity of a stock cumulatively owned by 401(k) plans might affect the demand for that specific stock. We label this the *stock level* channel.

The second channel through which 401(k) allocations could impact individual stocks' demand is by direct flows to mutual funds and ETFs, which, in turn, use that cash to increase their equity exposure. We hypothesize that funds managing the largest fraction of 401(k) assets might have more stable flows, and hence invest in different types of stocks compared to funds managing fewer 401(k) assets, and hold less cash. For example, some funds display a preference for stocks with high market beta (e.g., Christoffersen and Simutin (2017), Han, Roussanov, and Ruan (2022)). We label this the *fund level* channel.

We report several interesting findings. First, we test the stock-level channel mechanism, and find that the amount of company shares owned by 401(k) plans is an important characteristic – in fact, the most important one after size – in explaining the demand of mutual funds and ETFs for a specific stock. In response to a one standard deviation increase in 401(k) stock ownership, the average active mutual fund demands approximately 18.6% (t-stat: 11.16) more of the stock. The average active ETF also increases exposure to the stock by 11.5% (t-stat: 10.21) for each standard deviation increase in 401(k) stock ownership. Importantly, stock-level 401(k) ownership appears to be *distinct* from other forms of institutional ownership, such as total mutual fund (Chen, Jegadeesh, and Wermers, 2000) or largest (top 10) investors' ownership of a stock (Ben-David, Franzoni, Moussawi, and Sedunov, 2021). In fact, after controlling for these alternative types of ownership, the magnitude of the coefficient on our stock-level 401(k) ownership is barely affected, and so is its statistical significance. These results highlight the unique information content of stock-level 401(k) ownership for fund managers' decision. To the best of our knowledge, this is the first paper to highlight the specific role of stock-level pension allocations for fund manager decisions.

Motivated by the importance of stock-level 401(k) ownership for funds' investment decisions, we then explore the equilibrium price impact of a change in stock-level 401(k) ownership for the cross-section of stocks, over time. We estimate the institutional price pressure to be positive and increasing over our sample. For the median stock, the price impact raises from 0.2 in 2007 to 0.6 in 2020. For stocks lying on the 90th percentile of the price impact distribution, it hovers around 0.8 over our sample. We also compute the price impact for portfolios of stocks sorted on size, book-to-market, or beta (market risk). We find that the average price impact as a function of stock-level 401(k) has increased for large stocks, while it has remained relatively stable for small stocks. However, we do not observe noticeable differences for stocks sorted on book-to-market or betas, i.e., they are equally impacted. The positive trend of price impact, which increases almost monotonically between 2008 and 2020, is consistent with the shift from active to passive investing over the last decade documented in the literature (Koijen, Richmond, and Yogo, 2022). To further validate the direct impact 401(k) ownership has on individual stocks, we employ a matching procedure to pair stocks with similar fundamental characteristics but different levels (e.g., high vs. low) of 401(k) ownership. We find that stocks with positive 401(k) ownership tend to earn 3%-5% higher annual returns than similar stocks, in terms of characteristics and investor structure, not owned by 401(k) plans.

We also highlight the importance of stock-level 401(k) ownership by studying the impact that trading by 401(k) plans has on individual stock returns using two additional tests. Our first methodology exploits large changes in individual stock holdings by aggregate 401(k) plans (Ben-David, Franzoni, Moussawi, and Sedunov, 2021). We find that large changes in the holdings of an individual stock substantially affect its contemporaneous return. A large positive position (trade) taken by 401(k) plans in a stock generates a 12% higher return than that implied by an average trade, followed by a partial return reversal over the next two years. Our second test exploits the granular instrumental variable approach introduced by Gabaix and Koijen (2022). We find that a 10% increase in the (instrumented) stock demand of 401(k) plans generates an average stock price increase of 3.6%, after controlling for standard firm-specific drivers of stock returns.

Second, we analyze the fund-level channel of 401(k) ownership, and document that funds managing a larger fraction of 401(k) assets display greater demand for stocks. More in detail, 401(k) fund ownership is the most important variable, after firm size, in explaining how much of a stock funds demand. For one standard deviation increase in 401(k) fund ownership, the average active mutual fund demands approximately 33.3% (t-stat: 2.91) more of the average stock, while the demand from ETFs is almost unchanged. This test of the fund channel mechanism suggests that mutual fund managers take into account the amount of 401(k) assets they manage when deciding their portfolio allocation, and have more discretion than ETFs managers.

To gain further insight on the relation between 401(k) assets and fund managers' portfolio allocations, we then study how the investment strategies and performance of active mutual funds are affected by the amount of 401(k) assets they manage. First, we analyze the 401(k) asset-induced fund demand for specific stock characteristics. We find that fund demand for stocks is heterogeneous, as a function of 401(k) fund-level ownership. Funds managing a larger fraction of 401(k) assets tilt their portfolios toward winners, high beta and long duration stocks, and away from large stocks. This fund behavior could, for example, reinforce the well known betting-against-beta (Frazzini and Pedersen, 2014a) and duration anomalies. Second, we study the relative and risk-adjusted performance of a fund as a function of 401(k) fund-level ownership. We find that a large fraction of pension assets managed by funds improves their performance in terms of relative returns, but leaves the alpha (statistically) unaffected. This result is important: if pension plans choose relative returns as the main criterion for investment (rather than alpha), the better relative performance of funds with high 401(k) ownership can induce positive pension flows, triggering a spiral effect. Furthermore, the preference of fund managers for high beta and long duration stocks (holding alpha constant) provides support for the literature on benchmarking and manager incentives (Baker, Bradley, and Wurgler, 2011; Buffa, Vayanos, and Woolley, 2022b).

Lastly, we test whether investment funds perceive 401(k) flows to be more stable by studying the level of their cash holdings. We find this to be indeed the case. Mutual funds managing a large fraction of 401(k) assets have approximately 32% *less* cash holdings compared to other mutual funds.

Our paper is related to the emerging demand-based asset pricing literature. Koijen and Yogo (2019) develop the demand system approach and document that changes in latent demand (e.g., characteristics unobserved by the econometrician) are explaining 81 percent of the cross-sectional variance of stock returns. Bretscher, Schmid, Sen, and Sharma (2021) and Gabaix, Koijen, Mainardi, Oh, and Yogo (2022) estimate a demand system for corporate bonds and for high-net-worth investors, respectively. Koijen, Richmond, and Yogo (2022) use the demand-based system to study the impact of market trends, such as the shift from active to passive investing or the increased demand for green firms, on price informativeness. Haddad, Huebner, and Loualiche (2022) investigate the effect of the switch to passive investing, and document that this behavior has led to substantially more inelastic aggregate demand curves for individual stocks. Focusing on mutual funds, Ben-David, Li, Rossi, and Song (2022b) show that their ratings generate correlated demand that creates systematic price fluctuations. Furthermore, exploiting a reform to the Morningstar rating system, Ben-David, Li, Rossi, and Song (2022a) also document that demand effects generated by institutional frictions can influence systematic return predictability patterns in stocks and mutual funds.

Our contribution to this strand of the literature is to highlight the unique relevance of stock-level and fund-level 401(k) ownership in driving fund managers' investment decisions.

Our paper is also related to the literature on risk preferences and shifting of fund managers. Christoffersen and Simutin (2017) show that funds controlling large pension assets tend to increase their exposure to high beta stocks. Differently from this paper, we estimate the stock demand of funds as a function of 401(k) plan ownership, controlling for stock characteristics. Han, Roussanov, and Ruan (2022) document that underperforming funds increase their demand for risky stocks. Our contribution relative to this study is to emphasize the role of 401(k) defined contribution pension assets in determining fund managers' risk profile, e.g., the *types* of stocks demanded by fund managers. Dou, Kogan, and Wu (2022) show that active funds care about their size, which is affected by fund flows that obey a strong factor structure with the common component responding to macroeconomic shocks. They find that high-flow-beta stocks earn significantly higher excess returns and higher capital asset pricing model (CAPM) alphas in the cross-section. Relative to their work, we document that a key component of fund size is determined by 401(k) plans allocations, and that 401(k) ownership affects the types of stocks preferred by fund managers.

Lastly, our paper is also related to the literature on pension plans. Sialm and Starks (2012) study the investment strategies and performance of funds held primarily by retirement accounts versus those held by taxable investors. They do not find performance differences between funds held by different tax clienteles. In contrast to their paper, we document that a large fraction of pension assets managed by a fund influences its performance and asset selection. Sialm, Starks, and Zhang (2015) study the investment menu of pension plans, and find that flows into funds from defined contribution (DC) assets are less sticky and more sensitive to fund performance than non-DC flows, because of adjustments to the investment options by the plan sponsors. They document that plan participants exhibit inertia and do not react sensitively to prior fund performance. Pool, Sialm, and Stefanescu (2016) study whether mutual fund families acting as service providers in 401(k) plans display favoritism toward their own affiliated funds, and find that fund deletions and additions are less sensitive to prior performance for affiliated than unaffiliated funds. Differently from both studies, we do not focus on investment menu offered by plans, but directly estimate the demand of individual stocks by funds offered in 401(k) menus using a demand-based framework. Our quantification of the price and return impact of the stock-level channel of 401(k) ownership constitutes a unique contribution to this literature.

Moreover, whereas Sialm, Starks, and Zhang (2015) and Christoffersen and Simutin (2017) rely on survey data about DC assets from "Pensions & Investments" (P&I) administered to domestic equity funds, we instead observe the actual 401(k) plan holdings using a novel dataset, Brightscope. Using the same data, Egan, MacKay, and Yang (2021) address a different research question, and document heterogeneity in investment behavior of 401(k) participants, showing that higher income and more educated individuals tend to have higher equity exposure, whereas retirees and minorities tend to have lower equity exposure.

The remainder of the paper proceeds as follows. Section 3.2 describes the institutional framework and the data used in the paper, while section 3.3 introduces our demand-based framework and our testable hypotheses. Section 3.4 and section 3.5 present the stock and fund level results, respectively. Section 3.6 concludes.

3.2 Data

3.2.1 Data Sources

Our 401(k) plan holdings data comes from BrightScope Beacon. BrightScope Beacon provides comprehensive plan-level holdings data gathered from audited Form 5500 filings of private-sector defined contribution (DC) plans from 2007 to 2020. We focus exclusively on 401(k) defined contribution plans in this paper.[2] BrightScope reports annual data on the investment options (e.g., mutual funds) available to plan participants together with the total dollar amount invested in each option. In other words, for each 401(k) plan, we observe its asset allocation on equity mutual funds (including ETFs), allocation funds (including TDFs), bond mutual funds and other types of assets (e.g., trusts and common stocks), over time. The dataset covers 708,929 different 401(k) plans over the period 2007-2020, resulting in more than 8 million fund-by-plan-by-year observations. In addition, data on fund names, fees, and tickers is also available.

Mutual fund holdings and characteristics, such as their expense ratio, category, fund domicile, investment type (e.g., ETF flag), AUM, and tickers, are obtained from Morningstar Direct.[3] We match mutual funds in 401(k) plans with Morningstar by fund tickers and names.[4]

[2]BrightScope Beacon also provides holdings for 403(b) plans, although their total market value is small relative to that of 401(k) plans.

[3]Morningstar provides exhaustive mutual fund holdings compared to other mutual fund holding databases, such as CRSP. Schwarz and Potter (2016) find that CRSP misses many SEC mandated portfolios available in SEC filings.

[4]More precisely, we map mutual fund tickers in BrightScope Beacon to Morningstar mutual fund ID (variable: *fundid*) when tickers are available in both datasets. When fund tickers are missing in either

Given our interest in the impact of 401(k) plans on US stocks, we focus on domestic equity mutual funds. Specifically, we keep mutual funds with equity ratios greater than 0.75 and remove non-US equity funds based on the Morningstar fund domicile variable.[5] We also require funds to have at least 3 years of holdings data. We include only equity mutual funds and ETFs directly owned by 401(k) plans.[6] Our final dataset comprises a total of 2,156 funds, split between 1,763 mutual funds and 393 ETFs.

Lastly, we supplement the Morningstar holdings data with stock data from CRSP and Compustat. In our empirical analysis, we use the same stock characteristic as in Koijen and Yogo (2019), namely, log book equity, profitability, investment, dividends-to-book equity and market beta, in addition to the instrumented log market-to-book ratio, as in Koijen, Richmond, and Yogo (2022). Profitability is defined as operating profits scaled by book value of equity, investment as the annual growth rate of total assets, and dividends-to-book equity as the ratio of annual dividends to book equity. Stock market beta is estimated using a 60-month rolling window regression of monthly stock excess returns, over the 1-month Treasury-bill rate, on market excess returns, with at least 20 months of non-missing observations. Fund TNAs are winsorized at the 99th percentile at the end of every year to limit the impact of outliers. 3.A.3 describes the data cleaning procedures in detail.

3.2.2 Descriptive Statistics

Figure 3.1 displays the allocation of 401(k) plans to the various investment categories. These include direct ownership of individual stocks, separate accounts, guaranteed investment contracts (GIC),[7] mutual funds (including ETFs) and collective investment trusts (CIT).

Collective investment trusts (CIT), the second largest component, averaging 24% of

dataset, we match mutual funds by their names. We match 98.2% of mutual fund allocation in retirement plans, or a total of 3,182 mutual funds and ETFs.

[5] Additionally, we remove mutual funds whose portfolio weights reported by Morningstar are different from the correct portfolio weights calculated using holdings values and total net assets, as in Pástor, Stambaugh, and Taylor (2015).

[6] Target-date funds also invest in mutual funds and ETFs, but their rebalancing between equity and bonds is mechanical as a function of fund age. Hence, we only focus on funds directly selected by 401(k) pension plans.

[7] GICs are agreements between an investor and an insurance company, typically available in retirement plans, whereby the insurance company guarantees the investor a certain rate of return in exchange for holding the deposit for a fixed period of time.

401(k) assets under management over our sample period, are pooled investment vehicles established by banks or trust companies, that are only available to defined-contribution (DC) plan participants when the CITs are included as options in the DC plan menu.[8] The Goldman Sachs Core Plus Fixed Income (bonds) and T. Rowe Price Blue Chip Growth Trust (equity) are two examples of CIT options offered by large financial companies to DC plan sponsors.

The mutual fund category, which also includes ETFs, is the largest component comprising, on average, 43% of the total 401(k) assets. Figure 3.2 decomposes this category into five groups: US equity ETFs, US equity mutual funds, US index funds, allocation funds, and others. Allocation funds include target-date funds and balanced funds investing in a mix of equity and fixed income assets, while international mutual funds, bond mutual funds, money market mutual funds, and alternative investment funds are pooled together in the "Others" category. US index funds include mutual funds and ETFs that are index-tracking.[9]

Our focus is on the two remaining groups, active mutual funds and ETFs investing in US equities. We observe a substantial increase in mutual funds (orange bar) and ETFs (green bar) assets over time, with the former (latter) totaling around \$0.63tn (\$32bn) in 401(k) as of 2020. Active ETFs assets inside 401(k) plans are still somehow limited, but they are growing at the fastest rate over the last 5 years. In fact, the annual growth of ETF investments by 401(k) plans amounts to 16% over the last five years, and 25% over the period 2007-2020.

Table 3.1 reports the cross-sectional distribution, across years, of some 401(k) plan characteristics. The first variable, IO^{401k}, indicates the fraction of assets of an individual fund owned collectively by 401(k) plans. We observe that around 8% of fund assets are owned, on average, by 401(k) plans, making 401(k) plans among the largest fund investors. This number can also be backed out from Figure 3.2, which shows that 401(k) plans' investment in US equity funds, both active and indexed, is around \$1trillion in 2020, consistent with the

[8] Differently from mutual funds, CITs are not required to publicly disclose holdings. Moreover, while mutual funds can be bought by most investors through, for example, a brokerage firm, 100% of CIT assets linked to a DC plan can only be owned by DC participants. Therefore, even if the holdings were available, we would not be able to estimate the marginal impact of 401(k) ownership on CITs demand for stocks since there is no cross-sectional variation in 401(k) ownership across CITs.

[9] We define index-tracking ETFs as large cap ETFs that track the S&P500 index (based on Lipper code: "SP", S&P 500 Index Objective Funds). We define index mutual funds according to the Morningstar classification (e.g., index funds and enhanced index categories).

Table 3.1: Summary Statistics.

This table reports summary statistics of the cross-sectional distribution of 401(k) plans characteristics. IO^{401k} indicates the fraction of a fund assets collectively owned by 401(k) plans. The first row ("all funds") considers the universe of all US equity (active and index) funds. Index funds comprise mutual funds classified according to the Morningstar variables as "index funds" and "enhanced index", and ETFs with the S&P500 index as benchmark. The second and third rows only include US equity active mutual funds and ETFs, respectively. The fourth and fifth rows include the set of index (MFs and ETFs) and active (MFs and ETFs) funds, respectively. $IO^{401k}(n)$ represents the 401(k) plans ownership of stock n. Persistence on fund allocation is the AR(1) coefficient on the fraction of 401(k) plan assets invested in a specific fund. Total assets are the total net assets of 401(k) plans. The last three rows report the allocation of 401(k) plans into US equity index funds (both index MFs and ETFs), US equity active MFs, and US equity active ETFs, respectively. Annual data from 2007 to 2020.

	25th	Median	Mean	75th
IO^{401k} (all funds)	0.31%	2.72%	8.05%	10.46%
IO^{401k} (active MFs)	0.86%	3.87%	9.25%	12.59%
IO^{401k} (active ETFs)	0.02%	0.05%	0.89%	0.21%
IO^{401k} (index funds)	0.85%	3.99%	9.34%	14.53%
IO^{401k} (active funds)	0.28%	2.60%	7.91%	10.04%
$IO^{401k}(n)$	1.72%	2.79%	3.09%	4.19%
Persistence on fund allocation	0.27	0.59	0.54	0.82
Total assets of 401(k) plans ($ mln)	4.34	10.73	91.57	30.13
Allocation in US equity index funds ($ mln)	0.36	1.28	9.76	4.39
Allocation in US equity active MFs ($ mln)	0.83	2.78	14.98	8.44
Allocation in US equity active ETFs ($ mln)	0.11	0.45	3.84	1.64

US equity funds total assets under management of around $14 trillions.[10] The second row shows that 401(k) plans are amongst the largest investors when considering the universe of active mutual funds, with an average ownership of 9.25%, but this is not the case for active ETFs (0.89%, third row). However, 401(k) plans invest substantially in both index and active funds, with average ownerships of 9.34% and 7.91%, respectively (fourth and fifth rows). Most importantly, the dollar amount invested by a given 401(k) plan in a specific fund, as a fraction of the total plan assets, is quite persistent. When looking at the top 25% of the plan-fund distribution, we observe an annual autoregressive coefficient of 0.82. The seventh row displays the size distribution across 401(k) plans. We find that the average 401(k) plan size is around $92mln, while the median is only $11mln, suggesting that the cross-sectional distribution is extremely right skewed, consistent with Egan, MacKay, and Yang (2021). The last three rows report 401(k) plans' dollar allocation to index funds, US equity active mutual funds, and ETFs, respectively, and show that 401(k) plans invest substantially more in active mutual funds than ETFs over our sample period, while also allocating a relevant fraction of their assets to equity index funds.

Figure 3.3 shows the cross-sectional distribution of fund-level 401(k) ownership, $IO^{401k}_{i,t}$, over time. We notice that the variable is stationary, even at the 75th percentile of the distribution, where it fluctuates between 6% and 12%.

3.3 Estimating the Impact of 401(k) Plans on Stock Demand

As discussed in 3.2, 401(k) plans invest a substantial amount of assets in equity mutual funds and ETFs. In this section, we outline how we adapt the asset demand framework of Koijen and Yogo (2019) for our purpose, and highlight the two main channels through which retirement plan allocations can impact the demand of mutual funds and ETFs for individual stocks.

[10] Specifically, in 2020, 1.04 trillion of 401(k) assets was invested in US funds: 0.63 trillion in US equity mutual funds (orange bar), 0.03 in equity ETFs (green bar), and 0.38 in US equity index funds (red bar).

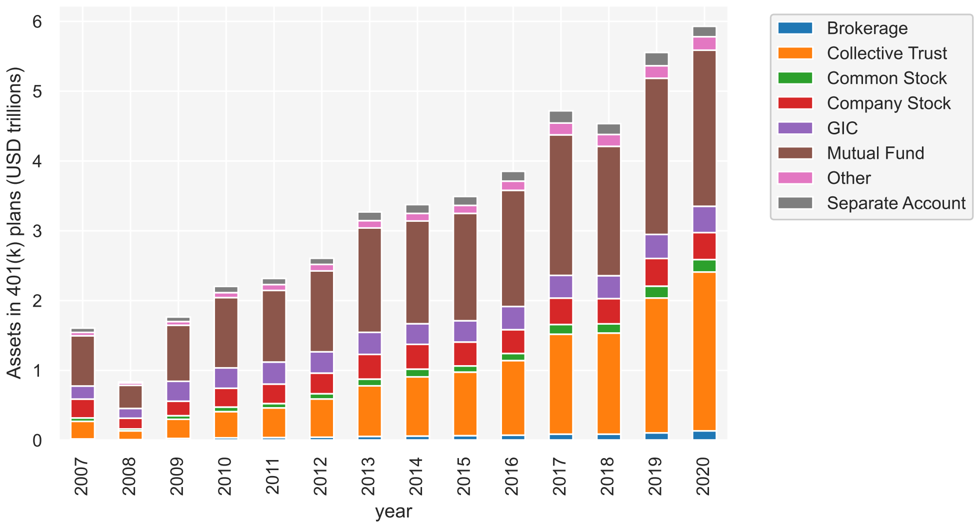


Figure 3.1: 401(k) Plan Assets.
This figure shows the distribution of 401(k) plan assets into the various investment options, over time. Annual data, from 2007 to 2020.

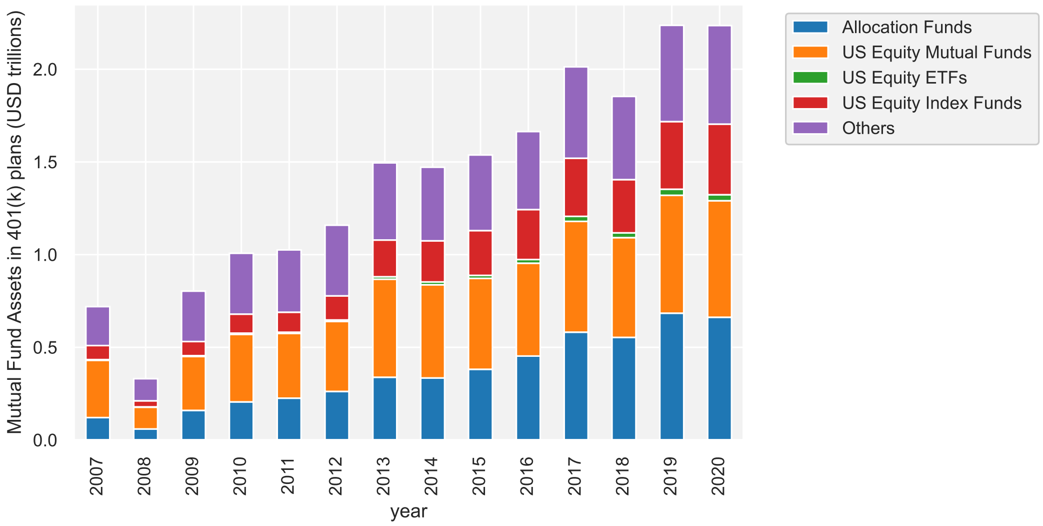


Figure 3.2: Distribution of Assets within the Mutual Fund Category.
This figure plots the value of 401(k) mutual fund investments split into various subgroups. Allocation funds are balanced funds investing in a mix of fixed income assets and equities depending on their objective, e.g., target-date funds. US equity mutual funds and ETFs include all active domestic equity funds. US equity index funds include both mutual funds and ETFs that are index-tracking. The category “Others” includes bond mutual funds, international equity mutual funds, money market funds and alternative investment funds.

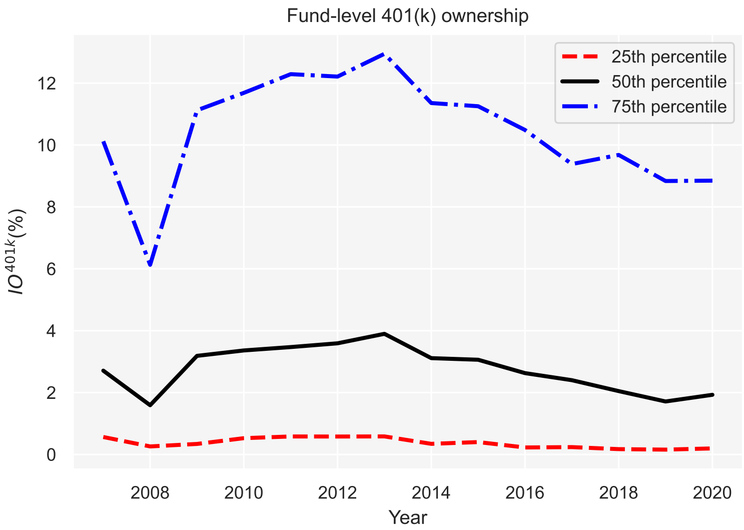


Figure 3.3: Fund-level 401(k) Ownership Over Time.
This figure shows the cross-sectional distribution of fund-level 401(k) ownership over time. Annual data, from 2007 to 2020.

3.3.1 Model

We extend Koijen and Yogo (2019), and define the demand curve of investor i for stock n as:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left\{b_{0,i,t} + \beta_{0,i} mb_t(n) + \boldsymbol{\beta}'_{\mathbf{1},\boldsymbol{i}} \mathbf{X}_t(n) + \beta_{2,i} IO^{401k}_{i,t}(n)\right\} \epsilon_{i,t}(n) \tag{3.1}$$

where $mb_t(n)$ is the log market-to-book equity of asset n at time t, $\mathbf{X}_t(n)$ is a vector of k observed characteristics of asset n at date t, and $w_{i,t}(0)$ is the portfolio weight on the outside asset. As in Koijen and Yogo (2019), we include log book equity, profitability, investment, dividend-to-book equity, and market beta as characteristics. In addition to the aforementioned stock characteristics, we augment the original model in Koijen and Yogo (2019) with one additional variable, potentially capturing variation in investor demand: 401(k) ownership of either the individual stock n (denoted $IO^{401k}_t(n)$), or the investor i (denoted $IO^{401k}_{i,t}$).

Following Koijen and Yogo (2019), we assume throughout that stock characteristics are exogenous to latent demand,

$$\mathbb{E}_t\left[\epsilon_{i,t}(n) \mid \mathbf{X}_t(n), IO^{401k}_{i,t}(n), IO^{401k}_{i,t}\right] = 1\ . \tag{3.2}$$

By explicitly controlling for variables such as book-to-market and profitability in the regressions, and instrumenting market equity as in Koijen and Yogo (2019) (see next paragraph), we limit potential endogeneity concerns for the fund-level 401(k) ownership. In other words, stock-specific characteristics that affect the behavior of fund managers, other than those explicitly used as regressors in the model, are unlikely to affect the allocation of 401(k) plans to funds, and their choice of individual stocks. However, 401(k) plans may select funds based on fund-specific characteristics, such as the fund style (e.g., "growth"), its manager, and the size of the fund. 3.A.1.3 provides robustness tests for the exogeneity of the fund-level 401(k) ownership along these additional dimensions.

Nevertheless, latent investor demand is likely correlated with a stock's market capitalization, i.e., $\mathbb{E}_t\left[\epsilon_{i,t}(n) \mid me_t(n)\right] \neq 0$, because some investors are large and their individual latent demand affects stock prices.[11] Hence, the model in (3.1) delivers biased and inconsistent estimates.

We therefore construct an instrument $z_{i,t}(n)$ for the endogenous market capitalization. Specifically, we follow Koijen, Richmond, and Yogo (2022) and use exogenous variation in investors' investment mandates to generate exogenous variation in demand. Let $\mathcal{S}_{i,t}$ denote the set of stocks held in period t and assume that any stock that investor i holds during the current year, or any of the previous 11 quarters, is part of her choice set, $\mathcal{N}_{i,t} = \cup_{k=0}^{2}\mathcal{S}_{i,t-k}$ where k is expressed in years.[12]

Note that if $n \notin \mathcal{N}_{i,t}$, it means that stock n is part of the outside asset for investor i at time t. When $w_{i,t}(n) = 0$, stock n belongs to the investment universe of investor i, but she does not hold the stock at time t, hence the characteristics-based demand in (3.1) is able to account for zero holdings of a stock. In order to construct an instrument that relies only on the fund investment universe, but not on the exact investor i holdings within the investment universe, we compute counterfactual market equity $z_{i,t}(n)$ (i.e., the instrument) as if investors held an equal-weighted portfolio of all the stocks in their investment universe,

[11] Market equity is the numerator of log market-to-book equity.

[12] For each fund i, the outside asset includes the complement set of stocks, those not in the investment universe.

and excluding the investor's own holdings:[13]

$$z_{i,t}(n) = \log \left(\sum_{j \neq i} A_{j,t} \frac{1_{n \in \mathcal{N}_{j,t}}}{1 + |\mathcal{N}_{j,t}|} \right)$$

where $1_{n \in \mathcal{N}_{j,t}}$ is an indicator function equal to one if the stock n belongs to investor j's choice set $\mathcal{N}_{j,t}$, $A_{i,t}$ denotes the dollar assets owned by investor i at time t, and $|\mathcal{N}_{j,t}|$ denotes number of stocks in an investor's choice set.[14]

3.3.2 Economic Channels

The first channel through which 401(k) plans affect the demand of individual stocks is by ownership of the stock itself.[15] We can think of the fraction of a stock held by 401(k) plans as a stock characteristic, similarly to book-to-market or momentum. Fund managers might take into account the information embedded into this additional stock characteristic when evaluating how many shares of a specific company to purchase.[16] In other words, the total percentage ownership of a stock by 401(k) plans might affect fund demand for that specific stock. We study this channel, labeled the *stock level* channel, in 3.4.

The second channel through which 401(k) allocations affect individual stock demand is by direct flows to mutual funds and ETFs, which, in turn, use that additional liquidity to increment their equity exposure. Since 401(k) plans tend to be low turnover investors, especially relative to other types of institutional investors such as hedge funds, mutual funds and ETFs managing a larger fraction of 401(k) assets might have a more stable investor base.[17] As a consequence, they might invest in different types of stocks compared to funds managing with fewer 401(k) assets, all else being equal. In other words, the "investor base" of mutual funds and ETFs might affect funds' asset allocation decisions, e.g., funds may

[13] Since we focus on US equity mutual funds and ETFs, we use their investment universe. Specifically, the summation in $z_{i,t}(n)$ spans all the mutual funds and ETFs that are held by retirement plans.

[14] Although there are $|\mathcal{N}_{j,t}| + 1$ assets including the outside asset, there are only $|\mathcal{N}_{j,t}|$ degrees of freedom implied by the budget constraint, since asset weights must sum to unity.

[15] We only focus on indirect ownership, e.g., through funds, since direct stock ownership by 401(k) plans of individual stocks is usually negligible.

[16] Institutional ownership of a stock is a characteristic known amongst investors; in particular, 401(k) plans ownership can be retrieved by public filings or third party data providers.

[17] Recall from 3.2 that the top quartile of 401(k) plans have allocations to funds that are persistent in percentage terms, with an annual autoregressive coefficient greater than 0.8.

increase exposures to specific stock characteristic (Christoffersen and Simutin, 2017), opting perhaps for riskier bets. We study this channel, labeled the *fund level* channel, in 3.5.

Koijen and Yogo (2019) highlight the importance of latent asset demand, defined as the component of the demand function unexplained by the model covariates. We conjecture that an important component of the variation in this latent asset demand is attributable to the two economic channels described above, e.g., the fraction of stock n owned in aggregate by 401(k) plans, and the fraction of fund i's assets under management owned by all 401(k) plans at time t. Next, we estimate the magnitude of these demand effects.

3.4 Stock Level Channel

We start our analysis by studying the relevance of 401(k) ownership at the individual stock level. The 401(k) ownership is a firm-specific characteristic, similar to, e.g., book-to-market or beta, and it may explain how much of a stock is demanded by funds. For example, fund managers may be more inclined to accumulate a position in a stock if they know it is largely owned by 401(k) plans when a large stock 401(k) ownership signals potential stability in the stock investors' base. This is plausible since 401(k) allocations to funds tend to be stable,[18] and individual fund allocations do not drastically change over time.[19] To this end, we calculate the fraction of stock n cumulatively owned by 401(k) plans:

$$IO_t^{401k}(n) = \frac{\sum_{j=1}^{I} IO_{j,t}^{401k} \times w_{j,t}(n) \times AUM_{j,t}}{ME_t(n)} \tag{3.3}$$

where $IO_{j,t}^{401k}$ is the fraction of fund j owned by all 401(k) at the end of year t, $w_{j,t}(n)$ denotes the portfolio weight of equity fund j on stock n at the end of year t, $AUM_{j,t}$ denotes the assets under management (size) of fund j, and $ME_t(n)$ is the market value of stock n. In words, this variable represents the total ownership of stock n by 401(k) plans through both mutual funds and ETFs. As illustrated in the sixth row of Table 3.1, the interquantile range ownership of individual stocks owned by 401(k) plans ranges from 1.7% to 4.2%.

[18]401(k) plans have persistent fund allocation in terms of proportions of assets under management, see 3.2.

[19]This is consistent with the presence of investment mandates. For example, Table 1 in Koijen and Yogo (2019) reports that, across institutions, more than 82 percent of stocks currently held by an institution were also held in the previous quarter.

We then estimate the following panel regression:

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO^{401k}_{-i,t}(n) + \alpha_{i,t} + \tilde{u}_{i,t}(n) \qquad (3.4)$$

where the dependent variable represents the demand of stock n by fund i at time t with respect to the outside asset, $\widehat{mb}_t(n)$ is the log market-to-book equity of firm n at time t instrumented with $z_{i,t}(n)$, $\mathbf{X}_t(n)$ is a vector of controls that includes the firm-specific characteristics specified in Koijen and Yogo (2019), and $IO^{401k}_{-i,t}(n)$ is the fraction of stock n cumulatively owned by 401(k) plans through funds, excluding that owned by fund i. Note that by excluding investor i from the $IO^{401k}_t(n)$ regressor in (3.3), we are studying how the portfolio choice of fund i is influenced by the stock-level 401(k) ownership through all *other* investors, thus reducing possible endogeneity concerns.[20] In addition to the variables used in Koijen and Yogo (2019), we also present results controlling for three alternative ownership variables that may influence fund demand for individual stocks: the fraction of a stock owned by the top ten investors (Ben-David, Franzoni, Moussawi, and Sedunov, 2021), a stock's total mutual fund ownership, and the stock ownership by institutional investors categorized by different levels of portfolio turnover and diversification (Bushee, 1998).

Panel A in Table 3.2 shows the results from the panel regression (3.4) for the entire universe of funds (columns (1)-(3)), mutual funds (columns (4)-(6)), and ETFs (columns (7)-(9)). We report three-way (funds, time and stock) clustered standard errors.[21] Fund-stock observations are AUM-weighted. Furthermore, to properly compare regression coefficients, we standardize all variables. Across specifications, the coefficient on stock-level 401(k) ownership, $IO^{401k}_{-i,t}(n)$, is positive, it ranks second in terms of magnitude after size (among the characteristics included in $\mathbf{X}_t(n)$), and it is statistically significant even after controlling for well known drivers of expected returns such as market beta, book-to-market, and profitability. This result highlights the relevance of stock-level 401(k) ownership as an important characteristic for fund allocation decisions. The coefficient for the universe of funds (0.149, t-stat=18.95, column (1)) is mostly determined by mutual funds. Indeed, mutual funds dis-

[20]Excluding investor i from the summation also addresses the concern that a stock owned only by one fund (a quite unlikely case) drives the results.

[21]In a previous version of the manuscript, we adopted two-way (funds and time) clustered standard errors and reach identical conclusions.

Table 3.2: Demand System Estimation: Stock Level $IO_t^{401k}(n)$.

This table reports estimates of the panel regression

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO_{-i,t}^{401k}(n) + \alpha_{i,t} + \tilde{u}_{i,t}(n)$$

where $\widehat{mb}_t(n)$ is the instrumented market-to-book equity, and $\mathbf{X}_t(n)$ includes the same variables as in Koijen and Yogo (2019), i.e., log book equity, operating profitability, stock market beta, investment, and dividend-to-book ratio. $IO_{-i,t}^{401k}(n)$ is the 401K plans ownership of stock n (excluding the effect through investor i), and $\alpha_{i,t}$ are fund-by-time fixed effects. The funds in the regressions are AUM-weighted. Panel A reports results for all funds owned by 401(k) plans, while Panel B employs only those not controlling 401(k) pension assets (hence, $IO_{-i,t}^{401k}(n) \equiv IO_t^{401k}(n)$). Columns (1)-(3) report results using all funds (including index mutual funds and ETFs), columns (4)-(6) using only active mutual funds, and columns (7)-(9) using only active ETFs. Variables are standardized to have unit-standard deviation. Standard errors are triple clustered by fund, time and stock. The sample period is from 2007 to 2020. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Funds owned by 401(k) pension plans

	All Funds				**Mutual Funds**				**ETFs**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$IO_{-i,t}^{401k}(n)$	0.15***	0.12***	0.11***	0.10***	0.19***	0.16***	0.12***	0.14***	0.12***	0.09***	0.09***	0.07***
	(17.19)	(15.86)	(12.8)	(8.73)	(11.09)	(9.9)	(7.86)	(8.83)	(9.67)	(8.59)	(7.74)	(5.51)
Log market-to-book	0.81***	0.81***	0.81***	0.77***	0.42***	0.41***	0.42***	0.38***	0.96***	0.96***	0.96***	0.92***
	(13.84)	(14.13)	(14.29)	(13.29)	(5.08)	(4.87)	(4.98)	(4.73)	(21.08)	(21.59)	(21.81)	(19.83)
Log book equity	1.41***	1.42***	1.43***	1.4***	0.99***	1.0***	1.01***	0.98***	1.522e-16	1.52***	1.52***	1.52e-16
	(26.96)	(26.52)	(26.61)	(27.26)	(12.01)	(11.62)	(11.65)	(12.05)	(60.71)	(64.14)	(63.55)	(60.55)
Operating profitability	0.03**	0.03**	0.03**	0.03**	0.07**	0.07**	0.08***	0.08***	0.02*	0.02*	0.02*	0.02*
	(3.26)	(3.55)	(3.61)	(3.54)	(4.21)	(4.42)	(4.59)	(4.68)	(2.22)	(2.86)	(2.87)	(2.79)
Beta	-0.0	-0.01	-0.01	-0.01	-0.02*	-0.02*	-0.02*	-0.02**	0.0	0.0	0.0	-0.0
	(-0.73)	(-1.1)	(-0.91)	(-1.63)	(-2.44)	(-2.62)	(-2.29)	(-3.22)	(0.57)	(0.04)	(0.12)	(-0.25)
Investment	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01
	(2.08)	(1.31)	(1.25)	(0.99)	(0.77)	(0.42)	(0.36)	(0.23)	(2.11)	(1.46)	(1.43)	(1.15)
Dividend-to-book	0.00	0.0	0.0	0.01	-0.01	-0.01	-0.01	-0.0	0.0	0.01	0.01	0.02
	(0.06)	(0.52)	(0.37)	(2.03)	(-1.29)	(-0.92)	(-1.12)	(-0.39)	(0.35)	(0.62)	(0.58)	(1.78)
Top10 ownership		0.06***	0.06***			0.06**	0.06**			0.05**	0.05**	
		(5.09)	(4.86)			(3.88)	(3.55)			(3.99)	(3.89)	
Mutual Fund ownership			0.03*				0.07**				0.01	
			(2.58)				(4.3)				(1.39)	
DED				0.04				0.04				0.05
				(1.52)				(1.33)				(1.62)
QIX				0.09***				0.09***				0.09***
				(5.25)				(4.49)				(4.93)
TRA				0.05***				0.03				0.05***
				(6.73)				(2.16)				(6.38)

Panel B: Funds not owned by 401(k) pension plans

	All Funds				**Mutual Funds**				**ETFs**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$IO_t^{401k}(n)$	0.12***	0.10***	0.10***	0.07***	0.12***	0.11***	0.10***	0.08**	0.10***	0.08***	0.08***	0.05***
	(7.0)	(6.2)	(6.28)	(5.07)	(6.07)	(5.44)	(4.92)	(4.05)	(5.39)	(4.76)	(5.05)	(4.28)
Log market-to-book	0.71***	0.71***	0.71***	0.72***	0.66***	0.65***	0.65***	0.67***	0.77***	0.76***	0.76***	0.77***
	(15.94)	(15.44)	(15.42)	(16.0)	(16.36)	(17.62)	(17.7)	(16.39)	(9.01)	(8.47)	(8.49)	(9.04)
Log book equity	1.29***	1.29***	1.29***	1.29***	1.19***	1.18***	1.18***	1.2***	1.4***	1.41***	1.41***	1.4***
	(19.89)	(18.6)	(18.58)	(20.48)	(18.42)	(19.22)	(19.19)	(18.57)	(16.03)	(15.1)	(15.16)	(16.68)
Operating profitability	0.01	0.01	0.01	0.0	0.0	-0.0	-0.0	-0.0	0.02	0.02	0.02	0.02
	(0.68)	(0.52)	(0.53)	(0.52)	(0.13)	(-0.14)	(-0.09)	(-0.07)	(1.79)	(1.53)	(1.51)	(1.82)
Beta	-0.01	-0.01	-0.01	-0.01	-0.03	-0.03	-0.03	-0.03	0.01	0.01	0.01	0.01
	(-1.13)	(-1.07)	(-1.06)	(-1.28)	(-1.89)	(-2.06)	(-2.02)	(-1.98)	(1.29)	(1.84)	(1.74)	(1.18)
Investment	0.02**	0.02**	0.02**	0.02**	0.02	0.02	0.02	0.02	0.02**	0.02**	0.02**	0.02**
	(3.65)	(3.46)	(3.43)	(3.65)	(2.1)	(2.01)	(1.95)	(2.14)	(4.03)	(3.63)	(3.73)	(3.88)
Dividend-to-book	-0.6	-0.51	-0.51	-0.13	-2.21*	-2.19*	-2.16*	-1.75	1.19	1.25	1.23	1.58**
	(-0.86)	(-0.72)	(-0.72)	(-0.2)	(-2.4)	(-2.41)	(-2.38)	(-1.94)	(2.1)	(2.03)	(2.01)	(3.06)
Top10 ownership		0.03*	0.03*			0.02	0.02			0.04*	0.04*	
		(2.8)	(2.8)			(1.45)	(1.44)			(3.1)	(3.03)	
Mutual Fund ownership			0.00				0.02				-0.02*	
			(0.4)				(2.17)				(-2.4)	
DED				-0.01				-0.02				0.01
				(-0.41)				(-0.78)				(0.47)
QIX				0.08**				0.07**				0.08***
				(3.95)				(3.1)				(4.53)
TRA				0.07***				0.06**				0.07***
				(5.42)				(3.30)				(5.62)

play a loading on stock-level 401(k) ownership of 0.186, which is sixty percent greater than that of ETFs, equal to 0.115.[22] Controlling for stock ownership by the top ten investors (columns 2, 6, and 11), or total mutual fund ownership (columns 3, 7, and 11) of a stock, does not affect our results. In columns (4), (8), and (12) we control for the three groups of institutional investors delineated in Bushee (1998): "quasi indexed (QIX)" (institutions that are widely diversified and do not trade much); "dedicated (DED)" (institutions whose holdings are more concentrated, but do not trade much); and "transient (TRA)" (institutions whose holdings are diversified but trade often in and out from individual stocks). Also in this case, the association between stock-level 401(k) ownership and mutual fund demand for individual stocks remains positive and statistically significant. These robustness checks highlight the uniqueness and relevance of 401(k) stock-ownership with respect to other types of institutional ownership.[23]

Although, specification (3.4) includes fund-by-time fixed effects, thus limiting the concern of a fund characteristic jointly affecting the portfolio weights and 401(k) ownership, in Panel B of Table 3.2 we repeat our analysis and study how 401(k) stock ownership affects fund allocations using a sample of funds that do *not* appear on the 401(k) menus, e.g., not owned by 401(k) plans. By doing so, we remove any potential selection effect arising from 401(k) plans choosing funds with specific characteristics (e.g., funds from large families) and with similar investment strategy (e.g., investing larger fraction of their portfolio in growth stocks). Note that for this particular sample of funds without any pension assets $IO^{401k}_{-i,t}(n) \equiv IO^{401k}_{t}(n)$, so we remove the $-i$ subscript. Importantly, we continue to find a large and statistically significant coefficient on $IO^{401k}_{t}(n)$.[24] Overall, the evidence in Table 3.2

[22]Appendix Table 3.A.1 reports the same results without weighting the observations by the fund AUM. The coefficients for mutual funds and ETFs are 0.122 (t-stat=11.07) and 0.082 (t-stat=7.80), respectively, thus confirming a stronger effect for the former. Appendix Table 3.A.2 reports the results without winsorizing fund size at the top 1% level. Our conclusions continue to hold. In fact, the estimates are even larger, with the coefficients for mutual funds and ETFs being 0.179 (t-stat=10.00) and 0.116 (t-stat=9.63), respectively.

[23]In Internet Appendix 3.A.2.1 we verify that our stock-level 401(k) results are robust to using s34 data instead of Morningstar.

[24]For the sample of mutual funds that do not control pension assets, the coefficient on $IO^{401k}_{t}(n)$ is 0.119 (t-stat=6.02) (Table 3.2, Panel B). Not only this coefficient is similar in magnitude to the one obtained in our benchmark sample of fund managers controlling pension assets, but also it is robust to alternative specifications. In particular, we estimate a loading of 0.109 (t-stat=6.09) if we do not weight observations by the fund AUM (Appendix Table 3.A.1, Panel B) and 0.099 (t-stat=3.65) when we do not winsorize fund TNA (Table 3.A.2, Panel B). Lastly, in Table 3.A.3, the coefficient remains sizable and statistically significant even when the stock-level 401(k) ownership enters the specification with a lag.

Stock-level 401(k) Ownership Fund-level 401(k) Ownership

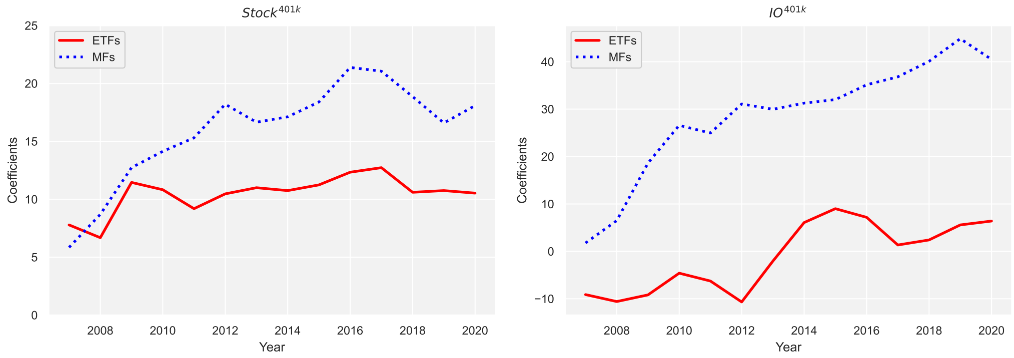


Figure 3.4: Coefficients on 401(k) Ownership.
This figure shows the annual coefficient in equations (3.4) (stock level, left) and (3.10) (fund level, right) and on 401(k) ownership, separately for mutual funds and ETFs, estimated by pooled OLS using assets under management as weights. The regression is estimated annually, and it includes fund-level fixed effect in the left panel. Variables are standardized (within each year) to make coefficients comparable. We multiply the coefficients on 401(k) ownership by 100, so that they can be interpreted as the percentage change in demand per one standard deviation change in the characteristic. The sample period is from 2007 through 2020.

demonstrates the relevance of 401(k) ownership in driving the funds' demand for stocks.

The left panel in Figure 3.4 shows the evolution of the coefficient on stock-level 401(k) ownership, $IO^{401k}_{-i,t}(n)$, over time.[25] The coefficient is always larger and more volatile for mutual funds than for ETFs; in general, the magnitude of the coefficients are in line with the values reported in Table 3.2. Panel A of Table 3.3 reports GMM estimates of the main specification of the non-linear version of equation (3.4). The result shows a positive on stock-level 401(k) ownership of 0.25 – the second largest within the set of characteristics $\mathbf{X}_t(n)$ – statistically significant at the 1% level (t-stat: 25.49).

Next, we study the equilibrium price impact of stock-level 401(k) ownership.

3.4.1 Equilibrium Price Impact of 401(k) Plans

In this section we quantify the equilibrium price impact of a change in 401(k) stock-level ownership for firm n, accounting for the trading of *all* investors. Specifically, we estimate

$$\frac{\partial p_t(n)}{\partial IO^{401k}_t(n)} \tag{3.5}$$

[25] Figure 3.A.1 shows the coefficients on the other covariates.

Table 3.3: Demand System Estimation: GMM with Stock- and Fund-level 401(k) Ownership.

This table reports GMM estimates of the regression

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left\{b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO_t^{401k} + \alpha_t\right\}\tilde{u}_{i,t}(n)$$

where $\widehat{mb}_t(n)$ is the instrumented log market equity-to-book equity, and $\mathbf{X}_t(n)$ includes the same variables as in Koijen and Yogo (2019), i.e., log book equity, operating profitability, stock market beta, investment, and dividend-to-book ratio. IO_t^{401k} indicates either the 401(k) plans ownership of the individual stock n excluding the effect through fund i (Panel A), or the 401(k) plans ownership of fund i (Panel B). We report results using only active mutual funds. The estimation includes observations of mutual funds with zero stock-holdings but still in the investment universe, and observations are AUM-weighted. Variables are standardized. Standard errors are double clustered by fund and time. The sample period is from 2007 to 2020. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Stock-level 401(k) ownership (mutual funds)

	Coefficient	s.e.	t-stat
$IO_{-i,t}^{401k}(n)$	0.250***	0.010	25.490
Log market-to-book	0.132***	0.034	3.890
Log book equity	0.590***	0.025	23.750
Operating profitability	0.067***	0.007	9.280
Beta	-0.124***	0.008	-14.720
Investment	-0.097***	0.007	-13.800
Dividend-to-book	0.014*	0.008	1.800

Panel B: Fund-level 401(k) ownership (mutual funds)

	Coefficient	s.e.	t-stat
$IO_{i,t}^{401k}$	0.048*	0.027	1.770
Log market-to-book	0.199***	0.036	5.570
Log book equity	0.530***	0.027	19.780
Operating profitability	0.051***	0.007	6.980
Beta	-0.131***	0.009	-15.020
Investment	-0.094***	0.007	-13.340
Dividend-to-book	-0.037***	0.008	-4.730

where p is the log price of stock n. Following Koijen and Yogo (2019) and Noh and Oh (2020), this derivative can be computed analytically, at any time t, as the diagonal elements of the matrix $\mathbf{M}$:[26]

$$\mathbf{M} = \left(\mathbf{I} - \sum_i \beta_{0,i} A_i \mathbf{H}^{-1}\mathbf{G_i}\right)^{-1} \left(\sum_i \beta_{2,i} A_i \mathbf{H}^{-1}\mathbf{G_i}\right), \tag{3.6}$$

where we recall that $\beta_{0,i}$ is the loading of investor i on market-to-book, and $\beta_{2,i}$ is the coefficient on 401(k) ownership (see equation (3.1)). The matrices $\mathbf{H} = \sum_{i=1}^{I} A_i \text{diag}(\mathbf{w}_i)$ and $\mathbf{G}_i = \text{diag}(\mathbf{w}_i) - \mathbf{w}_i \mathbf{w}_i'$ instead do not depend on estimated parameters, but only on investors' weights $\mathbf{w}$. Finally, A_i denotes the assets under management of investor i.

The n-th diagonal entry of $\mathbf{M}$, $M_{n,n}$, captures two effects. First, the matrix inside the inverse in equation (3.6) is the aggregate demand elasticity (Koijen and Yogo, 2019), and its diagonal elements are strictly positive when $\beta_{0,i} < 1$ for all investors. If a firm is held by less price elastic investors, then the firm price will react more due to institutional demand for the $IO_t^{401k}(n)$ characteristic. Second, the n-th diagonal entry of the matrix outside the inverse can be written as $\frac{\sum_i \beta_{2,i} A_i w_i(n)(1-w_i(n))}{\sum_i A_i w_i(n)}$, and represents an AUM weighted average of the coefficients on the 401(k) stock-level ownerhship (multiplied by $1 - w_i(n)$). This implies that the price pressure is larger if a firm faces owners that are large and exhibit a high coefficient on the $IO_t^{401k}(n)$. In other words, the institutional price pressure that a given firm n receives due to a change in the level of 401(k) ownership is a weighted average of $IO_t^{401k}(n)$ coefficients of its institutional owners, adjusted for their demand elasticities.

To compute the price impact $M_{n,n}$ we need to consider the entire investor universe, i.e., not only mutual funds and ETFs. To this end, we use data on institutional common stock holdings from the Thomson Reuters Institutional Holdings Database (s34 file). We follow the Koijen and Yogo (2019) classification of institutions into six types (i.e., $i = 1, \ldots, 6$): banks, insurance companies, investment advisors, mutual funds, pension funds, and other 13F institutions. We recall that the s34 file provides a different level of granularity relative

[26] To compute this expression one has to exploit the identity $\mathbf{p} = \log\left(\sum_i A_i \mathbf{w}_i\right) - \mathbf{s}$ (where $\mathbf{s}$ denotes the vector of shares outstanding) which holds by market clearing. See Appendix A in Noh and Oh (2020) for additional details.

to our analysis in 3.4, since it reports aggregate holdings at the investor level (e.g., for all funds managed by Fidelity).[27]

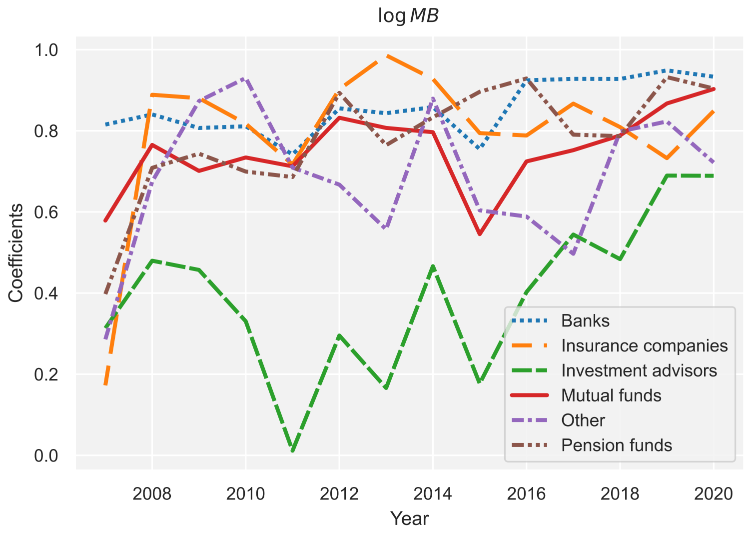
Figure 3.5 displays the two key ingredients required to compute the price impact: the coefficient on market-to-book driving demand elasticities (Panel A) and the coefficient on 401(k) stock-level ownership (Panel B) for each of the six groups of investors. These coefficients are estimated year-by-year by GMM, accounting for zero holdings, from model (3.1), under moment condition (3.2).[28] We confirm the results in Koijen and Yogo (2019) that mutual funds have less elastic demand than investment advisors for most of our sample period, and that insurance companies and pension funds have become less elastic over time. The coefficient in Panel B captures institutional demand for 401(k) stock-level ownership. When positive, it implies that investor i allocates at time t more weight to stocks with higher 401(k) ownership, controlling for other stock characteristics. We see that mutual funds, banks and insurance companies tilt their portfolio toward stocks with high-level of 401(k) ownership more than other types of institutions. In contrast, investment advisors do not manifest such a tilt. Interestingly, the tilt of pension funds toward stocks with high level of $IO_t^{401k}(n)$ increases over our sample period suggesting an intricate relation between the sample of funds offered by 401(k) plans, their holdings, 401(k) plan investor preferences, and the type of individual stocks preferred by pension plans (e.g., green stocks). Finally, the evidence in Panel B for investors other than mutual funds emphasizes the relevance of stock-level 401(k) ownership as an important characteristic while further alleviating endogeneity concerns: we use stock holdings of banks, insurance, etc., as left hand side variables, while we employ only mutual funds and ETFs holdings in the construction of our stock-level 401k ownership (right hand side variable).

Given estimates of $\beta_{0,i,t}$ and $\beta_{2,i,t}$ for each investor, we can calculate, each time period t, the firm-level institutional pressure with respect to 401(k) ownership. The top left panel

[27] Mindful of potential gaps in coverage of institutional holdings in the s34 files, we validate our price impact results by replacing s34 data with data on 13F filings from Backus, Conlon, and Sinkinson (2021) in Internet Appendix 3.A.2.2.

[28] To obtain the price impact, we estimate the coefficients as in Koijen and Yogo (2019). For institutions with more than 1,000 stocks in their holdings, we estimate coefficients by institution. For the remaining institutions, we group them by type (e.g., mutual funds) such that on average each group holds 2,000 stocks at any point in time. Variables are standardized within each institution (or group) and for each year. We instrument market-to-book with $z_{i,t}(n)$ as usual.

Panel A: Log Market-to-Book



Panel B: Stock-level 401(k) Ownership

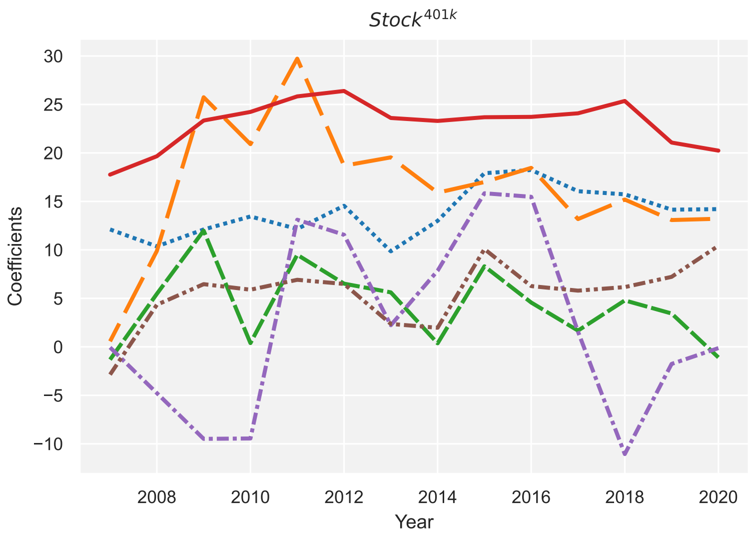


Figure 3.5: Price Impact: Relevant Coefficients.
This figure shows the annual coefficient on log market-to-book (top panel) and stock-level 401(k) ownership (bottom panel) for financial institutions in Thomson Reuters holding (s34) estimated annually by GMM with zero weights. Variables are standardized (within each year) to make coefficients comparable. We report the cross-sectional mean of the estimated coefficients by institution type, weighted by assets under management. The coefficient on 401(k) ownership is multiplied by 100. The sample period is from 2007 through 2020.

in Figure 3.6 shows the cross-sectional distribution of price impact across all stocks. The aggregate price impact for the median stock (solid black line) has generally increased over time, and the cross-sectional spread has also significantly expanded over our sample period. The stronger effect over time can be related to the shift from active to passive investing of

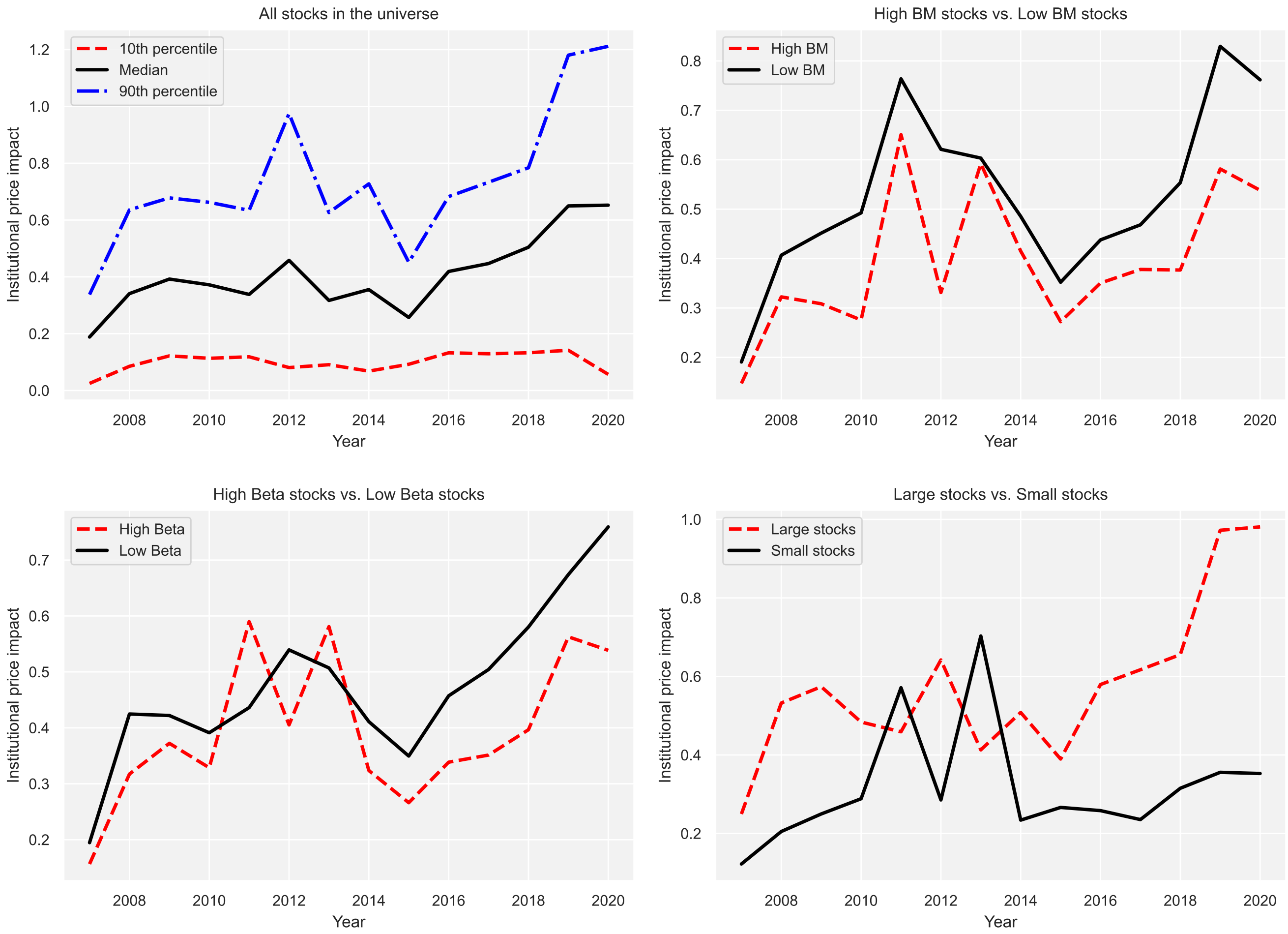


Figure 3.6: Institutional Price Impact.
This figure shows the price impact of a change in the stock-level 401(k) ownership estimated through the diagonal elements of the matrix **M** defined in (3.6). The top left panel shows the 10th percentile, median and 90th percentile of price impact across all stocks. The remaining panels plot the average price impact across the stocks in the top quintile and bottom quintile of portfolios sorted on (top right), beta (bottom left), and size (bottom right), using NYSE break points as cutoffs.

the last decade, since equation (3.6) implies that the presence of more inelastic investors results in larger price pressure. A one standard deviation increase in 401(k) ownership leads to a price impact (for the median stock) slightly less than 20 percent in 2007 and of about 60 percent in 2020.[29] The remaining panels display the aggregate price impact for extreme quintile portfolios of stocks sorted on book-to-market (top right panel), market beta and size (bottom left and right panels, respectively). We observe that the average price impact has increased for large stocks with a sharp jump in 2015, while it has remained relatively stable for small stocks. This resonates well with Haddad, Huebner, and Loualiche (2022) who find that investor elasticities are lower for larger stocks (i.e., investors are more reluctant to change their positions for large stocks than for small stocks), given tracking error concerns.[30]

We do not observe noticeable differences for stocks sorted on book-to-market or betas, which suggests that a change in 401(k) stock-level ownership variable has the same price impact on growth and value stocks. For book-to-market and betas-sorted portfolios, we again observe a positive low-frequency trend of price impact from 2008 to 2020. However, we also observe an interesting cyclical pattern around this trend, particularly for value and high-beta stocks.

3.4.1.1 Matched Sample of Low and High Stock-level 401(k) Ownership

In section 3.4, we estimated the impact of 401(k) plans for individual stock demand using the framework of Koijen and Yogo (2019). In this section, instead, we quantify the direct impact 401(k) ownership has on individual stock *returns* by employing a matching analysis: we compare otherwise identical stocks that only differ by 401(k) ownership, and analyze their return dynamics. In other words, we match pairs of similar stocks together, one displaying positive 401(k) ownership (the treated stock), while the other not owned by 401(k) plans (the control stock). This matching exercise allow us to evaluate whether stocks belonging to the treatment and control groups, which are otherwise identical, perform differently.

We start our analysis identifying, every year, the largest institutional investor for each

[29]The standard deviation of 401(k) ownership is 1% in 2007 and 2% in 2020; thus, the price of the median stock increases by 0.2% and 1.2%, respectively.

[30]In the U.S. stock market, large corporations like Apple make up a substantial fraction of total market capitalization and, as a consequence, a large change in those portfolio weights would cause a substantial impact on an institution's total portfolio return.

stock (e.g., Blackrock, Fidelity, etc.).[31] For each stock, we end up with a time series of its largest institutional investor. We then count the number of times each investor is ranked as the top one across all stocks and years, and extract the top ten investors' names. This list includes Blackrock, Vanguard, Fidelity, Dimensional Fund Advisors, among others.

Next, for each of these ten investors, we select the subset of stocks for which this investor (e.g., Vanguard) is the largest. Within this subset of stocks, we match stocks with positive 401(k) ownership (*treated* stock) with a comparable group made of stocks without 401(k) ownership (*control* stock). Comparable stocks share the same largest investor (e.g., Vanguard), and have similar (i) portfolio weights in the largest investor's portfolio; (ii) size; (iii) book-to-market. More precisely, we sort the candidate "matching" stocks on the difference between their market capitalization and the treated stock's market capitalization. This generates a "market cap rank," where the candidate stock with rank = 1 has a market cap closest to the one of the treated stock. We repeat the same ranking methodology with respect to the book-to-market. We then select the stock with the *smallest* sum of market cap and book-to-market ranks for each treated stock, every year, and include the "matched" stock in our control group.

We repeat the above matching procedure for each stock owned by all of the ten largest investors. Lastly, we estimate a panel regression of annual returns of the matched pair of stocks on a treated dummy variable and various stock-level controls. Controls include lagged size, book-to-market, beta, and momentum. Standard errors are double clustered by stock and time.

Panel A of Table 3.4 presents the average characteristics of the matched sample, while Panel B displays the regression results. The coefficient on the "treated dummy" is slightly above 5% in a specification without controls, and around 3.2% after controlling for main drivers of cross-sectional return variation, such as beta, book-to-market, log market equity and momentum. In other words, stocks with positive 401(k) ownership tend to earn 3%-5% more than similar stocks – in terms of characteristics and investor structure – not owned by 401(k) plans.

[31] Since 13F holdings are quarterly, we select the investor ranked at the top most of the quarters within a year. If there is a draw, we select the largest investor in terms of AUM.

Table 3.4: Matching Stocks: Impact of 401(k) Ownership.

Panel A reports the average stock characteristics of the stocks in the treatment and control groups. Panel B reports results from of regression on the matched sample. After matching stocks as described in Section 3.4.1.1, we estimate a panel regression of annual returns of the matched pair of stocks on a treated dummy variable and various stock-level controls. Controls include lagged size, book-to-market, beta, and momentum. Standard errors are double clustered by stock and time.

Panel A: Characteristics of the Matched Sample		
	Treated Group	Control Group
Number of Stocks	8963	8963
Market Capitalization	11.0 B	12.2 B
Book-to-market Ratio	0.51	0.56
Beta	1.15	1.01

Panel B: Panel Regressions			
	(1)	(2)	(3)
Treated dummy$_t$	0.050***	0.042***	0.032***
	(3.352)	(3.200)	(3.248)
Size$_{t-1}$		-0.027***	-0.027***
		(-2.866)	(-3.343)
Book-to-market$_{t-1}$			-0.056
			(-1.629)
Beta$_{t-1}$			0.024
			(0.627)
Momentum$_{t-1}$			0.018
			(0.447)
Year FEs	Yes	Yes	Yes
No. Observations	17,398	17,398	17,398

3.4.1.2 Price Impact of Trades by 401(k) Plans

Next, we study the impact of trading by 401(k) plans on individual stock returns. Similarly to Ben-David, Franzoni, Moussawi, and Sedunov (2021), for each stock-year pair, we calculate the percentage change in shares held by 401(k) plans. Then, we construct a large (small) trade dummy for 401(k) plans if the stock is in the top (bottom) quintile of the cross-sectional distribution of 401(k) trades for the year. We repeat the same exercise for the cumulative ownership of the top ten investors in every stock. By focusing on large changes in holdings of a stock by 401(k) plans, we identify positions that are actively traded, where the price impact of pension plans might be more relevant.

We then run a regression of individual annual stock returns on actively and non-actively traded 401(k) and top10 investors dummies, controlling for log size and time fixed effects.

Table 3.5: Stock-level 401(k) Trading and Returns.

This table reports estimates of regressions of stock returns on changes in 401(k) plans and top 10 institutions' holdings. The dependent variables are contemporaneous returns (columns (1)-(3)), next year (t+1) returns (column (4)-(6)), and cumulative t+1:t+3 returns (column (7)-(9)). Controls include log market equity and time fixed effects. Standard errors are double clustered by stock and time.

	ret_t			ret_{t+1}			$ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
401(k) dummy - Large Δ holdings	0.119***	0.113***	0.116***	-0.041***	-0.029***	-0.019***	-0.119***	-0.095***	-0.066***
	(4.015)	(3.849)	(4.563)	(-2.682)	(-2.650)	(-2.884)	(-4.074)	(-8.293)	(-4.270)
401(k) dummy - Small Δ holdings		-0.024	-0.033		0.049	0.039		0.098	0.092
		(-0.641)	(-0.886)		(1.124)	(0.964)		(1.128)	(1.124)
Top 10 investors dummy - Large Δ holdings			0.002			-0.018			-0.095***
			(0.100)			(-1.027)			(-2.655)
Top 10 investors dummy - Small Δ holdings			0.054***			0.068**			0.061
			(3.011)			(2.531)			(1.552)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.5 reports the estimates of the regression using contemporaneous returns (columns 1-3), 1-year ahead returns (columns 4-6), and cumulative 3-year ahead returns (columns 7-9). The results show that large holdings changes by 401(k) plans have a contemporaneous positive effect on individual stock returns. Quantitatively, a large position taken by 401(k) plans into a stock generates a contemporaneous annual return 12% higher than that obtained following a "normal" size trade by 401(k) plans. This evidence suggest that trading by 401(k) plans has a positive price impact on individual stocks. We also notice a return reversal of around 2% in the next year following large trading in individual stocks by 401(k) plans. This return reversal continues over the subsequent two years, but it is limited in magnitude, resulting in a permanent price impact caused by 401(k) large trades of more than 2% (e.g., 11.3%-9.5%).

Figure 3.7 shows the distribution of 401(k) large holdings changes across stocks, every year. Except during the Global Financial Crisis, where most 401(k) plans underweighted equities, 401(k) plans have not increased their exposure to the average stock over time. However, they do (indirectly) trade, as evidenced by the top and bottom quartile of change in holdings.

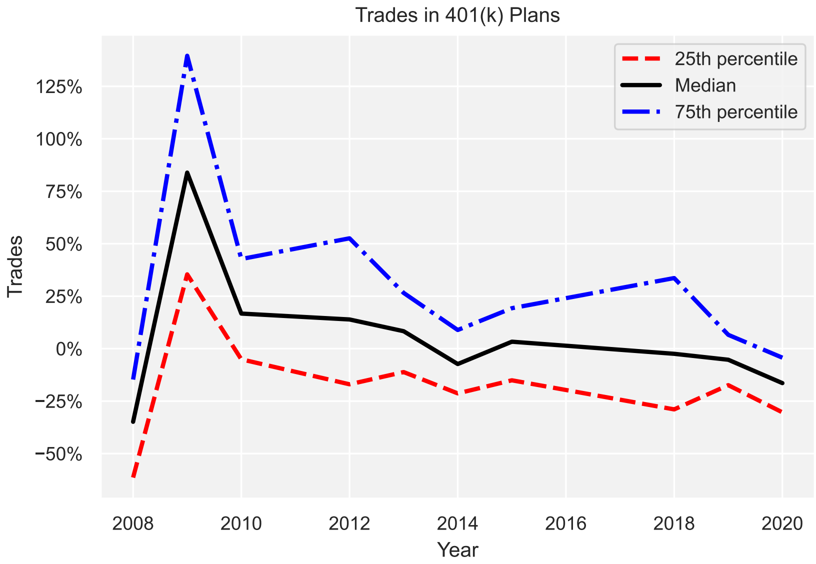


Figure 3.7: 401(k) Plans: Trades in Individual Stocks.
This figure plots the cross-sectional distribution of 401(k) plan trading in individual stocks, defined as the percentage changes of shares in holdings by all 401(k) plans. Annual data, 2008-2020.

3.4.1.3 Price Impact of 401(k) Plans Demand: A Granular Instrumental Variable Approach

The previous section has documented a relation between the trading activity originated by 401(k) plans and stock returns. However, 401(k) demand for stocks is possibly endogenous, e.g., it could be related to other stock characteristics that drive individual stock returns. To address this concern, we use the granular instrumental variable (GIV) approach of Gabaix and Koijen (2022).

Specifically, similar to Fan, Feng, Au, and Baronyan (2022), we define the value-weighted 401(k)'s demand for individual stocks as

$$\text{Demand}_t^{401(k),VW}(n) = \sum_{i=1}^{N_t(n)} w_{i,t-1}(n) \times \frac{\text{Shares}_{i,t}(n) - \text{Shares}_{i,t-1}(n)}{\text{Shares}_{i,t-1}(n)} \tag{3.7}$$

where $N_t(n)$ is the total number of 401(k) plans that own stock n at time t, and the weight $w_{i,t-1}(n)$ represents the proportion of stock n owned by 401(k) plan i at the end of the preceding year $t-1$, which is calculated as the ratio of the shares of stock n held by 401(k) plan i to the total shares of stock n collectively held by all 401(k) plans:

$$w_{i,t}(n) = \frac{\text{Shares}_{i,t}(n)}{\sum_{j=1}^{N_t(n)} \text{Shares}_{j,t}(n)}$$

We also compute the corresponding equally-weighted demand as:

$$\text{Demand}_t^{401(k),EW}(n) = \frac{1}{N_t(n)} \sum_{i=1}^{N_t(n)} \frac{\text{Shares}_{i,t}(n) - \text{Shares}_{i,t-1}(n)}{\text{Shares}_{i,t-1}(n)} \tag{3.8}$$

To estimate the relationship between (value-weighted) demand originated by 401(k) plans, $\text{Demand}_t^{401(k),VW}(n)$, and individual stock returns, we run the following stock-level panel regression:

$$r_t(n) = \beta_0 + \beta_1(n) \times \left(\widehat{\text{Demand}_t^{401(k),VW}}(n)\right) + \varepsilon_t(n)$$

by instrumenting $\text{Demand}_t^{401(k),VW}(n)$ with the demand "shock" ($\text{Demand}_t^{401(k),VW}(n) - \text{Demand}_t^{401(k),EW}(n)$), i.e., the difference between the value-weighted and equally-weighted flows.[32]

Table 3.6 reports the estimation results, controlling for size, beta, and book-to-market, stock- and time (year) fixed effects. We observe that, in the most stringent specification, the coefficient on the instrumented demand is about 0.37, suggesting that for a ten percent increase in 401(k) demand, stock prices increase by 3.7%.

3.5 Fund Level Channel

We define the fraction of fund i's assets under management owned by aggregate 401(k) plans at time t as

$$IO_{i,t}^{401k} = \frac{\sum_{p=1}^{M} AUM_{p,i,t}}{AUM_{i,t}} \tag{3.9}$$

where M denotes the total number of 401(k) retirement plans investing in fund i at time t, and $AUM_{p,i,t}$ denotes the dollar amount invested by 401(k) plan p in fund i at the end of year

[32]As in standard IV setups, we first regress the endogeneous $\text{Demand}_t^{401(k),VW}(n)$ on the difference between the value- and equally-weighted demand (first stage), and use the (exogeneous) fitted value as regressor in the second IV stage.

Table 3.6: Granular Instrumental Variable Regression.

This table reports estimates of the GIV stock-level panel regression

$$r_t(n) = \beta_0 + \beta_1(n) \times \left(\widehat{\text{Demand}_t^{401(k),VW}}(n) \right) + \varepsilon_t(n)$$

The dependent variable is annual stock returns in year t. The variable of interested is 401(k) plans' demand, instrumented by GIV $\widehat{\text{Demand}_t^{401(k),VW}}(n)$. Standard errors are double clustered by stock and time.

	(1)	(2)	(3)	(4)
$\widehat{\text{Demand}_t^{401(k),VW}}(n)$	0.481***	0.401***	0.472***	0.374***
	(7.070)	(10.070)	(8.510)	(9.330)
Size_{t-1}			-0.026***	-0.291***
			(-4.390)	(-4.920)
Beta_{t-1}			-0.003	0.011
			(-0.110)	(0.570)
$\text{Book-to-market}_{t-1}$			-0.056	0.035
			(-1.320)	(0.730)
Momentum_{t-1}			-0.027	-0.070*
			(-0.650)	(-1.950)
Stock FEs	No	Yes	No	Yes
Year FEs	Yes	Yes	Yes	Yes

t. $IO_{i,t}^{401k}$ is hence a fund-specific, time-varying characteristic. Our first specification focuses on the demand function for the average stock n. Specifically, we estimate the AUM-weighted panel regression:

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO_{i,t}^{401k} + \alpha_t + \tilde{u}_{i,t}(n) \tag{3.10}$$

where each fund-stock holding observation in the panel is weighted by assets under management of fund i. The dependent variable represents the demand of stock n by fund i at time t with respect to the outside asset; $\widehat{mb}_t(n)$ is the log market-to-book equity of firm n at time t instrumented with $z_{i,t}(n)$, $\mathbf{x}_t(n)$ is the same vector of firm-specific characteristics specified in Koijen and Yogo (2019), $IO_{i,t}^{401k}$ represents the fraction of fund i's assets under management owned by 401(k) plans at time t, and α_t are time (year) fixed effects. Note that $IO_{i,t}^{401k}$ does not vary across stocks, but only across funds and over time. Our coefficient of interest is β_2, representing the effect of 401(k) assets on fund i demand for the average stock n.

Table 3.7 shows the results from the panel regression for the entire universe of funds (Panel A), mutual funds only (Panel B) and ETFs only (Panel C). Throughout, we use two-way (funds and time) clustered standard errors. Furthermore, in order to gauge the relative importance of the variables in the demand system, we standardize all variables to have unit standard deviation. Across specifications, the coefficient on fund-level 401(k) ownership, $IO_{i,t}^{401k}$, is positive and statistically significant for mutual funds (0.333, t-stat= 2.91) but small and insignificant for ETFs (0.011, t-stat= 0.11).[33] In terms of magnitude, the coefficient of mutual funds on $IO_{i,t}^{401k}$ ranks second in the set of characteristics after book equity.

The evidence that mutual funds strongly respond to fund-level 401(k) ownership while ETFs do not is interesting. It suggests that mutual funds exert more discretion in selecting their holdings based on fund-level ownership, relative to ETFs. This holds true despite the fact that mutual funds and ETFs display similar demand elasticity (approximately captured by the coefficient $(1 - \beta_{0,i})$ on log market-to-book in column (4) and (7) of Table 3.7).[34] However, a word of caution is needed. An alternative interpretation could be inferred by

[33] Table 3.A.4 reports the same results for AUM unweighted regressions. The coefficients for mutual funds and ETFs are, respectively, 0.240 (t-stat= 4.29) and -0.060 (t-stat= -1.10), thus confirming our results.

[34] Recall that we consider only mutual funds and ETFs that are active by removing index mutual funds and ETFs.

Table 3.7: Demand System Estimation: Fund Level $IO_{i,t}^{401k}$.

This table reports estimates of the panel regression

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO_{i,t}^{401k} + \alpha_t + \tilde{u}_{i,t}(n)$$

where $\widehat{mb}_t(n)$ is the instrumented log market equity-to-book equity, and $\mathbf{X}_t(n)$ includes the same variables as in Koijen and Yogo (2019), i.e., log book equity, operating profitability, stock market beta, investment, and dividend-to-book ratio. $IO_{i,t}^{401k}$ is the 401K plans ownership of fund i, and α_t are time fixed effects. The funds in the regressions are AUM-weighted. Columns (1)-(3) report results using all funds (including index mutual funds and ETFs), columns (4)-(6) using only active mutual funds, and columns (7)-(9) using only active ETFs. Variables are standardized to have unit-standard deviation. Standard errors are double clustered by fund and time. The sample period is from 2007 to 2020. *p<0.1; **p<0.05; ***p<0.01.

	All Funds			**Mutual Funds**			**ETFs**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IO_{i,t}^{401k}$	0.169**	0.160**	0.157**	0.333**	0.328**	0.319**	0.011	0.008	0.008
	(2.390)	(2.260)	(2.240)	(2.910)	(2.890)	(2.830)	(0.110)	(0.080)	(0.090)
Log market-to-book	0.766***	0.750***	0.758***	0.637***	0.608***	0.610***	0.560***	0.540***	0.552***
	(7.340)	(7.250)	(7.390)	(9.510)	(9.130)	(9.120)	(4.540)	(4.430)	(4.590)
Log book equity	1.289***	1.331***	1.348***	1.032***	1.088***	1.112***	1.105***	1.117***	1.132***
	(14.170)	(14.170)	(14.540)	(11.050)	(11.350)	(11.740)	(9.930)	(9.790)	(10.000)
Operating profitability	0.036**	0.043***	0.048	0.031*	0.043**	0.054***	0.042**	0.049**	0.052**
	(2.800)	(3.270)	(3.630)	(1.810)	(2.510)	(3.250)	(2.660)	(2.890)	(2.910)
Beta	-0.033**	-0.043**	-0.035**	-0.042**	-0.050***	-0.041**	-0.064***	-0.079***	-0.073***
	(-2.660)	(-3.050)	(-2.580)	(-2.910)	(-3.340)	(-2.870)	(3.520)	(4.360)	(-4.060)
Investment	-0.013	-0.021	-0.022	-0.021	-0.029	-0.030*	-0.031*	-0.038**	-0.039**
	(-0.940)	(-1.390)	(-1.510)	(-1.280)	(-1.720)	(-1.830)	(2.030)	(2.530)	(-2.570)
Dividend-to-book	-0.047***	-0.030**	-0.023*	-0.090***	-0.065***	-0.054***	0.035	0.040*	0.045*
	(-3.600)	(-2.510)	(-1.870)	(-5.970)	(-4.770)	(-4.000)	(1.530)	(1.900)	(2.160)
Top10 ownership		0.136***	0.121***		0.162***	0.137***		0.081**	0.071**
		(7.060)	(6.280)		(7.680)	(6.370)		(3.160)	(2.810)
Mutual Fund ownership			0.142***			0.183***			0.115***
			(7.420)			(7.870)			(4.850)

Figure 3.2: the fraction of aggregate ETF assets cumulatively owned by 401(k) is currently small, hovering around $20-30bn, and, perhaps, not large enough to trigger a discernible demand shift. The last two rows of Table 3.1 confirm this, with the average dollar amount across 401(k) plan assets invested in US equity mutual funds being around $15mn, about four times the amount invested in ETFs. However, given the fast pace at which the investment of 401(k) plan in ETFs has been growing, results may differ in the future.

It is also interesting to compare the fund-level results for ETFs in Table 3.7 to the stock-level results in Table 3.2. Whereas a larger fund-level 401(k) ownership does not affect the ETFs' demand for stocks – consistent with the idea that, for example, a growth ETF cannot take riskier bets and become a value ETFs – the stock-level 401(k)-ownership does, e.g., a growth ETF may pick stock A over stock B, despite having similar growth prospects and risk, simply because the fraction of stock A owned by 401(k) plans is larger. There are several reasons why ETFs could prefer stocks with large 401(k) ownership, e.g., it could be that the stock-level 401(k) ownership characteristic is correlated with the probability of the stock being included in the benchmarks tracked by ETFs (e.g., a growth index), since stocks with large institutional 401(k) ownership have already been screened and vetted by investors that bought them, and hence are included in benchmarks.

The results presented in Table 3.7 mask some economically interesting trends. To this end, the right panel in Figure 3.4 shows the evolution over time of the coefficient on fund-level 401(k) ownership for both mutual funds and ETFs.[35] The figure shows that the loading of mutual funds on fund-level 401(k) ownership is positive throughout the sample, and strongly increasing over time (with an average value of about 0.29, similar to that reported in columns (4)-(6) of Table 3.7). In line with our previous discussion of a rapid growth of 401(k) allocation to ETFs, the effect of 401(k) ownership for ETF holdings becomes stronger over time, and marginally positive in the second part of our sample.

Finally, Panel B of Table 3.3 reports GMM estimates of the main specification of the non-linear version of equation (3.10). This allows us to take into account holdings of stocks

[35] Figure 3.A.2 shows the coefficients on the other covariates. We find that the coefficients of ETFs and mutual funds on profitability, investment, and beta are similar. This is important since it highlights the economic significance of the observed difference in fund-level 401(k) ownership coefficients between mutual funds and ETFs.

that are in the fund investment universe, but not currently owned by the fund. To ease exposition, we display the results only for mutual funds. The coefficient on fund-level 401(k) ownership is positive and statistically significant at the 10% level, even accounting for zero holdings.

3.5.1 Heterogeneous Demand for Stocks

The analysis so far shows that the amount of 401(k) assets managed by funds influence their average demand for stocks. In particular, the larger the 401(k) fund-level ownership, the stronger the demand for stocks, controlling for other prominent characteristics. However, the amount of 401(k) assets managed might not lift demand uniformly across stocks; rather, it may push fund managers toward certain types of stocks (e.g., winners) more than others (e.g., losers). In this section, we try to shed some light on the 401(k) asset-induced demand for specific stock characteristics.

We conjecture that the investment decisions of fund managers is related to the fraction of 401(k) assets they manage. Our first hypothesis is that funds controlling a larger fraction of 401(k) assets have preference for riskier assets, such as high-beta and momentum stocks.

Hypothesis 2.1. ***(Relationship between 401(k) asset base and fund investments.)*** *Funds managing more (sticky) 401(k) assets tend to invest in riskier assets (e.g., high-beta, momentum, and smaller stocks) given the risk of outflows from 401(k) plans is limited.*[36]

Our second hypothesis is that the stability of the investor base allows funds to invest in stocks with embedded real options and long term growth prospects. Formally, we test for this hypothesis by studying the preference of fund mangers for assets with long-duration of cashflows, which the literature has found to be less risky than short duration stocks.

Hypothesis 2.2. ***(Funds with more 401(k) assets prefer longer-duration assets.)*** *Funds managing more (sticky) 401(k) assets tend to invest in assets with longer-duration*

[36]401(k)plan participants make periodic retirement account contributions and withdrawals, which are persistent over time. In addition, they may evaluate their present and prospective fund holdings differently due to longer investment horizons. These factors may explain the documented inertia by DC plan participants in the previous literature (see Benartzi and Thaler (2001), Madrian and Shea (2001), Choi, Laibson, Madrian, and Metrick (2002), Agnew, Balduzzi, and Sundén (2003), Duflo and Saez (2003), Huberman and Jiang (2006), Carroll, Choi, Laibson, Madrian, and Metrick (2009)) whereby retirement savers have a tendency to rebalance and trade infrequently and to follow default options.

cashflows:

To test our hypotheses, we first define the universe of stocks as the union of the investment universes of all equity funds in our sample.[37] Next, we unconditionally sort these stocks into five portfolios based on a given stock characteristic X_1 (e.g., momentum). We then compute how much each fund i invest at time t, as a percentage of its assets, into the stocks within each quintile. This ensures that the fraction invested in all quintiles sums up to unity. As an example, a fund following a momentum strategy might invest 60% of its assets in stocks belonging to the top momentum quintile ("winners") and 10% in each of the other four quintiles.

Furthermore, for each quintile sorted on a given characteristic, we also calculate the value of *other* lagged characteristics $X_2, X_3, X_4, \ldots$, for that quintile. As an example, say that stocks A and B are the only two stocks in the winner portfolio (top quintile) at time t. We then calculate the book-to-market of the winner portfolio at time $t-1$ by value-weighting the book-to-market characteristic of stocks A and B. We focus on the characteristics implied by the Fama and French (2015b) five factor model, to which we add momentum. Hence, in our momentum example, X_2 is size, X_3 book-to-market, X_4 profitability, X_5 investment, and X_6 is the CAPM-beta.

We then estimate, using the "winner" portfolio as our running example, the following panel regression:

$$\%Share_{i,q,t+1} = \beta_1 \times \beta_{q,t}^{CAPM} + \beta_2 \times BM_{q,t} + \beta_3 \times Prof_{q,t} + \beta_4 \times Inv_{q,t} + \beta_5 \times Size_{q,t} + \\ + \beta_6 \times IO_{i,t}^{401k} + controls + u_{i,t} \quad (3.11)$$

where $\%Share_{i,q,t+1}$ is the fraction invested by fund i in the quintile q at time $t+1$, and the time t predictors are the characteristics from the FF5 model ($BM_{q,t}, Prof_{q,t}$ and $Inv_{q,t}$ are the book-to-market value, profitability, and investment rate of the winner quintile, and $Size_{q,t}$ is the market capitalization of the stocks included in the winner quintile), and $IO_{i,t}^{401k}$ is our variable of interest representing the fraction of mutual fund i owned by 401(k) pension plans. We also control for fund characteristics, namely fund size and the lagged fraction

[37]We do not consider the universe of stocks from, for example, the CRSP dataset, since most funds will have zero holdings for many stocks within that set.

invested by fund i in the top quintile, and for fund family fixed effects.

In other words, our two hypotheses can be equivalently stated as

$$H_1 : \beta_6 > 0, \, ifq = \text{mom,high-beta,small}$$

$$H_2 : \beta_6 > 0, \, ifq = \text{long-duration}$$

We estimate the predictive regression (3.11) for portfolios sorted on (i) market-beta, one of the main characteristics the literature found to be important in fund managers' choices (Christoffersen and Simutin (2017) and Han, Roussanov, and Ruan (2022)), (ii) momentum, (iii) size, and (iv) duration (computed as in Gormsen and Lazarus (2022)). In each instance, we exclude the left hand-side characteristic from the right-hand side predictors, e.g., if the dependent top quintile is "low-beta stocks", we do not include the lagged beta of the portfolio as a predictor. Importantly, this regression specification has on the left hand side the fraction invested in the quintile (defined by a specific characteristic) and, thus, it allows to determine the *portfolio* demand rather than the average individual stock demand, as in a standard demand-based regression framework.

Table 3.8 reports the results for the top quintile portfolio (Column 1), bottom quintile portfolio (Column 2), and their difference (Column 3). The first row reports our coefficient of interest, $IO^{401k}_{i,t}$, while the second row shows the coefficient on the lagged value of the portfolio share (i.e., the autoregressive coefficient of the dependent variable). Standard errors are reported below the coefficient estimates.

If a characteristic predicts returns with a negative sign (like size), then the bottom quintile contains large value for the characteristic (large stocks); in this way, a tilt toward the top portfolio and away from bottom one always captures an expected positive alpha.

First, we confirm the results by Christoffersen and Simutin (2017) that fund managers with large 401(k) ownership tend to increase their exposure to high-beta stocks (Panel A). Interestingly, we also observe a large decrease in their exposure to low-beta stocks.[38] Panel B in Table 3.8 documents a tilt away from short-duration stocks and, to a lesser extent, toward

[38] This is not mechanical. The increase in portfolio weights for the bottom portfolio could have come from a reduction in the middle quintiles.

Table 3.8: Effect of 401(k) Ownership on the Types of Stocks Preferred by Funds.

This table reports results from regressions of the fraction of assets invested by mutual funds in a given portfolio in year $t+1$, $w^P_{i,t+1}$ for $P = High, Low, High - Low$, on the 401(k) plans ownership of fund i, $IO^{401k}_{i,t}$, controlling for lagged portfolio weights, $w^P_{i,t}$, as well as for the value-weighted characteristics of the portfolio, fund size at the end of year t, and fund family fixed effects. The portfolio characteristics are log market equity, log market-to-book, operating profitability, stock market beta, asset growth, and past 12-month returns, where we exclude the variable from the regressors when it is used as dependent variable. From left to right, the columns report the top and the bottom quintiles, and their differences. Standard errors are reported in brackets below the coefficients. Annual data from 2007 through 2020. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Beta

	High (Low Beta)	Low (High Beta)	High-Low
	(1)	(2)	(3)
$IO^{401k}_{i,t}$	-0.027***	0.015***	-0.031***
	(0.006)	(0.004)	(0.009)
weight$_t$	0.883***	0.872***	0.897***
	(0.020)	(0.016)	(0.015)

Panel B: Duration

	High (Short Duration)	Low (Long Duration)	High-Low
	(1)	(2)	(3)
$IO^{401k}_{i,t}$	-0.028***	0.008**	-0.023***
	(0.007)	(0.003)	(0.006)
weight$_t$	0.890***	0.863***	0.900***
	(0.009)	(0.011)	(0.009)

Panel C: Momentum

	High (Winner)	Low (Losers)	High-Low
	(1)	(2)	(3)
$IO^{401k}_{i,t}$	0.021**	-0.006	0.028**
	(0.010)	(0.006)	(0.014)
weight$_t$	0.869***	0.808***	0.859***
	(0.039)	(0.019)	(0.034)

Panel D: Size

	High (Small)	Low (Large)	High-Low
	(1)	(2)	(3)
$IO^{401k}_{i,t}$	0.002	-0.015**	0.014
	(0.005)	(0.007)	(0.008)
weight$_t$	0.930***	0.996***	1.000***
	(0.023)	(0.003)	(0.005)

long-duration stocks, while Panel C and D show that managers take more risk (alpha) by tilting toward winners and away from large stocks, respectively. The tilts toward the smallest stocks or away from losers are insignificant, however.

These facts are interesting for several reasons. First, the tilt of fund managers' toward high-beta and long-duration stocks, and away from low-beta and short-duration stocks, could sustain the well known betting-against-beta (Frazzini and Pedersen, 2014a) and duration anomalies (Weber, 2018b). Similarly, the behavior of funds managing a large fraction of 401(k) assets tilting away from large stocks is consistent with the observed diminishing size premium. Second, the evidence for size and momentum suggest that fund managers try to improve not only relative returns (by investing in stocks with higher market beta), but they also care about absolute returns and alphas by attempting to reap the unconditional premium associated with size and momentum.

A natural question is whether the portfolio tilts implemented by mutual funds with large 401(k) ownership result in performances that beat the benchmarks. To this end, we estimate the fund relative returns (e.g., the difference between the fund return and its Morningstar category benchmark) and CAPM alphas as a function of lagged 401(k) ownership and other lagged fund characteristics, and report the results in Table 3.9. Column (2) shows that higher 401(k) ownership forecasts better performance relative to a style benchmark: a one-standard-deviation increase in 401(k) ownership increases relative performance (e.g., return spread with respect to the benchmark) by 194bps per year. In contrast, column (4) shows that higher 401(k) ownership is not associated with larger future alphas. This can be due to two effects. On the one hand, it is possible that the tilt toward winners and away from large stocks (e.g., positive alphas) is countervailed by the tilt toward high-beta and long-duration (e.g., negative alphas). Alternatively, it is plausible that the size of the tilts is not large enough to generate significant changes in alpha. Overall, a higher 401(k) ownership forecasts improved relative returns without a significant change in alpha, a result that is new to the literature. Interestingly, if pension plans care about relative returns more than absolute ones, then the relative outperformance documented in column (2) of Table 3.9 should have a positive effect on pension flows, triggering a potential feedback reaction, whereby 401(k) plans continue to invest more in those funds that beat their benchmarks (i.e., with better

Table 3.9: Fund Performance and Fund-level 401(k) Ownership.

This table reports estimates of yearly panel regressions of measures of mutual fund performance on various lagged fund characteristics. Columns (1)-(2) report results using the fund relative return (e.g., the difference between the annual fund return and Morningstar category benchmark) as dependent variable, while columns (3)-(4) use the fund CAPM-alpha. Fund β is estimated from a monthly CAPM regression each year. Log fund size is the logarithm of the fund AUM. Expenses is net expense ratio, which is the total net expenses divided by the fund's average net assets. Turnover is a measure of the fund's trading activity, which is computed by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing by average monthly net assets. Amihud illiquidity is the value-weighted average of individual stock illiquidity based on the market value of stocks in the fund. Individual stock illiquidity is defined as the past 12-month average of its daily absolute return scaled by dollar volume. $IO^{401k}_{i,t}$ is the fraction of fund assets owned by 401(k) plans. Regressions include year and fund family fixed effect. t-statistics (standard errors clustered by fund) are presented in parentheses.

	Relative return$_{t+1}$		Market α_{t+1}	
	(1)	(2)	(3)	(4)
Fund β_t	1.918***	1.851**	-0.458***	-0.465***
	(2.755)	(2.497)	(-6.472)	(-5.976)
Log fund size$_t$	0.065	0.040	0.029***	0.030***
	(0.995)	(0.617)	(4.089)	(3.623)
Expenses$_t$	0.742**	0.798**	0.072**	0.074*
	(2.196)	(2.350)	(2.171)	(1.681)
Relative return$_t$	-0.014	-0.015	0.000	0.000
	(-0.621)	(-0.657)	(0.263)	(0.238)
Turnover$_t$	-0.223	-0.223	0.003	0.003
	(-1.595)	(-1.594)	(0.110)	(0.109)
Amihud illiquidity$_t$	0.052	0.057	0.001	0.001
	(1.156)	(1.218)	(0.231)	(0.283)
$IO^{401k}_{i,t}$		1.938***		0.095
		(3.000)		(0.984)

relative returns), which in turn happen to be those managing larger pension assets.[39]

3.5.2 Cash Holdings of Mutual Funds and 401(k) Assets

Do active funds managing more 401(k) assets perceive their investor base to be more stable? If this were the case, one would expect funds managing a larger fraction of 401(k) assets to keep lower cash levels. In this section, we test this hypothesis by estimating the following panel regression

$$Cash_{i,t} = \alpha + \beta_1 HighIO^{401k}_{i,t} + controls_{i,t} + \varepsilon_{i,t} \tag{3.12}$$

where $Cash_{i,t}$ is the amount of cash as a percentage of assets of mutual fund i at time t (Chernenko and Sunderam, 2020)[40], High $IO^{401k}_{i,t}$ is a dummy equal to one if the fund level $IO^{401k}_{i,t}$ is larger than the median of $IO^{401k}_{i,t}$ in the sample, and zero otherwise. We also include standard fund controls such as lagged log fund size, expense ratio, and turnover. We focus on mutual funds, since equity ETFs might have little discretion in choosing their cash holdings.

Table 3.10 reports the estimation results. Columns (1)-(2) report the results using a dummy variable for 401(k) ownership, while column (3) using the continuous fund-level 401(k) ownership variable $IO^{401k}_{i,t}$.

The coefficient on the dummy is around -0.32, suggesting that mutual funds managing substantial 401(k) assets have 32% less cash holdings compared to other mutual funds. Similarly, a one percent increase in 401(k) ownership at the fund level is associated with 1.24% less mutual fund cash holdings, controlling for standard fund-level characteristics such as fund size, expense ratio, and turnover.

Overall, these results confirm our hypothesis on the stability of 401(k) flows channel, highlighting the importance of 401(k) assets in shaping investment funds' allocation decisions.

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[39] Christoffersen and Simutin (2017) provide anecdotal evidence (from investment policy statements of DC plans) that a large majority of DC plans list relative returns as the main criterion for investment.

[40] Cash holding of a fund is the sum of portfolio weights (as a percentage) on cash and cash equivalents in Morningstar mutual fund holdings, where cash and cash equivalents are defined by Morningstar with detail type id as 'B','BC','BD','BQ','BT','C','CA','CD','CH','CL','CQ','CR','CU','FM', 'OO','OS','P','PC', and 'Q'.

Table 3.10: Mutual Funds Cash Holdings.

This table reports the estimates of the following fund-year panel regression:

$$Cash_{i,t} = \alpha + \beta_1 HighIO_{i,t}^{401k} + controls_{i,t} + \varepsilon_{i,t}$$

The dependent variable is mutual fund cash holdings at the end of year t, which is the sum of portfolio weights (as a percentage) on cash and cash equivalents in Morningstar mutual fund holdings. High $IO_{i,t}^{401k}$ is a dummy equal to one if the fund level $IO_{i,t}^{401k}$ is larger than the median of $IO_{i,t}^{401k}$ in the sample, and zero otherwise. Log fund size is the logarithm of the fund AUM. Expenses is net expense ratio (as a percentage), which is the total net expenses divided by the fund's average net assets. Turnover is a measure of the fund's trading activity, which is computed by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing by average monthly net assets. Column (3) reports the result using the stock-level 401(k) ownership variable $IO_{i,t}^{401k}$. Standard errors are double clustered by fund and year.

	(1)	(2)	(3)
High $IO_{i,t}^{401k}$ (dummy)	-0.322**	-0.322**	
	(-2.048)	(-2.495)	
$IO_{i,t}^{401k}$			-1.240**
			(-2.117)
Log fund size$_t$	-0.001	-0.012	-0.020
	(-0.039)	(-0.461)	(-0.450)
Expense$_t$	2.270***	2.303***	-0.263
	(7.252)	(5.143)	(-0.268)
Turnover$_t$	-0.367*	-0.376*	0.024
	(-1.804)	(-1.838)	(0.492)
Fund FEs	No	No	Yes
Year FEs	No	Yes	Yes

3.6 Conclusion

In this paper, we study the impact of 401(k) ownership on investors' demand for individual stocks. More precisely, we estimate a demand system linking 401(k) plans' ownership of both stocks and funds to the quantity and type of stocks demanded by funds. To this purpose, we introduce a new variable, stock-level 401(k) ownership, and find it to be a key determinant of investors' demand for equities.

We hypothesize that 401(k) allocations can affect stock demand in two ways. The first channel through which 401(k) plans can affect the demand of individual stocks is related to the size of stock-level 401(k) ownership. The fraction of an individual stock owned by 401(k) plans can be seen as an additional stock characteristic, similarly to book-to-market or momentum. We label this the *stock level* channel.

The second channel through which 401(k) allocations influence stock demand is by direct flows to mutual funds and ETFs which, in turn, use that additional liquidity to increment their equity exposure. We label this the *fund level* channel.

Focusing on the stock-level channel, we find that the amount of company shares owned by 401(k) plans is an important characteristic – in fact, the most important one after size – in explaining the demand of mutual funds and ETFs for a specific stock. For a one standard deviation increase in 401(k) stock ownership, the average active mutual fund demands approximately 18.6% more of the stock. The average active ETF also increases exposure to the stock by 11.5% for each standard deviation increase in 401(k) stock ownership. Most importantly, stock-level 401(k) ownership appears to be *distinct* from other forms of institutional investors, such as total mutual fund or largest (top 10) investors' ownership of a stock. After controlling for these alternative types of ownership, the magnitude of the coefficient on 401(k) ownership is barely affected, and so is its statistical significance. These results highlight the unique information content of stock-level 401(k) ownership for fund managers' decision.

We then explore the equilibrium price impact of a change in stock-level 401(k) ownership for the cross-section of stocks, over time. We estimate the institutional price pressure to be positive and increasing over our sample. We also compute the price impact for portfolios of stocks sorted on size, book-to-market, or beta (market risk), and find that the average price impact as a function of stock-level 401(k) has increased for large stocks, while it has remained relatively stable for small stocks. The positive trend of price impact, which increases almost monotonically between 2008 and 2020 is consistent with the shift from active to passive investing of the last decade documented in the literature (Koijen, Richmond, and Yogo, 2022). To further validate the direct impact of 401(k) ownership on individual stock, we employ a matching procedure based on high and low 401(k) ownership stocks with similar characteristics, and find that stocks with positive 401(k) ownership tend to earn 3%-5% higher annual returns than similar stocks, in terms of characteristics and investor structure, not owned by 401(k) plans.

We also study the impact 401(k) plans' *trading* has on individual stock returns using two different tests. Our first methodology exploits large changes in individual stocks holdings by aggregate 401(k) plans, and find that large changes in the holdings of an individual stock substantially affect its contemporaneous return. A large positive position taken by 401(k) plans in a stock generates a 12% higher return than that implied by an average 401(k) plan trade, followed by a partial return reversal over the next two years. Our second test relies on the granular instrumental variable of Gabaix and Koijen (2022), and finds that a 10% increase in the (instrumented) demand of 401(k) plans generates an average stock price increase of 3.6%, after controlling for standard firm-specific drivers of stock returns.

As far as the fund-level channel is concerned, we document that funds managing a larger fraction of 401(k) assets display greater demand for stocks. For a standard deviation increase in 401(k) fund ownership, the average active mutual fund demands approximately 33.3% more of the average stock, while the demand from ETFs is almost unchanged. To gain further insight on the relation between 401(k) assets and fund managers' portfolio allocations, we study how the investment strategies and performance of mutual funds are affected by the amount of 401(k) assets they manage. First, we analyze the 401(k) asset-induced fund demand for specific stock characteristics. We find that fund demand for stocks is heterogeneous, as a function of 401(k) fund-level ownership. Funds managing a larger fraction of 401(k) assets tilt their portfolios toward winners, high beta and long duration stocks, and away from large stocks. This fund behavior can reinforce the well known betting-against-beta (Frazzini and Pedersen, 2014a) and duration anomalies. Second, we study the relative and risk-adjusted performance of a fund as a function of 401(k) fund-level ownership. We find that a large fraction of pension assets managed by funds improves their performance in terms of relative returns, but leaves (statistically) unaffected the alpha. Related to this point, we also find that mutual funds managing a large fraction of 401(k) assets have approximately 32% smaller cash holdings than other funds.

Overall, our results suggest that pension assets are a key determinant of asset allocation decisions and stock demand of investors. The key novel contribution of this paper is to quantify such effects.

Appendices

3.A.1 Robustness

3.A.1.1 Coefficients on Other Characteristics

Figure 3.A.2 shows annual estimates of the coefficients on market-to-book and characteristics for mutual funds (blue dotted line) and ETFs (red solid line) for the demand system that includes fund-level 401(k) ownership (see equation (3.10)). The coefficient on fund-level 401(k) ownership is displayed in the left panel of Figure 3.4.

To validate our estimation, we also report the coefficient estimates for index (mutual and ETF) funds (c.f., 3.2). If the estimation of our characteristics-based demand system is valid, one should recover a unit coefficient on log market equity, and zero on the other characteristics for an hypothetical index fund. Albeit the coefficient on market equity (which can be obtained from the coefficient on log market-to-book equity and log book equity) is not exactly one, we still notice that index funds are inelastic, and substantially more so than active mutual funds and ETFs. Furthermore, the coefficient of index funds on other characteristics is close to zero, the sole exception being the dividend-to-book equity. Thus we confirm the validity of our characteristics-based demand estimation and of our criteria to categorize index funds.

We also observe that, with the sole exception of dividend-to-book, ETFs and mutual funds display very similar coefficients on other prominent characteristics like betas, profitability and investment. This makes even more striking the large difference on 401(k) ownership loadings between mutual funds and ETFs documented in Figure 3.4.

Figure 3.A.1 shows annual estimates of the coefficients on market-to-book and the other characteristics for the demand system that includes stock-level 401(k) ownership (see equation (3.4)). Comparing Figure 3.A.2 to Figure 3.A.1, we see that the coefficients are almost identical across the two specifications. In particular, demand elasticity is almost unaffected in terms of magnitude and time variation by the inclusion of stock-level and exclusion of fund-level ownership in the demand system. This is comforting because it suggests that the different behavior of ETFs toward fund- and stock-level ownership cannot be attributed to changes originating from different demand system specifications (namely equations (3.10) and (3.4)).

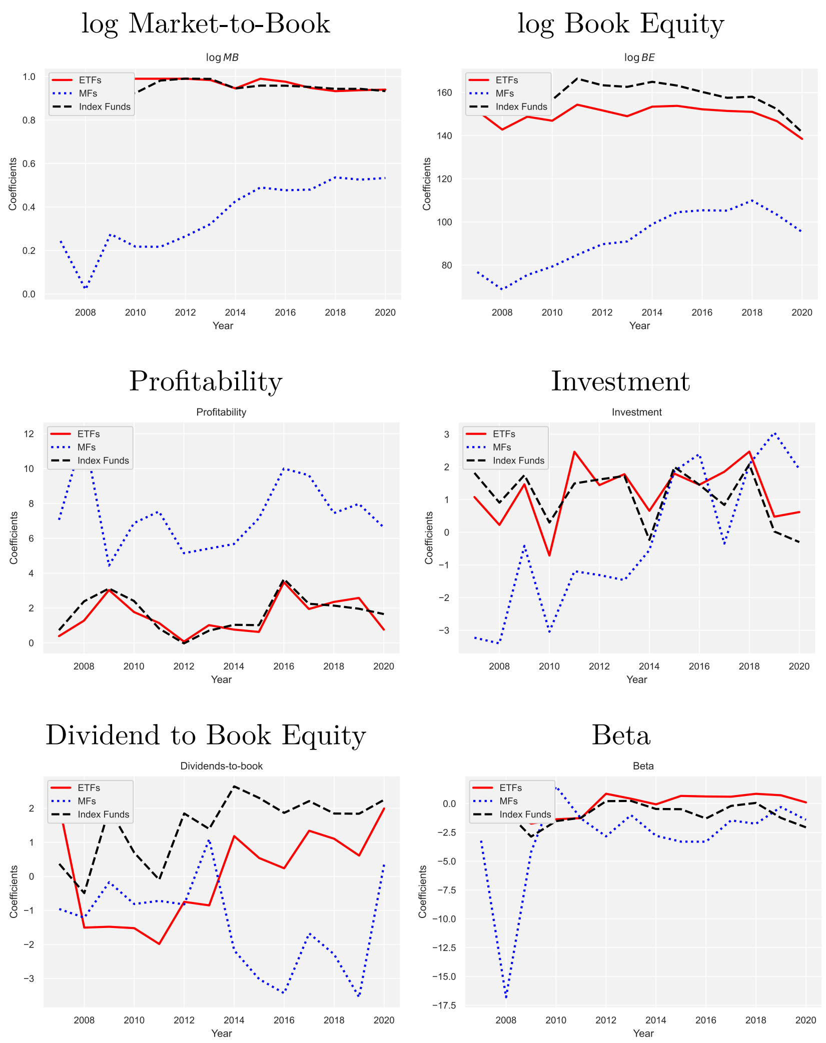

Figure 3.A.1: Coefficients on the Other Characteristics - Stock Level.
This figure shows the annual coefficients in (3.4), separately for mutual funds, ETFs, and index funds, estimated by pooled OLS using assets under management as weights. The regression is estimated year by year. Except for log market-to-book equity, we standardize characteristics (within each year) and multiply the coefficients by 100, so that they can be interpreted as the percentage change in demand per one standard deviation change in the characteristic. The sample period is from 2007 through 2020.

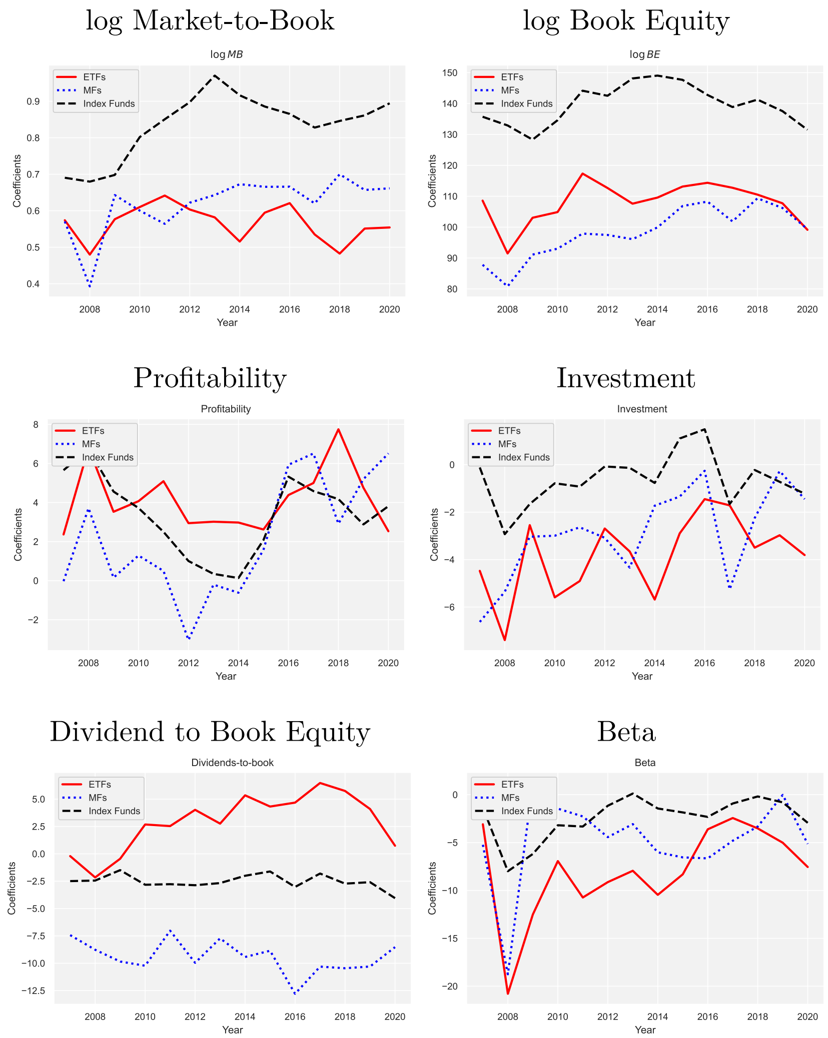

Figure 3.A.2: Coefficients on the Other Characteristics - Fund Level.
This figure shows the annual coefficients in (3.10), separately for mutual funds, ETFs, and index funds, estimated by pooled OLS using assets under management as weights. The regression is estimated year by year. Except for log market-to-book equity, we standardize characteristics (within each year) and multiply the coefficients by 100, so that they can be interpreted as the percentage change in demand per one standard deviation change in the characteristic. The sample period is from 2007 through 2020.

3.A.1.2 Robustness for stock-level $IO^{401k}_{i,t}(n)$ analysis

We repeat the analysis in Table 3.2 without weighting observation by AUM (see Table 3.A.1) or avoiding winsorization of fund TNA (Table 3.A.2). Across specifications, the coefficient on $IO^{401k}_{t}(n)$ is large and statistically significant. The coefficient is also not affected by the inclusion alternative ownership variables. For example, the coefficient is 0.109 without onwership controls and 0.097 when we include the mutual fund and top-10 ownership variables (columns (4) and (6) in Panel B of Table 3.A.1). Also, the coefficients for mutual funds and ETFs are 0.109 (t-stat=6.09) and 0.069 (t-stat=3.27), respectively, thus confirming a stronger effect for the former. For this result, however, the TNA winsorization matters. This is shown in Table 3.A.2 where – with no winsorization – the mutual funds and ETFs coefficients get closer in magnitude.

Table 3.A.1: Demand System Estimation: Stock Level $IO_t^{401k}(n)$, Observations not AUM-Weighted.

This table reports estimates of the panel regression

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO_{-i,t}^{401k}(n) + \alpha_{i,t} + \tilde{u}_{i,t}(n)$$

where $\widehat{mb}_t(n)$ is the instrumented market-to-book equity, and $\mathbf{X}_t(n)$ includes the same variables as in Koijen and Yogo (2019), i.e., log book equity, operating profitability, stock market beta, investment, and dividend-to-book ratio. $IO_{-i,t}^{401k}(n)$ is the 401K plans ownership of stock n (excluding the effect through investor i), and $\alpha_{i,t}$ are fund-by-time fixed effects. The funds in the regressions are not AUM-weighted. Panel A reports results for all funds owned by 401(k) plans, while Panel B employs only those not controlling 401(k) pension assets (hence, $IO_{-i,t}^{401k}(n) \equiv IO_t^{401k}(n)$). Columns (1)-(3) report results using all funds (including index mutual funds and ETFs), columns (4)-(6) using only active mutual funds, and columns (7)-(9) using only active ETFs. Variables are standardized to have unit-standard deviation. Standard errors are double clustered by fund and time. The sample period is from 2007 to 2020. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Mutual funds owned by pension plans									
	All Funds			**Mutual Funds**			**ETFs**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IO_{-i,t}^{401k}(n)$	0.116***	0.106***	0.099***	0.122***	0.117***	0.106***	0.082***	0.068***	0.066***
	(17.06)	(16.47)	(14.59)	(11.07)	(10.96)	(9.64)	(7.80)	(7.56)	(6.82)
Log market-to-book	0.580***	0.574***	0.576***	0.264***	0.254***	0.258***	0.784***	0.785***	0.786***
	(12.25)	(11.68)	(11.73)	(4.58)	(4.27)	(4.31)	(13.39)	(13.37)	(13.44)
Log book equity	1.117***	1.119***	1.121***	0.751***	0.745***	0.748***	1.326***	1.340***	1.341***
	(27.14)	(25.65)	(25.71)	(14.52)	(13.85)	(13.89)	(28.76)	(28.38)	(28.41)
Operating profitability	0.046***	0.048***	0.049***	0.066***	0.068***	0.069***	0.034***	0.036***	0.036***
	(8.03)	(7.87)	(7.91)	(8.6)	(7.9)	(7.97)	(3.73)	(3.85)	(3.85)
Beta	-0.014**	-0.018**	-0.017**	-0.031***	0.036***	-0.035**	0.006	0.002	0.002
	(-2.8)	(-2.72)	(-2.64)	(-3.56)	(-3.2)	(-3.13)	(1.41)	(0.51)	(0.58)
Investment	0.001	-0.002	-0.002	-0.006	0.010*	-0.010*	0.015**	0.012*	0.012*
	(0.33)	(-0.48)	(-0.52)	(-1.07)	(-1.85)	(-1.9)	(2.54)	(1.87)	(1.86)
Dividend-to-book	0.008	0.007	0.007	0.004	0.003	0.003	0.013	0.015	0.014
	(1.64)	(1.7)	(1.61)	(0.72)	(0.64)	(0.52)	(1.33)	(1.52)	(1.51)
Top10 ownership		0.023***	0.024***		0.003	0.004		0.037***	0.037***
		(3.85)	(3.79)		(0.52)	(0.53)		(4.17)	(4.14)
Mutual Fund ownership			0.016**			0.026***			0.006
			(2.8)			(3.66)			(1.01)
Panel B: Mutual funds not owned by pension plans									
	All Funds			**Mutual Funds**			**ETFs**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IO_{i,t}^{401k}(n)$	0.089***	0.077***	0.079***	0.109***	0.101***	0.097***	0.069***	0.057**	0.063**
	(6.02)	(5.98)	(6.14)	(6.09)	(6.08)	(5.96)	(3.27)	(2.86)	(2.99)
Log market-to-book	0.581***	0.582***	0.581***	0.485***	0.488***	0.488***	0.672***	0.670***	0.669***
	(14.26)	(13.42)	(13.4)	(13.53)	(13.36)	(13.34)	(10.45)	(9.67)	(9.66)
Log book equity	1.088***	1.097***	1.097***	0.914***	0.920***	0.920***	1.235***	1.249***	1.248***
	(17.54)	(16.85)	(16.85)	(14.97)	(14.50)	(14.46)	(14.60)	(13.99)	(14.00)
Operating profitability	0.011	0.011	0.011	0.006	0.005	0.005	0.017*	0.018	0.018
	(1.19)	(0.99)	(0.98)	(0.69)	(0.53)	(0.55)	(1.96)	(1.6)	(1.58)
Beta	-0.006	-0.006	-0.007	-0.023	-0.027	-0.027	0.008	0.011	0.010
	(-0.75)	(-0.67)	(-0.69)	(-1.65)	(-1.62)	(-1.63)	(1.23)	(1.76)	(1.68)
Investment	0.014***	0.014***	0.014***	0.012***	0.012***	0.012***	0.017***	0.016***	0.016***
	(5.19)	(4.54)	(4.51)	(3.87)	(3.87)	(3.68)	(4.76)	(3.8)	(3.91)
Dividend-to-book	0.454	0.483	0.480	-0.380	-0.484	-0.475	1.007**	1.155**	1.153**
	(1.56)	(1.49)	(1.49)	(-0.99)	(-1.22)	(-1.21)	(2.58)	(2.58)	(2.57)
Top10 ownership		0.024**	0.024**		0.012*	0.012*		0.029**	0.029**
		(3.06)	(3.01)		(2.19)	(2.16)		(2.87)	(2.81)
Mutual fund ownership			-0.005			0.008			-0.015*
			(-0.78)			(0.99)			(-2.16)

Table 3.A.2: Demand System Estimation: Stock Level $IO_t^{401k}(n)$ and no TNA Winsorization.

This table reports estimates of the panel regression

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO_{-i,t}^{401k}(n) + \alpha_{i,t} + \tilde{u}_{i,t}(n)$$

where $\widehat{mb}_t(n)$ is the instrumented market-to-book equity, and $\mathbf{X}_t(n)$ includes the same variables as in Koijen and Yogo (2019), i.e., log book equity, operating profitability, stock market beta, investment, and dividend-to-book ratio. $IO_{-i,t}^{401k}(n)$ is the 401K plans ownership of stock n (excluding the effect through investor i), and $\alpha_{i,t}$ are fund-by-time fixed effects. The funds in the regressions are AUM-weighted. Panel A reports results for all funds owned by 401(k) plans, while Panel B employs only those not controlling 401(k) pension assets (hence, $IO_{-i,t}^{401k}(n) \equiv IO_t^{401k}(n)$). Columns (1)-(3) report results using all funds (including index mutual funds and ETFs), columns (4)-(6) using only active mutual funds, and columns (7)-(9) using only active ETFs. Variables are standardized to have unit-standard deviation. Standard errors are double clustered by fund and time. The sample period is from 2007 to 2020. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Mutual funds owned by pension plans

	All Funds			**Mutual Funds**			**ETFs**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IO_{-i,t}^{401k}(n)$	0.133***	0.107***	0.096***	0.179***	0.140***	0.107***	0.116***	0.093***	0.088***
	(19.89)	(25.71)	(16.79)	(10.00)	(7.62)	(5.24)	(9.63)	(8.32)	(7.36)
Log market-to-book	0.939***	0.934***	0.939***	0.441***	0.429***	0.440***	0.961***	0.953***	0.955***
	(18.47)	(18.40)	(18.62)	(5.16)	(4.78)	(4.90)	(20.88)	(21.28)	(21.49)
Log book equity	1.572***	1.580***	1.583***	0.983***	0.994***	1.002***	1.518***	1.524***	1.525***
	(25.06)	(25.08)	(25.12)	(11.86)	(11.32)	(11.40)	(63.65)	(66.93)	(66.38)
Operating profitability	0.017**	0.018**	0.019**	0.065***	0.065***	0.068***	0.019**	0.022***	0.023***
	(2.92)	(2.90)	(2.97)	(4.01)	(4.29)	(4.46)	(2.73)	(3.57)	(3.55)
Beta	-0.003	-0.006	-0.004	-0.022**	-0.026**	-0.023*	0.002	-0.002	-0.001
	(-0.91)	(-1.52)	(-1.25)	(-2.41)	(-2.53)	(-2.23)	(0.30)	(-0.25)	(-0.15)
Investment	0.010**	0.009*	0.008*	0.000	-0.005	-0.005	0.010	0.006	0.006
	(2.95)	(1.86)	(1.81)	(-0.01)	(-0.33)	(-0.37)	(1.63)	(1.02)	(0.98)
Dividend-to-book	0.003	0.005	0.004	-0.024	-0.018	-0.019	0.006	0.007	0.007
	(0.60)	(1.20)	(0.99)	(-1.7)	(-1.27)	(-1.36)	(0.69)	(0.79)	(0.76)
Top10 ownership		0.054***	0.056***		0.075***	0.077***		0.049***	0.050***
		(6.54)	(5.93)		(3.68)	(3.46)		(5.21)	(4.79)
Mutual fund ownership			0.023**			0.074***			0.013
			(2.63)			(3.73)			(1.55)

Panel B: Mutual funds not owned by pension plans

	All Funds			**Mutual Funds**			**ETFs**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IO_{i,t}^{401k}(n)$	0.106***	0.085***	0.080**	0.099***	0.079**	0.063*	0.097***	0.074***	0.081***
	(4.75)	(3.53)	(3.11)	(3.65)	(2.53)	(1.78)	(4.82)	(4.23)	(4.69)
Log market-to-book	0.761***	0.765***	0.765***	0.719***	0.719***	0.718***	0.808***	0.811***	0.810***
	(18.7)	(18.33)	(18.31)	(14.47)	(13.91)	(14.23)	(10.64)	(10.12)	(10.13)
Log book equity	1.340***	1.354***	1.354***	1.262***	1.264***	1.263***	1.443***	1.462***	1.462***
	(21.70)	(20.65)	(20.60)	(17.64)	(17.10)	(17.43)	(17.85)	(17.21)	(17.22)
Operating profitability	0.007	0.006	0.006	0.001	-0.001	-0.001	0.023*	0.026	0.026
	(0.58)	(0.43)	(0.45)	(0.11)	(-0.14)	(-0.07)	(1.81)	(1.61)	(1.59)
Beta	-0.010	-0.011	-0.011	-0.022	-0.027*	-0.026*	0.009	0.012*	0.012
	(-1.17)	(-1.18)	(-1.15)	(-1.66)	(-1.83)	(-1.78)	(1.35)	(1.78)	(1.68)
Investment	0.018***	0.017**	0.017**	0.016*	0.016	0.016	0.017***	0.017***	0.017***
	(3.10)	(2.89)	(2.86)	(1.84)	(1.74)	(1.70)	(3.77)	(3.15)	(3.19)
Dividend-to-book	-0.868	-0.743	-0.727	-2.162*	-2.032*	-1.971*	0.996*	1.020*	1.003
	(-1.17)	(-1.01)	(-0.98)	(-2.10)	(-2.02)	(-1.91)	(1.95)	(1.80)	(1.77)
Top10 ownership		0.036***	0.036***		0.027*	0.026*		0.045***	0.044***
		(3.26)	(3.24)		(1.87)	(1.82)		(3.57)	(3.47)
Mutual fund ownership			0.011			0.037*			-0.015*
			(1.17)			(2.21)			(-1.92)

Table 3.A.3: Demand System Estimation: Lagged Stock Level $IO^{401k}_{t-1}(n)$.

This table reports estimates of the panel regression

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO^{401k}_{-i,t-1}(n) + \alpha_{i,t} + \tilde{u}_{i,t}(n)$$

where $\widehat{mb}_t(n)$ is the instrumented market-to-book equity, and $\mathbf{X}_t(n)$ includes the same variables as in Koijen and Yogo (2019), i.e., log book equity, operating profitability, stock market beta, investment, and dividend-to-book ratio. $IO^{401k}_{-i,t-1}(n)$ is the lagged 401K plans ownership of stock n (excluding the effect through investor i), and $\alpha_{i,t}$ are fund-by-time fixed effects. The funds in the regressions are AUM-weighted. Panel A reports results for all funds owned by 401(k) plans, while Panel B employs only those not controlling 401(k) pension assets (hence, $IO^{401k}_{-i,t}(n) \equiv IO^{401k}_{t}(n)$). Columns (1)-(3) report results using all funds (including index mutual funds and ETFs), columns (4)-(6) using only active mutual funds, and columns (7)-(9) using only active ETFs. Variables are standardized to have unit-standard deviation. Standard errors are triple clustered by fund, time and stock. The sample period is from 2007 to 2020. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Funds owned by 401(k) pension plans

	All Funds				Mutual Funds				ETFs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$IO^{401k}_{-i,t-1}(n)$	0.12***	0.10***	0.09***	0.08***	0.15***	0.12***	0.09***	0.11***	0.10***	0.07***	0.07***	0.06***
	(16.09)	(14.06)	(10.56)	(7.79)	(10.86)	(9.3)	(6.88)	(7.92)	(9.47)	(7.78)	(7.04)	(4.85)
Log market-to-book	0.83***	0.83***	0.84***	0.79***	0.43***	0.43**	0.44**	0.39***	0.98***	0.97***	0.97***	0.94***
	(12.84)	(13.41)	(13.67)	(12.36)	(4.67)	(4.55)	(4.75)	(4.33)	(20.57)	(21.18)	(21.4)	(19.43)
Log book equity	1.41***	1.43***	1.43***	1.4***	0.99***	1.01***	1.02***	0.98***	1.51***	1.52***	1.52***	1.5***
	(27.22)	(26.81)	(27.01)	(27.34)	(11.91)	(11.44)	(11.58)	(11.9)	(61.12)	(64.3)	(63.55)	(60.96)
Operating profitability	0.03*	0.03*	0.03*	0.03*	0.07**	0.07**	0.07**	0.08**	0.01	0.02	0.02	0.02
	(2.49)	(2.7)	(2.75)	(2.92)	(3.76)	(3.88)	(4.06)	(4.26)	(1.56)	(1.92)	(1.93)	(2.11)
Beta	-0.0	-0.01	-0.0	-0.01	-0.02*	-0.02*	-0.02	-0.03*	0.01	0.0	0.0	-0.0
	(-0.63)	(-0.73)	(-0.5)	(-1.34)	(-2.35)	(-2.34)	(-1.98)	(-3.02)	(0.62)	(0.44)	(0.51)	(-0.04)
Investment	0.01	0.0	0.0	0.0	0.0	0.0	0.0	-0.0	0.01	0.01	0.01	0.0
	(1.41)	(0.78)	(0.79)	(0.52)	(0.31)	(0.11)	(0.14)	(-0.16)	(1.47)	(0.83)	(0.83)	(0.74)
Dividend-to-book	-0.01	-0.0	-0.0	0.01	-0.02	-0.02	-0.02	-0.01	-0.0	0.0	0.0	0.01
	(-0.89)	(-0.34)	(-0.53)	(0.78)	(-1.93)	(-1.57)	(-1.89)	(-1.04)	(-0.29)	(0.25)	(0.2)	(1.14)
Top10 ownership		0.06***	0.06**			0.06**	0.06**			0.06**	0.06**	
		(4.86)	(4.64)			(3.85)	(3.43)			(4.02)	(3.98)	
Mutual Fund ownership			0.03*				0.08***				0.01	
			(2.97)				(5.11)				(1.2)	
DED				0.04				0.04				0.05
				(1.4)				(1.13)				(1.66)
QIX				0.08***				0.09***				0.08***
				(5.23)				(4.54)				(4.88)
TRA				0.05***				0.02				0.05***
				(5.46)				(1.37)				(5.3).

Panel B: Funds not owned by 401(k) pension plans

	All Funds				Mutual Funds				ETFs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$IO^{401k}_{t-1}(n)$	0.10***	0.09***	0.09***	0.07***	0.12***	0.11***	0.10***	0.09***	0.08***	0.06**	0.06**	0.04**
	(7.55)	(6.65)	(6.85)	(5.18)	(7.03)	(6.6)	(6.01)	(4.74)	(4.8)	(4.17)	(4.62)	(3.65)
Log market-to-book	0.7***	0.7***	0.7***	0.71***	0.64***	0.63***	0.63***	0.64***	0.78***	0.77***	0.77***	0.78***
	(15.46)	(14.84)	(14.81)	(15.58)	(14.67)	(15.4)	(15.46)	(14.85)	(9.75)	(9.23)	(9.21)	(9.83)
Log book equity	1.27***	1.28***	1.28***	1.29***	1.17***	1.15***	1.15***	1.18***	1.39***	1.4***	1.4***	1.39***
	(18.85)	(17.53)	(17.48)	(19.37)	(17.39)	(18.12)	(18.03)	(17.74)	(15.36)	(14.58)	(14.6)	(15.91)
Operating profitability	0.03	0.05	0.05	0.03	0.03	0.03	0.04	0.02	0.03	0.05	0.05	0.03
	(1.66)	(1.61)	(1.61)	(1.39)	(1.28)	(1.12)	(1.12)	(1.05)	(1.64)	(1.75)	(1.73)	(1.5)
Beta	-0.01	-0.01	-0.01	-0.01	-0.02	-0.03	-0.03	-0.02	0.01	0.01	0.01	0.01
	(-0.84)	(-0.79)	(-0.78)	(-1.0)	(-1.48)	(-1.62)	(-1.57)	(-1.61)	(1.23)	(1.64)	(1.53)	(1.17)
Investment	0.01	0.01	0.01	0.01	0.0	0.0	0.0	0.0	0.02	0.02	0.02	0.02*
	(1.72)	(1.53)	(1.5)	(2.06)	(0.36)	(0.24)	(0.19)	(0.67)	(2.17)	(2.02)	(2.04)	(2.35)
Dividend-to-book	-0.04	-0.04	-0.04	-0.04	-0.08**	-0.08*	-0.08**	-0.07*	-0.0	-0.01	-0.01	-0.0
	(-2.15)	(-2.1)	(-2.1)	(-1.86)	(-3.23)	(-3.24)	(-3.25)	(-2.72)	(-0.12)	(-0.67)	(-0.64)	(-0.3)
Top10 ownership		0.03*	0.03*			0.02	0.01			0.04**	0.04**	
		(2.56)	(2.54)			(1.3)	(1.15)			(3.35)	(3.36)	
Mutual Fund ownership			0.01				0.03*				-0.02*	
			(0.75)				(2.71)				(-2.37)	
DED				-0.01				-0.02				0.01
				(-0.45)				(-1.02)				(0.6)
QIX				0.07**				0.06*				0.07***
				(3.62)				(2.85)				(4.48)
TRA				0.06***				0.06*				0.06***
				(4.61)				(2.91)				(4.77)

3.A.1.3 Exogeneity of fund-level $IO_{i,t}^{401k}$

In this section, we conduct robustness tests to diffuse endogeneity concerns related to the fund-level 401(k) ownership variable $IO_{i,t}^{401k}$.

Equation (3.1) is estimated at the *stock* level, i.e., the individual stock demand by funds as a function of stock characteristics. Hence, perhaps, our $IO_{i,t}^{401k}$ variable could be endogeneous if other *stock-specific characteristics* affecting the behavior of mutual fund managers, other than those explicitly used as regressors in our model, are correlated with our variable. We believe that the fraction of a fund owned by 401(k) plans (e.g., our fund-level $IO_{i,t}^{401k}$ variable) is likely orthogonal to any other stock-specific characteristic not explicitly controlled for in the model (e.g., the regressors used in the Koijen and Yogo (2019) framework). As an example, the number of employees of Exxon Mobil is arguably orthogonal to the amount of money CalPers decides to invest in any BlackRock mutual fund.

However, there could be *fund-specific* characteristics correlated with the 401(k) ownership of a fund. For example, 401(k) plans might prefer to invest in larger mutual funds or ETFs. Among many potential fund-specific characteristics, 401(k) pension plans are likely selecting funds based on the following fund characteristics (Christoffersen and Simutin (2017): the fund strategy or style (e.g., "growth"), the investment manager (e.g., Blackrock), and the size of the fund. Table 3.A.5 presents our main results of Table 3.7, controlling for these additional fund-specific variables: fund size, fund style, and fund family fixed effects.[41] We confirm that the 401(k) fund ownership remains economically relevant, with the coefficient hovering above 0.2, and statistically significant in any of the specifications, suggesting that our $IO_{i,t}^{401k}$ variable is likely exogeneous. Our results are also robust to adding lagged portfolio weights to the regressions, although such specification it is not justified by the demand system framework.

Lastly, we run an additional econometric test aimed at diffusing any remaining concerns. First, we estimate our original model (3.1) *without* our 401(k) fund-level variable. This is the same exact original specification in Koijen and Yogo (2019). We save the residuals $\widehat{\varepsilon}_{i,t}$ from this estimation. Next, we regress our fund-level 401(k) variable $IO_{i,t}^{401k}$ on $\widehat{\varepsilon}_{i,t}$, and save the new residuals $\widehat{\eta}_{i,t}$ from this second regressions.

[41] The *fund style* and *fund family* variables are from Morningstar.

Table 3.A.4: Demand System Estimation: Fund Level $IO_{i,t}^{401k}$, Observations not AUM-Weighted.

This table reports estimates of the panel regression

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO_{i,t}^{401k} + \alpha_t + \tilde{u}_{i,t}(n)$$

where $\widehat{mb}_t(n)$ is the instrumented log market equity-to-book equity, and $\mathbf{X}_t(n)$ includes the same variables as in Koijen and Yogo (2019), i.e., log book equity, operating profitability, stock market beta, investment, and dividend-to-book ratio. $IO_{i,t}^{401k}$ is the 401K plans ownership of fund i, and α_t are time fixed effects. The funds in the regressions are not AUM-weighted. Columns (1)-(3) report results using all funds (including index mutual funds and ETFs), columns (4)-(6) using only active mutual funds, and columns (7)-(9) using only active ETFs. Variables are standardized to have unit-standard deviation. Standard errors are double clustered by fund and time. The sample period is from 2007 to 2020. *p<0.1; **p<0.05; ***p<0.01.

	All Funds			**Mutual Funds**			**ETFs**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IO_{i,t}^{401k}$	0.168***	0.167***	0.165***	0.240***	0.232***	0.228***	-0.060	-0.054	-0.053
	(3.38)	(3.31)	(3.28)	(4.29)	(4.1)	(4.06)	(-1.1)	(-1.01)	(-1.02)
Log market-to-book	0.457***	0.444***	0.452***	0.513***	0.490***	0.492***	0.416***	0.422***	0.431***
	(7.83)	(7.66)	(7.84)	(9.08)	(8.9)	(8.98)	(4.36)	(4.53)	(4.67)
Log book equity	0.949***	0.974***	0.995***	0.810***	0.834***	0.851***	0.961***	0.985***	0.999***
	(19.56)	(18.86)	(19.27)	(13.27)	(12.81)	(12.93)	(12.01)	(11.98)	(12.2)
Operating profitability	0.074***	0.083***	0.089***	0.033***	0.042***	0.049***	0.067***	0.069***	0.072***
	(8.87)	(9.21)	(9.73)	(3.6)	(4.41)	(5.32)	(4.13)	(4.00)	(4.15)
Beta	-0.064***	-0.075***	-0.067***	-0.053***	-0.061***	-0.054***	-0.070***	-0.079***	-0.074***
	(-5.69)	(-5.4)	(-4.88)	(-4.19)	(-4.05)	(-3.73)	(-3.84)	(-4.14)	(-3.87)
Investment	-0.067***	-0.076***	-0.077***	-0.061***	-0.070***	-0.070***	-0.038**	-0.044***	-0.044***
	(-6.6)	(-8.15)	(-8.34)	(-6.38)	(-8.6)	(-8.78)	(-3.02)	(-3.41)	(-3.48)
Dividend-to-book	-0.059***	-0.052***	-0.046***	-0.090***	-0.081***	-0.075***	0.007	0.011	0.013
	(-5.3)	(-4.94)	(-4.46)	(-8.56)	(-8.49)	(-7.87)	(0.34)	(0.53)	(0.64)
Top10 ownership		0.073***	0.056***		0.078***	0.059***		0.051**	0.043**
		(5.26)	(3.71)		(6.05)	(4.08)		(2.81)	(2.38)
Mutual Fund ownership			0.141***			0.124***			0.082***
			(11.68)			(10.54)			(5.71)

By construction, $\widehat{\eta}_{i,t}$ is the component of fund-level 401(k) ownership $IO_{i,t}^{401k}$ that is orthogonal to $\widehat{\varepsilon}_{i,t}$, e.g., the residual from the original model. In other words, it is exogeneous by construction. Lastly, we re-estimate (3.1) using $\widehat{\eta}_{i,t}$ (instead of $IO_{i,t}^{401k}$) as regressor. The coefficient on $\widehat{\eta}_{i,t}$ is 0.232 (t-stat: 2.03), which is very similar to the one on $IO_{i,t}^{401k}$ (0.169, t-stat: 2.39), highlighting that our fund-level 401(k) ownership variable $IO_{i,t}^{401k}$ is likely exogeneous.

Table 3.A.5: Robustness for Fund Level $IO^{401k}_{i,t}$.

This table reports estimates of the panel regression

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO^{401k}_{i,t} + Fundsize_{i,t} + \alpha_t + \tilde{u}_{i,t}(n)$$

where $\widehat{mb}_t(n)$ is the instrumented log market equity-to-book equity, and $\mathbf{X}_t(n)$ includes the same variables as in Koijen and Yogo (2019), i.e., log book equity, operating profitability, stock market beta, investment, and dividend-to-book ratio. $IO^{401k}_{i,t}$ is the 401K plans ownership of fund i, and α_t are time (year) fixed effects. We include additional fund-level controls to rule out potential endogeneity concerns. $Fundsize_{i,t}$ is the log value of a fund's assets under management. Column (1) reports results with time fixed effects, while column (2) reports results with time fixed effects and fund family fixed effects. Column (3) also includes fund style fixed effects. The funds in the regressions are AUM-weighted. The sample period is from 2007 to 2020. *p<0.1; **p<0.05; ***p<0.01.

	(1)	(2)	(3)
$IO^{401k}_{i,t}$	0.23***	0.26***	0.18**
	(3.42)	(3.29)	(2.33)
Log market-to-book	0.75***	0.70***	0.64***
	(7.89)	(6.87)	(6.25)
Log book equity	1.27***	1.21***	1.18***
	(15.29)	(13.32)	(13.59)
Operating Profitability	0.03**	0.04**	0.05***
	(2.66)	(2.84)	(4.09)
Beta	-0.03**	-0.03**	-0.03**
	(-2.87)	(-2.60)	(-2.83)
Investment	-0.01	-0.01	-0.01
	(-1.07)	(-1.20)	(-0.74)
Dividend-to-book	-0.04**	-0.04***	-0.02
	(-2.96)	(-3.01)	(-1.59)
Fund size	-0.40***	-0.30***	-0.22***
	(-5.87)	(-4.24)	(-3.72)
Time fixed effect	Yes	Yes	Yes
Fund family fixed effect	No	Yes	Yes
Fund style effect	No	No	Yes

3.A.2 Holdings Data: Additional Analysis and Robustness

3.A.2.1 Thomson Reuters s34 Holdings

The analysis in 3.4 relies on data from Morningstar, which provides detailed holdings of *individual* mutual funds and ETFs. Instead, the analysis in 3.4.1 relies on the Thomson Reuters' s34 file, which provides aggregated holdings of *all funds* under the manager's control (Koijen and Yogo (2019), Koijen, Richmond, and Yogo (2022)).

Table 3.A.1 repeats the same analysis presented in Table 3.2 but at the fund family level, i.e., using the s34 data. Importantly, the coefficient on stock-level ownership remains large and significant. In particular, we find that the coefficient of .218 is close in magnitude to the one reported in column (4) of Table 3.2, despite the fact that s34 fund-family holdings blend together ETFs and mutual funds.

Table 3.A.1: Demand System Estimation: Stock Level $IO_t^{401k}(n)$ with S34 Holdings.

This table reports estimates of the panel regression

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = b_0 + \beta_{0,i}\widehat{mb}_t(n) + \boldsymbol{\beta_1'}\mathbf{X}_t(n) + \beta_2 IO_t^{401k}(n) + \alpha_{i,t} + \tilde{u}_{i,t}(n)$$

where $\widehat{mb}_t(n)$ is the instrumented market-to-book equity, and $\mathbf{X}_t(n)$ includes the same variables as in Koijen and Yogo (2019), e.g., , log book equity, operating profitability, stock market beta, investment, and dividend-to-book ratio. $IO_t^{401k}(n)$ is the 401K plans ownership of stock n, and $\alpha_{i,t}$ are manager-by-year fixed effects. The mutual fund institutions in the regressions are AUM-weighted. Variables are standardized. Standard errors are double clustered by fund institution and time. The sample period is from 2007 to 2020. *p<0.1; **p<0.05; ***p<0.01.

Thomson Reuters (s34) holdings			
	Coefficient	s.e.	t-stat
$IO_t^{401k}(n)$	0.218***	0.037	5.830
Log market-to-book	1.514***	0.162	9.350
Log book equity	1.893***	0.067	28.300
Operating profitability	0.006	0.007	0.830
Beta	0.056*	0.030	1.840
Investment	0.036*	0.020	1.810
Dividend-to-book	-0.135***	0.031	-4.300

The coefficients on the other characteristics, e.g., beta, investment, and dividend-to-book are small in both datasets. Overall, it appears that the empirical results using the s34 dataset are in line with those reported in 3.4 and, thus, the analysis in 3.4.1 is informative of the equilibrium price impact of a change in 401(k) stock-level ownerhship.

3.A.2.2 Holdings scraped directly from 13F filings

In this section, we repeat our computation of the equilibrium price impact presented in 3.4.1 using the 13F filings data provided by Backus, Conlon, and Sinkinson (2021). These authors collected 13F filings from the SEC's EDGAR database since electronic filing was made mandatory in 1999, and addressed gaps in coverage and errors that appear in commercial datasets of institutional holdings (e.g., Thomson Reuters). The disadvantage of such dataset is that we cannot anymore exploit the Koijen and Yogo (2019) classification of institutions into six types. Thus, in the estimation, we abstract from investor types and (1) keep institutions with more than 1,000 strictly positive holdings separate; (2) group institutions with fewer than 1,000 holdings based on TNA, so that each group has on average 2,000 holdings.

Figure 3.A.1 is the counterpart of Figure 3.5. Importantly, both the coefficient governing the elasticity of demand, and the coefficient on 401(k) stock-level ownership display a similar range in terms of magnitude across the two datasets. It is therefore not surprising that the cross-sectional distribution of aggregate price impact across stocks reported in the top left panel of Figure 3.A.2 remains economically sizable: a one standard deviation increase in 401(k) ownership, around 1.3% in 2007 and 1.6% in 2016, leads to a price impact (for the median stock) slightly less than 40 percent in 2007 and about 90 percent in 2016. Similarly to the s34 dataset, we observe a stronger price impact for large stocks (bottom right panel), with a sharp increase in 2015, and little difference for stocks sorted on market betas (bottom left panel). The main difference across the two datasets is observed for stocks sorted on book-to-market. In particular, the scraped data of Backus, Conlon, and Sinkinson (2021) suggest a larger impact for growth stocks.

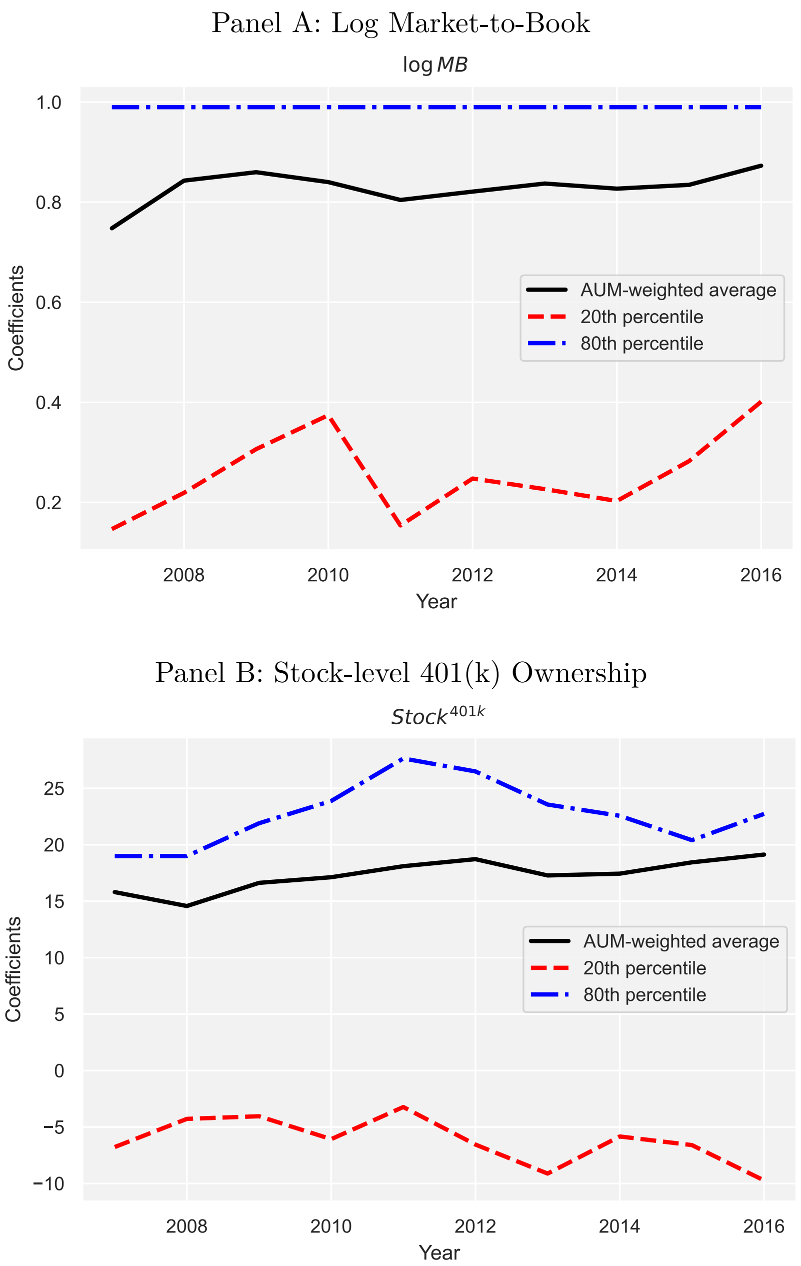

Figure 3.A.1: Price Impact: Relevant Coefficients.

This figure shows the annual coefficient on log market-to-book (top panel) and stock-level 401(k) ownership (bottom panel) for financial institutions in Backus, Conlon, and Sinkinson (2021), estimated annually, by GMM with zero weights. Variables are standardized (within each year) to make coefficients comparable. We report the cross-sectional mean of the estimated coefficients by institutions, weighted by assets under management. The coefficient on 401(k) ownership is multiplied by 100. The sample period is from 2007 through 2016.

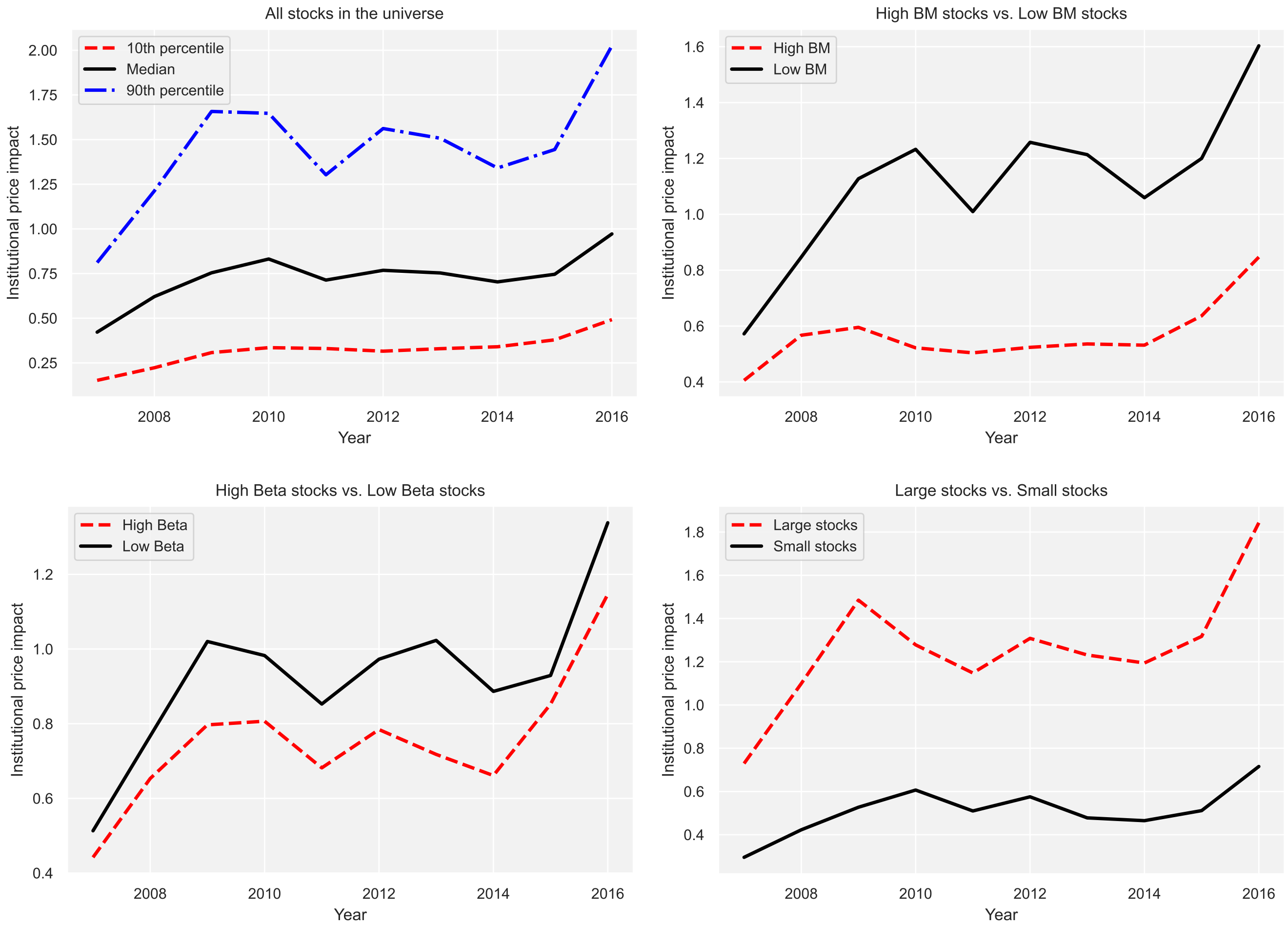

Figure 3.A.2: Institutional Price Impact.
This figure shows the price impact of a change in the stock-level 401(k) ownership estimated through the diagonal elements of the matrix M defined in (3.6) using holdings data from Backus, Conlon, and Sinkinson (2021). The top left panel shows the 10th percentile, median and 90th percentile of price impact across all stocks. The remaining panels plot the average price impact across the stocks in the top quintile and bottom quintile of portfolios sorted on (top right), beta (bottom left), and size (bottom right), using NYSE break points as cutoffs.

3.A.3 Data Cleaning Procedure

3.A.3.1 BrightScope and Morningstar (MS)

1. We match funds held in 401(k) plans with Morningstar holdings.

2. We remove mutual funds whose portfolio weights as reported by Morningstar are different from the correct portfolio weights calculated using holdings values and total net assets, as in Pástor, Stambaugh, and Taylor (2015).

3. We merge fund characteristics (e.g., fund TNA) from Morningstar with the dollar allocation of 401(k) plans to funds from BrightScope. We then calculate our $IO_{i,t}^{401k}$ variable, a fund's 401(k) ownership. We drop funds where $IO_{i,t}^{401k} < 0$ or $IO_{i,t}^{401k} > 1$.

4. Our analysis focuses on equities, hence we only keep equity mutual funds having an equity ratio ≥ 0.75.

5. We merge fund holdings with firm data from CRSP and COMPUSTAT, replacing missing dividends as zero.

6. We drop fund-stock observations with missing characteristics.

7. We define the investment universe for each fund as described in the paper. We only keep funds with clearly defined investment universes (e.g., the number of stocks in the investment universe is greater than zero)

8. We drop funds holding fewer stocks than the fifth percentile in the cross-section of funds, every year (approx. 15 stocks).

9. As in Koijen and Yogo (2019), each year, we winsorize profitability, investment, and market beta at the 2.5th and 97.5th percentiles to reduce the impact of outliers. Since dividends are positive, we winsorize dividends to book equity at the 97.5th percentile. We also winsorize log(book equity) at the 2.5th and 97.5th percentiles.

10. We winsorize funds' total net assets (TNA) at the 97.5th percentile, every year, to deal with outliers.

11. In the GMM estimation, we keep zero-weight holdings, e.g., stocks in a fund's investment universe, but currently not being held by the fund. Zero-weight holdings must have non-missing characteristics.

Estimation

- In the pooled regressions, we implement 2SLS with instrumented log market-to-book, and use fund TNA as weights.
- For GMM, we include zero holdings of a stock, and use fund TNA as weights.
- As in Koijen, Richmond, and Yogo (2022), we impose the economic constraint log(MB) < 1 in all the estimations.
- The price impact analysis is based on yearly GMM estimations.

3.A.3.2 Thomson Reuters s34 Holdings

1. We use the same institutional types as in Koijen and Yogo (2019).
2. We merge the s34 holdings data with CRSP and COMPUSTAT.
3. We define the investment universe for each institution.
4. In the GMM estimation of price impact, we pool institutions into groups by type and TNA as in Koijen and Yogo (2019), include holdings with zero weights (e.g., belonging to the investor's investment universe, but not currently owned), and calculate the instrument based on these pooled groups.

3.A.3.3 Scraped Holdings from 13F Filings

1. We follow Backus, Conlon, and Sinkinson (2021), and use their 13F scraped holdings between 2007 and 2016.
2. We merge these holdings with CRSP and COMPUSTAT, and define the investment universe for each institution.

3. We drop institutions holdings less than 100 stocks at any given time, and pool institutions into groups by TNA as in Haddad, Huebner, and Loualiche (2022). We then calculate the instrument based on these pooled groups.

4. We estimate the price impact via GMM, including holdings with zero weights (e.g., belonging to the investor's investment universe, but not currently owned).

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