Information-Driven Volatility

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Abstract: Standard asset pricing models with stochastic volatility predict a robust positive correlation between past realized volatility and future expected returns. Empirical work typically finds this relationship to be negative. We develop an asset pricing model where stock market volatility dynamics are driven by information. We show that under strong generalized risk sensitivity of preferences, information-driven volatility induces a negative correlation between past realized volatility and future expected returns. Using FOMC announcements and news-related stock market jump days to identify information events, we provide empirical evidence for the unique implications of the information-driven volatility channel.

Keywords: Information, Risk-Return Tradeoff, Volatility, Return Predictability, FOMC Announcements, ICAPM

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1 Introduction

Leading consumption-based asset pricing models with stochastic volatility, such as the habit model of Campbell and Cochrane (1999), the long-run risk model of Bansal and Yaron (2004), and the rare disaster model of Barro (2006) and Gabaix (2012), predict a robust positive relationship between past realized volatility and future expected returns. Empirically, many authors (e.g., Nelson (1991) and Glosten, Jagannathan, and Runkle (1993)) find a negative relationship between the two. More recently, Moreira and Muir (2017) demonstrate that the above negative relationship can be used to construct a volatility-managed portfolio that earns a higher average return than the market portfolio. In this paper, we develop a model with information-driven volatility. We show that information-driven volatility induces a negative relationship between past realized volatility and future expected returns. We provide empirical evidence for this channel and demonstrate that our model can account for several volatility-related asset pricing puzzles.

There are two main motivations for our theory of information-driven volatility. First, high-frequency financial market fluctuations, such as those at the monthly, daily, or even higher frequencies, are more likely to be driven by information than by the volatility of macroeconomic fundamentals. Standard consumption-based asset pricing models — such as Bansal, Kiku, Shaliastovich, and Yaron (2014) in the context of the long-run risk model and Wachter (2013) in the context of the rare disaster model — typically generate time-varying volatility of returns by assuming time-varying volatility of macroeconomic fundamentals. While these models can explain asset pricing moments quite well at lower frequencies (annual frequencies and above), the volatility of macroeconomic fundamentals in the data typically does not change substantially at high frequencies and is unlikely to explain high-frequency financial market volatilities. In contrast, information about the macroeconomy arrives continuously in financial markets and affects the stock return volatility at high frequencies.

Second, recent empirical evidence and theoretical work show that major informational events in financial markets are associated with significant risk compensation. Consistent with Savor and Wilson (2013) and Ai and Bansal (2018), we show that approximately 70% of the stock market risk premium during the 1961–2024 period is realized on a small number of days with significant macroeconomic announcements. Lucca and Moench (2015) find a similar pattern for FOMC announcements. Ai and Bansal (2018) demonstrate that expected

utility models are inconsistent with the announcement premium, and the existence of such a premium implies that investor preferences must satisfy generalized risk sensitivity (GRS). As we show in this paper, under expected utility, information-driven volatility is irrelevant for risk compensation and, therefore, for return predictability. Although GRS establishes that information requires risk compensation, it does not determine how compensation varies with informativeness. We propose the concept of strong generalized risk sensitivity to establish the link between the informativeness of news and the magnitude of the announcement premium. We demonstrate that under this condition, information-driven volatility induces a negative relationship between past realized volatility and future expected returns.

Our theory of information-driven volatility has two main theses. First, more precise public information about macroeconomic fundamentals is associated with larger stock market reactions and higher realized volatility upon the arrival of the information, and lower volatility afterward. Second, more precise public information about macroeconomic fundamentals is associated with higher stock market risk compensation upon the arrival of the information and lower risk compensation subsequently. As a result, time-varying information generates a negative correlation between realized volatility upon the arrival of information and expected returns afterward.

To understand the first thesis, the link between the informativeness of public information and volatility, consider the following variance decomposition identity:

$$\text{Var}\left[\theta_T\right] = \text{Var}\left[\mathbb{E}\left(\theta_T \mid s_t\right)\right] + \mathbb{E}[\text{Var}\left(\theta_T \mid s_t\right)]. \tag{1}$$

We interpret θ_T as macroeconomic fundamentals such as state variables that govern the dynamics of aggregate consumption and aggregate productivity, the value of which will be realized at the terminal time T. We interpret s_t as a public signal revealed at time $t < T$ that is informative about θ_T. One example of such a public signal is a macroeconomic announcement. The above formula then decomposes the total variance of macroeconomic fundamentals, $\text{Var}\left[\theta_T\right]$, into the variance realized on the announcement day t, $\text{Var}\left[\mathbb{E}\left(\theta_T \mid s_t\right)\right]$, and the variance that remains to be realized after the announcement at time T, $\mathbb{E}\left[\text{Var}\left(\theta_T \mid s_t\right)\right]$.

Traditional models of stochastic volatility generate time-varying volatility of returns through time-varying volatility of macroeconomic fundamentals, $\text{Var}\left[\theta_T\right]$. Because the volatility of macroeconomic fundamentals, such as aggregate consumption and aggregate productiv-

ity, is positively autocorrelated over time, high past realized volatility predicts high expected future volatility and therefore high expected future returns.

Given that the volatility of macroeconomic fundamentals does not change substantially at high frequencies, now consider varying the informativeness of the signal s_t by holding the total variance $\text{Var}[\theta_T]$ fixed. A more accurate signal s_t triggers a larger response in investors' conditional expectations about future cash flows, which is captured by the term $\text{Var}[\mathbb{E}(\theta_T \mid s_t)]$ and is associated with higher realized variance in financial markets upon the arrival of information. The variance decomposition identity (1) then implies that such a high realized variance, $\text{Var}[\mathbb{E}(\theta_T \mid s_t)]$, must be associated with a lower expected future variance, $\mathbb{E}[\text{Var}(\theta_T \mid s_t)]$. Intuitively, a more informative public signal resolves more uncertainty at the event date, leaving less uncertainty to be resolved in the future.

While the relationship between volatility and information is merely a consequence of the variance decomposition identity (1), how information affects risk compensation depends on investors' risk preferences. Under expected utility, the risk premium is completely determined by the covariance of the return and consumption growth. Changes in beliefs, i.e., $\mathbb{E}(\theta_T \mid s_t)$ in Equation (1), do not require risk compensation. As a result, the variance decomposition in (1) affects realized volatility in financial markets, but not risk compensation. Ai and Bansal (2018) demonstrate that information-driven volatility requires risk compensation if and only if investors' preferences satisfy GRS. The GRS property provides the condition under which changes in $\mathbb{E}(\theta_T \mid s_t)$ require a risk premium but does not characterize the relationship between the informativeness of the signal s_t and the magnitude of risk compensation.

In this paper, we extend the result of Ai and Bansal (2018) and demonstrate that under strong GRS, more precise information is associated with a higher expected return upon the informational event and a lower expected return afterward. Intuitively, GRS requires the certainty equivalent functional to satisfy a concavity condition; specifically, it must increase in second-order stochastic dominance. The concept of strong GRS imposes a lower bound on the Arrow-Pratt measure of absolute risk aversion of the certainty equivalent functional and represents a stronger concavity requirement. Our main theorem implies that under strong GRS, higher information-driven volatility is associated not only with lower future expected volatility but also with lower future expected returns.

To empirically test the above implications of the information-driven volatility theory and assess their quantitative importance, we calibrate a continuous-time asset pricing model with

time-varying informativeness of macroeconomic announcements. We conduct several tests of the information-driven volatility channel in the data and replicate these tests in our model.

In the data, FOMC announcements are among the most identifiable events that reveal information about the macroeconomy. To test the mechanism of information-driven volatility, we first develop an ex ante measure of the informativeness of FOMC announcements based on the term structure of option-implied variances. Using this measure, we show that higher informativeness predicts a larger FOMC announcement-day return and a larger implied variance reduction on announcement days. We then combine FOMC announcements with the news-related stock market jumps constructed by Baker, Bloom, Davis, and Sammon (2021) as information events, and show that higher informativeness — measured by the event-day implied variance reduction — predicts lower future excess returns and lower realized variance following these events.

Our theory of information-driven volatility does not fundamentally change the risk-return tradeoff in financial markets, that is, the positive relationship between future expected variance and future expected returns. In fact, the ICAPM holds in our model. We emphasize that financial market volatility may be driven by the volatility of macroeconomic fundamentals or the arrival of information. The positive autocorrelation of fundamental volatility and the negative autocorrelation of volatility induced by information confound traditional expected return–volatility tests. Using both aggregate stock market data and firm-level earnings announcement return data, we show that the weak or even negative volatility–expected return relationship found in prior literature is likely driven by the information-driven volatility channel. Once we appropriately account for the effect of information-driven volatility in ICAPM-style regressions, we find a robustly positive risk-return tradeoff. We calibrate our model and demonstrate that it matches conventional asset pricing moments and stock market dynamics around macroeconomic announcements. We replicate these statistical tests in our calibrated model. The results confirm both the consistency between model and data and the quantitative significance of the information-driven volatility channel.

Our results highlight the importance of identifying the driving force behind volatility in the study of the volatility–expected return relationship. The volatility of macroeconomic fundamentals, which varies at low frequencies, is important for understanding equity risk premiums over longer time horizons. However, information-driven volatility is likely to be much more important than the volatility of macroeconomic fundamentals in affecting stock

market dynamics and risk compensation at higher frequencies.

Related Literature This paper is closely related to the literature on the volatility–expected return relationship. A large body of empirical work documents a negative relationship between past realized volatility and future expected returns (Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993), though Harvey (1989) finds mixed evidence depending on the specification. Harrison and Zhang (1999) show that this negative relationship holds at short horizons but turns positive beyond a year, a pattern consistent with our theory. More recently, Moreira and Muir (2017) show that this pattern can be exploited to construct a volatility-managed portfolio that earns a higher average return than the market. Lochstoer and Muir (2022) develop a model of extrapolative expectations of volatility shocks to explain the variance risk premium predictability and the negative relationship between volatility and expected returns. We contribute to this literature by providing a rational explanation for this negative relationship based on the information-driven volatility channel.

This paper builds on the literature on macroeconomic announcements. From an empirical perspective, pre-scheduled macroeconomic announcements are the most salient informational events that are associated with significant realizations of the equity risk premium and volatility. The literature that documents significant macroeconomic announcement premiums — for example, Savor and Wilson (2013, 2014), Lucca and Moench (2015), Cieslak, Morse, and Vissing-Jorgensen (2019), and Hu, Pan, Wang, and Zhu (2022) — provides strong empirical support for the information-driven volatility mechanism emphasized in this paper. From a theoretical point of view, Ai and Bansal (2018) establish that the existence of the macroeconomic announcement premium implies that preferences must satisfy generalized risk sensitivity. We extend the Theorem of Generalized Risk Sensitivity of Ai and Bansal (2018) and provide conditions under which more precise announcements are associated with a higher expected return upon the announcement and a lower expected return afterward.

Our paper is also related to the literature that studies the information content of FOMC announcements. Bernanke and Kuttner (2005) study stock market reaction to FOMC announcements. Nakamura and Steinsson (2018) document the Fed information effect and provide a high-frequency identification for the non-neutrality of monetary policy. Bauer and Swanson (2023a) provide an alternative explanation of the Fed information effect. Our theory applies to all macroeconomic announcements, but we focus on FOMC announcements

because, as we show, their informativeness varies significantly over time. Unlike these papers, we examine the impact of FOMC announcements on the intertemporal allocation of stock market volatility and risk premium.

Our main theoretical result relates to the literature on non-expected utility analysis in economics and finance — including recursive preferences of Kreps and Porteus (1978) and Epstein and Zin (1989), robust control preferences of Hansen and Sargent (2005, 2008), and related multiplier preferences of Strzalecki (2011).[1] Ai, Bansal, Guo, and Yaron (2026) provide an asset pricing test for early resolution preferences, and Ai, Bansal, Guo, and Yaron (2024) develop and estimate a corresponding measure in structural asset pricing models.

Our model also builds on the literature on learning and information in financial markets. Prior work studies how learning, information quality, parameter uncertainty, and the value of information affect asset prices and risk compensation (David, 1997, 2008; Veronesi, 2000; Ai, 2010; Pastor and Veronesi, 2009; David and Veronesi, 2013; Bansal and Shaliastovich, 2010, 2011; Shaliastovich, 2015; Johannes, Lochstoer, and Mou, 2016; Collin-Dufresne, Johannes, and Lochstoer, 2016, 2017; Kadan and Manela, 2019, 2023). Ai, Bansal, and Han (2022) study the role of information acquisition in generating the pre-announcement high return and low volatility. In contrast, we provide theoretical conditions under which the time-varying informativeness of macroeconomic news affects risk compensation and evaluate its quantitative importance.

Several recent papers provide empirical evidence that is consistent with the information-driven volatility channel emphasized in this paper. Baker, Bloom, Davis, and Sammon (2021) document that higher news clarity is associated with lower realized volatility in the future. Zhang and Zhao (2023) provide evidence that in periods when public information is imprecise, the realized macroeconomic announcement premium is low. Chaudhry (2022) shows that announcement days are typically associated with uncertainty reductions and lower expected returns afterward.

[1] Epstein and Schneider (2010) provide a review of asset pricing studies with ambiguity-averse preferences. Skiadas (2009) provides an excellent textbook treatment of asset pricing theory based on recursive preferences. The long-run risk models of Bansal and Yaron (2004), Bansal (2007), and Hansen, Heaton, and Li (2008) build on recursive preferences. Borovicka and Stachurski (2020) provide necessary and sufficient conditions for the existence and uniqueness of recursive utility, and Borovicka and Stachurski (2021) study the stability of equilibrium in asset pricing models. Ju and Miao (2012) study the asset pricing implications of the smooth ambiguity preference, and Routledge and Zin (2010) focus on a model with disappointment aversion.

Our study contributes to the broader literature on the risk-return tradeoff, for example, Ghysels, Santa-Clara, and Valkanov (2005), Lundblad (2007), Lettau and Ludvigson (2010) and Manela and Moreira (2017). This literature finds limited empirical support for the positive relationship between future expected volatility and expected returns predicted by standard no-arbitrage models, and sometimes even evidence against it. Bekaert and Hoerova (2014) show that even with the help of the "best" volatility forecasting models, the expected volatility (in most cases) still significantly negatively predicts future monthly returns. Lochstoer and Muir (2022) echo this negative (but weak) relationship in the recent sample period with extensive robustness checks. The quantitative model we present in the paper provides an explanation for the empirical difficulty of the volatility–expected return relationship. On the one hand, the volatility of macroeconomic fundamentals, such as that of aggregate consumption, is positively correlated over time but requires a relatively small risk compensation. Information about the future of the macroeconomy, on the other hand, induces a negative correlation between past realized volatility and future expected volatility and requires a quantitatively larger risk compensation. The two driving forces of volatility induce opposite autocorrelations and make it difficult to identify the risk-return tradeoff empirically. We follow the approach of Guo and Whitelaw (2006) and show that once forward-looking measures of volatility, which account for the information-driven volatility channel more effectively, are included in expected return regressions, the risk-return tradeoff is robustly positive. This result is also consistent with risk premium measures inferred from option prices in Martin (2017) and Martin and Wagner (2019). More recently, He (2025) demonstrates that accounting for the information-driven volatility significantly improves the predictability of lagged volatility for future market returns.

The rest of the paper is organized as follows. Section 2 presents motivating facts for information-driven volatility. Section 3 presents the main theorem of the paper and demonstrates that under the assumption of strong GRS, more informative announcements are associated with higher expected returns upon announcements and lower expected returns afterward. Section 4 develops a dynamic model with time-varying informativeness of announcements, and Section 5 calibrates the model, develops direct empirical tests of the information-driven volatility channel using our measure of informativeness, and replicates these tests in the model. Section 6 provides additional empirical tests of the volatility–expected return relationship that do not rely on the informativeness measure. Section 7

concludes.

2 Motivating Facts for Information-Driven Volatility

In this section, we present two facts on volatility and stock market returns that motivate the development of our theory of information-driven volatility. The first fact motivates our focus on information as the main driver of high-frequency financial market volatility, and the second highlights its role as the main determinant of risk compensation.

1. Stock market volatility is much larger than the volatility of macroeconomic fundamentals and exhibits substantial variation at high frequencies.

   The classic excess volatility evidence of Shiller (1981) and LeRoy and Porter (1981) shows that stock prices fluctuate much more than can be accounted for by subsequent movements in dividends or other smoothly evolving fundamentals. Direct empirical comparisons of equity volatility to macroeconomic volatility reinforce this disconnect: Schwert (1989) shows that conventional macroeconomic volatility variables — including industrial production growth, money growth, and inflation — explain only a small fraction of the time-series variation in stock market volatility, and Engle and Rangel (2008) document that macroeconomic state variables account for the slow-moving component of equity volatility but not its higher-frequency fluctuations.

   This disconnect is especially sharp at high frequencies. Realized volatility studies document large and rapidly changing fluctuations in stock market volatility at daily and intraday horizons (Andersen, Bollerslev, Diebold, and Ebens, 2001; Andersen, Bollerslev, Diebold, and Labys, 2003), while aggregate fundamentals such as consumption, output, and dividends evolve much more smoothly and are observed at lower frequencies. Taken together, these patterns suggest that the proximate driver of stock market volatility — and especially its high-frequency variation — is unlikely to be cash flow fundamentals themselves. This motivates the central premise of our paper: the volatility of equity returns is driven primarily by the arrival of information about future fundamentals, rather than by realizations of those fundamentals.

2. A large fraction of the equity premium is realized on a small fraction of trading days with significant macroeconomic announcements.

Table 1 reports the average excess market returns on macroeconomic announcement days and non-announcement days from 1961 to 2024. In this period, on average, 45 trading days per year have significant macroeconomic announcements. At the daily level, the average stock market excess return is 10.58 basis points (bps) on announcement days and 1.14 bps on days without major macroeconomic announcements. As a result, the cumulative excess stock market return on the 45 announcement days averages 4.80% per year, accounting for about 70% of the annual equity premium (7.16%).

The above fact not only highlights the importance of information in determining stock market risk compensation but also motivates a GRS-based asset pricing model to explain the joint dynamics of information and asset returns. As shown in Ai and Bansal (2018), the existence of the macroeconomic announcement premium implies that investors' preferences must satisfy GRS. As we will demonstrate in this paper, under a condition slightly stronger than GRS, which we call strong GRS, information-driven volatility induces a negative relationship between past realized volatility and future expected returns.

Table 1: Macroeconomic Announcement Premium

	# of days p.a.	Daily prem.	Prem. p.a.	t-stat
Market	252	2.84 bps	7.16%	3.57
Ann	45	10.58 bps	4.80%	5.40
Non-Ann	206	1.14 bps	2.36%	1.31

This table presents the average daily excess return of the U.S. stock market on macroeconomic announcement days versus non-announcement days during 1961–2024. Following Ai and Bansal (2018), we select the top five pre-scheduled announcements ranked by Bloomberg user attention: Nonfarm Payrolls, CPI or PPI (whichever is released first each month, from 1971), scheduled FOMC meetings, GDP releases, and ISM Manufacturing (from 1996.11). "Prem. p.a." equals the daily premium times the number of event days, converted to percentage points.

3 Information-Driven Volatility and Risk Premium

Our theory has two theses. First, more precise information is associated with higher realized return volatility upon the informational event and lower volatility afterward. Second, more

precise information is associated with higher risk compensation upon the event and lower expected returns afterward. The first thesis follows directly from the variance decomposition formula in Equation (1) and requires no assumptions on preferences or technology. The second requires an equilibrium model of the stochastic discount factor. In this section, we extend the model of Ai and Bansal (2018) to prove a general result: under a slight strengthening of GRS, the magnitude of the announcement premium increases monotonically with informativeness, and post-announcement expected returns are lower following more informative announcements.

Consider a continuous-time endowment economy in which aggregate consumption is an arbitrary continuous diffusion process for which the representative agent's utility is well defined. To fix ideas, we use a two-period discrete-time formulation with $t = \Delta > 0$ and $T = 2\Delta$ and study the limit $\Delta \to 0$. At T, the fundamental θ_T is realized. We compare two economies that differ only in the informativeness of the announcement that arrives at time t: a vague announcement economy with signal $s_t = \eta$, and an informative announcement economy with signal $s_t = (\eta, \varepsilon)$. By time T both economies share the same information θ_T.[2] We refer to the return earned over $(0, t]$ as the announcement return and over $(t, T]$ as the post-announcement return.

Following Ai and Bansal (2018), intertemporal preferences are represented by a pair of aggregators $\{u, \mathcal{I}\}$ so that utility can be computed recursively as:

$$V_\tau = \left(1 - e^{-\rho\Delta}\right) u\left(C_\tau\right) + e^{-\rho\Delta} \mathcal{I}\left[V_{\tau+\Delta}\right], \tag{2}$$

where ρ is the subjective discount rate, C represents aggregate consumption, and the certainty equivalent functional admits the representation $\mathcal{I}[V] = \phi^{-1}\{\mathbb{E}[\phi(V)]\}$ for some strictly increasing and three times continuously differentiable function ϕ. This class nests the recursive utility of Kreps and Porteus (1978) and Epstein and Zin (1989), the robust control preferences of Hansen and Sargent (2008), and the second-order expected utility of Ergin and Gul (2009). The associated announcement stochastic discount factor that prices

[2] Formally, the three information sets η, (η, ε), and θ_T are ranked by informativeness in the sense of Blackwell (1953). Using Blackwell (1953)'s notation for the "more informative than" relationship, $\theta_T \supset (\eta, \varepsilon) \supset \eta$. This means that the information set θ_T contains more information than the joint information set (η, ε), which, in turn, contains more information than the information set η alone.

the (t, s_t)-state-contingent payoff into time 0 is

$$SDF_{0,t}(0, s_t) = e^{-\rho t} \frac{u'(C_t)}{u'(C_0)} \frac{\phi'[V_t(s_t)]}{\phi' \circ \phi^{-1}\{\mathbb{E}[\phi \circ V_t(s_t)]\}}, \tag{3}$$

where $s_t \in \{\eta, (\eta, \varepsilon)\}$, with the interpretation that $s_t = (\eta, \varepsilon)$ represents the case of the informative announcement economy and $s_t = \eta$ is the case of the vague announcement economy. The post-announcement stochastic discount factor that prices the (T, s_T)-state-contingent payoff into (t, s_t) consumption units is given by:

$$SDF_{t,T}(s_t, s_T) = e^{-\rho(T-t)} \frac{u'(C_T)}{u'(C_t)} \frac{\phi'[V_T(s_T)]}{\phi' \circ \phi^{-1}\{\mathbb{E}[\phi \circ V_T(s_T) \mid s_t]\}}. \tag{4}$$

To obtain a sharp theoretical result, we consider the continuous-time limit as $\Delta \to 0$. We denote $s^+ = \lim_{\Delta \to 0} s_\Delta$, and the stochastic discount factors as $SDF^+(0, s^+) = \lim_{\Delta \to 0} SDF_{0,\Delta}(0, s_\Delta)$ and $SDF^{++}(s^+, \theta_T) = \lim_{\Delta \to 0} SDF_{\Delta,2\Delta}(s_\Delta, \theta_T)$.

We compare the expected returns in the vague announcement and informative announcement economies by comparing the entropy of the stochastic discount factors, $\mathcal{H}(SDF)$, which is defined as $\mathcal{H}(SDF) = -\mathbb{E}[\ln SDF]$. As shown in Bansal and Lehmann (1997) and Backus, Chernov, and Zin (2014), no arbitrage implies that $\mathcal{H}(SDF) \geq \mathbb{E}[\ln R]$ holds true for any risky return R. That is, $\mathcal{H}(SDF)$ represents the highest expected return of any asset.[3] Under complete markets, the highest expected return, as measured by $\mathbb{E}[\ln R]$, can be achieved by the growth optimal portfolio. Our theoretical result will be stated in terms of $\mathcal{H}(SDF)$ with the understanding that $\mathcal{H}(SDF)$ is both a measure of the variability of the stochastic discount factor and the highest expected return of the economy.[4]

[3] In the rest of this section, we will use the term expected return for $\mathbb{E}[\ln R]$, as empirically, expected returns are often measured in log units.

[4] To see why $\mathcal{H}(SDF)$ can be interpreted as a measure of variability, note that Jensen's inequality implies $\mathbb{E}[f(SDF)] - f(\mathbb{E}[SDF]) \geq 0$ for any convex function f. For a strictly convex f, this gap is zero when SDF is constant and increases with the dispersion of SDF, so it serves as a natural measure of variability. One example is $f(x) = x^2$, which gives variance. Our entropy measure corresponds to $f(x) = -\ln x$. Since $\mathbb{E}[SDF] = 1/R_f$ by no-arbitrage, where R_f is the risk-free rate, we have $\ln(\mathbb{E}[SDF]) + \ln R_f = 0$. Therefore, under our definition, $\mathcal{H}(SDF) \equiv \mathbb{E}[-\ln(SDF)] = \mathbb{E}[-\ln(SDF)] + \ln(\mathbb{E}[SDF]) + \ln R_f$, where the first two terms form a non-negative Jensen-gap component. If SDF is lognormally distributed, then $\mathcal{H}(SDF) = \frac{1}{2}\mathrm{Var}[\ln SDF] + \ln R_f$.

The variance decomposition formula (1), together with Jensen's inequality, implies that

$$\mathrm{Var}\left(\mathbb{E}\left[\theta_T \mid \eta, \varepsilon\right]\right) \geq \mathrm{Var}\left(\mathbb{E}\left[\theta_T \mid \eta\right]\right), \text{ and } \mathbb{E}\left[\mathrm{Var}\left(\theta_T \mid \eta, \varepsilon\right)\right] \leq \mathbb{E}\left[\mathrm{Var}\left(\theta_T \mid \eta\right)\right]. \tag{5}$$

Since prices respond to beliefs, the first inequality says announcement-return variance is higher under the informative announcement, while the second says expected post-announcement variance is lower. This is the first thesis, which follows from the variance decomposition formula. The next result shows that an analogous ordering holds for $\mathcal{H}(SDF)$ and expected returns under a slight strengthening of GRS.

To state our main result, we first provide a definition of strong GRS. The theorem of generalized risk sensitivity in Ai and Bansal (2018) demonstrates that the announcement premium is positive if and only if the certainty equivalent functional $\mathcal{I}$ satisfies GRS, which, under the representation $\mathcal{I}[V] = \phi^{-1} \circ \mathbb{E}[\phi(V)]$, is equivalent to the concavity of ϕ.[5] Define $\mathcal{R}(V) = -\frac{V\phi''(V)}{\phi'(V)}$ as the Arrow-Pratt measure of relative risk aversion for ϕ. Under this formulation, GRS is equivalent to $\mathcal{R}(V) \geq 0$. Strong GRS imposes the following restriction on the elasticity of $\mathcal{R}(V)$.

Definition 1. *(Strong Generalized Risk Sensitivity) An intertemporal preference represented by the aggregator $\{u, \mathcal{I}\}$, where $\mathcal{I}$ has the representation $\mathcal{I}[V] = \phi^{-1} \circ \mathbb{E}[\phi(V)]$, and ϕ is a strictly increasing and three times continuously differentiable function, is said to satisfy GRS if $\mathcal{R}(V) = -\frac{V\phi''(V)}{\phi'(V)} \geq 0$. It is said to satisfy strong GRS if it satisfies GRS and*

$$\frac{d\ln \mathcal{R}(V)}{d\ln V} \geq 1 - \mathcal{R}(V). \tag{6}$$

The above condition has an intuitive interpretation. If $\mathcal{R}(V)$ is constant, that is, if ϕ is CRRA, then the above condition requires $\mathcal{R}(V) \geq 1$. In general, it requires that as V grows, the Arrow-Pratt measure of relative risk aversion cannot decline too fast.

For example, the standard recursive utility with constant risk aversion γ and constant intertemporal elasticity of substitution (IES) ψ can be formulated as (2) by choosing $u(C) = \frac{1}{1-1/\psi} C^{1-\frac{1}{\psi}}$ and $\phi(V) = \frac{\left(\left(1-\frac{1}{\psi}\right)V\right)^{\frac{1-\gamma}{1-\frac{1}{\psi}}}}{1-\gamma}$. For this class of utility functions, GRS is equivalent to $\gamma \geq \frac{1}{\psi}$, and strong GRS requires, in addition, $\gamma \geq 1$. Another example is the negative

[5] See Observation (ii) in Section 4.3 under the Subsection "Generalized Risk Sensitivity and Uncertainty Aversion" in Ai and Bansal (2018).

exponential function, $\phi(x) = -e^{-\alpha x}$. The robust control model and the recursive utility with unit IES can be formulated in the form of (2) by using the negative exponential function. In this case, $\phi = -e^{-\alpha x}$ satisfies the condition for all $\alpha > 0$.

The following proposition summarizes our main result regarding information-driven volatility and the risk premium. A detailed proof can be found in Appendix A.1.

Proposition 1. *(Information-Driven Volatility and Risk Premium) Suppose the preference represented by $\{u, \mathcal{I}\}$ satisfies strong GRS. The entropy of the announcement SDF is higher in the informative announcement economy relative to the vague announcement economy; that is,*

$$\mathcal{H}\left[SDF^{+}(0,(\eta,\varepsilon))\right] \geq \mathcal{H}\left[SDF^{+}(0,\eta)\right], \tag{7}$$

but the entropy of the post-announcement SDF is lower:

$$\mathcal{H}\left[SDF^{++}((\eta,\varepsilon),\theta_T)\right] \leq \mathcal{H}\left[SDF^{++}(\eta,\theta_T)\right]. \tag{8}$$

Under additively separable expected utility, (7) and (8) hold with equality. That is, the informativeness of announcements does not affect the announcement and post-announcement SDFs.

The above proposition formalizes the second thesis. More informative announcements simultaneously raise announcement-window expected returns and lower post-announcement expected returns on the growth optimal portfolio. Under additively separable utility, ϕ is linear, and both sides of (7) and (8) are zero.

A more informative announcement triggers a stronger price response, raising realized variance over $(0, t]$; under strong GRS, this is accompanied by a higher expected return on the growth optimal portfolio. Because the same announcement resolves more residual uncertainty about θ_T, both post-announcement expected variance and post-announcement expected returns on the growth optimal portfolio are reduced. Combining the two theses delivers a negative correlation between past realized variance around announcements and future expected returns on the growth optimal portfolio.

It is important to note that the information-driven volatility channel affects the timing of the realization of stock market volatility but does not resolve the puzzle of the low volatility of macroeconomic fundamentals relative to the high volatility of stock market returns. The

variance decomposition formula also imposes an upper bound on the variance of conditional expectations: it is bounded by the total variance of macroeconomic fundamentals.[6] Although this bound does not apply directly to asset prices, it suggests that information by itself cannot resolve the excess volatility puzzle of Shiller (1981) and LeRoy and Porter (1981). In this respect, we build on the long-run risk mechanism of Bansal and Yaron (2004): stock market volatility reflects information about the long-run trend of economic growth. In contrast to Bansal and Yaron (2004), our model focuses on how the informativeness of information events affects the volatility–expected return relationship. In the next section, we embed the information-driven volatility mechanism into an otherwise standard long-run risk model to assess the quantitative importance of the information-driven volatility channel.

4 A Dynamic Model

In this section, we develop a dynamic model with time-varying informativeness of announcements. Our model provides a quantitative framework for replicating the empirical tests that we develop in the next section and for assessing the importance of the information-driven volatility channel for stock market return predictability. To provide a realistic model of stock market volatility dynamics, we incorporate both low-frequency variations in fundamental volatility and high-frequency movements in information-driven volatility. The presence of fundamental volatility allows our model to capture the well-documented positive autocorrelation of realized volatility of stock returns in the data. The presence of information-driven volatility allows our model to explain the puzzling relationship between realized volatility and expected returns in the data. We provide details of the model solutions and derivations in Appendix A.2.

Preferences and Endowment We consider an endowment economy where the representative agent has a Duffie and Epstein (1992) recursive preference with time discount rate ρ, constant risk aversion γ, and constant intertemporal elasticity of substitution (IES) ψ. This preference has the representation $\mathcal{I}[V] = \phi^{-1} \circ \mathbb{E}[\phi(V)]$ with $\phi(x) = \frac{1}{1-\gamma}\left[\left(1-\frac{1}{\psi}\right)x\right]^{\frac{1-\gamma}{1-1/\psi}}$. As we noted in the last section, this preference satisfies strong GRS if and only if $\gamma \geq \frac{1}{\psi}$ and

[6] However, Augenblick and Lazarus (2026) derive a bound on the variation in option-implied (risk-neutral) beliefs about future asset returns.

$\gamma \geq 1$. This parameterization coincides with standard long-run risk calibrations and will be assumed throughout this section.

We assume that aggregate consumption follows a diffusion process of the form

$$\frac{dY_t}{Y_t} = \theta_t dt + \sigma_Y dB_{Y,t}, \tag{9}$$

where $B_{Y,t}$ is a standard Brownian motion, and $\{\theta_t\}_{t\geq 0}$ is the latent long-run component of the aggregate consumption growth rate, which is a two-state Markov process with the state space $\Theta = \{\theta_H, \theta_L\}$, where $\theta_H > \theta_L$. The transition probability for θ_t over an infinitesimal interval Δ is given by

$$\begin{bmatrix} e^{-\lambda_H \Delta} & 1 - e^{-\lambda_H \Delta} \\ 1 - e^{-\lambda_L \Delta} & e^{-\lambda_L \Delta} \end{bmatrix}, \tag{10}$$

where the intensity λ_H is the rate of transition from a high state to a low state, and λ_L is the transition intensity from low to high. To highlight the information-driven volatility channel, we deliberately eliminate any stochastic volatility in consumption by assuming σ_Y is constant.

Information Quality and Announcements We assume that the latent state variable θ_t is unobservable to investors. However, information about θ_t is continuously revealed in financial markets. Because θ_t is not observable, equilibrium prices and quantities are functions of investors' posterior beliefs about θ_t. Thanks to the assumption of a two-state Markov chain, the posterior distribution can be fully summarized by the posterior probability of $\theta_t = \theta_H$, that is, $\pi_t = \Pr_t(\theta_t = \theta_H)$. Given π_t, we define $\hat{\theta}_t = \mathbb{E}_t[\theta_t]$ to be the posterior mean of θ_t (i.e., $\hat{\theta}_t = \pi_t \theta_H + (1 - \pi_t)\theta_L$). Because π_t and $\hat{\theta}_t$ have a one-to-one relationship, we find it more convenient to use $\hat{\theta}_t$ as the state variable that summarizes the posterior distribution.

Investors observe two sources of information about θ_t: the continuous endowment process (9), and discrete pre-scheduled announcements at times $T, 2T, \ldots, nT$ for $n = 1, 2, \ldots$.[7] We assume the following timing convention for announcements. At time nT^-, investors

[7] Our benchmark model matches the quantitative results based on FOMC announcements, which are pre-scheduled and periodically announced. However, our theory of information-driven volatility does not rely on the assumption of fixed announcements. Instead, we show that our results still hold if announcements arrive as an unexpected Poisson process.

observe a signal ν_n, which is an information quality parameter. The signal does not affect investors' beliefs about θ, summarized by $\hat{\theta}^-_{nT}$, but carries information about the quality of the upcoming announcement at nT. The announcement at time nT carries a noisy signal s_n about θ_{nT}, which reveals the true value of θ_{nT} with probability ν_n. The distribution of the signal is given as follows: if $\theta_{nT} = \theta_H$, that is, the true state is the high growth state,

$$\begin{array}{lll} s_n = \theta_H & \text{with prob.} & \nu_n \\ s_n = \theta_L & \text{with prob.} & 1 - \nu_n \end{array}, \tag{11}$$

and if $\theta_{nT} = \theta_L$, that is, the true state is the low growth state,

$$\begin{array}{lll} s_n = \theta_H & \text{with prob.} & 1 - \nu_n \\ s_n = \theta_L & \text{with prob.} & \nu_n \end{array}. \tag{12}$$

Here $\nu_n \in \left[\frac{1}{2}, 1\right]$ is the key state variable in our model that measures the *information quality*, or the time-varying *informativeness* of announcements. When $\nu_n = 1$, announcements carry perfectly accurate information because the signal reveals the true state with probability one. In contrast, $\nu_n = 0.5$ indicates that announcements are completely uninformative. That is, the signal matches the true state with probability one half and mismatches it with probability one half, so it carries no information. For simplicity, we assume that $\nu_1, \nu_2, \ldots$ are i.i.d. over time.

Investors update their belief, $\hat{\theta}_t$, according to Bayes' rule. As a result, in the interior of $((n-1)\,T, nT)$ without announcements, investors learn from the observed endowment process (9), and the posterior mean of θ_t satisfies the following optimal filtering equation:

$$d\hat{\theta}_t = (\lambda_H + \lambda_L)(\bar{\theta} - \hat{\theta}_t)dt + \frac{(\theta_H - \hat{\theta}_t)(\hat{\theta}_t - \theta_L)}{\sigma_Y} d\hat{B}_{Y,t}, \tag{13}$$

where $\bar{\theta} = \frac{\lambda_L \theta_H + \lambda_H \theta_L}{\lambda_L + \lambda_H}$ is the steady-state mean of θ_t, and $\hat{B}_{Y,t}$ is the innovation process defined by $d\hat{B}_{Y,t} = \frac{1}{\sigma_Y}\left(\frac{dY_t}{Y_t} - \hat{\theta}_t dt\right)$, which indicates the surprises from the difference between observed and expected consumption growth.

Investors also learn from s_n at nT, $n = 1, 2, \ldots$. In our model, because announcements occur periodically at multiples of T, equilibrium prices and quantities can be formulated as functions of two Markov state variables, $(\hat{\theta}_t, t \bmod T)$. We use these state variables to solve

for forward-looking equilibrium asset prices. Because $t \bmod T \in [0, T)$, we can without loss of generality focus on one representative announcement cycle, $[0, T]$. We use T for the announcement time and T^- and T^+ for the instants immediately before and after the announcement, respectively. In this representative-cycle notation, 0 should be understood as T^+ (right after the previous announcement), and T should be understood as T^-, right before the next announcement. This convention allows us to use $(\hat{\theta}_t, t)$ as the Markov state variables in the following sections.

In Appendix A.2.1, we show that given the prior belief $\hat{\theta}_T^-$ before the announcement, the posterior distribution of $\hat{\theta}_T^+$ after the announcement follows

$$\hat{\theta}_T^+ = \begin{cases} \theta_L + \frac{\left(\hat{\theta}_T^- - \theta_L\right)\nu(\theta_H - \theta_L)}{\left(\hat{\theta}_T^- - \theta_L\right)\nu + \left(\theta_H - \hat{\theta}_T^-\right)(1-\nu)} & \text{w.p.} \quad \frac{\hat{\theta}_T^- - \theta_L}{\theta_H - \theta_L}\nu + \frac{\theta_H - \hat{\theta}_T^-}{\theta_H - \theta_L}(1-\nu) \\ \theta_L + \frac{\left(\hat{\theta}_T^- - \theta_L\right)(1-\nu)(\theta_H - \theta_L)}{\left(\hat{\theta}_T^- - \theta_L\right)(1-\nu) + \left(\theta_H - \hat{\theta}_T^-\right)\nu} & \text{w.p.} \quad \frac{\hat{\theta}_T^- - \theta_L}{\theta_H - \theta_L}(1-\nu) + \frac{\theta_H - \hat{\theta}_T^-}{\theta_H - \theta_L}\nu \end{cases}. \tag{14}$$

The informativeness ν governs the conditional distribution of the posterior mean through (14). At the boundaries, this recovers the expected limits: when $\nu = 1$ the announcement is perfectly informative and reveals the true state, and when $\nu = 0.5$ it is uninformative, so $\hat{\theta}^+ = \hat{\theta}^-$ with probability one.

Asset Prices We assume that the aggregate stock market is a claim to the following dividend process:

$$\frac{dD_t}{D_t} = \left[\xi_\theta(\hat{\theta}_t - \bar{\theta}) + \bar{\theta}\right] dt + \xi_Y \sigma_Y d\hat{B}_{Y,t} + \omega_t dB_{\omega,t}, \tag{15}$$

where ξ_θ and ξ_Y are the leverage parameters, and $dB_{\omega,t}$ is a Brownian motion uncorrelated with the consumption shock $dB_{Y,t}$ or θ_t. Here, we allow the idiosyncratic volatility ω_t in the dividend growth rate to be time-varying and assume that it follows a two-state Markov chain with the state space $\{\omega_H, \omega_L\}$, where $\omega_H > \omega_L$. The transition matrix for ω_t takes the same form as (10), $\begin{bmatrix} e^{-\kappa_H \Delta} & 1 - e^{-\kappa_H \Delta} \\ 1 - e^{-\kappa_L \Delta} & e^{-\kappa_L \Delta} \end{bmatrix}$ with κ_H (κ_L) the rate of transition from ω_H to ω_L (ω_L to ω_H). This specification allows our model to capture the low-frequency movements in fundamental volatility and generate a positive autocorrelation in realized stock market volatility, which is an important feature of the data. Because this idiosyncratic component

is orthogonal to the SDF, it does not command risk compensation and therefore does not generate any return predictability in our model.

The lifetime utility of the representative agent can be written as a function of state variables: $V(\hat{\theta}_t, t, Y_t) = \frac{1}{1-\gamma} H(\hat{\theta}_t, t) Y_t^{1-\gamma}$. As a result, changes in beliefs about θ_t are immediately reflected through the variations in the continuation utility $H(\hat{\theta}_t, t)$. We show the solutions of the value function in Lemma 2 in Appendix A.2.1. As in Lucas (1978), individuals optimally choose consumption endogenously given equilibrium prices, and market-clearing conditions pin down a unique equilibrium system of stochastic discount factors, $\{M_t\}_{t=0}^{\infty}$. Given the value function, we can construct the stochastic discount factor process M_t. The law of motion of M_t in the interior of $(0, T)$ without announcements can be written as

$$\frac{dM_t}{M_t} = -r(\hat{\theta}_t, t)dt - \sigma_M(\hat{\theta}_t, t)d\hat{B}_{Y,t}. \tag{16}$$

where the risk-free rate $r(\hat{\theta}_t, t)$ and the market price of risk $\sigma_M(\hat{\theta}_t, t)$ are given in Equations (A.31) and (A.32) in Appendix A.2.2.

Let $p(\hat{\theta}_t, t)$ denote the price-to-dividend ratio so that the stock price is given by $p(\hat{\theta}_t, t)D_t$. By definition, the stock price is the discounted value of future cash flows:

$$p(\hat{\theta}_t, t)D_t = \mathbb{E}\left[\int_0^{\infty} \frac{M_{t+s}}{M_t} D_{t+s} ds \,\middle|\, \hat{\theta}_t, t\right]. \tag{17}$$

We provide the expression for the partial differential equation (PDE), together with the boundary conditions that determine the solution of $p(\hat{\theta}_t, t)$ in Appendix A.2.2. To avoid complicating the notation, we use $p(\hat{\theta}_T^-, T^-)$ to denote the price-to-dividend ratio at T^- before observing the signal ν, and $p(\nu, \hat{\theta}_T^-, T^-)$ to denote the price-to-dividend ratio at T^- after observing ν. More generally, we write p with two arguments $(\hat{\theta}_t, t)$ between announcements, and add ν as a third argument only at the announcement boundary T^- to make the dependence on the just-realized informativeness explicit. The same convention applies to the implied variance function IV^* below. With the stochastic discount factor and the price-to-dividend ratio, the market risk premium is given by the following proposition.

Proposition 2. *(Equity Premium) In the interior of* $(0, T)$*, the instantaneous risk premium*

is given by

$$\mathbb{E}_t\left[\frac{d[p(\hat{\theta}_t,t)D_t]+D_t dt}{p(\hat{\theta}_t,t)D_t}\right]-r(\hat{\theta}_t,t)dt=\sigma_M(\hat{\theta}_t,t)\left(\frac{p_\theta(\hat{\theta}_t,t)}{p(\hat{\theta}_t,t)}\frac{\sigma_\theta(\hat{\theta}_t)}{\sigma_Y}+\xi_Y\sigma_Y\right)dt, \tag{18}$$

where $\sigma_\theta(\hat{\theta}_t)=(\theta_H-\hat{\theta}_t)(\hat{\theta}_t-\theta_L)$ *and* $\frac{p_\theta(\hat{\theta}_t,t)}{p(\hat{\theta}_t,t)}=\frac{\partial p(\hat{\theta}_t,t)/\partial\hat{\theta}_t}{p(\hat{\theta}_t,t)}$. *At announcement* T, *the announcement premium is given by*

$$\mathbb{E}_{T^-}\left[\frac{p(\hat{\theta}_T^+,T^+)}{p(\hat{\theta}_T^-,T^-)}\right]-1=\frac{\left(\mathbb{E}_{T^-}\left[H(\hat{\theta}_T^+,T^+)\right]\right)^B\mathbb{E}_{T^-}\left[p(\hat{\theta}_T^+,T^+)\right]}{\mathbb{E}_{T^-}\left[H(\hat{\theta}_T^+,T^+)^B p(\hat{\theta}_T^+,T^+)\right]}-1. \tag{19}$$

where $B\equiv(1/\psi-\gamma)/(1-\gamma)$, *and* $\hat{\theta}_T^+$ *is drawn from the distribution in Equation (14).*

In Appendix A.2.2, we show that $\frac{H(\hat{\theta}_T^+,T^+)^B}{\left\{\mathbb{E}_{T^-}\left[H(\hat{\theta}_T^+,T^+)\right]\right\}^B}$ is the announcement SDF. By the maintained strong GRS assumption, the continuation utility $H(\hat{\theta}_t,t)$ decreases in $\hat{\theta}_t$, whereas the price-to-dividend ratio $p(\hat{\theta}_t,t)$ increases in $\hat{\theta}_t$. Therefore, $\text{Cov}\left[H(\hat{\theta}_T^+,T^+)^B,p(\hat{\theta}_T^+,T^+)\right]<0$. This negative covariance implies that announcements require positive risk compensation. At the announcement, investors' beliefs jump from $\hat{\theta}_T^-$ to $\hat{\theta}_T^+$ as new aggregate information is revealed, according to Equation (14). Because both continuation utility and the price-to-dividend ratio depend on $\hat{\theta}_t$, this belief updating induces simultaneous comovements in the SDF and asset prices. Intuitively, the arrival of information over a short interval generates substantial variation in continuation utility, so investors require compensation for bearing this risk. The risk premium is realized when uncertainty is resolved. This mechanism generates a positive average macroeconomic announcement premium, consistent with Savor and Wilson (2013). The special case $\gamma=1/\psi$ corresponds to additively separable expected utility, for which the announcement premium vanishes (Proposition 1).

Finally, we define the implied variance of the stock return at time t as the conditional variance of the cumulative log return from t to τ under the risk-neutral measure $\mathbb{Q}$, where $\tau\geq t$ is the expiration date and $h=\tau-t$ is the time to maturity:

$$IV_{t,\tau}^*(\hat{\theta}_t,\omega_t,t)=\text{Var}_t^*\left[\ln[p(\hat{\theta}_\tau,\tau)D_\tau]-\ln[p(\hat{\theta}_t,t)D_t]\right], \tag{20}$$

where $\text{Var}_t^*[\cdot]$ denotes the conditional variance under the risk-neutral measure $\mathbb{Q}$, which maps

directly to our measure of implied variance, VIX^2 in empirical exercises. The risk-neutral measure $\mathbb{Q}$ is constructed from the stochastic discount factor process M_t in Appendix A.3. Because the log price $\ln[p(\hat{\theta}_t, t)D_t]$ is known at time t, the second term in Equation (20) is deterministic and drops out of the conditional variance. We provide solutions to our model-implied variance in Lemmas 5 and 6 in Appendix A.3.

Comparative Statics with Respect to Informativeness of Announcements We now use the policy functions of the model to illustrate the two main theses of our theory of information-driven volatility, as highlighted in Section 3. We provide the formulas for the policy functions in Appendix C.1.

Under strong GRS, the announcement premium in (19) is not only positive but also increasing in the informativeness of announcements, as we demonstrated in Proposition 1. We define the implied variance reduction at the announcement as

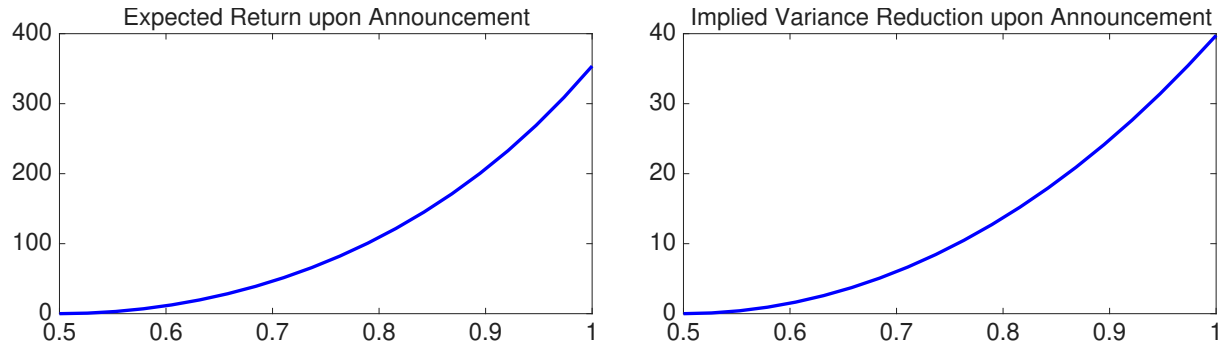
$$\Delta IV_T^* = IV^*_{T^-,\tau}(\nu, \hat{\theta}_T^-, \omega_T^-, T^-) - IV^*_{T^+,\tau}(\hat{\theta}_T^+, \omega_T^+, T^+), \tag{21}$$

and show in Appendix A.3 that ΔIV_T^* equals the risk-neutral variance of the announcement return.

In Figure 1, we plot the announcement premium in the left panel and the implied variance reduction upon announcements in the right panel as functions of the informativeness ν. We plot the implied variance reduction rather than the variance of the announcement return because it is a market-based measure of announcement-return variance and is the object used in our empirical exercises.

As shown in Figure 1, at $\nu = 0.5$, the announcement is completely uninformative. The expected announcement return and the implied variance reduction upon announcements are both zero. As ν increases from 0.5 to 1, the announcement becomes increasingly informative, and therefore, the expected return and the implied variance reduction rise monotonically. Consistent with the intuition in Proposition 1, the expected return and the implied variance reduction at the announcement are both increasing functions of the informativeness of the announcement. Because of the monotonic relationship between the informativeness ν and the implied variance reduction ΔIV_T^*, the latter provides a market-based measure of the informativeness of announcements, which we exploit in the empirical exercises in the following

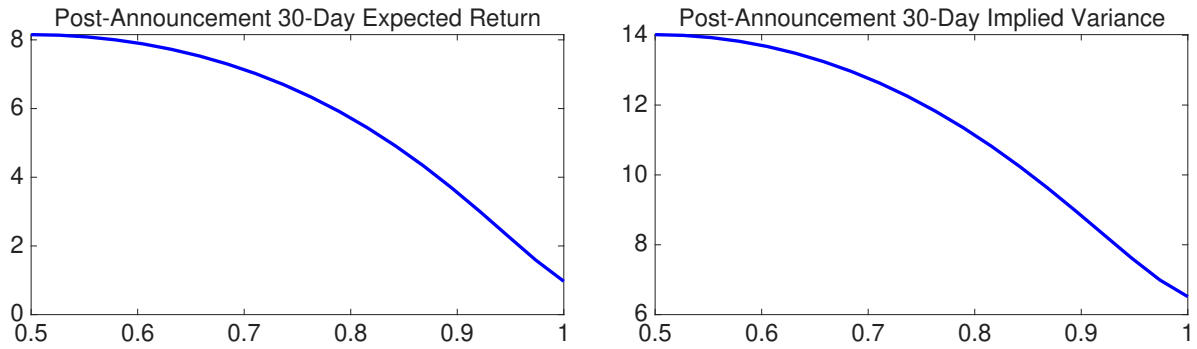
Figure 1: Expected Returns and Implied Variance Reduction upon Announcements



The left panel displays the model-implied expected announcement return (defined in Equation (19)) as a function of informativeness ν, with expected returns measured in basis points. The right panel shows the implied variance reduction upon announcements, as defined in Equation (21), as a function of informativeness ν, measured in monthly percentage squared.

section.

Figure 2: Post-Announcement 30-Day Expected Return and Implied Variance



The left panel plots the expected 30-day return during the post-announcement period as a function of the informativeness ν implied by our model, with expected returns measured in annualized percent. The right panel shows the 30-day implied variance after the announcement implied by our model, measured in monthly percentage squared.

The second implication of our theory of information-driven volatility is that more informative announcements are associated with a lower expected return and lower volatility during the period after the announcement. In Figure 2, we plot the model-implied expected return during the 30-day period after the announcement (left panel), and the 30-day implied variance during the same period (right panel) as a function of the informativeness ν.

As informativeness rises, both quantities fall monotonically, consistent with Proposition 1. The model therefore generates the negative correlation between past variance realized upon announcements and future expected returns.

5 Quantitative Results

In this section, we calibrate our model to match a broad set of moments for aggregate consumption growth, asset returns, and announcement returns. We then develop empirical tests for the information-driven volatility channel and replicate these tests in our model. Finally, we show that the information-driven volatility channel is quantitatively significant: more informative announcements predict higher announcement-day returns and larger implied variance reductions, while predicting lower future realized variance and lower future expected returns.

Data We use several sources of data to calibrate and test our model. For annual moments of consumption growth, dividend growth, total market excess returns, and the risk-free rate, we use the longest available sample period, 1929–2024. Specifically, we use BEA data on real per capita annual consumption growth of nondurables and services; CRSP value-weighted portfolios of all stocks traded on NYSE, Amex, and NASDAQ to impute annual dividends; and Kenneth French's data library for stock market excess returns and risk-free rates. All nominal quantities are adjusted for inflation using the CPI, at annual frequency for annual moments and using a trailing 12-month rolling average for monthly moments.

The dates for FOMC meetings are sourced from the Federal Reserve Board's website. Following Savor and Wilson (2014), we include only the pre-scheduled FOMC meetings. About eight pre-scheduled FOMC meetings occur each year. In total, there are 242 FOMC announcement days during 1994.09–2024.12.[8] To identify information events, we combine FOMC announcement days with news-related stock market jump days obtained from Baker, Bloom, Davis, and Sammon (2021); the precise definition of a news-related jump day is given

[8]In our FOMC robustness analysis, we control for the orthogonalized monetary policy surprise, along with the six macroeconomic and financial control variables from Table 1 of Bauer and Swanson (2023b): the nonfarm payroll surprise, the 12-month log change in nonfarm payrolls, the 3-month log S&P 500 return, the 3-month change in the yield curve slope, the 3-month log Bloomberg commodity index return, and the implied skewness of the 10-year Treasury yield. These data are available through 2023.12.

below.

Our high-frequency data come from TickData.com, from which we obtain 1-minute returns on S&P 500 E-mini futures to measure daily realized variance and futures returns for the predictability regressions. The futures sample spans 1997.09–2024.12. We obtain data on the VIX index from the Chicago Board Options Exchange (CBOE) for the period 1990.01–2024.12. The CBOE's VIX is a model-free measure of implied variance computed from S&P 500 Index option prices. To construct an ex ante measure of informativeness and a fixed-expiration measure of implied variance reduction, we use S&P 500 Index options obtained from OptionMetrics, with a sample period of 1996.01–2024.12. Appendix B.1 provides a detailed description of the construction of high-frequency returns, realized variance, and option-implied variance.

We estimate the ICAPM using excess returns from Kenneth French's data library. Realized variance is computed by summing squared daily log market returns. Following Guo and Whitelaw (2006), we include as controls the log dividend-price ratio, the consumption-wealth ratio from the Goyal, Welch, and Zafirov (2024) dataset, and the risk-free rate. These data are available from 1952.01 to 2024.12.

Our cross-sectional earnings tests rely on actual announcement dates from I/B/E/S Summary, adjusting after-hours announcements to the next trading day. To construct firm-level realized variance, we combine intraday trade data from Trade and Quote (TAQ) with overnight returns backed out from CRSP daily close-to-close returns and open prices, following the standard intraday-overnight decomposition. Forecast dispersion is constructed from individual analyst earnings forecasts in I/B/E/S Detail. The sample spans 1993.01–2024.12.

Parameter Values We divide our model parameters into three groups. The first group consists of preference parameters, which we choose based on prior literature. We set $\rho = 0.1\%$, risk aversion $\gamma = 20$, and IES $\psi = 2$, in line with the long-run risk literature, for example, Bansal and Shaliastovich (2013) and Schorfheide, Song, and Yaron (2018).[9]

The second group of parameters consists of those that govern consumption and dividend

[9]Our $\gamma = 20$ is virtually identical to Bansal and Shaliastovich (2013)'s estimate of $\gamma = 20.90$; Schorfheide, Song, and Yaron (2018) and Bansal, Kiku, and Yaron (2016) report somewhat lower values, with $\gamma = 8.89$ and $\psi = 1.97$ in the former and risk aversion ranging from 9.7 to 14.8 in the latter, depending on the level of aggregation. We use a risk aversion at the higher end of its estimated value in the literature so that the risk premium implied by our model is in line with the data without assuming preference shocks, such as those in Schorfheide, Song, and Yaron (2018).

dynamics. We choose these parameters to match the estimates in Schorfheide, Song, and Yaron (2018). They use a mixed-frequency approach that accounts for measurement errors in consumption levels to estimate consumption and dividend growth parameters *without* using asset pricing data. Their model is estimated at monthly frequency. We take the leverage parameters of dividends, $\xi_\theta = 3.52$ and $\xi_Y = 0.82$, directly from their estimation, because they do not depend on the frequency of the model. Other parameters are frequency-specific. To match their estimates, we choose the consumption growth parameters σ_Y, θ_H, θ_L, λ, so that our continuous-time model matches the first and second moments of annual consumption growth and their variance ratios from their estimated model. We choose variance ratios for consumption growth because, as shown in Cochrane (1988), these moments are effective in identifying the volatility of the persistent component of consumption growth. Table 2 compares the moments of our continuous-time model and those simulated from their model.[10]

We set the stochastic volatility parameters of dividend growth, ω_H, ω_L, κ_H, and κ_L in our model similarly. In their model, log volatility follows an AR(1) process. To match their stochastic volatility dynamics, we first compute the annualized realized volatility of monthly dividend growth for our model and for theirs. We then choose the parameters of our model to match the mean, standard deviation, and the first five autocorrelations of the log annualized realized volatility sequence. These moments are displayed in the bottom panel of Table 2. We impose a symmetry condition, $\lambda_H = \lambda_L = \lambda$ and $\kappa_H = \kappa_L = \kappa$, because the relevant processes in Schorfheide, Song, and Yaron (2018) are symmetric.

The last group of parameters is unique to our model. We assume $\nu \in \{\nu_L, \nu_H\}$, where the parameters ν_H and ν_L govern the informativeness of the announcements, and q_L denotes the probability that $\nu = \nu_L$. In our calibration, we set $\nu_H = 0.9$, $\nu_L = 0.65$, and $q_L = 0.6$ to best match the mean and standard deviation of the implied variance reduction on FOMC announcement days as well as the average announcement day return. We choose $T = 1/8$ so that there are eight announcements per year in our model, matching the frequency of pre-scheduled FOMC announcements in the data. We use FOMC announcements as the quantitative target of the model for two reasons. First, as documented by Lucca and Moench (2015), FOMC announcements require significant risk compensation. Second, compared to

[10] We do not directly match these moments of consumption data for two reasons: first, as shown in Schorfheide, Song, and Yaron (2018), measurement errors in consumption will bias estimates of parameters, and second, higher-order variance ratios are not precisely estimated in the data due to data limitations.

Table 2: Moments of consumption and dividend growth

Consumption	Mean	Std	VR(2)	VR(3)	VR(4)	VR(5)	VR(6)
SSY	1.92	1.96	1.62	2.03	2.34	2.56	2.74
Model	1.94	2.12	1.61	2.02	2.32	2.53	2.69
Dividend	Mean	Std	AC(1)	AC(2)	AC(3)	AC(4)	AC(5)
SSY	-4.18	0.80	0.75	0.57	0.42	0.32	0.24
Model	-4.17	0.81	0.76	0.57	0.43	0.33	0.25

This table compares the simulated moments from the Schorfheide, Song, and Yaron (2018) (SSY) estimation and those from our calibrated model. Variance ratios of consumption growth are defined by $VR(k) = \frac{\text{Var}[\Delta_k \ln C]}{k \cdot \text{Var}[\Delta_1 \ln C]}$ at horizons $k = 2, \ldots, 6$ years, where $\Delta_k \ln C = \ln C_{t+k} - \ln C_t$. The top panel reports moments of consumption growth, and the bottom panel reports moments of log realized annual volatility of dividend growth. To compute realized annual volatility of dividend growth, we simulate our continuous-time model at the daily frequency and SSY at the monthly frequency. We define annual realized volatility as the realized volatility of monthly dividend growth within each year, and report statistics of the annual series of the log realized volatility of dividend growth.

other macroeconomic announcements, the informativeness of FOMC announcements is more likely to vary over time because these announcements typically reflect the Federal Reserve's contingent response to macroeconomic conditions. In contrast, other macro announcements, such as GDP releases, the unemployment report, or producer price index releases, typically provide a given statistic of the macroeconomy, and their informativeness is likely to be relatively constant over time.

Table 3: Calibrated Parameters

σ_Y	Endowment growth volatility	0.0136	ω_L	Low dividend idiosyncratic volatility	0.02
θ_H	High endowment growth state	0.040	κ	ω transition prob.	0.14
θ_L	Low endowment growth state	–0.001	ν_H	High informativeness of announcement	0.9
λ	θ transition prob.	0.29	ν_L	Low informativeness of announcement	0.65
ω_H	High dividend idiosyncratic volatility	0.12	q_L	Prob. of low informativeness	0.6

This table reports the annualized parameter values used in the model.

Basic Statistics of Model-Implied Unconditional Moments We list the asset pricing moments in the data and the corresponding statistics for our calibrated model in Table 4.

We simulate our continuous-time model, aggregate quantities to an annual frequency, and compare annual moments implied by our model simulation and those in the data in Panel A of Table 4.

Table 4: Asset Pricing Moments

Panel A: Aggregate market moments		Data	Model
$\mathbb{E}[R]-r$	Equity premium	7.75%	5.12%
$\text{Std}[R]$	Vol of stock market return	18.55%	12.85%
$\mathbb{E}[r]$	Average risk-free rate	0.16%	0.32%
$\text{Std}[r]$	Vol of risk-free rate	1.08%	0.72%
$\mathbb{E}[dY/Y]$	Consumption growth rate	1.72%	1.94%
$\text{Std}[dY/Y]$	Vol of consumption growth rate	2.74%	2.12%
$\text{AC}[dY/Y]$	AC(1) of consumption growth rate	0.34	0.61
$\mathbb{E}[dD/D]$	Dividend growth rate	1.51%	1.62%
$\text{Std}[dD/D]$	Vol of dividend growth rate	10.72%	9.06%
$\text{AC}[dD/D]$	AC(1) of dividend growth rate	0.19	0.44
$\text{Corr}(dY/Y, dD/D)$	Corr b.t. consumption and dividend	0.50	0.59
$\text{AC}[RVol]$	AC(1) of annual realized volatility	0.58	0.61
Panel B: Announcement-day moments		Data	Model
$\mathbb{E}[R^A]$	A-day average return	21.15 bps	25.22 bps
$\mathbb{E}[R^N]$	NA-day average return	2.08 bps	0.91 bps
$\mathbb{E}[\Delta IV_T]$	Av. IV reduction on A-days	1.85	4.01
$\text{Std}[\Delta IV_T]$	Std. of IV reduction on A-days	10.57	7.76

This table displays the asset pricing moments in the data and those implied by the model. The data in Panel A are for the period 1929.01–2024.12. The data in Panel B are for the period 1994.09–2024.12.

Our model generally matches both the asset market return and volatility moments in the data well. The average equity market premium in the model is 5.12%, and the volatility of annual market return is 12.85%. Our model generates an average risk-free rate of 0.32% with a standard deviation of 0.72%. The standard deviation of the risk-free rate in the data is 1.08%, slightly higher than in our model. However, the risk-free rate in our data is computed as the nominal interest rate minus realized inflation. We also follow Ang, Bekaert, and Wei (2007) to construct a measure of the real interest rate as the nominal interest rate minus expected inflation by using the median forecast of inflation from the Survey of Professional Forecasters. The standard deviation of this measure of the risk-free rate is 0.62% per year, very close to that in our model. Our model is not calibrated to directly match the moments

of consumption growth and dividend growth in the data due to concerns about measurement errors as emphasized in Schorfheide, Song, and Yaron (2018). We nevertheless compare these moments with the data to facilitate comparison of our calibration with the literature.

Several key moments in the data are particularly important in assessing the quantitative importance of the information-driven volatility channel. First, as we explained earlier, changes in fundamental volatility and information-driven volatility both affect the dynamics of stock return volatility. Fundamental volatility induces a positive autocorrelation of return volatility, and information-driven volatility induces a negative autocorrelation. The autocorrelation of stock market return volatility in the data therefore provides discipline on how strong the information-driven volatility channel can be: a large magnitude of information-driven volatility may result in a counterfactually negative autocorrelation of return volatility. Thanks to the stochastic volatility in dividend growth, our calibration matches the autocorrelation of stock market return volatility quite well. The first-order autocorrelation of realized volatility of annual stock market returns is 0.58, and the same moment is 0.61 in our model.

Second, our model successfully matches moments of implied variance reduction on announcement days. As noted earlier, ΔIV_T provides a market-based measure of the informativeness of announcements. In our model, announcements occur instantaneously, and ΔIV_T is given in Equation (21). In the data, we measure ΔIV_T using the daily change in the implied variance of S&P 500 Index options. Specifically, we define ΔIV_T as the squared VIX index at market close on the day before the announcement minus the squared VIX index at market close on the announcement day: $\Delta IV_T = IV_{T-1,\tau-1} - IV_{T,\tau}$, where $IV \equiv \text{VIX}^2$ and $\tau = T + 30$, with 30 denoting the VIX's days to maturity. In Table 4, the implied variance reduction is significantly positive on announcement days, with a mean of 1.85 (measured in monthly percentage squared units, i.e., $(\text{VIX}^2_{T-1} - \text{VIX}^2_T)/12$) and a standard deviation of 10.57. Our model generates an average implied variance reduction of similar magnitude, with a standard deviation comparable to that observed in the data.

However, under this construction, $IV_{T-1,\tau-1}$ does not cover the 30th day after the announcement, whereas $IV_{T,\tau}$ does. As a result, market expectations about variance on the 30th day after the announcement may introduce measurement error in ΔIV_T as a proxy for the information-induced variance reduction on the announcement day. To address this issue, we also compute a fixed-expiration measure of implied variance reduction: $\Delta IV_T = IV_{T-1,T+30} - IV_{T,T+30}$, where $IV_{T-1,T+30}$ has a maturity of 31 days and is computed

using a standard interpolation method.[11] This alternative measure yields a mean of 3.74 and a standard deviation of 11.91. The fixed-expiration measure of implied variance reduction does not include the implied variance on the 30th day and is therefore closer to the implied variance reduction in our model. Its higher mean, 3.74, is closer to the same moment in our model.

In what follows, we use VIX^2 reduction as our benchmark measure of ΔIV_T because the VIX index is publicly available, dates back to 1990, and can be traded indirectly through VIX futures and options contracts. Whenever applicable, we also present robustness analysis using the fixed-expiration implied variance reduction. Appendix B.2 further shows that our model reproduces the full distribution of implied variance reduction across announcement days, including the occasional post-announcement increases observed in the data (Table B.8).

Testing the Information-Driven Volatility Channel This section conducts several statistical tests of the two main implications of our theory of information-driven volatility. We first present these tests using U.S. stock market return data and then replicate them using simulated data from our model. For ease of comparison with the empirical evidence, we use the day as the unit of time throughout the rest of this section. For example, $t+1$ refers to one day after time t.

Our first set of tests examines the relationship between the informativeness of announcements and the mean and volatility of announcement returns, as illustrated in Figure 1. These tests require return predictability regressions using a measure of the informativeness of FOMC announcements. A natural candidate is the option-implied variance reduction on announcement days. However, we cannot use implied variance reduction directly in return predictability regressions because it contains information revealed after the announcement.[12] An ideal measure of informativeness should therefore rely only on *ex ante* information available before announcements and be a good predictor of implied variance reduction after announcements.

[11] If $T-1$ is not a trading day, we replace it with the closest preceding trading day on which option prices are observed and adjust the maturity accordingly so that implied variances refer to the same expiration date. Observations for which the gap between the announcement day and the preceding trading day exceeds five calendar days are excluded.

[12] In fact, implied variance and stock returns are well known to be strongly negatively correlated. This ex post negative correlation may simply reflect the "leverage effect" and may have nothing to do with the relationship between informativeness and the announcement premium.

Our construction of the ex ante informativeness measure is based on the following intuition. Suppose implied variance reflects the realized return variance induced by the arrival of information, and suppose FOMC announcement days have more information arrivals than non-announcement days. Let $Info$ denote the variance of information on the upcoming announcement day, and let $InfoN$ denote the variance of information on non-announcement days. One day before the announcement, at time $T-1$, suppose we observe an option-implied variance with 9 days to maturity ($IV_{T-1,T+8}$) and another with 30 days to maturity ($IV_{T-1,T+29}$). These two implied variances allow us to back out the two unknowns, $Info$ and $InfoN$:[13]

$$IV_{T-1,T+8} = Info + 8 \times InfoN, \tag{22}$$

$$IV_{T-1,T+29} = Info + 29 \times InfoN. \tag{23}$$

Empirically, whenever more than two implied variance maturities are available, we use all of them by choosing $Info$ and $InfoN$ to minimize the mean squared error of equations analogous to (22) and (23) constructed from all available options with maturities between 1 and 30 calendar days. Restricting attention to maturities of 30 days or less ensures that each option spans at most one scheduled FOMC meeting.

In Table 5, we present the results of the following two regressions using the informativeness measure constructed above:

$$R_T^A = \alpha + \beta \times Info_{T-1} + \varepsilon_T, \tag{24}$$

$$\Delta IV_T = \alpha + \beta \times Info_{T-1} + \varepsilon_T, \tag{25}$$

where R_T^A is the announcement-day return, defined as the close-to-close log return on the announcement day; $\Delta IV_T = IV_{T-1,T+29} - IV_{T,T+30}$ is the implied variance reduction on announcement days, measured using squared VIX; and $Info_{T-1}$ is the informativeness measure constructed from option prices observed on the day before the announcement.

First, as shown in Table 5, our ex ante measure of informativeness has strong predictive

[13]This approach makes the simplifying assumption that the variance of all non-announcement days is the same. Alternatively, one can allow the non-announcement-day variance to vary with event time around the announcement. We do not present this alternative because the two approaches yield highly correlated measures of informativeness.

Table 5: Announcement Return and IV Reduction Predictability by Informativeness

		R_T^A	ΔIV_T
$Info_{T-1}$	Data	11.22	1.30
		(6.64)	(2.97)
R^2 (%)		20.16	31.61
	Model	5.96	1.04

This table reports the coefficients from the return predictability regression defined in Equation (24) and the implied variance reduction predictability regression defined in Equation (25). R_T^A is the close-to-close log return on S&P 500 E-mini futures on the FOMC announcement day, measured in daily basis points. The announcement-day implied variance reduction ΔIV_T is the squared VIX on the day before the announcement minus the squared VIX on the announcement day. Informativeness $Info_{T-1}$ is constructed from option-implied variance using actual traded options with maturities of 1 to 30 calendar days on the trading day preceding each FOMC announcement, ensuring that each option spans at most one scheduled FOMC meeting. Both $Info_{T-1}$ and ΔIV_T are measured in monthly percentage squared units. Newey-West t-statistics with 4 lags are reported in parentheses. R^2 is from OLS. The data cover the period 2006.01–2024.12, as the construction of informativeness requires at least two traded options with maturities below 30 days, which are available starting in 2006, covering 149 FOMC announcements. The bottom panel reports model-implied regression coefficients, where the model analog of $Info_{T-1}$ is the pre-announcement risk-neutral variance over the announcement interval, $IV^*_{T^-,T^+}(\nu, \hat{\theta}_T^-, \omega_T^-)$, given by Equation (A.108) in Appendix A.3 and measured in monthly percentage squared units.

power for implied variance reduction on announcement days. The coefficient is significantly positive, with a t-statistic of 2.97 and an R^2 of 31.61%. This result indicates that $Info_{T-1}$ is an effective measure of the informativeness of the upcoming announcement as perceived by the market. The point estimate of the regression coefficient, 1.30, is close to 1, consistent with interpreting $Info_{T-1}$ as a measure of informativeness.

Second, the coefficient on $Info_{T-1}$ in the return predictability regression is positive and significant, with a t-statistic of 6.64. This regression has a notably high R^2 of 20.16%, especially given that daily returns are notoriously difficult to predict. This evidence shows that more informative announcements are associated with a higher risk premium on announcement days and provides empirical support for Proposition 1. In Tables B.1 and B.2 of Appendix B.2, we show that these patterns of return predictability and implied variance reduction predictability remain robust when using fixed-expiration measures of ΔIV_T (defined as $\Delta IV_T = IV_{T-1,T+\tau} - IV_{T,T+\tau}$ for $\tau \in \{30, 9, 7\}$ calendar days) or extending the sample to 1997–2024 with interpolated implied variance.

In the model, we run the same regressions as in the data, using the model analog of the ex ante informativeness measure $Info_{T-1}$. Specifically, we use the pre-announcement risk-neutral variance over the announcement interval, $IV^*_{T^-,T^+}(\nu, \hat{\theta}^-_T, \omega^-_T)$, which is conditional on the realized informativeness ν and the pre-announcement state $(\hat{\theta}^-_T, \omega^-_T)$. The announcement return and implied variance reduction are defined in Equations (19) and (21), respectively. Our model produces significantly positive regression coefficients of 5.96 and 1.04 for predicting announcement returns and implied variance reductions on announcement days, which are close to the counterparts in the data. These results are consistent with the policy function evidence in Figure 1: higher informativeness is associated with higher expected returns and higher expected variance upon the arrival of information.

Our second set of tests examines the relationship between the informativeness of news and the returns and realized variances following information events. Relative to the specification in Table 5, we make two modifications. First, because our objective here is to predict post-event returns and realized variances, we replace the ex ante informativeness measure $Info_{T-1}$ with the event-day drop in implied variance, ΔIV_T, which more directly captures the information revealed on day T.

Second, we expand the set of information events to include news-related stock market jumps alongside FOMC announcements. Following Baker, Bloom, Davis, and Sammon (2021), stock jump days are defined as days on which the S&P 500 Index close-to-close return exceeds 2.5% or falls below –2.5%. For each such day, trained readers of major newspapers identify the news event that triggered the jump. We classify a jump as news-related if at least half of those readers identify a link between the jump and a news event. Unlike FOMC announcements, news-related jumps are not predictable in advance, so we cannot include them in the announcement-day return and variance regressions reported in Table 5. They can, however, be used in the post-event predictability regressions, where the informativeness measure is constructed from realized implied variance reductions around the information event, as discussed above. Although incorporating stock market jump days increases the power of our tests, we also provide robustness analyses in Table B.4 of Appendix B.2 using only FOMC announcement days, with and without additional controls.

We consider the following regressions for realized variance predictability and realized

excess return predictability:

$$RV_{t,t+h} = \alpha_h + \beta_{1,h}\Delta IV_t + \beta_{2,h}RV_{t-2,t-1} + \varepsilon_{t,t+h}, \quad (26)$$

$$R_{t,t+h} - r_{t,t+h} = \alpha_h + \beta_{1,h}\Delta IV_t + \beta_{2,h}RV_{t-2,t-1} + \varepsilon_{t,t+h}. \quad (27)$$

In these regressions, $RV_{t,t+h}$ and $R_{t,t+h}$ denote realized variance and realized return, respectively, from the day after the information event t through h days after the event, and $r_{t,t+h}$ denotes the risk-free rate over the same period. We consider several horizons: $h = 1, 2, 3, 4, 5, 30, 60$, corresponding to horizons of up to two months. We include $RV_{t-2,t-1}$, the pre-event realized variance, as a measure of the level of uncertainty before the information event, to control for the impact of fundamental volatility. Our main coefficients of interest are those on the informativeness measure, ΔIV_t. We run the same regressions in the model and report the results in Table 6. Expressions for $R_{t,t+h}$, $r_{t,t+h}$, and $RV_{t,t+h}$ in the model are provided in Appendix C.2.

Consistent with the information-driven volatility mechanism, in the data, larger implied variance reductions on information event days are associated with lower realized variance and lower excess returns after the events. This pattern holds for both daily and weekly horizons and extends to the two-month horizon, although the magnitude of the regression coefficients declines over time. Although our model is not calibrated to match these regression coefficients and generally produces coefficients smaller in magnitude than their empirical counterparts, it generates the same robust pattern of negative predictability. The $\beta_{1,h}$ coefficients in regressions (26) and (27) are negative across all horizons in the model-simulated data. The gradual decline in predictability over longer horizons further supports the view that information-driven volatility is particularly important for explaining expected returns and variance at high frequencies.

In Table B.3 of Appendix B.2, we further show that these negative return and variance predictability patterns remain robust when the event-day drop in implied variance is measured using the fixed-expiration versions of ΔIV_T introduced above at the 30-, 9-, and 7-day horizons. Table B.5 of Appendix B.2 combines this fixed-expiration measure with the FOMC-only subsample and confirms that the negative relationship between event informativeness and post-event variance and returns remains robust.

The information-driven volatility channel induces negative autocorrelation in realized

Table 6: Variance and Excess Return Predictability by IV Reduction

h		1	2	3	4	5	30	60
$RV_{t,t+h}$	Data	–0.08	–0.07	–0.07	–0.06	–0.06	–0.03	–0.02
		(–3.49)	(–4.02)	(–5.14)	(–4.75)	(–5.40)	(–4.88)	(–4.29)
R^2 (%)		64.96	66.03	63.68	60.49	59.75	40.61	36.00
	Model	–0.07	–0.07	–0.07	–0.07	–0.07	–0.07	–0.07
$R_{t,t+h} - r_{t,t+h}$	Data	–1.65	–0.88	–0.47	–0.44	–0.38	–0.11	–0.06
		(–3.71)	(–3.51)	(–2.41)	(–2.31)	(–2.06)	(–3.54)	(–3.78)
R^2 (%)		7.33	3.84	1.49	2.20	1.74	1.04	0.63
	Model	–0.23	–0.15	–0.17	–0.17	–0.16	–0.09	–0.06

This table presents the results of the realized variance predictability regression (Equation (26)) and the excess return predictability regression (Equation (27)) in the data and in the model. Columns 3–9 report horizons $h = 1, 2, 3, 4, 5, 30$, and 60 calendar days in the model, corresponding to 1–5, 21, and 42 trading days in the data. The cumulative log return on S&P 500 E-mini futures from t to $t + h$ is denoted $R_{t,t+h}$, so that $R_{t,t+h} - r_{t,t+h}$ is the cumulative log excess return, where $r_{t,t+h}$ is the cumulative log risk-free rate. Realized variance $RV_{t,t+h}$ is computed over the same window as the sum of squared 1-minute log futures returns. The implied variance reduction ΔIV_t is the drop in squared VIX from day $t-1$ to t, measured in monthly percentage squared units. Returns are reported in daily basis points, and realized variances are reported in daily percentage squared. Model regressors are normalized. All data specifications include year fixed effects, and Newey-West t-statistics with lag length h are reported in parentheses. The R^2 is from the corresponding OLS regressions without fixed effects. The data sample combines FOMC and news-related jump days over 1997.09–2024.12, where news-related jump days are defined as days on which the absolute S&P 500 daily return exceeds 2.5% and at least 50% of trained human readers identified a link between the stock market jump and a specific news event. The Model rows report regression coefficients estimated on simulated data.

volatility, but does not affect the positive relationship between *expected variance* and expected returns, that is, the positive risk-return tradeoff. As shown in Figure 2, more informative announcements predict both lower future variance and lower future expected returns, consistent with the positive relationship between expected variance and expected returns. We test this implication of our model by replacing the implied variance reduction ΔIV_t in the return predictability regression in Equation (27) with predicted future variance $\widehat{RV}_{t,t+h}$, defined as the fitted value from the realized variance regression in Equation (26). Overall, the positive relationship between expected variance and expected returns reported in Table 7 is consistent with the basic mechanism of information-driven volatility illustrated in Figures 1 and 2.

Table 7: Excess Return Predictability by Predicted Realized Variance

h		1	2	3	4	5	30	60
$\widehat{RV}_{t,t+h}$	Data	19.91	12.26	6.80	7.10	6.08	3.87	3.19
		(3.71)	(3.51)	(2.41)	(2.31)	(2.06)	(3.54)	(3.78)
R^2 (%)		5.74	1.49	0.14	0.38	0.02	4.07	8.95
	Model	3.25	2.13	2.39	2.42	2.32	1.37	0.97

This table reports the coefficient on predicted future variance $\widehat{RV}_{t,t+h}$ in the excess return predictability regression of Equation (27), where $\widehat{RV}_{t,t+h}$ is the fitted value from the realized variance regression of Equation (26). Columns correspond to horizons $h = 1-5$, 30 and 60 calendar days in the model, mapped to 1–5, 21, and 42 trading days in the data. All variables are defined as in Table 6. Returns are reported in daily basis points, and realized variances in daily percentage squared. All data specifications include year fixed effects, and Newey-West t-statistics with lag length h are reported in parentheses. The R^2 is from the corresponding OLS regressions without fixed effects. The data sample combines FOMC and news-related jump days over 1997.09–2024.12, as defined in Table 6. The Model row reports the second-stage slope on $\widehat{RV}_{t,t+h}$ estimated on simulated data.

6 Additional Empirical Tests of the Volatility–Expected Return Relationship

In the previous section, we tested the information-driven volatility channel directly using our measure of informativeness. In this section, we provide additional tests that do not rely on this measure and instead examine the relationship between past realized variance, future expected variance, and future expected returns. Our model has three unique implications for these relationships:

1. Realized stock market volatility has two sources: shocks to fundamentals ($dB_{Y,t}$ and $dB_{\omega,t}$) and shocks to information, reflected in $\hat{\theta}_t$. Fundamental volatility is positively autocorrelated, whereas information-driven volatility induces negative autocorrelation in the volatility of $\hat{\theta}_t$. As a result, realized volatility is generally positively autocorrelated, but this autocorrelation weakens substantially and can even turn negative after information events.

2. Because information-driven volatility resolves uncertainty at the event, high realized volatility on information-event days predicts lower future expected variance and lower future expected returns relative to non-information days.

3. The information-driven volatility channel does not overturn the positive risk-return tradeoff between expected volatility and expected returns. Once expected volatility is constructed to account for the information channel, it positively predicts future expected returns.

The rest of the section proceeds as follows. We first derive an ICAPM relationship that guides the specification of the return predictability regressions used throughout. In "Realized Variance and Expected Returns," we test Implications 1 and 2 by examining how past realized variance predicts future expected variance and future expected returns differently following information events. In "Expected Variance and Expected Returns," we test Implication 3 by constructing a variance forecast that accounts for the information channel. In "Firm-Level Evidence," we use earnings announcements as firm-level information events to provide additional tests of all three implications. Finally, we validate our informativeness measure, ΔIV, using changes in analyst forecast dispersion.

The ICAPM expresses the risk premium on any asset as the sum of a conditional variance term and a hedging-demand term. To formalize this in our model, let dR_t denote the instantaneous return on any asset; for example, the return on the dividend claim is $dR_t = \frac{d\left[p\left(\hat{\theta}_t,t\right)D_t\right]+D_t dt}{p\left(\hat{\theta}_t,t\right)D_t}$. The following proposition states the ICAPM relationship in our model.

Proposition 3. *(ICAPM) Let W_t denote the present value of the consumption claim. For $(0,T)$, the instantaneous risk premium on any return dR_t is given by*

$$\mathbb{E}_t\left[dR_t\right] - r\left(\hat{\theta}_t,t\right)dt = \gamma Cov_t\left(dR_t, \frac{dW_t}{W_t}\right) - \frac{1}{\psi}\frac{H_\theta\left(\hat{\theta}_t,t\right)}{H\left(\hat{\theta}_t,t\right)}Cov_t\left(dR_t, d\hat{\theta}_t\right). \tag{28}$$

Proof. See Appendix A.4. □

To motivate our empirical regressions, we apply Proposition 3 to the return on the aggregate wealth claim, setting $dR_t = dW_t/W_t$. The proposition then implies that the expected excess return on the consumption claim is proportional to its conditional variance, after controlling for the hedging term $\frac{1}{\psi}\frac{H_\theta\left(\hat{\theta}_t,t\right)}{H\left(\hat{\theta}_t,t\right)}Cov_t\left(dR_t, d\hat{\theta}_t\right)$. This ICAPM relationship holds in our model and provides the theoretical foundation for Guo and Whitelaw (2006) (henceforth, GW), which studies the volatility–expected return relationship. We apply their methodology to test Implications 1–3.

Realized Variance and Expected Returns We test Implications 1 and 2 by replicating the ICAPM regressions in GW and adding an information-event interaction. We obtain two main findings. First, realized variance is strongly positively autocorrelated on average, but this autocorrelation weakens substantially after information events (Implication 1). Second, when expected volatility is constructed from past realized volatility, its relationship with expected returns is negative or insignificant, consistent with earlier findings in Nelson (1991) and Glosten, Jagannathan, and Runkle (1993). We further show that this negative relationship is driven by information events: in information periods, past realized variance predicts both future variance and future returns more negatively than in non-information periods (Implication 2). Taken together, these findings suggest that the negative volatility–return relationship documented in earlier work is likely driven by information events.

To test Implication 1, we estimate a variance predictability regression with an information-event interaction:

$$RV_{t,t+h} = \alpha + \beta_1 RV_{t-h,t} + \beta_2 RV_{t-h,t} \times \mathbf{1}_{\text{info}} + \beta_3 \mathbf{1}_{\text{info}} + \beta_X' X_{t-h,t} + \varepsilon_{t,t+h}. \tag{29}$$

Here, $RV_{t,t+h}$ and $RV_{t-h,t}$ denote realized variance from t to $t+h$ and from $t-h$ to t, respectively, $\mathbf{1}_{\text{info}}$ is a dummy equal to one if the period contains an information event — defined as either a scheduled FOMC announcement or a news-related stock market jump — and $X_{t-h,t} = \{\log(D/P), CAY, r\}$ is the set of GW state variables capturing the hedging-demand component of the ICAPM: the log dividend-price ratio, the consumption-wealth ratio, and the risk-free rate. We use weekly frequency ($h = 7$) because it allows us to distinguish information periods from non-information periods more precisely; in our 1952–2024 sample, roughly 15% of weeks (565 out of 3,778) are information weeks. As a robustness check, monthly results and a direct comparison with GW are reported in Table B.6 of Appendix B.2.

The top panel of Table 8 reports the results. Realized variance exhibits strong positive autocorrelation overall, with a persistence coefficient of 0.69 ($t = 9.55$), but this autocorrelation weakens significantly following information events: the interaction coefficient is –0.24. This provides direct evidence for Implication 1.

To test Implication 2, we follow GW and estimate return predictability in two steps. In the first step, we construct an expected variance forecast from the OLS regression $RV_{t,t+h} =$

$\alpha + \beta RV_{t-h,t} + \varepsilon_{t,t+h}$, which yields $\widehat{RV}_{t,t+h} = \hat{\alpha} + \hat{\beta} RV_{t-h,t}$. In the second step, we use this forecast in a return predictability regression with an information-event interaction:[14]

$$R_{t,t+h} - r_{t,t+h} = \alpha + \gamma \widehat{RV}_{t,t+h} + \gamma_{\text{info}} \widehat{RV}_{t,t+h} \times \mathbf{1}_{\text{info}} + \beta_{\text{info}} \mathbf{1}_{\text{info}} + \beta_X' X_{t-h,t} + \varepsilon_{t,t+h}. \quad (30)$$

The bottom panel of Table 8 reports the results. In non-information weeks, the coefficient on predicted variance is positive ($\gamma = 4.98$, $t = 1.42$). The information-event interaction, however, is significantly negative: $\gamma_{\text{info}} = -7.69$ with $t = -2.11$. As a result, in information weeks the implied coefficient falls to $\gamma + \gamma_{\text{info}} = -2.71$ ($t = -2.62$). In other words, past realized variance predicts future excess returns much more negatively in information periods than in non-information periods, and the puzzling negative relationship highlighted in earlier work is concentrated precisely in those weeks. This provides direct evidence for Implication 2. Pooling the two regimes, the unconditional regression of excess returns on $\widehat{RV}_{t,t+h}$ yields a negative coefficient of -1.83 ($t = -1.62$), in line with Table IV of GW and the earlier literature.

Expected Variance and Expected Returns We test Implication 3 by constructing a variance forecast that accounts for the information-driven volatility channel and embedding it in the GMM framework of GW. Following their notation, we specify a state vector Z_t that forms the best predictor of expected variance and a subvector $X_t \subset Z_t$ that proxies for the hedging-demand component of the ICAPM in Equation (28).

We construct two forward-looking variables to include in the state vector Z_t to capture the information-driven volatility channel. The first is implied variance, $IV_t = \text{VIX}_t^2$, defined as the squared VIX index at the end of week t. The second is $C\Delta IV_t$, the cumulative implied variance reduction across all information-event days during week t. That is, $C\Delta IV_t$ is the within-period sum of the event-day ΔIV introduced in Section 5. By construction, $C\Delta IV_t = 0$ if there is no information event during week t. The full state vector is $Z_{t-h,t} = \{IV_t, C\Delta IV_t, X_{t-h,t}\}$, where $X_{t-h,t} = \{RV_{t-h,t}, \log(D/P), CAY, r\}$ is the same vector of hedging-demand controls used in the previous subsection, augmented with the previous week's realized variance.

[14] GW estimate the variance predictability equation and the return predictability equation jointly using GMM. In the simple setup considered here, OLS and GMM are equivalent.

Table 8: Realized Variance and Excess Return Predictability with Information-Event Interaction

		$RV_{t-h,t}$	$RV_{t-h,t} \times \mathbf{1}_{\text{info}}$	$\mathbf{1}_{\text{info}}$	R^2 (%)
$RV_{t,t+h}$	Data	0.69	–0.24	0.00	25.97
		(9.55)	(–1.69)	(1.83)	
	Model	1.24	–1.19	0.20	
		$\widehat{RV}_{t,t+h}$	$\widehat{RV}_{t,t+h} \times \mathbf{1}_{\text{info}}$	$\mathbf{1}_{\text{info}}$	R^2 (%)
$R_{t,t+h} - r_{t,t+h}$	Data	4.98	–7.69	0.01	1.22
		(1.42)	(–2.11)	(3.82)	
	Model	19.77	–17.82	5.48	

This table reports OLS estimates of variance predictability (top panel, Equation (29)) and excess return predictability (bottom panel, Equation (30)) at weekly frequency ($h = 7$ days). $RV_{t,t+h}$ is next week's realized variance, and $RV_{t-h,t}$ is the current week's realized variance, both measured as the sum of squared daily log returns within the week. $R_{t,t+h} - r_{t,t+h}$ is the excess return over the next week, and $\widehat{RV}_{t,t+h}$ is the fitted value from the first-stage OLS regression of $RV_{t,t+h}$ on $RV_{t-h,t}$. The dummy $\mathbf{1}_{\text{info}}$ equals one if the week contains an information event, defined as either a scheduled FOMC announcement or a news-related market jump in the data, and a scheduled FOMC announcement in the model. In the data, all regressions include the ICAPM hedging-demand controls from GW: the log dividend-price ratio, CAY, and the risk-free rate (coefficients not reported); the model has no analog of these controls and they are omitted from the model regressions. The data sample spans 1952–2024, reflecting the availability of the CAY series, and contains 3,778 weeks. Newey-West t-statistics with 12 lags are reported in parentheses. The Model rows report regression coefficients estimated on simulated data using non-overlapping 7-day windows, with the information-event dummy equal to one whenever the predictor week contains a scheduled announcement.

We use the same GMM procedure as GW and assume that variance dynamics follow

$$RV_{t,t+h} = \omega_0 + \omega_1' Z_{t-h,t} + \varepsilon_{t,t+h}, \tag{31}$$

where ω_1 is the vector of coefficients on $Z_{t-h,t}$. We assume that the hedging component is given by $\phi_0 + \phi_1' X_{t-h,t}$. We then jointly estimate by GMM the variance dynamics equation and the following return dynamics equation, which imposes the ICAPM restriction from Proposition 3:

$$R_{t,t+h} - r_{t,t+h} = \gamma \left[\omega_0 + \omega_1' Z_{t-h,t}\right] + \left[\phi_0 + \phi_1' X_{t-h,t}\right] + \epsilon_{t,t+h}, \tag{32}$$

which corresponds to Model 4 in GW.[15] The coefficient γ is imposed as a common multiplier on the variance forecast across the IV and $C\Delta IV$ channels, yielding one overidentifying restriction.

We report the results in Table 9. Panel A presents the coefficients from the realized variance predictability regression, and Panel B presents the coefficients from the return predictability regression. We make two observations. First, the estimates imply a positive and statistically significant relationship between predicted variance and future expected returns: $\gamma > 0$ with $t = 3.45$, as shown in Panel B. Second, in the variance predictability regression in Panel A, the coefficient on IV is positive, while the coefficient on $C\Delta IV$ is negative, and both are statistically significant. This pattern is consistent with the interpretation that greater informativeness of information events is associated with lower future realized variance. Taken together, these results show that once expected variance is constructed to account for the information-driven volatility channel, the positive risk-return tradeoff is restored in the data. As a robustness check, we report the monthly counterpart of these system GMM estimates in Table B.7 of Appendix B.2.

Firm-Level Evidence At the aggregate level, the number of identified information events is relatively small, which limits the power of some of the tests above. In this section, we use firm-level data and earnings announcements as information events to provide additional tests of the model's implications.

We test Implications 1 and 2 by examining how information events affect variance predictability and return predictability in firm-level versions of regressions (29) and (30). Let $\mathbf{1}_{\text{EA}}$ be a dummy variable equal to one if firm i has an earnings announcement on day t. In Table 10, we report the results of the following panel regressions:

$$RV_{i,t,t+h} = \alpha_i + \mu_t + \beta_{1,h} RV_{i,t-1,t} + \beta_{2,h} RV_{i,t-1,t} \times \mathbf{1}_{\text{EA}} + \beta_{3,h} \mathbf{1}_{\text{EA}} + \text{Controls}_{i,t} + \varepsilon_{i,t+h}, \quad (33)$$

$$R_{i,t,t+h} = \alpha_i + \mu_t + \gamma_{1,h} RV_{i,t-1,t} + \gamma_{2,h} RV_{i,t-1,t} \times \mathbf{1}_{\text{EA}} + \gamma_{3,h} \mathbf{1}_{\text{EA}} + \text{Controls}_{i,t} + \varepsilon_{i,t+h}, \quad (34)$$

where $RV_{i,t,t+h}$ and $R_{i,t,t+h}$ denote the cumulative realized variance and cumulative return of firm i from day t to day $t+h$, respectively; α_i and μ_t denote firm and date fixed effects;

[15] We omit Models 5 and 6 because including the volatility-feedback effect does not affect the point estimate of the variance–return relationship.

Table 9: ICAPM Risk-Return Tradeoff: System GMM Estimates

Panel A: Variance predictability						*Panel B: Return predictability*			
		IV_t	$C\Delta IV_t$	$RV_{t-h,t}$	$R^2(\%)$			γ	$R^2(\%)$
$RV_{t,t+h}$	Data	0.63	–0.38	0.28	45.96	$R_{t,t+h} - r_{t,t+h}$	Data	8.31	2.67
		(9.98)	(–2.64)	(3.71)				(3.45)	
	Model	1.03	–0.04	0.01			Model	4.24	

This table reports system GMM estimates of the variance equation (31) and return equation (32), estimated jointly at the weekly frequency ($h = 7$ days) with a single γ imposed across both the IV and $C\Delta IV$ channels, yielding one overidentifying restriction. $RV_{t,t+h}$ is next week's realized variance, and $RV_{t-h,t}$ is the current week's realized variance, both measured as the sum of squared daily log returns within the week. $R_{t,t+h} - r_{t,t+h}$ is the excess return over the next week. $IV_t = \text{VIX}_t^2$ is the squared VIX index at the end of week t; $C\Delta IV_t$ is the cumulative implied variance reduction across information-event days in week t, equal to zero otherwise. Both are measured in weekly decimal variance units. Panel A reports the coefficients ω_1 on IV_t, $C\Delta IV_t$, and $RV_{t-h,t}$. Panel B reports the coefficient γ. In the data, constants and the remaining hedging-demand coefficients on $RV_{t-h,t}$, log dividend yield, CAY, and the risk-free rate are estimated but not reported; the model has no analog of the GW state controls, so the model state vector is restricted to $\{1, IV_t, C\Delta IV_t, RV_{t-h,t}\}$. R^2 is the squared correlation between actual and fitted values. The system is estimated by two-step GMM with an identity initial weighting matrix at weekly frequency. The data sample covers 1990.01–2024.12, based on the availability of the VIX index. Newey-West t-statistics with 12 lags are reported in parentheses. The Model rows report system GMM estimates on simulated data, with $C\Delta IV_t$ summed across scheduled announcements within each week.

and $\text{Controls}_{i,t}$ includes the day-t return $R_{i,t-1,t}$, the realized variance on the previous day $RV_{i,t-2,t-1}$, and their interactions with $\mathbf{1}_{\text{EA}}$.

Table 10 reports the results. The first row of Panel A shows that realized variance is significantly positively autocorrelated, consistent with well-established evidence in the literature. This positive autocorrelation is significantly weaker after earnings announcements: the coefficient on $RV_{i,t-1,t} \times \mathbf{1}_{\text{EA}}$ is negative and statistically significant. The corresponding t-statistics are large in magnitude, indicating that the parameters are precisely estimated given the large sample size in the firm-level regressions. This is consistent with Implication 1: earnings announcements reveal information about firm fundamentals and induce negative autocorrelation in realized variance.

Panel B shows a similar pattern in the return predictability regressions. The coefficient on $RV_{i,t-1,t} \times \mathbf{1}_{\text{EA}}$ is significantly negative, indicating that realized variance on earnings-announcement days has more negative predictive power for future returns than on other days, in line with Implication 2.

Table 10: Realized Variance and Return Predictability around Earnings Announcements

h	1	2	3	4	5	21	42
Panel A: Variance predictability							
$RV_{i,t-1,t}$	0.27	0.24	0.22	0.21	0.20	0.14	0.11
	(132.37)	(119.29)	(108.51)	(101.01)	(94.45)	(57.30)	(43.34)
$RV_{i,t-1,t} \times \mathbf{1}_{\text{EA}}$	–0.24	–0.22	–0.20	–0.19	–0.19	–0.13	–0.10
	(–101.17)	(–101.29)	(–95.85)	(–91.49)	(–86.96)	(–56.05)	(–42.63)
$\mathbf{1}_{\text{EA}}$	2.60	1.31	0.81	0.53	0.36	–0.11	–0.12
	(32.20)	(26.87)	(21.08)	(15.52)	(11.43)	(–5.14)	(–6.14)
R^2 (%)	31.75	40.56	45.00	47.70	49.51	56.17	57.82
within R^2 (%)	12.97	16.94	18.84	19.89	20.48	18.90	15.22
N	39,829,292	39,083,381	38,494,983	38,011,055	37,600,420	34,421,729	32,597,355
Panel B: Return predictability							
$RV_{i,t-1,t}$	0.06	0.02	0.01	0.01	0.01	0.01	0.01
	(6.66)	(3.38)	(2.45)	(2.34)	(2.01)	(2.29)	(4.33)
$RV_{i,t-1,t} \times \mathbf{1}_{\text{EA}}$	–0.11	–0.06	–0.04	–0.03	–0.02	–0.01	–0.01
	(–5.00)	(–4.25)	(–3.16)	(–2.56)	(–2.64)	(–2.04)	(–3.51)
$\mathbf{1}_{\text{EA}}$	–5.71	–5.65	–4.65	–3.62	–2.51	0.07	–0.30
	(–5.93)	(–8.60)	(–8.88)	(–8.28)	(–6.66)	(0.43)	(–2.70)
R^2 (%)	9.16	10.23	11.05	11.72	12.25	16.27	18.42
within R^2 (%)	0.67	0.53	0.47	0.41	0.37	0.13	0.06
N	40,810,157	40,789,627	40,769,090	40,748,578	40,728,012	40,399,413	39,969,282

This table reports panel regressions of variance predictability (Equation (33)) in Panel A and return predictability (Equation (34)) in Panel B. Columns correspond to horizons $h = 1, 2, 3, 4, 5, 21$, and 42 trading days. The dependent variable is cumulative realized variance in Panel A and cumulative return in Panel B. The indicator $\mathbf{1}_{\text{EA}}$ equals one if firm i has an earnings announcement on day t and zero otherwise. Control variables, included but not reported, are the day-t return, the realized variance one day before, and their interactions with $\mathbf{1}_{\text{EA}}$ (coefficients are not reported). Returns are in daily bps and realized variances are in daily percentage squared. Returns and realized variances are winsorized at the 0.5th and 99.5th percentiles. All specifications include firm and date fixed effects. Standard errors are two-way clustered by firm and date, with t-statistics reported in parentheses. The sample period spans 1993.01–2024.12.

Second, we test Implication 3 by comparing two return predictability regressions. The first uses past realized variance, while the second uses predicted variance from Equation (33), which accounts for the different variance dynamics on information and non-information days:

$$R_{i,t,t+h} = \alpha_i + \mu_t + \beta_h RV_{i,t-1,t} + \varepsilon_{i,t+h}, \tag{35}$$

$$R_{i,t,t+h} = \alpha_i + \mu_t + \gamma_h \widehat{RV}_{i,t,t+h} + \varepsilon_{i,t+h}. \tag{36}$$

Panel A of Table 11 reports the results from the first regression using realized variance. Unconditionally, we find a negative relationship between past realized variance and future returns following earnings announcement days, consistent with the aggregate evidence. This relationship is mainly driven by information-driven volatility, as shown in the previous table. Panel B reports the results using predicted variance from Equation (33). Because the variance prediction model accounts for the difference in realized variance dynamics between information and non-information days, we obtain a positive and significant relationship between predicted variance and future returns. This contrast further highlights the importance of information-driven volatility in explaining the variance–expected return relationship.

Table 11: Return Predictability around Earnings Announcements

h	1	2	3	4	5	21	42
Panel A: $R_{i,t,t+h} = \alpha_i + \mu_t + \beta_h RV_{i,t-1,t} + \varepsilon_{i,t+h}$							
$RV_{i,t-1,t}$	–0.012	–0.025	–0.024	–0.021	–0.018	–0.004	0.004
	(–1.36)	(–4.23)	(–5.03)	(–5.00)	(–4.83)	(–2.06)	(3.54)
R^2 (%)	8.06	9.30	10.20	10.93	11.50	15.85	18.06
N	42,292,490	42,270,783	42,249,036	42,227,309	42,205,572	41,858,272	41,404,188
Panel B: $R_{i,t,t+h} = \alpha_i + \mu_t + \gamma_h \widehat{RV}_{i,t,t+h} + \varepsilon_{i,t+h}$							
$\widehat{RV}_{i,t,t+h}$	0.173	0.076	0.060	0.053	0.047	0.047	0.086
	(6.23)	(3.49)	(3.18)	(3.08)	(2.82)	(3.82)	(10.28)
R^2 (%)	8.55	9.76	10.63	11.36	11.92	16.16	18.37
N	40,810,157	40,789,627	40,769,090	40,748,578	40,728,012	40,399,413	39,969,282

This table reports panel regressions of return predictability around earnings announcements. Panel A reports results from Equation (35), using lagged realized variance $RV_{i,t-1,t}$. Panel B reports results from Equation (36), using the predicted variance $\widehat{RV}_{i,t,t+h}$ obtained from a first-stage estimation of Equation (33) run separately for each horizon h. Columns correspond to horizons $h = 1, 2, 3, 4, 5, 21$, and 42 trading days. The dependent variable is the cumulative return $R_{i,t,t+h}$. Returns are in daily bps and realized variances are in daily percentage squared. Returns and realized variances are winsorized at the 0.5th and 99.5th percentiles. Both panels include firm and date fixed effects. Standard errors are clustered by date, with t-statistics reported in parentheses. The sample period spans 1993.01–2024.12.

Validating the Informativeness Measure Finally, we provide evidence supporting the validity of our measure of information-event informativeness, ΔIV_T, defined as the implied variance reduction realized on the event day and used in Section 5. The logic is straightfor-

ward: if ΔIV_T captures informativeness, then events with higher ΔIV_T should be associated with larger reductions in belief uncertainty. To test this implication, we use the cross-sectional dispersion of analysts' earnings forecasts as a measure of belief uncertainty and examine how information events affect uncertainty about firm-level earnings forecasts using the following regression:

$$\Delta Disp_{i,t} = \alpha + \beta_1 \Delta IV_t + \beta_2 RV_{t-1} + \gamma_i + \varepsilon_{i,t}, \tag{37}$$

where $\Delta Disp_{i,t} = Disp_{i,t-10,t-1} - Disp_{i,t+1,t+10}$ measures the reduction in the dispersion of analysts' earnings forecasts for firm i before and after an information event at time t. Here, $Disp_{i,t-10,t-1}$ denotes the dispersion in earnings forecasts reported between 10 days before and 1 day before the information event, and $Disp_{i,t+1,t+10}$ denotes the dispersion in earnings forecasts reported between 1 day after and 10 days after the information event. Table 12 presents several specifications of this regression. A positive regression coefficient β_1 on ΔIV_t is consistent with the hypothesis that more informative information events are associated with greater reductions in uncertainty about firm-level earnings forecasts. We find β_1 to be positive and statistically significant across all specifications. Columns (2) and (3) add controls for analyst coverage — the change in the number of forecasting analysts and the pre-event number of analysts, respectively — and columns (4)–(6) replicate columns (1)–(3) over a wider 21-trading-day window; the sign and significance of β_1 are unchanged, indicating that the result is not driven by shifts in analyst participation or the choice of window.

7 Conclusion

In this paper, we present a model of information-driven volatility. Traditional asset pricing models with stochastic volatility typically rely on high-frequency variations in the volatility of macroeconomic fundamentals, which lack strong empirical support. We argue that information is more likely to be responsible for high-frequency variations in financial market volatility than the volatility of macroeconomic fundamentals. We develop the concept of strong generalized risk sensitivity in preferences and demonstrate that under this condition, the informativeness of macroeconomic news impacts not only financial market volatility but also expected returns. Based on these insights, we present a quantitative asset pricing

Table 12: Informativeness and Analyst Forecast Dispersion

	(1)	(2)	(3)	(4)	(5)	(6)
ΔIV_t	0.001	0.001	0.001	0.001	0.001	0.001
	(2.62)	(2.67)	(2.67)	(2.53)	(2.66)	(2.63)
RV_{t-1}	–0.010	–0.010	–0.010	–0.013	–0.013	–0.012
	(–2.56)	(–2.55)	(–2.55)	(–2.83)	(–2.80)	(–2.72)
$\Delta I_{i,t}$		0.029	0.040		0.022	0.037
		(4.37)	(3.38)		(3.48)	(4.33)
$I_{i,t-10,t-1}$			–0.022			–0.031
			(–1.22)			(–2.14)
R^2 (%)	9.80	9.80	9.80	8.10	8.10	8.10
N	194,764	194,764	194,764	492,733	492,733	492,733

This table reports panel regressions of analyst forecast dispersion changes on the informativeness of information events, as specified in Equation (37). Event informativeness is measured by ΔIV_t, the implied variance reduction on the event day, the drop in squared VIX from day $t-1$ to t, and RV_{t-1} is the realized variance prior to the event. ΔIV_t is in monthly percentage squared and RV_{t-1} is in daily percentage squared. Informational event dates combine FOMC announcements and news-related jump days, as defined in Table 6. The forecast dispersion change is defined as $\Delta Disp_{i,t} = Disp_{i,t-10,t-1} - Disp_{i,t+1,t+10}$, where $Disp_{i,t-10,t-1}$ is the cross-sectional variance of analysts' annual earnings per share (EPS) forecasts for firm i, computed from each analyst's most recent forecast within $[t-10, t-1]$ trading days before the event, and $Disp_{i,t+1,t+10}$ uses each analyst's earliest forecast within $[t+1, t+10]$ trading days after. Firm-events are retained only if at least two analysts issue forecasts both before and after the event. Column (1) reports the baseline specification. Column (2) adds a control for the change in analyst coverage, $\Delta I_{i,t} = I_{i,t-10,t-1} - I_{i,t+1,t+10}$, the difference in the number of analysts issuing forecasts before and after the event. Column (3) further controls for the total number of analysts before the event. Columns (4)–(6) replicate Columns (1)–(3) using a wider window of 21 trading days before and after the event. All regressions include firm fixed effects. Standard errors are double-clustered at the firm and event-date level, and t-statistics are reported in parentheses. The dependent variable is winsorized at the top and bottom 0.5%. The forecast data are from I/B/E/S and span from 1997.09 to 2024.12.

model and show that the information-driven volatility channel can resolve several prominent volatility-related asset pricing puzzles, including the negative relationship between past realized volatility and future expected returns.

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Internet Appendix (for Online Publication)

This Internet Appendix collects the proofs, derivations, and additional results that support the analysis in the main text. In Section A, we present the proofs and model solutions. In Section B, we describe the empirical methodology and the robustness analysis. In Section C, we describe the numerical solutions used to solve our dynamic model.

A Proofs and Model Solutions

In this section, we first prove our main results on information-driven volatility and the risk premium in Section A.1. In Section A.2, we present the solutions and derivations of the infinite-horizon model, covering preferences and beliefs as well as asset prices. In Section A.3, we compute the forward-looking measure of implied variance in our model. Finally, in Section A.4, we establish the ICAPM relationship.

A.1 Information-Driven Volatility and Risk Premium

We first prove a lemma that translates the strong GRS condition (6) into a convexity condition on $\Phi \equiv \phi' \circ \phi^{-1}$ and the concavity of $\ln \Phi$.

Lemma 1. *(Strong GRS) Define $\Phi \equiv \phi' \circ \phi^{-1}$. Let $\mathcal{R}(V) = -\frac{V\phi''(V)}{\phi'(V)}$. Under the assumption that ϕ is three times continuously differentiable, the strong GRS condition, (6), is equivalent to the concavity of $\ln \Phi$.*

Proof. Let $x = \phi(V)$, so that $V = \phi^{-1}(x)$ and $\Phi(x) = \phi'(V)$. The first-order derivative of $\ln \Phi(x)$ can be computed as

$$(\ln \Phi)'(x) = \frac{\Phi'(x)}{\Phi(x)} = \frac{1}{\phi'(V)} \times \phi''(V) \times \frac{dV}{dx} = -\frac{\mathcal{R}(V)}{V\,\phi'(V)},$$

where the third equality uses $dV/dx = 1/\phi'(V)$ and replaces $\frac{\phi''(V)}{\phi'(V)}$ with $-\frac{\mathcal{R}(V)}{V}$ by using the definition of $\mathcal{R}(V)$. Taking the second derivative, we have:

$$(\ln \Phi)''(x) = \frac{d}{dV}\left[-\frac{\mathcal{R}(V)}{V\,\phi'(V)}\right] \times \frac{dV}{dx} = \frac{d}{dV}\left[-\frac{\mathcal{R}(V)}{V\,\phi'(V)}\right] \cdot \frac{1}{\phi'(V)}.$$

Because ϕ is strictly increasing, $(\ln \Phi)''(x) \leq 0$ if and only if $\frac{d}{dV}\left[-\frac{\mathcal{R}(V)}{V\,\phi'(V)}\right] \leq 0$.

$$\begin{aligned}\frac{d}{dV}\left[-\frac{\mathcal{R}(V)}{V\,\phi'(V)}\right] &= -\frac{\mathcal{R}'(V)V\phi'(V) - \mathcal{R}(V)\cdot\left(\phi'(V) + V\phi''(V)\right)}{(V\phi'(V))^2} \\ &= \frac{\mathcal{R}(V)(1-\mathcal{R}(V)) - V\mathcal{R}'(V)}{V^2\,\phi'}.\end{aligned}$$

$\mathcal{R}(V)(1-\mathcal{R}(V)) - V\mathcal{R}'(V) \leq 0$ is equivalent to the strong GRS condition (6). □

Proof of Proposition 1 Let $V^+(s^+) \equiv \lim_{\Delta\to 0} V_\Delta(s_\Delta)$ and $V^{++}(\theta_T) \equiv \lim_{\Delta\to 0} V_{2\Delta}(\theta_T)$. As $\Delta \to 0$, the flow-utility term $(1-e^{-\rho\Delta})u(C_\tau)$ in (2) vanishes, and the consumption-ratio and discount terms in (3) and (4) converge to 1 by the continuity of C_t, which follows from the diffusion assumption. We therefore obtain the limit recursion

$$V^+(s^+) = \phi^{-1}\left\{\mathbb{E}\left[\phi \circ V^{++}(\theta_T) \,\middle|\, s^+\right]\right\}, \tag{A.1}$$

where $s^+ = (\eta, \varepsilon)$ in the informative announcement economy, and $s^+ = (\eta)$ in the vague announcement economy. In the limit, the announcement and post-announcement SDFs are:

$$SDF^+(0, s^+) = \frac{\phi'(V^+(s^+))}{\phi' \circ \phi^{-1}\mathbb{E}\left[\phi \circ V^+(s^+)\right]},\ SDF^{++}(s^+, \theta_T) = \frac{\phi'(V^{++}(\theta_T))}{\phi'(V^+(s^+))}.$$

Using the definition of Φ, we write the announcement SDFs as:

$$SDF^+(0,(\eta,\varepsilon)) = \frac{\Phi(\phi \circ V^+(\eta,\varepsilon))}{\phi' \circ \phi^{-1}\mathbb{E}\left[\phi \circ V^+(\eta,\varepsilon)\right]},\ SDF^+(0,\eta) = \frac{\Phi(\phi \circ V^+(\eta))}{\phi' \circ \phi^{-1}\mathbb{E}\left[\phi \circ V^+(\eta)\right]}. \tag{A.2}$$

Similarly, we write the post-announcement SDFs as:

$$SDF^{++}((\eta,\varepsilon),\theta_T) = \frac{\phi'(V^{++}(\theta_T))}{\Phi(\phi \circ V^+((\eta,\varepsilon)))},\ SDF^{++}(\eta,\theta_T) = \frac{\phi'(V^{++}(\theta_T))}{\Phi(\phi \circ V^+(\eta))} \tag{A.3}$$

We first note that the certainty equivalent at η, $V^+(\eta) = \phi^{-1}\mathbb{E}\left[\phi \circ V^{++}(\theta_T) \,|\, \eta\right]$, and the certainty equivalent at (η,ε), $V^+(\eta,\varepsilon) = \phi^{-1}\mathbb{E}\left[\phi \circ V^{++}(\theta_T) \,|\, \eta,\varepsilon\right]$ satisfy

$$\phi \circ V^+(\eta) = \mathbb{E}\left[\phi \circ V^+(\eta,\varepsilon) \,\middle|\, \eta\right]. \tag{A.4}$$

To see that this is true, we apply the law of iterated expectations to write:

$$V^+(\eta) = \phi^{-1}\mathbb{E}\left[\mathbb{E}\left\{\phi \circ V^{++}(\theta_T) \,\middle|\, \eta,\varepsilon\right\} \,\middle|\, \eta\right] = \phi^{-1}\mathbb{E}\left[\phi \circ \underbrace{\phi^{-1}\mathbb{E}\left\{\phi \circ V^{++}(\theta_T) \,\middle|\, \eta,\varepsilon\right\}}_{V^+(\eta,\varepsilon)} \,\middle|\, \eta\right].$$

Applying ϕ to both sides of the above equation, we obtain (A.4).

Taking expectations in Eq. (A.4) implies that the denominators of the two SDFs in (A.2) are the same. To compare the entropy of the two SDFs in (A.2), we therefore only need to compare the entropy of the numerators to prove

$$\mathcal{H}(\Phi(\phi \circ V^+(\eta, \varepsilon))) \geq \mathcal{H}(\Phi(\phi \circ V^+(\eta))),$$

that is

$$-\mathbb{E}\left[\ln \Phi(\phi \circ V^+(\eta, \varepsilon))\right] \geq -\mathbb{E}\left[\ln \Phi(\phi \circ V^+(\eta))\right]. \tag{A.5}$$

It is enough to show that for every η, $\mathbb{E}\left[\ln \Phi(\phi \circ V^+(\eta, \varepsilon)) \,|\, \eta\right] \leq \ln \Phi(\phi \circ V^+(\eta))$, which is implied by (A.4) and the fact that $\ln \Phi$ is concave. This establishes the first part of the proposition, condition (7).

To compare the entropy of the post-announcement SDF and establish (8), we need to show

$$-\mathbb{E}\left[\ln \frac{\phi'(V^{++}(\theta_T))}{\Phi(\phi \circ V^+((\eta, \varepsilon)))}\right] \leq -\mathbb{E}\left[\ln \frac{\phi'(V^{++}(\theta_T))}{\Phi(\phi \circ V^+(\eta))}\right]. \tag{A.6}$$

Note that

$$\begin{aligned} & \mathbb{E}\left[\ln \frac{\phi'(V^{++}(\theta_T))}{\Phi(\phi \circ V^+((\eta, \varepsilon)))}\right] - \mathbb{E}\left[\ln \frac{\phi'(V^{++}(\theta_T))}{\Phi(\phi \circ V^+(\eta))}\right] \\ = \; & \mathbb{E}\left[\ln \Phi(\phi \circ V^+(\eta))\right] - \mathbb{E}\left[\ln \Phi(\phi \circ V^+((\eta, \varepsilon)))\right] \geq 0. \end{aligned}$$

Eq. (A.6) therefore follows from the concavity of $\ln \Phi$ and Jensen's inequality. If ϕ is linear, then Φ is constant and all four limiting SDFs equal one; hence both inequalities hold with equality under additively separable expected utility.

A.2 The Infinite-Horizon Model Solutions

A.2.1 Preferences and Beliefs

In this section, we begin by deriving the posterior belief of a representative agent who has access to two sources of information. First, we solve for the process of learning from observable consumption using optimal filtering. Then, we proceed to derive the belief updating process upon receiving announcements. Finally, we provide solutions for the value functions and outline the associated boundary conditions at the time of the announcement. Throughout

this appendix, we suppress the subscript T on $\hat{\theta}^-$ and $\hat{\theta}^+$ when the announcement time is clear from context.

Learning in the Interior The two-state Markov chain can be conveniently represented as an integral with respect to Poisson processes. Specifically, let $\{N_{j,t}\}_{t\geq 0}$ be a Poisson process with intensity λ_j, for $j = H, L$. Let $I_{\{x\}}$ be an indicator function defined as $I_{\{\theta_j\}}(\theta_t) = \begin{cases} 1 & \text{if } \theta_t = \theta_j \\ 0 & \text{if } \theta_t \neq \theta_j \end{cases}$. Then $\{\theta_t\}$ can be represented as the following compound Poisson process:

$$d\theta_t = (\theta_H - \theta_L)\eta(\theta_t^-)dN_t \tag{A.7}$$

where $\eta(\theta)$ and $N(t)$ are vectors:

$$\eta(\theta_t) = \left[-I_{\{\theta_H\}}(\theta_t), I_{\{\theta_L\}}(\theta_t)\right], \text{and } N(t) = \left[N_{H,t}, N_{L,t}\right]^\top. \tag{A.8}$$

Here we use the convention that $\{\theta_t\}$ is right-continuous with left limits, and use the notation $\theta_t^- = \lim_{s\to t, s<t}\theta_s$. $N_{j,t}$ is the counting process with intensity λ_j. That is,

$$dN_{j,t} = \begin{cases} 1 & \text{with prob. } \lambda_j dt \\ 0 & \text{with prob. } 1-\lambda_j dt \end{cases}. \tag{A.9}$$

For example, if the true state is the high growth state, $\theta_t^- = \theta_H$, and the transition from the high state to the low state happens, i.e., $dN_{H,t} = 1$, then $\eta(\theta_t) = [-1, 1]$ gives rise to $d\theta_t = (\theta_H - \theta_L)(-I_{\{\theta_H\}}(\theta_t)dN_{H,t} + I_{\{\theta_L\}}(\theta_t)dN_{L,t}) = \theta_L - \theta_H$. Therefore, $\theta_t^+ = \theta_t^- + d\theta_t = \theta_L$.

Applying optimal filtering (see Chapter 9 of Liptser and Shiryaev (2001)), we can obtain

$$d\pi_t = \left[\lambda_L - (\lambda_H + \lambda_L)\pi_t\right]dt + \frac{\pi_t(1-\pi_t)(\theta_H - \theta_L)}{\sigma_Y}d\hat{B}_{Y,t}, \tag{A.10}$$

where $\hat{B}_{Y,t}$ is the innovation process defined in the main text. Note that the mapping between $\hat{\theta}_t$ and π_t is one-to-one, so we can equivalently use $\hat{\theta}_t$ as the state variable. By definition, $\hat{\theta}_t = \pi_t\theta_H + (1-\pi_t)\theta_L$. This recovers π_t from $\hat{\theta}_t$,

$$\pi_t = \frac{\hat{\theta}_t - \theta_L}{\theta_H - \theta_L}. \tag{A.11}$$

Applying Ito's lemma, we obtain Eq. (13) in the main text.

Learning upon the Announcements At the announcement, investors observe a noisy signal s_n whose distribution is given by

$$\begin{aligned}\Pr(s_H|\theta_H) &= \nu,\ \Pr(s_L|\theta_H) = 1-\nu \\ \Pr(s_H|\theta_L) &= 1-\nu,\ \Pr(s_L|\theta_L) = \nu.\end{aligned}$$

Here we denote by s_j the event that investors receive a signal of θ_j upon the announcement. Given the prior distribution $\Pr^-(\theta_H) = \pi^-$, we need to compute the posterior distribution of π^+. Applying Bayes' rule, we have:

$$\overset{+}{\Pr}(\theta_i|s_j) = \frac{\Pr(s_j|\theta_i)\Pr^-(\theta_i)}{\sum_{\theta_i\in\Theta}\Pr(s_j|\theta_i)\Pr^-(\theta_i)}.$$

That is, given that $\Pr^-(\theta_H) = \pi^-$,

$$\overset{+}{\Pr}(\theta_H|s_H) = \frac{\pi^-\nu}{\pi^-\nu+(1-\pi^-)(1-\nu)}; \overset{+}{\Pr}(\theta_L|s_H) = 1-\overset{+}{\Pr}(\theta_H|s_H) = \frac{(1-\pi^-)(1-\nu)}{\pi^-\nu+(1-\pi^-)(1-\nu)},$$
$$\overset{+}{\Pr}(\theta_H|s_L) = \frac{\pi^-(1-\nu)}{\pi^-(1-\nu)+(1-\pi^-)\nu}; \overset{+}{\Pr}(\theta_L|s_L) = 1-\overset{+}{\Pr}(\theta_H|s_L) = \frac{(1-\pi^-)\nu}{\pi^-(1-\nu)+(1-\pi^-)\nu}.$$

This is equivalent to saying that if we observe s_H, then $\pi^+ = \frac{\pi^-\nu}{\pi^-\nu+(1-\pi^-)(1-\nu)}$, and if we observe s_L, $\pi^+ = \frac{\pi^-(1-\nu)}{\pi^-(1-\nu)+(1-\pi^-)\nu}$. Therefore, π^+ can only take on two possible values, depending on whether investors observe s_H or s_L. Let h_{s_H} and h_{s_L} represent the probabilities of observing s_H and s_L at the announcement, respectively:

$$\begin{aligned}h_{s_H} &= \Pr(s_H|\theta_H)\bar{\Pr}(\theta_H) + \Pr(s_H|\theta_L)\bar{\Pr}(\theta_L) = \pi^-\nu + (1-\pi^-)(1-\nu) \\ h_{s_L} &= \Pr(s_L|\theta_H)\bar{\Pr}(\theta_H) + \Pr(s_L|\theta_L)\bar{\Pr}(\theta_L) = \pi^-(1-\nu) + (1-\pi^-)\nu.\end{aligned}$$

For notational convenience, define

$$\pi^+_{s_H} = \frac{\pi^-\nu}{\pi^-\nu+(1-\pi^-)(1-\nu)} \text{ and } \pi^+_{s_L} = \frac{\pi^-(1-\nu)}{\pi^-(1-\nu)+(1-\pi^-)\nu} \tag{A.12}$$

as the posterior probabilities that $\theta^+ = \theta_H$ after observing s_H and s_L, respectively.

It is important to note that our signal generates the "correct" result with probability ν and produces a "wrong" signal with probability $1-\nu$. In other words, the conditional distribution of π^+ is as follows: if the true state is θ_H, then $\pi^+ = \begin{cases}\pi^+_{s_H} & \text{w.p. } \nu \\ \pi^+_{s_L} & \text{w.p. } 1-\nu\end{cases}$, and if

the true state is θ_L, $\pi^+ = \begin{cases} \pi^+_{s_L} & \text{w.p. } \nu \\ \pi^+_{s_H} & \text{w.p. } 1-\nu \end{cases}$.

Since the mapping between $\hat{\theta}_t$ and π_t is one-to-one, we can instead use $\hat{\theta}$ as the state variable. Substituting Eq. (A.11) into the expressions above, we derive the probabilities of observing s_H and s_L at the announcement, respectively, as:

$$h_{s_H} = \frac{\hat{\theta}^- - \theta_L}{\theta_H - \theta_L}\nu + \frac{\theta_H - \hat{\theta}^-}{\theta_H - \theta_L}(1-\nu), \tag{A.13}$$

$$h_{s_L} = \frac{\hat{\theta}^- - \theta_L}{\theta_H - \theta_L}(1-\nu) + \frac{\theta_H - \hat{\theta}^-}{\theta_H - \theta_L}\nu. \tag{A.14}$$

Also, given $\pi^+ = \left\{\pi^+_{s_H}, \pi^+_{s_L}\right\}$, we can compute $\hat{\theta}^+ = \theta_L + \pi^+(\theta_H - \theta_L)$ using Eq. (A.12). Therefore, with probabilities h_{s_H} and h_{s_L}, the posterior mean becomes:

$$\hat{\theta}^+_{s_H} = \theta_L + \frac{(\hat{\theta}^- - \theta_L)\nu(\theta_H - \theta_L)}{(\hat{\theta}^- - \theta_L)\nu + (\theta_H - \hat{\theta}^-)(1-\nu)}, \tag{A.15}$$

$$\hat{\theta}^+_{s_L} = \theta_L + \frac{(\hat{\theta}^- - \theta_L)(1-\nu)(\theta_H - \theta_L)}{(\hat{\theta}^- - \theta_L)(1-\nu) + (\theta_H - \hat{\theta}^-)\nu}. \tag{A.16}$$

Here $\hat{\theta}^+_{s_H}$ and $\hat{\theta}^+_{s_L}$ indicate the two possible values of the posterior mean $\hat{\theta}^+$ after observing s_H and s_L, respectively.

In summary, the *conditional* distribution of $\hat{\theta}^+$ is as follows: if the underlying state is θ_H, $\hat{\theta}^+ = \begin{cases} \hat{\theta}^+_{s_H} & \text{w.p. } \nu \\ \hat{\theta}^+_{s_L} & \text{w.p. } 1-\nu \end{cases}$. If the true state is θ_L, then $\hat{\theta}^+ = \begin{cases} \hat{\theta}^+_{s_L} & \text{w.p. } \nu \\ \hat{\theta}^+_{s_H} & \text{w.p. } 1-\nu \end{cases}$.

The probabilities h_{s_H} and h_{s_L} integrate over the unobserved true state θ, whereas investors observe only the signal realization s. The *unconditional* distribution of $\hat{\theta}^+$ after the announcement is therefore $\hat{\theta}^+ = \hat{\theta}^+_{s_H}$ if $s = s_H$, w.p. h_{s_H}, and $\hat{\theta}^+ = \hat{\theta}^+_{s_L}$ if $s = s_L$, w.p. h_{s_L}.

Using this unconditional distribution, for any function f, define

$$f(\nu, \hat{\theta}^-, T) = \mathbb{E}\left[f(\hat{\theta}^+, 0) \,\middle|\, \nu, \hat{\theta}^-, T\right] = h_{s_H} f(\hat{\theta}^+_{s_H}, 0) + h_{s_L} f(\hat{\theta}^+_{s_L}, 0) \tag{A.17}$$

$$\begin{aligned} &= \left[\frac{\hat{\theta}^- - \theta_L}{\theta_H - \theta_L}\nu + \frac{\theta_H - \hat{\theta}^-}{\theta_H - \theta_L}(1-\nu)\right] f\left(\theta_L + \frac{(\hat{\theta}^- - \theta_L)\nu(\theta_H - \theta_L)}{(\hat{\theta}^- - \theta_L)\nu + (\theta_H - \hat{\theta}^-)(1-\nu)}, 0\right) \\ &+ \left[\frac{\hat{\theta}^- - \theta_L}{\theta_H - \theta_L}(1-\nu) + \frac{\theta_H - \hat{\theta}^-}{\theta_H - \theta_L}\nu\right] f\left(\theta_L + \frac{(\hat{\theta}^- - \theta_L)(1-\nu)(\theta_H - \theta_L)}{(\hat{\theta}^- - \theta_L)(1-\nu) + (\theta_H - \hat{\theta}^-)\nu}, 0\right). \end{aligned} \tag{A.18}$$

The Value Function of the Representative Agent The representative agent's preferences are specified by a pair of aggregators $(f, \mathcal{A})$ such that:

$$dV_t = [-f(Y_t, V_t) - \frac{1}{2}\mathcal{A}(V_t)||\sigma_V(t)||^2]dt + \sigma_V(t)dB_t \tag{A.19}$$

for a square-integrable process $\sigma_V(t)$. We adopt the convenient normalization $\mathcal{A}(V_t) = 0$ (Duffie and Epstein, 1992), and let $\bar{f}$ denote the normalized aggregator. Under this normalization, for $\psi \neq 1$, $\bar{f}(Y_t, V_t)$ is defined as:

$$\bar{f}(Y_t, V_t) = \frac{\rho}{1 - 1/\psi} \frac{Y_t^{1-1/\psi} - ((1-\gamma)V_t)^{\frac{1-1/\psi}{1-\gamma}}}{((1-\gamma)V_t)^{\frac{1-1/\psi}{1-\gamma}-1}}. \tag{A.20}$$

The Hamilton-Jacobi-Bellman (HJB) equation for the recursive utility is

$$\bar{f}(Y_t, V(\hat{\theta}, t, Y_t)) + \mathcal{L}[V(\hat{\theta}, t, Y_t)] = 0, \tag{A.21}$$

where $\mathcal{L}$ is the infinitesimal generator defined as $\mathcal{L}(V_t) = \lim_{\Delta \to 0} \frac{1}{\Delta}\mathbb{E}_t\left[V_{t+\Delta} - V_t\right]$. We use the homogeneous form

$$V(\hat{\theta}_t, t, Y_t) = \frac{1}{1-\gamma} H(\hat{\theta}_t, t) Y_t^{1-\gamma}. \tag{A.22}$$

The state dynamics are

$$\frac{dY_t}{Y_t} = \hat{\theta}_t dt + \sigma_Y d\hat{B}_{Y,t}, \tag{A.23}$$

$$d\hat{\theta}_t = \mu_{\theta,t} dt + \frac{\sigma_{\theta,t}}{\sigma_Y} d\hat{B}_{Y,t}, \tag{A.24}$$

where $\mu_{\theta,t} = (\lambda_H + \lambda_L)(\bar{\theta} - \hat{\theta}_t)$ and $\sigma_{\theta,t} = (\theta_H - \hat{\theta}_t)(\hat{\theta}_t - \theta_L)$. The following lemma summarizes the solution to the value function, with details for numerical solutions available in Internet Appendix C.2.

Lemma 2. *In the interior* $(0, T)$, $H(\hat{\theta}_t, t)$ *satisfies the following HJB equation*

$$\begin{aligned} 0 = & \frac{1}{(1-\gamma)H}\left\{H_t + H_\theta\left[\mu_{\theta,t} + (1-\gamma)\sigma_{\theta,t}\right] + \frac{\sigma_{\theta,t}^2}{2\sigma_Y^2} H_{\theta\theta}\right\} \\ & + \frac{\rho}{1 - \frac{1}{\psi}}(H^{B-1} - 1) + (\hat{\theta}_t - \frac{1}{2}\gamma\sigma_Y^2). \end{aligned} \tag{A.25}$$

where we use the following notation: $H_t = \frac{\partial H(\hat{\theta}_t, t)}{\partial t}$, $H_\theta = \frac{\partial H(\hat{\theta}_t, t)}{\partial \hat{\theta}_t}$, *and* $H_{\theta\theta} = \frac{\partial^2 H(\hat{\theta}_t, t)}{\partial \hat{\theta}_t^2}$.

Assuming the informativeness of the announcement ν *takes* m *values, i.e.,* $\nu_1, \nu_2, \nu_3, \ldots, \nu_m$,

with the associated probabilities $q_1, q_2, q_3, \ldots, q_m$*, the boundary condition at the announcement is as follows:*

$$H(\nu, \hat{\theta}^-, T) = \mathbb{E}\left[H(\hat{\theta}^+, 0) \,\middle|\, \nu, \hat{\theta}^-, T\right] = h_{s_H} H(\hat{\theta}^+_{s_H}, 0) + h_{s_L} H(\hat{\theta}^+_{s_L}, 0), \tag{A.26}$$

$$\text{and } H(\hat{\theta}^-, T) = \mathbb{E}\left[H(\nu, \hat{\theta}^-, T) \,\middle|\, \hat{\theta}^-, T\right] = \sum_{j=1}^{m} q_j H(\nu_j, \hat{\theta}^-, T), \tag{A.27}$$

where h_{s_H}*,* h_{s_L}*,* $\hat{\theta}^+_{s_H}$*, and* $\hat{\theta}^+_{s_L}$ *are defined in Eqs. (A.13) to (A.16).*

Proof. The form of the value function implies: $\bar{f}(Y, V) = \frac{\rho}{1-\frac{1}{\psi}} Y^{1-\gamma}(H^{1-\frac{1-\frac{1}{\psi}}{1-\gamma}} - H)$. Using Ito's lemma, we have

$$\begin{aligned}\frac{\mathcal{L}\left[V(\hat{\theta}_t, t, Y_t)\right]}{Y_t^{1-\gamma}} =& \frac{\mathcal{L}\left[H(\hat{\theta}_t, t) Y_t^{1-\gamma}\right]}{(1-\gamma) Y_t^{1-\gamma}} \\ =& H(\hat{\theta}_t - \frac{1}{2}\gamma\sigma_Y^2) + \frac{1}{1-\gamma}(H_t + H_\theta \mu_{\theta,t} + \frac{1}{2\sigma_Y^2} H_{\theta\theta}\sigma_{\theta,t}^2) + H_\theta \sigma_{\theta,t}.\end{aligned} \tag{A.28}$$

Therefore, the HJB equation is written as Eq. (A.25).

The boundary condition upon the announcement satisfies

$$H(\hat{\theta}^-, T) = \mathbb{E}\left[\mathbb{E}\left[H(\hat{\theta}^+, 0) \,\middle|\, \nu, \hat{\theta}^-, T\right] \,\middle|\, \hat{\theta}^-, T\right]. \tag{A.29}$$

To understand the above boundary condition, we provide the timeline and the two steps in the table below.

Time	T (or T^-)		0 (or T^+)
	don't know ν	draw ν, know ν	after announcement
Information set	$\left\{\hat{\theta}^-, T\right\}$	$\left\{\nu, \hat{\theta}^-, T\right\}$	$\left\{\nu, \hat{\theta}^+, 0\right\}$
Continuation utility	$H(\hat{\theta}^-, T)$	$H(\nu, \hat{\theta}^-, T)$	$H(\hat{\theta}^+, 0)$
Step1: $H(\nu, \hat{\theta}^-, T) = \mathbb{E}\left[H(\hat{\theta}^+, 0) \,\middle|\, \nu, \hat{\theta}^-, T\right]$			
Step2: $H(\hat{\theta}^-, T) = \mathbb{E}\left[H(\nu, \hat{\theta}^-, T) \,\middle|\, \hat{\theta}^-, T\right]$			

In Step 1, we draw the i.i.d. random variable ν. Because investors know the distribution of ν, they can update their beliefs about the associated realized values and probabilities of $\hat{\theta}^+$ according to (14), conditioning on each ν. It is useful to denote this intermediate step as: $H(\nu, \hat{\theta}^-, T) = \mathbb{E}\left[H(\hat{\theta}^+, 0) \,\middle|\, \nu, \hat{\theta}^-, T\right]$, where $\mathbb{E}\left[H(\hat{\theta}^+, 0) \,\middle|\, \nu, \hat{\theta}^-, T\right]$ is defined in (A.18).

In this step, we calculate the expected value of the continuation utility right after the announcement conditional on the information set $\left\{\nu, \hat{\theta}^-, T\right\}$, as defined in Eq. (A.26).

In Step 2, we compute the unconditional expectation by integrating over all possible realizations of ν to get Eq. (A.27). This step allows us to derive the expected value function based on the information set $\left\{\hat{\theta}^-, T\right\}$ right before the announcement. If, for example, ν only takes two values, ν_H and ν_L, with probabilities q and $1-q$, then

$$H(\hat{\theta}^-, T) = \mathbb{E}\left[H(\nu, \hat{\theta}^-, T) \,\middle|\, \hat{\theta}^-, T\right] = qH(\nu_H, \hat{\theta}^-, T) + (1-q)H(\nu_L, \hat{\theta}^-, T). \tag{A.30}$$

□

A.2.2 Asset Prices

In this section, we begin by deriving the stochastic discount factor process. We then derive the risk-free rate, the price-to-dividend ratio, and its boundary condition at the announcement. Finally, we calculate the cumulative return and the risk premium.

Stochastic Discount Factor and the Risk-Free Rate We first prove the law of motion of the stochastic discount factor process M_t, which satisfies the stochastic differential equation (SDE) of Eq. (16), with

$$r(\hat{\theta}_t, t) = \rho + \frac{1}{\psi}\hat{\theta}_t - \frac{1+\frac{1}{\psi}}{2}\gamma\sigma_Y^2 + \frac{B(1-\frac{1}{\psi})}{2(1-\gamma)}(\frac{H_\theta}{H})^2\frac{\sigma_{\theta,t}^2}{\sigma_Y^2} + B\frac{H_\theta}{H}\sigma_{\theta,t}, \tag{A.31}$$

$$\sigma_M(\hat{\theta}_t, t) = \gamma\sigma_Y - B\frac{H_\theta}{H}\frac{\sigma_{\theta,t}}{\sigma_Y}, \tag{A.32}$$

where $\sigma_{\theta,t} = (\theta_H - \hat{\theta}_t)(\hat{\theta}_t - \theta_L)$, $H_\theta \equiv \partial H(\hat{\theta}_t, t)/\partial\hat{\theta}_t$, and $H_{\theta\theta} \equiv \partial^2 H(\hat{\theta}_t, t)/\partial\hat{\theta}_t^2$.

Proof. Denote $B \equiv (1/\psi - \gamma)/(1-\gamma)$. The stochastic discount factor is defined as

$$\frac{dM_t}{M_t} = \frac{d\bar{f}_Y(Y,V)}{\bar{f}_Y(Y,V)} + \bar{f}_V(Y,V)dt, \tag{A.33}$$

where $\bar{f}_Y(Y,V) = \rho H^B Y^{-\gamma}$, and $\bar{f}_V(Y,V) = \rho\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}}H^{B-1} - \rho\frac{1-\gamma}{1-\frac{1}{\psi}}$. Applying Ito's lemma,

$$\begin{aligned}\frac{d\bar{f}_Y(Y,V)}{\bar{f}_Y(Y,V)} &= \frac{d[H^B Y_t^{-\gamma}]}{H^B Y_t^{-\gamma}} = \left\{-\gamma\hat{\theta}_t + \frac{1}{2}\gamma(\gamma+1)\sigma_Y^2 + B\left(\frac{H_t}{H} + \frac{H_\theta}{H}\mu_{\theta,t}\right)\right.\\ &\left. + \frac{1}{2}\left[\frac{B\left(\frac{1}{\psi}-1\right)}{1-\gamma}\left(\frac{H_\theta}{H}\right)^2 + B\frac{H_{\theta\theta}}{H}\right]\frac{\sigma_{\theta,t}^2}{\sigma_Y^2} - \gamma B\frac{H_\theta}{H}\sigma_{\theta,t}\right\}dt + \left(-\gamma\sigma_Y + B\frac{H_\theta}{H}\frac{\sigma_{\theta,t}}{\sigma_Y}\right)d\hat{B}_{Y,t}.\end{aligned} \tag{A.34}$$

Matching the drift and diffusion of Eq. (16), we obtain (A.32) and the risk-free rate

$$\begin{aligned} r_t &= -\frac{B}{H}\left[H_t + H_\theta \mu_{\theta,t} + \frac{1}{2}\left(\frac{\frac{1}{\psi}-1}{1-\gamma}\frac{H_\theta^2}{H} + H_{\theta\theta}\right)\frac{\sigma_{\theta,t}^2}{\sigma_Y^2} - \gamma H_\theta \sigma_{\theta,t}\right] \\ &\quad +\gamma\hat{\theta}_t - \frac{1}{2}\gamma(\gamma+1)\sigma_Y^2 - \rho\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}}H^{B-1} + \rho\frac{1-\gamma}{1-\frac{1}{\psi}}. \end{aligned} \tag{A.35}$$

Using the HJB equation to simplify r_t by multiplying both sides of (A.25) by $\frac{1}{\psi}-\gamma$,

$$\begin{aligned} 0 &= \frac{B}{H}\left\{H_t + H_\theta\left[\mu_{\theta,t} + (1-\gamma)\sigma_{\theta,t}\right] + \frac{1}{2}H_{\theta\theta}\frac{\sigma_{\theta,t}^2}{\sigma_Y^2}\right\} \\ &\quad +\frac{\rho\left(\frac{1}{\psi}-\gamma\right)}{1-\frac{1}{\psi}}(H^{B-1}-1) + (\hat{\theta}_t - \frac{1}{2}\gamma\sigma_Y^2)\left(\frac{1}{\psi}-\gamma\right), \end{aligned} \tag{A.36}$$

and adding this equation to (A.35), we obtain the risk-free rate in the main text. □

Price-to-Dividend Ratio The solution for $p(\hat{\theta}_t, t)$ is presented in the following lemma. Further details on numerical solutions can be found in Internet Appendix C.2.

Lemma 3. *In the interior $(0,T)$, the price-to-dividend ratio $p(\hat{\theta}_t,t)$ satisfies the PDE below, where p_t, p_θ, and $p_{\theta\theta}$ denote the derivatives of $p(\hat{\theta}_t,t)$ with respect to t and $\hat{\theta}_t$:*

$$\varpi(\hat{\theta}_t,t)p = p_t + p_\theta \varrho(\hat{\theta}_t,t) + \frac{1}{2}p_{\theta\theta}\sigma_{\theta,t}^2/\sigma_Y^2 + 1, \tag{A.37}$$

with

$$\begin{aligned} \varpi(\hat{\theta}_t,t) &= (\xi_\theta - 1)\bar{\theta} + \rho - \frac{1}{2}\gamma\sigma_Y^2\left(\frac{1}{\psi}+1\right) + \xi_Y\gamma\sigma_Y^2 - \left(\xi_\theta - \frac{1}{\psi}\right)\hat{\theta}_t \\ &\quad +\frac{\left(\frac{1}{\psi}-\gamma\right)\left(1-\frac{1}{\psi}\right)}{2(1-\gamma)^2}\left(\frac{H_\theta}{H}\right)^2\frac{\sigma_{\theta,t}^2}{\sigma_Y^2} + (1-\xi_Y)\frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_\theta}{H}\sigma_{\theta,t} \\ \varrho(\hat{\theta}_t,t) &= \mu_{\theta,t} + (\xi_Y - \gamma)\sigma_{\theta,t} + \frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_\theta}{H}\frac{\sigma_{\theta,t}^2}{\sigma_Y^2}, \end{aligned}$$

with the boundary condition at the announcement satisfying

$$p(\nu,\hat{\theta}_T^-,T) = \mathbb{E}\left[\frac{H(\hat{\theta}_T^+,0)^B p(\hat{\theta}_T^+,0)}{\mathbb{E}\left[H(\hat{\theta}_T^+,0)\,\middle|\,\nu,\hat{\theta}_T^-,T\right]^B}\,\middle|\,\nu,\hat{\theta}_T^-,T\right] = \frac{h_{s_H}H(\hat{\theta}_{s_H}^+,0)^B p(\hat{\theta}_{s_H}^+,0) + h_{s_L}H(\hat{\theta}_{s_L}^+,0)^B p(\hat{\theta}_{s_L}^+,0)}{\left[h_{s_H}H(\hat{\theta}_{s_H}^+,0) + h_{s_L}H(\hat{\theta}_{s_L}^+,0)\right]^B}, \tag{A.38}$$

$$p(\hat{\theta}_T^-, T) = \mathbb{E}\left[\frac{H(\nu, \hat{\theta}_T^-, T)^B p(\nu, \hat{\theta}_T^-, T)}{\mathbb{E}\left[H(\nu, \hat{\theta}_T^-, T)\,\middle|\,\hat{\theta}_T^-, T\right]^B}\,\middle|\,\hat{\theta}_T^-, T\right] = \frac{\sum_{j=1}^m q_j H(\nu_j, \hat{\theta}_T^-, T)^B p(\nu_j, \hat{\theta}_T^-, T)}{\left[\sum_{j=1}^m q_j H(\nu_j, \hat{\theta}_T^-, T)\right]^B}, \tag{A.39}$$

where h_{s_H}, h_{s_L}, $\hat{\theta}^+_{s_H}$, *and* $\hat{\theta}^+_{s_L}$ *are defined in Eqs. (A.13) to (A.16).*

Proof. The present value relationship (17) implies

$$M_t D_t dt + \mathcal{L}\left[M_t p(\hat{\theta}_t, t) D_t\right] = 0. \tag{A.40}$$

This gives $\frac{\mathcal{L}\left[M_t p(\hat{\theta}_t,t) D_t\right]}{M_t p(\hat{\theta}_t,t) D_t} + \frac{1}{p(\hat{\theta}_t,t)} = 0$. Applying Ito's lemma and using Eqs. (15) and (16),

$$\begin{aligned}\frac{\mathcal{L}\left[M_t p(\hat{\theta}_t, t) D_t\right]}{M_t p(\hat{\theta}_t, t) D_t} &= -r_t + \frac{1}{p}\left(p_t + p_\theta \mu_{\theta,t} + \frac{1}{2} p_{\theta\theta}\frac{\sigma_{\theta,t}^2}{\sigma_Y^2}\right) \\ &\quad + \xi_\theta(\hat{\theta}_t - \bar{\theta}) + \bar{\theta} + \xi_Y \frac{p_\theta}{p}\sigma_{\theta,t} - \sigma_{M,t}\left(\xi_Y \sigma_Y + \frac{p_\theta}{p}\frac{\sigma_{\theta,t}}{\sigma_Y}\right).\end{aligned} \tag{A.41}$$

Plugging in r_t from Eq. (A.31) gives the PDE for $p(\hat{\theta}_t, t)$.

We next solve the boundary condition. Another way to write Eq. (A.33) is $M_t = \bar{f}_Y(Y_t, V_t) e^{\int_0^t \bar{f}_V(Y_s, V_s) ds}$. From this formula, the announcement SDF is

$$\frac{M_T^+}{M_T^-} = \frac{\bar{f}_Y(Y_T^+, V_T^+)}{\bar{f}_Y(Y_T^-, V_T^-)} = \frac{H(\hat{\theta}_T^+, 0)^B}{\mathbb{E}\left[H(\hat{\theta}_T^+, 0)\,\middle|\,\hat{\theta}_T^-, T\right]^B}.$$

The intuition is as follows. Upon the announcement, Y_t is continuous, whereas the continuation utility $H(\hat{\theta}_t, t)$ jumps when new information about $\hat{\theta}_t$ arrives because of generalized risk sensitivity in preferences (Ai and Bansal, 2018). Therefore, using the announcement SDF, the boundary condition for $p(\hat{\theta}_t, t)$ is

$$p(\hat{\theta}_T^-, T) = \mathbb{E}\left[\frac{H(\hat{\theta}_T^+, 0)^B p(\hat{\theta}_T^+, 0)}{\mathbb{E}\left[H(\hat{\theta}_T^+, 0)\,\middle|\,\hat{\theta}_T^-, T\right]^B}\,\middle|\,\hat{\theta}_T^-, T\right]. \tag{A.42}$$

As before, we decompose the boundary condition into two steps. First, conditioning on a given ν, the distribution of $\hat{\theta}_T^+$ is given by Eqs. (A.13)-(A.16). This intermediate step $p(\nu, \hat{\theta}_T^-, T)$ can be computed in Eq. (A.38). Next, we compute the unconditional expectation by averaging over all possible realizations of ν, as shown in Eq. (A.39). □

Risk Premium Here, we present a proof for Proposition 2. To simplify notation, let $\mu_{R,t} = \mathbb{E}\left[\frac{d(p(\hat{\theta}_t,t)D_t)+D_t dt}{p(\hat{\theta}_t,t)D_t}\right]$ denote the expected return and let $\sigma_{R,t}$ denote the instantaneous return volatility. We show the following lemma holds.

Lemma 4. *The cumulative return takes the following form*

$$\frac{dR_t}{R_t} = \mu_{R,t}dt + \sigma_{R,t}d\hat{B}_{Y,t} + \omega_t dB_{\omega,t}, \tag{A.43}$$

where

$$\mu_{R,t} = \frac{1}{p}(1 + p_t + p_\theta \mu_{\theta,t} + \frac{1}{2}p_{\theta\theta}\frac{\sigma^2_{\theta,t}}{\sigma^2_Y}) + \xi_\theta(\hat{\theta}_t - \bar{\theta}) + \bar{\theta} + \xi_Y \frac{p_\theta}{p}\sigma_{\theta,t}, \tag{A.44}$$

$$\sigma_{R,t} = \frac{p_\theta}{p}\frac{\sigma_{\theta,t}}{\sigma_Y} + \xi_Y\sigma_Y. \tag{A.45}$$

Proof. The cumulative return can be computed as

$$\frac{dR_t}{R_t} = \frac{d(p(\hat{\theta}_t,t)D_t) + D_t dt}{p(\hat{\theta}_t,t)D_t} = \frac{1}{p}dt + \frac{d(pD_t)}{pD_t}. \tag{A.46}$$

Applying Ito's lemma and using (15),

$$\begin{aligned}\frac{d(p(\hat{\theta}_t,t)D_t)}{p(\hat{\theta}_t,t)D_t} &= \left[\frac{1}{p}(p_t + p_\theta\mu_{\theta,t} + \frac{1}{2}p_{\theta\theta}\frac{\sigma^2_{\theta,t}}{\sigma^2_Y}) + \xi_\theta(\hat{\theta}_t - \bar{\theta}) + \bar{\theta} + \xi_Y\frac{p_\theta}{p}\sigma_{\theta,t}\right]dt \\ &\quad + (\frac{p_\theta}{p}\frac{\sigma_{\theta,t}}{\sigma_Y} + \xi_Y\sigma_Y)d\hat{B}_{Y,t} + \omega_t dB_{\omega,t}.\end{aligned} \tag{A.47}$$

Combined with the expression for the stochastic discount factor (16), we can obtain the risk premium as:

$$\begin{aligned}\mu_{R,t} - r_t &= -\mathrm{Cov}_t\left[\frac{dM_t}{M_t}, \frac{dR_t}{R_t}\right] \\ &= \sigma_{M,t}\sigma_{R,t} = (\gamma\sigma_Y - B\frac{H_\theta}{H}\frac{\sigma_{\theta,t}}{\sigma_Y})(\frac{p_\theta}{p}\frac{\sigma_{\theta,t}}{\sigma_Y} + \xi_Y\sigma_Y),\end{aligned} \tag{A.48}$$

which corresponds to Eq. (18) in Proposition 2.

Upon the announcement, since dividend flow is continuous, the announcement premium is given by $(\mathbb{E}\left[p(\hat{\theta}^+_T, 0)/p(\hat{\theta}^-_T, T)\,\middle|\,\hat{\theta}^-_T, T\right] - 1)$. Using the boundary condition for the price-to-dividend ratio (A.42), we can therefore obtain Eq. (19). □

A.3 Forward-Looking Measure of Implied Variance

In this section, we compute the model-implied forward-looking measure of variance, defined as the conditional variance of the cumulative log return from t to τ under the risk-neutral measure $\mathbb{Q}$,

$$IV^*_{t,\tau}(\hat{\theta}_t, \omega_t, t) = \mathrm{Var}^*_t \left[\underbrace{\ln \left[p(\hat{\theta}_\tau, \tau) D_\tau \right] - \ln \left[p(\hat{\theta}_t, t) D_t \right]}_{\equiv \ln R_{t,\tau}} \right],$$

where $\mathbb{E}^*_t[\cdot]$ and $\mathrm{Var}^*_t[\cdot]$ denote conditional expectation and variance under the risk-neutral measure $\mathbb{Q}$. Throughout the appendix, $\mathbb{P}$ denotes the physical (data-generating) measure and $\mathbb{Q}$ denotes the risk-neutral (pricing) measure; expectations and variances without a star are taken under $\mathbb{P}$, while those with a star are taken under $\mathbb{Q}$. This object corresponds directly to the empirical VIX^2 used in the main text, which is computed from option prices and therefore measures variance under the risk-neutral measure. Because the SDF in our economy has two components—a continuous Brownian component between announcements and a discrete component at the announcement—we handle the interior and the boundary separately.

Between announcements, the stochastic discount factor in Eq. (16) admits the following decomposition

$$\frac{M_t}{M_0} = \underbrace{\exp\left\{ -\int_0^t r(\hat{\theta}_s, s) ds \right\}}_{\text{risk-free deflator}} \times \underbrace{\exp\left\{ -\tfrac{1}{2} \int_0^t \sigma_M^2(\hat{\theta}_s, s) ds - \int_0^t \sigma_M(\hat{\theta}_s, s) d\hat{B}_{Y,s} \right\}}_{\equiv Z_t}.$$

The second factor Z_t is a strictly positive martingale and satisfies $\mathbb{E}[Z_t] = 1$ for every t under the physical measure, so it qualifies as a Radon-Nikodym density. We define the interior risk-neutral measure $\mathbb{Q}$ by $d\mathbb{Q}/d\mathbb{P}|_t = Z_t$, so that risk-neutral expectations of any random variable X_τ realized at time τ are computed as

$$\mathbb{E}^*_t[X_\tau] = \mathbb{E}_t \left[\frac{Z_\tau}{Z_t} X_\tau \right]. \tag{A.49}$$

By Girsanov's theorem, the process $\tilde{B}_{Y,t} \equiv \hat{B}_{Y,t} + \int_0^t \sigma_M(\hat{\theta}_s, s) ds$ is a standard Brownian motion under $\mathbb{Q}$. Equivalently,

$$d\hat{B}_{Y,t} = d\tilde{B}_{Y,t} - \sigma_M(\hat{\theta}_t, t) dt. \tag{A.50}$$

Substituting Eq. (A.50) into the law of motion of every state variable shifts each drift by $-\sigma_M(\hat{\theta}_t, t)$ times its diffusion coefficient and leaves diffusion coefficients unchanged.

At an announcement T, information arrives discretely, so Girsanov's theorem does not apply across the announcement. The change of measure is instead defined directly by the Radon-Nikodym density implied by the announcement SDF:

$$\frac{M_{T^+}}{M_{T^-}} \equiv \frac{H(\hat{\theta}_T^+, 0)^B}{\mathbb{E}\left[H(\hat{\theta}_T^+, 0) \,\middle|\, \hat{\theta}_T^-, T\right]^B} = \underbrace{\frac{\mathbb{E}\left[H(\hat{\theta}_T^+, 0)^B \,\middle|\, \hat{\theta}_T^-, T\right]}{\mathbb{E}\left[H(\hat{\theta}_T^+, 0) \,\middle|\, \hat{\theta}_T^-, T\right]^B}}_{\text{risk-free deflator}} \times \underbrace{\frac{H(\hat{\theta}_T^+, 0)^B}{\mathbb{E}\left[H(\hat{\theta}_T^+, 0)^B \,\middle|\, \hat{\theta}_T^-, T\right]}}_{\equiv Z^+},$$

where $B \equiv \frac{1/\psi - \gamma}{1-\gamma}$. The first term is the risk-free deflator because it is the conditional expected SDF across the announcement. The second factor Z^+ is strictly positive (since $H > 0$) and satisfies $\mathbb{E}\left[Z^+ \,\middle|\, \hat{\theta}_T^-, T\right] = 1$, so it is the Radon-Nikodym density that defines the change of measure across the announcement. Risk-neutral expectations of any post-announcement quantity $X(\hat{\theta}_T^+, T^+)$ are computed as: $\mathbb{E}^*\left[X(\hat{\theta}_T^+, T^+) \,\middle|\, \hat{\theta}_T^-, T\right] = \mathbb{E}\left[Z^+ X(\hat{\theta}_T^+, T^+) \,\middle|\, \hat{\theta}_T^-, T\right]$, or equivalently,

$$\mathbb{E}^*\left[X(\hat{\theta}_T^+, T^+) \,\middle|\, \hat{\theta}_T^-, T\right] = \frac{\mathbb{E}\left[H(\hat{\theta}_T^+, 0)^B X(\hat{\theta}_T^+, T^+) \,\middle|\, \hat{\theta}_T^-, T\right]}{\mathbb{E}\left[H(\hat{\theta}_T^+, 0)^B \,\middle|\, \hat{\theta}_T^-, T\right]}. \tag{A.51}$$

Each signal realization $s = 1, \ldots, m$ corresponds to an informativeness ν_s with prior probability q_s; the conditional weights h_{s_H}, h_{s_L} and post-announcement states $\hat{\theta}_{s_H}^+, \hat{\theta}_{s_L}^+$ are given by Eqs. (A.13)–(A.16) evaluated at $\nu = \nu_s$. The explicit discrete form of Eq. (A.51) is then

$$\mathbb{E}^*\left[X(\hat{\theta}_T^+, T^+) \,\middle|\, \hat{\theta}_T^-, T\right] = \frac{\sum_{s=1}^m q_s \left[h_{s_H} H(\hat{\theta}_{s_H}^+, 0)^B X(\hat{\theta}_{s_H}^+, T^+) + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)^B X(\hat{\theta}_{s_L}^+, T^+)\right]}{\sum_{s=1}^m q_s \left[h_{s_H} H(\hat{\theta}_{s_H}^+, 0)^B + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)^B\right]}. \tag{A.52}$$

With the change of measure in place, we compute $IV_{t,\tau}^*(\hat{\theta}_t, \omega_t, t)$ by simplifying the log return. The law of motion of dividends from Eq. (15) implies:

$$\ln D_\tau = \ln D_t + \int_t^\tau (\xi_\theta \hat{\theta}_s + \bar{\theta}(1 - \xi_\theta) - \frac{1}{2}\xi_Y^2 \sigma_Y^2 - \frac{1}{2}\omega_s^2) ds + \int_t^\tau (\xi_Y \sigma_Y d\hat{B}_{Y,s} + \omega_s dB_{\omega,s}).$$

For simplicity, we define

$$\delta(t) = \int_0^t (\xi_\theta \hat{\theta}_s + \bar{\theta}(1-\xi_\theta) - \frac{1}{2}\xi_Y^2\sigma_Y^2)ds + \int_0^t \xi_Y \sigma_Y d\hat{B}_{Y,s},$$

or equivalently,

$$d\delta(t) = \left[\xi_\theta \hat{\theta}_t + \bar{\theta}(1-\xi_\theta) - \frac{1}{2}\xi_Y^2\sigma_Y^2\right]dt + \xi_Y\sigma_Y d\hat{B}_{Y,t}. \tag{A.53}$$

Substituting Eq. (A.50), the law of motion of $\delta(t)$ under $\mathbb{Q}$ is

$$d\delta(t) = \mu^*_{\delta,t}dt + \xi_Y\sigma_Y d\tilde{B}_{Y,t}, \tag{A.54}$$

where the risk-neutral drift of δ_t is

$$\mu^*_{\delta,t} \equiv \xi_\theta\hat{\theta}_t + \bar{\theta}(1-\xi_\theta) - \frac{1}{2}\xi_Y^2\sigma_Y^2 - \xi_Y\sigma_Y\sigma_M(\hat{\theta}_t, t). \tag{A.55}$$

The law of motion of $\hat{\theta}_t$ in Eq. (13) under $\mathbb{Q}$ is

$$d\hat{\theta}_t = \mu^*_{\theta,t}dt + \frac{(\theta_H - \hat{\theta}_t)(\hat{\theta}_t - \theta_L)}{\sigma_Y}d\tilde{B}_{Y,t}. \tag{A.56}$$

where the risk-neutral drift of $\hat{\theta}_t$ is

$$\mu^*_{\theta,t} \equiv (\lambda_H + \lambda_L)(\bar{\theta} - \hat{\theta}_t) - \frac{(\theta_H - \hat{\theta}_t)(\hat{\theta}_t - \theta_L)}{\sigma_Y}\sigma_M(\hat{\theta}_t, t). \tag{A.57}$$

The diffusion coefficients are unchanged; only the drifts shift by an amount equal to the diffusion coefficient times $-\sigma_M(\hat{\theta}_t, t)$. Therefore, the log return can be simplified as

$$\ln R_{t,\tau} = \ln p(\hat{\theta}_\tau, \tau) - \ln p(\hat{\theta}_t, t) + \delta(\tau) - \delta(t) + \int_t^\tau (-\frac{1}{2}\omega_s^2 ds + \omega_s dB_{\omega,s}). \tag{A.58}$$

Then the implied variance under $\mathbb{Q}$ can be decomposed as

$$\begin{aligned} IV^*_{t,\tau} \;=\; & \mathrm{Var}^*_t\left[\ln p(\hat{\theta}_\tau, \tau)\right] + 2\mathrm{Cov}^*_t\left[\ln p(\hat{\theta}_\tau, \tau), \delta(\tau) - \delta(t)\right] \\ & + \mathrm{Var}^*_t\left[\delta(\tau) - \delta(t)\right] + \mathrm{Var}_t\left[-\int_t^\tau \frac{1}{2}\omega_s^2 ds + \int_t^\tau \omega_s dB_{\omega,s}\right], \end{aligned} \tag{A.59}$$

where we use the fact that $\ln p(\hat{\theta}_t, t)$ is known at time t, and $dB_{\omega,t}$ is uncorrelated with $\hat{B}_Y$ and $\hat{\theta}$. Note that the last term remains under the physical measure because ω_s and $B_{\omega,s}$ are independent of $\hat{B}_{Y,s}$ under $\mathbb{P}$, and the Radon-Nikodym density that defines $\mathbb{Q}$ depends only on $\hat{B}_Y$, so the joint $\mathbb{Q}$-distribution of (ω, B_ω) equals its $\mathbb{P}$-distribution. Hence the last term

can be evaluated under $\mathbb{P}$, and its covariance with $\hat{\theta}$ and δ terms is zero. The four terms in Eq. (A.59) can be further decomposed into:

$$\begin{aligned}
\text{Var}_t^*\left[\ln p(\hat{\theta}_\tau,\tau)\right] &= \mathbb{E}_t^*\left[(\ln p(\hat{\theta}_\tau,\tau))^2\right] - \mathbb{E}_t^*\left[\ln p(\hat{\theta}_\tau,\tau)\right]^2, \quad \text{(A.60)}\\
\text{Cov}_t^*\left[\ln p(\hat{\theta}_\tau,\tau), \delta(\tau)-\delta(t)\right] &= \mathbb{E}_t^*\left[\ln p(\hat{\theta}_\tau,\tau)(\delta(\tau)-\delta(t))\right]\\
&\quad -\mathbb{E}_t^*\left[\ln p(\hat{\theta}_\tau,\tau)\right]\mathbb{E}_t^*\left[(\delta(\tau)-\delta(t))\right], \quad \text{(A.61)}\\
\text{Var}_t^*\left[\delta(\tau)-\delta(t)\right] &= \mathbb{E}_t^*\left[\{\delta(\tau)-\delta(t)\}^2\right] - \mathbb{E}_t^*\left[\delta(\tau)-\delta(t)\right]^2, \quad \text{(A.62)}\\
\text{Var}_t\left[-\int_t^\tau \frac{1}{2}\omega_s^2 ds + \int_t^\tau \omega_s dB_{\omega,s}\right] &= \mathbb{E}_t\left[(-\int_t^\tau \frac{1}{2}\omega_s^2 ds + \int_t^\tau \omega_s dB_{\omega,s})^2\right]\\
&\quad -\mathbb{E}_t\left[-\int_t^\tau \frac{1}{2}\omega_s^2 ds + \int_t^\tau \omega_s dB_{\omega,s}\right]^2. \quad \text{(A.63)}
\end{aligned}$$

The first term on the right-hand side of the last equation above is equivalent to

$$\begin{aligned}
&\frac{1}{4}\mathbb{E}_t\left[(\int_t^\tau \omega_s^2 ds)^2\right] + \mathbb{E}_t\left[(\int_t^\tau \omega_s dB_{\omega,s})^2\right] - \mathbb{E}_t\left[(\int_t^\tau \omega_s^2 ds)(\int_t^\tau \omega_s dB_{\omega,s})\right]\\
= \;& \frac{1}{4}\mathbb{E}_t\left[(\int_t^\tau \omega_s^2 ds)^2\right] + \mathbb{E}_t\left[\int_t^\tau \omega_s^2 ds\right],
\end{aligned}$$

where we applied Ito's isometry for $\mathbb{E}_t\left[(\int_t^\tau \omega_s dB_{\omega,s})^2\right] = \mathbb{E}_t\left[\int_t^\tau \omega_s^2 ds\right]$. As a result, Eq. (A.63) can be simplified to

$$\text{Var}_t\left[-\frac{1}{2}\int_t^\tau \omega_s^2 ds + \int_t^\tau \omega_s dB_{\omega,s}\right] = \frac{1}{4}y(\omega_t,t) + g(\omega_t,t) - \frac{1}{4}g^2(\omega_t,t), \quad \text{(A.64)}$$

where $g(\omega_t,t) = \mathbb{E}_t\left[\int_t^\tau \omega_s^2 ds\right]$ and $y(\omega_t,t) = \mathbb{E}_t\left[(\int_t^\tau \omega_s^2 ds)^2\right]$. Using the simplified notation defined above, we obtain the following lemma. We provide details for numerical solutions in Internet Appendix C.2.

Lemma 5. *For $0 \le t \le \tau$, the implied variance under the risk-neutral measure is given by*

$$\begin{aligned}
IV_{t,\tau}^*(\hat{\theta}_t,\omega_t,t) &= w_2^*(\hat{\theta}_t,t) - w_1^*(\hat{\theta}_t,t)^2 + 2\left[a_3^*(\hat{\theta}_t,t) - w_1^*(\hat{\theta}_t,t)a_1^*(\hat{\theta}_t,t)\right]\\
&\quad + a_2^*(\hat{\theta}_t,t) - a_1^*(\hat{\theta}_t,t)^2 + \frac{1}{4}y(\omega_t,t) + g(\omega_t,t) - \frac{1}{4}g^2(\omega_t,t), \quad \text{(A.65)}
\end{aligned}$$

where

$$
\begin{aligned}
w_1^*(\hat{\theta}_t, t) &= \mathbb{E}_t^* \left[\ln p(\hat{\theta}_\tau, \tau) \right], && \text{(A.66)} \\
w_2^*(\hat{\theta}_t, t) &= \mathbb{E}_t^* \left[(\ln p(\hat{\theta}_\tau, \tau))^2 \right], && \text{(A.67)} \\
a_1^*(\hat{\theta}_t, t) &= \mathbb{E}_t^* \left[\delta(\tau) - \delta(t) \right], && \text{(A.68)} \\
a_2^*(\hat{\theta}_t, t) &= \mathbb{E}_t^* \left[\{\delta(\tau) - \delta(t)\}^2 \right], && \text{(A.69)} \\
a_3^*(\hat{\theta}_t, t) &= \mathbb{E}_t^* \left[\ln p(\hat{\theta}_\tau, \tau) \{\delta(\tau) - \delta(t)\} \right], && \text{(A.70)}
\end{aligned}
$$

and $g(\omega_t, t) = \mathbb{E}_t \left[\int_t^\tau \omega_s^2 ds \right]$ *and* $y(\omega_t, t) = \mathbb{E}_t \left[(\int_t^\tau \omega_s^2 ds)^2 \right]$ *are unchanged from the physical-measure case and have the following closed-form solutions*

$$
\begin{aligned}
g(\omega_H, t) &= \frac{\kappa_H \omega_L^2 + \kappa_L \omega_H^2}{\kappa_H + \kappa_L}(\tau - t) + \kappa_H \frac{\omega_H^2 - \omega_L^2}{(\kappa_H + \kappa_L)^2} \left[1 - e^{-(\kappa_H + \kappa_L)(\tau - t)} \right], && \text{(A.71)} \\
g(\omega_L, t) &= \frac{\kappa_H \omega_L^2 + \kappa_L \omega_H^2}{\kappa_H + \kappa_L}(\tau - t) - \kappa_L \frac{\omega_H^2 - \omega_L^2}{(\kappa_H + \kappa_L)^2} \left[1 - e^{-(\kappa_H + \kappa_L)(\tau - t)} \right]. && \text{(A.72)}
\end{aligned}
$$

$$
\begin{aligned}
y(\omega_H, t) &= \frac{(\omega_H^2 \kappa_L + \kappa_H \omega_L^2)^2}{(\kappa_H + \kappa_L)^2}(\tau - t)^2 + \frac{2\kappa_H(\omega_H^2 - \omega_L^2)(1 - e^{-(\kappa_H + \kappa_L)(\tau - t)})(\kappa_H \omega_H^2 - 2\omega_H^2 \kappa_L - \kappa_H \omega_L^2 + 2\kappa_L \omega_L^2)}{(\kappa_H + \kappa_L)^4} \\
&\quad + \frac{2\kappa_H(\omega_H^2 - \omega_L^2)\left[-e^{-(\kappa_H + \kappa_L)(\tau - t)}(\kappa_H \omega_H^2 + \kappa_L \omega_L^2) + 2\omega_H^2 \kappa_L + \kappa_H \omega_L^2 - \kappa_L \omega_L^2 \right]}{(\kappa_H + \kappa_L)^3}(\tau - t), && \text{(A.73)} \\
y(\omega_L, t) &= \frac{(\omega_H^2 \kappa_L + \kappa_H \omega_L^2)^2}{(\kappa_H + \kappa_L)^2}(\tau - t)^2 + \frac{2\kappa_L(\omega_H^2 - \omega_L^2)(1 - e^{-(\kappa_H + \kappa_L)(\tau - t)})(-2\kappa_H \omega_H^2 + \omega_H^2 \kappa_L + 2\kappa_H \omega_L^2 - \kappa_L \omega_L^2)}{(\kappa_H + \kappa_L)^4} \\
&\quad + \frac{2\kappa_L(\omega_H^2 - \omega_L^2)\left[\kappa_H \omega_H^2 + e^{-(\kappa_H + \kappa_L)(\tau - t)}(\kappa_H \omega_H^2 + \kappa_L \omega_L^2) - \omega_H^2 \kappa_L - 2\kappa_H \omega_L^2 \right]}{(\kappa_H + \kappa_L)^3}(\tau - t). && \text{(A.74)}
\end{aligned}
$$

All of these functions also depend on the expiration date τ, which we suppress for brevity. We first solve for $g(\omega_t, t)$ and $y(\omega_t, t)$, where $\omega_t \in \{\omega_H, \omega_L\}$ is a two-state Markov chain. We construct the following martingale

$$
\mathbb{E}_t \left[\int_0^\tau \omega_s^2 ds \right] = \mathbb{E}_t \left[\int_t^\tau \omega_s^2 ds \right] + \mathbb{E}_t \left[\int_0^t \omega_s^2 ds \right] = g(\omega_t, t) + \int_0^t \omega_s^2 ds. \tag{A.75}
$$

For $s < t$, $\mathbb{E}_s \left[\mathbb{E}_t \left[\int_0^\tau \omega_u^2 du \right] \right] = \mathbb{E}_s \left[\int_0^\tau \omega_u^2 du \right]$, so $\mathbb{E}_t \left[\int_0^\tau \omega_s^2 ds \right]$ is a martingale. Therefore, applying the generator, we have:

$$
\mathcal{L}\left[g(\omega_t, t) \right] + \omega_t^2 = 0, \tag{A.76}
$$

with the boundary condition $g(\omega_\tau, \tau) = \mathbb{E}_\tau\left[\int_\tau^\tau \omega_s^2 ds\right] = 0$. The above can be written as:

$$\omega_H^2 + \frac{\partial}{\partial t} g(\omega_H, t) + \kappa_H \left[g(\omega_L, t) - g(\omega_H, t)\right] = 0, \tag{A.77}$$

$$\omega_L^2 + \frac{\partial}{\partial t} g(\omega_L, t) + \kappa_L \left[g(\omega_H, t) - g(\omega_L, t)\right] = 0, \tag{A.78}$$

which gives Eqs. (A.71) and (A.72). We use the same methodology to solve for $y(\omega_t, t)$. Denote $z(t) = \int_0^t \omega_s^2 ds$; then $\int_0^\tau \omega_s^2 ds = z(t) + \int_t^\tau \omega_s^2 ds$.

$$\begin{aligned}\mathbb{E}_t\left[(\int_0^\tau \omega_s^2 ds)^2\right] &= \mathbb{E}_t\left[(\int_0^t \omega_s^2 ds)^2 + (\int_t^\tau \omega_s^2 ds)^2 + 2(\int_0^t \omega_s^2 ds)(\int_t^\tau \omega_s^2 ds)\right] \\ &= z(t)^2 + y(\omega_t, t) + 2z(t) g(\omega_t, t). \end{aligned} \tag{A.79}$$

We show that $\mathbb{E}_t\left[(\int_0^\tau \omega_s^2 ds)^2\right]$ is a martingale, since for any $s < t$, the law of iterated expectations gives $\mathbb{E}_s\left[\mathbb{E}_t\left[(\int_0^\tau \omega_u^2 du)^2\right]\right] = \mathbb{E}_s\left[(\int_0^\tau \omega_u^2 du)^2\right]$. Therefore,

$$\begin{aligned} 0 &= \mathcal{L}\left\{z(t)^2 + y(\omega_t, t) + 2z(t) g(\omega_t, t)\right\} \\ &= 2z(t)z'(t) + \mathcal{L}y(\omega_t, t) + 2z(t)\mathcal{L}g(\omega_t, t) + 2z'(t) g(\omega_t, t). \end{aligned} \tag{A.80}$$

Noting that $z'(t) = \omega_t^2$, the above condition can be written as

$$2z(t)\left[\omega_t^2 + \mathcal{L}g(\omega_t, t)\right] + \mathcal{L}y(\omega_t, t) + 2\omega_t^2 g(\omega_t, t) = 0. \tag{A.81}$$

Because $z(t)$ is a random variable and can take any value, for the above to hold, we must have (A.76) and

$$\mathcal{L}y(\omega_t, t) + 2\omega_t^2 g(\omega_t, t) = 0, \tag{A.82}$$

together with the boundary condition $y(\omega_\tau, \tau) = 0$. This implies the following ODEs for $y(\omega_t, t)$:

$$\frac{\partial}{\partial t} y(\omega_H, t) + \kappa_H \left[y(\omega_L, t) - y(\omega_H, t)\right] + 2\omega_H^2 g(\omega_H, t) = 0 \tag{A.83}$$

$$\frac{\partial}{\partial t} y(\omega_L, t) + \kappa_L \left[y(\omega_H, t) - y(\omega_L, t)\right] + 2\omega_L^2 g(\omega_L, t) = 0. \tag{A.84}$$

which further gives Eqs. (A.73) and (A.74) in Lemma 5.

Next, we solve separately for w_j^*, $j = 1, 2$, and for a_j^*, $j = 1, 2, 3$, as defined in Lemma 5. In general, there are two cases. In the first case, $\tau < T$ so that there is no announcement before expiration τ. We construct martingales under $\mathbb{Q}$ and use the martingale property to

determine the PDE and the associated boundary condition for each variable. In the second case, $\tau \geq T$, and the forward-looking implied variance covers one announcement before expiration. In this case, we solve w_j^* and a_j^* using backward induction in three steps: after, upon, and before the announcement. The post-announcement and pre-announcement pieces are obtained from the same PDEs as in the interior case; the jump across the announcement instant is handled by averaging post-announcement values weighted by the discrete density Z^+ derived above. We summarize the results in the following lemma.

Lemma 6. *Denote by $\mathcal{L}^*$ the infinitesimal generator under the risk-neutral measure $\mathbb{Q}$:*

$$\mathcal{L}^* f(\hat{\theta}_t, t) \equiv \frac{\partial f}{\partial t} + \mu^*_{\theta,t} \frac{\partial f}{\partial \hat{\theta}} + \frac{1}{2} \frac{\sigma^2_{\theta,t}}{\sigma^2_Y} \frac{\partial^2 f}{\partial \hat{\theta}^2}, \tag{A.85}$$

where $\mu^*_{\theta,t}$ and $\mu^*_{\delta,t}$ are the risk-neutral drifts of $\hat{\theta}_t$ and $\delta(t)$, respectively, as defined in Eqs. (A.57) and (A.55). If $0 \leq t \leq \tau < T$, so that no announcement occurs before expiration, then $w_j^*(\hat{\theta}_t, t)$ $(j = 1, 2)$ and $a_j^*(\hat{\theta}_t, t)$ $(j = 1, 2, 3)$ satisfy

$$\mathcal{L}^* w_j^*(\hat{\theta}_t, t) = 0, \tag{A.86}$$

$$\mathcal{L}^* a_1^*(\hat{\theta}_t, t) + \mu^*_{\delta,t} = 0, \tag{A.87}$$

$$\mathcal{L}^* a_2^*(\hat{\theta}_t, t) + 2a_1^*(\hat{\theta}_t, t)\mu^*_{\delta,t} + 2\xi_Y \sigma_{\theta,t} \frac{\partial a_1^*}{\partial \hat{\theta}} + \xi_Y^2 \sigma_Y^2 = 0, \tag{A.88}$$

$$\mathcal{L}^* a_3^*(\hat{\theta}_t, t) + w_1^*(\hat{\theta}_t, t)\mu^*_{\delta,t} + \xi_Y \sigma_{\theta,t} \frac{\partial w_1^*}{\partial \hat{\theta}} = 0, \tag{A.89}$$

with boundary conditions at $t = \tau$:

$$w_1^*(\hat{\theta}_\tau, \tau) = \ln p(\hat{\theta}_\tau, \tau), \quad w_2^*(\hat{\theta}_\tau, \tau) = (\ln p(\hat{\theta}_\tau, \tau))^2, \quad a_j^*(\hat{\theta}_\tau, \tau) = 0. \tag{A.90}$$

If $0 \leq t < T \leq \tau$, so that there is one announcement before expiration, we proceed as follows. First, we solve the PDEs on $[T^+, \tau]$ with boundary conditions (A.90) at τ. This gives the post-announcement values $w_j^*(\hat{\theta}_T^+, T^+)$ and $a_j^*(\hat{\theta}_T^+, T^+)$. These post-announcement values are then mapped back to T^- using the announcement-day risk-neutral expectation:

$$w_j^*(\hat{\theta}_T^-, T^-) = \mathbb{E}^* \left[w_j^*(\hat{\theta}_T^+, T^+) \,\middle|\, \hat{\theta}_T^-, T \right], \tag{A.91}$$

$$a_j^*(\hat{\theta}_T^-, T^-) = \mathbb{E}^* \left[a_j^*(\hat{\theta}_T^+, T^+) \,\middle|\, \hat{\theta}_T^-, T \right], \tag{A.92}$$

where $\mathbb{E}^* \left[\cdot \,\middle|\, \hat{\theta}_T^-, T \right]$ is the announcement-day risk-neutral expectation defined in Eq. (A.52).

Finally, we solve the same PDEs on $[0, T^-]$ with boundary conditions at T^- given by (A.91) and (A.92).

Proof. **Case 1: IV * for $0 \le t \le \tau < T$: no announcement before expiration.**

PDE for $w_j^*(\hat{\theta}_t, t)$. For any $s \le t \le \tau$ and $j = 1, 2$, the law of iterated expectations under $\mathbb{Q}$ gives $\mathbb{E}_s^*\left[w_j^*(\hat{\theta}_t, t)\right] = \mathbb{E}_s^*\left[\mathbb{E}_t^*\left[(\ln p(\hat{\theta}_\tau, \tau))^j\right]\right] = \mathbb{E}_s^*\left[(\ln p(\hat{\theta}_\tau, \tau))^j\right] = w_j^*(\hat{\theta}_s, s)$, so $w_j^*(\hat{\theta}_t, t)$ is a $\mathbb{Q}$-martingale. A martingale has zero drift. Therefore,

$$\mathcal{L}^* w_1^*(\hat{\theta}_t, t) = 0 \text{ and } \mathcal{L}^* w_2^*(\hat{\theta}_t, t) = 0, \tag{A.93}$$

which is exactly Eq. (A.86), with boundary condition (A.90).

PDE for $a_1^*(\hat{\theta}_t, t)$. By definition, $a_1^*(\hat{\theta}_t, t) = \mathbb{E}_t^*[\delta(\tau) - \delta(t)]$. Since $\delta(t)$ is time-t measurable, $a_1^*(\hat{\theta}_t, t) + \delta(t) = \mathbb{E}_t^*[\delta(\tau)]$, which is a $\mathbb{Q}$-martingale by the law of iterated expectations: for $s \le t \le \tau$,

$$\mathbb{E}_s^*\left[a_1^*(\hat{\theta}_t, t) + \delta(t)\right] = \mathbb{E}_s^*[\mathbb{E}_t^*[\delta(\tau)]] = \mathbb{E}_s^*[\delta(\tau)] = a_1^*(\hat{\theta}_s, s) + \delta(s). \tag{A.94}$$

Applying Ito's lemma to $a_1^*(\hat{\theta}_t, t) + \delta(t)$ under the laws of motion (A.56) and (A.54), and using the martingale property, the drift must vanish.

$$\mathcal{L}^* a_1^*(\hat{\theta}_t, t) + \mu_{\delta,t}^* = 0, \tag{A.95}$$

which is exactly Eq. (A.87), with boundary condition $a_1^*(\hat{\theta}_\tau, \tau) = 0$.

PDE for $a_2^*(\hat{\theta}_t, t)$. By definition, $a_2^*(\hat{\theta}_t, t) = \mathbb{E}_t^*\left[\{\delta(\tau) - \delta(t)\}^2\right]$. Writing $\delta(\tau) = (\delta(\tau) - \delta(t)) + \delta(t)$ and pulling the time-t-measurable $\delta(t)$ out of $\mathbb{E}_t^*$ to obtain

$$\begin{aligned}\mathbb{E}_t^*\left[\delta^2(\tau)\right] &= \mathbb{E}_t^*\left[(\delta(\tau) - \delta(t))^2\right] + 2\delta(t)\mathbb{E}_t^*[\delta(\tau) - \delta(t)] + \delta(t)^2 \\ &= a_2^*(\hat{\theta}_t, t) + 2a_1^*(\hat{\theta}_t, t)\delta(t) + \delta(t)^2.\end{aligned} \tag{A.96}$$

The left-hand side is a $\mathbb{Q}$-martingale by the law of iterated expectations, so the right-hand side is too. Applying Ito's lemma to $\delta(t)^2 + 2a_1^*(\hat{\theta}_t, t)\delta(t) + a_2^*(\hat{\theta}_t, t)$, the $\mathbb{Q}$-martingale property forces its drift to vanish,

$$2\delta_t\left[\mu_{\delta,t}^* + \mathcal{L}^* a_1^*(\hat{\theta}_t, t)\right] + \xi_Y^2\sigma_Y^2 + 2a_1^*\mu_{\delta,t}^* + 2\xi_Y\sigma_{\theta,t}\frac{\partial a_1^*}{\partial\hat{\theta}} + \mathcal{L}^* a_2^*(\hat{\theta}_t, t) = 0. \tag{A.97}$$

Since this must hold for all δ_t, matching the coefficient on δ_t recovers Eq. (A.87) and matching the constant gives Eq. (A.88), with boundary condition $a_2^*(\hat{\theta}_\tau, \tau) = 0$.

PDE for $a_3^*(\hat{\theta}_t, t)$. Decomposing $\delta(\tau) = \delta(t) + (\delta(\tau) - \delta(t))$ inside $\mathbb{E}_t^* \left[\ln p(\hat{\theta}_\tau, \tau)\delta(\tau)\right]$ and pulling out the time-t-measurable $\delta(t)$ give

$$\mathbb{E}_t^* \left[\ln p(\hat{\theta}_\tau, \tau)\delta(\tau)\right] = \delta(t) \underbrace{\mathbb{E}_t^* \left[\ln p(\hat{\theta}_\tau, \tau)\right]}_{= w_1^*(\hat{\theta}_t, t)} + \underbrace{\mathbb{E}_t^* \left[\ln p(\hat{\theta}_\tau, \tau)\left\{\delta(\tau) - \delta(t)\right\}\right]}_{= a_3^*(\hat{\theta}_t, t)}. \tag{A.98}$$

The left-hand side is again a $\mathbb{Q}$-martingale, so the right-hand side is too. Applying Ito's lemma to $w_1^*(\hat{\theta}_t, t)\delta(t) + a_3^*(\hat{\theta}_t, t)$ and using $\mathcal{L}^* w_1^* = 0$, the $\mathbb{Q}$-martingale property forces its drift to vanish,

$$w_1^* \mu_{\delta,t}^* + \xi_Y \frac{\partial w_1^*}{\partial \hat{\theta}} \sigma_{\theta,t} + \mathcal{L}^* a_3^*(\hat{\theta}_t, t) = 0, \tag{A.99}$$

which is exactly Eq. (A.89), with boundary condition $a_3^*(\hat{\theta}_\tau, \tau) = 0$.

Case 2: IV * for $\tau \geq T$: one announcement before expiration.

Case 1 computes the expectations only for $\tau < T$. If $\tau \geq T$, the forward-looking implied variance covers one announcement before expiration, and the announcement boundary requires separate treatment. The timeline is:

$$t < T^- < T^+ \leq \tau.$$

We address it through three steps of backward induction: we start from T^+, move back to (T^-, ν), and then proceed to T^- without knowing ν. Each step's output feeds into the next.

Step 1: To move from $T^+ \to \tau$, we use the PDEs and boundary conditions (A.90) in Lemma 6 to calculate $w_j^*(\hat{\theta}_T^+, T^+)$ for $j = 1, 2$ and $a_j^*(\hat{\theta}_T^+, T^+)$ for $j = 1, 2, 3$.

Step 2: To transition from $T^- \to T^+$, we calculate the boundary conditions. Since $\delta(t)$ is a stochastic integral, it must be continuous. Therefore, we have $\delta(T^+) = \delta(T^-)$, which yields $\mathbb{E}_{T^-}^* [\delta(T^+)] = \delta(T^-)$. The conditional expectation under $\mathbb{Q}$ across the announcement uses the announcement-day Radon-Nikodym density Z^+. Using Eqs. (A.93), (A.94), (A.97), and (A.98), the $\mathbb{Q}$-martingale property implies that the pre-announcement value of each martingale equals the risk-neutral expectation of its post-announcement value. For w_j^*, $j = 1, 2$, this gives

$$w_j^*(\hat{\theta}_T^-, T^-) = \mathbb{E}_{T^-}^* \left[w_j^*(\hat{\theta}_T^+, T^+)\right].$$

For the a_j^* terms, the $\mathbb{Q}$-martingales established in Case 1 are $a_1^*(\hat{\theta}_t, t) + \delta_t$, $\delta_t^2 + 2\delta_t a_1^*(\hat{\theta}_t, t) + a_2^*(\hat{\theta}_t, t)$, and $w_1^*(\hat{\theta}_t, t)\delta_t + a_3^*(\hat{\theta}_t, t)$. Applying the martingale property between T^- and T^+

and using $\delta(T^+) = \delta(T^-)$ to cancel the δ-terms — for instance, $a_1^*(\hat{\theta}_T^-, T^-) + \delta(T^-) = \mathbb{E}_{T^-}^* \left[a_1^*(\hat{\theta}_T^+, T^+) + \delta(T^+) \right] \Rightarrow a_1^*(\hat{\theta}_T^-, T^-) = \mathbb{E}_{T^-}^* \left[a_1^*(\hat{\theta}_T^+, T^+) \right]$ — yields

$$a_j^*(\hat{\theta}_T^-, T^-) = \mathbb{E}_{T^-}^* \left[a_j^*(\hat{\theta}_T^+, T^+) \right], \qquad j = 1, 2, 3.$$

These identities are exactly Eqs. (A.91) and (A.92) of Lemma 6; expanding $\mathbb{E}_{T^-}^* [\cdot]$ via the discrete form in Eq. (A.52) gives the explicit averages

$$w_j^*(\hat{\theta}_T^-, T^-) = \frac{\sum_{s=1}^m q_s \left[h_{s_H} H(\hat{\theta}_{s_H}^+, 0)^B w_j^*(\hat{\theta}_{s_H}^+, T^+) + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)^B w_j^*(\hat{\theta}_{s_L}^+, T^+) \right]}{\sum_{s=1}^m q_s \left[h_{s_H} H(\hat{\theta}_{s_H}^+, 0)^B + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)^B \right]} \tag{A.100}$$

$$a_j^*(\hat{\theta}_T^-, T^-) = \frac{\sum_{s=1}^m q_s \left[h_{s_H} H(\hat{\theta}_{s_H}^+, 0)^B a_j^*(\hat{\theta}_{s_H}^+, T^+) + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)^B a_j^*(\hat{\theta}_{s_L}^+, T^+) \right]}{\sum_{s=1}^m q_s \left[h_{s_H} H(\hat{\theta}_{s_H}^+, 0)^B + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)^B \right]} \tag{A.101}$$

Step 3: To move from $t \to T^-$, we use the PDEs from Step 1 to solve for the paths with the boundary conditions $w_j^*(\hat{\theta}_T^-, T^-)$ and $a_j^*(\hat{\theta}_T^-, T^-)$ obtained from Step 2. □

Implied Variance Reduction upon the Announcement With the implied variance under $\mathbb{Q}$ from Lemma 5, we can calculate the implied variance reduction upon the announcement. Right after the announcement, the IV is

$$\begin{aligned} IV_{T^+,\tau}^*(\hat{\theta}_T^+, \omega_T^+, T^+) =& w_2^*(\hat{\theta}_T^+, T^+) - w_1^*(\hat{\theta}_T^+, T^+)^2 + a_2^*(\hat{\theta}_T^+, T^+) - a_1^*(\hat{\theta}_T^+, T^+)^2 \\ &+ 2 \left[a_3^*(\hat{\theta}_T^+, T^+) - w_1^*(\hat{\theta}_T^+, T^+) a_1^*(\hat{\theta}_T^+, T^+) \right] \\ &+ \frac{1}{4} y(\omega_T^+, T^+) + g(\omega_T^+, T^+) - \frac{1}{4} g^2(\omega_T^+, T^+). \end{aligned} \tag{A.102}$$

Right before the announcement, conditional on informativeness ν, we define the ν-conditional risk-neutral expectation

$$\mathbb{E}^* \left[X(\hat{\theta}_T^+, T^+) \,\middle|\, \nu, \hat{\theta}_T^-, T^- \right] \equiv \frac{\mathbb{E} \left[H(\hat{\theta}_T^+, 0)^B X(\hat{\theta}_T^+, T^+) \,\middle|\, \nu, \hat{\theta}_T^-, T^- \right]}{\mathbb{E} \left[H(\hat{\theta}_T^+, 0)^B \,\middle|\, \nu, \hat{\theta}_T^-, T^- \right]}, \tag{A.103}$$

which is the analog of Eq. (A.51) but with $\nu = \nu_s$ held fixed rather than averaged over the prior $\{q_s\}$. The explicit discrete form, the analog of Eq. (A.52), is

$$\mathbb{E}^* \left[X(\hat{\theta}_T^+, T^+) \,\middle|\, \nu_s, \hat{\theta}_T^-, T^- \right] = \frac{h_{s_H} H(\hat{\theta}_{s_H}^+, 0)^B X(\hat{\theta}_{s_H}^+, T^+) + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)^B X(\hat{\theta}_{s_L}^+, T^+)}{h_{s_H} H(\hat{\theta}_{s_H}^+, 0)^B + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)^B}. \tag{A.104}$$

Applying this formula to $X(\hat{\theta}_T^+, T^+) = w_j^*(\hat{\theta}_T^+, T^+)$ and $X(\hat{\theta}_T^+, T^+) = a_j^*(\hat{\theta}_T^+, T^+)$ produces the ν-conditional pre-announcement values

$$w_j^*(\nu, \hat{\theta}_T^-, T^-) \equiv \mathbb{E}^* \left[w_j^*(\hat{\theta}_T^+, T^+) \,\middle|\, \nu, \hat{\theta}_T^-, T^- \right], \quad a_j^*(\nu, \hat{\theta}_T^-, T^-) \equiv \mathbb{E}^* \left[a_j^*(\hat{\theta}_T^+, T^+) \,\middle|\, \nu, \hat{\theta}_T^-, T^- \right]. \tag{A.105}$$

In terms of these quantities, the pre-announcement IV is

$$\begin{aligned} IV_{T^-,\tau}^*(\nu, \hat{\theta}_T^-, \omega_T^-, T^-) &= \mathrm{Var}^* \left[\ln \left\{ p(\hat{\theta}_\tau, \tau) D_\tau \right\} - \ln \left\{ p(\nu, \hat{\theta}_T^-, T^-) D_{T^-} \right\} \,\middle|\, \nu, \hat{\theta}_T^-, T^- \right] \\ &= w_2^*(\nu, \hat{\theta}_T^-, T^-) - w_1^*(\nu, \hat{\theta}_T^-, T^-)^2 + a_2^*(\nu, \hat{\theta}_T^-, T^-) - a_1^*(\nu, \hat{\theta}_T^-, T^-)^2 \\ &\quad + 2 \left[a_3^*(\nu, \hat{\theta}_T^-, T^-) - w_1^*(\nu, \hat{\theta}_T^-, T^-) a_1^*(\nu, \hat{\theta}_T^-, T^-) \right] \\ &\quad + \frac{1}{4} y(\omega_T^-, T^-) + g(\omega_T^-, T^-) - \frac{1}{4} g^2(\omega_T^-, T^-). \end{aligned} \tag{A.106}$$

Therefore, the implied variance reduction is defined as

$$\Delta IV_T^* = IV_{T^-,\tau}^*(\nu, \hat{\theta}_T^-, \omega_T^-, T^-) - IV_{T^+,\tau}^*(\hat{\theta}_T^+, \omega_T^+, T^+), \tag{A.107}$$

which corresponds to Eq. (21) in the main text. The first term is the implied variance before the announcement, computed as the conditional variance of the future log return given information at T^- *and* the realized informativeness ν. Conditioning on ν (rather than integrating it out) directly captures investors' belief updating upon observing ν, yielding a more precise measure of information-induced changes in implied variance. Thus, ΔIV_T^* measures the announcement-induced reduction in risk-neutral uncertainty for a given informativeness realization ν.

Measure of Informativeness For the informativeness measure reported in Table 5, we consider the special case in our model where the maturity coincides with the announcement instant itself, $\tau = T^+$. In this case, $IV_{T^-,T^+}^*(\nu, \hat{\theta}_T^-, \omega_T^-, T^-)$ is the ν-conditional risk-neutral variance of the announcement jump from T^- to T^+. Because dividends and idiosyncratic volatility do not accumulate over an instantaneous interval, the flow terms a_1^*, a_2^*, a_3^*, as well as the g and y terms, all vanish over this instantaneous interval. Applying Eq. (A.104) to $X = \ln p(\hat{\theta}_T^+, T^+)$ and to $X = \left[\ln p(\hat{\theta}_T^+, T^+) \right]^2$ gives

$$Info_{T^-} \equiv IV_{T^-,T^+}^*(\nu, \hat{\theta}_T^-, \omega_T^-, T^-) = w_{2,T}^*(\nu, \hat{\theta}_T^-, T^-) - \left[w_{1,T}^*(\nu, \hat{\theta}_T^-, T^-) \right]^2, \tag{A.108}$$

where $w^*_{1,T}$ and $w^*_{2,T}$ denote the ν-conditional risk-neutral first and second moments of $\ln p(\hat{\theta}^+_T, T^+)$ evaluated at T^-. Numerically, we compute these two moments using the same ν-conditional boundary update as in Eq. (A.104), evaluate them at the simulated $\hat{\theta}^-_T$ and realized ν, and report $Info_{T^-}$ in monthly percentage squared units.

A.4 ICAPM

We prove the ICAPM relationship in Proposition 3 by re-expressing the agent's value function in terms of wealth and applying the standard wealth-form characterization of the risk premium.

Let W_t denote the agent's wealth. Since $V(\hat{\theta}_t, t, Y_t) = \frac{1}{1-\gamma} H(\hat{\theta}_t, t) Y_t^{1-\gamma}$ is homogeneous of degree $(1-\gamma)$ in Y_t and $C_t = Y_t$ in equilibrium, wealth scales linearly with consumption,

$$W_t = w(\hat{\theta}_t, t) Y_t. \tag{A.109}$$

The Epstein–Zin first-order condition equates the marginal benefit of consumption with the marginal value of wealth,

$$\bar{f}_Y(Y_t, V_t) = V_W. \tag{A.110}$$

Using $\bar{f}_Y = \rho H^{(1/\psi-\gamma)/(1-\gamma)} Y_t^{-\gamma}$ and $V_W = (\partial V/\partial Y_t)(\partial Y_t/\partial W_t) = H\, Y_t^{-\gamma}/w$, the FOC pins down w and gives

$$\frac{W_t}{Y_t} = \frac{1}{\rho} H(\hat{\theta}_t, t)^{\frac{1-1/\psi}{1-\gamma}}. \tag{A.111}$$

Inverting Eq. (A.111) and substituting into V expresses the value function in wealth form,

$$V(\hat{\theta}_t, t, Y_t) = \frac{1}{1-\gamma} \rho^{1-\gamma} H(\hat{\theta}_t, t)^{1/\psi} W_t^{1-\gamma}. \tag{A.112}$$

Direct differentiation gives

$$V_W = \rho^{1-\gamma} H^{1/\psi} W_t^{-\gamma}, \quad V_{WW} = -\gamma\, \rho^{1-\gamma} H^{1/\psi} W_t^{-\gamma-1}, \quad V_{W\theta} = \frac{1}{\psi} \rho^{1-\gamma} H^{1/\psi-1} H_\theta W_t^{-\gamma}, \tag{A.113}$$

so the relative-risk-aversion and hedging-demand coefficients reduce to

$$-\frac{W_t\, V_{WW}}{V_W} = \gamma, \qquad \frac{V_{W\theta}}{V_W} = \frac{1}{\psi} \frac{H_\theta(\hat{\theta}_t, t)}{H(\hat{\theta}_t, t)}. \tag{A.114}$$

For any traded return, no-arbitrage requires

$$\mathbb{E}_t\left[dR_t\right] - r(\hat{\theta}_t, t)dt = -Cov_t(dR_t, \frac{dM_t}{M_t}). \tag{A.115}$$

The Epstein–Zin stochastic discount factor satisfies $dM_t/M_t = d\bar{f}_Y/\bar{f}_Y + \bar{f}_V\, dt$ (Eq. (A.33)), and the FOC (A.110) identifies $\bar{f}_Y = V_W$ along the optimal path, so the diffusion of M_t coincides with that of V_W. Applying Ito's lemma to $V_W(\hat{\theta}_t, t, W_t)$ and substituting into Eq. (A.115) yields the wealth-form ICAPM,

$$\mathbb{E}_t\left[dR_t\right] - r(\hat{\theta}_t, t)dt = -\frac{W_t\, V_{WW}}{V_W}\, Cov_t(dR_t, \frac{dW_t}{W_t}) - \frac{V_{W\theta}}{V_W}\, Cov_t(dR_t, d\hat{\theta}_t). \tag{A.116}$$

Substituting the coefficients in Eq. (A.114) gives Eq. (28) of Proposition 3,

$$\mathbb{E}_t\left[dR_t\right] - r(\hat{\theta}_t, t)dt = \gamma\, Cov_t(dR_t, \frac{dW_t}{W_t}) - \frac{1}{\psi}\frac{H_\theta(\hat{\theta}_t, t)}{H(\hat{\theta}_t, t)} Cov_t(dR_t, d\hat{\theta}_t). \tag{A.117}$$

Eq. (A.117) holds for any traded return. Setting $dR_t = dW_t/W_t$ gives the equation for the return on aggregate wealth used in the ICAPM regressions of Section 6,

$$\mathbb{E}_t\left[\frac{dW_t}{W_t}\right] - r(\hat{\theta}_t, t)dt = \gamma\, Var_t(\frac{dW_t}{W_t}) - \frac{1}{\psi}\frac{H_\theta(\hat{\theta}_t, t)}{H(\hat{\theta}_t, t)} Cov_t(\frac{dW_t}{W_t}, d\hat{\theta}_t). \tag{A.118}$$

B Empirical Methodology and Robustness

We first describe the empirical methodology (Section B.1) and then present robustness analyses (Section B.2).

B.1 Empirical Methodology

High-Frequency Return and Variance In the empirical analysis, we use S&P 500 E-mini futures (CME ticker ES) at the daily frequency for return predictability regressions and at the 1-minute frequency to construct realized variance over multiple horizons. The high-frequency data are 1-minute ES tick data obtained from TickData.com, spanning 1997.09.10 through 2024.12.31. Because the ES contract trades almost 24 hours a day, we follow the CBOE trading-date convention and define the "trading day" from 18:00 ET of the previous calendar date through 17:59 ET of the current calendar date.

Let P_t denote the ES 1-minute close price at time t, let dt denote the high-frequency sampling interval at which intraday returns are measured, and let h denote the horizon, expressed in trading days, over which a log return or realized variance is defined. In our implementation dt is fixed at one minute, so that each trading day contains $1/dt = 1{,}440$ one-minute subintervals, and h takes the values $1, 2, 3, 4, 5, 21$, and 42 trading days, corresponding to one day, two days, three days, four days, one week, one month, and two months; the number of 1-minute subintervals that make up the h-day window is therefore $h/dt = 1{,}440\,h$.

We adopt the notation used in the main text: $R_{t,t+h}$ denotes the log return over the horizon $[t, t+h]$, $r_{t,t+h}$ denotes the cumulative log risk-free return over the same horizon, $R_{t,t+h} - r_{t,t+h}$ denotes the log excess return, and $RV_{t,t+h}(dt)$ denotes the realized variance constructed from squared log returns sampled at frequency dt. Over the short interval $[t, t+dt]$ during which dividends are negligible, the one-minute log return is $R_{t,t+dt} = \ln P_{t+dt} - \ln P_t$. The h-day log return is the sum of the 1-minute log returns inside the window; the h-day realized variance is the sum of their squares:

$$R_{t,t+h} = \sum_{j=1}^{h/dt} R_{t+(j-1)dt,\,t+jdt} = \ln P_{t+h} - \ln P_t, \qquad RV_{t,t+h}(dt) = \sum_{j=1}^{h/dt} \left[R_{t+(j-1)dt,\,t+jdt}\right]^2.$$

We therefore compute $R_{t,t+h}$ directly from consecutive 18:00 ET close prices and reserve the 1-minute series for the realized variance $RV_{t,t+h}(dt)$. The log excess return over the same

horizon is obtained by subtracting the cumulative log risk-free return:

$$R_{t,t+h} - r_{t,t+h} = R_{t,t+h} - \sum_{k=1}^{h} \ln(1 + r^f_{t+k}),$$

where r^f_{t+k} is the daily risk-free rate on trading day $t+k$ from Kenneth French's daily factor, so that $r_{t,t+h} \equiv \sum_{k=1}^{h} \ln(1 + r^f_{t+k})$. Log returns and log excess returns are reported in basis points, and the realized variance inherits the units of percent squared. In the predictive regressions, multi-day log excess returns and realized variances are further normalized by the horizon h, so that coefficients are directly comparable across h and retain the units of basis points of daily return and squared percent of daily realized variance, respectively.

Option-Implied Variance Construction We use S&P 500 options data from OptionMetrics for the period 1996.01 to 2024.12. We merge each option with the matched zero-coupon interest rate $r_{t,\tau}$ and projected dividend yield $q_{t,\tau}$ (using the closest available maturity), with both rates expressed in decimal form, and construct the forward price $F_{t,\tau} = S_t \exp\left[(r_{t,\tau} - q_{t,\tau})\tau/365\right]$. Moneyness is defined as K/S_t.

Following Bakshi, Kapadia, and Madan (2003) (BKM), we exclude options with zero open interest, zero or negative bids, non-positive bid-ask spreads, or mid-quotes (bid+ask)/2 below 3/8 (which we treat as illiquid). We further drop observations with missing or non-positive Black-Scholes implied volatilities. We limit the sample to out-of-the-money (OTM) options, defined as calls with $K/S_t > 1$ and puts with $K/S_t < 1$, as required for the model-free implied variance. We retain observations for which both OTM calls and OTM puts are available.

We define $IV_{t,\tau}$ as the time-t price of the τ-maturity quadratic payoff on the underlying stock, given by $IV_{t,\tau} \equiv e^{-r_{t,\tau}\tau}\mathbb{E}^{\mathbb{Q}}_t\left[(\ln R_{t,t+\tau})^2\right]$, where $r_{t,\tau}$ is the continuously compounded zero-coupon interest rate matched to maturity τ, and $\ln R_{t,t+\tau}$ is the log return over the interval of length τ. BKM show that $IV_{t,\tau}$ can be derived from the prices of OTM call and put options as follows:

$$IV_{t,\tau} = \int_{S_t}^{\infty} \frac{1 - \ln(K/S_t)}{K^2/2} C_t(\tau; K) dK + \int_0^{S_t} \frac{1 + \ln(S_t/K)}{K^2/2} P_t(\tau; K) dK, \tag{B.1}$$

where S_t is the price of the underlying stock, and $C_t(\tau; K)$ and $P_t(\tau; K)$ are call and put prices with maturity τ and strike K, respectively.

We compute $IV_{t,\tau}$ for each (date, maturity) pair. In theory, computing $IV_{t,\tau}$ requires a continuum of strike prices, but in practice we only have access to a discrete and finite set of them. Following Jiang and Tian (2005) and others, we discretize the integrals in Eq. (B.1) on a fixed grid of 1,001 strike points spanning moneyness $K/S_t \in [1/3, 3]$. Specifically, we place 501 equally spaced points on $[S_t/3, S_t]$ for the OTM put integrand and 501 equally spaced points on $[S_t, 3S_t]$ for the OTM call integrand, yielding 1,001 distinct strikes across the combined range $[S_t/3, 3S_t]$.

First, within each (date, maturity) group we linearly interpolate the OptionMetrics Black-Scholes implied volatilities across observed strikes. Second, for grid points outside the observed strike range we extrapolate by flat continuation: grid strikes above the largest (below the smallest) observed strike take the implied volatility of the largest (smallest) observed strike. Third, we calculate option prices at each of the 1,001 strikes using the formula of Black and Scholes (1973), evaluated with the interpolated/extrapolated implied volatility and the matched zero-coupon rate $r_{t,\tau}$. Fourth, we numerically evaluate the integrals in Eq. (B.1) as the discretized BKM volatility contract, following BKM Eqs. (7) and (38), to obtain $IV_{t,\tau}$ at each observed (date, maturity) pair.

The above procedure yields a daily panel of $IV_{t,\tau}$ at the maturities quoted in OptionMetrics, which vary across days. To construct a constant-maturity term structure, within each date we linearly interpolate and extrapolate the annualized implied variance $\sigma^2_{t,\tau} \equiv IV_{t,\tau}/\tau$ onto the target calendar days $\tau \in \{1, 2, \ldots, 31, 61, 91\}$. We then recover the τ-day implied variance as $IV_{t,\tau} = \tau\, \sigma^2_{t,\tau}$. Negative interpolated values, which occasionally arise on days with sparse option coverage, are replaced by the same-maturity implied variance from the most recent preceding trading day.

To address the measurement error issue in implied variance reduction, we construct a fixed-expiration measure: $\Delta IV_{t,\tau} \equiv IV_{t-k,\tau+k} - IV_{t,\tau}$, where $t-k$ is the closest preceding trading day on which option prices are observed and the lagged maturity $\tau + k$ is adjusted so that $IV_{t-k,\tau+k}$ and $IV_{t,\tau}$ refer to the same calendar expiration date. Observations for which the gap between t and the preceding trading day exceeds five calendar days are excluded.

B.2 Robustness Analysis

In this section, we present additional robustness analyses for the empirical evidence reported in Sections 5 and 6. In addition, we examine the distribution of implied variance reduction on announcement days in both the data and the model.

Announcement-Day Return and Variance Predictability We first present two robustness analyses of the announcement-day return and variance predictability results in Table 5 using fixed-expiration implied variance reductions and option maturities shorter than 30 days. Shorter-maturity options can help reduce measurement error in ΔIV_T. For example, an implied variance $IV_{T-1,T+30}$ spans not only the announcement day but also the following 30 non-announcement days. As a result, when $\Delta IV_T = IV_{T-1,T+30} - IV_{T,T+30}$ is used as a measure of informativeness, changes in beliefs about variance over the remaining period from T to $T+30$ may introduce measurement error. Using shorter-maturity options may reduce this problem, although such options are less widely available, especially in earlier sample periods. We show that our main empirical findings are robust across different maturity choices.

Specifically, we replace the squared VIX dependent variable with fixed-expiration implied variance reductions ΔIV_{30}, ΔIV_9, and ΔIV_7, where $\Delta IV_\tau = IV_{T-\delta,T+\tau} - IV_{T,T+\tau}$ for $\tau \in \{30, 9, 7\}$, and δ is the number of calendar days between the announcement day and the preceding trading day. Table B.1 uses only traded option prices to construct the informativeness measure $Info_{T-1}$, so its sample is limited to 2006.01–2024.12. The second robustness analysis, reported in Table B.2, extends the sample to 1997.09–2024.12 by allowing interpolated and extrapolated implied volatility in the construction of $Info_{T-1}$. Table B.2 reports predictability results for both the announcement-day return R_T^A and the fixed-expiration implied variance reduction ΔIV_τ at the 30-, 9-, and 7-day horizons.

Overall, both analyses confirm the patterns documented in Table 5: our informativeness measure positively predicts implied variance reduction on FOMC announcement days, with regression coefficients close to 1, and has significantly positive predictive power for S&P 500 returns on FOMC announcement days.

Post-Information-Event Return and Variance Predictability In this section, we present several robustness analyses for the post-information-event return and variance pre-

Table B.1: Implied Variance Reduction Predictability by Informativeness (Fixed-Expiration)

	ΔIV_{30}	ΔIV_9	ΔIV_7
$Info_{T-1}$	1.61	1.12	1.07
	(2.80)	(2.94)	(2.96)
R^2 (%)	36.84	57.34	61.71

This table reports a robustness check for Table 5, replacing the squared VIX dependent variable with fixed-expiration implied variance reductions $\Delta IV_{30} = IV_{T-\delta,T+30} - IV_{T,T+30}$, $\Delta IV_9 = IV_{T-\delta,T+9} - IV_{T,T+9}$, and $\Delta IV_7 = IV_{T-\delta,T+7} - IV_{T,T+7}$. Here, $IV_{T-\delta,T+\tau}$ is the option-implied variance measured on the trading day immediately preceding the announcement for options expiring on date $T+\tau$, $IV_{T,T+\tau}$ is the corresponding option-implied variance measured on the announcement day, and δ is the number of calendar days between the announcement day and the preceding trading day. Observations with $\delta > 5$ are excluded. R_T^A is the close-to-close log return on S&P 500 E-mini futures on the FOMC announcement day, measured in daily basis points. Informativeness $Info_{T-1}$ is constructed from option-implied variance using actual traded options with maturities of 1 to 30 calendar days on the trading day preceding each FOMC announcement, ensuring that each option spans at most one scheduled FOMC meeting. $Info_{T-1}$ and the ΔIV measures are expressed in monthly percentage squared units. Newey-West t-statistics with 4 lags are reported in parentheses. R^2 is from OLS. The sample spans 2006.01–2024.12 and covers 149 FOMC announcements.

Table B.2: Announcement Return and Implied Variance Reduction Predictability by Informativeness (Extended Sample)

	R_T^A	ΔIV_T	ΔIV_{30}	ΔIV_9	ΔIV_7
$Info_{T-1}$	7.56	0.96	1.20	0.97	0.95
	(4.29)	(2.46)	(2.15)	(3.54)	(3.82)
R^2 (%)	10.42	23.86	27.66	58.60	65.31

This table reports a robustness check for Table 5, extending the sample to 1997.09–2024.12 by constructing $Info_{T-1}$ from interpolated and extrapolated implied variance. R_T^A is the close-to-close log return on S&P 500 E-mini futures on the FOMC announcement day, measured in daily basis points. The fixed-expiration implied variance reductions ΔIV_{30}, ΔIV_9, and ΔIV_7 use the same definitions as in Table B.1, where δ is the number of calendar days between the announcement day and the preceding trading day. Observations with $\delta > 5$ are excluded. $Info_{T-1}$ and the ΔIV measures are expressed in monthly percentage squared units. Newey-West t-statistics with 4 lags are reported in parentheses. R^2 is from OLS. The sample spans 1997.09–2024.12 and covers 218 FOMC announcements.

dictability regressions in Section 5. First, we provide a robustness check for Table 6 in the main text. Specifically, Table B.3 reports results using a fixed-expiration measure of ΔIV_T, defined as $\Delta IV_T = IV_{T-\delta,T+\tau} - IV_{T,T+\tau}$ for $\tau \in \{30, 9, 7\}$ calendar days, where δ is the

number of calendar days between the announcement day and the preceding trading day.

The results are similar to those in Table 6: the informativeness of the event, as measured by ΔIV_T, has significantly negative predictive power for realized variance and realized returns following information events.

Our second robustness analysis restricts the definition of information events to FOMC announcements only, excluding non-FOMC-related stock market jumps. In Table B.4, we report post-FOMC return and variance predictability regressions, (26) and (27), under several specifications. Panel A presents the benchmark regression, identical to that in Table 6, except that information events are defined using only FOMC announcement days. Panel B adds year fixed effects. Panels C and D report regressions with a richer set of control variables.

The negative relationship between the informativeness of FOMC announcements and post-FOMC realized variance and realized returns is identified under the assumption that total variance is constant and uncorrelated with the informativeness of announcements. In practice, both total variance and the informativeness of announcements may depend on macroeconomic conditions. For example, the informativeness of FOMC announcements may reflect an endogenous response of monetary policy to macroeconomic conditions that also affect stock market variance. To address this concern, Panel C reports return and variance predictability regressions that include macroeconomic variables to which FOMC announcements may respond. Following Bauer and Swanson (2023), we include the six macroeconomic and financial variables from Table 1 of their paper as control variables. In Panel D, we further include a measure of long-term variance, defined as the annualized forward implied variance between 60 and 90 calendar days. Overall, the coefficient on the informativeness measure remains negative and statistically significant across most specifications.

In Table B.5, we present an additional robustness analysis focusing on the FOMC announcement subsample and using a fixed-expiration construction of ΔIV_T as the measure of informativeness. Specifically, ΔIV_T is defined as $\Delta IV_T = IV_{T-\delta,T+\tau} - IV_{T,T+\tau}$, where δ is the number of calendar days between the announcement day and the preceding trading day. Panel A uses $\tau = 30$, Panel B uses $\tau = 9$, and Panel C uses $\tau = 7$. The coefficient on this alternative informativeness measure remains negative and statistically significant across all three horizons.

Table B.3: Variance and Excess Return Predictability by IV Reduction (Fixed-Expiration)

h	1	2	3	4	5	21	42
Panel A: 30-Day Fixed-Expiration							
$RV_{t,t+h}$	–0.08	–0.07	–0.06	–0.06	–0.06	–0.03	–0.02
	(–3.61)	(–4.14)	(–5.19)	(–4.77)	(–5.24)	(–4.93)	(–4.11)
R^2 (%)	66.03	66.25	63.54	60.39	59.61	40.48	36.03
$R_{t,t+h} - r_{t,t+h}$	–1.29	–0.70	–0.36	–0.34	–0.28	–0.09	–0.04
	(–3.14)	(–2.89)	(–1.78)	(–2.06)	(–1.75)	(–2.87)	(–2.80)
R^2 (%)	5.84	3.14	1.12	1.78	1.18	0.78	0.33
Panel B: 9-Day Fixed-Expiration							
$RV_{t,t+h}$	–0.13	–0.11	–0.11	–0.10	–0.10	–0.04	–0.03
	(–3.26)	(–3.87)	(–5.30)	(–5.08)	(–6.08)	(–5.20)	(–4.30)
R^2 (%)	64.56	65.28	63.48	60.16	59.24	39.34	34.93
$R_{t,t+h} - r_{t,t+h}$	–2.10	–0.89	–0.43	–0.52	–0.44	–0.12	–0.05
	(–2.48)	(–2.24)	(–1.25)	(–1.89)	(–1.88)	(–2.59)	(–2.83)
R^2 (%)	5.12	1.58	0.50	1.43	1.00	0.75	0.46
Panel C: 7-Day Fixed-Expiration							
$RV_{t,t+h}$	–0.14	–0.12	–0.12	–0.10	–0.11	–0.05	–0.03
	(–2.71)	(–3.24)	(–4.49)	(–4.30)	(–5.38)	(–4.93)	(–4.02)
R^2 (%)	63.43	64.01	62.49	59.19	58.32	38.75	34.43
$R_{t,t+h} - r_{t,t+h}$	–2.40	–0.94	–0.46	–0.55	–0.49	–0.13	–0.06
	(–2.37)	(–2.08)	(–1.15)	(–1.78)	(–1.85)	(–2.33)	(–2.70)
R^2 (%)	4.94	1.31	0.45	1.26	0.94	0.69	0.46

This table reports a robustness check for Table 6, replacing the squared VIX drop with fixed-expiration implied variance reductions: Panel A uses $\Delta IV_t = IV_{t-\delta,t+30} - IV_{t,t+30}$; Panel B uses $\Delta IV_t = IV_{t-\delta,t+9} - IV_{t,t+9}$; and Panel C uses $\Delta IV_t = IV_{t-\delta,t+7} - IV_{t,t+7}$, where $IV_{t-\delta,t+\tau}$ is the option-implied variance measured on the trading day immediately preceding the information event for options expiring on date $t+\tau$, $IV_{t,t+\tau}$ is the corresponding option-implied variance measured on the event day, and δ is the number of calendar days between the event day and the preceding trading day. Observations with $\delta > 5$ are excluded. $R_{t,t+h}$ is the cumulative log return on S&P 500 E-mini futures from t to $t+h$, so that $R_{t,t+h} - r_{t,t+h}$ is the cumulative log excess return, where $r_{t,t+h}$ is the cumulative log risk-free rate. Realized variance $RV_{t,t+h}$ is computed over the same window as the sum of squared 1-minute log futures returns. Columns report horizons $h = 1, 2, 3, 4, 5, 21$, and 42 trading days. Returns are measured in daily basis points, realized variances in daily percentage squared units, and ΔIV_t in monthly percentage squared units. All specifications include year fixed effects, and Newey-West t-statistics with lag length h are reported in parentheses. R^2 is from the corresponding OLS regressions without fixed effects. The sample combines FOMC announcement days and news-related jump days over 1997.09–2024.12.

Table B.4: Variance and Excess Return Predictability by IV Reduction: FOMC

h	1	2	3	4	5	21	42
Panel A: No FE, No Controls							
$RV_{t,t+h}$	–0.03	–0.03	–0.02	–0.02	–0.02	–0.05	–0.03
	(–4.17)	(–3.44)	(–2.26)	(–1.84)	(–1.82)	(–2.42)	(–1.91)
R^2 (%)	79.97	81.02	73.70	64.50	62.20	68.20	44.89
$R_{t,t+h} - r_{t,t+h}$	–2.63	–0.97	–1.07	–1.01	–0.63	–0.03	–0.14
	(–2.25)	(–1.29)	(–2.77)	(–2.58)	(–1.98)	(–0.25)	(–1.51)
R^2 (%)	7.47	1.25	3.39	5.38	1.82	5.71	3.06
Panel B: Year FE, No Controls							
$RV_{t,t+h}$	–0.04	–0.03	–0.03	–0.03	–0.02	–0.05	–0.03
	(–4.28)	(–3.87)	(–2.70)	(–2.33)	(–2.47)	(–2.60)	(–2.52)
R^2 (%)	80.10	81.23	74.71	65.41	63.04	68.64	44.93
$R_{t,t+h} - r_{t,t+h}$	–2.55	–0.81	–0.98	–0.94	–0.59	–0.05	–0.16
	(–2.16)	(–1.06)	(–2.31)	(–1.97)	(–1.71)	(–0.38)	(–1.57)
R^2 (%)	7.64	1.03	3.26	5.12	1.34	5.67	2.93
Panel C: Year FE + Full MP Controls							
$RV_{t,t+h}$	–0.04	–0.04	–0.03	–0.03	–0.03	–0.05	–0.03
	(–5.16)	(–4.65)	(–3.38)	(–3.03)	(–3.40)	(–2.99)	(–4.22)
R^2 (%)	84.79	86.06	81.48	73.27	71.14	71.64	48.09
$R_{t,t+h} - r_{t,t+h}$	–2.80	–1.09	–1.29	–1.18	–0.77	–0.15	–0.22
	(–2.22)	(–1.31)	(–2.84)	(–2.43)	(–1.98)	(–0.87)	(–3.71)
R^2 (%)	18.77	7.70	7.02	7.82	3.37	10.28	5.63
Panel D: Year FE + Full MP Controls + Long-Term Variance							
$RV_{t,t+h}$	–0.03	–0.03	–0.03	–0.02	–0.02	–0.05	–0.05
	(–3.28)	(–3.97)	(–3.40)	(–2.57)	(–2.57)	(–2.02)	(–4.35)
R^2 (%)	87.36	87.24	83.10	75.58	74.28	71.89	48.14
$R_{t,t+h} - r_{t,t+h}$	–2.39	–1.40	–1.92	–1.49	–1.22	0.02	–0.14
	(–2.12)	(–1.58)	(–3.12)	(–3.18)	(–3.25)	(0.10)	(–2.07)
R^2 (%)	18.90	8.77	8.51	8.44	4.86	13.68	7.73

This table reports a robustness check for Table 6, restricting information events to scheduled FOMC announcements only and excluding non-FOMC-related stock market jumps. All variables, horizons, and units are defined as in Table 6. Specifications differ across panels. Panel A includes no fixed effects or additional controls. Panel B adds year fixed effects. Panel C further adds the orthogonalized monetary policy surprise MPS_ORTH from Bauer and Swanson (2023) together with the six macroeconomic and financial controls from Table 1 of Bauer and Swanson (2023): nonfarm payroll surprise, 12-month payroll growth, the 3-month S&P 500 return, the 3-month change in the yield-curve slope, the 3-month change in the Bloomberg commodity index, and Treasury yield skewness. Panel D further adds a long-term variance control, defined as the annualized forward implied variance between 60 and 90 calendar days, $(90V_{90} - 60V_{60})/30$, where V_{60} and V_{90} are the annualized implied variances at 60- and 90-day maturities. Newey-West t-statistics with lag length h are reported in parentheses. R^2 is from the corresponding OLS regressions without fixed effects. Panel A spans 1997.09–2024.12, while Panels B–D span 1997.09–2023.12 because of the availability of the monetary policy controls.

Table B.5: Variance and Excess Return Predictability by IV Reduction: Fixed-Expiration (FOMC Sample)

h	1	2	3	4	5	21	42
Panel A: 30-Day Fixed-Expiration							
$RV_{t,t+h}$	–0.03	–0.03	–0.02	–0.02	–0.02	–0.04	–0.03
	(–4.37)	(–3.32)	(–2.22)	(–2.01)	(–2.39)	(–4.88)	(–3.27)
R^2 (%)	83.88	84.95	80.26	72.14	70.01	72.32	48.17
$R_{t,t+h} - r_{t,t+h}$	–2.71	–1.32	–1.32	–1.15	–0.77	–0.17	–0.18
	(–2.84)	(–2.20)	(–4.05)	(–2.95)	(–2.33)	(–1.05)	(–4.57)
R^2 (%)	19.97	9.34	8.31	8.77	3.90	10.28	5.29
Panel B: 9-Day Fixed-Expiration							
$RV_{t,t+h}$	–0.05	–0.05	–0.04	–0.03	–0.03	–0.10	–0.06
	(–3.03)	(–3.38)	(–3.21)	(–3.19)	(–3.79)	(–5.65)	(–5.38)
R^2 (%)	82.73	84.38	80.01	72.01	69.85	73.44	49.06
$R_{t,t+h} - r_{t,t+h}$	–3.54	–1.33	–2.05	–1.65	–1.15	0.02	–0.25
	(–1.58)	(–1.02)	(–3.17)	(–2.09)	(–1.89)	(0.11)	(–2.73)
R^2 (%)	17.13	6.94	6.82	6.59	2.95	10.42	5.00
Panel C: 7-Day Fixed-Expiration							
$RV_{t,t+h}$	–0.05	–0.05	–0.04	–0.04	–0.04	–0.11	–0.07
	(–2.60)	(–3.11)	(–3.30)	(–3.40)	(–3.98)	(–5.58)	(–4.69)
R^2 (%)	82.47	84.19	79.88	71.92	69.77	73.63	49.22
$R_{t,t+h} - r_{t,t+h}$	–3.79	–1.34	–2.27	–1.75	–1.18	0.09	–0.26
	(–1.52)	(–0.92)	(–3.16)	(–2.05)	(–1.79)	(0.40)	(–2.74)
R^2 (%)	16.98	6.78	6.76	6.33	2.75	10.58	4.93

This table reports a robustness check for Panel C of Table B.4, restricting information events to scheduled FOMC announcements and replacing the squared VIX drop with fixed-expiration implied variance reductions. Panel A uses $\Delta IV_t = IV_{t-\delta,t+30} - IV_{t,t+30}$, Panel B uses $\Delta IV_t = IV_{t-\delta,t+9} - IV_{t,t+9}$, and Panel C uses $\Delta IV_t = IV_{t-\delta,t+7} - IV_{t,t+7}$, where δ is the number of calendar days between the announcement day and the preceding trading day. $R_{t,t+h}$ is the cumulative log return on S&P 500 E-mini futures from t to $t+h$, and $R_{t,t+h} - r_{t,t+h}$ is the cumulative log excess return. Realized variance $RV_{t,t+h}$ is the sum of squared 1-minute log futures returns over the same window. Returns are measured in daily basis points, and realized variances are measured in daily percentage squared units. All specifications include year fixed effects, the orthogonalized monetary policy surprise MPS_ORTH from Bauer and Swanson (2023), and the six macroeconomic and financial controls from Table 1 of Bauer and Swanson (2023). Newey-West t-statistics with lag length h are reported in parentheses. R^2 is from the corresponding OLS regressions without fixed effects. The sample spans 1997.09–2023.12 because of the availability of the monetary policy controls.

Realized Variance and Expected Returns In this section, we present the monthly counterpart to the weekly return and variance predictability regressions reported in Table 8. As shown in Table B.6, the patterns are similar to those in the weekly regressions. Overall, realized variance is strongly positively autocorrelated, but this autocorrelation is significantly weaker following information-event months. The interaction coefficient is –0.57 with a t-statistic of –2.64. Similarly, relative to non-information-event months, realized variance has significantly more negative predictive power for future realized returns: $\gamma_{\text{info}} = -15.87$ ($t = -2.13$).

Table B.6: Realized Variance and Excess Return Predictability with Information-Event Interaction (Monthly)

	$RV_{t-h,t}$	$RV_{t-h,t} \times \mathbf{1}_{\text{info}}$	$\mathbf{1}_{\text{info}}$	R^2 (%)
$RV_{t,t+h}$	0.95	–0.57	0.00	18.84
	(5.52)	(–2.64)	(2.15)	
	$\widehat{RV}_{t,t+h}$	$\widehat{RV}_{t,t+h} \times \mathbf{1}_{\text{info}}$	$\mathbf{1}_{\text{info}}$	R^2 (%)
$R_{t,t+h} - r_{t,t+h}$	15.00	–15.87	0.03	1.98
	(2.10)	(–2.13)	(2.40)	

This table reports a robustness check for Table 8, estimating by OLS the variance predictability regression (Panel A, Eq. (29)) and the excess return predictability regression (Panel B, Eq. (30)) at monthly frequency ($h = 30$). $RV_{t,t+h}$ is next month's realized variance, and $RV_{t-h,t}$ is the current month's realized variance; both are measured as the sum of squared daily log returns within the month. $R_{t,t+h} - r_{t,t+h}$ is the excess return over the next month, and $\widehat{RV}_{t,t+h}$ is the fitted value from the first-stage OLS regression of $RV_{t,t+h}$ on $RV_{t-h,t}$. The dummy $\mathbf{1}_{\text{info}}$ equals one if the month contains an information event, defined as either a scheduled FOMC announcement or a news-related market jump. All regressions include the ICAPM hedging-demand controls from Guo and Whitelaw (2006): the log dividend-price ratio, CAY, and the risk-free rate (corresponding coefficients are not reported). The sample spans 1952–2024 and contains 873 months, reflecting the availability of the CAY series. Newey-West t-statistics with 6 lags are reported in parentheses.

Expected Variance and Expected Returns In this section, we present the results of the ICAPM regressions (31) and (32) using monthly data. As in the weekly regressions reported in Table 9, the estimate of γ is positive in Table B.7, although its statistical significance is weaker. This likely reflects the fact that most months contain information events, leaving limited cross-period heterogeneity in informativeness to distinguish information months from non-information months. In particular, once scheduled FOMC announcements become

available in 1994, roughly 77% of months contain at least one information event, compared with only about 26% of weeks over the same post-1994 period. This sharply reduces the variation available to identify the information channel at the monthly frequency.

Table B.7: ICAPM Risk-Return Tradeoff: System GMM Estimates (Monthly)

Panel A: Variance predictability					*Panel B: Return predictability*		
	IV_t	$C\Delta IV_t$	$RV_{t-h,t}$	$R^2(\%)$		γ	$R^2(\%)$
$RV_{t,t+h}$	0.59	0.09	0.20	33.38	$R_{t,t+h} - r_{t,t+h}$	6.75	1.86
	(2.77)	(0.68)	(0.93)			(1.34)	

This table reports a robustness check for Table 9, estimating jointly by system GMM the variance equation (31) and the return equation (32) at the monthly frequency ($h = 30$), with a single γ imposed across both the IV and $C\Delta IV$ channels, yielding one overidentifying restriction. $RV_{t,t+h}$ is next month's realized variance, and $RV_{t-h,t}$ is the current month's realized variance, both measured as the sum of squared daily log returns within the month. $R_{t,t+h} - r_{t,t+h}$ is the excess return over the next month. $IV_t = \text{VIX}_t^2$ is the squared VIX index at the end of month t; $C\Delta IV_t$ is the cumulative implied variance reduction across information-event days in month t, equal to zero otherwise. Both are measured in monthly decimal variance units. Panel A reports the coefficients ω_1 on IV_t, $C\Delta IV_t$, and $RV_{t-h,t}$. Panel B reports the coefficient γ. Constants and the remaining hedging-demand coefficients on $RV_{t-h,t}$, log dividend yield, CAY, and the risk-free rate are estimated but not reported. R^2 is the squared correlation between actual and fitted values. The system is estimated by two-step GMM with an identity initial weighting matrix over 1990.01–2024.12, reflecting the availability of the VIX index. Newey-West t-statistics with 6 lags are reported in parentheses.

Distribution of Implied Variance Reductions Although our calibration is fairly simple, it matches a key feature of implied variance reduction in the data quite well: implied variance typically drops right after announcements but occasionally *increases*. In Table B.8, we report percentiles of ΔIV_T in both the data and the model. Consistent with the data, our model generates a positive average reduction in implied variance (see Table 4), while also producing negative values at the fifth percentile, reflecting occasional increases in implied variance after announcements. In our model, implied variance is primarily determined by investors' posterior variance of the latent variable θ_t. Below, we illustrate this pattern using the variance decomposition identity.

First, a positive average reduction in implied variance after announcements is a general implication of Bayesian updating. Because $\text{Var}\left[\mathbb{E}\left(\theta_T|s_t\right)\right] \geq 0$, Eq. (1) implies that $\text{Var}\left[\theta_T\right] \geq \mathbb{E}\left[\text{Var}\left(\theta_T|s_t\right)\right]$. That is, *on average*, the conditional variance must decline after

the arrival of new information. Second, the possibility of an increase in implied variance after an announcement requires a deviation from a Gaussian distribution. Under the Kalman filter with a Gaussian distribution, $\mathrm{Var}(\theta_T|s_t)$ is deterministic and independent of the specific realization of s_t. In this case, $\mathrm{Var}[\theta_T] \geq \mathrm{Var}(\theta_T|s_t)$ holds for every realization, so implied variance can only decline after an announcement. In general, however, the inequality $\mathrm{Var}[\theta_T] \geq \mathbb{E}[\mathrm{Var}(\theta_T|s_t)]$ allows the possibility of $\mathrm{Var}[\theta_T] < \mathrm{Var}(\theta_T|s_t)$ for some realizations of s_t. In our setup with a two-state Markov chain, signals are incorrect with probability $1-\nu$ (see Eqs. (11) and (12)). A surprise signal far from investors' prior beliefs about θ_t may trigger an increase in the posterior variance and therefore an increase in the implied variance of stock returns.

Table B.8: Distribution of Implied Variance Reductions

	Q5	Q25	Q50	Q75	Q95
Data (VIX^2)	–5.60	–0.36	1.16	4.18	12.47
Data (fixed-exp.)	–3.92	0.28	2.35	6.15	17.69
Model	–1.43	0.06	0.97	4.54	24.44

This table reports percentiles of implied variance reduction on scheduled FOMC announcement days in the data and in the model. In the data, the implied variance reduction, ΔIV_T, is defined as the squared VIX on the day before the announcement minus the squared VIX on the announcement day, measured in monthly percentage-squared units. The sample period is 1994.09–2024.12. The second row reports a fixed-expiration measure of ΔIV_T over 1996.01–2024.12. In the model, ΔIV_T is the reduction in 30-day implied variance on announcement days.

The second row of Table B.8 reports the same percentiles for a fixed-expiration measure of implied variance reduction, defined as $\Delta IV_T = IV_{T-\delta,T+30} - IV_{T,T+30}$, where δ is the number of calendar days between the announcement day and the preceding trading day. This alternative measure exhibits a similar pattern: its median is positive (2.35), while its fifth percentile is negative, again indicating that implied variance rises after FOMC announcements in a nontrivial fraction of the sample.

C Numerical Solutions

In this section, we first present the policy functions used to plot the figures in Section C.1. In Section C.2, we describe the finite-difference method we use to solve our dynamic model.

C.1 Policy Functions

In all of the computations below, we plot policy functions for different choices of $\nu \in [0.5, 1]$. We assume that $\hat{\theta}_T^- = \bar{\theta} = \frac{\lambda_L \theta_H + \lambda_H \theta_L}{\lambda_L + \lambda_H}$. Given $\hat{\theta}_T^- = \bar{\theta}$ and a value of ν, the distribution of $\hat{\theta}_T^+$ is given by Eq. (14), or equivalently, Eqs. (A.13) to (A.16).

Announcement Premium Define the return earned upon the announcement as $R^A = \frac{p(\hat{\theta}_T^+, 0)}{p(\nu, \hat{\theta}_T^-, 0)}$. For a given ν, the announcement premium in the model is

$$\mathbb{E}\left[R^A \,\middle|\, \nu, \hat{\theta}_T^-, T^-\right] - 1 = \frac{\mathbb{E}\left[p(\hat{\theta}_T^+, T^+) \,\middle|\, \nu, \hat{\theta}_T^-, T^-\right]}{p(\nu, \hat{\theta}_T^-, T^-)} - 1 = \frac{h_{s_H} p(\hat{\theta}_{s_H}^+, T^+) + h_{s_L} p(\hat{\theta}_{s_L}^+, T^+)}{p(\nu, \hat{\theta}_T^-, T^-)} - 1, \tag{C.1}$$

where $p(\nu, \hat{\theta}_T^-, T^-)$ is defined in Eq. (A.38).

Implied Variance Reduction upon the Announcement For the policy function plots, we report the ν-conditional risk-neutral variance of the announcement-induced log price change. Since dividends are continuous at the announcement, the announcement-period log return is driven only by the jump in the price-to-dividend ratio: $\ln p(\hat{\theta}_T^+, T^+) - \ln p(\nu, \hat{\theta}_T^-, T^-)$. We therefore have

$$\begin{aligned} \Delta IV_T^* &= \mathrm{Var}^*\left[\ln p(\hat{\theta}_T^+, T^+) - \ln p(\nu, \hat{\theta}_T^-, T^-) \,\middle|\, \nu, \hat{\theta}_T^-, T^-\right] = \mathrm{Var}^*\left[\ln p(\hat{\theta}_T^+, T^+) \,\middle|\, \nu, \hat{\theta}_T^-, T^-\right] \\ &= \mathbb{E}^*\left[(\ln p(\hat{\theta}_T^+, T^+))^2 \,\middle|\, \nu, \hat{\theta}_T^-, T^-\right] - (\mathbb{E}^*\left[\ln p(\hat{\theta}_T^+, T^+) \,\middle|\, \nu, \hat{\theta}_T^-, T^-\right])^2, \end{aligned} \tag{C.2}$$

where $\mathbb{E}^*\left[\cdot \,\middle|\, \nu, \hat{\theta}_T^-, T^-\right]$ is the ν-conditional risk-neutral expectation defined in Eq. (A.103), with explicit form in Eq. (A.104).

Post-Announcement 30-Day Implied Variance For the policy function plots, we also report the expected 30-day implied variance after the announcement under the risk-neutral

measure:

$$IV^*_{T^+,T+\Delta}(\hat{\theta}^+_T, \omega^+_T, T^+) = \mathrm{Var}^* \left[\ln p(\hat{\theta}_{T+\Delta}, T+\Delta) + \ln D_{T+\Delta} \,\middle|\, \hat{\theta}^+_T, \omega^+_T, T^+ \right]. \tag{C.3}$$

where $\Delta = \frac{1}{12}$ for a monthly return horizon. Note that $IV^*_{T^+,\tau}$ is a random variable that depends on the realization of $\hat{\theta}^+_T$. This is the same as the risk-neutral implied variance defined in Eq. (A.102). To obtain a single number for each ν in the policy function plot, we average over announcement realizations under the ν-conditional risk-neutral expectation $\mathbb{E}^*$ from Eq. (A.104):

$$\begin{aligned} &\mathbb{E}^* \left[IV^*_{T^+,T+\Delta}(\hat{\theta}^+_T, \omega^+_T, T^+) \,\middle|\, \nu, \hat{\theta}^-_T, \omega^-_T, T^- \right] \\ &= \frac{h_{s_H} H(\hat{\theta}^+_{s_H}, 0)^B IV^*_{T^+,T+\Delta}(\hat{\theta}^+_{s_H}, \omega^+_T, T^+) + h_{s_L} H(\hat{\theta}^+_{s_L}, 0)^B IV^*_{T^+,T+\Delta}(\hat{\theta}^+_{s_L}, \omega^+_T, T^+)}{h_{s_H} H(\hat{\theta}^+_{s_H}, 0)^B + h_{s_L} H(\hat{\theta}^+_{s_L}, 0)^B}. \end{aligned} \tag{C.4}$$

Post-Announcement 30-Day Expected Return Let $a_1(\hat{\theta}^+_T, T^+) \equiv \mathbb{E}\left[\delta(T+\Delta) - \delta(T^+) \,\middle|\, \hat{\theta}^+_T, T^+ \right]$ and $g(\omega^+_T, T^+) \equiv \mathbb{E}\left[\int_{T^+}^{T+\Delta} \omega_s^2 \, ds \,\middle|\, \omega^+_T, T^+ \right]$ denote the physical-measure counterparts of the risk-neutral a_1^* and g in Section A.3, obtained by replacing $\mu^*_{\delta,t}$ with $\mu_{\delta,t}$ in the corresponding PDEs. The expected 30-day log return after the announcement under the physical measure is

$$ER_{T,T+\Delta}(\hat{\theta}^+_T, T^+) = \mathbb{E}\left[\ln \left[\frac{p(\hat{\theta}_{T+\Delta}, T+\Delta) D_{T+\Delta} + \int_{T^+}^{T+\Delta} D_s \, ds}{p(\hat{\theta}^+_T, T^+) D_{T^+}} \right] \,\middle|\, \hat{\theta}^+_T, T^+ \right]. \tag{C.5}$$

We simplify this in three steps. First, apply the right-endpoint approximation $\int_{T^+}^{T+\Delta} D_s \, ds \approx D_{T+\Delta}\Delta$ and factor:

$$ER_{T,T+\Delta}(\hat{\theta}^+_T, T^+) \approx \mathbb{E}\left[\ln \left[\frac{D_{T+\Delta}\big(p(\hat{\theta}_{T+\Delta}, T+\Delta) + \Delta\big)}{p(\hat{\theta}^+_T, T^+) D_{T^+}} \right] \,\middle|\, \hat{\theta}^+_T, T^+ \right].$$

Second, split the log into the price piece, the dividend ratio piece, and a constant:

$$\begin{aligned} ER_{T,T+\Delta}(\hat{\theta}^+_T, T^+) \;\approx\; & \underbrace{\mathbb{E}\left[\ln\big[p(\hat{\theta}_{T+\Delta}, T+\Delta) + \Delta \big] \,\middle|\, \hat{\theta}^+_T, T^+ \right]}_{\equiv w_3(\hat{\theta}^+_T, T^+)} \\ & - \ln p(\hat{\theta}^+_T, T^+) + \mathbb{E}\left[\ln \frac{D_{T+\Delta}}{D_{T^+}} \,\middle|\, \hat{\theta}^+_T, \omega^+_T, T^+ \right]. \end{aligned}$$

Third, evaluate $\mathbb{E}\left[\ln(D_{T+\Delta}/D_{T^+})\middle|\hat{\theta}_T^+, \omega_T^+, T^+\right]$. From Eq. (A.58) (with τ replaced by $T+\Delta$),

$$\ln \frac{D_{T+\Delta}}{D_{T^+}} = \delta(T+\Delta) - \delta(T^+) - \tfrac{1}{2}\int_{T^+}^{T+\Delta} \omega_s^2\, ds + \int_{T^+}^{T+\Delta} \omega_s\, dB_{\omega,s}. \tag{C.6}$$

Taking the conditional expectation and using the zero-mean property of the Ito integral $\mathbb{E}[\int_{T^+}^{T+\Delta} \omega_s\, dB_{\omega,s}|\cdot] = 0$:

$$\mathbb{E}\left[\ln \frac{D_{T+\Delta}}{D_{T^+}} \,\middle|\, \hat{\theta}_T^+, \omega_T^+, T^+\right] = \underbrace{\mathbb{E}\left[\delta(T+\Delta) - \delta(T^+) \,\middle|\, \hat{\theta}_T^+, T^+\right]}_{=a_1(\hat{\theta}_T^+, T^+)} - \tfrac{1}{2}\underbrace{\mathbb{E}\left[\int_{T^+}^{T+\Delta} \omega_s^2\, ds \,\middle|\, \omega_T^+, T^+\right]}_{=g(\omega_T^+, T^+)}. \tag{C.7}$$

Combining,

$$ER_{T,T+\Delta}(\hat{\theta}_T^+, \omega_T^+, T^+) \approx w_3(\hat{\theta}_T^+, T^+) - \ln p(\hat{\theta}_T^+, T^+) + a_1(\hat{\theta}_T^+, T^+) - \tfrac{1}{2} g(\omega_T^+, T^+), \tag{C.8}$$

where $w_3(\hat{\theta}_T^+, T^+)$ is computed by the same backward procedure as the risk-neutral w_1^* in Section A.3, with the physical generator $\mathcal{L}$ in place of $\mathcal{L}^*$ and terminal condition $w_3(\hat{\theta}_{T+\Delta}, T+\Delta) = \ln\left[p(\hat{\theta}_{T+\Delta}, T+\Delta) + \Delta\right]$.

The average expected return across announcement realizations under the physical ν-conditional probabilities h_{s_H}, h_{s_L} is

$$\mathbb{E}\left[ER_{T,T+\Delta}(\hat{\theta}_T^+, \omega_T^+, T^+) \,\middle|\, \nu, \hat{\theta}_T^-, T^-\right] = h_{s_H} ER_{T,T+\Delta}(\hat{\theta}_{s_H}^+, T^+) + h_{s_L} ER_{T,T+\Delta}(\hat{\theta}_{s_L}^+, T^+). \tag{C.9}$$

For the policy function plot, both 30-day quantities still depend on ω_T^+ (through g and y in $IV^*_{T^+,T+\Delta}$ and through $-g/2$ in $ER_{T,T+\Delta}$). To obtain a single number for each ν, we further integrate over ω_T^+ under its stationary distribution, $\Pr(\omega_t = \omega_H) = \kappa_L/(\kappa_H + \kappa_L)$.

C.2 Finite Difference Method

We describe the numerical methods we use to solve our dynamic model. We first explain how we compute daily returns and realized variance from simulated sample paths. We then present the finite-difference method we use to solve for the value function, the price-to-dividend ratio, and the implied variance.

Computing Returns The return earned from t to $t+\Delta$ is defined as

$$R_{t,t+\Delta} = \frac{p(\hat{\theta}_{t+\Delta}, t+\Delta)D_{t+\Delta} + \int_t^{t+\Delta} D_s ds}{p(\hat{\theta}_t, t)D_t}.$$

Numerically, with $\Delta = 1/360$ for a daily return horizon, we divide numerator and denominator by D_t and approximate the dividend ratio $D_{t+\Delta}/D_t \approx 1 + dD_t/D_t$ and the dividend integral $\int_t^{t+\Delta}(D_s/D_t)\,ds$ by the trapezoidal rule:

$$\begin{aligned} R_{t,t+\Delta} &= \frac{p(\hat{\theta}_{t+\Delta}, t+\Delta)\frac{D_{t+\Delta}}{D_t} + \int_t^{t+\Delta}\frac{D_s}{D_t}ds}{p(\hat{\theta}_t, t)} = \frac{p(\hat{\theta}_{t+\Delta}, t+\Delta)(1+\frac{dD_t}{D_t}) + \int_t^{t+\Delta}(1+\frac{dD_{s-t}}{D_t})ds}{p(\hat{\theta}_t, t)} \\ &= \frac{p(\hat{\theta}_{t+\Delta}, t+\Delta)(1+\frac{dD_t}{D_t}) + (1+1+\frac{dD_t}{D_t})\frac{\Delta}{2}}{p(\hat{\theta}_t, t)} = \frac{p(\hat{\theta}_{t+\Delta}, t+\Delta)(1+\frac{dD_t}{D_t}) + (\Delta + \frac{dD_t}{D_t}\frac{\Delta}{2})}{p(\hat{\theta}_t, t)}. \end{aligned}$$

Computing Realized Variance In the data, we compute

$$RV_{t,t+\Delta}(dt) = \sum_{j=1}^{\Delta/dt}\left[\ln R_{t+(j-1)dt,\,t+jdt}\right]^2,$$

Over a 1-minute interval, subtracting the mean is quantitatively irrelevant. It can be shown that as $dt \to 0$, the above quantity converges to the quadratic variation of the return:

$$\lim_{dt\to 0} RV_{t,t+\Delta}(dt) = \int_t^{t+\Delta}(\sigma_{R,s}^2 + \omega_s^2)ds + \sum_{t\le s\le t+\Delta} I_{\{s\}}\left[\ln p(\hat{\theta}_s^+, s^+) - \ln p(\nu_s, \hat{\theta}_s^-, s^-)\right]^2,$$

where $I_{\{s\}}$ is the announcement indicator, equal to one if $s \bmod T = 0$. Therefore, numerically, over a day, that is, $\Delta = \frac{1}{360}$, we simply compute

$$\begin{aligned} RV_{t,t+\Delta} \;\approx\; & \frac{1}{2}\left[\sigma_R^2(\hat{\theta}_t, t) + \sigma_R^2(\hat{\theta}_{t+\Delta}, t+\Delta) + \omega_t^2 + \omega_{t+\Delta}^2\right]\Delta \\ & + \sum_{t\le s\le t+\Delta} I_{\{s\}}\left[\ln p(\hat{\theta}_s^+, s^+) - \ln p(\nu_s, \hat{\theta}_s^-, s^-)\right]^2. \end{aligned} \tag{C.10}$$

Calculating the Risk-Free Rate Using the expression for the risk-free rate in (A.31), the cumulative risk-free return from t to $t+\Delta$ is:

$$e^{\int_t^{t+\Delta} r(\hat{\theta}_s, s)ds} \approx \exp\left\{\sum_{j=1}^{\Delta/dt} r(\hat{\theta}_{t+(j-1)dt}, t+(j-1)dt)dt\right\}. \tag{C.11}$$

This allows us to accumulate the daily risk-free return to compute the annual rate for $\Delta = 1$.

Solve for the H Function We use the finite difference method to solve for the value function. The HJB equation in Eq. (A.25) can be rewritten as:

$$(1-\gamma)(\frac{\rho}{1-\frac{1}{\psi}} - \hat{\theta}_t + \frac{1}{2}\gamma\sigma_Y^2)H = H_t + H_\theta\left[\mu_{\theta,t} + (1-\gamma)\sigma_{\theta,t}\right] + \frac{1}{2}H_{\theta\theta}\frac{\sigma_{\theta,t}^2}{\sigma_Y^2} + \frac{\rho(1-\gamma)}{1-\frac{1}{\psi}}H^B.$$

We use the finite difference method and approximate the function $H(\hat{\theta}_t, t)$ at I discrete points in the state dimension, $\hat{\theta}_i$, $i = 1, 2, ..., I$. Denote $H_i^n = H(\hat{\theta}_i, t^n)$, where the time index $n = 0, 1, 2, ..., N$. Denote

$$\beta_i = (1-\gamma)(\frac{\rho}{1-\frac{1}{\psi}} - \hat{\theta}_i + \frac{1}{2}\gamma\sigma_Y^2), \text{ and } u_i^{n+1} = \frac{\rho(1-\gamma)}{1-\frac{1}{\psi}}(H_i^{n+1})^B. \tag{C.12}$$

We use the implicit method to update the value function,

$$\begin{aligned}\beta_i H_i^n &= \frac{H_i^{n+1} - H_i^n}{\Delta t} + u_i^{n+1} + \frac{1}{2}\partial_{\theta\theta}H_i^n\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \\ &\quad + \partial_{\theta,F}H_i^n\left[\mu_{\theta,i} + (1-\gamma)\sigma_{\theta,i}\right]^+ + \partial_{\theta,B}H_i^n\left[\mu_{\theta,i} + (1-\gamma)\sigma_{\theta,i}\right]^-.\end{aligned} \tag{C.13}$$

We use the upwind scheme to approximate the derivatives $\partial_\theta H_i^n$ and $\partial_{\theta\theta}H_i^n$,

$$\begin{aligned}\beta_i H_i^n &= \frac{H_i^{n+1} - H_i^n}{\Delta t} + u_i^{n+1} + \frac{1}{2}\frac{H_{i+1}^n - 2H_i^n + H_{i-1}^n}{(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \\ &\quad + \frac{H_{i+1}^n - H_i^n}{\Delta\hat{\theta}}\left[\mu_{\theta,i} + (1-\gamma)\sigma_{\theta,i}\right]^+ + \frac{H_i^n - H_{i-1}^n}{\Delta\hat{\theta}}\left[\mu_{\theta,i} + (1-\gamma)\sigma_{\theta,i}\right]^-.\end{aligned} \tag{C.14}$$

Collecting terms, we rewrite the HJB equation as

$$\beta_i H_i^n = \frac{H_i^{n+1} - H_i^n}{\Delta t} + u_i^{n+1} + H_{i-1}^n x_i + H_i^n y_i + H_{i+1}^n z_i \tag{C.15}$$

where

$$x_i = -\frac{\left[\mu_{\theta,i} + (1-\gamma)\sigma_{\theta,i}\right]^-}{\Delta\hat{\theta}} + \frac{1}{2(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \tag{C.16}$$

$$y_i = -\frac{\left[\mu_{\theta,i} + (1-\gamma)\sigma_{\theta,i}\right]^+}{\Delta\hat{\theta}} + \frac{\left[\mu_{\theta,i} + (1-\gamma)\sigma_{\theta,i}\right]^-}{\Delta\hat{\theta}} - \frac{1}{(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \tag{C.17}$$

$$z_i = \frac{\left[\mu_{\theta,i} + (1-\gamma)\sigma_{\theta,i}\right]^+}{\Delta\hat{\theta}} + \frac{1}{2(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \tag{C.18}$$

Rewriting in matrix notation,

$$\beta H^n = u^{n+1} + \mathbf{A}^{n+1} H^n + \frac{H^{n+1} - H^n}{\Delta t}, \tag{C.19}$$

where

$$\mathbf{A}^{n+1} = \begin{bmatrix} y_1 & z_1 & 0 & \cdots & 0 \\ x_2 & y_2 & z_2 & 0 & \vdots \\ 0 & x_3 & y_3 & z_3 & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots \\ 0 & \cdots & 0 & x_I & y_I \end{bmatrix}, H^n = \begin{bmatrix} H_1 \\ H_2 \\ H_3 \\ \vdots \\ H_I \end{bmatrix}, \beta = \begin{bmatrix} \beta_1 & 0 & & & \cdots \\ 0 & \beta_2 & & & \\ & & \beta_3 & & \\ & & & \ddots & 0 \\ \vdots & & & & \beta_I \end{bmatrix}, u^{n+1} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_I \end{bmatrix}.$$

At the endpoints $\hat{\theta} = \theta_L$ and $\hat{\theta} = \theta_H$, the diffusion coefficient $\sigma_\theta = (\theta_H - \hat{\theta})(\hat{\theta} - \theta_L)$ vanishes and the drift $\mu_\theta = (\lambda_H + \lambda_L)(\bar{\theta} - \hat{\theta})$ points inward, so $x_1 = z_I = 0$ automatically and no explicit boundary condition is required for the spatial grid. The system can be written as

$$\mathbf{B}^{n+1} H^n = b^{n+1}, \ \mathbf{B}^{n+1} = (\frac{1}{\Delta t} + \beta) - \mathbf{A}^{n+1}, \ b^{n+1} = u^{n+1} + \frac{1}{\Delta t} H^{n+1}. \tag{C.20}$$

The boundary condition is

$$H(\hat{\theta}^-, T) = \mathbb{E}\left[H(\nu, \hat{\theta}^-, T) \,\middle|\, \hat{\theta}^-, T \right]; \ H(\nu, \hat{\theta}^-, T) = \mathbb{E}\left[H(\hat{\theta}^+, 0) \,\middle|\, \nu, \hat{\theta}^-, T \right],$$

where, from Eqs. (A.27) and (A.26),

$$\begin{aligned} H(\nu, \hat{\theta}^-, T) &= h_{s_H} H(\hat{\theta}^+_{s_H}, 0) + h_{s_L} H(\hat{\theta}^+_{s_L}, 0) \\ &= \left[\frac{\hat{\theta}^- - \theta_L}{\theta_H - \theta_L} \nu + \frac{\theta_H - \hat{\theta}^-}{\theta_H - \theta_L} (1 - \nu) \right] H(\theta_L + \frac{(\hat{\theta}^- - \theta_L)\nu(\theta_H - \theta_L)}{(\hat{\theta}^- - \theta_L)\nu + (\theta_H - \hat{\theta}^-)(1 - \nu)}, 0) \\ &+ \left[\frac{\hat{\theta}^- - \theta_L}{\theta_H - \theta_L} (1 - \nu) + \frac{\theta_H - \hat{\theta}^-}{\theta_H - \theta_L} \nu \right] H(\theta_L + \frac{(\hat{\theta}^- - \theta_L)(1 - \nu)(\theta_H - \theta_L)}{(\hat{\theta}^- - \theta_L)(1 - \nu) + (\theta_H - \hat{\theta}^-)\nu}, 0). \end{aligned} \tag{C.21}$$

$$H(\hat{\theta}^-, T) = \mathbb{E}\left[H(\nu, \hat{\theta}^-, T) \,\middle|\, \hat{\theta}^-, T \right] = \sum_{j=1}^{m} q_j H(\nu_j, \hat{\theta}^-, T). \tag{C.22}$$

Solve for the Price-to-Dividend Ratio Similarly, the PDE for $p(\hat{\theta}_t, t)$ is given in Lemma 3. We use the finite difference method and approximate the function $p(\hat{\theta}_t, t)$ at I discrete points in the state dimension, $\hat{\theta}_i$, $i = 1, 2, ..., I$. Denote $p_i^n = p(\hat{\theta}_i, t^n)$, where the time index

$n = 0, 1, 2, ..., N$. Denote

$$\varpi_i^{n+1} = (\xi_\theta - 1)\bar{\theta} + \rho - \frac{1}{2}\gamma\sigma_Y^2(\frac{1}{\psi} + 1) + \xi_Y\gamma\sigma_Y^2 - (\xi_\theta - \frac{1}{\psi})\hat{\theta}_i + \frac{(\frac{1}{\psi} - \gamma)(1 - \frac{1}{\psi})}{2(1-\gamma)^2}(\frac{H_{\theta,i}^{n+1}}{H_i^{n+1}})^2\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} + (1 - \xi_Y)\frac{\frac{1}{\psi} - \gamma}{1-\gamma}\frac{H_{\theta,i}^{n+1}}{H_i^{n+1}}\sigma_{\theta,i} \tag{C.23}$$

$$\varrho_i^{n+1} = \mu_{\theta,i} + (\xi_Y - \gamma)\sigma_{\theta,i} + \frac{\frac{1}{\psi} - \gamma}{1-\gamma}\frac{H_{\theta,i}^{n+1}}{H_i^{n+1}}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2}. \tag{C.24}$$

We use the implicit method to update the price-to-dividend ratio (A.37),

$$\varpi_i^{n+1}p_i^n = \frac{p_i^{n+1} - p_i^n}{\Delta t} + 1 + \frac{1}{2}\partial_{\theta\theta}p_i^n\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} + \partial_{\theta,F}p_i^n(\varrho_i^{n+1})^+ + \partial_{\theta,B}p_i^n(\varrho_i^{n+1})^-. \tag{C.25}$$

We use the upwind scheme to approximate the derivatives $\partial_\theta p_{i,j}^n$ and $\partial_{\theta\theta}p_{i,j}^n$,

$$\varpi_i^{n+1}p_i^n = \frac{p_i^{n+1} - p_i^n}{\Delta t} + 1 + \frac{1}{2}\frac{p_{i+1}^n - 2p_i^n + p_{i-1}^n}{(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} + \frac{p_{i+1}^n - p_i^n}{\Delta\hat{\theta}}(\varrho_i^{n+1})^+ + \frac{p_i^n - p_{i-1}^n}{\Delta\hat{\theta}}(\varrho_i^{n+1})^-. \tag{C.26}$$

Collecting terms, we rewrite the PDE as

$$\varpi_i^{n+1}p_i^n = \frac{p_i^{n+1} - p_i^n}{\Delta t} + 1 + p_{i-1}^n x_i^{n+1} + p_i^n y_i^{n+1} + p_{i+1}^n z_i^{n+1} \tag{C.27}$$

where

$$x_i^{n+1} = -\frac{(\varrho_i^{n+1})^-}{\Delta\hat{\theta}} + \frac{1}{2(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \tag{C.28}$$

$$y_i^{n+1} = -\frac{(\varrho_i^{n+1})^+}{\Delta\hat{\theta}} + \frac{(\varrho_i^{n+1})^-}{\Delta\hat{\theta}} - \frac{1}{(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \tag{C.29}$$

$$z_i^{n+1} = \frac{(\varrho_i^{n+1})^+}{\Delta\hat{\theta}} + \frac{1}{2(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \tag{C.30}$$

Rewriting in matrix notation,

$$\varpi^{n+1}p^n = 1 + \mathbf{A}^{n+1}p^n + \frac{p^{n+1} - p^n}{\Delta t}, \tag{C.31}$$

The system can be written as

$$\mathbf{B}^{n+1}p^n = b^{n+1},\ \mathbf{B}^{n+1} = (\frac{1}{\Delta t} + \varpi^{n+1}) - \mathbf{A}^{n+1},\ b^{n+1} = 1 + \frac{1}{\Delta t}p^{n+1}. \tag{C.32}$$

where

$$p^n = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ \vdots \\ p_I \end{bmatrix}, \ \varpi^{n+1} = \begin{bmatrix} \varpi_1 & 0 & & & \cdots \\ 0 & \varpi_2 & & & \\ & & \varpi_3 & & \\ & & & \ddots & 0 \\ \vdots & & & & \varpi_I \end{bmatrix}.$$

At the boundary,

$$p(\nu, \hat{\theta}_T^-, T) = \frac{h_{s_H} H(\hat{\theta}_{s_H}^+, 0)^B p(\hat{\theta}_{s_H}^+, 0) + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)^B p(\hat{\theta}_{s_L}^+, 0)}{\left[h_{s_H} H(\hat{\theta}_{s_H}^+, 0) + h_{s_L} H(\hat{\theta}_{s_L}^+, 0)\right]^B} \tag{C.33}$$

$$p(\hat{\theta}^-, T) = \frac{\sum_{j=1}^m q_j H(\nu_j, \hat{\theta}^-, T)^B p(\nu_j, \hat{\theta}^-, T)}{\left[\sum_{j=1}^m q_j H(\nu_j, \hat{\theta}^-, T)\right]^B}. \tag{C.34}$$

Solve for the Implied Variance The PDEs for the risk-neutral w_j^*, a_j^* in Section A.3 and their physical analogs w_3, a_1 in the policy function share a common discretized template; we present it generically using $\mu_{\theta,i}, \mu_{\delta,i}$ for the drifts. The physical and risk-neutral drifts are

$$\mu_{\theta,t} = (\lambda_H + \lambda_L)(\bar{\theta} - \hat{\theta}_t), \qquad \mu_{\delta,t} = \xi_\theta \hat{\theta}_t + \bar{\theta}(1 - \xi_\theta) - \tfrac{1}{2}\xi_Y^2 \sigma_Y^2, \tag{C.35}$$

$$\mu_{\theta,t}^* = \mu_{\theta,t} - \tfrac{\sigma_{\theta,t}}{\sigma_Y} \sigma_M(\hat{\theta}_t, t), \qquad \mu_{\delta,t}^* = \mu_{\delta,t} - \xi_Y \sigma_Y \sigma_M(\hat{\theta}_t, t), \tag{C.36}$$

with $\sigma_{\theta,t} = (\theta_H - \hat{\theta}_t)(\hat{\theta}_t - \theta_L)$ and $\sigma_M(\hat{\theta}_t, t) = \gamma \sigma_Y - B \frac{H_\theta(\hat{\theta}_t, t)}{H(\hat{\theta}_t, t)} \frac{\sigma_{\theta,t}}{\sigma_Y}$, evaluated using $H_i, H_{\theta,i}$ from the H-function step. In the template below, $\mu_{\theta,i}, \mu_{\delta,i}$ are read as $\mu_{\theta,i}^*, \mu_{\delta,i}^*$ for the risk-neutral solve (in which case the $*$ superscript on w_j, a_j is dropped to streamline notation) and as $\mu_{\theta,i}, \mu_{\delta,i}$ for the physical solve. The PDEs take the general form

$$0 = \frac{w_i^{n+1} - w_i^n}{\Delta t} + u_i^{n+1} + \frac{1}{2} \frac{w_{i+1}^n - 2w_i^n + w_{i-1}^n}{(\Delta \hat{\theta})^2} \frac{\sigma_{\theta,i}^2}{\sigma_Y^2} + \frac{w_{i+1}^n - w_i^n}{\Delta \hat{\theta}} \mu_{\theta,i}^+ + \frac{w_i^n - w_{i-1}^n}{\Delta \hat{\theta}} \mu_{\theta,i}^-, \tag{C.37}$$

where $u_i^{n+1} = 0$ for $w_1 = \mathbb{E}_t\left[\ln p(\hat{\theta}_\tau, \tau)\right]$ and $w_2 = \mathbb{E}_t\left[(\ln p(\hat{\theta}_\tau, \tau))^2\right]$. For a_1, a_2 and a_3,

$$u_i^{n+1} = \mu_{\delta,i} \tag{C.38}$$

$$u_i^{n+1} = 2a_{1,i}^{n+1}\mu_{\delta,i} + 2\xi_Y \frac{a_{1,i+1}^{n+1} - a_{1,i}^{n+1}}{\Delta\hat{\theta}}\sigma_{\theta,i} + \xi_Y^2\sigma_Y^2 \tag{C.39}$$

$$u_i^{n+1} = w_{1,i}^{n+1}\mu_{\delta,i} + \xi_Y \frac{w_{1,i+1}^{n+1} - w_{1,i}^{n+1}}{\Delta\hat{\theta}}\sigma_{\theta,i}. \tag{C.40}$$

Therefore, we rewrite the PDE as

$$0 = \frac{w_i^{n+1} - w_i^n}{\Delta t} + u_i^{n+1} + w_{i-1}^n x_i + w_i^n y_i + w_{i+1}^n z_i, \tag{C.41}$$

where

$$x_i = -\frac{\mu_{\theta,i}^-}{\Delta\hat{\theta}} + \frac{1}{2(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \tag{C.42}$$

$$y_i = -\frac{\mu_{\theta,i}^+}{\Delta\hat{\theta}} + \frac{\mu_{\theta,i}^-}{\Delta\hat{\theta}} - \frac{1}{(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2} \tag{C.43}$$

$$z_i = \frac{\mu_{\theta,i}^+}{\Delta\hat{\theta}} + \frac{1}{2(\Delta\hat{\theta})^2}\frac{\sigma_{\theta,i}^2}{\sigma_Y^2}. \tag{C.44}$$

Rewriting in matrix notation,

$$0 = u^{n+1} + \mathbf{A}^{n+1}w^n + \frac{w^{n+1} - w^n}{\Delta t}. \tag{C.45}$$

The system can be written as

$$\mathbf{B}^{n+1}w^n = b^{n+1},\ \mathbf{B}^{n+1} = \frac{1}{\Delta t}\mathbf{I} - \mathbf{A}^{n+1},\ b^{n+1} = u^{n+1} + \frac{1}{\Delta t}w^{n+1}. \tag{C.46}$$

where the boundary condition for $\mathbb{E}_t\left[\ln p(\hat{\theta}_\tau, \tau)\right]$ is:

$$w_1(\hat{\theta}, \tau) = \ln p(\hat{\theta}_\tau, \tau),$$

and the boundary condition for $\mathbb{E}_t\left[(\ln p(\hat{\theta}_\tau, \tau))^2\right]$ is:

$$w_2(\hat{\theta}, \tau) = (\ln p(\hat{\theta}_\tau, \tau))^2,$$

and the remaining boundary conditions are

$$a_1(\hat{\theta}_\tau, \tau) = 0,\ a_2(\hat{\theta}_\tau, \tau) = 0 \text{ and } a_3(\hat{\theta}_\tau, \tau) = 0.$$

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