The Cross-section of monetary policy announcement premium

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We show that monetary policy announcements require a significant risk compensation in the cross-section of equity returns. Empirically, we use the expected reduction in implied volatility after FOMC announcements to measure the sensitivity of stock returns with respect to monetary policy announcements and find a significant monetary policy announcement premium. We develop a model of macroeconomic announcements to account for the cross-section of the monetary policy announcement premium in equity returns.

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1 Introduction

Recent literature, for example, Savor and Wilson (2013), Lucca and Moench (2015) and Ai and Bansal (2018) document that the Federal Open Market Committee's monetary policy announcements are associated with substantial risk compensations on equity markets during short announcement windows. In this paper, we show that the exposure to monetary policy announcements are priced in the cross-section of equity returns, and as a result, firm's expected sensitivity with respect to monetary policy announcements strongly predicts their returns on announcement days. A long-short portfolio formed on our monetary policy sensitivity measure produces an average announcement-day return of 30 bps, which is statistically and economically significant even after controlling for standard risk factors.

To study whether monetary policy announcements are priced in the cross section of equity returns, we first develop a measure of sensitivity with respect to these announcements. We use expected drop in implied volatility on FOMC announcement days to measure the market expected sensitivity of the return of a stock with respect to FOMC announcements. Our measure is motivated by the fact that option implied volatility drops significantly after announcements and the size of volatility drop is increasing in the sensitivity of the return with respect to the upcoming announcement.

We demonstrate that expected sensitivity sorted portfolios yield a significant spread in average return on FOMC announcement days, but not on non-announcement days. In addition, we show that the excess returns of portfolios remain significant after controlling for their market beta. We also provide supporting evidence for the hypothesis that the announcement premium of the expected sensitivity sorted portfolios is compensation for monetary policy announcements by showing that the premium for expected sensitivity sorted portfolios can be explained by the sensitivity of portfolio returns with respect to monetary policy surprises.

From the perspective of the cross section of equity returns, our results for the monetary policy announcement premium provide supporting evidence for previous findings of the macroeconomic announcement premium. Our CAPM result, however, poses challenge to the theory as previous theoretical models and empirical findings that CAPM held well on macroeconomic announcement days, see for example, Savor and Wilson (2014), Wachter and Zhu (2018) and Ai, Bansal, Im, and Ying (2018).

To quantitatively account for the cross-sectional announcement returns, we develop a model with macroeconomic announcements with generalized risk sensitive preferences (Ai and Bansal (2018)). In our model, aggregate consumption growth is driven by a latent state variable, x_t (long-run risks), and an i.i.d. component (short-run risks). The true value of expected consumption growth is not observable to investors but revealed by monetary policy announcements periodically. We specify a cross-section of dividend process that differ in both the sensitivity with respect to the long-run and the short-run component of aggregate growth rates.

In our model, the size of the reduction of implied volatility on announcement days provides an accurate measure of equities' risk exposure to monetary policy announcements. On non-announcement days, investors do not observe the true value of x_t and update their beliefs about it based on noisy signals. Scheduled macroeconomic announcements reveal the true value of x_t and as a result, investors' posterior belief about x_t jumps on announcement days and resets to its true value upon the announcement. Stocks that have a high exposure to x_t will experience a large drop in implied volatility on announcement days.

In this setup, our model matches several stylized features of the cross-sectional announcement returns. First, the average announcement-day excess return of the market is about 36 bps, and the spread on announcement-day return of expected sensitivity sorted portfolios is about 30 bps, both of which are close to their empirical counterparts. Due to generalized risk sensitivity, risk in announcements about x_t is priced (Ai and Bansal (2018)). As a result, stocks that have a higher sensitivity with respect to monetary policy announcements than others will also receive a higher risk premium on announcement days.

Second, CAPM fails to account for the announcement return of expected sensitivity sorted portfolios in our model. On non-announcement days, aggregate stock market return is primarily driven by the short-run component of growth rate shocks, as short-run shocks are much more volatile than long-run shocks. Therefore, CAPM beta is very sensitive to the exposure of equity returns with respect to short-run shocks, but responds only mildly to the exposure of returns with respect to long-run shocks. As a result, expected sensitivity sorted portfolios exhibits a small dispersion in CAPM β, not enough to account for their announcement day returns.

Third, despite the failure of CAPM to account for the expected return of expected sensitivity sorted portfolios, it explains the announcement returns of β sorted portfolios very well. In the data, as documented by Savor and Wilson (2013), β sorted portfolios exhibit significant differences in announcement premium, which can be explained by the CAPM. In our model, because the elasticity of β with respect to stocks' exposure to x_t shock is low, conditioning on β, small dispersion in β can lead to relatively significant differences in exposure to x_t. When sorted on β directly, the portfolios differ in expected sensitivity and therefore differ in announcement day returns. However, the dispersion of β in β sorted portfolios is much larger than the dispersion of β in expected sensitivity sorted portfolios, and is enough to explain the heterogeneity in announcement-day returns.

Related literature Our paper is related to the recent literature that emphasize the importance of macroeconomic announcements in understanding asset market returns. Savor and Wilson (2013) document a significant equity market return on days with major macroeconomic announcements, Brusa, Savor, and Wilson (2015) show that the same holds for many other countries. Cieslak, Morse, and Vissing-Jorgensen (forthcoming) provide evidence for stock market returns over FOMC announcement cycles. Neuhierl and Weber (2018) document that the return drift around FOMC announcements depends on whether the monetary policy is expansionary or contractionary. Bollerslev, Li, and Xue (forthcoming) find that after the FOMC meetings, both volatility and volume increase, but the intraday volume-volatility elasticity is systematically below unity. Mueller, Tahbaz-Salehi, and Vedolin (2017) and Karnaukh (2018) study the impact of FOMC announcements on the foreign exchange market.

Several papers study the relationship between monetary policy and the cross section of expected returns. Savor and Wilson (2014) demonstrate that the CAPM holds well for macroeconomic announcement days, but not for non-announcement days. Lucca and Moench (2015) documents a FOMC pre-announcement drift. Ozdagli and Velikov (forthcoming) use observable firm characteristics to measure firm exposure to monetary policy and find that stocks react more positively to expansionary monetary policy surprises earn lower returns. Chava and Hsu (2015) find that financially constrained firms earn lower returns than unconstrained firms when there are unanticipated increases in Federal funds target rate. None of the above papers measure sensitivity to monetary policy announcement directly as we do.

Our theoretical model builds on recent development in asset pricing models for the macroeconomic announcement premium. Ai and Bansal (2018) provide a revealed preference theory for the macroeconomic announcement premium. Wachter and Zhu (2018) and Ai, Bansal, Im, and Ying (2018) develop quantitative models of the announcement premium.

The rest of the paper is organized as follows. In Section 2, we develop a measure of expected sensitivity with respect to monetary policy announcements and present cross-sectional evidence for the relationship between expected sensitivity and expected returns. In Section 3, we develop a continuous-time model with monetary policy announcements and explain cross-sectional equity returns. We present our quantitative analysis and demonstrate that our model is able to account for the stylized features of the cross-sectional announcement premium in Section 4. Section 5 concludes.

2 Empirical Evidence

In this section, we provide evidence that stocks that are more sensitive to monetary policy announcements earns a significantly higher premium on FOMC announcement days. In addition, the cross section of monetary policy announcement premium cannot be explained by the CAPM.

2.1 Measuring expected sensitivity

We use market expected volatility reduction around FOMC announcement days as the measure of expected sensitivity to monetary policy shocks. To motivate our measure, we first show that both market- and firm-level implied volatility significantly decreases after the FOMC announcement, when the uncertainty related to monetary policy is revealed. Furthermore, we demonstrate that there is a significant heterogeneity in the reduction in implied volatility across firms after the FOMC announcement, suggesting that firms have significantly different exposures to monetary policy shocks. We first discuss the data used in this study before presenting the empirical evidence.

Data To measure the firm-level sensitivity to monetary policy shocks around Federal Open Market Committee (FOMC) days, we use equity options data from OptionMetrics for the period of January 1, 1996 to December 31, 2015. We obtain stock return data from the Center for Research in Security Prices (CRSP) and merge with the OptionMetrics data. The dates of FOMC meetings are from the website of Federal Reserve Board. Following Savor and Wilson (2014), we only include the scheduled FOMC meetings during our data period. When the meeting lasts for two days, we consider the second day as the FOMC announcement day. There are about eight regularly scheduled FOMC meetings each year and 160 announcements in our data period. Details of data construction can be found in Appendix A.

Implied volatility around monetary policy announcements Both market- and firm-level implied volatility significantly drop after the FOMC announcement. Panel A of Table 1 compares the market level implied variance (VIX^2) on the FOMC days with the value one-day before. As documented in Savor and Wilson (2013), VIX significantly decreases after the FOMC announcement. On average the daily decrease is about 5.7% (in logarithm). At the firm level, we observe the same pattern as shown in Table 1. Firms' implied volatility becomes lower after the FOMC announcement. On average, the firm level implied variance drops by 2.4%.

Moreover, there is a significant heterogeneity in the reduction in implied volatility across firms. Figure 1 plots the distribution of the intercept and coefficient when we regress firm level implied volatility reduction on changes of market implied volatility (VIX^2). To ensure we can make appropriate inference from linear regression, we transform implied volatility into its logarithm. We see a high level of dispersion of the intercept and coefficient. We also find the regression coefficients are positive and almost evenly distributed. Although almost all firms' implied volatility drops after the FOMC announcement, the amount of reduction varies across firms. Table 2 reports the option-implied volatility on the FOMC day and one-day before the FOMC day for various quantiles. Typically implied volatility is lower on the FOMC days comparing to the value one-day before. Reduction of implied volatility on FOMC announcement days, when the uncertainty associated with monetary policy is resolved, is significant for most of the firms. The media the implied volatility reduction is about 3.6% on FOMC announcement days, and the reduction is statistically significant.

To measure the *expected* sensitivity with respect to monetary policy announcements for each individual firm, we rely on the historical pattern on how the firm reacts to the macroeconomic announcements. We use the average of implied volatility reduction around all macroeconomic announcements during the past eight months as the forecast of implied volatility reduction for the upcoming FOMC announcement.[1] The average autocorrelation of implied volatility reduction upon macroeconomic announcement is 0.55 across all firms in our data. As a result our measure of the average past volatility reduction has a fairly significant predictive power for future volatility reduction.

2.2 Portfolio return sorted on expected sensitivity

Using the expected sensitivity measure constructed above, we sort stocks into decile portfolios and examine their returns on FOMC announcement days. Because some of the FOMC meeting last two days, for each of the FOMC announcement, we form portfolios two days before the announcement, hold the portfolio on and after the announcement day, and rebalance the portfolio two days before the next FOMC announcement using an updated

[1] Our results are robust if we use implied variance reduction around macroeconomic announcements during the past six to twelve months.

measure of expected sensitivity. Our measure of FOMC announcement premium for each of the portfolio is computed as the average FOMC announcement day return— if the FOMC meeting lasts for two days, we treat the last day as the announcement day.

Panel A of Table 3 reports the portfolio returns on FOMC announcement days and other days (non-FOMC days). To better present the results portfolios 1 and 2 in are the bottom two decile portfolios; portfolios 4 and 5 are the top two decile portfolios; and portfolio 3 contains other decile portfolios. On FOMC announcement days, the top decile portfolio (with the highest expected sensitivity) earns higher expected returns than the bottom decile portfolio (with the lowest expected sensitivity), and on average the long-short portfolio earns a raw return of 29.5 basis points. It means that our trading strategy earns an annual return of 2.36% (29.5×8). As a sharp contrast, most portfolios, as well as the long-short portfolio, do not earn significant returns on non-FOMC days.

To confirm that expected sensitivity is a good ex ante measure of monetary policy sensitivity, we regress the sorted portfolio returns on the monetary policy shocks on FOMC days. Our measure of monetary policy shocks follow Nakamura and Steinsson (2018), who use the high-frequency federal funds futures and Eurodollar futures to calculate the unexpected changes in interest rates over a 30-minute window surrounding the scheduled FOMC announcement.

Figure 2 plots the regression coefficient. Portfolio returns monotonically react to the monetary policy shocks. Our portfolios indeed capture firms' sensitivity to monetary policy shocks.

We next report results from CAPM regressions for our sorted portfolios. To distinguish FOMC announcement day and non-announcement day, we consider the following regression:

$$R_t^i - r_f = \alpha + \beta_{FOMC} \cdot \mathbf{1}_{FOMC} + \beta \left(R_t^M - r_f\right) + \varepsilon_t^i, \tag{1}$$

where R_t^i is the daily return of the portfolio, R_t^M is the daily return of the market, r_f is the daily risk-free rate, and $\mathbf{1}_{FOMC}$ is a dummy variable that takes a value of 1 only on FOMC announcement days. We report the result from the above CAPM regression in panel B of Table 3. Note that the difference between the FOMC dummies for portfolio 5 and portfolio 1 is positive and significant. The spread between the high sensitivity portfolio and the low sensitivity portfolio averages 28 basis points after controlling for market returns. In unreported robustness check, we find that our findings are robust even after including Fama-French three or five factors in the above regression.

2.3 CAPM $\beta-$sorted portfolios

Previous literature have shown that CAPM holds well on macroeconomic announcement days (for example, Savor and Wilson (2014)). It is the failure of CAPM in explaining the cross section of expected sensitivity sorted portfolios and the success of CAPM in accounting for the announcement return of β sorted portfolios together pose a serious challenge for structural model of the cross section of the macroeconomic announcement premium. In this section, we present evidence for the announcement premium for CAPM β sorted portfolios. Our sorting procedure is very similar with the one using expected sensitivity introduced in the last section. For each FOMC meeting, we rank all stocks into decile portfolios based on the CAPM beta, which is calculated using daily return during the past twelve months, two days before the FOMC announcement. We then document the daily portfolio returns until the next re-balancing date, which is two days before the next FOMC announcement day.

Panel A of Table 4 reports the portfolio returns of FOMC announcement days and non-FOMC days. We find that on FOMC days, high beta stocks do earn high expected returns; on average the long-short portfolio can generate a raw return of 59 basis points. On the other hand, there is no obvious pattern in portfolio returns during non-FOMC days. This return pattern indicates that the CAPM may only hold on FOMC days.

In Panel B, we report alpha and beta in the CAPM. It is natural to see that beta monotonically increases across the portfolios. When we further include a FOMC dummy in the CAPM, the coefficients on the FOMC dummy are insignificant for all portfolios, including the long-short portfolio. This insignificant FOMC dummy is consistent with the findings in the previous literature that the $\beta-$sorted long-short portfolio cannot generate any abnormal returns on FOMC days relative to the CAPM model.

3 Model Setup and Solution

In this section, we set up a continuous-time model with monetary policy announcements and study its implications on the cross-section of announcement returns.

Consumption and Preferences We consider a continuous-time representative agent economy, where the representative agent has a recursive preference with risk aversion γ and IES ψ. The growth rate of aggregate consumption contains a predictable component, x_t, and an i.i.d. component modeled by increments of a Brownian motion:

$$\frac{dC_t}{C_t} = x_t dt + \sigma dB_{C,t}.$$

Similar to the model of Ai (2010), we assume that x_t is a continuous-time AR(1) process (an Ornstein-Uhlenbeck process) unobservable to the agent in the economy. The law of motion of x_t is

$$dx_t = a_x \left(\bar{x} - x_t\right) dt + \sigma_x dB_{x,t}, \tag{2}$$

where $B_{C,t}$ and $B_{x,t}$ are independent standard Brownian motions.

Information and announcements We assume that the prior belief of the representative agent about x_0 can be represented by a normal distribution. The agent can use two sources of information to update beliefs about x_t. First, the realized consumption path contains information about x_t, and second, at pre-scheduled discrete time points $T, 2T, 3T, \cdots$, additional signals about x_t are revealed through announcements. For $n = 1, 2, 3, \cdots$, we denote s_n as the signal observed at time nT and assume $s_n = x_{nT} + \varepsilon_n$, where ε_n is i.i.d. over time, and normally distributed with mean zero and variance σ_S^2.

Because the posterior distribution of x_t is Gaussian, it can be summarized by the first two moments. We define $\hat{x}_t = \mathbb{E}_t \left[x_t\right]$ as the posterior mean and $q_t = \mathbb{E}_t \left[\left(x_t - \hat{x}_t\right)^2\right]$ as the posterior variance, respectively, of x_t given information up to time t. At time $t = nT$, where n is an integer, the agent updates his beliefs using Bayes' rule:

$$\hat{x}_{nT}^+ = q_{nT}^+ \left[\frac{1}{\sigma_S^2} s_n + \frac{1}{q_{nT}^-} \hat{x}_{nT}^-\right]; \qquad \frac{1}{q_{nT}^+} = \frac{1}{\sigma_S^2} + \frac{1}{q_{nT}^-}, \tag{3}$$

where $\hat{x}_{nT}^+$ and q_{nT}^+ are the posterior mean and variance after announcements, and $\hat{x}_{nT}^-$ and q_{nT}^- are the posterior mean and variance before announcements, respectively.

In the interior of $(nT, (n+1)\,T)$, the agent updates his beliefs based on the observed consumption process using the Kalman-Bucy filter:

$$d\hat{x}_t = a_x \left(\bar{x} - \hat{x}_t\right) dt + \frac{q_t}{\sigma} d\tilde{B}_{C,t}, \tag{4}$$

where the innovation process, $\tilde{B}_{C,t}$ is defined by $d\tilde{B}_{C,t} = \frac{1}{\sigma}\left[\frac{dC_t}{C_t} - \hat{x}_t dt\right]$. The posterior variance, q_t satisfies the Riccati equation:

$$dq_t = \left[\sigma_x^2 - 2a_x q_t - \frac{1}{\sigma^2} q_t^2\right] dt. \tag{5}$$

The cross-section of equity We assume that there is a cross-section of equity claims, indexed by i. Equity i is the claim to the following dividend process:

$$\frac{dD_t^i}{D_t^i} = \left[\bar{x} + \xi_i \left(\hat{x}_t - \bar{x}\right)\right] dt + \eta_i \sigma d\tilde{B}_{C,t} + \sigma_i dB_{i,t}, \tag{6}$$

where $dB_{i,t}$ is the idiosyncratic shock to each firm i, which is uncorrelated with $dB_{C,t}$ and $dB_{x,t}$. The parameters (ξ_i, η_i) measure the sensitivity of the dividend with respect to long-run and short-run risks, respectively. We assume that ξ_i is uniformly distributed on the interval $\left[\underline{\xi}, \overline{\xi}\right]$ and η_i is uniformly distributed on $\left[\underline{\eta}, \overline{\eta}\right]$, and the distributions of ξ_i and η_i are independent.

Define the price-to-dividend ratio of firm i as $p\left(\hat{x}_t, q_t \middle| \xi_i, \eta_i\right)$. The function $p\left(\hat{x}_t, q_t \middle| \xi_i, \eta_i\right)$ is defined as

$$p\left(\hat{x}_t, q_t \middle| \xi_i, \eta_i\right) D_t^i = \mathbb{E}_t\left[\int_0^\infty \frac{\pi_{t+s}}{\pi_t} D_{t+s}^i ds \middle| \hat{x}_t, q_t\right],$$

where the law of motion of D_t^i is given in (6). The return to the market during the period $(t, t+\Delta)$ is given by:

$$R_{t,t+\Delta} = \int \frac{p(\hat{x}_{t+\Delta}, q_{t+\Delta} \mid \xi_i, \eta_i)\frac{D_{t+\Delta}^i}{D_t^i} + \int_t^{t+\Delta} \frac{D_s^i}{D_t^i} ds}{p\left(\hat{x}_t, q_t \mid \xi_i, \eta_i\right)} di.$$

For simplicity, we denote the firm-specific price-to-dividend ratio as $p^i\left(\hat{x}_t, t\right)$ henceforth.

Model solution For $n = 1, 2, \cdots$, in the interior of $(nT, (n+1)T)$, the law of motion of the state price density, π_t satisfies the stochastic differential equation:

$$d\pi_t = \pi_t\left[-r\left(\hat{x}_t, q_t\right) dt - \sigma_{\pi,t} d\tilde{B}_{C,t}\right], \tag{7}$$

where

$$r\left(\hat{x}_t, t\right) = \rho + \frac{1}{\psi}\hat{x}_t - \frac{1}{2}\gamma\left(1 + \frac{1}{\psi}\right)\sigma^2 + \frac{\frac{1}{\psi} - \gamma}{a_x + \rho} q_t + \frac{\left(\frac{1}{\psi} - \gamma\right)\left(1 - \frac{1}{\psi}\right)}{2\left(1-\gamma\right)^2}\left(\frac{1-\gamma}{a_x + \rho}\frac{q_t}{\sigma}\right)^2 \tag{8}$$

is the risk-free interest rate, and

$$\sigma_\pi(t) = \gamma\sigma - \frac{\frac{1}{\psi} - \gamma}{a_x + \rho}\frac{q_t}{\sigma} \tag{9}$$

is the market price of the Brownian motion risk.

The price-to-dividend ratio $p^i(\hat{x}_t, t)$ must satisfy the following PDE:

$$1 - p^i(\hat{x}_t, t)\,\varpi^i(\hat{x}_t, t) + p^i_t(\hat{x}_t, t) - p^i_x(\hat{x}_t, t)\,\nu^i(\hat{x}_t, t) + \frac{1}{2}p^i_{xx}(\hat{x}_t, t)\left(\frac{q_t}{\sigma}\right)^2 = 0, \tag{10}$$

where the functions $\varpi^i(\hat{x}_t, t)$ and $\nu^i(\hat{x}_t, t)$ are defined by:

$$\begin{aligned}
\varpi^i(\hat{x}_t, t) &= \rho - \frac{1}{2}\gamma\left(1 + \frac{1}{\psi}\right)\sigma^2 + \gamma\sigma^2\eta_i + \frac{1}{\psi}\hat{x}_t - \bar{x} - \xi_i(\hat{x}_t - \bar{x}) \\
&\quad + \frac{\frac{1}{\psi} - \gamma}{a_x + \rho}q_t(1 - \eta_i) + \frac{1}{2}\frac{\left(\frac{1}{\psi} - \gamma\right)\left(1 - \frac{1}{\psi}\right)}{(1-\gamma)^2}\left(\frac{1-\gamma}{a_x + \rho}\frac{q_t}{\sigma}\right)^2 && (11)\\
\nu^i(\hat{x}_t, t) &= a_x(\hat{x}_t - \bar{x}) + (\gamma - \eta_i)\,q_t - \frac{\frac{1}{\psi} - \gamma}{a_x + \rho}\left(\frac{q_t}{\sigma}\right)^2. && (12)
\end{aligned}$$

In addition, at announcement time T, the boundary condition satisfies:

$$p^i\left(\hat{x}_T^-, T^-\right) = \frac{\mathbb{E}\left[e^{\frac{1-\gamma}{a_x+\rho}\hat{x}_T^+}p^i\left(\hat{x}_T^+, T^+\right) \mid \hat{x}_T^-, q_T^-\right]}{e^{\frac{1-\gamma}{a_x+\rho}\hat{x}_T^- + \frac{1}{2}\left(\frac{1-\gamma}{a_x+\rho}\right)^2\left[q_T^- - q_T^+\right]}}. \tag{13}$$

We provide details of the model solutions in the appendix.

Calibration We choose preference parameters and parameters of aggregate consumption growth to be in line with the standard long-run risk literature. We set $\underline{\xi} = \underline{\eta} = 1$, and $\overline{\xi} = \overline{\eta} = 7$. This specification allows us to match the aggregate stock market equity premium and at the same time, creates enough dispersion in the cross section of expected returns. The calibrated parameter values are listed in Table 5.

4 Quantitative Implications

Aggregate FOMC announcement premium In Table 6, we report the average FOMC announcement day return and non-announcement return in the data and that in the model. As documented by the previous literature, the equity market earns significant average excess returns on FOMC announcement days. Our model matches this pattern in the data quite well, generating an announcement day return of 20 basis points.

The intuition of our results is the same as that demonstrated in Ai and Bansal (2018). In our model, there are two source of risks, short-run risks, as captured by the Brownian motion $dB_{C,t}$, and long-run risks, as captured by changes in (the belief about) x_t. Prior to the announcements, investors do not observe the true value of x_t and update their beliefs about it, denoted $\hat{x}_t$. Announcements reveal the true value of x_t and the posterior mean of x_t jumps from $\hat{x}_t$ to its true value.

Because investors' preferences satisfy generalized risk sensitivity, marginal utility is decreasing in continuation utility, which is a function of the expected future consumption growth, $\hat{x}_t$. Because announcements carry news about $\hat{x}_t$, they correlate with marginal utilities and are risky from investors' perspective. As a result, returns that are sensitive to changes in x_t require a compensation upon announcements.

Expected sensitivity sorted portfolio In our model, because announcement premiums are compensations for shocks to beliefs about $\hat{x}_t$, stocks that are more sensitive to $\hat{x}_t$ require a higher compensation in terms of the announcement returns. The sensitivity of stock return with respect to announcements depends primarily on ξ_i. The dividend growth rate of stocks with high ξ_i are more sensitive to x_t. Therefore, their price-to-dividend ratio and return are respond more to news about $\hat{x}_t$ and requires a high risk compensation.

In our model, ξ_i is fixed over time; therefore, past volatility reductions on announcement days is a perfect measure of expected sensitivity in the future. If we sort on expected sensitivity in our model, high ξ stocks will be allocated to high expected sensitivity portfolios and therefore have a high announcement day return on average. In Table 7 we compare the average announcement-day return of expected sensitivity sorted portfolios in our model and that in the data. Our model replicates the monotone pattern of the announcement premium for expected sensitivity sorted portfolios quite well.

In addition, the announcement premium in our model is not explained by the CAPM. We run the same CAPM regression for the expected sensitivity sorted portfolios and compare our model output and their data counterparts in Table 8. On one hand, the spread in announcement returns is large and significant across expected sensitivity sorted portfolios. On the other hand, β is only slightly increasing in expected sensitivity. As a result, as in the data, the coefficient on FOMC dummy is significant for all portfolios.

To understand our result, in the left panel of Figure 3, we plot the sensitivity of a stock's announcement return with respect to $\hat{x}_t$ as a function of ξ normalized by the same sensitivity measure of market return, i.e. $\frac{p_x^i(\hat{x}_t,t)}{p^i(\hat{x}_t,t)} / \frac{p_x(\hat{x}_t,t)}{p(\hat{x}_t,t)}$. Because the sensitivity of announcement return with respect to $\hat{x}_t$ depends both on ξ and η, we plot it for three different values of η: $\eta_i = 2, 4, 6$. In our model, dividend is continuous, the announcement return of a stock depends only on its price-to-dividend ratio and can be written as $\frac{p_x^i(\hat{x}_t,t)}{p^i(\hat{x}_t,t)}$. It is clear from the left panel of Figure 3, the sensitivity of stock return with respect to announcement depends only on ξ and not on η: sorting on expected sensitivity is the same as sorting on ξ in our model.

In the right panel, we plot the local CAPM β at announcement as a function of ξ for $\eta_i = 2, 4, 6$. Local β is computed as follows:

$$\frac{Cov\left[dR_t^i, dR_t\right]}{Var\left[dR_t\right]} = \frac{\eta_i \sigma + \frac{p_x^i(\hat{x}_t,t)}{p^i(\hat{x}_t,t)} \frac{q_t}{\sigma}}{\eta \sigma + \frac{p_x(\hat{x}_t,t)}{p(\hat{x}_t,t)} \frac{q_t}{\sigma}}. \tag{14}$$

Note that β is increasing in both ξ and η, because returns depend on both long-run and short-run shocks. However, β is much more sensitive to η than to ξ. On non-announcement days, all shocks are driven by $d\tilde{B}_{C,t}$. ξ affects β only because $d\tilde{B}_{C,t}$ impacts the posterior belief $\hat{x}_t$. The CAPM β is only mildly increasing in ξ because the posterior variance of $\hat{x}_t$ in equation (14), q_t is much smaller compared to σ. As a result, the small dispersion in β of the expected sensitivity sorted portfolios cannot fully account for the difference in the announcement returns. The FOMC announcement dummies are quite significant in our model, as in the data.

Beta sorted portfolios Savor and Wilson (2014) show that CAPM explains very well the announcement premium of CAPM β sorted portfolios. As we have shown in the last section, in our model the stochastic discount factor is driven by two sources risks, and a one factor model such as the CAPM cannot fully account for the cross section of announcement premium. However, as we demonstrate below, despite the failure of CAPM, our model can account for the pattern of announcement return of CAPM β sorted portfolios quite well.

Table 9 presents the announcement premium for β sorted portfolios in the data and that in the model. As in the data, the announcement premiums are significant and monotonically increasing in β in our model. The average return on non-announcement days are much smaller for all portfolios and so are the spreads between these portfolios. In Table 10, we present the results from CAPM regressions for β sorted portfolios in the model. As in the data, the

CAPM α and the coefficient on FOMC announcement day dummy are both insignificant. The difference in FOMC announcement premium disappears once we control for market β.

To understand our result, note that β in our model is jointly determined by ξ and η. As we show in the last section, because β is not very sensitive to ξ, sorting on ξ (or equivalently sorting on expected sensitivity) does not generate significant dispersion in ξ, and that is why CAPM fails to account for the cross section of expected sensitivity sorted portfolios. However, sorting on β, as we show in Table 9, does generate a significant dispersion in ξ. The average ξ is monotonically increasing in β sorted portfolios. This explains the significant announcement premium for β sorted portfolios. At the same time, because β is also monotone for β sorted portfolios — by construction, the dispersion in announcement premium can be fully explained by the dispersion in β.

5 Conclusion

In this paper, we provide empirical evidence and an equilibrium model for the cross-section of announcement day returns. We show that in the data, stocks that are more sensitive to monetary policy announcements require a higher risk compensation upon FOMC announcements. Our evidence is supportive of the recent literature that emphasize the importance of risk compensation for macroeconomic announcements and in particular, monetary policy announcements.

Table 1: Implied Variance Around FOMC Announcement Days

Panel A: VIX^2

	VIX_t^2	VIX_{t-1}^2	$VIX_t^2 - VIX_{t-1}^2$	$\log(\frac{VIX_t^2}{VIX_{t-1}^2})$
Mean	41.844	44.444	-2.600	-0.057
Std. Dev			9.874	0.133
t-stats			-3.331	-5.387

Panel B: Average Firm-level Implied Variance

	IV_t	IV_{t-1}	$IV_t - IV_{t-1}$	$\log(\frac{IV_t}{IV_{t-1}})$
Mean	311.467	314.351	-6.242	-0.024
Std. Dev			16.018	0.039
t-stats			-4.929	-7.675

Our full period is from January 1996 to December 2015 with 160 FOMC days. During this sample period, there are 5150 common stocks with trading options. Among these 5150 firms in our sample, there are 4246 firms with at least one observation on these 160 FOMC days. In panel A, we report changes in VIX^2 (monthly percentage squared) around FOMC days and their time-series statistics when testing whether the change is significantly different from zero. In panel B, we report the cross-sectional average of the changes in option-implied variance (monthly percentage squared) around FOMC annoucement days and their time-series statistics.

Table 2: Heterogenous Change in Firm-level Implied Variance

	IV_t	IV_{t-1}	$IV_t - IV_{t-1}$	$\log(\frac{IV_t}{IV_{t-1}})$
Q10				
Mean	249.519	262.100	-12.749	-0.033
Std. Dev			60.452	0.108
t-stats			-2.441	-3.549
Q50				
Mean	111.550	116.927	-4.968	-0.036
Std. Dev			14.777	0.086
t-stats			-3.774	-4.614
Q90				
Mean	152.329	154.911	-1.835	-0.013
Std. Dev			20.234	0.079
t-stats			-1.010	-1.776

Our full period is from January 1996 to December 2015 with 160 FOMC days. During this sample period, there are 5150 common stocks with trading options. Among these 5150 firms in our sample, there are 4246 firms with at least one observation on these 160 FOMC days. We report the changes in option-implied variance (monthly percentage squared) around FOMC announcement days for the 10th, 50th and 90th cross-sectional quantiles (based on the time-series mean) among firms with 100 or more observations out of these 160 FOMC days.

Table 3: Portfolio Returns Sorted on Expected Sensitivity Drops

Panel A: Average Returns

	1	2	3	4	5	(5 − 1)
FOMC Return	37.84	49.35	34.05	48.16	67.39	29.54
	(2.24)	(3.29)	(3.70)	(3.82)	(3.74)	(2.91)
Non-FOMC Return	1.68	2.88	3.39	2.66	3.35	1.67
	(0.55)	(1.06)	(1.95)	(1.09)	(1.16)	(0.89)

Panel B: CAPM

	1	2	3	4	5	(5 − 1)
CAPM alpha	-2.31	-0.49	0.48	-0.53	0.33	2.63
	(-1.39)	(-0.35)	(2.06)	(-0.53)	(0.23)	(1.44)
CAPM Beta	1.41	1.31	0.99	1.24	1.38	-0.02
FOMC Dummy	-10.71	2.83	-2.25	4.16	18.04	28.75
	(-1.27)	(0.43)	(-1.64)	(0.79)	(2.27)	(2.95)

Our full period is from January 1996 to December 2015 with 160 FOMC days. During this sample period, there are 5150 common stocks with trading options. Among these 5150 firms in our sample, there are 4246 firms with at least one observation on these 160 FOMC days. We conduct an applicable trading strategy two days before the last day of the FOMC announcement days. We first compute the past 8-month average changes in the implied variance around employment rate, consumer price index and FOMC announcement days. We sort firms into five portfolios with the third portfolio taking 60 percents of the firms and each of the rest four portfolios taking 10 percents of the firms. This is to further highlight the differences in returns when sorted based on the expected sensitivity drops. Once the five portfolios are formed, the daily return series are computed accordingly. These portfolios are rebalanced two days before the next FOMC announcement days, and etc. Panel A reports the time-series average and Newey West t statistics of returns (basis points) on FOMC announcement days and non-FOMC announcement days. Panel B reports CAPM alpha (basis points) and beta from the regressions with all trading days in our sample. We also report the FOMC dummy from the same regression where we assume the beta are the same on all trading days while the alpha may be different on FOMC announcement days.

Table 4: Portfolio Returns Sorted on CAPM Beta

Panel A: Average Returns

	1	2	3	4	5	(5 − 1)
FOMC Return	14.92	21.75	34.75	58.49	74.86	59.94
	(2.51)	(3.12)	(3.54)	(3.25)	(3.36)	(2.91)
Non-FOMC Return	3.12	3.32	3.12	2.31	3.44	0.32
	(2.71)	(2.37)	(1.66)	(0.74)	(0.92)	(0.09)

Panel B: CAPM

	1	2	3	4	5	(5 − 1)
CAPM alpha	1.05	0.89	0.05	-1.59	-0.48	-1.54
	(1.41)	(1.27)	(0.14)	(-1.14)	(-0.24)	(-0.62)
CAPM Beta	0.51	0.70	1.05	1.59	1.76	1.25
FOMC Dummy	-5.11	-4.86	-3.39	3.17	12.73	17.83
	(-1.21)	(-1.29)	(-1.90)	(0.47)	(1.28)	(1.39)

Our full period is from January 1996 to December 2015 with 160 FOMC days. During this sample period, there are 5150 common stocks with trading options. Among these 5150 firms in our sample, there are 4246 firms with at least one observation on these 160 FOMC days. We conduct an applicable trading strategy two days before the last day of the FOMC announcement days. We first compute the beta exposures of each firm based on the past 12-month daily returns. We sort firms into five portfolios with the third portfolio taking 60 percents of the firms and each of the rest four portfolios taking 10 percents of the firms. Once the five portfolios are formed, the daily return series are computed accordingly. These portfolios are rebalanced two days before the next FOMC announcement days, and etc. Panel A reports the time-series average and Newey West t statistics of returns (basis points) on FOMC announcement days and non-FOMC announcement days. Panel B reports CAPM alpha (basis points) and beta from the regressions with all trading days in our sample. We also report the FOMC dummy in the same regression where we assume the beta are the same on all trading days while the alpha may be different on FOMC announcement days.

Table 5: Model Parameters

Parameter	Description	Values
ρ	Time Discount Rate	0.02
γ	Risk Aversion	10
ψ	IES	2
$\bar{x}$	Consumption Growth Rate Stationary Mean	1.5%
σ	Consumption Growth Rate Volatility	3.16%
a_x	Mean Reversion Rate of Unobservable Consumption Growth	0.1
σ_x	Volatility of Unobservable Consumption Growth	0.54%
σ_i	Idiosyncratic Shock Volatility	50%
q_0	Initial Value of Posterior Variance	0.005%
$[\overline{\xi}, \underline{\xi}]$	Long-Run Risk Sensitivity	[1,7]
$[\overline{\eta}, \underline{\eta}]$	Short-Run Risk Sensitivity	[1,7]

This table reports the parameter values used in the model. All parameters are annual. We assume that announcements are made at the monthly frequency, that is, $T = \frac{1}{12}$.

Table 6: Average Market FOMC Announcement-Day Return

	Data	
	Non-Ann. Days	FOMC Days
Average Return	2.87	36.2
	Model	
	Non-Ann. Days	FOMC Days
Average Return	1.93	22.13

This table documents the average daily return in basis points on the non-announcement days ("Non-Ann. Days") and FOMC announcement days ("FOMC Days"). The top panel is the data from January 1996 to March 2014 with 146 FOMC days. The bottom panel is the model implied average daily excess returns in basis points for 400 stocks with 20 valid years (40 years simulation and 20 years burn-in) (240 FOMC days). We simulate 500 independent sample paths with daily frequency and report the value weighted average excess returns on FOMC and non-FOMC days.

Table 7: Announcement Premium for Expected Sensitivity Sorted Portfolios

	1	2	3	4	5	(5-1)
Data						
FOMC Return	37.84	49.35	34.05	48.16	67.39	29.54
	(2.24)	(3.29)	(3.70)	(3.82)	(3.74)	(2.91)
Non-FOMC Return	1.68	2.88	3.39	2.66	3.35	1.67
	(0.55)	(1.06)	(1.95)	(1.09)	(1.16)	(0.89)
Model						
	1	2	3	4	5	(5-1)
FOMC Return	8.04	15.32	22.40	29.10	35.79	27.74
	(1.05)	(1.09)	(1.10)	(1.09)	(1.08)	(1.03)
Non-FOMC Return	1.66	1.83	1.95	2.05	2.18	0.52
	(1.81)	(1.87)	(1.88)	(1.89)	(1.92)	(0.94)

This table documents the announcement and non-announcement returns for expected sensitivity sorted portfolios in basis points. The top panel is based on the data from January 1996 to December 2015 with 160 FOMC days. We sort stocks based on the implied volatility (IV) reduction two days before FOMC dates, and record the long-short portfolio returns on FOMC days. We report FOMC and non-FOMC returns on five portfolios (column 2 to 6), long-short portfolio (column 7) and the associated Newey-West t-statistics (in parentheses). The bottom panel is the model implied average daily excess returns in basis points for 400 stocks with 20 valid years (40 years simulation and 20 years burn-in) (240 FOMC days). We sort 5 portfolios based on long-run sensitivity ξ and report average excess return of each portfolio on FOMC and non-FOMC days. We simulate 500 independent sample paths with daily frequency and report the mean portfolio excess returns.

Table 8: CAPM for Expected Sensitivity Sorted Portfolios

	1	2	3	4	5	(5-1)
Data						
CAPM Alpha	-2.31	-0.49	0.48	-0.53	0.33	2.63
	(-1.39)	(-0.35)	(2.06)	(-0.53)	(0.23)	(1.44)
CAPM Beta	1.4052	1.3092	0.9872	1.2405	1.3808	-0.0244
FOMC Dummy	-10.71	2.83	-2.25	4.16	18.04	28.75
	(-1.27)	(0.43)	(-1.64)	(0.79)	(2.27)	(2.95)
Model	1	2	3	4	5	(5-1)
CAPM Alpha	0.31	0.16	-0.01	-0.15	-0.31	-0.62
	(0.67)	(0.42)	(-0.03)	(-0.39)	(-0.68)	(-0.81)
CAPM Beta	0.70	0.86	1.00	1.14	1.27	0.57
FOMC Dummy	-7.33	-3.47	0.28	3.88	7.30	14.63
	(-2.86)	(-1.66)	(0.14)	(1.84)	(2.88)	(3.40)

This table documents the CAPM regression for expected sensitivity sorted portfolios. The top panel is based on the data from January 1996 to December 2015 with 160 FOMC days. We sort stocks based on the implied volatility (IV) reduction two days before FOMC dates. We run CAPM regression on value weighted market return and FOMC dummy. We report CAPM alpha, beta and coefficient of FOMC dummy on five portfolios (column 2 to 6), long-short portfolio (column 7) and the associated Newey-West t-statistics (in parentheses). The bottom panel reports the model implied CAPM regression coefficients with 20 valid years (40 years simulation and 20 years burn-in) (240 FOMC days) and 400 stocks. We sort 5 portfolios based on long-run sensitivity ξ and run CAPM regression on market excess return and FOMC dummy. We simulate 500 independent sample paths with daily frequency and calculate the mean values. We report the simulated CAPM alpha, beta and coefficient of FOMC dummy of each portfolio on FOMC and non-FOMC days and the associated t-statistics.

Table 9: Announcement Premium for Beta Sorted Portfolios

	1	2	3	4	5	(5-1)
Data						
FOMC Return	14.92	21.75	34.75	58.49	74.86	59.94
	(2.51)	(3.12)	(3.54)	(3.25)	(3.36)	(2.91)
Non-FOMC Return	3.12	3.32	3.12	2.31	3.44	0.32
	(2.71)	(2.37)	(1.66)	(0.74)	(0.92)	(0.09)
Model	1	2	3	4	5	(5-1)
$\mathbb{E}[\xi_i]$	2.17	3.36	4.07	4.68	5.72	3.56
$\mathbb{E}[\eta_i]$	2.23	3.24	3.95	4.73	5.85	3.62
FOMC Return	12.52	19.31	22.80	25.03	28.50	15.98
	(1.07)	(1.09)	(1.09)	(1.08)	(1.07)	(1.03)
Non-FOMC Return	1.08	1.60	1.94	2.27	2.73	1.66
	(1.66)	(1.83)	(1.89)	(1.91)	(1.91)	(1.69)

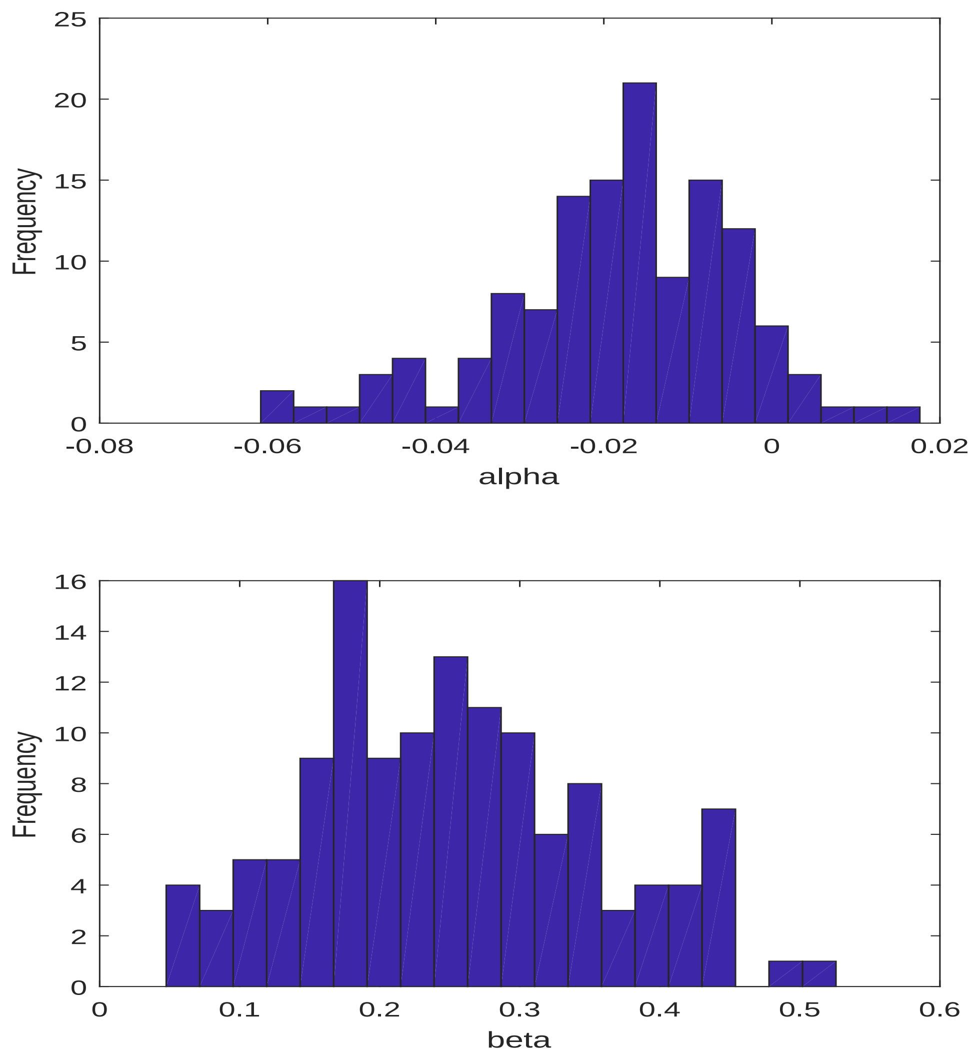
This table documents the announcement and non-announcement returns for beta sorted portfolios in basis points. The top panel is based on the data from January 1996 to December 2015 with 160 FOMC days. We sort stocks based on the CAPM regression coefficient of single stock return on value weighted market return. We report FOMC and non-FOMC returns on five portfolios (column 2 to 6), long-short portfolio (column 7) and the associated Newey-West t-statistics (in parentheses). The bottom panel is the model implied average excess returns in basis points for 400 stocks. We simulate 40 years with 10 years burn-in and sort 5 portfolios based on the following 10 years single stock's CAPM beta coefficients. We simulate 500 independent sample paths with daily frequency and report the mean portfolio ξ, η and simulated average excess return of each portfolio on FOMC and non-FOMC days using the left 20 valid years (240 FOMC days).

Table 10: CAPM for Beta Sorted Portfolios

	Data					
	1	2	3	4	5	(5-1)
CAPM Alpha	1.05	0.89	0.05	-1.59	-0.48	-1.54
	(1.41)	(1.27)	(0.14)	(-1.14)	(-0.24)	(-0.62)
CAPM Beta	0.51	0.70	1.05	1.59	1.76	1.25
FOMC Dummy	-5.11	-4.86	-3.39	3.17	12.73	17.83
	(-1.21)	(-1.29)	(-1.90)	(0.47)	(1.28)	(1.39)
	Model					
	1	2	3	4	5	(5-1)
$\mathbb{E}[\xi_i]$	2.17	3.36	4.07	4.68	5.72	3.56
$\mathbb{E}[\eta_i]$	2.23	3.24	3.95	4.73	5.85	3.62
CAPM Alpha	-0.02	-0.03	-0.01	0.02	0.05	0.07
	(-0.06)	(-0.09)	(-0.03)	(0.06)	(0.12)	(0.13)
CAPM Beta	0.57	0.84	1.01	1.16	1.39	0.82
FOMC Dummy	0.36	1.16	0.99	-0.18	-1.68	-2.04
	(0.19)	(0.57)	(0.50)	(-0.09)	(-0.83)	(-0.71)

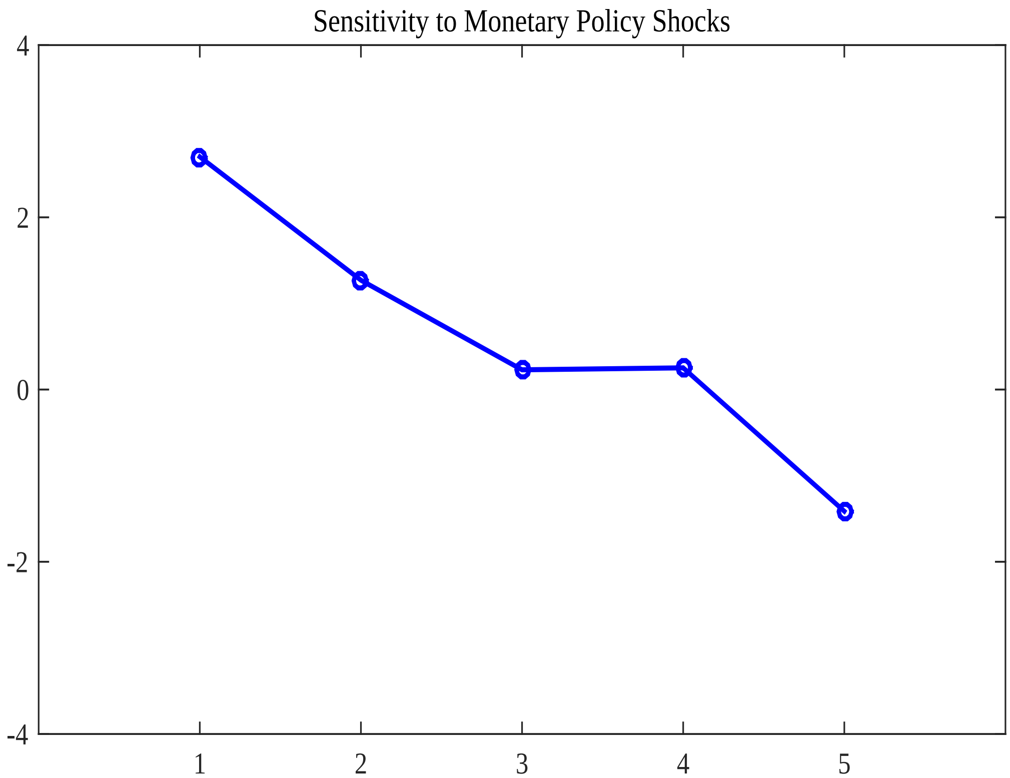
This table documents the CAPM regression for beta sorted portfolios in basis points. The top panel is based on the data from January 1996 to December 2015 with 160 FOMC days. We sort stocks based on the CAPM regression coefficient of single stock return on value weighted market return. We run CAPM regression on value weighted market return and FOMC dummy. We report CAPM alpha, beta and coefficient of FOMC dummy on five portfolios (column 2 to 6), long-short portfolio (column 7) and the associated Newey-West t-statistics (in parentheses). The bottom panel reports the model implied CAPM regression coefficients for 400 stocks. We simulate 40 years with 10 years burn-in and sort 5 portfolios based on the following 10 years single stock's CAPM beta coefficients. We run CAPM regression using the left 20 valid years (240 FOMC days) of portfolio excess return on simulated market excess return and FOMC dummy. We simulate 500 independent sample paths with daily frequency and report the mean portfolio ξ, η and simulated CAPM alpha, beta, coefficient of FOMC dummy of each portfolio on FOMC and non-FOMC days and the associated t-statistics.

Figure 1: Heterogeneous Response to Market Variance Drop Around FOMC days



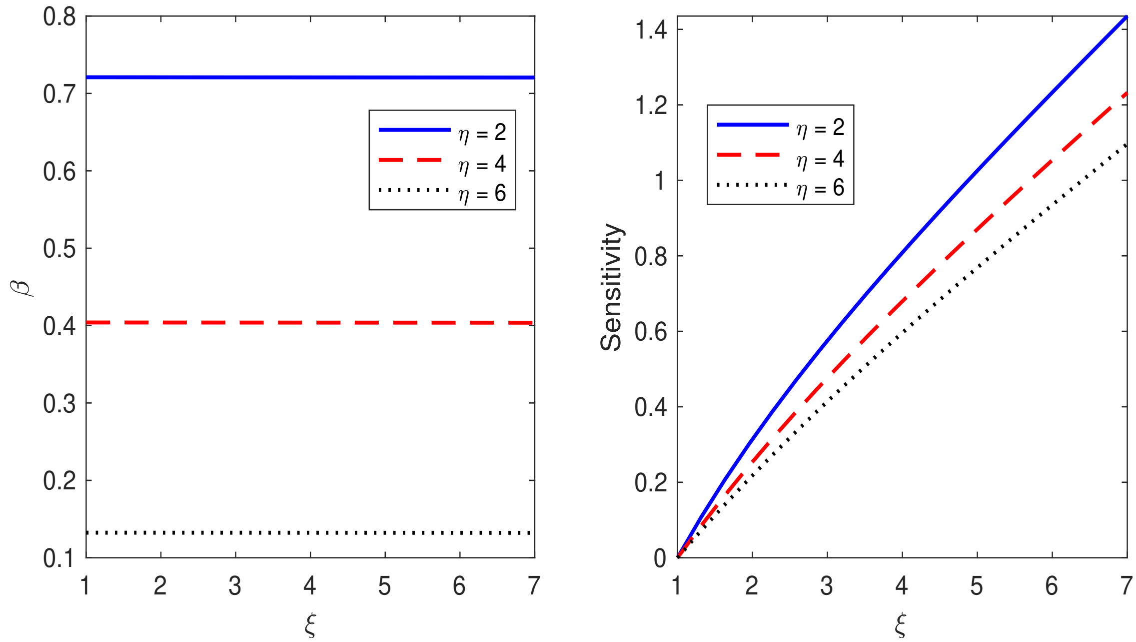
This figure plots the distribution of the alpha (Top) and beta (bottom) from the time-series regression of firm-level logarithm of implied variance changes on the logarithm of VIX^2 changes on FOMC announcement days. For illustration purpose, we only report firms with 100 or more observations out of these 160 FOMC days and the middle 95 percents of the beta values.

Figure 2: Sensitivity to Monetary Policy Shocks



The figure plots the portfolio returns sensitivity to monetary policy shock surprises, where we use the measure constructed in citetNS2018 for monetary shock surprises.

Figure 3: Sensitivity with respect to market returns and FOMC announcements



This figure plots the sensitivity of stock returns with respect market returns, i.e. CAPM $\beta' s$ (see equation (14))(left panel) and sensitivity of stock returns with respect to FOMC announcements as functions of ξ for different values of η. For simplicity, we fix q_t and $\hat{x}_t$ at middle point of $\bar{x}$.

Appendix

A Data appendix

To measure the firm-level sensitivity to monetary policy shocks around Federal Open Market Committee (FOMC) days, we use equity options data from OptionMetrics for the period of January 1, 1996 to December 31, 2015. We exclude those options with missing bid-ask prices and zero bids, or with negative bid-ask spreads. Following Conrad, Dittmar, and Ghysels (2013), we further exclude options that do not satisfy the usual option price bounds, and options with less than 7 days to maturity. We use out-of-the-money call and put options with positive open interest and with maturity between 8 to 45 days. Since equity options are American, we use the implied volatilities of each option provided by OptionMetrics, which are computed using a proprietary algorithm based on the Cox, A.Ross, and Rubinstein (1979) model, and account for the early exercise premium. Using these implied volatilities, we can treat the option prices obtained through the Black and Scholes formula as being European. Finally we estimate the model-free risk-neutral volatility by following Bakshi, Kapadia, and Madan (2003).

We obtain stock return data from the Center for Research in Security Prices (CRSP) and merge with the OptionMetrics data. During our data period, there are 5150 individual firms with traded options. In our empirical analysis, we only consider those stocks that have a CRSP share code of 10 or 11, and we exclude those stocks with a price less than $5. Fama-French risk factors are from Kenneth French's Data library.

The dates of FOMC meetings are from the website of Federal Reserve Board. Following Savor and Wilson (2014), we only include the scheduled FOMC meetings during our data period. There are about eight regularly scheduled FOMC meetings each year. When the meeting lasts for two days, we consider the second day as the FOMC announcement day. There are 160 FOMC announcement days in our data period. 904 out of 5150 firms have no option data on any of the 160 FOMC days. We obtain the monetary policy news shock data from Nakamura and Steinsson (2018), who used the high-frequency federal funds futures and Eurodollar futures and calculated the unexpected changes in interest rates over a 30-minute window surrounding the scheduled FOMC announcement. Nakamura and Steinsson have argued that this high-frequency data based approach captures unexpected monetary news shock well and have large effects on the economy (real interest rates). We use the data period of January 1996 to March 2014, which is the longest sample period available. These data are available from Nakamura's website at https://eml.berkeley.edu/~enakamura/papers.html.

B Details of the Continuous-time Model

Value function of the representative agent Because announcements fully reveal the value of x_t at nT, $q_{nT}^{+} = q_0$. In the interior of $(0, T)$, the standard optimal filtering implies that the posterior mean and variance of x_t are given by equations (4) and (5). Here q_t is deterministic and has a closed form solution:

$$q\left(t\right) = \frac{\sigma_x^2 \left(1 - e^{-2\hat{a}(t+t^*)}\right)}{\left(\hat{a} - a_x\right) e^{-2\hat{a}(t+t^*)} + a_x + \hat{a}}, \tag{15}$$

where $\hat{a} = \sqrt{a_x^2 + \left(\sigma_x/\sigma\right)^2}$ and $t^* = \frac{1}{2\hat{a}} \ln \frac{\sigma_x^2 + (\hat{a} - a_x) q_0}{\sigma_x^2 - (\hat{a} + a_x) q_0}$. In general, we can write $q_t = q\left(t \bmod T\right)$ for all t.[2]

Using the results from Duffie and Epstein (1992), the representative consumer's preference is specified by a pair of aggregators $(f, \mathcal{A})$ such that the utility of the representative agent, V_t is the solution to the following stochastic differential equation:

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

for some square-integrable process $\sigma_V(t)$. We adopt the convenient normalization $\mathcal{A}(V) = 0$ (Duffie and Epstein (1992)). Then the normalized aggregator $\bar{f}$ is ,

$$\bar{f}(C_t, V_t) = \frac{\rho}{1 - 1/\psi} \frac{C_t^{1-1/\psi} - \left(\left(1-\gamma\right) V_t\right)^{\frac{1-1/\psi}{1-\gamma}}}{\left(\left(1-\gamma\right) V_t\right)^{\frac{1-1/\psi}{1-\gamma} - 1}} \tag{16}$$

for $\psi \neq 1$ and

$$\bar{f}(C, V) = \rho \left\{\left(1-\gamma\right) V \ln C - V \ln\left[\left(1-\gamma\right) V\right]\right\}$$

for unit IES $\psi = 1$.

Hamilton–Jacobi–Bellman (HJB) equation for recursive utility satisfies

$$\bar{f}\left(C_t, V\left(\hat{x}_t, t, C_t\right)\right) + \mathcal{L}\left[V\left(\hat{x}_t, t, C_t\right)\right] = 0. \tag{17}$$

[2]We use the notation $t \bmod T$ for the remainder of t divided by T.

Due to homogeneity, consider the value function is of the form

$$V\left(\hat{x}_t, t, C_t\right) = \frac{1}{1-\gamma} H\left(\hat{x}_t, t\right) C_t^{1-\gamma}, \tag{18}$$

where $H\left(\hat{x}_t, t\right)$ satisfies the following HJB equation:

$$\begin{aligned} 0 \;=\; & \frac{\rho}{1-\frac{1}{\psi}}\left(H\left(\hat{x}_t, t\right)^{-\frac{1-\frac{1}{\psi}}{1-\gamma}} - 1\right) + \left(\hat{x}_t - \frac{1}{2}\gamma\sigma^2\right) + \frac{1}{1-\gamma}\frac{H_t\left(\hat{x}_t, t\right)}{H\left(\hat{x}_t, t\right)} \\ & + \left[\frac{1}{1-\gamma} a_x\left(\bar{x} - \hat{x}_t\right) + q_t\right]\frac{H_x\left(\hat{x}_t, t\right)}{H\left(\hat{x}_t, t\right)} + \frac{1}{2\left(1-\gamma\right)}\frac{H_{xx}\left(\hat{x}_t, t\right)}{H\left(\hat{x}_t, t\right)}\left(\frac{q_t}{\sigma}\right)^2 \end{aligned} \tag{19}$$

with the boundary condition

$$H\left(\hat{x}_{nT}^{-}, nT\right) = \mathbb{E}\left[H\left(\hat{x}_{nT}^{+}, nT\right) | \hat{x}_{nT}^{-}, q_{nT}^{-}\right], \; n = 1, 2, \ldots. \tag{20}$$

Proof. Given (16),

$$\bar{f}\left(C_t, V\right) = \frac{\rho}{1-\frac{1}{\psi}} C_t^{1-\gamma}\left[H\left(\hat{x}_t, t\right)^{1-\frac{1-\frac{1}{\psi}}{1-\gamma}} - H\left(\hat{x}_t, t\right)\right].$$

Further,

$$\begin{aligned} \frac{d\left[H\left(\hat{x}_t, t\right) C_t^{1-\gamma}\right]}{C_t^{1-\gamma}} \;=\; & \left(1-\gamma\right) H\left(\hat{x}_t, t\right)\left(\hat{x}_t dt + \sigma d\tilde{B}_{C,t}\right) - \frac{1}{2}\gamma\left(1-\gamma\right) H\left(\hat{x}_t, t\right)\sigma^2 dt \\ & + H_t\left(\hat{x}_t, t\right) dt + H_x\left(\hat{x}_t, t\right)\left[a_x\left(\bar{x} - \hat{x}_t\right) dt + \frac{q_t}{\sigma} d\tilde{B}_{C,t}\right] \\ & + \frac{1}{2} H_{xx}\left(\hat{x}_t, t\right)\left(\frac{q_t}{\sigma}\right)^2 dt + \left(1-\gamma\right) H_x\left(\hat{x}_t, t\right) q_t dt \end{aligned}$$

$$\begin{aligned} \frac{\mathcal{L}\left[V\left(\hat{x}_t, t, C_t\right)\right]}{C_t^{1-\gamma}} = \frac{\mathcal{L}\left[H\left(\hat{x}_t, t\right) C_t^{1-\gamma}\right]}{\left(1-\gamma\right) C_t^{1-\gamma}} \;=\; & \left(\hat{x}_t - \frac{1}{2}\gamma\sigma^2\right) H\left(\hat{x}_t, t\right) + \frac{1}{\left(1-\gamma\right)}\Big[H_t\left(\hat{x}_t, t\right) \\ & + H_x\left(\hat{x}_t, t\right) a_x\left(\bar{x} - \hat{x}_t\right) + \frac{1}{2} H_{xx}\left(\hat{x}_t, t\right)\left(\frac{q_t}{\sigma}\right)^2\Big] + H_x\left(\hat{x}_t, t\right) q_t \end{aligned}$$

Therefore, divided both sides of (17) by $C_t^{1-\gamma} H\left(\hat{x}_t, t\right)$, we get (19). □

Asset prices For $n=1,2,\cdots$, in the interior of $(nT,(n+1)T)$, the law of motion of the state price density, π_t satisfies the stochastic differential equation,

$$\frac{d\pi_t}{\pi_t} = -r(\hat{x}_t,t)\,dt - \sigma_\pi(t)\,d\tilde{B}_{C,t} \tag{21}$$

where the risk-free interest rate is

$$r(\hat{x}_t,t) = \rho + \frac{1}{\psi}\hat{x}_t - \frac{1}{2}\gamma\left(1+\frac{1}{\psi}\right)\sigma^2 + \frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_x(\hat{x}_t,t)}{H(\hat{x}_t,t)}q_t + \frac{\left(\frac{1}{\psi}-\gamma\right)\left(1-\frac{1}{\psi}\right)}{2(1-\gamma)^2}\left(\frac{H_x(\hat{x}_t,t)}{H(\hat{x}_t,t)}\frac{q_t}{\sigma}\right)^2. \tag{22}$$

and the market price of the Brownian motion risk is

$$\sigma_\pi(t) = \gamma\sigma - \frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_x(\hat{x}_t,t)}{H(\hat{x}_t,t)}\frac{q_t}{\sigma}. \tag{23}$$

Proof. Pricing kernel is defined as

$$\frac{d\pi_t}{\pi_t} = \frac{d\bar{f}_C(C,V)}{f_C(C,V)} + \bar{f}_V(C,V)\,dt \tag{24}$$

where

$$\bar{f}_C(C,V) = \rho H(\hat{x}_t,t)^{\frac{\frac{1}{\psi}-\gamma}{1-\gamma}} C_t^{-\gamma}$$

$$\bar{f}_V(C,V) = \rho\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}} H(\hat{x}_t,t)^{-\frac{1-\frac{1}{\psi}}{1-\gamma}} - \rho\frac{1-\gamma}{1-\frac{1}{\psi}}.$$

$$\begin{aligned}\frac{d\bar{f}_C(C,V)}{f_C(C,V)} = \frac{d[H^{\frac{\frac{1}{\psi}-\gamma}{1-\gamma}}C_t^{-\gamma}]}{H^{\frac{\frac{1}{\psi}-\gamma}{1-\gamma}}C_t^{-\gamma}} \quad = \quad & \left\{-\gamma\hat{x}_t + \frac{1}{2}\gamma(\gamma+1)\sigma^2 + \frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_t}{H} + \frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_x}{H}a_x(\bar{x}-\hat{x}_t)\right. \\ & + \frac{1}{2}\left[\frac{\left(\frac{1}{\psi}-\gamma\right)\left(\frac{1}{\psi}-1\right)}{(1-\gamma)^2}\left(\frac{H_x}{H}\right)^2 + \frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_{xx}}{H}\right]\left(\frac{q_t}{\sigma}\right)^2 \\ & \left. -\gamma\frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_x}{H}q_t\right\}dt + \left[-\gamma\sigma + \frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_x(\hat{x}_t,t)}{H(\hat{x}_t,t)}\frac{q_t}{\sigma}\right]d\tilde{B}_{C,t}.\end{aligned}$$

Matching the drift and diffusion of (21) and (24), we can get (23) and

$$
\begin{aligned}
r(\hat{x}_t, t) &= -\frac{\frac{1}{\psi}-\gamma}{1-\gamma}\left\{\frac{H_t}{H} + \frac{H_x}{H}a_x(\bar{x}-\hat{x}_t) + \frac{1}{2}\left[\frac{\frac{1}{\psi}-1}{1-\gamma}\left(\frac{H_x}{H}\right)^2 + \frac{H_{xx}}{H}\right]\left(\frac{q_t}{\sigma}\right)^2 - \gamma\frac{H_x}{H}q_t\right\} \\
&\quad +\gamma\hat{x}_t - \frac{1}{2}\gamma(\gamma+1)\sigma^2 - \rho\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}}H(\hat{x}_t,t)^{-\frac{1-\frac{1}{\psi}}{1-\gamma}} + \rho\frac{1-\gamma}{1-\frac{1}{\psi}}. \qquad (25)
\end{aligned}
$$

Use the HJB equation to simplify $r(\hat{x}_t, t)$ by multiplying $\left(\frac{1}{\psi}-\gamma\right)$ on both sides of (19),

$$
\begin{aligned}
0 &= \rho\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}}\left(H(\hat{x}_t,t)^{-\frac{1-\frac{1}{\psi}}{1-\gamma}} - 1\right) + \left(\frac{1}{\psi}-\gamma\right)\left(\hat{x}_t - \frac{1}{2}\gamma\sigma^2\right) + \frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_t(\hat{x}_t,t)}{H(\hat{x}_t,t)} \\
&\quad + \left(\frac{1}{\psi}-\gamma\right)\left[\frac{1}{1-\gamma}a_x(\bar{x}-\hat{x}_t) + q_t\right]\frac{H_x(\hat{x}_t,t)}{H(\hat{x}_t,t)} + \frac{\frac{1}{\psi}-\gamma}{2(1-\gamma)}\frac{H_{xx}(\hat{x}_t,t)}{H(\hat{x}_t,t)}\left(\frac{q_t}{\sigma}\right)^2
\end{aligned}
$$

and adding up with (25), we can get equation (22). For simplicity, following Ai and Bansal (2018), approximate $\frac{H_x(\hat{x}_t,t)}{H(\hat{x}_t,t)} \approx \frac{1-\gamma}{a_x+\rho}$, finally we will get (8) and (9). □

We denote $p^i(\hat{x}_t, t)$ as the price-to-dividend ratio for firm i. The present value relationship (3) implies that

$$
\pi_t D_t^i + \lim_{\Delta\to 0}\frac{1}{\Delta}\left\{\mathbb{E}_t\left[\pi_{t+\Delta}p^i(\hat{x}_{t+\Delta}, t+\Delta)D_{t+\Delta}^i\right] - \pi_t p^i(\hat{x}_t,t)D_t^i\right\} = 0 \qquad (26)
$$

The above equation can be used to show that the price-to-dividend ratio function must satisfy the PDE (10). Also, it can be used to derive the boundary condition (13).

Proof. Equation (26) implies

$$
1 + p^i(\hat{x}_t,t)\frac{\mathcal{L}\left[\pi_t p^i(\hat{x}_t,t)D_t\right]}{\pi_t p^i(\hat{x}_t,t)D_t} = 0.
$$

Using Ito's lemma and equation (6) and (21),

$$
\begin{aligned}
\frac{\mathcal{L}\left[\pi_t p^i\left(\hat{x}_t,t\right)D_t\right]}{\pi_t p^i\left(\hat{x}_t,t\right)D_t} &= -r\left(\hat{x}_t,t\right)+\frac{1}{p^i\left(\hat{x}_t,t\right)}\left[p_t^i\left(\hat{x}_t,t\right)+p_x^i\left(\hat{x}_t,t\right)a_x\left(\bar{x}-\hat{x}_t\right)+\frac{1}{2}p_{xx}^i\left(\hat{x}_t,t\right)\frac{q_t^2}{\sigma^2}\right] \\
&\quad +\left[\bar{x}+\xi_i\left(\hat{x}_t-\bar{x}\right)\right]+\frac{p_x^i\left(\hat{x}_t,t\right)}{p^i\left(\hat{x}_t,t\right)}q_t\eta_i \\
&\quad -\left(\gamma\sigma-\frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_x\left(\hat{x}_t,t\right)}{H\left(\hat{x}_t,t\right)}\frac{q_t}{\sigma}\right)\left[\eta_i\sigma+\frac{p_x^i\left(\hat{x}_t,t\right)}{p^i\left(\hat{x}_t,t\right)}\frac{q_t}{\sigma}\right].
\end{aligned}
$$

Then we can derive the PDE for firm i's price-to-dividend ratio as

$$
\begin{aligned}
&-\rho-\frac{1}{\psi}\hat{x}_t+\frac{1}{2}\gamma\left(1+\frac{1}{\psi}\right)\sigma^2+\frac{\gamma-\frac{1}{\psi}}{1-\gamma}\frac{H_x\left(\hat{x}_t,t\right)}{H\left(\hat{x}_t,t\right)}q_t-\frac{1}{2}\frac{\left(\frac{1}{\psi}-\gamma\right)\left(1-\frac{1}{\psi}\right)}{\left(1-\gamma\right)^2}\left(\frac{H_x\left(\hat{x}_t,t\right)}{H\left(\hat{x}_t,t\right)}\frac{q_t}{\sigma}\right)^2 \\
&\quad +\frac{1}{p^i\left(\hat{x}_t,t\right)}\left[1+p_t^i\left(\hat{x}_t,t\right)+p_x^i\left(\hat{x}_t,t\right)a_x\left(\bar{x}-\hat{x}_t\right)+\frac{1}{2}p_{xx}^i\left(\hat{x}_t,t\right)\frac{q_t}{\sigma^2}\right] \\
&\quad +\bar{x}+\xi_i\left(\hat{x}_t-\bar{x}\right)+\frac{p_x^i\left(\hat{x}_t,t\right)}{p^i\left(\hat{x}_t,t\right)}q_t\eta_i-\left(\gamma\sigma-\frac{\frac{1}{\psi}-\gamma}{1-\gamma}\frac{H_{xx}\left(\hat{x}_t,t\right)}{H\left(\hat{x}_t,t\right)}\frac{q_t}{\sigma}\right)\left[\eta_i\sigma+\frac{p_x^i\left(\hat{x}_t,t\right)}{p^i\left(\hat{x}_t,t\right)}\frac{q_t}{\sigma}\right] = 0.
\end{aligned}
$$

Using $\frac{H_x(\hat{x}_t,t)}{H(\hat{x}_t,t)} \approx \frac{1-\gamma}{a_x+\rho}$, we can rewrite the above equation to get (10). Again, we focus on the steady-state and denote $p^i\left(\hat{x},0\right)=p^i\left(\hat{x},nT^+\right)$ and $p^i\left(\hat{x},T\right)=p^i\left(\hat{x},nT^-\right)$, and the boundary condition (13) can be derived accordingly. □

We define the cumulative return as

$$
\frac{dR_t^i}{R_t^i}=\mu_{R,t}^i dt+\sigma_{R,t}^i d\tilde{B}_{C,t}+\sigma_i dB_{i,t} \tag{27}
$$

where $\mu_{R,t}^i$ and $\sigma_{R,t}^i$ are the risky asset return and volatility for firm i, respectively,

$$
\begin{aligned}
\mu_{R,t}^i &= \frac{1}{p^i\left(\hat{x}_t,t\right)}\left[1+p_t^i\left(\hat{x}_t,t\right)+p_x^i\left(\hat{x}_t,t\right)a_x\left(\bar{x}-\hat{x}_t\right)+\frac{1}{2}p_{xx}^i\left(\hat{x}_t,t\right)\frac{q_t^2}{\sigma^2}\right] \\
&\quad +\bar{x}+\xi_i\left(\hat{x}_t-\bar{x}\right)+\frac{p_x^i\left(\hat{x}_t,t\right)}{p^i\left(\hat{x}_t,t\right)}q_t\eta_i, \qquad (28) \\
\sigma_{R,t}^i &= \eta_i\sigma+\frac{p_x^i\left(\hat{x}_t,t\right)}{p^i\left(\hat{x}_t,t\right)}\frac{q_t}{\sigma}. \qquad (29)
\end{aligned}
$$

In the interior of $(nT, (n+1)T)$, the instantaneous risk premium is

$$\mu_{R,t} - r(\hat{x}_t, t) = \left[\gamma\sigma - \frac{\frac{1}{\psi} - \gamma}{a_x + \rho} \frac{q_t}{\sigma}\right] \left[\eta_i \sigma + \frac{p_x^i(\hat{x}_t, t)}{p^i(\hat{x}_t, t)} \frac{q_t}{\sigma}\right]. \tag{30}$$

Proof. The cumulative return can be computed as

$$\frac{dR_t^i}{R_t^i} = \frac{1}{p^i(\hat{x}_t, t) D_t^i} \left[D_t^i dt + d\left[p^i(\hat{x}_t, t) D_t^i\right]\right].$$

Applying Ito's lemma,

$$\begin{aligned} \frac{d\left[p^i(\hat{x}_t, t) D_t^i\right]}{p^i(\hat{x}_t, t) D_t^i} &= \left\{\frac{1}{p^i(\hat{x}_t, t)} \left[p_t^i(\hat{x}_t, t) + p_x^i(\hat{x}_t, t) a_x(\bar{x} - \hat{x}_t) + \frac{1}{2} p_{xx}^i(\hat{x}_t, t) \frac{q_t^2}{\sigma^2}\right] \right. \\ &\quad \left. + \bar{x} + \xi_i(\hat{x}_t - \bar{x}) + \frac{p_x^i(\hat{x}_t, t)}{p^i(\hat{x}_t, t)} q_t \eta_i \right\} dt + \left[\eta_i \sigma + \frac{p_x^i(\hat{x}_t, t)}{p^i(\hat{x}_t, t)} \frac{q_t}{\sigma}\right] d\tilde{B}_{C,t} + dB_{i,t}. \end{aligned}$$

Matching the drift and diffusion terms with equation (27), we can get (29) and (29).

The instantaneous risk premium (30) can be obtained from

$$\begin{aligned} \mu_{R,t}^i - r(\hat{x}_t, t) &= -Cov_t\left[\frac{d\left[p^i(\hat{x}_t, t) D_t^i\right]}{p^i(\hat{x}_t, t) D_t^i}, \frac{d\pi_t}{\pi_t}\right] \\ &= \left[\gamma\sigma - \frac{\frac{1}{\psi} - \gamma}{1 - \gamma} \frac{H_x(\hat{x}_t, t)}{H(\hat{x}_t, t)} \frac{q_t}{\sigma}\right] \left[\eta_i \sigma + \frac{p_x^i(\hat{x}_t, t)}{p^i(\hat{x}_t, t)} \frac{q_t}{\sigma}\right] \\ &= \gamma\eta_i\sigma^2 + \left[\gamma \frac{p_x^i(\hat{x}_t, t)}{p^i(\hat{x}_t, t)} - \frac{\frac{1}{\psi} - \gamma}{1 - \gamma} \eta_i \frac{H_x(\hat{x}_t, t)}{H(\hat{x}_t, t)}\right] q_t - \frac{\frac{1}{\psi} - \gamma}{1 - \gamma} \frac{H_x(\hat{x}_t, t)}{H(\hat{x}_t, t)} \frac{p_x^i(\hat{x}_t, t)}{p^i(\hat{x}_t, t)} \left(\frac{q_t}{\sigma}\right)^2. \end{aligned}$$

□

Numerical Solutions To solve the PDE (10) with the boundary condition (13) for each firm i, we consider the following auxiliary problem[3]:

$$p(\hat{x}_t, t) = \mathbb{E}\left[\int_t^T e^{-\int_t^s \varpi(\hat{x}_u, u) du} ds + e^{-\int_t^T \varpi(\hat{x}_u, u) du} p(\hat{x}_T, T)\right], \tag{31}$$

[3] We fix (ξ_i, η_i) for each firm and calculate the firm-specific price-to-dividend $p^i(\hat{x}_t, t)$. The procedures are the same for each firm, thus we drop i for simplicity.

where the state variable $\hat{x}_t$ follows the law of motion

$$d\hat{x}_t = -\nu(\hat{x}_t, t)\, dt + \frac{q_t}{\sigma} dB_t. \tag{32}$$

Note that the solution to (31) and (13) satisfies the same PDE. Given an initial guess of the pre-announcement price-to-dividend ratio, $p^-(\hat{x}_\tau, \tau)$, we can solve (31) by the Markov chain approximation method (Kushner and Dupuis (2001))[4]

1. We first start with an initial guess of a pre-announcement price-to-dividend ratio $p(\hat{x}_T, T) = 1/\rho$.

2. With the initial guess of $p(\hat{x}_T, T)$, for $t = T - \Delta$, $T - 2\Delta$, etc, we use the Markov chain approximation to compute the discounted problem in (31) backwards recursively:

$$p(\hat{x}_t, t) = \Delta + e^{-\varpi(\hat{x}_t, t)\Delta} \mathbb{E}\left[p(\hat{x}_{t+\Delta}, t+\Delta)\right],$$

until we obtain $p(\hat{x}_t, 0)$.[5]

3. Compute an updated pre-announcement price-to-dividend ratio function, $p(\hat{x}_T, T)$ using (13)[6]

$$p\left(\hat{x}_T^-, T^-\right) = \frac{\mathbb{E}\left[e^{\frac{1-\gamma}{a_x+\rho}\hat{x}_T^+} p\left(\hat{x}_T^+, 0\right) \Big| \hat{x}_T^-, q_T^-\right]}{e^{\frac{1-\gamma}{a_x+\rho}\hat{x}_T^- + \frac{1}{2}\left(\frac{1-\gamma}{a_x+\rho}\right)^2 \left[q_T^- - q_T^+\right]}}.$$

[4]We construct a locally consistent Markov chain approximation of the diffusion process (32) as follows. We choose a small $d\hat{x}$, let $Q = |\nu(\hat{x}, t)|\, d\hat{x} + \left(\frac{q_t}{\sigma}\right)^2$, and define the time increment $\Delta = \frac{d\hat{x}^2}{Q}$ be a function of $d\hat{x}$. Define the following Markov chain on the space of $\hat{x}$:

$$\begin{aligned} \Pr(\hat{x} + d\hat{x} \,|\hat{x}) &= \frac{1}{Q}\left[-\nu(\hat{x}, t)^+ d\hat{x} + \frac{1}{2}\left(\frac{q_t}{\sigma}\right)^2\right], \\ \Pr(\hat{x} - d\hat{x} \,|\hat{x}) &= \frac{1}{Q}\left[-\nu(\hat{x}, t)^- d\hat{x} + \frac{1}{2}\left(\frac{q_t}{\sigma}\right)^2\right]. \end{aligned}$$

One can verify that as $d\hat{x} \to 0$, the above Markov chain converges to the diffusion process (32) (In the language of Kushner and Dupuis (2001), this is a Markov chain that is locally consistent with the diffusion process (32)).

[5]Define log price-to-dividend ratio $\varrho(\hat{x}_t, t) \equiv \ln p(\hat{x}_t, t)$,

$$\begin{aligned} \varrho(\hat{x}_t, t) &= \ln\left[\mathit{\Delta} + e^{-\varpi(\hat{x}_t, t)\mathit{\Delta}} \mathbb{E}\left[p(\hat{x}_{t+\mathit{\Delta}}, t+\mathit{\Delta})\right]\right] \\ &= \ln\left[\mathit{\Delta} + e^{-\varpi(\hat{x}_t, t)\mathit{\Delta}} e^{\varrho(\hat{x}_{t+\mathit{\Delta}}, t+\mathit{\Delta}) - \varrho_x(\hat{x}_t, t)\nu(\hat{x}_t, t)\mathit{\Delta} + \frac{1}{2}\mathit{\Delta}\varrho_x^2(\hat{x}_t, t)\left(\frac{q_t}{\sigma}\right)^2}\right] \\ &= \ln\left[\mathit{\Delta} + e^{\varrho(\hat{x}_{t+\mathit{\Delta}}, t+\mathit{\Delta}) - [\varpi(\hat{x}_t, t) + \nu(\hat{x}_t, t)]\mathit{\Delta} + \frac{1}{2}\mathit{\Delta}\varrho_x^2(\hat{x}_t, t)\left(\frac{q_t}{\sigma}\right)^2}\right]. \end{aligned}$$

[6]Using Gaussian Quadrature to approximate the expectation:
First, generate random variable nodes $\mathbf{n}$ and weights $\boldsymbol{\omega}$ for multivariate normal distribution.

4. Go back to step 1 and iterate until the function $p\left(\hat{x}_T, T\right)$ converges.

If $\hat{x}$ is in the interior $\left[\bar{x} - 5\frac{\sigma_x}{\sqrt{2a_x}} + \max\left(\mathbf{n}\right), \bar{x} + 5\frac{\sigma_x}{\sqrt{2a_x}} + \max\left(\mathbf{n}\right)\right]$, use Gaussian quadrature

$$\varrho\left(\hat{x}_T^-, T^-\right) = \ln \mathbb{E}\left[e^{\frac{1-\gamma}{a_x+\rho}\hat{x}_T^+ + \varrho\left(\hat{x}_T^+, T^+\right)} \mid \hat{x}_T^-, q_T^-\right] - \left(\frac{1-\gamma}{a_x+\rho}\hat{x}_T^- + \frac{1}{2}\left(\frac{1-\gamma}{a_x+\rho}\right)^2\left[q_T^- - q_T^+\right]\right)$$

where

$$\mathbb{E}\left[e^{\frac{1-\gamma}{a_x+\rho}\hat{x}_T^+ + \varrho\left(\hat{x}_T^+, T^+\right)} \mid \hat{x}_T^-, q_T^-\right] = \boldsymbol{\omega}' e^{\frac{1-\gamma}{a_x+\rho}\hat{x}_T^+ + \varrho\left(\hat{x}_T^+, T^+\right)}, \ \hat{x}_T^+ = \hat{x}_T^- + \mathbf{n}.$$

If $\hat{x}$ is close to the boundary, use local approximation:

$$\varrho\left(\hat{x}_T, T\right) + \varrho_x\left(\hat{x}_T, T\right)\left[\frac{1-\gamma}{a_x+\rho} + \frac{1}{2}\varrho_x\left(\hat{x}_T, T\right)\right]\left[q_T^- - q_T^+\right].$$

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