Monetary Policy and Anomalies

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November 18, 2025

Abstract: We show that long-short anomaly portfolios exhibit significantly negative returns on monetary policy announcement days, in contrast to positive returns on other days. This effect is persistent and especially pronounced during periods of accommodative monetary policy. To quantitatively account for these findings, we develop a model in which monetary policy announcements reveal the Fed's interest rate target, generating discount rate shocks. Heterogeneity in the sensitivity of stock valuations to these shocks gives rise to cross-sectional differences in announcement-day risk compensation. This sensitivity depends endogenously on anomaly signals: overpriced stocks have longer duration, are more exposed to interest rate risk, and therefore require higher expected returns than underpriced stocks. Lower interest rate environments reinforce this mechanism by increasing valuation sensitivity, leading to more negative anomaly portfolio returns.

Keywords: Anomalies, Monetary Policy, FOMC Announcements, Earnings Announcements, Subjective Expectations.

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1 Introduction

The literature on the cross-section of expected returns has identified a large number of firm characteristics that predict stock returns above and beyond the CAPM or standard factor models. These anomalies are typically interpreted either as reflecting differences between investors' and econometricians' information sets or as compensation for missing risk factors in asset-pricing models. At the same time, the cross-section of expected returns is very well explained by the CAPM on FOMC announcement days (Savor and Wilson, 2014), a fact often interpreted as implying that mispricing relative to the CAPM is negligible on those days.[1]

In this paper, we challenge this view by showing that the impact of anomaly signals on the level of asset prices is amplified on FOMC announcement days. Empirically, portfolios that appear overpriced relative to the CAPM experience significantly higher price appreciation on FOMC days than underpriced portfolios, and this difference in announcement returns cannot be fully explained by the CAPM. We present empirical evidence and a theoretical model showing that anomaly-related return patterns arise from differences between investors' subjective beliefs about future cash flows and the econometrician's benchmark, and that FOMC announcements amplify these effects through risk compensation.

To study the implications of monetary policy announcements for the cross-section of expected returns, we construct sorted portfolios based on a broad set of return-predictability factors, or anomaly signals. Using a composite of 171 anomaly signals, we show that long-short portfolios earn –38 bps on monetary policy announcement days, compared with +4 bps on other days—a statistically significant difference of 42 bps.[2] Both the long and short legs of the portfolio earn higher risk premia on announcement days, but short-leg stocks are more sensitive to monetary policy shocks and earn even higher average returns. The effect remains significant after controlling for both unconditional and FOMC-specific market betas: the return difference declines to –18 bps but still economically and statistically significant. Adjusting for additional risk factors such as size, value, and momentum has limited impact on the long-short returns. Overall, monetary policy announcements exert a substantial

[1] For expositional convenience, throughout the paper we use the terminology *mispricing* to refer to any deviation of the market valuation from the fundamental value under full-information rational expectations. Stocks on the long leg are underpriced—exhibiting higher average future returns—while stocks on the short leg are overpriced with lower average returns.

[2] These results hold across various anomaly sets documented in the literature, including Dong, Li, Rapach, and Zhou (2022), Engelberg, McLean, and Pontiff (2018), Daniel, Hirshleifer, and Sun (2020), Novy-Marx and Velikov (2016), Stambaugh and Yuan (2017), Jensen, Kelly, and Pedersen (2023) and Hou, Xue, and Zhang (2020), although the magnitude varies slightly depending on how the composite is constructed.

influence on cross-sectional, risk-adjusted returns.

We present several pieces of empirical evidence that support a risk-based explanation for the amplification effect of FOMC announcements on pricing anomalies. First, we find that the pricing effect of FOMC announcements is especially strong during periods of accommodative monetary policy. Specifically, a 100 bps decline in the real interest rate level is associated with an additional 17.1 bps drop in anomaly portfolio returns. This result remains robust after controlling for market beta and its interaction with interest rates.

Second, beyond high average announcement-day returns, we study how anomaly portfolios respond to realized monetary policy surprises. Using the Bernanke and Kuttner (2005) approach, we regress anomaly-sorted portfolio returns on monetary policy surprise constructed by Bauer and Swanson (2023). The estimated betas are significantly negative and decline monotonically across deciles: returns fall after contractionary and rise after expansionary surprises, with overpriced portfolios more sensitive than underpriced ones. In addition, we provide show our anomaly signal indeed captures subjective cash flow expectations and differences in equity duration. Anomaly portfolio characteristics are monotone in long-term earnings growth (LTG) forecasts (Bordalo, Gennaioli, Porta, and Shleifer (2019, 2024)) and in equity duration measures from Gonçalves (2021) and Dechow, Sloan, and Soliman (2004): more overpriced stocks have higher LTG forecasts and longer durations.

Third, we demonstrate that the impact of monetary policy is highly persistent and long-lasting. First, there is no significant reversal one day, one week, or two weeks following FOMC announcements relative to non-FOMC days. Second, when we examine returns around the sorting month—when the anomaly signal is first identified by econometricians and becomes publicly observed—we find that about 40% of the subsequent year's returns reflect the correction of mispricing amplified by just eight FOMC announcements. Looking backward, these same eight announcements account for almost all of the mispricing built up over the prior year. Taken together, about 90% of non-FOMC returns over a two-year window can be attributed to the gradual unwinding of mispricing amplified by only sixteen FOMC announcements.

To quantitatively explain these findings, we develop an equilibrium model in which FOMC announcements periodically reveal the Fed's interest rate target, generating discount rate shocks. Following Ai and Bansal (2018), we assume that the stochastic discount factor (SDF) depends on interest rate shocks, which become more volatile on announcement days. A positive interest rate surprise raises the interest rate and increases the investor's marginal utility, which lowers asset valuations and leads to negative returns. The reverse holds for neg-

ative surprises. Regardless of the sign of the monetary surprise, because these shocks induce a negative covariance between returns and the SDF, they require positive announcement-day risk compensation. As a result, all stocks earn a positive announcement-day risk premium.

We show that firms differ in their sensitivity to interest rate shocks—i.e., their equity duration—and that this sensitivity depends on anomaly signals. Consequently, our model generates cross-sectional return differences across anomaly portfolios on monetary policy announcement days.

To illustrate the model's mechanism, consider a simple setting in which firm-specific dividend growth g is unobservable and i.i.d. over time. Let $\tilde{g}$ denote the best estimate based on all available public information—that is, the objective belief under rational expectations—and let $\hat{g}$ represent the marginal investor's subjective expectation, which determines the market price through the Gordon growth formula: $P/D = 1/(r - \hat{g})$. We allow $\hat{g}$ to deviate temporarily from $\tilde{g}$, generating mispricing: an overestimated $\hat{g}$ implies a higher stock valuation, while an underestimated $\hat{g}$ implies a lower valuation. Under this interpretation, stocks with $\hat{g} > \tilde{g}$ are overpriced and form the short leg of the anomaly portfolio, whereas those with $\hat{g} < \tilde{g}$ are underpriced and form the long leg. As subjective expectations gradually mean-revert toward their rational benchmark in the long run, the long-short portfolio earns positive returns on non-announcement days.

Over short FOMC announcement windows, interest rate shocks are the only priced risk. Accordingly, the sensitivity of stock valuation to interest rate changes, i.e., the stock's duration, determines the equity risk premium. In this setup, duration is given by $\left|\frac{d(P/D)}{dr}\right| = \frac{1}{(r-\hat{g})^2}$. Holding other factors constant, overpriced stocks in the short leg tend to have higher $\hat{g}$, and thus longer duration and greater sensitivity to interest rate shocks. In equilibrium, these stocks earn higher risk premia on FOMC days. Conversely, underpriced stocks in the long leg have lower duration, are less sensitive to monetary policy surprises, and therefore earn lower announcement premia. As a result, long-short anomaly portfolios earn negative returns on monetary policy announcement days. In other words, monetary policy amplifies rather than corrects existing mispricing—cross-sectional valuation gaps widen on FOMC announcement days.

The effect is further amplified under expansionary monetary policy regimes. When levels of interest rates are low, the discount rate r is small, which increases duration of overpriced stocks and makes them even more sensitive to monetary policy shocks.

We calibrate the model to match standard asset pricing moments and show that it reproduces several key empirical features of anomaly portfolio returns. Specifically, the model

generates an average FOMC announcement-day excess market return of 41 bps, and the spread in long-short portfolio returns sorted by belief distortions about firm cash flows is about –27 bps on announcement days, compared with +2 bps on other days. Both values closely match their empirical counterparts. Moreover, the model produces a more negative announcement-day long-short portfolio spread in low interest rate regimes, consistent with the data.

Our key empirical evidence concerns the amplification of anomalies, not their existence or initial formation. The existence of anomalies can reflect either missing risk factors or deviations in investors' beliefs from those of econometricians. We provide several pieces of evidence that point to subjective expectations as an important driver of anomaly formation.

First, we show that monetary policy amplifies mispricing, whereas earnings announcements help correct it. Earnings announcements provide news about true firm cash flows, causing $\hat{g}$ to jump toward $\tilde{g}$. Underpriced (long-leg) stocks experience positive revisions, while overpriced (short-leg) stocks experience negative revisions, pushing prices on the long leg up and on the short leg down. As a result, long-short anomaly portfolios earn significantly higher returns on earnings announcement days, as in Engelberg, McLean, and Pontiff (2018). We classify each stock based on whether its FOMC-day return is consistent with its anomaly signal ranking. A stock is considered *consistent* if its FOMC announcement return aligns with the anomaly signal ranking—for example, a long-leg stock with a below-median FOMC return, or a short-leg stock with an above-median return. Inconsistent stocks move in the opposite direction. We find that consistent stocks earn more than twice the earnings-announcement return of inconsistent stocks. This evidence supports our mechanism: FOMC announcements amplify belief-driven valuation dispersion, and these distortions are subsequently corrected when firm-specific information is revealed on earnings announcement days.

Second, although we use a composite index of anomaly signals, not all of these signals are necessarily related to subjective expectations or duration. To isolate those most relevant for our mechanism, we show that anomalies aligned with subjective expectations and duration earn more negative FOMC-day returns and exhibit greater sensitivity to monetary policy surprises than unaligned anomalies. Specifically, we define subjective expectations aligned (unaligned) anomalies as those for which the short leg has higher (lower) average LTG forecasts than the long leg, and we find a similar pattern when sorting anomalies by whether the short leg has longer equity duration. These results reinforce our mechanism: stocks with higher subjective expectations or longer duration exhibit stronger sensitivity to monetary policy shocks.

Finally, we show that the negative long-short anomaly returns on FOMC days are not driven by shifts in subjective cash-flow expectations at the announcement itself. Using analysts' LTG and earnings-per-share (EPS) forecast revisions, we find that revisions move in the correcting direction—down for short-leg (overpriced) stocks and up for long-leg (underpriced) stocks. Moreover, LTG revisions do not adjust systematically on FOMC days, and EPS revisions, if anything, adjust more in the correcting rather than the amplifying direction. This evidence rules out greater subjective belief dispersion as the main driver of our results.

Related Literature Our paper is closely related to the broader literature on monetary policy and the macroeconomic announcement premium. A large literature documents significant excess returns around macroeconomic—especially FOMC—announcement days. Examples include Lucca and Moench (2015), Savor and Wilson(2013; 2014), Mueller, Tahbaz-Salehi, and Vedolin (2017), Cieslak, Morse, and Vissing-Jorgensen (2019), and Hu, Pan, Wang, and Zhu (2022) for empirical evidence, and Ai and Bansal (2018) and Wachter and Zhu (2022) for theoretical foundations. While these studies focus on aggregate equity returns, we contribute to understanding the cross-sectional variation in expected returns. Closely related, Ai, Han, Pan, and Xu (2022) propose the expected option-implied variance reduction (EVR) as a measure of stocks' sensitivity to monetary policy surprises and show that higher-EVR stocks experience larger uncertainty reductions and thus earn higher FOMC announcement premia. However, it remains unclear what stock characteristics the EVR measure captures. We show that overpriced stocks are more sensitive to monetary policy surprises and therefore command a higher monetary policy announcement premium.

Beyond the ex-ante premium that is independent of the sign of policy surprises, our paper also contributes to the literature on monetary policy transmission to the equity market. A large body of work shows that realized monetary policy shocks have substantial effects on asset prices. In particular, expansionary policy shocks are typically followed by higher equity prices and lower risk premia. In the seminal study of Bernanke and Kuttner (2005), a surprise 25-basis-point cut in the federal funds target rate increases aggregate equity prices by about 1%. To provide microfoundations for this relationship, Kekre and Lenel (2022) show in a heterogeneous-agent New Keynesian model that expansionary policy redistributes wealth toward households with a greater propensity to bear risk, lowering the aggregate risk premium. Pflueger and Rinaldi (2022) introduce time-varying risk aversion to explain high-frequency financial-market responses to monetary shocks, and Bauer, Pflueger, and

Sunderam (2024) highlight how investors' imperfect information about the policy rule affects transmission. We connect this macro-finance literature with the announcement-premium literature by showing that expansionary (contractionary) policy shocks raise (lower) equity prices and reduce (increase) investors' marginal utility. Regardless of the shock's sign, these movements induce a negative covariance between returns and the stochastic discount factor, generating a positive announcement premium.

Empirical work further examines firm-level heterogeneity in monetary policy exposure, often emphasizing financial constraints and other firm characteristics (e.g., Ozdagli (2018); Ozdagli and Velikov (2020); Chava and Hsu (2020)). However, the evidence on the role of financial constraints remains mixed.[3] We control for standard measures of financial constraint (e.g., the Whited–Wu Index) and find no explanatory power for FOMC anomaly returns. Instead, we show that anomaly signals partially reflect equity duration, such that stocks on the short leg of anomaly portfolios earn lower returns following contractionary surprises.

Our paper is also connected to the asset-pricing anomaly literature (e.g., Stambaugh, Yu, and Yuan (2012; 2015; 2017); Daniel, Hirshleifer, and Sun (2020); Dong, Li, Rapach, and Zhou (2022)). We contribute in two ways. First, a long-standing debate concerns whether anomalies reflect risk compensation or mispricing (e.g., Hou, Xue, and Zhang (2020); Fama and French (2016); Lochstoer and Tetlock (2020)). We argue that the two are interacted: risk exposures arise endogenously from mispricing, consistent with De Long, Shleifer, Summers, and Waldmann (1990). Second, Van Binsbergen, Boons, Opp, and Tamoni (2023) show that anomaly-related mispricing builds up and corrects slowly, exhibiting long-lasting persistence and influencing firms' real decisions (Van Binsbergen and Opp (2019)). We contribute by identifying a new channel for persistent mispricing—monetary policy announcements amplify existing mispricing, leading to long-lasting effects in anomaly formation.

Broadly, this paper contributes to the emerging literature that uses subjective expectations to explain asset prices and return patterns. Engelberg, McLean, and Pontiff (2018) show that anomaly profits are concentrated around firm-specific news, consistent with returns being driven by belief errors. Likewise, Bordalo, Gennaioli, Porta, and Shleifer(2019, 2024) find that stocks with overly optimistic long-term growth forecasts subsequently underperform, indicating diagnostic expectations. Closely related, Delao, Han, and Myers (2024) show that persistent, only partially corrected errors in subjective cash-flow expectations ex-

[3]Ozdagli (2018) and Ozdagli and Velikov (2020) find that financially constrained firms earn significantly higher returns than unconstrained firms following contractionary surprises, while Chava and Hsu (2020) find the opposite—financially constrained firms earn lower returns following surprise rate increases. Thus, the role of financial constraints in driving stock sensitivities remains unclear.

plain a sizable part of the cross-sectional variation in price ratios, consistent with aggregate evidence in Delao and Myers(2021). We show that persistent subjective cash-flow beliefs make anomaly returns persistent, which in turn makes monetary policy's amplification of these returns persistent. Relatedly, Cui, Delao, and Myers (2024) find that a subjective belief factor explains two-thirds of excess return differences across 176 anomalies. Our contribution is to connect the subjective-expectations channel to monetary policy transmission—a dimension that the existing literature has not emphasized.

Finally, we show that the evolution of anomalies depends on the nature of information. Our results are consistent with Engelberg, McLean, and Pontiff (2018), who find that anomaly returns are higher on corporate news and earnings announcement days and attribute these patterns to mispricing driven by biased expectations. Extending their insight, we jointly explain the negative anomaly returns on FOMC days and the positive anomaly returns on earnings days. We argue that FOMC announcements primarily convey aggregate discount-rate information, which amplifies mispricing, whereas earnings announcements reveal firm-specific cash-flow information, which helps correct mispricing by correcting biased beliefs. To our knowledge, this is the first paper to theoretically distinguish the informational content of FOMC and earnings announcements and examine their distinct implications for anomaly dynamics.

The rest of the paper is organized as follows. Section 2 presents the empirical evidence on long-short anomaly returns around FOMC announcement days. Section 3 develops a dynamic asset pricing model with monetary policy and biased expectations to explain the cross section of anomaly returns. Section 4 provides the quantitative analysis and shows that the model can account for the key empirical features of the cross-sectional FOMC announcement premium. Section 5 concludes.

2 Empirical Evidence

In this section, we present our main empirical findings. We show that long-short anomaly portfolios earn significantly lower returns on FOMC announcement days relative to other days. Overpriced stocks, which are more sensitive to monetary policy shocks, earn significantly higher risk premiums on FOMC days than underpriced stocks. Furthermore, the cross-sectional pattern in announcement-day returns cannot be explained by the CAPM or other standard risk factors. Second, we find that the effect is more pronounced during periods of accommodative monetary policy, when interest rates are low. Third, the pricing

impact of FOMC announcements is highly persistent and long-lasting.

2.1 Data

We construct a composite anomaly portfolio using 171 representative anomaly signals.[4] To construct this composite measure, we proceed in three steps. First, each month, we sort stocks into deciles based on the next month's return as predicted by each anomaly and assign them scores according to their decile ranking, from 1 (lowest expected return) to 10 (highest expected return). Second, for each stock-month, we compute a composite signal by averaging its anomaly-specific scores, sort stocks into deciles based on this average, and compute value-weighted daily returns for each decile. Finally, we construct a long-short portfolio that goes long the top decile (most underpriced) and short the bottom decile (most overpriced). By construction, the long leg consists of stocks with higher average future returns than the short leg. Throughout the paper, our focus is on the performance of anomaly strategies—which involve monthly rebalancing of stock portfolios—rather than on the properties of individual stocks. Our sample spans from 1995 to 2024. We use pre-scheduled FOMC announcement dates obtained from the Federal Reserve Board's official website.

2.2 Empirical Findings

2.2.1 Anomaly Portfolio Returns on FOMC and Non-FOMC days

Our first empirical finding shows that long-short anomaly portfolios earn significantly lower returns on FOMC announcement days compared to other days. To estimate this effect, we regress portfolio returns on a dummy variable that indicates FOMC announcement days:

$$R_{t,i} = \alpha_i + \beta_i \cdot \mathbf{1}_{FOMC} + \epsilon_{t,i}, \tag{1}$$

where $R_{t,i}$ denotes the daily value-weighted return of portfolio i, and $i = 1, \ldots, 10$ indexes decile portfolios sorted by the composite anomaly signal. Decile 1 corresponds to the most overpriced stocks (short leg), and Decile 10 to the most underpriced stocks (long leg). The dummy variable $\mathbf{1}_{\text{FOMC}}$ equals one on pre-scheduled FOMC announcement days and zero otherwise. In this specification, α_i captures average returns on non-FOMC days, and β_i captures the return difference on FOMC days.

[4]The methodology follows Stambaugh, Yu, and Yuan (2012; 2015), who show that individual anomaly returns are weakly correlated with each other but strongly correlated with the return of a composite long-short portfolio, indicating that each anomaly captures a distinct dimension of aggregate mispricing.

The regression results are reported in Table 1. The estimated FOMC coefficients are positive and increase monotonically across portfolios. This indicates that all decile portfolios earn higher announcement premia on FOMC days. The largest positive return, 49 bps, appears in the short leg, which consists of overpriced stocks, while the smallest, 7 bps, appears in the long leg, composed of underpriced stocks. The fifth (market) portfolio earns an average return of 27 bps on FOMC days, which is 22 bps higher than its return on non-FOMC days. This magnitude is consistent with the FOMC announcement premium documented in Lucca and Moench (2015) and Ai, Han, Pan, and Xu (2022).

Crucially, the FOMC dummy coefficient for the long-short portfolio is negative and statistically significant. Specifically, the long-short portfolio earns 42 bps less on FOMC announcement days than on other days. This implies an average return of –38 bps on FOMC days, compared to +4 bps on non-FOMC days. This pattern suggests that monetary policy announcements amplify rather than correct mispricing: cross-sectional valuation dispersion widens on monetary policy announcement days.

In contrast, on non-FOMC days, the long-short anomaly portfolio earns a significant average return of +4 bps per day, reflecting a gradual correction of mispricing over time. Since the anomaly portfolio is constructed to capture abnormal returns, it is expected to yield positive returns on typical non-announcement days. In Appendix Table A.1, we show that these results are robust across alternative anomaly sets from the literature, including Engelberg, McLean, and Pontiff (2018), Daniel, Hirshleifer, and Sun (2020), Novy-Marx and Velikov (2016), Stambaugh and Yuan (2017), Jensen, Kelly, and Pedersen, and Hou, Xue, and Zhang (2020). While the magnitude of the FOMC-day return varies—ranging from –17 to –42 bps depending on the composite construction—the qualitative pattern remains consistent. We also confirm that the results hold when using equal-weighted portfolios.

Next, we show that our results are robust to controlling for market betas. Savor and Wilson (2014) find that the CAPM performs well for portfolios sorted by market beta on macroeconomic announcement days, suggesting that unconditional market beta could potentially explain the cross-section of FOMC-day anomaly returns. It is also possible that time-varying beta contributes to the observed return patterns across anomaly portfolios. To address these concerns, we estimate a CAPM regression that includes both the unconditional market beta and a conditional beta specific to FOMC days. Specifically, we estimate the following regression for the anomaly composite sorted portfolios:

$$R_{t,i} = \alpha_i + \alpha_{i,FOMC} \cdot \mathbf{1}_{FOMC} + \beta_i \left(R_t^M - r_{f,t}\right) + \beta_{i,FOMC} \left(R_t^M - r_{f,t}\right) \cdot \mathbf{1}_{FOMC} + \epsilon_{t,i}, \quad (2)$$

Table 1: Anomaly Portfolio Returns around FOMC and non-FOMC announcement days

Anomaly deciles	α_i	t_α	β_i	t_β
1 (short)	0.01	(0.71)	0.49	(3.71)
2	0.04	(2.03)	0.46	(3.90)
3	0.04	(2.53)	0.32	(3.20)
4	0.05	(3.35)	0.34	(3.58)
5	0.05	(3.41)	0.27	(2.94)
6	0.05	(3.71)	0.21	(2.56)
7	0.05	(4.01)	0.23	(3.04)
8	0.05	(4.06)	0.17	(2.37)
9	0.05	(4.70)	0.11	(1.71)
10 (long)	0.05	(5.24)	0.07	(1.14)
(10-1)	**0.04**	**(1.87)**	**-0.42**	**(-4.20)**

This table reports the results from daily regressions of the form: $R_{t,i} = \alpha_i + \beta_i \cdot \mathbf{1}_{FOMC} + \epsilon_{t,i}$, where the dependent variable is the daily return of value-weighted portfolios constructed from anomaly signals. Each month, stocks are sorted into deciles based on a composite index formed from 171 individual anomaly signals. Decile 1 (10) corresponds to the most overpriced (underpriced) stocks, forming the short (long) leg of the anomaly portfolio. Portfolios are rebalanced monthly, and daily returns are calculated over the subsequent month. Value weights are based on market capitalization as of previous trading day. The dummy variable $\mathbf{1}_{FOMC}$ equals one on pre-scheduled FOMC announcement days and zero otherwise. Newey-West adjusted t-statistics with 12 lags are reported in parentheses. The sample period spans from 1995 to 2024.

where $R_{t,i}$ is the daily return of portfolio i, R_t^M is the daily market return, and $r_{f,t}$ is the daily risk-free rate. The FOMC dummy variable $\mathbf{1}_{\text{FOMC}}$ equals one on scheduled FOMC announcement days and zero otherwise. In this specification, β_i captures the unconditional (non-FOMC day) market beta, and $\beta_{i,FOMC}$ captures the conditional beta on FOMC days. This allows both the intercept and market beta to vary on FOMC days.

Table 2 reports the results of this regression. Controlling for these factors reduces the magnitude of the long-short return difference from 42 bps to 18 bps, but the effect remains highly statistically significant. Although market beta accounts for a substantial portion of the cross-sectional variation, consistent with Savor and Wilson (2014), it does not fully account for anomaly returns on either FOMC announcement days, or on other days. In Appendix Table A.2, we further show that the results remain almost unchanged when controlling for additional standard risk factors such as size, value, and momentum.

2.2.2 Monetary Policy and Long-short Anomaly Portfolio Returns

Beyond the average announcement effect, we next examine how monetary policy conditions influence long-short anomaly returns. Specifically, we assess whether the pricing impact of FOMC announcements depends on the level of interest rates. To test this, we regress the daily return of the long-short anomaly portfolio on the FOMC day dummy, the level of the

Table 2: Anomaly Portfolio Returns around FOMC days Controlling for Market Betas

Anomaly deciles	β_i	$\beta_{i,FOMC}$	$t_{\beta_{FOMC}}$	α_i	t_α	$\alpha_{i,FOMC}$	$t_{\alpha_{FOMC}}$
1 (short)	1.48	0.07	(1.208)	-0.03	(-3.12)	0.10	(2.25)
2	1.26	0.12	(2.74)	-0.00	(-0.59)	0.11	(2.92)
3	1.15	0.03	(1.01)	0.00	(0.66)	0.02	(0.64)
4	1.06	0.07	(2.44)	0.02	(3.00)	0.05	(1.88)
5	0.99	0.06	(1.47)	0.02	(3.17)	0.00	(0.03)
6	0.92	0.03	(1.02)	0.02	(3.68)	-0.03	(-1.17)
7	0.86	0.04	(1.43)	0.02	(4.01)	0.00	(0.16)
8	0.83	-0.02	(-0.60)	0.02	(3.81)	-0.04	(-1.26)
9	0.76	-0.07	(-2.37)	0.03	(4.45)	-0.06	(-2.02)
10 (long)	0.66	-0.05	(-1.26)	0.03	(4.76)	-0.08	(-2.37)
(10-1)	-0.83	-0.12	(-1.45)	**0.06**	**(4.27)**	**-0.18**	**(-2.76)**

This table reports the results from the following daily CAPM regression: $R_{t,i} = \alpha_i + \alpha_{i,FOMC} \cdot \mathbf{1}_{FOMC} + \beta_i \left(R_t^M - r_{f,t}\right) + \beta_{i,FOMC} \left(R_t^M - r_{f,t}\right) \cdot \mathbf{1}_{FOMC} + \epsilon_{t,i}$, where $R_{t,i}$ is the daily return of value-weighted portfolio i, R_t^M is the daily market return, and $r_{f,t}$ is the daily risk-free rate. The dummy variable $\mathbf{1}_{\text{FOMC}}$ equals one on scheduled FOMC announcement days and zero otherwise. The dependent variable is constructed from portfolios sorted into deciles each month based on a composite index formed from 171 individual anomaly signals. Decile 1 (10) corresponds to the most overpriced (underpriced) stocks, forming the short (long) leg of the anomaly portfolio. Portfolios are rebalanced monthly, and daily returns are calculated over the subsequent month. Value weights are based on market capitalization as of previous trading day. t-statistics are reported in parentheses. The sample period spans from 1995 to 2024.

interest rate on the prior trading day, and their interaction:

$$R_t = \alpha + \alpha_{FOMC} \cdot \mathbf{1}_{FOMC} + \gamma_{FOMC} \cdot \mathbf{1}_{FOMC} \cdot r_{t-1} + \gamma \cdot r_{t-1} + \epsilon_t, \tag{3}$$

where R_t is the daily return of the long-short anomaly portfolio, and r_{t-1} is the demeaned federal funds rate as of the previous trading day. Panel A of Table 3 shows that the pricing impact of FOMC announcements is especially pronounced during periods of accommodative monetary policy. Specifically, a 100 bps drop in the annualized real interest rate level is associated with an *additional* 17.1 bps decline in long-short portfolio returns on FOMC days. Panel B of Table 3 confirms that this result remains robust after controlling for both unconditional and conditional market betas, as well as the interaction between market returns and the FOMC dummy (coefficients for these control variables are omitted for brevity). Taken together, these findings indicate that the effect of monetary policy announcements on mispricing is amplified in low interest rate environments.

2.2.3 Return Sensitivity to Monetary Policy Surprises

We next examine how stocks with different anomaly signals respond to realized monetary policy surprises. Following Bernanke and Kuttner (2005), we regress the daily returns of

Table 3: Interest Rate Environment and FOMC-Day Anomaly Returns

Panel A: Interest Rate Effect on FOMC Returns				
Rank	α	$\mathbf{1}_{FOMC}$	r_{t-1}	$\mathbf{1}_{FOMC} \cdot r_{t-1}$
(10-1)	0.035	-0.417	-0.016	**0.171**
	(1.88)	(-4.36)	(-1.62)	**(3.06)**
Panel B: Controlling for Market Betas				
Rank	α	$\mathbf{1}_{FOMC}$	r_{t-1}	$\mathbf{1}_{FOMC} \cdot r_{t-1}$
	0.061	-0.188	-0.008	**0.115**
	(4.31)	(-2.98)	(-1.09)	**(3.31)**

This table examines how the effect of monetary policy announcements on long-short anomaly portfolio returns varies with the level of the federal funds rate. Panel A reports results from the following regression:

$$R_t = \alpha + \alpha_{FOMC} \cdot \mathbf{1}_{FOMC} + \gamma_{FOMC} \cdot \mathbf{1}_{FOMC} \cdot r_{t-1} + \gamma \cdot r_{t-1} + \epsilon_t,$$

where R_t is the daily return of the value-weighted long-short anomaly portfolio, and r_{t-1} is the demeaned real interest rate as of the end of previous month. The dummy variable $\mathbf{1}_{\text{FOMC}}$ equals one on scheduled FOMC announcement days and zero otherwise. The long-short portfolio is constructed using extreme decile portfolios based on a composite index of 100 individual anomaly signals. Decile 1 (10) corresponds to the most overpriced (underpriced) stocks. Portfolios are rebalanced monthly. Panel B extends the regression by controlling for market exposure. Specifically, it includes both unconditional and FOMC-specific conditional market betas, as well as interaction terms between market returns and the interest rate level:

$$\begin{aligned} R_t \quad = \quad & \alpha + \alpha_{FOMC} \cdot \mathbf{1}_{FOMC} + \gamma_{FOMC} \cdot \mathbf{1}_{FOMC} \cdot r_{t-1} + \gamma \cdot r_{t-1} + \beta(R_t^M - r_{f,t}) + \beta_{\text{FOMC}}(R_t^M - r_{f,t}) \cdot \mathbf{1}_{\text{FOMC}} \\ & + \theta(R_t^M - r_{f,t}) \cdot r_{t-1} + \theta_{FOMC}(R_t^M - r_{f,t}) \cdot r_{t-1} \cdot \mathbf{1}_{\text{FOMC}} + \delta \cdot r_{t-1} + \varepsilon_t, \end{aligned}$$

where R_t^M is the market return and $r_{f,t}$ is the real interest rate. Returns are expressed in percentage points. Newey-West adjusted t-statistics are reported in parentheses. The sample period is from 1995 to 2024.

each decile portfolio—sorted by the composite anomaly signal—on the monetary policy surprise measure constructed by Bauer and Swanson (2023).[5] Table 4 reports the results. We find that all beta coefficients are significantly negative, consistent with the existing literature: expansionary policy surprises are associated with higher equity prices and lower risk premia, whereas contractionary surprises correspond to lower prices and higher premia following FOMC announcements. Moreover, return sensitivity increases monotonically across decile portfolios—the short-leg portfolio (Decile 1) has a more negative beta than the long-leg portfolio (Decile 10). This cross-sectional pattern confirms that overpriced stocks are more exposed to monetary policy shocks than underpriced stocks, consistent with our model's prediction that monetary policy announcements disproportionately affect high-duration, high-valuation firms.

[5]As a robustness check, Appendix Table A.6 replaces the Bauer and Swanson (2023) shocks with those from Jarociński and Karadi and yields nearly identical results: stock returns react negatively to monetary policy surprises, with short-leg (overpriced) stocks exhibiting greater sensitivity. Decomposing these shocks into conventional monetary policy and central bank information (CBI) components shows that CBI shocks raise stock prices, and their sensitivities decline monotonically across anomaly portfolios.

Table 4: Return sensitivity to FOMC surprise

Anomaly Ranking	β	(t-stat)
1 (short)	-0.09	(-3.46)
2	-0.07	(-3.14)
3	-0.06	(-3.39)
4	-0.04	(-2.65)
5	-0.05	(-3.34)
6	-0.04	(-2.86)
7	-0.05	(-3.61)
8	-0.04	(-3.06)
9	-0.03	(-2.84)
10 (long)	-0.02	(-1.85)
10-1	0.07	(2.96)

This table reports the sensitivity of anomaly portfolio daily returns to realized monetary policy surprises on FOMC announcement days. For each decile portfolio sorted by the anomaly signal, we estimate the following regression: $R_t = \alpha + \beta \text{MPS_ORTH}_t + \varepsilon_t$. Monetary policy surprises are measured using the approach of Bauer and Swanson (2023).

Subjective Expectations and Duration We provide evidence that our anomaly signal captures subjective expectations about firm-specific cash flows and differences in equity duration. Specifically, we use long-term growth (LTG) forecasts data from I/B/E/S as a proxy for the subjective expectation about a firm's long-run cash flow. We also measure equity duration using data constructed by Gonçalves (2021), and our results are robust to using the duration measure from Dechow, Sloan, and Soliman (2004). Table 5 reports average LTG and average duration across anomaly-sorted portfolios. We find that portfolio return is monotonic in both measures: more overpriced stocks (those in the short leg) have higher LTG forecasts and longer durations.

2.2.4 Persistence

Lastly, we show that the effect of monetary policy announcements on anomaly returns is highly persistent and long-lasting.

First, we test for short-term reversal following FOMC announcements by including dummy variables for one day, one week, and two weeks after the announcement. Specifically, we estimate the following regression:

$$R_t = \alpha + \alpha_{FOMC} \cdot \mathbf{1}_{FOMC} + \beta_{1d} \cdot \mathbf{1}_{FOMC_{1d}} + \beta_{1w} \cdot \mathbf{1}_{FOMC_{1w}} + \beta_{2w} \cdot \mathbf{1}_{FOMC_{2w}} + \epsilon_t, \qquad (4)$$

where $\mathbf{1}_{FOMC_{1d}}$ =1 if day t+1 is the trading day after an FOMC announcement, $\mathbf{1}_{FOMC_{1w}} = 1$ for days t+2 to t+5, and $\mathbf{1}_{FOMC_{2w}} = 1$ for days t+6 to t+10. Panel A of Table 6 shows that

Table 5: Anomaly Signal's Consistency

Anomaly Ranking	LTG	Duration
1 (short)	23.3	87.3
2	19.2	70.8
3	16.8	65.3
4	14.5	62.4
5	13.4	61.0
6	12.3	59.8
7	11.8	58.6
8	11.1	56.7
9	10.6	56.2
10 (long)	9.6	51.9
10-1	-13.7	-35.4

This table reports the average long-term growth (LTG) forecasts from I/B/E/S and average equity duration (following Gonçalves (2021)) across decile portfolios sorted by our anomaly composite index. Decile 1 represents the most overpriced stocks (short leg), and Decile 10 the most underpriced stocks (long leg).

all post-announcement dummy coefficients are statistically indistinguishable from zero. This indicates that there is no significant reversal in anomaly returns in the two weeks following FOMC announcements compared to a typical non-FOMC day, suggesting that the impact is not short-lived.

Table 6: Post-FOMC Reversal

α	α_{FOMC}	β_{1d}	β_{1w}	β_{2w}
0.023	-0.407	-0.017	0.031	0.026
(1.00)	(-4.03)	(-0.13)	(0.39)	(0.48)

This table examines the persistence of the pricing impact from FOMC announcements on long-short anomaly portfolio returns. It tests for short-term reversal following FOMC announcements by estimating the following regression: $R_t = \alpha + \alpha_{FOMC} \cdot \mathbf{1}_{FOMC} + \beta_{1d} \cdot \mathbf{1}_{FOMC_{1d}} + \beta_{1w} \cdot \mathbf{1}_{FOMC_{1w}} + \beta_{2w} \cdot \mathbf{1}_{FOMC_{2w}} + \epsilon_t$, where R_t is the daily return of the long-short anomaly portfolio. The dummy $\mathbf{1}_{FOMC}$ equals one on FOMC announcement days. $\mathbf{1}_{FOMC_{1d}}$, $\mathbf{1}_{FOMC_{1w}}$, and $\mathbf{1}_{FOMC_{2w}}$ equal one if the trading day falls within one day, one week (days $t+2$ to $t+5$), or two weeks (days $t+6$ to $t+10$) after an FOMC announcement, respectively. The coefficients test whether the announcement effect reverses over the two-week window following the event. Panel B reports annualized returns during the one-year lead and lag windows around the month in which anomaly portfolios are sorted. The sorting is based on a composite index of 100 individual anomaly signals. Portfolios are rebalanced monthly and returns are split by FOMC and non-FOMC days. The sample period is from 1994 to 2022. All returns are expressed in percentage points. t-statistics are reported in parentheses.

Second, we examine the cumulative impact of FOMC announcements around the sorting month, when the anomaly signal is first identified and becomes publicly available. Table 7 reports cumulative annual returns over one-year (and two-year) lead and lag windows relative to the sorting month, separating returns into those accumulated over on FOMC days and those accumulated over non-FOMC days. The goal is to quantify how much of the observed

anomaly portfolio return is driven by a small number of FOMC announcements, and how much of the subsequent return reflects the correction of prior mispricing.

After sorting, arbitrageurs begin trading, and anomaly portfolios earn positive returns of 8.98% on non-FOMC days. However, these gains primarily reflect the gradual correction of mispricing that were previously amplified on FOMC days. In fact, in the one year following sorting, 41% of the non-FOMC gains—3.66% out of the total 8.98% —come from offsetting the impact of just eight FOMC announcements. Looking backward, mispricing was already building up prior to the sorting month. We find that eight FOMC announcements account for more than 80% of anomaly buildup; –4.32% out of the -5.22% total pre-sorting return over the one-year window. Taken together, about 90% of non-FOMC anomaly returns over the two-year window surrounding the sorting month are devoted to correcting anomaly returns amplified by only 16 FOMC announcement days, as calculated by $(3.66 + 4.32)/8.98 = 89\%$. Expanding the window to two years before and after the sorting month yields similar results. These findings demonstrate that the pricing impact of monetary policy announcements is not only economically large but also remarkably persistent—monetary policy shocks drive much of the observed time variation in anomaly returns.

Table 7: Persistence

	1-year-lag	1-year-lead	2-year-lag	2-year-lead
FOMC	-4.32	-3.66	-8.26	-6.55
Non-FOMC	-0.90	8.98	-17.11	14.22
Total	-5.22	5.32	-25.37	7.67

This table examines the persistence of the pricing impact from FOMC announcements on long-short anomaly portfolio returns. We calculate cumulative anomaly portfolio returns during the one-year (two-year) lead and lag windows around the month in which anomaly portfolios are sorted, keeping the portfolio fixed through the calculating periods. The sorting is based on a composite index of 171 individual anomaly signals. Monthly returns are split by FOMC and non-FOMC days. The sample period of ranking month is from 1997 to 2022. All returns are expressed in percentage points.

2.2.5 Robustness

In the appendix, we present several additional empirical facts that support our main findings. First, Appendix Table A.3 shows that long-short anomaly portfolios also earn negative returns on other major macroeconomic announcement days. While the magnitude and statistical significance are lower than those observed on FOMC days, the direction remains consistent. This pattern arises because mispriced stocks are particularly sensitive to monetary policy shocks, which directly affect discount rates. Other macro announcements, such as GDP or employment reports, primarily convey information about aggregate cash flows

rather than interest rate shocks. While such cash-flow news can influence discount rates in general equilibrium, it does so only indirectly, leading to a weaker overall effect.

Second, one might conjecture that investors revise their beliefs about firm cash flows on FOMC days, thereby widening belief and valuation gaps. In contrast, our mechanism attributes the amplification of valuation deviations to changes in sensitivity to discount-rate shocks, with belief gaps remaining largely unchanged. We demonstrate that the negative long-short portfolio return on FOMC days is not a consequence of belief updating. To test this, we examine analyst forecast revisions for earnings per share (EPS) and long-term growth (LTG) around FOMC announcements. The results are displayed in Tables 13, A.4, and A.5 in the Appendix. Analysts revise LTG and EPS forecasts downward for overpriced stocks and upward for underpriced stocks, implying gradual belief correction rather than amplification. This evidence indicates that monetary policy shocks do not increase belief dispersion. These results reinforce our conclusion that the negative long-short anomaly returns on FOMC days stem from sensitivity changes, not from changes in expectations about firm fundamentals.

Lastly, we show that our results remain robust after controlling for other well-documented risk factors that could potentially explain the cross-section of monetary policy announcement returns. Specifically, we control for expected variance reduction (EVR) as developed in Ai, Han, Pan, and Xu (2022), and for financial constraints as documented in Chava and Hsu (2020) and Ozdagli (2018). The results, reported in the Appendix, confirm that our main findings on anomaly returns around FOMC announcements are not driven by these alternative explanations.

3 An Equilibrium Model

Motivated by the empirical evidence, in this section, we develop a model in which monetary policy announcements reveal the Fed's interest rate target. This revelation induces interest rate shocks that require risk compensation, thereby giving rise to an announcement premium. We show that the sensitivity of stock valuations with respect to interest rate shocks depends endogenously on distortions in subjective expectations, leading to cross-sectional differences in announcement-day returns across anomaly portfolios. We begin by presenting the model's setup and solution. We then discuss its implications for the cross-section of anomaly returns on FOMC days. Details of the model solution and derivations are provided in Appendix B.

3.1 Monetary Policy and SDF

Suppose the Fed's *unobserved* target interest rate follows a continuous-time AR (1) process:

$$d\theta_t = b\left(\bar{\theta} - \theta_t\right)dt + \sigma_\theta dB_t. \tag{5}$$

where b is the mean reversion rate, $\bar{\theta}$ is the long-run mean, σ_θ is the volatility, and B_t is a standard Brownian motion. We assume the public does not observe θ_t continuously; it is only revealed periodically through FOMC announcements.

FOMC announcements occur at pre-scheduled times $t = 0, T, 2T, \cdots$. At each announcement, the actual interest rate r_t is revealed and set to the target rate. That is, for $t = 0, T, 2T, \cdots$, $r_t = \theta_t$. Between announcements, the interest rate r_t remains constant at the previously announced value. Summarizing both cases, for all $t \in [0, \infty)$,

$$r_t = \theta_{\lfloor t/T \rfloor \times T}, \tag{6}$$

where $\lfloor t/T \rfloor$ denotes the floor function, i.e., the greatest integer less than or equal to t/T.

We assume that aggregate consumption follows

$$\frac{dC_t}{C_t} = \mu_C dt + \sigma_C dB_{C,t}, \tag{7}$$

where μ_C is the consumption growth rate, σ_C is the volatility, and $B_{C,t}$ is an independent Brownian motion.

To price assets, we introduce a state price density π_t, which follows:

$$\frac{d\pi_t}{\pi_t} = -r_t dt - \psi r_t dB_{C,t} + \sigma_\pi dN_t, \tag{8}$$

where σ_π is the market price of interest rate risk and the market price of consumption risk equals ψr_t. Define $dN_t \equiv \sum_{n \geq 1} J_n \mathbf{1}_{\{t=nT\}}$ with $J_n \equiv r_{nT^+} - \mathbb{E}^-_{nT}[r_{nT}]$ is a martingale that captures monetary policy surprises—i.e., unanticipated changes in the interest rate at announcement times. Because r_t is constant between announcements, $dN_t = 0$ except at the discrete announcement dates, where it captures the surprise component of monetary policy. In the Appendix, we show that the interest rate surprise is normally distributed with mean zero and variance $\frac{\sigma_\theta^2}{2b}(1 - e^{-2bT})$. In this economy, there are two sources of priced risk. On non-announcement days, shocks to aggregate consumption require a risk premium, with price of risk ψr_t. This captures the documented evidence that discount rates affect

risk premia (Bernanke and Kuttner (2005); Kekre and Lenel (2022)). At announcement times, there is an additional priced risk associated with jumps in the interest rate r_t, which generates the FOMC announcement premium, consistent with the announcement premium theory developed in Ai and Bansal (2018).

We assume that the price of risk σ_π is constant and positive. This implies that a positive interest rate surprise raises the interest rate and increases the investor's marginal utility. In other words, higher interest rates are perceived as a "bad state" by investors—tightening monetary policy reduces asset prices and makes consumption more costly—thus requiring compensation for bearing this risk.[6] Since a higher interest rate reduces the price-dividend ratio, stock prices fall and returns decline. A negative interest rate shock, conversely, lowers the interest rate, reduces marginal utility, and increases stock valuations, leading to higher returns. In both cases, interest rate shocks induce a *negative* covariance between the SDF and returns, which gives rise to a *positive* announcement premium. Importantly, because the announcement premium reflects the expected return prior to the FOMC announcement, it is independent of the realization or direction of the interest rate surprise.

3.2 Asset Prices

We now specify the dividend process for firm i. Suppose the dividend of firm i is given by

$$D_t^i = \delta_t^i C_t, \tag{9}$$

where δ_t^i denotes the firm-specific cash flow component (i.e., the dividend-consumption ratio, or the firm's share in aggregate consumption). We assume that δ_t^i follows a geometric Brownian motion:

$$\frac{d\delta_t^i}{\delta_t^i} = g_t^i dt + \sigma_D dB_{D,t}^i, \tag{10}$$

where g_t^i is the firm's true cash flow growth rate, and σ_D denotes the volatility of the dividend-consumption ratio. The true growth rate g_t^i evolves as an Ornstein-Uhlenbeck process:

$$dg_t^i = a\left(\bar{g} - g_t^i\right) dt + \sigma_g dB_{g,t}^i, \tag{11}$$

[6] While in general σ_π could be time-varying, firm-specific, or depend on the interest rate itself, we assume it is constant to isolate our mechanism. This allows us to attribute cross-sectional return differences solely to heterogeneity in interest rate sensitivity across stocks, rather than to differences in prices of risk.

where a is the mean reversion rate, $\bar{g}$ is the long-run average growth rate, and σ_g is the volatility of the growth rate. All Brownian shocks $\left(B_C, B_D, B_\theta, B_g^i\right)$ are supposed to be independent. We assume g_t^i is unobserved by the public. Therefore, market participants must form expectations about it.

Econometricians or arbitrageurs form beliefs about g_t based on Bayesian learning under rational expectations. Dropping the firm index i for simplicity, their posterior belief $\tilde{g}_t$ evolves as:

$$d\tilde{g}_t = a\left(\bar{g} - \tilde{g}_t\right) dt + \frac{q_t}{\sigma_D} d\tilde{B}_{D,t}, \tag{12}$$

where $d\tilde{B}_{D,t} = \frac{1}{\sigma_D}\left(\frac{d\delta_t}{\delta_t} - \tilde{g}_t dt\right)$ is the innovation in dividend growth relative to their belief, and q_t is the posterior variance, which follows the deterministic process: $dq_t = \left(\sigma_g^2 - 2aq_t - \frac{q_t^2}{\sigma_D^2}\right) dt$.

However, the marginal investor forms a subjective belief $\hat{g}_t$, which evolves as:

$$d\hat{g}_t = a\left(\bar{g} - \hat{g}_t\right) dt + \phi \frac{q_t}{\sigma_D} d\hat{B}_{D,t}, \tag{13}$$

where ϕ measures the degree of biased expectations.This specification is consistent with the "diagnostic Kalman filter" of Bordalo, Gennaioli, Porta, and Shleifer (2019). [7] Here, $d\hat{B}_{D,t} = \frac{1}{\sigma_D}\left(\frac{d\delta_t}{\delta_t} - \hat{g}_t dt\right)$ is the innovation in dividend growth relative to the investor's subjective belief. The parameter ϕ captures belief distortion: $\phi > 1$ corresponds to overreaction to news, and $\phi = 1$ recovers rational expectations. Relative to the standard Kalman filter, biased beliefs place excessive weight on new signals, causing investors to overvalue firms receiving good news and undervalue those receiving bad news. Although in the long run, $\hat{g}_t$ is mean-reverting toward the rational expectation $\tilde{g}_t$, short-run deviations between $\hat{g}_t$ and $\tilde{g}_t$ creates mispricing, i.e., price deviations from fundamentals. Specifically, if $\hat{g}_t > \tilde{g}_t$, the stock is perceived as overpriced; if $\hat{g}_t < \tilde{g}_t$, it is underpriced.

To solve for asset prices, we focus on a typical announcement cycle where $t \in [0, T)$, during which the interest rate r remains fixed. For notational convenience, we define T (or T^-) as the moment just before the FOMC announcement and T^+ (or 0) as the moment

[7] We refer to biased expectations as beliefs that deviate from full-information rational expectations. The source of this deviation may be either rational (e.g., due to information frictions (Coibion and Gorodnichenko (2015)) or heterogeneous information (Han (2025))) or behavioral (e.g., diagnostic expectations (Bordalo, Gennaioli, Porta, and Shleifer (2019)) or noise trader risk (De Long, Shleifer, Summers, and Waldmann (1990))). Following Proposition 1 in Bordalo, Gennaioli, Porta, and Shleifer (2019) we adopt their framework to generate price deviations in the economy and use their calibrated value for our quantitative analysis. In particular, their $1 + \theta$ corresponds to our ϕ. However, this is not the only possible way to model biased expectations.

immediately afterward. The price-dividend ratio at time t, denoted $p(r, \hat{g}_t, t)$, satisfies:

$$p\left(r, \hat{g}_t, t\right) D_t = \mathbb{E}_t \left[\underbrace{\int_t^T e^{-\lambda(s-t)} \frac{\pi_s}{\pi_t} D_s ds}_{\text{before announcement}} + \underbrace{e^{-\lambda(T-t)} \frac{\pi_T^+}{\pi_t} p\left(r_T^+, \hat{g}_T^+, T^+\right) D_T}_{\text{upon the announcement}} \right]. \tag{14}$$

where r_T^+ and $\hat{g}_T^+$ denote the values immediately after the announcement, and λ is the Poisson exit rate at which firms die. Thus, the asset price consists of two components: the expected discounted cash flows between t and T before the announcement, and the discounted continuation value at the time of the announcement T. Our model has semi-closed-form solutions, which are provided in Appendix B.

Given the price-to-dividend ratio, we then compute the expected return realized at the announcement, i.e., the announcement premium, as:

$$R_A = \frac{\mathbb{E}_T \left[p\left(r_T^+, \hat{g}_T, T^+\right) \right]}{p\left(r, \hat{g}_T, T\right)} - 1. \tag{15}$$

Thus, the announcement premium is determined by two state variables known prior to the announcement: the last announced interest rate r and the subjective belief about dividend growth $\hat{g}_T$ immediately before the announcement. Cross-sectional differences in announcement-day returns across stocks arise from heterogeneity in their sensitivity to interest rate shocks, which is governed by the level of $\hat{g}_T$.

Empirically, $\hat{g}_T$ can be proxied using anomaly signals. Stocks in the short leg of anomaly portfolios are overpriced, meaning $\hat{g} - \tilde{g} > 0$, and on average have higher perceived growth $\hat{g}$ and lower valuations relative to the rational benchmark. These stocks exhibit longer duration and sensitivity to monetary policy shocks, thereby requiring higher risk compensation on FOMC days. In contrast, underpriced stocks in the long leg have $\hat{g} - \tilde{g} < 0$, lower perceived growth, and higher valuations, making them less exposed to interest rate risk and requiring lower compensation.

We therefore use $\hat{g}_T - \tilde{g}_T$ as a model-based measure of mispricing: higher values indicate more overpriced stocks, and lower values indicate more underpriced stocks. Sorting on this measure generates cross-sectional variation in announcement-day returns. These differences in interest rate sensitivity explain why long-short anomaly portfolios earn negative returns on FOMC announcement days.

To gain some intuition for why the announcement premium is related to subjective expectations, note that when shocks are small, the risk premium is given by the covariance

between the SDF and asset returns and can be approximated by:

$$R_A = Cov\left(\frac{d\pi_t}{\pi_t}, \frac{d\left(p\left(r_t, \hat{g}_t, t\right) D_t\right)}{p\left(r_t, \hat{g}_t, t\right) D_t}\right) \approx -\underbrace{\frac{d \ln p\left(r_t, \hat{g}_t, t\right)}{dr_t}}_{\text{equity duration}} \sigma_\theta \sigma_\pi, \tag{16}$$

where the term $-\frac{d \ln p(r_t, \hat{g}_t, t)}{dr_t}$ measures the sensitivity of the stock price to interest rate shocks—commonly referred to as the asset's duration. When shocks are Brownian motions, the approximation in the equation above holds with equality. In our model, the interest rate jumps at the announcement. As a result, Equation (16) is a local approximation. While we do not obtain a closed-form solution for the general case, we derive in Appendix B an approximate expression under simplifying assumptions: if $r_t = \theta_t$ and $\hat{g}$ is constant, then:

$$-\frac{d \ln p\left(r_t, \hat{g}, t\right)}{dr_t} \approx \frac{1}{\bar{\theta} - \hat{g} + b - \frac{\sigma_\theta^2}{2b^2} + \frac{\sigma_\theta}{b}\sigma_\pi}. \tag{17}$$

Obviously, stocks with higher $\hat{g}$ have longer duration and are more sensitive to interest rate shocks—implying a higher required risk compensation.

3.3 Model Implications

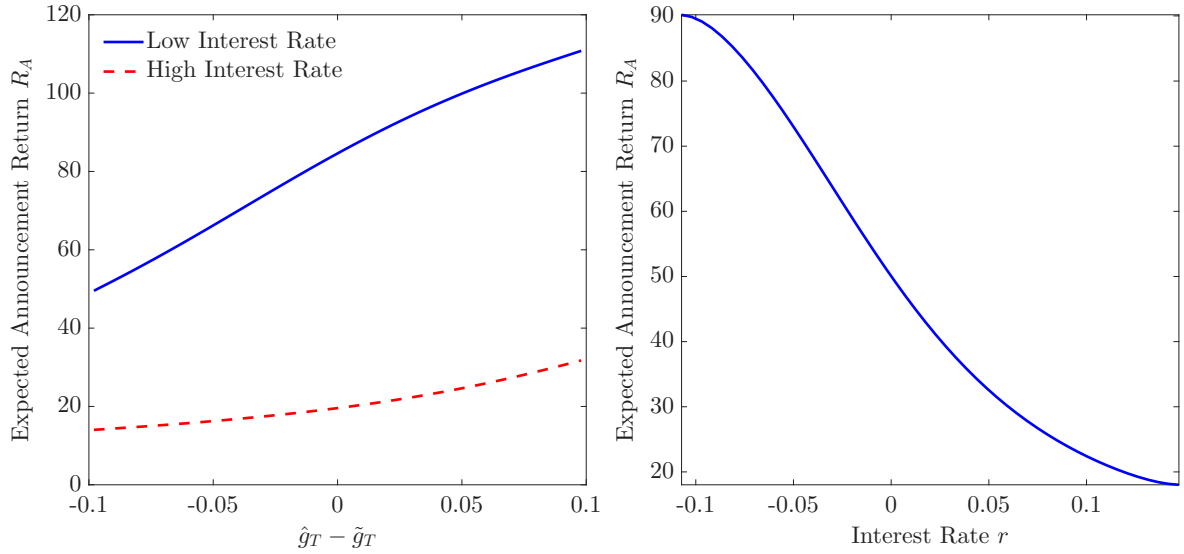
In this section, we plot the model's policy functions to illustrate its implications.

First, we show that all stocks earn a positive risk premium on FOMC announcement days, as investors require compensation for monetary policy surprises. This risk premium is therefore positive for both overpriced and underpriced stocks. However, because overpriced stocks have longer duration and are more sensitive to interest rate shocks, they earn a larger announcement premium. As a result, the long-short anomaly portfolio—which is long underpriced stocks and short overpriced ones—experiences negative returns on announcement days.

The left panel of Figure 1 plots the announcement premium (in bps) as a function of the measure for mispricing, $\hat{g}_T - \tilde{g}_T$, holding the interest rate r constant and set $\tilde{g}_T = \bar{g}$. The premium increases monotonically with $\hat{g}_T - \tilde{g}_T$, reflecting greater sensitivity of stock valuations to interest rate shocks among overpriced stocks.

Second, we examine how the level of the interest rate influences the magnitude of announcement premia. When interest rates are low, asset valuations are more sensitive to interest rate shocks, requiring greater risk compensation. The middle panel of Figure 1 plots the announcement premium as a function of the interest rate r, holding others constant. The

Figure 1: Policy Functions



This figure plots the model-implied announcement premium (in bps). The left panel shows the premium as a function of mispricing, measured by $\hat{g}_T - \tilde{g}_T$, holding the interest rate r constant. The middle panel plots the premium as a function of the interest rate r. The right panel plots the premium against mispricing under different interest rate regimes: the red solid line represents the low-rate regime, and the blue dashed line represents the high-rate regime. We set $\tilde{g}_T = \bar{g}$ for all panels. Parameter values used in the numerical solution are reported in Appendix Table 8.

figure shows that the premium decreases with r, implying that long-short anomaly returns become more negative in low interest rate environments.

The right panel of Figure 1 compares the risk premium as a function of $\hat{g}_T - \tilde{g}_T$ across high- and low-interest rate regimes. The red solid line represents the low-rate regime, while the blue dashed line corresponds to the high-rate regime. Under low interest rates, the long-short return averages approximately 30 bps, compared to about 20 bps under high rates. These magnitudes are consistent with the empirical results reported in Section 2.2. This pattern further supports our finding that monetary policy tends to amplify the inverse of anomaly returns more under accommodative monetary policy conditions.

3.4 Quantitative Results

This section presents a quantitative analysis and demonstrates that the model can account for the stylized empirical facts documented in Section 2.

Estimates Table 8 reports the estimated and calibrated benchmark parameter values used in the model. All parameters are expressed at an annual frequency, with $T = 1/8$ indicating eight FOMC announcements per year, consistent with the frequency of pre-scheduled FOMC

meetings in the data.

We first set several parameters directly from the literature. The Poisson exit rate for individual firms is set to $\lambda = 10\%$, following Luttmer (2010). We set average consumption growth to $\mu_C = 1\%$ and its standard deviation to $\sigma_C = 3\%$, in line with Ai, Han, Pan, and Xu (2022) and the long-run risk literature (Bansal and Yaron (2004)), to match the first and second moments of aggregate consumption in the data. Finally, the degree of biased expectations is set to $\phi = 2$ to match long-short portfolio returns on non-FOMC days. This choice is in line with Bordalo, Gennaioli, Porta, and Shleifer (2024), who show that investors overreact to information in long-term growth forecasts and that forecasters respond about twice as strongly to information as would be implied by rational beliefs.

Second, several parameters are calibrated to match moments from outside data. We set $\bar{\theta} = 2\%$, $\sigma_\theta = 1.2\%$, and $b = 0.04$ to match the mean, volatility, and autocorrelation of the risk-free interest rate. The model produces an annualized mean of 2.13%, volatility of 1.96%, and first-order autocorrelation of 0.83, compared to 1.12%, 1.54%, and 0.98 in the monthly federal funds rate data from 1995 to 2024.

The dividend growth parameters are calibrated to match U.S. dividend data. We set $\bar{g} = 1\%$, $\sigma_g = 0.008$, and $a = 0.03$ to match the first two moments and autocorrelation of dividend growth. The model produces an annual mean growth rate of 2.04%, volatility of 13.59%, and autocorrelation of 0.20, compared to 1.6%, 10.8%, and 0.19 in the data. We set $\sigma_D = 16\%$ to match return volatility. The model implies a volatility of 19.03%, close to 18.29% in the data. All nominal quantities are adjusted for inflation using the annual CPI.

The prices of risk are calibrated to match returns on FOMC and non-FOMC announcement days. We choose $\sigma_\pi = 8$ and $\psi = 20$ so that in our calibration, the average market excess returns on FOMC and non-FOMC announcement days are 41.46 bps and 3.47 bps, respectively, close to the corresponding values of 36.6 bps and 2.0 bps reported in Lucca and Moench (2015) and Ai, Han, Pan, and Xu (2022).

Portfolios Sorted on Distortions in Subjective Expectations In our model, mispricing arises from the deviation of beliefs about firm-specific cash flow, $\hat{g}$, from rational expectations, $\tilde{g}$. Stocks with $\hat{g} > \tilde{g}$ are overpriced, while those with $\hat{g} < \tilde{g}$ are underpriced. We therefore sort stocks into decile portfolios based on $\hat{g} - \tilde{g}$. To form the long-short anomaly portfolio, we go long the lowest decile ($\hat{g} - \tilde{g}$ low, underpriced) and and short the highest decile ($\hat{g} - \tilde{g}$ high, overpriced) one day before FOMC announcements, following the same procedure as in the data. This portfolio generates positive average returns on non-FOMC

Table 8: Parameters

Para.	Value	Description	Para.	Value	Description
μ_C	0.01	consumption growth rate	a	0.03	persistence of cash flow
σ_C	0.03	vol of consumption growth	σ_g	0.008	vol of latent cash flow
b	0.04	interest rate persistence	ϕ	2	degree of biased expectation
$\bar{\theta}$	0.02	mean interest rate	σ_π	8	price of interest rate risk
σ_θ	0.012	vol of interest rate	ψ	20	price of consumption risk
σ_D	0.16	vol of dividend growth rate	λ	0.1	death probability
$\bar{g}$	0.01	mean dividend growth rate			

This table displays annualized parameter values used in the simulations.

days, as biased beliefs gradually converge to rational expectations in the long run. The model produces a monotonic pattern in α_i across deciles in Table 9, consistent with the data. Our model yields a long-short portfolio return of 2 bps, which is close to the 3 bps observed in the data (Table 9).

In our model, stocks with higher $\hat{g}-\tilde{g}$ are more sensitive to interest rate shocks and therefore require higher compensation in terms of announcement-day returns. As a result, these stocks earn higher FOMC announcement-day premia. As our model implies, the FOMC dummy coefficients β_i are positive and monotonically increasing across portfolios, consistent with the data. The largest announcement premium, 54 bps, occurs in the short leg (overpriced stocks), compared to 48 bps in the data. The long-short portfolio earns –27 bps on FOMC days compared to other days, closely replicating the –43 bps observed in the data (Table 9).

Next, we replicate the regression in equation (3) from Section 2.2.2, where the long-short portfolio return is regressed on the FOMC dummy, the interaction of the dummy with the lagged interest rate, and the level of the interest rate itself:

$$R_t = 0.02 + (-0.28) \times \mathbf{1}_{FOMC} + 0.02 \times \mathbf{1}_{FOMC} \times r_{t-1} + (-0.01) \cdot r_{t-1}$$

The model captures the positive average return on non-FOMC days, the negative return on FOMC days, and the positive interaction with the interest rate, consistent with the data. Although the coefficient on the interaction term is smaller than in the data, the signs and qualitative patterns are correctly reproduced.

To further evaluate the model's implications under different interest rate regimes, we split

Table 9: Model-implied Anomaly Portfolio Returns around FOMC and non-FOMC announcement days

	Data		Model	
Anomaly deciles	α_i	β_i	α_i	β_i
1 (short)	0.01	0.49	0.03	0.54
2	0.04	0.46	0.04	0.48
3	0.04	0.32	0.04	0.45
4	0.05	0.34	0.04	0.42
5	0.05	0.27	0.04	0.40
6	0.05	0.21	0.04	0.38
7	0.05	0.23	0.04	0.36
8	0.05	0.17	0.04	0.34
9	0.05	0.11	0.05	0.32
10 (long)	0.05	0.07	0.05	0.28
(10-1)	**0.04**	**-0.42**	**0.02**	**-0.27**

This table reports the results from daily regressions of the form: $R_{t,i} = \alpha_i + \beta_i \cdot \mathbf{1}_{FOMC} + \epsilon_{t,i}$, where the dependent variable is the daily portfolio return constructed from anomaly signals. Columns 2 and 3 reproduce the empirical estimates from Table 1, while Columns 4 and 5 report the corresponding model-implied moments.

the sample into high- and low-rate regimes based on whether the lagged interest rate before FOMC announcements is above or below the median. The results are reported in Table 10. The model replicates the empirical finding that average portfolio returns are higher under low-rate regimes and decline monotonically across anomaly portfolios on FOMC days. The long-short spread is –27.6 bps under low-rate regimes, compared to –21.8 bps under high-rate regimes, while the data show –6.03 bps and –23.4 bps, respectively. The model also generates the empirical pattern that long-short portfolio returns are higher under low-rate regimes on non-FOMC days (1.6 bps vs. 1.3 bps under high-rate regimes), consistent with the data (5.1 bps vs. 2.0 bps).

4 Empirical Tests of Additional Model Predictions

In this section, we derive additional empirical predictions from our model and test them using the data. First, we examine whether anomaly returns are indeed driven by mispricing, which in our model arises from biased expectations. We show that monetary policy announcements tend to amplify mispricing, whereas earnings announcements help correct them. Second, we show that anomaly signal is monotonic in measures of subjective cash flow and equity duration.

Table 10: Portfolio Returns Across Interest Rate Regimes

	Data				Model			
	Low		High		Low		High	
Anomaly deciles	α_i^L	β_i^L	α_i^H	β_i^H	α_i^L	β_i^L	α_i^H	β_i^H
1 (short)	-0.008	0.633	0.040	0.333	0.019	0.577	0.040	0.427
2	0.014	0.503	0.057	0.405	0.024	0.511	0.043	0.371
3	0.020	0.355	0.058	0.271	0.024	0.479	0.045	0.343
4	0.022	0.332	0.075	0.333	0.027	0.454	0.046	0.323
5	0.027	0.293	0.067	0.234	0.028	0.432	0.047	0.306
6	0.036	0.221	0.060	0.188	0.028	0.412	0.047	0.291
7	0.037	0.211	0.058	0.246	0.028	0.392	0.049	0.275
8	0.030	0.194	0.060	0.139	0.031	0.370	0.049	0.260
9	0.031	0.141	0.068	0.070	0.031	0.345	0.051	0.240
10 (long)	0.042	0.029	0.060	0.099	0.034	0.301	0.053	0.209
(10-1)	0.051	-0.603	0.020	-0.234	0.016	-0.276	0.013	-0.218

This table reports the results from daily regressions of the form: $R_{t,i} = \alpha_i + \beta_i \cdot \mathbf{1}_{FOMC} + \epsilon_{t,i}$, where the dependent variable is the daily portfolio return constructed from anomaly signals. The sample is split into low- and high-interest-rate regimes, defined by whether the interest rate level before the FOMC announcement is below or above the median. Columns 2–5 present data moments, while Columns 6–9 report the corresponding model-implied moments.

FOMC versus Earnings Announcement Our first test leverages the distinct informational roles of FOMC and earnings announcements. FOMC announcements primarily convey aggregate discount rate information, which can amplify the effects of biased expectations and widen valuation gaps. In contrast, earnings announcements provide firm-specific cash flow information. As shown by Engelberg, McLean, and Pontiff (2018), such announcements help correct biased subjective expectations, reduce mispricing, and are associated with higher anomaly portfolio returns. Specifically, they document a +25 bps average return on earnings announcement days for anomaly portfolios.

In our model, earnings announcements reveal information about the true dividend growth rate g, causing the subjective belief $\hat{g}$ to converge toward the rational expectation $\tilde{g}$. For overpriced stocks (where $\hat{g} > \tilde{g}$), this correction represents negative news and leads to price declines. For underpriced stocks (where $\hat{g} < \tilde{g}$), the revision is positive, leading to price increases. Thus, long-short anomaly portfolios earn positive returns on earnings announcement days.

Based on this insight, we test a key prediction of our model: because FOMC announcements amplify mispricing by increasing the price impact of distortions in subjective expectations, FOMC-day returns can be used to further identify mispricing. To test this idea, we classify each stock as either consistent or inconsistent based on whether its FOMC-day return aligns with its anomaly ranking. A stock is considered consistent if (i) it is in the

long leg and earns a below-median return on FOMC days, or (ii) it is in the short leg and earns an above-median return. These consistent stocks represent cases in which FOMC announcements amplify the initial mispricing.

We then estimate a Fama-MacBeth regression of earnings announcement-day returns using the following specification:

$$R_{t,j} = \alpha_j + \beta_j \text{Anomaly_rank}_{t,j} + \gamma \text{Anomaly_rank}_{t,j} \cdot Const_{t,j} + \delta_j Const_{t,j} + \epsilon_{t,j}, \quad (18)$$

where $\text{Const}_{t,j} = 1$ if stock j is classified as consistent, and 0 otherwise. $\text{AnomalyRank}_{t,j}$ is the composite anomaly ranking (1 = most overpriced, 10 = most underpriced).

Panel A of Table 11 reports the results. We find that, on average, the long-short anomaly portfolio earns 14.4 bps on earnings announcement days (i.e., $0.016 \times (10-1) \times 100$), consistent with Engelberg, McLean, and Pontiff (2018). Strikingly, consistent stocks—those whose FOMC-day return aligns with their anomaly ranking—earn more than twice as much as inconsistent stocks. Specifically, consistent stocks earn a total of 31.5 bps, including an additional 17.1 bps premium relative to inconsistent stocks. These findings support our core mechanism: FOMC announcements amplify the pricing impacts of biased expectations, while earnings announcements help correct them through firm-specific information. Panel B runs the similar tests on all non-FOMC days including the earnings and non-earnings days. We find similar results that consistent stocks generate higher anomaly returns compared to inconsistent stocks. These results suggest that the cross-section of returns on FOMC days provides incrementally useful information in identifying anomaly signals.

Anomaly Signals Aligned with Subjective Cash-Flow Expectations or Duration Although we use a composite index of anomaly signals, not all signals are necessarily related to subjective expectations or duration. To isolate those most relevant for our mechanism, Table 12 splits anomalies into groups based on how well they align with long-term growth (LTG) forecasts and equity duration. In Panel A, anomalies are sorted into terciles of the difference between average LTG in the long and short legs. The lowest-difference tercile ("LTG aligned," where LTG is higher in the short leg) has the most negative FOMC-day returns—about –40 bps (–23.3 bps after controlling for CAPM beta)—while the "LTG not aligned" group even exhibits slightly positive FOMC-day returns. Aligned signals also have the largest beta with respect to monetary policy surprises, whereas the "LTG not aligned" group has a beta close to zero and a near-zero MPS beta. Panel B repeats this exercise using equity duration and finds a similar pattern: anomalies for which the short leg has longer

Table 11: Mispricing Consistency

Anomaly_rank	Anomaly_rank · *Const*	*Const*
Panel A: on earnings and non-FOMC days		
0.016	0.019	-0.28
(1.77)	(2.03)	(1.87)
Panel B: on non-FOMC days		
0.007	0.003	-0.010
(3.47)	(2.40)	(-1.32)

This table reports the results of Fama-MacBeth regressions of individual stock returns on earnings announcement days (Panel A) and non-FOMC days (Panel B) within each FOMC cycle. The regression specification is:

$$R_{t,j} = \alpha_j + \beta_j \text{Anomaly_rank}_{t,j} + \gamma \text{Anomaly_rank}_{t,j} \cdot Const_{t,j} + \delta_j Const_{t,j} + \epsilon_{t,j}.$$

For each FOMC announcement, stocks are ranked into deciles based on their latest FOMC-day returns to define a "consistency" indicator: $\text{Const}_{t,j} = 1$ if a stock's FOMC return rank and anomaly rank are both above or both below the median; otherwise, $\text{Const}_{t,j} = 0$. We then merge the stock returns on earnings days or non-FOMC days that occur between that FOMC announcement and the next one. The sample period is from 1995 to 2024. All returns are expressed in percentage points. Newey-West adjusted t-statistics are reported in parentheses.

duration load more strongly on monetary policy surprises than those where duration is not aligned. Overall, aligned anomalies earn more negative FOMC-day returns and exhibit greater sensitivity to monetary policy surprises than unaligned anomalies. These results reinforce our mechanism: stocks with higher subjective cash-flow expectations or longer duration exhibit stronger sensitivity to monetary policy shocks.

One might ask whether measures of subjective cash-flow expectations such as LTG or duration should be used directly to sort stocks, rather than relying on our anomaly composite index. However, both LTG and duration are noisy: LTG forecasts are only available for a subset of firms, and duration estimates are difficult to measure precisely.

Analysts' Forecast Revisions Around FOMC Announcements Our theory implies that the FOMC-day risk premium arises from cross-sectional heterogeneity in existing anomaly signals through their effect on interest-rate sensitivity, not from contemporaneous revisions in firm-level cash-flow expectations. A natural alternative explanation is that the negative long-short portfolio return reflects changes in subjective expectations on FOMC days—for example, if analysts revised forecasts upward for short-leg (overpriced) stocks and downward for long-leg (underpriced) stocks, pushing valuations further away from fundamentals.

Table 13 shows that this is not the case. Analysts' long-term growth (LTG) forecasts

Table 12: FOMC Returns for Aligned vs. Not-Aligned Anomalies

Panel A: LTG	β	α	$\beta^{\text{CAPM-adj}}$	$\alpha^{\text{CAPM-adj}}$	β^{MPS}
Aligned	-0.400	0.001	-0.233	0.025	0.06
	(-3.92)	(0.04)	(-2.81)	(1.52)	(2.70)
Rest	-0.225	0.044	-0.121	0.061	0.03
	(-2.78)	(2.83)	(-1.93)	(5.21)	(1.51)
Not aligned	0.083	0.032	0.121	0.040	0.004
	(1.08)	(2.57)	(1.60)	(3.14)	(0.29)
Panel B: Duration	β	α	$\beta^{\text{CAPM-adj}}$	$\alpha^{\text{CAPM-adj}}$	β^{MPS}
Aligned	-0.277	0.005	-0.152	0.056	0.07
	(-3.60)	(0.41)	(-2.03)	(3.74)	(2.88)
Rest	-0.405	0.022	-0.190	0.028	0.04
	(-3.70)	(1.08)	(-2.81)	(2.08)	(2.26)
Not aligned	-0.199	0.066	0.057	0.038	0.02
	(-2.18)	(4.26)	(0.94)	(3.22)	(1.38)

This table reports FOMC-day announcement coefficients for long-short anomaly portfolios, split by alignment groups. Columns (2)-(3) show β_i and α_i from the regression $R_{t,i} = \alpha_i + \beta_i \mathbf{1}_{\text{FOMC},t} + \varepsilon_{t,i}$ (Table 1). Columns (4)-(5) report the CAPM-adjusted coefficients $\beta_i^{\text{CAPM-adj}}$ and $\alpha_i^{\text{CAPM-adj}}$ from $R_{t,i} = \alpha_i^{\text{CAPM-adj}} + \beta_i^{\text{CAPM-adj}} \mathbf{1}_{\text{FOMC},t} + \beta_i (R_t^M - r_{f,t}) + \beta_{i,\text{FOMC}} (R_t^M - r_{f,t}) \mathbf{1}_{\text{FOMC},t} + \varepsilon_{t,i}$ (Table 2). Column (6) reports the monetary-policy-surprise beta β^{MPS} from $R_t = \alpha + \beta^{\text{MPS}} \text{MPS_ORTH}_t + \varepsilon_t$ (Table 4). In Panel A, anomalies are sorted into terciles based on the difference between the average long-term growth (LTG) forecast in the long leg and the short leg; the lowest-difference tercile is labeled "LTG aligned," the highest "LTG not aligned," and the middle tercile "Rest." Panel B applies the same procedure using average equity duration, defining "Duration aligned," "Not aligned," and "Rest" analogously.

depend systematically on anomaly signals: LTG is revised downward for short-leg (overpriced) stocks and upward for long-leg (underpriced) stocks. The coefficient on anomaly rank is significantly positive, 0.0068 ($t = 4.91$) —indicating that investors gradually revise their beliefs about firm cash flows in a way that slowly corrects mispricing over time. Crucially, the coefficient on the interaction between anomaly rank and the FOMC indicator is 0.0024 ($t = 0.74$), implying that the sensitivity of LTG revisions to anomaly ranking does not change in the week following FOMC announcements. In other words, FOMC news does not trigger stronger or systematically different belief revisions across anomaly portfolios than in the pre-announcement period.

Appendix Tables 13 and A.5 show that these results are robust when we use earnings-per-share (EPS) forecast revisions and when we focus exclusively on LTG revisions made on FOMC days. In both cases, analysts revise forecasts in the correcting direction—down for short-leg (overpriced) stocks and up for long-leg (underpriced) stocks. Thus, belief revisions around FOMC days operate in a correcting—rather than amplifying—direction and cannot explain the negative long-short anomaly returns.

Table 13: Analyst LTG Revisions following FOMC Announcements

Anomaly_rank	Anomaly_rank · FOMC_1w	FOMC_1w
Panel A: without fixed effect		
0.0068	0.0024	0.0115
(4.91)	(0.74)	(0.66)
Panel B: with fixed effect		
0.0102	0.0005	0.0190
(2.51)	(0.12)	(0.92)

This table tests whether analysts' long-term growth (LTG) revisions, measured with respect to anomaly ranking, differ following FOMC announcements. The regression specification is:

$$Up_LTG_{i,j,t} = \alpha + \beta \text{Anomaly_rank}_{i,t} + \gamma \text{Anomaly_rank}_{i,t} \cdot \text{FOMC_1w}_t + \delta \text{FOMC_1w}_t + \epsilon_{i,j,t}.$$

Up_LTG is a indicator variable that equals to one if the LTG forecast of stock i made by analyst j in the his/her forecast made in day t is greater than his/her previous forecast. $FOMC_1w$ is an indicator that equals to one if the forecast is made within 1 week following the FOMC announcements. Panel A does not include any fixed effects, whereas Panel B include analyst and stock-year fixed effects. The sample period is from 1995 to 2024. t-statistics that are double clustered at analyst and date levels are reported in parentheses.

5 Conclusion

To conclude, this paper identifies a new channel through which monetary policy transmits to the cross-section of stock returns—through stocks associated with anomaly signals. Empirically, we show that long-short anomaly portfolios earn significantly negative risk premia on FOMC announcement days relative to other days, especially earnings announcement days, and that this effect is more pronounced under accommodative monetary policy. The impact of monetary policy is persistent and accounts for a substantial buildup of mispricing, implying that monetary policy can worsen market efficiency.

To account for these findings, we develop a model in which monetary policy announcements generate shocks to the discount rate. In the model, monetary policy affects risk compensation for stocks with anomaly signals through heterogeneity in valuation sensitivity to interest rate shocks. This sensitivity depends on anomaly rankings: when investors' subjective beliefs about firm cash flows exceed rational expectations, stock prices become more sensitive to interest rate shocks. Overpriced stocks—those with higher subjective cash-flow beliefs—have longer duration, greater exposure to interest rate risk, and therefore higher announcement premia, while underpriced stocks are less exposed. Low interest rate environments further amplify this mechanism, leading to the negative long-short returns observed on FOMC days.

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A Appendix

Table A.1 shows that our results are robust across alternative anomaly sets from the literature, including Engelberg, McLean, and Pontiff (2018), Daniel, Hirshleifer, and Sun (2020), Novy-Marx and Velikov (2016), Stambaugh and Yuan (2017), Jensen, Kelly, and Pedersen (2023) and Hou, Xue, and Zhang (2020).

Table A.2 show that the results remain almost unchanged when controlling for additional standard risk factors such as size, value, and momentum.

Table A.1: FOMC Effects Using Alternative Anomaly Sets

Anomaly	α_i	t_α	β_i	t_β
Dong, Li, Rapach, and Zhou (JF 2022)	0.04	(2.34)	-0.42	(-3.95)
Engelberg, Mclean, and Pontiff (JF 2018)	0.05	(3.10)	-0.30	(-3.44)
Daniel, Hirshleifer, Sun (RFS 2020)	0.07	(4.65)	-0.20	(-2.34)
Novy-Marx and Velikov (RFS 2016)	0.04	(2.16)	-0.36	(-3.44)
Stambaugh and Yuan (RFS 2017)	0.05	(3.66)	-0.17	(-2.12)
Jensen, Kelly, Pedersen (JF 2023)	0.06	(3.17)	-0.38	(-3.65)
Hou, Xue, and Zhang (RFS 2020)	0.03	(1.51)	-0.40	(-4.06)

This table reports results based on alternative anomaly sets from the literature, corresponding to the regressions in Table 1. We estimate daily regressions of the form: $R_{t,i} = \alpha_i + \beta_i \cdot \mathbf{1}_{FOMC} + \epsilon_{t,i}$, where the dependent variable is the daily return of long-short value-weighted portfolios constructed from various anomaly signals. Each month, stocks are sorted into deciles based on a composite index formed from individual anomaly signals drawn from the respective literature. Portfolios are rebalanced monthly, and daily returns are measured over the following month. Value weights are based on market capitalization at the end of the previous trading day. The dummy variable $\mathbf{1}_{FOMC}$ equals one on pre-scheduled FOMC announcement days and zero otherwise. The sample period spans from 1995 to 2024.

Table A.3 repeats the analysis of Table 1 using indicators for other macroeconomic announcements. Panel A shows that long-short anomaly returns are also negative around GDP, unemployment, and CPI announcement days. Panel B demonstrates that these results remain robust after controlling for CAPM betas, as in Table 2.

Table A.4 shows that analysts' earnings-per-share (EPS) forecast revisions depend systematically on anomaly signals: forecasts are revised downward for short-leg (overpriced) stocks and upward for long-leg (underpriced) stocks. The coefficient on anomaly rank is significantly positive, 0.0101 ($t = 11.16$), indicating that investors gradually revise their beliefs about firm cash flows in a way that slowly corrects valuation deviations over time. Importantly, the interaction between anomaly rank and the FOMC indicator is 0.0044 ($t = 2.30$), implying that the sensitivity of EPS revisions to anomaly ranking becomes stronger in the week following FOMC announcements. In other words, investors revise beliefs more strongly in the correcting direction after announcements, reducing belief dispersion and narrowing valuation gaps. This finding contrasts with our earlier evidence that valuation dispersion in-

Table A.2: Anomaly Portfolio Returns around FOMC days Controlling for FF3 and FFC4 factors

Anomaly deciles	FF3 factors				FFC 4 factors			
	α_i	t_α	$\alpha_{i,FOMC}$	$t_{\alpha_{FOMC}}$	α_i	t_α	$\alpha_{i,FOMC}$	$t_{\alpha_{FOMC}}$
1 (short)	-0.03	(-3.35)	0.09	(2.22)	-0.02	(-2.41)	0.10	(2.65)
2	-0.00	(-0.54)	0.11	(2.85)	-0.00	(-0.08)	0.11	(3.04)
3	0.00	(0.57)	0.02	(0.71)	0.00	(0.73)	0.02	(0.77)
4	0.01	(2.96)	0.06	(2.06)	0.01	(3.01)	0.06	(2.10)
5	0.01	(3.17)	0.00	(0.17)	0.01	(3.07)	0.00	(0.15)
6	0.02	(3.85)	-0.03	(-1.00)	0.02	(3.54)	-0.03	(-1.06)
7	0.02	(4.22)	0.01	(0.36)	0.02	(3.91)	0.01	(0.29)
8	0.02	(3.95)	-0.03	(-1.06)	0.02	(3.47)	-0.03	(-1.22)
9	0.02	(4.66)	-0.06	(-1.94)	0.02	(4.13)	-0.06	(-2.15)
10 (long)	0.03	(4.99)	-0.08	(-2.26)	0.02	(4.16)	-0.09	(-2.68)
(10-1)	0.06	(4.71)	-0.16	(-2.72)	0.06	(3.69)	-0.19	(-3.29)

This table reports the results from the following daily CAPM regression: $R_{t,i} = \alpha_i + \alpha_{i,FOMC} \cdot \mathbf{1}_{FOMC} + \beta_i \left(R_t^M - r_{f,t}\right) + \beta_{i,FOMC} \left(R_t^M - r_{f,t}\right) \cdot \mathbf{1}_{FOMC} + Other\ factor + \epsilon_{t,i}$, where $R_{t,i}$ is the daily return of value-weighted portfolio i, R_t^M is the daily market return, and $r_{f,t}$ is the daily risk-free rate. For the left four columns, the other factors include SMB and HML factors; for the right four columns, other factors include SMB, HML, and MOM factor. The dummy variable $\mathbf{1}_{\text{FOMC}}$ equals one on scheduled FOMC announcement days and zero otherwise. The dependent variable is constructed from portfolios sorted into deciles each month based on a composite index formed from 171 individual anomaly signals. Decile 1 (10) corresponds to the most overpriced (underpriced) stocks, forming the short (long) leg of the anomaly portfolio. Portfolios are rebalanced monthly, and daily returns are calculated over the subsequent month. Value weights are based on market capitalization as of previous trading day. t-statistics are reported in parentheses. The sample period spans from 1995 to 2024.

Table A.3: Other Macro Announcements

Panel A: FOMC and Other macro news					
Rank	α	FOMC	GDP	Unemp	CPI
(10-1)	0.056	-0.416	-0.181	-0.113	-0.142
	(2.82)	(-4.21)	(-2.42)	(-1.29)	(-1.73)
Panel B: Controlling for Market Betas					
Rank	α	FOMC	GDP	Unemp	CPI
	0.071	-0.209	-0.072	-0.012	-0.123
	(4.62)	(-3.05)	(-1.13)	(-0.18)	(-1.95)

This table examines the long-short anomaly portfolio returns on other macro news announcement days (GDP, unemployment, and CPI). Panel B further controls for market beta. Returns are expressed in percentage points. Newey-West adjusted t-statistics are reported in parentheses. The sample period is from 1995 to 2024.

creases following FOMC announcements. Therefore, the negative long-short anomaly return observed around FOMC days cannot be attributed to greater belief heterogeneity. Instead, the evidence suggests that monetary policy announcements primarily affect discount-rate dynamics rather than changing biased expectations about firm fundamentals.

Table A.5 tests whether analysts' long-term growth (LTG) forecast revisions, measured

Table A.4: Analyst EPS Forecast Revisions following FOMC Announcements

Anomaly_rank	Anomaly_rank · FOMC_1w	FOMC_1w
Panel A: without fixed effect		
0.0101	0.0044	0.0199
(11.16)	(2.30)	(2.13)
Panel B: with analyst and stock fixed effect		
0.0197	0.0050	0.0121
(16.16)	(2.67)	(1.42)

This table tests whether analysts' earnings per share (EPS) revisions, measured with respect to anomaly ranking, differ following FOMC announcements. The regression specification is:

$$Up_EPS_{i,j,t} = \alpha + \beta \text{Anomaly_rank}_{i,t} + \gamma \text{Anomaly_rank}_{i,t} \cdot \text{FOMC_1w}_t + \delta \text{FOMC_1w}_t + \epsilon_{i,j,t}.$$

$Up_EPS_{i,j,t}$ is an indicator variable equal to one if analyst j's annual EPS forecast for stock i on day t exceeds his or her previous forecast. $FOMC_1w$ is an indicator equal to one if the forecast is made within one week following an FOMC announcement. Panel A does not include fixed effects, while Panel B includes both analyst and stock fixed effects. The sample period covers 1995–2024. t-statistics, double-clustered at the analyst and date levels, are reported in parentheses.

with respect to anomaly ranking, differ on FOMC announcement days. This table provides further evidence consistent with the previous results: focusing only on FOMC announcement days yields the same pattern. Analysts revise LTG forecasts downward for short-leg (overpriced) stocks and upward for long-leg (underpriced) stocks, indicating that belief corrections occur even when restricting attention to FOMC days.

Table A.5: Analyst LTG Revisions on FOMC Announcement Days

Anomaly_rank	Anomaly_rank · FOMC	FOMC
Panel A: without fixed effect		
0.0106	0.0048	0.0169
(12.27)	(1.27)	(0.87)
Panel B: with fixed effect		
0.0204	0.0070	0.0009
(16.91)	(2.06)	(0.05)

This table tests whether analysts' long-term growth (LTG) forecast revisions, measured with respect to anomaly ranking, differ on FOMC announcement days. The regression specification is:

$$\Delta Log(LTG)_{i,j,t} = \alpha + \beta \text{Anomaly_rank}_{i,t} + \gamma \text{Anomaly_rank}_{i,t} \cdot \text{FOMC}_t + \delta \text{FOMC}_t + \epsilon_{i,j,t}.$$

$\Delta Log(LTG)_{i,j,t}$ denotes the change in analyst j's long-term growth forecast for stock i on day t. $FOMC_t$ is an indicator equal to one if the forecast is made on an FOMC announcement day. Panel A does not include fixed effects, whereas Panel B includes both analyst and stock fixed effects. The sample period is 1995–2024. t-statistics, double-clustered at the analyst and date levels, are reported in parentheses.

Table A.6 repeats the exercise in Section 2.2.3 , where we regress daily portfolio returns on monetary policy surprises. In Column 2, we use the shocks constructed by Jarociński and Karadi (2020), who take the first principal component of surprises in interest rate derivatives with maturities from one month to one year. The results are essentially identical to those obtained using Bauer and Swanson (2023) shocks: stock returns react negatively to monetary policy surprises, and short-leg stocks are more sensitive to these shocks.

Columns 4 and 5 use the Jarociński and Karadi (2020) decomposition, which imposes sign restrictions to separate monetary policy surprises into a central bank information (CBI) component and a conventional monetary policy (MP) component. By construction, these two shocks add up to the first principal component used in Column 2. Our main interest lies in the CBI shocks. Here, sensitivities are positive across all anomaly portfolios: a positive information shock indicates that the Fed is conveying private information about the macroeconomy, which raises stock prices. Moreover, the sensitivities decrease monotonically across anomaly portfolios, indicating that short-leg stocks are more sensitive to information shocks than long-leg stocks.

Note that the information shock does not offset the effect of conventional monetary policy shocks in Column 4. Moreover, this finding is consistent with our theory: if firm cash flow has both an aggregate component G and a firm-specific component $\hat{g}_i$, so that total expected growth is $\hat{g} = G + \hat{g}_i$, then the Gordon growth formula implies $\left|\frac{d(P/D)}{dG}\right| = \frac{1}{(r-\hat{g})^2}$. This delivers the same comparative statics as the sensitivity to interest rate shocks. While we do not explicitly introduce aggregate cash flow (information) shocks in our model—since our focus is on conventional monetary policy surprises—the empirical evidence on information shocks is fully consistent with our model's implications.

B Appendix: Model Solution and Derivations

Interest Rate Surprise The closed-form solution for θ_T is:

$$\theta_T = e^{-b(T-t)}\theta_t + (1 - e^{-b(T-t)})\bar{\theta} + \int_t^T e^{-b(T-u)}\sigma_\theta dB_u, \tag{A.1}$$

so that $\theta_T - \theta_t = \left(1 - e^{-b(T-t)}\right)\left(\bar{\theta} - \theta_t\right) + \int_t^T e^{-b(T-u)}\sigma_\theta \, dB_u$. At time $(n+1)T$, this becomes:

$$\theta_{(n+1)T} - \theta_{nT} = \left(1 - e^{-bT}\right)\left(\bar{\theta} - \theta_{nT}\right) + \int_{nT}^{(n+1)T} e^{-b((n+1)T-u)}\sigma_\theta dB_u.$$

Table A.6: Sensitivity of Anomaly Portfolios to Jarociński and Karadi (2020) Shocks

Anomaly Ranking	JK	(t-stat)	MP	CBI
1 (short)	-0.10	(-4.48)	-0.16	0.14
2	-0.06	(-3.31)	-0.11	0.11
3	-0.06	(-3.91)	-0.10	0.07
4	-0.04	(-2.79)	-0.07	0.04
5	-0.04	(-3.02)	-0.06	0.06
6	-0.03	(-2.36)	-0.05	0.03
7	-0.04	(-3.79)	-0.06	0.02
8	-0.03	(-2.31)	-0.04	0.02
9	-0.02	(-1.95)	-0.03	0.02
10 (long)	-0.01	(-0.83)	-0.02	0.01
10-1	0.09	(4.72)	0.14	-0.13

This table reports the sensitivity of portfolio daily returns to the shocks (JK) identified by Jarociński and Karadi (2020) on FOMC announcement days. For each decile portfolio sorted by the anomaly index, we estimate the following regression: $R_t = \alpha + \beta \text{JK shock}_t + \varepsilon_t$. We also separately include the central bank information shock component (CBI) and the monetary policy shock component (MP) in the regression of anomaly portfolio returns on FOMC announcement days. By construction, the variables satisfy JK=MPS+CBI.

Table A.7: FOMC effect on Treasury Strategy

US Treasury index	α_i	β_i
Short-term bond	0.009	0.001
	(21.39)	(0.30)
Long-term bond	0.017	0.102
	(1.95)	(1.84)
Long-short	0.08	0.101
	(0.095)	(1.84)

This table reports the results from daily regressions of the form: $R_{t,i} = \alpha_i + \beta_i \cdot \mathbf{1}_{FOMC} + \epsilon_{t,i}$, where the dependent variable is the daily return of a bond index. "Short-term" refers to the Bloomberg US Short Treasury Index, whereas "long-term" refers to the Bloomberg US Long Treasury Total Return Index. Returns are expressed in percentages. Sample period is from 1998 to 2024.

Thus, the expected jump is

$$\mathbb{E}_{nT}\left[dr_{(n+1)T}\right] = \left(1 - e^{-bT}\right)\left(\bar{\theta} - \theta_{nT}\right). \tag{A.2}$$

The interest rate surprise at the announcement is:

$$\begin{aligned} dN_{(n+1)T} = dr_{(n+1)T} - \mathbb{E}^{-}_{nT}\left[dr_{(n+1)T}\right] &= \left[\theta_{(n+1)T} - \theta_{nT}\right] - \mathbb{E}^{-}_{nT}\left[\theta_{(n+1)T} - \theta_{nT}\right] \\ &= \int_{nT}^{(n+1)T} e^{-b((n+1)T-u)}\sigma_\theta dB_u. \end{aligned}$$

Clearly, this surprise is normally distributed with mean zero and variance:

$$\mathbb{V}\text{ar}\left[dN_{(n+1)T}\right] = \sigma_\theta^2 \int_0^T e^{-2b(T-s)} ds = \frac{\sigma_\theta^2}{2b}(1 - e^{-2bT}). \tag{A.3}$$

The law of motion of posterior variance under Bayesian belief is $dq_t = \left(\sigma_g^2 - 2aq_t - \frac{q_t^2}{\sigma_D^2}\right) dt$. The closed-form solution for q_t is

$$q_t = \frac{\sigma_g^2 \left(1 - he^{-2\hat{a}t}\right)}{(\hat{a} - a)\, he^{-2\hat{a}t} + a + \hat{a}},$$

where $\hat{a} = \sqrt{a^2 + (\sigma_g/\sigma_D)^2}$ and $h = \frac{\sigma_g^2 + (\hat{a}-a)q_0}{\sigma_g^2 - (\hat{a}+a)q_0}$. The steady state is $\bar{q} = q_\infty = -a\sigma_D^2 + \sigma_D\sqrt{a^2\sigma_D^2 + \sigma_g^2}$.

Price-Dividend Ratio After learning, the dividend dynamics are

$$\begin{aligned}
\frac{dD_t}{D_t} &= (\mu_C + \hat{g}_t)\, dt + \sigma_C dB_{C,t} + \sigma_D d\hat{B}_{D,t}, && \text{(A.4)}\\
\frac{d\delta_t}{\delta_t} &= \hat{g}_t dt + \sigma_D d\hat{B}_{D,t}, && \text{(A.5)}\\
d\hat{g}_t &= a\,(\bar{g} - \hat{g}_t)\, dt + \phi \frac{q_t}{\sigma_D} d\hat{B}_{D,t}. && \text{(A.6)}
\end{aligned}$$

We have the following closed-form solutions:

$$\begin{aligned}
\hat{g}_s &= e^{-a(s-t)}\hat{g}_t + (1 - e^{-a(s-t)})\bar{g} + \int_t^s e^{-a(s-u)}\phi \frac{q_u}{\sigma_D} d\hat{B}_{D,u}, && \text{(A.7)}\\
\delta_s &= \delta_t e^{\int_t^s \left(\hat{g}_u - \frac{1}{2}\sigma_D^2\right)du + \int_t^s \sigma_D d\hat{B}_{D,u}}. && \text{(A.8)}
\end{aligned}$$

Since

$$\begin{aligned}
\int_t^s \hat{g}_u du &= \int_t^s \left[e^{-a(u-t)}\hat{g}_t + (1 - e^{-a(u-t)})\bar{g} + \int_t^u e^{-a(u-v)}\phi \frac{q_v}{\sigma_D} d\hat{B}_{D,v}\right] du\\
&= \frac{1}{a}\hat{g}_t \left(1 - e^{-a(s-t)}\right) + \bar{g}\,(s-t) - \frac{1}{a}\bar{g}\left(1 - e^{-a(s-t)}\right) + \int_t^s \left[\int_t^u e^{-a(u-v)}\phi \frac{q_v}{\sigma_D} d\hat{B}_{D,v}\right] du\\
&= \bar{g}\,(s-t) + \frac{1}{a}\left(1 - e^{-a(s-t)}\right)(\hat{g}_t - \bar{g}) + \int_t^s \phi \frac{q_v}{\sigma_D}\left[\int_v^s e^{-a(u-v)} du\right] d\hat{B}_{D,v}\\
&= \bar{g}\,(s-t) + \frac{1}{a}\left(1 - e^{-a(s-t)}\right)(\hat{g}_t - \bar{g}) + \int_t^s \phi \frac{q_u}{a\sigma_D}\left(1 - e^{-a(s-u)}\right) d\hat{B}_{D,u},
\end{aligned}$$

define

$$k_1(u;s) \equiv \phi \frac{q_u}{a\sigma_D}\left(1 - e^{-a(s-u)}\right) + \sigma_D,$$

which gives

$$\delta_s = \delta_t e^{\left(\bar{g} - \frac{1}{2}\sigma_D^2\right)(s-t) + \frac{1}{a}\left(1-e^{-a(s-t)}\right)(\hat{g}_t - \bar{g}) + \int_t^s k_1(u;s) d\hat{B}_{D,u}}. \tag{A.9}$$

The stochastic integral is normally distributed with

$$\int_t^s k_1(u;s)\, d\hat{B}_{D,u} \sim \mathcal{N}\left(0, \int_t^s \left[\phi \frac{q_u}{a\sigma_D}\left(1 - e^{-a(s-u)}\right) + \sigma_D\right]^2 du\right). \tag{A.10}$$

We also define the term in the stochastic integral of $\hat{g}$ in (A.7) as

$$k_2(u;s) \equiv e^{-a(s-u)} \phi \frac{q_u}{\sigma_D},$$

so that

$$\int_t^s k_2(u;s)\, d\hat{B}_{D,u} \sim \mathcal{N}\left(0, \int_t^s \left(e^{-a(s-u)} \phi \frac{q_u}{\sigma_D}\right)^2 du\right). \tag{A.11}$$

The closed-form solution for C_t is

$$C_s = C_t e^{\left(\mu_C - \frac{1}{2}\sigma_C^2\right)(s-t) + \int_t^s \sigma_C dB_{C,u}}.$$

Next, we solve for the price–dividend ratio. For $t \in [0, T)$, it satisfies

$$p(r, \hat{g}_t, t)\, \delta_t C_t = \mathbb{E}_t\left[\int_t^T \frac{\pi_s}{\pi_t} e^{-\lambda(s-t)} \delta_s C_s ds + e^{-\lambda(T-t)} \frac{\pi_T^+}{\pi_t} p\left(r_T^+, \hat{g}_T^+, T^+\right) \delta_T C_T\right]. \tag{A.12}$$

For simplicity, factorize the SDF as $\pi_t = m_t n_t$,with

$$\frac{dm_t}{m_t} = -r_t dt + \sigma_\pi dN_t \tag{A.13}$$

$$\frac{dn_t}{n_t} = -\psi r_t dB_{C,t}. \tag{A.14}$$

Since between announcements, r is constant. Thus, on $[t, s)$,

$$m_s = m_t e^{-r(s-t)},\ n_s = n_t e^{-\frac{1}{2}\psi^2 r^2 (s-t) - \int_t^s \psi r dB_{C,u}}.$$

Hence,

$$\frac{n_s}{n_t}\frac{C_s}{C_t} = e^{\left(\mu_C - \frac{1}{2}\sigma_C^2 - \frac{1}{2}\psi^2 r^2\right)(s-t) + \int_t^s (\sigma_C - \psi r) dB_{C,u}},$$

and taking expectations over $B_{C,t}$ (using $\mathbb{E}\left[e^{a\int_t^s dB_{C,u}}\right] = e^{\frac{1}{2}a^2(s-t)}$) yields

$$\mathbb{E}_t\left[\frac{n_s}{n_t}\frac{C_s}{C_t}\middle| B_t, \hat{B}_{D,t}, B_{g,t}\right] = e^{(\mu_C - \psi\sigma_C r)(s-t)}.$$

Therefore, Equation (A.12) can be written as:

$$p\left(r, \hat{g}_t, t\right)\delta_t = \mathbb{E}_t\left[\int_t^T \frac{m_s}{m_t} e^{(\mu_C - \psi\sigma_C r - \lambda)(s-t)}\delta_s ds + \frac{m_T^+}{m_t} p\left(r_T^+, \hat{g}_T^+, T^+\right)\delta_T e^{(\mu_C - \psi\sigma_C r - \lambda)(T-t)}\right].$$

We now define

$$\tilde{\pi}_t = m_t e^{\int_0^t (\mu_C - \psi\sigma_C r_u - \lambda) du}. \tag{A.15}$$

Using the dynamics of (A.13), we obtain

$$\frac{d\tilde{\pi}_t}{\tilde{\pi}_t} = -\left[\left(1 + \psi\sigma_C\right) r_t + \left(\lambda - \mu_C\right)\right] dt + \sigma_\pi dN_t. \tag{A.16}$$

Change variables:

$$\tilde{r}_t = \left(1 + \psi\sigma_C\right) r_t + \left(\lambda - \mu_C\right), \tag{A.17}$$

$$\bar{\tilde{\theta}} = \left(1 + \psi\sigma_C\right)\bar{\theta} + \left(\lambda - \mu_C\right), \tag{A.18}$$

$$\tilde{\sigma}_\pi = \frac{1}{1 + \psi\sigma_C}\sigma_\pi, \tag{A.19}$$

$$\tilde{\sigma}_\theta = \left(1 + \psi\sigma_C\right)\sigma_\theta, \tag{A.20}$$

and

$$d\tilde{N}_t = d\tilde{r}_t - \mathbb{E}_t^-\left[d\tilde{r}_t\right] = \left(1 + \psi\sigma_C\right)\left(dr_t - \mathbb{E}_t^-\left[dr_t\right]\right).$$

This allows us to rewrite the present value as

$$p\left(\tilde{r}, \hat{g}_t, t\right)\delta_t = \mathbb{E}_t\left[\int_t^T \frac{\tilde{\pi}_s}{\tilde{\pi}_t}\delta_s ds + \frac{\tilde{\pi}_T^+}{\tilde{\pi}_t} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\delta_T\right], \tag{A.21}$$

with

$$\frac{d\tilde{\pi}_t}{\tilde{\pi}_t} = -\tilde{r}_t dt + \tilde{\sigma}_\pi d\tilde{N}_t, \tag{A.22}$$

$$d\tilde{\theta}_t = b\left(\bar{\tilde{\theta}} - \tilde{\theta}_t\right) dt + \tilde{\sigma}_\theta dB_t. \tag{A.23}$$

Therefore, the first component of (A.21) becomes

$$\begin{aligned}
&\mathbb{E}_t\left[\int_t^T \frac{\tilde{\pi}_s}{\tilde{\pi}_t}\delta_s ds\right] = \mathbb{E}_t\left[\int_t^T e^{-\tilde{r}(s-t)}\delta_s ds\right] \\
=&\delta_t \mathbb{E}_t\left[\int_t^T e^{-\left(\tilde{r}-\bar{g}+\frac{1}{2}\sigma_D^2\right)(s-t)+\frac{1}{a}\left(1-e^{-a(s-t)}\right)(\hat{g}_t-\bar{g})+\int_t^s\left[\phi\frac{q_u}{a\sigma_D}\left(1-e^{-a(s-u)}\right)+\sigma_D\right]d\hat{B}_{D,u}} ds\right] \\
=&\delta_t \int_t^T e^{-\left(\tilde{r}-\bar{g}+\frac{1}{2}\sigma_D^2\right)(s-t)+\frac{1}{a}\left(1-e^{-a(s-t)}\right)(\hat{g}_t-\bar{g})+\frac{1}{2}\int_t^s\left[\phi\frac{q_u}{a\sigma_D}\left(1-e^{-a(s-u)}\right)+\sigma_D\right]^2 du} ds
\end{aligned}$$

The second component of (A.21) represents the expected price at T, denoted as $P(T)$, which is the present value of dividends from T to ∞. This value is then discounted back to time t using the SDF $\frac{\tilde{\pi}_T^+}{\tilde{\pi}_t}$. To compute this term, we proceed in two steps.

First, at an FOMC announcement, the SDF has only a jump component. Hence

$$\frac{\tilde{\pi}_T^+}{\tilde{\pi}_T} = e^{-\frac{1}{2}\tilde{\sigma}_\pi^2\sigma_N^2+\tilde{\sigma}_\pi d\tilde{N}_T}. \tag{A.24}$$

From Equation (A.3), we have

$$d\tilde{N}_T \sim \mathcal{N}\left(0, \sigma_N^2\right), \text{ with } \sigma_N^2 = \frac{\tilde{\sigma}_\theta^2}{2b}(1-e^{-2bT}). \tag{A.25}$$

The correction ensures that the expected jump factor is one (i.e., $\mathbb{E}[\tilde{\pi}_T^+/\tilde{\pi}_T] = 1$), preserving the martingale property of the SDF. Using the solution to the OU process (Equations (A.1) and (A.7)), and the fact that $t = 0$ (last announcement), $\theta_0 = r(T^-) = r$ at the last announcement, $\theta_T = r(T^+)$,

$$\begin{aligned}
\tilde{r}_T^+ &= e^{-bT}\tilde{r} + (1-e^{-bT})\bar{\tilde{\theta}} + d\tilde{N}_T = e^{-bT}\tilde{r} + (1-e^{-bT})\bar{\tilde{\theta}} + \int_0^T e^{-b(T-u)}\tilde{\sigma}_\theta dB_u, \\
\hat{g}_T^+ &= e^{-aT}\hat{g}_0 + (1-e^{-aT})\bar{g} + \int_0^T k_2(u;T)\, d\hat{B}_{D,u}.
\end{aligned}$$

So that

$$p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right) = p\left(e^{-bT}\tilde{r} + (1-e^{-bT})\bar{\tilde{\theta}} + d\tilde{N}_T, e^{-aT}\hat{g}_0 + (1-e^{-aT})\bar{g} + \int_0^T k_2\left(u;T\right) d\hat{B}_{D,u}, T^+\right).$$

Therefore, we compute $\mathbb{E}_t\left[\frac{\tilde{\pi}_T^+}{\tilde{\pi}_t} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\delta_T\right]$ in two steps. First, condition on information at time T,

$$\mathbb{E}_T\left[\frac{\tilde{\pi}_T^+}{\tilde{\pi}_T} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\right] = \mathbb{E}_T\left[e^{-\frac{1}{2}\tilde{\sigma}_\pi^2\sigma_N^2 + \tilde{\sigma}_\pi d\tilde{N}_T} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\right].$$

Then, discount this value back to time t using the law of iterated expectations:

$$\mathbb{E}_t\left[\frac{\tilde{\pi}_T^+}{\tilde{\pi}_t} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\delta_T\right] = \mathbb{E}_t\left[\frac{\tilde{\pi}_T}{\tilde{\pi}_t}\mathbb{E}_T\left[\frac{\tilde{\pi}_T^+}{\tilde{\pi}_T} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\delta_T\right]\right] = \frac{\tilde{\pi}_T}{\tilde{\pi}_t}\mathbb{E}_t\left[\frac{\tilde{\pi}_T^+}{\tilde{\pi}_T} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\delta_T\right]$$

Using $\frac{\tilde{\pi}_T}{\tilde{\pi}_t} = e^{-\tilde{r}(T-t)}$ and from (A.15) to get

$$\delta_T = \delta_t e^{\left(\bar{g}-\frac{1}{2}\sigma_D^2\right)(T-t) + \frac{1}{a}\left(1-e^{-a(T-t)}\right)(\hat{g}_t - \bar{g}) + \int_t^T k_1(u;T) d\hat{B}_{D,u}}.$$

We obtain

$$\begin{aligned} & \frac{\tilde{\pi}_T}{\tilde{\pi}_t}\mathbb{E}_t\left[\frac{\tilde{\pi}_T^+}{\tilde{\pi}_T} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\delta_T\right] \\ = \; & e^{Term_t}\delta_t\mathbb{E}_t\left[e^{-\frac{1}{2}\tilde{\sigma}_\pi^2\sigma_N^2 + \tilde{\sigma}_\pi d\tilde{N}_T + \int_t^T k_1(u;T) d\hat{B}_{D,u}} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\right], \end{aligned}$$

where

$$Term_t = -\left(\tilde{r} - \bar{g} + \frac{1}{2}\sigma_D^2\right)(T-t) + \frac{1}{a}\left(1-e^{-a(T-t)}\right)(\hat{g}_t - \bar{g})$$

Finally, combining both components, we obtain

$$\begin{aligned} p\left(\tilde{r}, \hat{g}_t, t\right) = & \int_t^T e^{-\left(\tilde{r}-\bar{g}+\frac{1}{2}\sigma_D^2\right)(s-t) + \frac{1}{a}\left(1-e^{-a(s-t)}\right)(\hat{g}_t-\bar{g}) + \int_t^s k_1(u;s) d\hat{B}_{D,u}} ds \\ & + e^{Term_t}\mathbb{E}_t\left[e^{-\frac{1}{2}\tilde{\sigma}_\pi^2\sigma_N^2 + \tilde{\sigma}_\pi d\tilde{N}_T + \int_t^T k_1(u;T) d\hat{B}_{D,u}} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\right]. \end{aligned} \tag{A.26}$$

Given $p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right) = p\left(\tilde{r}_T^+, \hat{g}_T^+, 0^+\right)$, we obtain a fixed-point problem. We therefore begin

by computing $p\left(\tilde{r}, \hat{g}_0^+, 0^+\right)$, the P/D ratio immediately after the announcement at $t = 0$:

$$p\left(\tilde{r}, \hat{g}_0^+, 0^+\right) = \int_0^T e^{-\left(\tilde{r}-\bar{g}+\frac{1}{2}\sigma_D^2\right)s+\frac{1}{a}\left(1-e^{-as}\right)(\hat{g}_0-\bar{g})+\frac{1}{2}\int_0^s [k_1(u;s)]^2 du} ds$$
$$+ e^{Term_0}\mathbb{E}\left[e^{-\frac{1}{2}\tilde{\sigma}_\pi^2\sigma_N^2+\tilde{\sigma}_\pi d\tilde{N}_T+\int_0^T k_1(u;T)d\hat{B}_{D,u}} p\left(\tilde{r}_T^+, \hat{g}_T^+, 0^+\right)\right], \tag{A.27}$$

where $Term_0 = -\left(\tilde{r} - \bar{g} + \frac{1}{2}\sigma_D^2\right)T + \frac{1}{a}\left(1 - e^{-aT}\right)(\hat{g}_0 - \bar{g})$.

Now we have three random variables: $\int_0^T k_1(u;T)\, d\hat{B}_{D,u}$ (from dividends), $d\tilde{N}_T$ (from r_T^+), and $\int_0^T k_2(u;T)\, d\hat{B}_{D,u}$ (from $\hat{g}_T^+$). All are mean-zero. By independence, the covariances between $d\tilde{N}_T$ and the other two variables are zero, leaving only: $Cov\left(\int_0^T k_1(u;T)\, d\hat{B}_{D,u}, \int_0^T k_2(u;T)\, d\hat{B}_{D,u}\right)$. Using Ito's isometry, the covariance is

$$\mathbb{E}\left[\left(\int_0^T k_1(u;T)\, d\hat{B}_{D,u}\right)\left(\int_0^T k_2(u;T)\, d\hat{B}_{D,u}\right)\right]$$
$$= \mathbb{E}\left[\left(\int_0^T k_1(u;T)\, k_2(u;T)\, du\right)\right] = \int_0^T k_1(u;T)\, k_2(u;T)\, du.$$

Thus, the joint distribution of these three random variables is mean-zero with the following variance-covariance matrix:

$$\begin{pmatrix} \sigma_N^2 & 0 & 0 \\ 0 & \int_0^T [k_1(u;T)]^2\, du & \int_0^T k_1(u;T)\, k_2(u;T)\, du \\ 0 & \int_0^T k_1(u;T)\, k_2(u;T)\, du & \int_0^T [k_2(u;T)]^2\, du \end{pmatrix}$$

Using the above joint distribution, Equation (A.27) can be solved numerically via value function iteration. Once $p\left(\tilde{r}, \hat{g}_T^+, T^+\right)$ is obtained, we can solve for $p\left(\tilde{r}, \hat{g}_t, t\right)$ for any $t \in [0, T)$ using Equation (A.26):

$$p\left(\tilde{r}, \hat{g}_t, t\right) = \int_t^T e^{-\left(\tilde{r}-\bar{g}+\frac{1}{2}\sigma_D^2\right)(s-t)+\frac{1}{a}\left(1-e^{-a(s-t)}\right)(\hat{g}_t-\bar{g})+\int_t^s k_1(u;s)d\hat{B}_{D,u}} ds$$
$$+ e^{Term_t}\mathbb{E}_t\left[e^{-\frac{1}{2}\tilde{\sigma}_\pi^2\sigma_N^2+\tilde{\sigma}_\pi d\tilde{N}_T+\int_t^T k_1(u;T)d\hat{B}_{D,u}} p\left(\tilde{r}_T^+, \hat{g}_T^+, T^+\right)\right], \tag{A.28}$$

where

$$\tilde{r}_T^+ = e^{-bT}\tilde{r} + (1 - e^{-bT})\bar{\tilde{\theta}} + d\tilde{N}_T = e^{-bT}\tilde{r} + (1 - e^{-bT})\bar{\tilde{\theta}} + \int_0^T e^{-b(T-u)}\tilde{\sigma}_\theta dB_u,$$
$$\hat{g}_T^+ = e^{-a(T-t)}\hat{g}_t + (1 - e^{-a(T-t)})\bar{g} + \int_t^T k_2(u;T)\, d\hat{B}_{D,u}.$$

The corresponding variance–covariance matrix becomes

$$\begin{pmatrix} \sigma_N^2 & 0 & 0 \\ 0 & \int_t^T [k_1(u;T)]^2\,du & \int_t^T k_1(u;T)\,k_2(u;T)\,du \\ 0 & \int_t^T k_1(u;T)\,k_2(u;T)\,du & \int_t^T [k_2(u;T)]^2\,du \end{pmatrix}.$$

Announcement premium In the above setup, suppose at time T^- the discount rate is $\tilde{r}$. At time T^+, the P/D ratio is $p\left(\tilde{r}_T^+, \hat{g}_T^+, 0^+\right)$. Using (A.26),

$$p\left(\tilde{r}, \hat{g}_T^-, T^-\right) = \mathbb{E}_T^- \left[e^{-\frac{1}{2}\tilde{\sigma}_\pi^2 \sigma_N^2 + \tilde{\sigma}_\pi d\tilde{N}_T} p\left(\tilde{r}_T^+, \hat{g}_T^+, 0^+\right) \right],$$

since $T^- \to T^+$ the cash-flow integral vanishes and only the jump-discounted continuation remains. Because no dividend news arrives at the instant T, there is no jump in $\hat{g}$: $\hat{g}_T^+ = \hat{g}_T$. The expected announcement return is

$$R_A = \frac{\mathbb{E}_T^- \left[p\left(\tilde{r}_T^+, \hat{g}_T, 0^+\right) \right]}{p\left(\tilde{r}, \hat{g}_T, T^-\right)} - 1.$$

It must be an *expected* return because at T^- the realization of $\tilde{r}_T^+$ is unknown to everyone, so we need to take expectations at T^- to compute the expected announcement premium.

Simplification Suppose the asset price follows:

$$dP_t = P_t \left[\mu_P dt + \sigma_P dB_t \right].$$

Let the asset price be given by $P_t = p(\theta_t) D_t$, where $p(\theta_t)$ is the price-dividend ratio and D_t is the dividend. Using Itô's lemma and assuming constant perceived dividend growth $\hat{g}$, the dynamics of P_t are:

$$dP_t = d\left[p\left(\theta_t\right) D_t\right] = p\left(\theta_t\right) D_t \hat{g} dt + p'\left(\theta_t\right) b\left(\bar{\theta} - \theta_t\right) D_t dt + \frac{1}{2} p''\left(\theta_t\right) \sigma_\theta^2 D_t dt + p'\left(\theta_t\right) D_t \sigma dt,$$

where we use the martingale condition $\pi_t D_t dt + \mathcal{L}\left[\pi_t P_t\right] = 0$. Matching terms, the return volatility is: $\sigma_{P,t} = \frac{p'(\theta_t)}{p(\theta_t)} \sigma_\theta = \frac{d \ln p(\theta_t)}{d\theta_t} \sigma_\theta$. Hence, the risk premium is:

$$\mu_P + \frac{D_t}{P_t} - r_t = -\sigma_P \sigma_\pi = -\frac{d \ln p\left(\theta_t\right)}{d\theta_t} \sigma_\theta \sigma_\pi.$$

This shows that the risk premium depends entirely on the sensitivity of the price-dividend ratio to interest rate shocks. That is, duration (measured by $-\frac{d \ln p(\theta_t)}{d\theta_t}$) provides a sufficient

statistic for the risk premium.

Asset prices are now computed as follows:

$$p\left(\theta_0\right) D_0 = \mathbb{E}_0\left[\int_0^\infty \frac{\pi_t}{\pi_0} D_0 e^{\hat{g}t} dt\right].$$

Note that $d\ln\pi_t = \left(-\theta_t - \frac{1}{2}\sigma_\pi^2\right)dt + \sigma_\pi dB_t$, or

$$\pi_t = \pi_0 e^{\int_0^t\left(-\theta_s - \frac{1}{2}\sigma_\pi^2\right)ds + \int_0^t \sigma_\pi dB_s}.$$

Using (A.1), we can write

$$\begin{aligned}
&\int_0^t \left(\theta_s + \frac{1}{2}\sigma_\pi^2\right) ds - \int_0^t \sigma_\pi dB_s \\
= &\int_0^t \left(e^{-bs}\left(\theta_0 - \bar{\theta}\right) + \bar{\theta} + \frac{1}{2}\sigma_\pi^2\right) ds + \int_0^t \left[\frac{\sigma_\theta}{b}\left(1 - e^{-b(t-u)}\right)\right] dB_u - \int_0^t \sigma_\pi dB_u \\
= &\left(\bar{\theta} + \frac{1}{2}\sigma_\pi^2\right) t + \frac{1}{b}\left(1 - e^{-bt}\right)\left(\theta_0 - \bar{\theta}\right) + \int_0^t \left[\frac{\sigma_\theta}{b}\left(1 - e^{-b(t-u)}\right) - \sigma_\pi\right] dB_u
\end{aligned}$$

We write the PD ratio relationship as:

$$\begin{aligned}
p\left(\theta_0; \hat{g}\right) &= \mathbb{E}_0\left[\int_0^\infty e^{\xi t - \left(\bar{\theta} + \frac{1}{2}\sigma_\pi^2\right)t - \frac{1}{b}\left(1 - e^{-bt}\right)\left(\theta_0 - \bar{\theta}\right) - \int_0^t \left[\frac{\sigma_\theta}{b}\left(1 - e^{-b(t-u)}\right) - \sigma_\pi\right] dB_u} dt\right]. \\
&= \int_0^\infty e^{-\left(\bar{\theta} - \hat{g} + \frac{1}{2}\sigma_\pi^2\right)t - \frac{1}{b}\left(1 - e^{-bt}\right)\left(\theta_0 - \bar{\theta}\right) + \frac{1}{2}\int_0^t \left[\frac{\sigma_\theta}{b}\left(1 - e^{-b(t-u)}\right) - \sigma_\pi\right]^2 du} dt. \qquad \text{(A.29)}
\end{aligned}$$

Note that as $t \to \infty$, only the term $-\left(\bar{\theta} - \hat{g} + \frac{1}{2}\sigma_\pi^2\right)t$ and $\frac{1}{2}\int_0^t \left[\frac{\sigma_\theta}{b}\left(1 - e^{-b(t-s)}\right) - \sigma_\pi\right]^2 ds$ survives, where

$$\begin{aligned}
\frac{1}{2}\int_0^t \left[\frac{\sigma_\theta}{b}\left(1 - e^{-b(t-s)}\right) - \sigma_\pi\right]^2 ds &= \frac{1}{2}\int_0^t \left[\left(\frac{\sigma_\theta}{b} - \sigma_\pi\right)^2 - \frac{2\sigma}{b}\left(\frac{\sigma_\theta}{b} - \sigma_\pi\right) e^{-b(t-s)} + \frac{\sigma_\theta^2}{b^2} e^{-2b(t-s)}\right] ds \\
&= \frac{1}{2}\left(\frac{\sigma_\theta}{b} - \sigma_\pi\right)^2 t - \frac{\sigma_\theta}{b^2}\left(\frac{\sigma_\theta}{b} - \sigma_\pi\right)\left(1 - e^{-bt}\right) + \frac{\sigma_\theta^2}{4b^2}\left(1 - e^{-2bt}\right) \\
&\to \frac{1}{2}\left(\frac{\sigma_\theta}{b} - \sigma_\pi\right)^2 t.
\end{aligned}$$

As a result, as t gets large,

$$\begin{aligned}
& e^{-\left(\bar{\theta} - \hat{g} + \frac{1}{2}\sigma_\pi^2\right)t - \frac{1}{b}\left(1 - e^{-bt}\right)\left(\theta_0 - \bar{\theta}\right) + \frac{1}{2}\int_0^t \left[\frac{\sigma_\theta}{b}\left(1 - e^{-b(t-s)}\right) - \sigma_\pi\right]^2 ds} \\
\to\ & e^{-\left(\bar{\theta} - \hat{g} + \frac{1}{2}\sigma_\pi^2\right)t + \frac{1}{2}\left(\frac{\sigma_\theta}{b} - \sigma_\pi\right)^2 t} = e^{-t\left(\bar{\theta} - \hat{g} - \frac{\sigma_\theta^2}{2b^2} + \frac{\sigma_\theta}{b}\sigma_\pi\right)}.
\end{aligned}$$

That is, $\hat{g} < \bar{\theta} - \frac{\sigma^2}{2b^2} + \frac{\sigma}{b}\sigma_\pi$, the present value is finite.

We are interested in how $-\frac{d\ln p(\theta_0;\xi)}{d\theta_0}$ depends on $\hat{g}$. Note that $-\frac{d\ln p(\theta_0;\xi)}{d\theta_0} = -\frac{1}{p(\theta_0;\xi)}\frac{dp(\theta_0;\xi)}{d\theta_0}$, which implies

$$-\frac{d\ln p(\theta_0;\xi)}{d\theta_0} = \frac{1}{b}\left\{1 - \frac{\int_0^\infty e^{\left\{-bt-\left(\bar{\theta}-\hat{g}+\frac{1}{2}\sigma_\pi^2\right)t-\frac{1}{b}\left(1-e^{-bt}\right)\left(\theta_0-\bar{\theta}\right)+\frac{1}{2}\int_0^t\left[\frac{\sigma_\theta}{b}\left(1-e^{-b(t-s)}\right)-\sigma_\pi\right]^2 ds\right\}}dt}{\int_0^\infty e^{\left\{-\left(\bar{\theta}-\hat{g}+\frac{1}{2}\sigma_\pi^2\right)t-\frac{1}{b}\left(1-e^{-bt}\right)\left(\theta_0-\bar{\theta}\right)+\frac{1}{2}\int_0^t\left[\frac{\sigma_\theta}{b}\left(1-e^{-b(t-s)}\right)-\sigma_\pi\right]^2 ds\right\}}dt}\right\}.$$

In general, if we have an integral of the form: $\int_0^\infty e^{-(\lambda t)}dt = \frac{1}{\lambda}$, then the above can be roughly approximated by (For large t, the dominant term is dt)

$$\frac{1}{b}\left\{1 - \frac{\frac{1}{\bar{\theta}-\hat{g}+b+\frac{1}{2}\sigma_\pi^2-\frac{1}{2}\left(\frac{\sigma_\theta}{b}-\sigma_\pi\right)^2}}{\frac{1}{\bar{\theta}-\hat{g}+\frac{1}{2}\sigma_\pi^2-\frac{1}{2}\left(\frac{\sigma_\theta}{b}-\sigma_\pi\right)^2}}\right\} = \frac{1}{b}\left\{1 - \frac{\bar{\theta}-\hat{g}-\frac{1}{2}\left(\frac{\sigma_\theta}{b}-\sigma_\pi\right)^2}{\bar{\theta}-\hat{g}+b-\frac{1}{2}\left(\frac{\sigma_\theta}{b}-\sigma_\pi\right)^2}\right\} = \frac{1}{\bar{\theta}-\hat{g}+b-\frac{\sigma_\theta^2}{2b^2}+\frac{\sigma}{b}\sigma_\pi}. \tag{A.30}$$