The Cross-Section of Monetary Policy Announcement Premium

Hengjie Ai, Leyla Jianyu Han, Xuhui Pan and Lai Xu *

December 10, 2019

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 option-implied variance upon FOMC announcements to measure the sensitivity of stock returns with respect to monetary policy announcement surprises. A long-short portfolio formed on the sensitivity measure produces an average announcement-day return of 31 bps, which is both statistically and economically significant and is robust after controlling for standard risk factors. We develop an equilibrium model to account for the dynamics of implied variances and the cross-section of returns of the expected variance reduction sorted portfolios around FOMC announcements.

JEL Code: D81, G12, E44

Key words: FOMC Announcement, Implied Variance, Cross-Section of Equity Returns

*Hengjie Ai (hengjie@umn.edu) is affiliated with the Carlson School of Management, University of Minnesota; Leyla Jianyu Han (hanjyu@connect.hku.hk) is associated with the Faculty of Business and Economics, University of Hong Kong; Xuhui (Nick) Pan (xpan@ou.edu) is at the Price College of Business, University of Oklahoma; and Lai Xu (lxu100@syr.edu) is at the Whitman School of Management, Syracuse University. We thank Grace Xing Hu, Annette Vissing-Jorgensen, Nishad Kapadia, Yang Liu, Jun Pan, Morad Zekhnini, Lei Zhang, participants of WFA, University of Houston, University of Hong Kong, Tsinghua University (PBC), and Tulane University for helpful comments.
1 Introduction

Pre-scheduled monetary policy announcements are associated with large realizations of equity market excess returns on announcement days, for example, Savor and Wilson (2013) and Lucca and Moench (2015). Ai and Bansal (2018) demonstrate that, interpreted as risk premiums, the substantial equity market returns realized on FOMC announcement days imply that preferences in macro and finance models must satisfy generalized risk sensitivity. Because the choice of preference is of fundamental importance in welfare analysis and policy evaluations, the existence of the monetary policy announcement premium is not only important for understanding equity market risk compensations, but also provides guidance for policy-making.

The purpose of this paper is to use empirical evidence from the cross-section of equity returns to examine the existence of the monetary policy announcement premium. We show that exposures to monetary policy announcement surprises are priced in the cross-section of equity returns. As a result, market expectations about firms’ sensitivity with respect to monetary policy announcements strongly predict their equity returns on announcement days. A long-short portfolio formed on our monetary policy sensitivity measure produces an average announcement-day return of 31.67 bps, which is statistically and economically significant, even after controlling for standard risk factors.

To evaluate whether firms differ in their sensitivity with respect to monetary policy announcements also differ in expected returns on announcement days, we first develop a novel measure of market expectations of sensitivity with respect to monetary policy surprises. A natural choice would be the elasticity (or $\beta$) of firms’ equity returns with respect to measures of monetary policy surprises. However, because FOMC announcements are infrequent (eight times a year), estimates of $\beta$ are likely to be noisy and inaccurate especially if the true sensitivity varies over time. To overcome this difficulty, we use information from option-implied variance. Our intuition is that FOMC announcements resolve uncertainty about the macroeconomy and monetary policy and are associated with reductions in option-implied variance. Firms that are more sensitive with respect to monetary policy announcements should experience a larger amount of implied variance reduction after announcements. Expectations for the implied variance reduction can therefore
measure sensitivity with respect to monetary policy announcements.

We find that the expected implied variance reduction (EVR) sorted portfolios yield a significant spread in average returns on FOMC announcement days, but not on non-announcement days. A long-short portfolio formed on our monetary policy sensitivity measure produces an average announcement-day return of 31.67 bps. In addition, the returns of EVR-sorted portfolios remain significant after controlling for market beta and other standard risk factors. To further demonstrate that the spread on the EVR-sorted portfolios reflects risk compensation for monetary policy announcements, we use measures of monetary policy announcement surprises constructed by Nakamura and Steinsson (2018) to show that i) the average monetary policy announcement surprises are indifferent from zero and therefore rational expectations hold well in our sample period; and ii) returns of the EVR-sorted portfolios are monotone in their sensitivity 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 suggest that the CAPM holds well on macroeconomic announcement days. Savor and Wilson (2014), for example, find that CAPM holds well for $\beta$ sorted portfolios, the Fama-French size and book-to-market sorted portfolios, and industry portfolios on announcement days. Wachter and Zhu (2018), Ai, Bansal, Im, and Ying (2018) demonstrate that this pattern of CAPM is consistent with theoretical models of announcement premiums.

To quantitatively account for the cross-sectional announcement returns, we develop a model where FOMC announcement surprises require risk compensations because they reveal the Federal Reserve’s private information about the prospect of future economic growth and where investors’ preference satisfy generalized risk sensitivity (Ai and Bansal, 2018). In our model, aggregate economic growth is driven by a latent state variable and an i.i.d. component (short-run shocks). The Federal Reserve has private information about the true value of the latent growth variable, which is revealed through monetary policy announcements periodically. We specify a cross-section of dividend process that differs in both the sensitivity with respect to Federal Reserve’s announcement
surprises and the publicly observable contemporaneous growth rate shocks.

In our model, the size of the reduction of implied variance on announcement days provides an accurate measure of equities’ risk exposure to surprises in monetary policy announcements. Sorting firms on implied variance reduction is equivalent to sorting on sensitivity with respect to news in FOMC announcements. This is because on non-announcement days, investors do not observe the true value of the latent growth variable and update their beliefs about it based on noisy signals contained in realized economic growth. Scheduled macroeconomic announcements reveal the true value of the latent variable and as a result, investors’ posterior belief jumps on announcement days and resets to its true value upon the announcement. Stocks that have a high exposure to policy surprises will experience a large drop in implied variance 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 36.2 bps, and the spread on announcement-day return of expected sensitivity sorted portfolios is about 42.1 bps, both of which are close to their empirical counterparts. Due to generalized risk sensitivity, announcement surprises carry news about the future prospect of the economy and are priced (Ai and Bansal, 2018). As a result, stocks that have a higher sensitivity with respect to monetary policy announcement surprises than others will also receive a higher risk premium on announcement days.

Second, the CAPM fails to account for the announcement return of EVR-sorted portfolios in our model. In the model, expected reductions in implied variance is an accurate measure of the sensitivity with respect to policy announcement surprises. CAPM $\beta$, however, depends both on the sensitivity of the stock return with respect to policy announcement surprises and more importantly, on that with respect to contemporaneous shocks to economic growth, which account for a quantitatively larger fraction of variations in equity market valuations. EVR-sorted portfolios therefore exhibit large dispersion in sensitivity with respect to policy announcement surprises but a small dispersion in CAPM $\beta$, which is not enough to account for their announcement day returns.

Third, despite the failure of CAPM to account for the expected returns of EVR-sorted portfolios, it explains the announcement returns of $\beta-$ sorted portfolios quite well. In the data,
as documented by Savor and Wilson (2014), $\beta-$ sorted portfolios exhibit significant differences in their announcement premium, which can be explained by the CAPM. In our model, $\beta-$ sorted portfolios exhibit a large dispersion in CAPM $\beta$ but a small dispersion in sensitivity with respect to monetary surprises, as quantitatively, $\beta$ reflects mostly elasticity with respect to contemporaneous shocks to economic growth and is only weakly correlated with sensitivity with respect to FOMC announcements. As a result, the announcement-day return of $\beta-$ sorted portfolios is mostly absorbed by difference in $\beta$, making it difficult to reject the CAPM with a finite sample.

**Related literature** Our paper is related to the literature that emphasize the impact of monetary policy announcements on equity market returns. Bernanke and Kuttner (2005) demonstrate that stock markets respond strongly to monetary policy announcements. Gürkaynak, Sack, and Swanson (2005) document evidence that both monetary policy action and announcements have important impacts on asset markets.

Within this literature, most related to ours are several recent papers emphasizing the impact of FOMC announcements on equity market excess return. Lucca and Moench (2015) document an FOMC pre-announcement drift. Cieslak, Morse, and Vissing-Jorgensen (2019) provide evidence for stock market returns over FOMC announcement cycles. Cieslak and Pang (2019) provide a decomposition of shocks that drives stock and bond market variations to explain stock and bond returns over the FOMC announcement cycle. Neuhierl and Weber (2018) document that the return drift around FOMC announcements depends on whether the monetary policy is expansionary or contradictory. Bollerslev, Li, and Xue (2018) find that after the FOMC meetings, both volatility and volume increase, but the intra-day volume-volatility elasticity is systematically below unity. While the above papers study the aggregate equity market excess returns around FOMC announcement days, our paper examines the heterogeneous impact of FOMC announcements on the cross-section of the stock market.\footnote{Related, Mueller, Tahbaz-Salehi, and Vedolin (2017) and Karnaukh (2018) study the impact of FOMC announcements on the foreign exchange market.}

Our paper is also related to the broader literature on macroeconomic announcement premium. Savor and Wilson (2013) document a significant equity market return on days with major
macroeconomic announcements. Brusa, Savor, and Wilson (2019) show that the same holds for many other countries. Savor and Wilson (2014) demonstrate that the CAPM holds well for macroeconomic announcement days, but not for non-announcement days. Hu, Pan, Wang, and Zhu (2019) provide evidence that option-implied variance increases before announcements and drops afterwards and attribute the FOMC announcement premium to heightened stock market uncertainty. Amengual and Xiu (2018) argue that the large declines in option-implied variance after the FOMC announcements are associated with a resolution of policy uncertainty. The above empirical evidences are all broadly consistent with our equilibrium model where announcements resolve macroeconomic uncertainty and are associated with reductions in option-implied variance of equity market returns.

Our work is also related to papers that study monetary policy and the cross-section of equity returns. Ozdagli and Velikov (2019) use observable firm characteristics to measure the 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. The above papers study monetary policies in general, but not necessarily monetary policy announcements. In fact, none of them focuses on returns realized on FOMC announcement days, nor do they find a significant premium realized upon announcements.

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 information channel we emphasize in our paper is consistent with the recent work by Nakamura and Steinsson (2018), who provide empirical evidence and develop a theoretical model to show that Fed announcements affect beliefs not only about monetary policy but also about economic fundamentals.

The rest of the paper is organized as follows. In Section 2, we develop a measure of expected sensitivity with respect to monetary policy announcement surprises 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 announcement surprises earn significantly higher premiums 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

To study whether risk exposures with respect to monetary policy announcements are priced in the cross-section of equity returns, our strategy is to measure the sensitivity of firms’ equity returns with respect to monetary policy announcements and to evaluate whether differences in the sensitivities are reflected in the expected returns on firms’ equity realized on announcement days. This exercise requires constructing a firm-level measure of sensitivity with respect to FOMC announcement surprises, sorting stocks into portfolios based on such a measure, and estimating expected returns by computing average returns of the sensitivity-sorted portfolios.

Because our purpose is to measure the expected returns of the sensitivity sorted portfolios, the measure of sensitivity should be based on market expectations and cannot depend on the information not available at the time of portfolio formation in order to avoid any look-ahead bias. Because the FOMC makes announcements only eight times a year, estimates of this sensitivity based on historical announcement data is likely to be noisy due to lack of observations. In addition, if the true sensitivity is time-varying, estimates for the sensitivity using historical announcements are likely to be inaccurate.
To overcome the above difficulty, our measure of sensitivity is based on option-implied variance. In contrast to estimated sensitivity using historical announcement data, option-implied variance is capable of capturing changes in market expectations in a timely manner. The construction of our measure is based on the intuition that FOMC announcements reduce uncertainty about the macroeconomy and monetary policy, and are associated with reductions in option-implied variance. In the cross-section, firms that are more sensitive to monetary policy announcement surprises should experience higher implied variance reductions upon announcements. To avoid the look-ahead bias, we construct a measure of market expected implied variance reduction, or EVR for abbreviation. In what follows, we first present evidence on implied variance reductions on FOMC announcement days and then detail the construction of our measure of EVR.

**Implied variance around monetary policy announcements** We first establish that there are significant reductions in option-implied variance on FOMC announcement days both at the market level and at the firm level. We also show that firm-level implied variance reduction exhibits substantial heterogeneity. Together, the above evidence supports the two premises of our empirical exercises: i) implied variance reduction can be used to measure the firm level sensitivity with respect to monetary policy announcement surprises, and ii) there is a considerable heterogeneity in this sensitivity across firms.

We use the squared option-implied volatility index, VIX^2, to measure implied variance of the market return. We obtain data on VIX from the Chicago Board Option Exchange (CBOE). The CBOE’s VIX is a model-free measure of implied volatility computed from the S&P 500 index option prices. For the firm-level implied variance, on each day and for each time to maturity, we follow Bakshi, Kapadia, and Madan (2003) to estimate the implied variance by averaging the weighted prices of out-of-money puts and out-of-money calls over a wide range of strike prices. We then obtain the 7-day implied variance by interpolating or extrapolating the implied variance in the maturity dimension. We use the 7-day implied variance because the short-maturity option prices are likely to be more sensitive to announcement surprises than the long-maturity option prices. Our option data are from OptionMetrics. The sample period is from January 1996 to December 2017.
In our data period there are 176 pre-scheduled FOMC meetings. If a FOMC meeting lasts for two days, we treat the last day as the announcement day.

We document the patterns of implied variance reduction on FOMC announcement days in Table 1. Panel A of the table compares the market level implied variance ($VIX_t^2$) on FOMC announcement days with the same moment one-day before announcements, $VIX_{t-1}^2$. Consistent with the previous literature, for example, Savor and Wilson (2013), VIX significantly decreases after FOMC announcements. On average, the daily reduction in VIX$^2$ is about 2.41 (monthly percentage squared). We observe the same pattern at the firm level. As shown in the Panel B of Table 1, the average reduction in implied variance at the firm level is about 4.95 and significant.

Moreover, there is a significant heterogeneity in announcement-day reductions in implied variance across firms. We rank firms by their average announcement-day implied variance reduction and plot the histogram of these reductions in Figure 1. The implied variance decreases after announcements for almost all firms, and the magnitude of reduction differs substantially.

### 2.2 Expected Variance Reduction

Motivated by the above evidence, we measure market expected sensitivity with respect to FOMC announcement surprises using expected implied variance reduction. For any FOMC announcement day $t$, the Expected Variance Reduction (EVR) is computed as:

$$EVR = IV_{t-2} - Median \ of \ Historical \ IV.$$  \hspace{1cm} (1)

In the above equation, $IV_{t-2}$ is the 7-day implied variance (IV) for a firm computed from the closing price of its options two days before the FOMC announcement. We use two days before announcements to ensure that our measure is not affected by the pre-FOMC announcement drift documented by Lucca and Moench (2015). The historical median $IV$ in the above equation is

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2It is important to note that our measure is different from the variance risk premium (VRP) in the literature, for example, Bollerslev, Tauchen, and Zhou (2009), Drechsler and Yaron (2011) and Bollerslev, Marrone, Xu, and Zhou (2014). VRP is the difference between variance under the Q-measure and that under the P-measure, whereas our measure is designed to capture the upcoming announcements and do not use any variance measure under the physical probability.
computed as the median value of IV during day $-15$ and day $-8$, where the announcement day is normalized to 0.\textsuperscript{3} In our construction, the historical IV is not affected by the upcoming FOMC announcement, while $IV_{t-2}$ is. A sudden increase in $IV_{t-2}$ relative to its historical level indicates the market expectation that the equity of the firm will be sensitive to the upcoming FOMC announcement.

Our measure of expected variance reduction has significant predictive powers for the actual implied variance reduction on FOMC announcement days. In the equation below, we report results from a panel regression of the actual implied variance reduction on our measure of expected implied variance reduction. The regression coefficient on expected variance reduction is significantly positive with a t-statistic of 8.63 (based on the day-clustered standard error) and a $R^2$ of 5.9\%.

\[
\text{Actual Variance Reduction} = 0.0019 + 0.2054 \times \text{Expected Variance Reduction.} \tag{2}
\]

The key advantage of using implied variance to measure expected sensitivity is that implied variance reflects market expectations in a timely manner. Alternative measures such as market $\beta$ on previous announcement days do not incorporate the same forward looking information contained in implied variance and may not necessarily reflect market expectations on the upcoming announcement.

\subsection{2.3 Return of Portfolios Sorted on EVR}

Using the EVR measure constructed above, we sort stocks into decile portfolios and examine their returns on FOMC announcement days. Consider a FOMC announcement day. We compute our EVR measure for each stock two days ahead of the announcement day and sort stocks into decile portfolios using the EVR measure. Stocks in the top (bottom) portfolio have the highest (lowest) EVR and are most (least) sensitive to the upcoming FOMC announcement. We keep track of the

\textsuperscript{3}Our results remain robust if we use the mean value of historical IV during this period to adjust $IV_{t-2}$ or if we use a longer period to measure historical IV such as during day $-22$ and day $-8$.

\textsuperscript{4}In Appendix A.2, we provide other additional implied variance reduction forecasts for comparison. The results show that this model predicts the actual implied variance reduction better than others.
value-weighted portfolio returns and rebalance the portfolios until the next sorting date, which is two days before the next FOMC announcement day. We repeat the above procedure and compute the average FOMC announcement-day return and non-FOMC announcement day return for each of the portfolios.

Panel A of Table 2 reports the portfolio returns on FOMC announcement days and other days (non-FOMC days). To save space, we present the returns for portfolios 1, 2, 9, and 10, and the return for the consolidated portfolios 3 to 8. 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. On average the long-short portfolio earns a raw return of 31.67 basis points on the FOMC announcement days. This tradable strategy that invests only on the eight FOMC announcement days earns an average annual return of 2.53% (31.67 × 8). In contrast, most portfolios, as well as the long-short portfolio, do not earn significant returns on non-FOMC days. We confirm that the portfolio returns on FOMC announcement days are not driven by standard firm characteristics such as size or B/M.

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

\[ R^i_t - r_{f,t} = \alpha^i_{\text{Non}} \cdot 1_{\text{Non}} + \alpha^i_{\text{FOMC}} \cdot 1_{\text{FOMC}} + \beta \left( R^M_t - r_{f,t} \right) + \epsilon^i_t, \]  

(3)

where \( R^i_t \) is the daily return of the sorted portfolio, \( R^M_t \) is the daily return of the market, and \( r_{f,t} \) is the daily risk-free rate. \( 1_{\text{Non}} \) and \( 1_{\text{FOMC}} \) are dummy variables that take values of 1 only on non-FOMC and FOMC announcement days, respectively. Panel B of Table 2 reports results of the above CAPM regression. Note that the FOMC dummy is monotonically increasing across portfolios and the FOMC dummy of the long-short portfolio is positive and statistically significant. The spread between the high sensitivity portfolio and the low sensitivity portfolio averages at 30.70 basis points on FOMC announcement days after controlling for market returns. Our results suggest that the CAPM fails to account for the cross-section of returns of the expected sensitivity sorted portfolios on FOMC announcement days.
The above portfolio return results remain robust if we exclude the recent financial crisis period (July 2008 to June 2009) or if we exclude firms whose earning announcement dates coincide with the FOMC announcement days, as shown in Appendix A.2. In unreported robustness check, we find that our results are robust even after including Fama-French three or five factors in the above regression.

2.4 CAPM for $\beta$-Sorted Portfolios

The literature has shown that CAPM holds well on macroeconomic announcement days (for example, Savor and Wilson (2014)). In this section, we present evidence for the FOMC announcement premium for CAPM $\beta$-sorted portfolios. Our sorting procedure is very similar with the one using the expected sensitivity introduced in the last section. For each FOMC meeting, we sort all stocks into decile portfolios based on their 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 3 reports the portfolio returns on 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 55.17 basis points. On the other hand, portfolio returns on non-FOMC days are rather low and there is no obvious pattern. This result indicates that the CAPM may only hold on FOMC days.

In Panel B, we test the CAPM using $\beta$-sorted portfolios. It is natural to see that beta monotonically increases across the portfolios. When we further include a FOMC dummy and a non-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 returns of the $\beta$-sorted portfolios can be explained by the CAPM.

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 returns of $\beta -$ sorted portfolios together pose a serious challenge for the structural model of the cross-section of the macroeconomic announcement premium.

### 2.5 Exposures with Respect to Monetary Policy Announcement Surprises

We argue that the cross-sectional returns in the sensitivity sorted portfolios are risk compensations for surprises in monetary policy announcements. In this section, we use two measures of monetary policy surprises constructed by Nakamura and Steinsson (2018) to provide additional evidence on this. The first measure is the changes in Fed fund futures rate on FOMC announcement days. The second is a composite measure constructed as the first principle component of the unanticipated change over the 30-minute FOMC announcement windows in a basket of five interest rates.

First, we show that rational expectations hold well in the period of our portfolio sorting exercise. In Table 4, we report the first and second moments of the two measures of monetary policy surprises: changes in Fed fund futures rates on announcement days (labeled as FFR), and the composite measure of policy news constructed in Nakamura and Steinsson (2018) (labeled as policy news). There are substantial variations in both measures of monetary policy surprises; however, the average surprises are not significantly different from zero for both measures. This implies that there are no systematic biases in the market’s forecast about monetary policy announcements during this period, and the excess return of the market and that of the expected sensitivity sorted portfolios must be compensations for risk, rather than reflecting biases in expectations.

Second, we show that the cross-section returns of expected sensitivity sorted portfolios monotonically react to policy surprises. We compute the beta’s of expected sensitivity sorted portfolios with respect to both measures of monetary policy surprises. We run the following regression on FOMC announcement days:

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_{\text{News}}^i \Delta g_t + \beta_{\text{Mkt}}^i (R_{M,t} - r_{f,t}) + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return of portfolio $i$, and $\Delta g_t$ stands for policy surprises on the FOMC announcement.
day $t$. We plot the slope coefficient of the above regression, $\beta_{i_{\text{News}}}^i$, for each of the portfolios in Figure 2.

The slope efficient $\beta_{i_{\text{News}}}^i$ are monotonically increasing for both measures of policy surprises. Upon a surprised interest rate hike, the return of high expected sensitivity portfolio increases and that of low expected sensitivity portfolio decreases, after controlling for the market returns. The fact that the high expected sensitivity portfolio is more sensitive to interest rate hikes is consistent with Nakamura and Steinsson (2018)’s interpretation that monetary policy announcements convey Fed’s private information about the economy and surprised interest rate hikes are associated with information that economic fundamentals are stronger than expected. Consistent with the above information effect, Nakamura and Steinsson (2018) document that in response to an unexpected increase in the real interest rate (a monetary tightening), survey estimates of expected output growth rise. In the next section, we develop an equilibrium model in which FOMC announcements reveal Fed’s private information about the economic growth to account for the expected returns of the cross-section of expected sensitivity sorted portfolios.

3 Model Setup and Solution

In this section, we set up a continuous-time equilibrium model where Federal Reserve’s monetary policy announcements reveal its private information about the growth prospect of the economy and study the implications on the cross-section of announcement returns. In our model, aggregate economic growth is driven by a latent state variable and an i.i.d. component (short-run shocks). The Fed has private information about the true value of the latent growth variable, which is revealed through monetary policy announcements periodically.

Consumption and preference We consider a continuous-time representative agent economy, where the representative agent has a recursive preference with constant risk aversion $\gamma$ and intertemporal elasticity of substitution (IES) $\psi$. The growth rate of aggregate consumption contains a latent predictable component, $x_t$, and an i.i.d. component modeled by increments of Brownian
motion $B_{C,t}$ with constant volatility $\sigma$:

$$\frac{dC_t}{C_t} = x_t dt + \sigma dB_{C,t}. \tag{5}$$

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

$$dx_t = a_x (\bar{x} - x_t) dt + \sigma_x dB_{x,t}, \tag{6}$$

where $B_{x,t}$ is a Brownian motion independent of $B_{C,t}$.

**Information and announcements** To build a parsimonious model where Federal Reserve has private information about the future growth prospect of the economy, we assume that investors in the economy do not observe the latent variable $x_t$. The Fed has more information about $x_t$ than investors, and its private information about $x_t$ is revealed through pre-scheduled FOMC announcements.

Specifically, an investor’s prior belief about $x_t$ is represented by a normal distribution. Since the posterior distribution of $x_t$ is also Gaussian, it can be summarized by the first two moments. We define $\hat{x}_t = \mathbb{E}_t [x_t]$ as the posterior mean and $q_t = \mathbb{E}_t [(x_t - \hat{x}_t)^2]$ as the posterior variance of $x_t$ given information up to time $t$. Investors can use two sources of information to update beliefs about $x_t$ at time $t$. First, the realized consumption path contains information about $x_t$. 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 $\varepsilon_n$ is i.i.d. and normally distributed with mean zero and variance $\sigma_s^2$.

At time $t = nT$, where $n$ is an integer, investors update beliefs based on the signals $s_t$ about $x_t$ using Bayes’ rule:

$$\hat{x}_{nT}^+ = q_{nT}^+ \left[ \frac{1}{\sigma_s^2} s_n + \frac{1}{q_{nT}^-} \hat{x}_{nT}^- \right]; \quad \frac{1}{q_{nT}^+} = \frac{1}{\sigma_s^2} + \frac{1}{q_{nT}^-}, \tag{7}$$

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 \((nT, (n + 1) T)\), investors update beliefs based on the observed consumption process using Kalman-Bucy filter:

\[
d\hat{x}_t = a_x (\bar{x} - \hat{x}_t) dt + \frac{q_t}{\sigma} dB_{C,t},
\]
where the innovation process is defined by \(dB_{C,t} = \frac{1}{\sigma} \left[ \frac{dC_t}{C_t} - \hat{x}_t dt \right]\). The posterior variance, \(q_t\), satisfies the Riccati equation:

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

The intuition of our results is the same as that demonstrated in Ai and Bansal (2018). In our model, there are two sources of risks: consumption growth risk, as captured by the Brownian motion \(dB_{C,t}\), and news about latent growth risk, as captured by changes in (the beliefs about) \(x_t\). Prior to the announcements, investors do not observe the true value of \(x_t\) and update their beliefs about it, with the posterior \(\hat{x}_t\). Announcements are associated with immediate updates of investors’ beliefs. That is, the posterior mean of \(x_{nT}\) jumps instantaneously from \(\hat{x}_{nT}^-\) to \(\hat{x}_{nT}^+\).

**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:

\[
\frac{dD_t^i}{D_t} = [\bar{x} + \xi_i (\hat{x}_t - \bar{x})] dt + \eta_i \sigma dB_{C,t} + \sigma_i dB_{i,t},
\]
where \(dB_{i,t}\) is the idiosyncratic shock to each firm \(i\) which is uncorrelated with \(dB_{C,t}\) and \(dB_{x,t}\). \(\sigma_i\) is the idiosyncratic volatility, and the parameters \((\xi_i, \eta_i)\) measure the sensitivity of the dividend with respect to news about the latent growth and the consumption growth risk, respectively. We assume that \(\xi_i\) is uniformly distributed over the interval \([\xi, \bar{\xi}]\) and \(\eta_i\) is uniformly distributed over \([\eta, \bar{\eta}]\), and the distributions of \(\xi_i\) and \(\eta_i\) are independent.

Define the price-to-dividend ratio of firm \(i\) as \(p(\hat{x}_t, q_t | \xi_i, \eta_i)\), which depends on both \(\xi_i\) and \(\eta_i\).
The function \( p(\hat{x}_t, q_t | \xi_i, \eta_i) \) is defined as

\[
p(\hat{x}_t, q_t | \xi_i, \eta_i) D^i_t = \mathbb{E}_t \left[ \int_0^\infty \frac{\pi_t + s}{\pi_t} D^i_{t+s} ds \bigg| \hat{x}_t, q_t \right],
\]

where the law of motion of \( D^i_t \) is given in (10) and the solution for state price density \( \pi_t \) is provided later in this section. For simplicity, we denote the firm-specific price-to-dividend ratio as \( p^i(\hat{x}_t, t) \) henceforth. The return on firm \( i \)'s equity during the period \((t, t + \Delta)\) is given by:

\[
R^i_{t, t+\Delta} = \frac{p^i(\hat{x}_{t+\Delta}, t + \Delta) D^i_{t+\Delta} + \int_t^{t+\Delta} \frac{D^i_s}{D^i_t} ds}{p^i(\hat{x}_t, t)}.
\]

**Model solution** In the interior of \((nT, (n + 1) T), n = 1, 2, \cdots,\), the law of motion of the state price density, \( \pi_t \), satisfies the following stochastic differential equation:

\[
d\pi_t = \pi_t \left[ -r(\hat{x}_t, q_t) dt - \sigma_{\pi,t} dB_{C,t} \right],
\]

where

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

is the risk-free interest rate, and

\[
\sigma_{\pi,t} = \gamma \sigma + \frac{\gamma - \frac{1}{\psi}}{a_x + \rho} q_t
\]

is the market price of the Brownian motion risk, \( \tilde{B}_{C,t} \). Equation (14) contains both the compensation for the i.i.d. shock \( B_{C,t} \) and that for the changes in the belief about \( x_t \), captured by the term \( \frac{\gamma - \frac{1}{\psi}}{a_x + \rho} q_t \).

There are two sources of fundamental risks in the economy, \( B_{C,t} \) and \( B_{X,t} \). However, investors do not observe \( x_t \) and cannot distinguish whether a change in consumption growth is due to \( B_{C,t} \) or due to innovations in \( B_{X,t} \). Innovations in consumption growth, from investors perspective, affect both the contemporaneous consumption growth rate and their beliefs about \( x_t \). As in Ai (2010), \( \sigma_{\pi,t} \) summarizes risk compensations from both channels.

As we show in Appendix A.3.2, each firm’s price-to-dividend ratio \( p^i(\hat{x}_t, t) \) must satisfy the partial differential equation of (A.16). In addition, at announcements \( nT, n = 1, 2, 3, \ldots, \) the boundary
condition satisfies:

\[
p^i \left( \hat{x}_{nT}^-, nT^- \right) = E \left[ \frac{\frac{1}{2} - \gamma}{e^{\alpha_x + \rho} \hat{x}^+_{nT}} p^j \left( \hat{x}^+_{nT}, nT^+ \right) \mid \hat{x}_{nT}^-, q_{nT}^- \right] \]  

(15)

Under the assumption of generalized risk sensitivity, \( \gamma > \frac{1}{\psi} \) the term \( e^{\alpha_x + \rho} \hat{x}^+_{nT} \) is negatively correlated with the posterior belief, \( x_{nT}^+ \), which is updated immediately upon announcements. As a result, assets with payoffs increasing in the announcement about \( x_{nT}^+ \) requires a positive risk premium and the magnitude of announcement premium is increasing in the sensitivity of the asset’s payoff with respect to announcements about \( x_{nT}^+ \).

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 higher compensations in terms of announcement returns. The sensitivity of stock return with respect to announcement surprises depends primarily on the parameter \( \xi_i \). From equation (10), a stock with a higher \( \xi_i \) in its dividend growth rate is more sensitive to \( x_t \). Therefore, the price-to-dividend ratio and return respond more to news about \( x_t \) so that this stock require a high risk compensation.

We provide details of the model solutions in the Appendix A.3.

4 Quantitative Implications

**Calibration** We choose parameters to match the dynamic of consumption growth and implied variance, and we report this calibration in Table 5. First, we choose parameters of preference and the consumption growth rate in our model to be consistent with standard long-run risk literature. Following Bansal and Yaron (2004) and Ai (2010) among others, we set the discount rate \( \rho = 0.01 \), the risk aversion \( \gamma = 10 \), and IES \( \psi = 2 \). We choose the average consumption growth \( \bar{x} = 1.5\% \) and standard deviation of consumption growth \( \sigma = 3.0\% \) to match the first and second moment of aggregate consumption in the sample period of 1929-2018. We also choose the auto-correlation \( \alpha_x \) and the standard deviation of \( x_t \) to be in line with standard long-run risk models, such as Bansal
and Yaron (2004) and Ai (2010).

The parameters of investors’ beliefs and the cross-section of dividend processes are specific to our model. We choose the parameters of investors’ beliefs and the cross-section of dividend processes to match the dynamic of implied variances in our sample. We set $\sigma_i = 57\%$ to match the cross-sectional average implied variance of stocks on non-announcement days. Our model gives implied variance of 274.23 in the monthly percentage squared unit, which is close to 276.21 in our data reported in Table 1. We choose the parameter for the informativeness of FOMC announcements, $\sigma_s = 4.33\%$ so that our model matches the standard deviation of aggregate stock market return on announcement days of 110 basis point, as reported in Ai and Bansal (2018). Finally, we choose $\xi = \eta = 1$, and $\bar{\xi} = \bar{\eta} = 5$ to match the slope in the cross-section of expected returns. The calibrated parameter values are listed in Table 5.

We simulate our model for 122 years, we discard the first 100 years and keep the rest of 22 years so that the time span of our simulation is the same as that of our data, and we can compare not only the point estimates but also t-statistics in our model and their counterparts in the data. Our model matches several moments in the data well that our calibration does not explicitly target. In our calibration, the average FOMC announcement day and non-FOMC day return are 36.2 bps and 1.8 bps, very close to the same moment reported in Lucca and Moench (2015) (36.6 bps and 2.0 bps). The average drop in implied variance in our model is 9.2 in monthly percentage squared unit, comparable to the same number we reported in Table 1 in our data.

**Aggregate FOMC announcement premium** In Table 6, we report the average FOMC announcement day return and non-announcement market excess 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.

The intuition of our results is the same as that demonstrated in Ai and Bansal (2018). In our model, there are two sources of risks, consumption growth risk, as captured by the Brownian motion $d\tilde{B}_{C,t}$, and news about the latent growth risk, as captured by changes in (the belief about) $x_t$, i.e. $\hat{x}_{nT}^- - \hat{x}_{nT}^+$. Prior to the announcements, investors do not observe the true value of $x_t$.
and update their beliefs based on observed consumption growth. Because consumption growth is
 driven by Brownian motion shocks, the posterior belief, $\hat{x}_t$, updates continuously. At pre-scheduled announcement times, FOMC announcements are associated with discrete jumps of the posterior belief from $\hat{x}^{-nT}$ to $\hat{x}^{+nT}$.

Because investors’ preferences satisfy generalized risk sensitivity, marginal utility is decreasing in the continuation value, which is a function of the posterior belief $\hat{x}_t$. Because announcements carry news about $\hat{x}_t$, they correlate with marginal utilities and are risky from investors’ perspectives. As a result, stocks that are more sensitive to changes in $x_t$ require larger compensations upon announcements. We now turn to the implications of our model in the cross-section of equity returns.

**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 higher compensations in terms of announcement returns. The sensitivity of stock return with respect to announcement surprises depends primarily on the sensitivity of dividend growth with respect to announcements, $\xi_i$. From equation (10), a stock with a higher sensitivity with respect to future economic growth, which is captured by the parameter $\xi_i$, is more sensitive to $x_t$. Therefore, its price-to-dividend ratio and return respond more to news about $x_t$ and requires a high risk compensation.

In our model, as we show in Appendix A.3.4, the implied variance reduction upon announcements is given by:

$$\Delta IV_i = \left( \frac{\xi_i - \frac{1}{\psi}}{a_x + \bar{p}} \right)^2 \left( \frac{q^{-2}}{q^{nT} + \sigma^2} \right),$$

where $\bar{p}$ is the inverse of steady state price-to-dividend ratio of firm $i$. $\Delta IV_i$ is a strictly increasing function of $\xi_i$, the sensitivity of dividend with respect to news about the latent growth. Therefore, in our model, sorting on implied variance reduction is equivalent to sorting on sensitivity with respect to news in FOMC announcements. In model simulations, because EVR is a perfect measure of $\xi_i$, high $\xi_i$ stocks are allocated to high EVR portfolios and therefore have a high announcement day return on average. In Table 7, we compare the average FOMC-day and non-FOMC day return of expected sensitivity sorted portfolios in our model and that in the data. Our model replicates the
pattern of the FOMC announcement premiums for expected sensitivity sorted portfolios.

In addition, the FOMC 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 the data counterparts in Table 8. On one hand, the spread in announcement returns is large and significant across $\xi$ sorted portfolios. On the other hand, $\beta$ is only slightly increasing in expected sensitivity. As a result, as in the data, the coefficient on FOMC dummy is significant for most portfolios. Moreover, our model replicates the monotonic pattern of the FOMC dummy across expected sensitivity sorted portfolios quite well.

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 $\xi$ normalized by the same sensitivity measure of market return, i.e., $p_x(\hat{x}_t, t) / p(\hat{x}_t, t)$. Because the sensitivity of announcement return with respect to $\hat{x}_t$ depends both on $\xi$ and $\eta$, we plot it for three different values of $\eta$: $\eta = 1, 3, 5$. 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 $p_x(\hat{x}_t, t) / p(\hat{x}_t, t)$. It is clear from the left panel of Figure 3, the sensitivity of stock return with respect to announcement surprises depends mostly on $\xi$ and not on $\eta$: sorting on expected sensitivity reduction is the equivalent as sorting on $\xi$ in our model.

In the right panel, we plot the local CAPM $\beta$ at the announcements as a function of $\xi$ for $\eta = 1, 3, 5$. Local $\beta$ is computed as follows:

$$
\beta^i = \frac{\text{Cov}[dR^i_t, dR_t]}{\text{Var}[dR^i_t]} = \frac{\eta_i \sigma + p_x(\hat{x}_t, t) \eta_i \sigma}{\eta_i \sigma + p_x(\hat{x}_t, t) \eta_i \sigma}.
$$

(17)

In our model, on non-announcement days, because investors do not observe the latent growth variable $x_t$, the only shock that affect stock market returns is the surprise in consumption growth, $d\tilde{B}_{C,t}$. As we explain before, innovations in consumption growth affect both the contemporaneous growth rate of consumption and the posterior belief about future consumption growth, $\hat{x}_t$. Therefore, qualitatively, the sensitivity of stock return with respect to contemporaneous consumption growth, captured by the parameter $\eta_i$, and the sensitivity of stock return with respect to the latent growth variable, determined by the parameter $\xi_i$, will both affect the estimated CAPM
\( \beta \). Therefore, the estimate of \( \beta_i \) increases in both \( \xi_i \) and \( \eta_i \).

Quantitatively, however, the estimated \( \beta \) increases strongly with respect to \( \eta_i \) but only mildly with respect to \( \xi_i \). As a result, EVR-sorted portfolios display a significant dispersion in \( \xi_i \) but a small dispersion in estimated \( \beta \). In the model, although investors do not observe the true value of \( x_t \), periodical FOMC announcements provide information about \( x_t \), and the posterior variance of \( x_t, q_t \), is much smaller relative to \( \sigma \) in equation (17). Because estimated \( \beta \) is more sensitive to \( \eta_i \) and less sensitive to \( \xi_i \), the EVR-sorted portfolios have a small dispersion in \( \beta \), which cannot fully account for the difference in the announcement returns in CAPM regressions. As shown in Table 8, the FOMC announcement dummies are quite significant and monotonically increasing in our model, as in the data.

**Beta sorted portfolios** Savor and Wilson (2014) show that CAPM explains the announcement premiums of CAPM \( \beta \)-sorted portfolios very well. As we have shown in the last section, the stochastic discount factor in our model is driven by two sources of risks. 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 in explaining the EVR-sorted portfolios, our model can account for the pattern of announcement returns of CAPM \( \beta \)-sorted portfolios quite well.

Table 9 presents the announcement premium for \( \beta \)-sorted portfolios in the data and that in the model. As in the data, the announcement premiums are significant and monotonically increasing in \( \beta \) 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 the CAPM regressions for \( \beta \)-sorted portfolios in the model. As in the data, the coefficients of non-FOMC and FOMC dummy are both insignificant. The FOMC announcement premium of the long-short portfolio disappears once we control for market \( \beta \).

To understand our results, note that \( \beta \) in our model is jointly determined by \( \xi_i \) and \( \eta_i \). As shown in the last section, because \( \beta \) is not very sensitive to \( \xi_i \), sorting on \( \xi_i \) (or equivalently sorting on expected sensitivity) does not generate significant dispersion in \( \beta \), and that is why the CAPM fails to
account for the returns of cross-section of expected sensitivity sorted portfolios. However, sorting on individual firm’s $\beta$, as we show in Table 9, does generate a significant dispersion in CAPM $\beta$. Although not as much spread as sorting directly on $\xi_i$, the average $\xi$ is still monotonically increasing in $\beta-$ sorted portfolios. This explains the significant announcement premium for $\beta-$ sorted portfolios. At the same time, because CAPM $\beta$ is also monotone for $\beta-$ sorted portfolios — by construction, the dispersion in announcement premium can be fully explained by the dispersion in $\beta$ in a finite sample.

5 Conclusion

In this paper, we provide empirical evidence and an equilibrium model for the cross-section of the FOMC announcement day returns. We show that in the data, stocks that are more sensitive to monetary policy announcement surprises require higher risk compensations upon FOMC announcements. Our evidence is supportive of the recent literature that emphasizes the importance of risk compensation for macroeconomic announcements, in particular, monetary policy announcements. We develop an equilibrium model where FOMC announcements reveal the Federal Reserve’s private information about the prospect for future economic growth and stock returns differ in their sensitivity with respect to economic growth rates to account for the cross-section of FOMC announcement returns.
| Panel A: $VIX^2$ |  |
|---|---|---|
| $VIX_t^2$ | $VIX_{t-1}^2$ | $VIX_t^2 - VIX_{t-1}^2$ |
| Mean | 39.526 | 41.940 | -2.414 |
| t-stats | -3.387 |  |

| Panel B: Average Firm-level Implied Variance |  |
|---|---|---|
| $IV_t$ | $IV_{t-1}$ | $IV_t - IV_{t-1}$ |
| Mean | 276.210 | 281.165 | -4.954 |
| t-stats | -4.579 |  |

Our full sample period is from January 1996 to December 2017 with 176 FOMC days. During this period, there are 6652 common stocks with trading options. Among these 6652 firms in our sample, there are 5446 firms with at least one observed option-implied variance on these 176 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 cross-sectional average of changes in firm-level option-implied variance (monthly percentage squared) around FOMC announcement days and their time-series statistics. The firm-level implied variance uses 7-day interpolated or extrapolated variance.
We conduct a tradable strategy two days before the FOMC announcement days. We measure firm level sensitivity to monetary policy by the expected implied variance reduction around FOMC announcement, which is the difference between implied variance two days before the announcement and the median value of implied variance from day $-8$ to day $-15$. Based on this measurement, we sort firms into five portfolios with the third portfolio containing 60 percent of all firms and each of the rest four portfolios containing 10 percent, and document the value-weighted portfolio returns. These portfolios are rebalanced two days before next FOMC announcement days. Panel A reports the time-series average and Newey-West t statistics (with 12 lags) of portfolio returns (basis points) on FOMC announcement days and non-FOMC announcement days. Panel B reports daily regression results of CAPM beta and coefficients of a non-FOMC dummy and a FOMC dummy, as well as the Newey-West t statistics.
Table 3: Portfolio Returns Sorted on CAPM Beta

Panel A: Average Returns

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3 – 8</th>
<th>9</th>
<th>10</th>
<th>(10 – 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FOMC Return</td>
<td>13.05</td>
<td>17.40</td>
<td>30.66</td>
<td>51.74</td>
<td>68.23</td>
<td>55.17</td>
</tr>
<tr>
<td></td>
<td>(2.27)</td>
<td>(2.98)</td>
<td>(2.89)</td>
<td>(2.55)</td>
<td>(2.70)</td>
<td>(2.41)</td>
</tr>
<tr>
<td>Non-FOMC Return</td>
<td>3.09</td>
<td>3.63</td>
<td>3.57</td>
<td>2.61</td>
<td>4.05</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>(3.25)</td>
<td>(3.10)</td>
<td>(2.30)</td>
<td>(1.02)</td>
<td>(1.33)</td>
<td>(0.34)</td>
</tr>
</tbody>
</table>

Panel B: CAPM

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3 – 8</th>
<th>9</th>
<th>10</th>
<th>(10 – 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAPM Beta</td>
<td>0.47</td>
<td>0.68</td>
<td>1.02</td>
<td>1.58</td>
<td>1.73</td>
<td>1.26</td>
</tr>
<tr>
<td>Non-FOMC Dummy</td>
<td>1.13</td>
<td>1.19</td>
<td>0.32</td>
<td>-1.92</td>
<td>-0.86</td>
<td>-1.99</td>
</tr>
<tr>
<td></td>
<td>(1.72)</td>
<td>(1.89)</td>
<td>(0.89)</td>
<td>(-1.68)</td>
<td>(-0.50)</td>
<td>(-0.93)</td>
</tr>
<tr>
<td>FOMC Dummy</td>
<td>-2.78</td>
<td>-4.93</td>
<td>-2.63</td>
<td>1.04</td>
<td>12.50</td>
<td>15.28</td>
</tr>
<tr>
<td></td>
<td>(-0.67)</td>
<td>(-1.47)</td>
<td>(-1.67)</td>
<td>(0.17)</td>
<td>(1.46)</td>
<td>(1.34)</td>
</tr>
</tbody>
</table>

We conduct a tradable strategy two days before the FOMC announcement days. This table reports CAPM beta sorted portfolio results. We first compute beta exposures of each firm based on past 12-month daily returns. We sort firms into five portfolios with the third portfolio containing 60 percent of the firms and each of the rest four portfolios containing 10 percent of the firms, and document the value-weighted portfolio returns. These portfolios are rebalanced two days before next FOMC announcement days. Panel A reports the time-series average and Newey-West t statistics (with 12 lags) of the portfolio returns (basis points) on FOMC announcement days and non-FOMC announcement days. Panel B reports daily regression results of the CAPM beta, and coefficients of a non-FOMC dummy and a FOMC dummy, as well as the Newey-West t statistics.

Table 4: Monetary Policy Shocks

<table>
<thead>
<tr>
<th></th>
<th>Policy News</th>
<th>FFR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0037</td>
<td>-0.0055</td>
</tr>
<tr>
<td>std</td>
<td>0.0342</td>
<td>0.0445</td>
</tr>
<tr>
<td>t-stat</td>
<td>1.30</td>
<td>-1.50</td>
</tr>
</tbody>
</table>

This table reports the average value and its t-statistics of monetary policy news shocks (Policy News) and federal fund rate (FFR) shocks from Nakamura and Steinsson (2018). The data sample spans from 1996 to 2014. The policy news shock is the first principle component of the change in five interest rates over a 30-minute window around the FOMC announcement. Federal fund rate shock is constructed using the price change of the federal funds futures over a 30-minute window around the FOMC announcement.
Table 5: Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>Time Discount Rate</td>
<td>0.01</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Risk Aversion</td>
<td>10</td>
</tr>
<tr>
<td>$\psi$</td>
<td>IES</td>
<td>2</td>
</tr>
<tr>
<td>$\bar{x}$</td>
<td>Consumption Growth Rate Stationary Mean</td>
<td>1.5%</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Consumption Growth Rate Volatility</td>
<td>3%</td>
</tr>
<tr>
<td>$\omega_x$</td>
<td>Mean Reversion Rate of Unobserved Consumption Growth</td>
<td>0.085</td>
</tr>
<tr>
<td>$\sigma_x$</td>
<td>Volatility of Unobserved Consumption Growth Rate</td>
<td>0.71%</td>
</tr>
<tr>
<td>$\sigma_i$</td>
<td>Idiosyncratic Shock Volatility</td>
<td>57%</td>
</tr>
<tr>
<td>$\sigma_x$</td>
<td>Signal Volatility</td>
<td>4.33%</td>
</tr>
<tr>
<td>$[\xi, \xi]$</td>
<td>Sensitivity with respect to News about Latent Growth</td>
<td>[1,5]</td>
</tr>
<tr>
<td>$[\eta, \eta]$</td>
<td>Sensitivity with respect to Consumption Growth Risk</td>
<td>[1,5]</td>
</tr>
</tbody>
</table>

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

Table 6: Market Excess Return on FOMC and non-FOMC Announcement Days

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Non-FOMC</th>
<th>Pre-FOMC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Return</td>
<td></td>
<td>2.0</td>
<td>36.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Model</th>
<th>Non-FOMC Days</th>
<th>FOMC Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Return</td>
<td></td>
<td>1.8</td>
<td>36.2</td>
</tr>
</tbody>
</table>

The top panel reports the FOMC excess return from Lucca and Moench (2015) (January 1980 to March 2011) and the corresponding non-FOMC days excess return of S&P500. The bottom panel is the model implied average daily excess returns for 400 stocks with 22 valid years (122 years simulation and 100 years burn-in) (264 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. All numbers are in basis points.
Table 7: Announcement Premium for Expected Sensitivity Sorted Portfolios

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 2 3-8 9 10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FOMC Return</td>
<td>36.57 28.78 29.40 48.05 68.24</td>
<td>31.67</td>
<td>(1.93)</td>
<td>(2.35)</td>
<td>(3.36)</td>
<td>(3.53)</td>
</tr>
<tr>
<td>Non-FOMC Return</td>
<td>3.42 3.33 3.55 4.16 3.23</td>
<td>-0.19</td>
<td>(1.40)</td>
<td>(1.71)</td>
<td>(2.60)</td>
<td>(2.28)</td>
</tr>
</tbody>
</table>

|                  | Model         |               |       |       |       |       |
|                  | 1 2 3-8 9 10  |               |       |       |       |       |
| FOMC Return      | 12.87 19.09 36.28 50.95 55.02 | 42.16 | (1.84) | (1.95) | (2.00) | (1.95) | (1.86) |
| Non-FOMC Return  | 1.54 1.67 1.88 2.06 2.14 | 0.60 | (0.35) | (0.37) | (0.46) | (0.39) | (0.40) | (0.14) |

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 2017 with 176 FOMC days. We sort stocks based on the implied variance (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 the decile 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 returns in basis points and the associated Newey-West t-statistics for 400 stocks with 22 valid years (122 years simulation and 100 years burn-in) (264 FOMC days). We sort 10 portfolios based on expected sensitivity $\xi$ 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

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<tr>
<td>CAPM Beta</td>
<td>1.41</td>
<td>1.15</td>
<td>0.92</td>
<td>1.22</td>
<td>1.44</td>
<td>0.03</td>
</tr>
<tr>
<td>Non-FOMC Dummy</td>
<td>-0.69</td>
<td>-0.19</td>
<td>0.57</td>
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<td>-0.96</td>
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<tr>
<td></td>
<td>(-0.58)</td>
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<td>(1.96)</td>
<td>(0.66)</td>
<td>(-0.80)</td>
<td>(-0.21)</td>
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<td>FOMC Dummy</td>
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<td>-1.26</td>
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<td>(-1.38)</td>
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<td>(-0.80)</td>
<td>(1.88)</td>
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<td>(2.87)</td>
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<table>
<thead>
<tr>
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<td>2</td>
<td>3-8</td>
<td>9</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>CAPM Beta</td>
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<td>0.72</td>
<td>1.00</td>
<td>1.23</td>
<td>1.29</td>
<td>0.67</td>
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<td>Non-FOMC Dummy</td>
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<td>-0.23</td>
<td>-0.64</td>
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<tr>
<td></td>
<td>(0.68)</td>
<td>(0.60)</td>
<td>(0.24)</td>
<td>(-0.36)</td>
<td>(-0.41)</td>
<td>(-0.72)</td>
</tr>
<tr>
<td>FOMC Dummy</td>
<td>-9.34</td>
<td>-6.78</td>
<td>0.15</td>
<td>5.82</td>
<td>7.47</td>
<td>16.81</td>
</tr>
<tr>
<td></td>
<td>(-2.91)</td>
<td>(-2.20)</td>
<td>(0.12)</td>
<td>(1.90)</td>
<td>(2.38)</td>
<td>(3.52)</td>
</tr>
</tbody>
</table>

This table documents the CAPM regression for expected sensitivity sorted portfolios. The top panel is based on the data from January 1996 to December 2017 with 176 FOMC days. We sort stocks based on the implied variance (IV) reduction two days before FOMC dates. We run CAPM regression on value weighted market return, non-FOMC dummy and FOMC dummy. We report CAPM beta and coefficients of non-FOMC dummy, FOMC dummy on the decile 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 22 valid years (122 years simulation and 100 years burn-in) (264 FOMC days) and 400 stocks. We sort 10 portfolios based on expected sensitivity $\xi$ and run CAPM regressions on simulated market return, non-FOMC dummy and FOMC dummy. We report simulated CAPM beta, coefficients of non-FOMC dummy, FOMC dummy of each portfolio on the decile portfolios (column 2 to 6), long-short portfolio (column 7) and the associated t-statistics. We simulate 500 independent sample paths with daily frequency and report the mean portfolio $\xi, \eta$. 

28
Table 9: Announcement Premium for Beta Sorted Portfolios

<table>
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<tr>
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<tr>
<td>FOMC Return</td>
<td>13.05</td>
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</tr>
<tr>
<td></td>
<td>(2.27)</td>
<td>(2.98)</td>
</tr>
<tr>
<td>Non-FOMC Return</td>
<td>3.09</td>
<td>3.63</td>
</tr>
<tr>
<td></td>
<td>(3.25)</td>
<td>(3.10)</td>
</tr>
</tbody>
</table>

|                  | 1          | 2          | 3-8     | 9           | 10         | (10-1)  |
| FOMC Return      | 18.22      | 23.32      | 36.58   | 46.23       | 48.35      | 30.13   |
|                  | (1.96)     | (1.96)     | (2.00)  | (1.96)      | (1.95)     | (1.83)  |
| Non-FOMC Return  | 1.11       | 1.45       | 1.87    | 2.23        | 2.60       | 1.50    |
|                  | (1.61)     | (1.86)     | (2.45)  | (2.19)      | (2.24)     | (1.53)  |

| $E[\xi]$         | 1.40       | 1.82       | 3.03    | 4.11        | 4.49       | 3.10    |
| $E[\eta]$        | 1.81       | 2.40       | 2.97    | 3.69        | 4.27       | 2.46    |

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 2017 with 176 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 returns in basis points and the associated Newey-West t-statistics for 400 stocks. We simulate 130 years with 100 years burn-in and sort 10 portfolios based on the following 8 years’ single stock’s CAPM beta coefficients. We simulate 500 independent sample paths with daily frequency and report the mean portfolio $\xi$, $\eta$ and simulated average return of each portfolio on FOMC and non-FOMC days using the left 22 valid years (264 FOMC days).
### Table 10: CAPM for Beta Sorted Portfolios

<table>
<thead>
<tr>
<th></th>
<th>1</th>
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<th>10</th>
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<td><strong>Data</strong></td>
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</tr>
<tr>
<td>CAPM Beta</td>
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<td>0.68</td>
<td>1.02</td>
<td>1.58</td>
<td>1.73</td>
<td>1.26</td>
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<tr>
<td>Non-FOMC Dummy</td>
<td>1.13</td>
<td>1.19</td>
<td>0.32</td>
<td>-1.92</td>
<td>-0.86</td>
<td>-1.99</td>
</tr>
<tr>
<td>(1.72)</td>
<td>(1.89)</td>
<td>(0.89)</td>
<td>(-1.68)</td>
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<tr>
<td>FOMC Dummy</td>
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<td>-4.93</td>
<td>-2.63</td>
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<td>12.50</td>
<td>15.28</td>
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<tr>
<td>(-0.67)</td>
<td>(-1.47)</td>
<td>(-1.67)</td>
<td>(0.17)</td>
<td>(1.46)</td>
<td>(1.34)</td>
<td></td>
</tr>
<tr>
<td><strong>Model</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>CAPM Beta</td>
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<td>0.71</td>
<td>1.00</td>
<td>1.25</td>
<td>1.37</td>
<td>0.83</td>
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<tr>
<td>Non-FOMC Dummy</td>
<td>0.11</td>
<td>0.15</td>
<td>0.04</td>
<td>0.03</td>
<td>0.00</td>
<td>-0.03</td>
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<tr>
<td>(0.21)</td>
<td>(0.27)</td>
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<td>FOMC Dummy</td>
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<td>0.59</td>
<td>-1.71</td>
<td>-0.52</td>
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<tr>
<td>(-0.40)</td>
<td>(-0.73)</td>
<td>(0.36)</td>
<td>(0.19)</td>
<td>(-0.58)</td>
<td>(-0.13)</td>
<td></td>
</tr>
<tr>
<td>E[ξ_i]</td>
<td>1.40</td>
<td>1.82</td>
<td>3.03</td>
<td>4.11</td>
<td>4.49</td>
<td>3.10</td>
</tr>
<tr>
<td>E[η_i]</td>
<td>1.81</td>
<td>2.40</td>
<td>2.97</td>
<td>3.69</td>
<td>4.27</td>
<td>2.46</td>
</tr>
</tbody>
</table>

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 2017 with 176 FOMC days. We sort stocks based on the CAPM regression coefficient of single stock return on value weighted market return. We run the CAPM regression on value weighted market return, non-FOMC dummy and FOMC dummy. We report CAPM beta and coefficients of non-FOMC dummy, FOMC dummy on the decile 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 130 years with 100 years burn-in and sort 10 portfolios based on the following 8 years’ single stock’s CAPM beta coefficients. We run CAPM regression using the left 22 valid years (264 FOMC days) of portfolio excess return on simulated market return and FOMC dummy. We simulate 500 independent sample paths with daily frequency and report the mean portfolio ξ, η and simulated CAPM beta, coefficients of non-FOMC dummy, FOMC dummy of each portfolio on five portfolios (column 2 to 6), long-short portfolio (column 7) and the associated t-statistics.
This figure plots the histogram of the time series mean of firm-level logarithm implied variance changes (in %) on FOMC announcement days. For illustration purpose, we only report those firms with 160 or more observations out of these 176 FOMC days in our data sample.
This figure plots the EVR-sorted portfolio return sensitivity to monetary policy shocks. We regress FOMC announcement day portfolio excess returns on monetary policy news shocks or federal fund rate (FFR) shocks, controlling for the market excess returns. The blue circle (red square) line plots the coefficients of monetary policy news shocks (FFR shocks). Monetary policy news shocks and FFR shocks are from Nakamura and Steinsson (2018).
This left panel plots the sensitivity of stock returns with respect to FOMC announcement surprises, normalized by the market sensitivity, as functions of $\xi$ for different values of $\eta$, i.e. $\frac{p_i(x,t)}{p(x,\bar{t})}/\frac{p(x,\bar{t})}{p_i(x,\bar{t})}$. The right panel plots the sensitivity of stock returns with respect to market returns, i.e. CAPM $\beta$'s (see equation (17)). For simplicity, we fix $t = \bar{t} = 16$ as the middle of the month and $\hat{x}_t = \bar{x}$. 
Appendix

A Appendix

A.1 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, 2017. We exclude options with missing or negative bid-ask spread, zero bid, or zero open interest. We restrict the sample to out-of-the-money options to estimate the model-free implied variance (Bakshi, Kapadia, and Madan (2003)). To ensure that our results are not driven by misleading prices, we follow Conrad, Dittmar, and Ghysels (2013) and exclude options that do not satisfy the usual option price bounds, missing implied variance. We further remove options with less than 3 days to maturity. For a firm on a given day and a given maturity, we do not compute the implied variance if there are less than four OTM options.

Define \( V_t(\tau) \) as the time-\( t \) price of the \( \tau \)-maturity quadratic payoff on the underlying stock. We use this price as an approximate for our implied variance \( IV_t \). Bakshi, Kapadia, and Madan (2003) show that \( V_t(\tau) \) can be recovered from the prices of out-of-the-money (OTM) call and put options as follows:

\[
V_t(\tau) = \int_{S_t}^{\infty} \frac{1 - \ln(K/S_t)}{K^2/2} C_t(\tau; K) dK + \int_0^{S_t} \frac{1 + \ln(S_t/K)}{K^2/2} P_t(\tau; K) dK. \tag{A.1}
\]

where \( S_t \) is the price of underlying stock, and \( C_t(\tau; K) \) and \( P_t(\tau; K) \) are call and put prices with maturity \( \tau \) and strike \( K \), respectively. The risk-neutral expectation of the quadratic payoff is then

\[
\mathbb{E}_t^Q [r_{t,t+\tau}^2] = e^{r_f \tau} V_t(\tau), \text{ where } r_f \text{ is the continuously compounded interest rate.}
\]

We compute \( V_t(\tau) \) for each firm on each day and by each days-to-maturity. In theory, computing \( V_t(\tau) \) requires a continuum of strike prices, while in practice we only observe a discrete and finite set of them. Following Jiang and Tian (2005) and others, we discretize the integrals in equation (A.1) by setting up a total of 1001 grid points in the moneyness \((K/S_t)\) range from 1/3 to 3. First, we
use cubic splines to interpolate the implied volatility inside the available moneyness range. Second, we extrapolate the implied volatility using the boundary values to fill the rest of the grid points. Third, we calculate option prices from these 1001 implied volatilities using the formula of Black and Scholes (1973).\footnote{We apply these steps to the estimation of individual risk-neutral expected quadratic payoffs. The individual equity options are American. Therefore, directly using the mid-quotes of individual options is inappropriate because the early exercise premium may confound our results. To avoid this issue, we use the implied volatilities provided by OptionMetrics. These implied volatilities are computed using a proprietary algorithm based on the Cox, Ross, and Rubinstein (1979) model, which takes the early exercise premium into account.} Next, we compute $V_t(\tau)$ if there are four or more OTM options (e.g., Conrad, Dittmar, and Ghysels (2013) and others). Lastly, to obtain $V_t(7)$ for a firm on a given day, we interpolate and extrapolate $V_t(\tau)$ with available $\tau$. This process yields a daily time series of the risk-neutral expected quadratic payoff for each eligible firm with a fixed maturity of 7-days. Due to the extrapolation, there are some negative values. We treat these as missing observations.

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 6652 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 or daily return larger than 500 percent or less than -500 percent. We also exclude stocks with annualized implied variance larger than 25.

Fama-French risk factors are from Kenneth French’s Data library. Monetary policy news shocks and FFR shocks are from Nakamura and Steinsson (2018).

The dates of FOMC meetings are from the website of Federal Reserve Board. Following Savor and Wilson (2014), we only include the pre-scheduled FOMC meetings during our data period (1996-2017). There are about eight regularly pre-scheduled FOMC meetings each year. When the meeting lasts for two days, we consider the second day as the FOMC announcement day. In total, there are 176 FOMC announcement days in our data period. Among the 6652 firms in our sample, there are 5446 firms with at least one observed option-implied variance on these 176 FOMC days.
### A.2 Additional Tables

**Table A1: Firm Characteristics of Expected Sensitivity Reduction Sorted Portfolios**

<table>
<thead>
<tr>
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<tr>
<td>Size (in $million)</td>
<td>4813</td>
<td>6899</td>
<td>11012</td>
<td>8050</td>
<td>4722</td>
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<td>B/M</td>
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<td>0.48</td>
<td>0.50</td>
<td>0.48</td>
<td>0.48</td>
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<tr>
<td>Amihud Illiquidity ($10^6$)</td>
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<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
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</table>

This table reports firm characteristics of the decile portfolios sorted on expected sensitivity drops, including the average firm size (in $million) and B/M. Book equity is calculated following Davis, Fama, and French (2000) and market equity is the market capitalization calculated as stock price times the shares outstanding. We also report the value-weighted Amihud illiquidity measure multiplied by $10^6$.

**Table A2: Implied Variance Reduction Forecasts**

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<tr>
<td>Predicted Reduction</td>
<td>0.0466</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.0018</td>
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</table>

This table reports the results when regressing the actual IV reduction on various IV reduction forecasts. In column 1 (2) we use the median (mean) of IV reduction on FOMC days during the last twelve months as the current IV reduction forecast. In column 3 (4) we adjust IV by the median (mean) historical realized variance at the every sorting date to get the IV reduction forecast. T-statistics using the day-clustered standard error are reported in parenthesis.
Table A3: Portfolio Returns Sorted on Expected Sensitivity Reduction (Robustness Check)

Panel A: Exclude the Financial Crisis

<table>
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<tr>
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<th>1</th>
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<th>3 - 8</th>
<th>9</th>
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<tbody>
<tr>
<td>CAPM Beta</td>
<td>1.44</td>
<td>1.19</td>
<td>0.93</td>
<td>1.24</td>
<td>1.45</td>
<td>0.01</td>
</tr>
<tr>
<td>Non-FOMC Dummy</td>
<td>-0.94</td>
<td>-0.48</td>
<td>0.51</td>
<td>0.15</td>
<td>-1.51</td>
<td>-0.57</td>
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<tr>
<td></td>
<td>(-0.81)</td>
<td>(-0.53)</td>
<td>(1.79)</td>
<td>(0.20)</td>
<td>(-1.27)</td>
<td>(-1.27)</td>
</tr>
<tr>
<td>FOMC Dummy</td>
<td>-14.69</td>
<td>-9.51</td>
<td>0.21</td>
<td>8.20</td>
<td>13.81</td>
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<tr>
<td></td>
<td>(-2.08)</td>
<td>(-2.06)</td>
<td>(0.14)</td>
<td>(1.97)</td>
<td>(1.94)</td>
<td>(3.13)</td>
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</table>

Panel B: Exclude the Firm Earning Announcements

<table>
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<th>10</th>
<th>(10 - 1)</th>
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<tr>
<td>CAPM Beta</td>
<td>1.40</td>
<td>1.14</td>
<td>0.90</td>
<td>1.16</td>
<td>1.33</td>
<td>-0.07</td>
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<tr>
<td>Non-FOMC Dummy</td>
<td>-0.66</td>
<td>-0.35</td>
<td>0.57</td>
<td>0.11</td>
<td>-0.73</td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td>(-0.56)</td>
<td>(-0.39)</td>
<td>(1.98)</td>
<td>(0.16)</td>
<td>(-0.62)</td>
<td>(-0.05)</td>
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<td>FOMC Dummy</td>
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<tr>
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<td>(-1.45)</td>
<td>(-2.11)</td>
<td>(-0.66)</td>
<td>(2.09)</td>
<td>(2.44)</td>
<td>(2.97)</td>
</tr>
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</table>

This table reports the robustness check of our portfolio sorting results. In Panel A, we exclude the recent financial crisis period of July 2008 to June 2009; in Panel B we exclude those firms reporting earnings on the FOMC days. We use COMPUSTAT variable "RDQ" as the report date of quarterly earnings. Number of firms reporting earnings on the FOMC days in our sample changes from 1 to 123. On average there are 25 firms reporting earnings on each FOMC days.
Table A4: CAPM of Portfolio Returns Controlling for VIX

Panel A: Portfolio Sorted on Expected Sensitivity Reduction

<table>
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<td>1.26</td>
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<tr>
<td>Non-FOMC Dummy</td>
<td>-1.09</td>
<td>-0.47</td>
<td>0.64</td>
<td>0.35</td>
<td>-1.34</td>
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<th>(−0.95)</th>
<th>(−0.53)</th>
<th>(2.19)</th>
<th>(0.47)</th>
<th>(−1.13)</th>
<th>(−0.19)</th>
</tr>
</thead>
</table>

Panel B: Portfolio Sorted on CAPM Beta

<table>
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<th>8</th>
<th>9</th>
<th>10</th>
<th>(10−1)</th>
</tr>
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<tr>
<td>CAPM Beta</td>
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<td>1.01</td>
<td>1.67</td>
<td>1.95</td>
<td>1.53</td>
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<tr>
<td>Non-FOMC Dummy</td>
<td>1.33</td>
<td>1.49</td>
<td>0.38</td>
<td>-2.27</td>
<td>-1.61</td>
<td>-2.94</td>
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<tr>
<td>FOMC Dummy</td>
<td>-3.22</td>
<td>-5.59</td>
<td>-2.75</td>
<td>1.84</td>
<td>14.18</td>
<td>17.41</td>
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<table>
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<th>(2.01)</th>
<th>(2.40)</th>
<th>(1.05)</th>
<th>(-1.98)</th>
<th>(-0.97)</th>
<th>(-1.40)</th>
</tr>
</thead>
</table>

This table reports the regression coefficients of the non-FOMC dummy and the FOMC dummy in the following regression:

\[ R_{it} - r_{ft} = \alpha_{1Non} \cdot 1_{Non} + \alpha_{1FOMC} \cdot 1_{FOMC} + \beta \left( R_{it}^{MF} - r_{ft} \right) + \gamma \Delta VIX_t^2 + \varepsilon_t, \]

where \( R_{it} \) is the daily return of the portfolio, \( R_{it}^{MF} \) is the daily return of the market, and \( r_{ft} \) is the daily risk-free rate. \( \Delta VIX_t^2 \) is the daily change in VIX^2. \( 1_{Non} \) and \( 1_{FOMC} \) are dummy variables that take values of 1 only on non-FOMC and FOMC announcement days, respectively.

A.3 Details of the Continuous-time Model

A.3.1 Value function of the representative agent

Ricatti equation solution Because announcements provide signals containing the true value of \( x_t \) at \( nT \), the posterior variance after each announcement drops from \( q_{nT}^{-} \) to \( q_{nT}^{+} = q_0 \). In the interior of \((0, T)\), the standard optimal filtering implies that the posterior mean and variance of \( x_t \) are given by equations (8) and (9). It is easy to see that \( q_t \) is deterministic and has a closed form solution:

\[ q(t) = \sigma_x^2 \left( \frac{1 - e^{-2\tilde{a}(t + t^*)}}{\tilde{a} - a_x} \right) e^{-2\tilde{a}(t + t^*)} + a_x + \tilde{a}, \quad (A.2) \]
where \( \hat{a} = \sqrt{a_x^2 + (\sigma_x/\sigma)^2} \) and \( t^* = \frac{1}{2a} \ln \frac{\sigma_x^2 + (\hat{a} - a_x)q_0}{\sigma_x^2 - (\hat{a} + a_x)q_0} \).

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

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

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

\[
\bar{f}(C_t, V_t) = \rho \frac{C_t^{1-1/\psi} - ((1 - \gamma) V_t)^{1-1/\psi}}{((1 - \gamma) V_t)^{1-1/\psi} - 1}
\]

for \( \psi \neq 1 \) and

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

for unit IES \( (\psi = 1) \).

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

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

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

\[
V(\hat{x}_t, t, C_t) = \frac{1}{1 - \gamma} H(\hat{x}_t, t) C_t^{1-\gamma},
\]

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

\[
0 = \rho \frac{1}{1-\frac{1}{\psi}} \left( \frac{H(\hat{x}_t, t)}{1-\gamma} \right)^{\frac{1}{1-\gamma}} - 1 \right) + \left( \frac{\hat{x}_t}{2} \right) + \frac{1}{1 - \gamma} H_t(\hat{x}_t, t) \\
+ \left[ \frac{1}{1 - \gamma} a_x (\bar{x} - \hat{x}_t) + q_t \right] H_x(\hat{x}_t, t) + \frac{1}{2 (1 - \gamma)} \frac{H_{xx}(\hat{x}_t, t)}{H(\hat{x}_t, t)} \left( \frac{q_t}{\sigma} \right)^2
\]
Proof. Given (A.3),

$$f(C_t, V) = \frac{\rho}{1 - \frac{1}{\psi}} C_t^{1 - \gamma} \left[ H(\hat{x}_t, t)^{1 - \frac{1}{2}} - H(\hat{x}_t, t) \right].$$

Further, using Ito’s lemma,

$$d \left[ C_t^{1 - \gamma} H(\hat{x}_t, t) \right] = (1 - \gamma) H(\hat{x}_t, t) \left( \hat{x}_t dt + \sigma dB_{C,t} \right) - \frac{1}{2} \gamma (1 - \gamma) \sigma^2 dt$$

$$+ H_t(\hat{x}_t, t) dt + H_x(\hat{x}_t, t) \left[ a_x(\bar{x} - \hat{x}_t) dt + \frac{q_t}{\sigma} dB_{C,t} \right]$$

$$+ \frac{1}{2} H_{xx}(\hat{x}_t, t) \left( \frac{q_t}{\sigma} \right)^2 dt + (1 - \gamma) H_x(\hat{x}_t, t) q_t dt,$$

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

Therefore, divide both sides of (A.4) by $C_t^{1 - \gamma} H(\hat{x}_t, t)$, we get (A.6).

Guess $H(x_t, t)$ takes the exponential form: $H(x_t, t) = e^{Bx_t + h(t)}$. Therefore, $H_t(\hat{x}_t, t) = H'(x_t, t) h'(t)$, $H_x(\hat{x}_t, t) = BH(x_t, t)$, $H_{xx}(\hat{x}_t, t) = B^2 H(x_t, t)$. Substituting into (A.6), we would get

$$0 = \rho \left( 1 - \frac{1 - \gamma}{1} \right) \left( e^{\frac{1}{2} \gamma \sigma^2} - 1 \right) + \left( 1 - \gamma \right) \left( \hat{x}_t - \frac{1}{2} \gamma \sigma^2 \right) + h'(t)$$

$$+ \left[ a_x(\bar{x} - \hat{x}_t) + (1 - \gamma) q_t \right] B + \frac{1}{2} B^2 \left( \frac{q_t}{\sigma} \right)^2.$$ 

Using $e^z - 1 \approx z$ to approximate and simplify, the above equation becomes,

$$0 = -\rho [B\hat{x}_t + h(t)] + (1 - \gamma) \left( \hat{x}_t - \frac{1}{2} \gamma \sigma^2 \right) + h'(t) + \left[ a_x(\bar{x} - \hat{x}_t) + (1 - \gamma) q_t \right] B + \frac{1}{2} B^2 \left( \frac{q_t}{\sigma} \right)^2.$$ 

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Matching the coefficients of $\hat{x}_t$ and $t$ yields:

\begin{align}
B &= \frac{1 - \gamma}{a_x + \rho}, \\
\rho h'(t) &= \rho h(t) + \frac{1}{2} \gamma (1 - \gamma) \sigma^2 - Ba_x \bar{x} - (1 - \gamma) B q_t - \frac{1}{2} B^2 \left( \frac{q_t}{\sigma} \right)^2. 
\end{align}

(A.7) (A.8)

$h(t)$ can be solved completely by using the following boundary condition:

\textbf{Boundary conditions} Assume there are pre-determined announcements every period at time $nT (n = 1, 2, \ldots)$. On non-announcement days, investors solve optimization problems in the interior $(0^+ \leq t \leq nT^-, n = 1, 2, \ldots)$. At the announcements, investors solve the optimization problems at the boundary. For simplicity, denote $t = 0 = nT^+$ as the moment right after the announcement (or at the announcements), and $t = T = nT^-$ as the moment right before the announcement. The boundary condition satisfies:

\[ H \left( \hat{x}^-_{nT}, T \right) = E \left[ H \left( x_{nT}, 0 \right) \mid \hat{x}^-_{nT}, q(T) \right], \ n = 1, 2, \ldots \]  

(A.9)

where $x_t \sim (\hat{x}_t, q_t)$.

The intuition is, the continuation value of $H$ function right before the announcement must equal to its expected value right after the announcement, conditional on the information at $nT^-$ (before the announcement).

Using the conjectured functional form, the boundary condition can be rewritten as,

\[ e^{B \hat{x}^-_{nT} + h(T)} = E \left[ e^{B x_{nT} + h(0)} \mid \hat{x}^-_{nT}, q(T) \right] \]

\[ = e^{B \hat{x}^-_{nT} + \frac{1}{2} B^2 q(T) + h(0)}, \]

which gives

\[ h(T) = h(0) + \frac{1}{2} B^2 q(T). \]  

(A.10)

Equation (A.8) and (A.10) could jointly be used to solve $h(t)$ function in closed form. Note that
in order to solve for asset prices, we do not really need the functional form of \( h(t) \). However, we need to know it in order to compute welfare gains.

### A.3.2 Asset prices

**State price density and risk free rate** For \( n = 1, 2, \cdots \), in the interior of \((nT, (n+1)T)\), the law of motion of the state price density, \( \pi_t \), satisfies the stochastic differential equation (12), where the risk-free interest rate is

\[
 r(\hat{x}_t, t) = \rho + \frac{1}{\psi} \hat{x}_t - \frac{1}{2} \gamma \left( 1 + \frac{1}{\psi} \right) \sigma^2 + \frac{1}{\psi - \gamma} H_x(\hat{x}_t, t) \psi + \frac{1}{1 - \gamma} H(\hat{x}_t, t) \psi t + \frac{1}{2} \left( \frac{1}{\psi - \gamma} \right) \left( \frac{1 - 1}{\psi} \right) \left( H_x(\hat{x}_t, t) \psi \right)^2 . \tag{A.11}
\]

and the market price of the Brownian motion risk is

\[
 \sigma_\pi(t) = \gamma \sigma - \frac{1}{\psi - \gamma} H_x(\hat{x}_t, t) \psi t . \tag{A.12}
\]

**Proof.** Pricing kernel is defined as

\[
 \frac{d\pi_t}{\pi_t} = \frac{d\bar{f}_C(C,V)}{f_C(C,V)} + \bar{f}_V(C,V) \, dt, \tag{A.13}
\]

where \( \bar{f}_C(C,V) = \rho H(\hat{x}_t, t)^{1-\gamma} C_t^{1-\gamma} \); \( \bar{f}_V(C,V) = \rho \frac{1}{1-\psi} H(\hat{x}_t, t)^{1-\gamma} - \rho \frac{1}{1-\psi} \). Applying Ito’s lemma,

\[
 \frac{df_C(C,V)}{f_C(C,V)} = \frac{d[\frac{\psi}{1-\gamma} C_t^{1-\gamma}]}{H^{1-\gamma} C_t^{1-\gamma}} = \left\{ -\gamma \hat{x}_t + \frac{1}{2} (\gamma + 1) \sigma^2 + \frac{1}{\psi - \gamma} H_t + \frac{1}{1 - \gamma} H \phantom{a} \right. + \frac{1}{2} \left[ \left( \frac{1}{\psi - \gamma} \right) \left( \frac{1}{\psi - 1} \right) \left( \frac{H_x}{H} \right)^2 + \frac{1}{1 - \gamma} H_{xx} \right] \left( \frac{q}{\sigma} \right)^2 \\
 - \frac{1}{\psi - \gamma} H_x \psi t \right\} dt + \left[ -\gamma \sigma + \frac{1}{\psi - \gamma} H(\hat{x}_t, t) \psi t \frac{q_t}{\sigma} \right] dB_{C,t}. \]
Matching the drift and diffusion of (12) and (A.13), we can get (A.12) and
\[
 r(\hat{x}_t, t) = -\frac{1}{\psi} - \gamma \left\{ \frac{H_t}{H} + \frac{H_x}{H} a_x (\bar{x} - \hat{x}_t) + \frac{1}{2} \left[ \frac{1}{\psi} - \gamma \left( \frac{H_x}{H} \right)^2 + \frac{H_{xx}}{H} \right] (\frac{q_t}{\sigma})^2 - \gamma \frac{H_x}{H} \right\} \\
+ \gamma \hat{x}_t - \frac{1}{2} \gamma (\gamma + 1) \sigma^2 - \rho \frac{1}{\psi} \left( \frac{H_t (\hat{x}_t, t)}{1 - \gamma} + \frac{1}{2} \frac{1}{\psi} \right) + \rho \frac{1 - \gamma}{1 - 1/\psi}. 
\]
(A.14)

Use the HJB equation to simplify \( r(\hat{x}_t, t) \) by multiplying \( \frac{1}{\psi} - \gamma \) on both sides of (A.6),
\[
0 = \rho \frac{1}{\psi} - \gamma \left( H (\hat{x}_t, t) - \frac{1}{1 - \gamma} \frac{1}{\psi} - 1 \right) + \left( \frac{1}{\psi} - \gamma \right) \left( \frac{H_t (\hat{x}_t, t)}{1 - \gamma} + \frac{1}{2} \frac{1}{\psi} \right) \\
+ \left( \frac{1}{\psi} - \gamma \right) \left[ \frac{1}{1 - \gamma} a_x (\bar{x} - \hat{x}_t) + q_t \right] \frac{H_x (\hat{x}_t, t)}{H (\hat{x}_t, t)} + \frac{1}{2} \left( \frac{1}{\psi} - \gamma \right) \frac{H_{xx} (\hat{x}_t, t)}{H (\hat{x}_t, t)} \left( \frac{q_t}{\sigma} \right)^2 
\]
and adding up with (A.14), we can get equation (A.11). Finally, substituting \( H (x_t, t) = e^{x_t + h(t)} \) back, we will get (13) and (14).

**Price-to-dividend ratio** Denote \( p^i(\hat{x}_t, t) \) as the price-to-dividend ratio for firm \( i \). The present value relationship (11) implies that
\[
\pi_t D_t^i + \lim_{\Delta \to 0} \frac{1}{\Delta} \left\{ E_t \left[ \pi_{t+\Delta} p^i(\hat{x}_{t+\Delta}, t+\Delta) D_{t+\Delta}^i - \pi_t p^i(\hat{x}_t, t) D_t^i \right] \right\} = 0 \quad (A.15) 
\]

The above equation can be used to show that \( p^i(\hat{x}_t, t) \) must satisfy the following PDE:
\[
1 - p^i(\hat{x}_t, t) \omega^i(\hat{x}_t, t) + p^i_\hat{x}(\hat{x}_t, t) \nu^i(\hat{x}_t, t) + \frac{1}{2} p^i_{\hat{x}\hat{x}}(\hat{x}_t, t) \left( \frac{q_t}{\sigma} \right)^2 = 0, \quad (A.16) 
\]
where \( \varpi^i (\hat{x}_t, t) \) and \( \nu^i (\hat{x}_t, t) \) are defined by:

\[
\varpi^i (\hat{x}_t, t) = \rho - \frac{1}{2} \gamma \left( 1 + \frac{1}{\psi} \right) \sigma^2 + \gamma \sigma^2 \eta_t + \frac{1}{\psi} \hat{x}_t - \bar{x} - \xi_i (\hat{x}_t - \bar{x}) \]
\[
+ \frac{1}{\psi} - \gamma \frac{1 - \eta_t}{\rho + \alpha_x (1 - \eta_t)} + \frac{1}{2} \left( \frac{1}{\psi} - \gamma \right) \left( 1 - \frac{1}{\psi} \right) \left( \frac{q_t}{\sigma} \right)^2,
\]
\[
\nu^i (\hat{x}_t, t) = \alpha_x (\hat{x}_t - \bar{x}) + (\gamma - \eta_t) q_t - \frac{1}{\alpha_x + \rho} \left( \frac{q_t}{\sigma} \right)^2.
\]

**Proof.** Equation (A.15) implies

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

Using Ito’s lemma and equation (10) and (12),

\[
\frac{\mathcal{L} [\pi t p^i (\hat{x}_t, t) D_t]}{\pi t p^i (\hat{x}_t, t) D_t} = - r (\hat{x}_t, t) + \frac{1}{p^i (\hat{x}_t, t)} \left[ p^i_t (\hat{x}_t, t) + p^i_x (\hat{x}_t, t) a_x (\bar{x} - \hat{x}_t) + \frac{1}{2} p^i_{xx} (\hat{x}_t, t) \frac{q_t^2}{\sigma^2} \right]
\]
\[
+ \left[ \bar{x} + \xi_i (\hat{x}_t - \bar{x}) \right] + \frac{p^i_t (\hat{x}_t, t)}{p^i (\hat{x}_t, t)} q_t \eta_t
\]
\[
- \left( \gamma \sigma - \frac{1}{\psi} - \gamma \frac{H_x (\hat{x}_t, t)}{1 - \gamma} \frac{q_t}{\sigma} \right) \left[ \eta_t \sigma + \frac{p^i_x (\hat{x}_t, t) q_t}{p^i (\hat{x}_t, t) \sigma} \right].
\]

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

\[
- \rho - \frac{1}{\psi} \hat{x}_t + \frac{1}{2} \gamma \left( 1 + \frac{1}{\psi} \right) \sigma^2 + \gamma \frac{1}{\psi} \frac{H_x (\hat{x}_t, t)}{1 - \gamma} \frac{q_t}{\sigma} - \frac{1}{2} \left( \frac{1}{\psi} - \gamma \right) \left( 1 - \frac{1}{\psi} \right) \left( \frac{H_x (\hat{x}_t, t)}{H (\hat{x}_t, t) \sigma} \right)^2
\]
\[
+ \left[ 1 + p^i_t (\hat{x}_t, t) + p^i_x (\hat{x}_t, t) a_x (\bar{x} - \hat{x}_t) + \frac{1}{2} p^i_{xx} (\hat{x}_t, t) \frac{q_t^2}{\sigma^2} \right]
\]
\[
+ \left[ \bar{x} + \xi_i (\hat{x}_t - \bar{x}) \right] + \left( \gamma - \frac{1}{\psi} - \gamma \frac{H_{xx} (\hat{x}_t, t)}{1 - \gamma} \frac{q_t}{\sigma} \right) \left[ \eta_t \sigma + \frac{p^i_x (\hat{x}_t, t) q_t}{p^i (\hat{x}_t, t) \sigma} \right] = 0.
\]

Using \( \frac{H_x (\hat{x}_t, t)}{H (\hat{x}_t, t)} = \frac{1 - \gamma}{a_x + \rho} \), we can rewrite the above equation to get (A.16).

\[\square\]

In order to pin down the price-to-dividend ratio in terms of PDE as shown in equation (A.16), next we need to solve the boundary condition. Denote \( p^i (\hat{x}, 0) = p^i (\hat{x}, nT^+) \) and
\( p^i (\hat{x}, T) = p^i (\hat{x}, nT^-), \) and the boundary condition (15) can be derived as follows.

In general, under recursive utility, the stochastic discount factor for a small interval \( \Delta \) is,

\[
SDF_{t,t+\Delta} = e^{-\rho \Delta} \left( \frac{C_{t+\Delta}}{C_t} \right)^{-\frac{1}{\psi}} \left[ \frac{W_{t+\Delta}}{\mathbb{E} [W_{t+\Delta}^{1-\gamma}]} \right]^{\frac{1}{\psi} - \gamma}
\]

where \( W_t = [(1 - \gamma) V (\hat{x}_t, t, C_t)]^{\frac{1}{1-\gamma}} \). Thus,

\[
SDF_{t,t+\Delta} = e^{-\rho \Delta} \left( \frac{C_{t+\Delta}}{C_t} \right)^{-\frac{1}{\psi}} \left[ \frac{(H_{t+\Delta} C_t^{1-\gamma})^{\frac{1}{1-\gamma}}}{\mathbb{E} [H_{t+\Delta} C_t^{1-\gamma}]} \right]^{\frac{1}{\psi} - \gamma}.
\]

At the announcement, \( \Delta \to 0 \), therefore,

\[
SDF_{t,t+\Delta} = \frac{\frac{1}{\psi} - \gamma}{\mathbb{E} [H_{t+\Delta}]^{\frac{1}{1-\gamma}}} = \frac{\frac{1}{\psi} - \gamma}{\mathbb{E} \left[ e^{\frac{1}{\psi} - \gamma \hat{x}_t} \right]^{\frac{1}{1-\gamma}}}.
\]

The boundary condition for price-to-dividend ratio at announcements \( nT \) can be derived as:

\[
p^i (\hat{x}_{nT}^-, nT^-) = \mathbb{E} \left[ e^{\frac{1}{\psi} - \gamma \hat{x}_{nT}^+} p^i (\hat{x}_{nT}^+, nT^+) \bigg| \hat{x}_{nT}^-, q_{nT}^- \right] = \mathbb{E} \left[ e^{\frac{1}{\psi} - \gamma \hat{x}_{nT}^+} p^i (\hat{x}_{nT}^+, nT^+) \bigg| \hat{x}_{nT}^-, q_{nT}^- \right] \frac{\frac{1}{\psi} - \gamma}{\left( e^{\frac{1}{\psi} - \gamma \hat{x}_{nT}^+ + \frac{1}{2 (\alpha_x + \rho)} [q_{nT}^- - q_{nT}^+]} \right)^{\frac{1}{1-\gamma}}}
\]

which corresponds to equation (15) in the main text. Combining this boundary condition with equation (A.16) would pin down the solutions for each firm’s price-to-dividend ratio.
**Risk premium** We define the cumulative return as

\[
\frac{dR^i_t}{R^i_t} = \mu^i_{R,t} dt + \sigma^i_{R,t} dB_{C,t} + \sigma_i dB_{i,t}
\]  \hspace{1cm} (A.17)

where \(\mu^i_{R,t}\) and \(\sigma^i_{R,t}\) are the risky asset return and volatility for firm \(i\), respectively,

\[
\mu^i_{R,t} = \frac{1}{p^i(\hat{x}_t,t)} \left[ 1 + p^i_t(\hat{x}_t,t) + p^i_x(\hat{x}_t,t) a_x(\bar{x} - \hat{x}_t) + \frac{1}{2} p^i_{xx}(\hat{x}_t,t) \frac{q^2_t}{\sigma^2} \right] + \bar{x} + \xi_i (\hat{x}_t - \bar{x}) + \frac{p^i_x(\hat{x}_t,t)}{p^i(\hat{x}_t,t)} q_t \eta_i,
\]  \hspace{1cm} (A.18)

\[
\sigma^i_{R,t} = \eta_i \sigma + \frac{p^i_x(\hat{x}_t,t)}{p^i(\hat{x}_t,t)} q_t \sigma.
\]  \hspace{1cm} (A.19)

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

\[
\mu_{R,t} - r(\hat{x}_t,t) = \left[ \gamma \sigma - \frac{1}{a_x + \rho} - \frac{\gamma q_t}{\sigma} \right] \left[ \eta_i \sigma + \frac{p^i_x(\hat{x}_t,t)}{p^i(\hat{x}_t,t)} q_t \right].
\]  \hspace{1cm} (A.20)

**Proof.** The cumulative return can be computed as

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

Applying Ito’s lemma,

\[
\frac{d \left[ p^i(\hat{x}_t,t) D_t^i \right]}{p^i(\hat{x}_t,t) D_t^i} = \left\{ \frac{1}{p^i(\hat{x}_t,t)} \left[ p^i_t(\hat{x}_t,t) + p^i_x(\hat{x}_t,t) a_x(\bar{x} - \hat{x}_t) + \frac{1}{2} p^i_{xx}(\hat{x}_t,t) \frac{q^2_t}{\sigma^2} \right] \right. \\
\left. + \bar{x} + \xi_i (\hat{x}_t - \bar{x}) + \frac{p^i_x(\hat{x}_t,t)}{p^i(\hat{x}_t,t)} q_t \eta_i \right\} dt + \left[ \eta_i \sigma + \frac{p^i_x(\hat{x}_t,t)}{p^i(\hat{x}_t,t)} q_t \right] d\hat{B}_{C,t} + dB_{i,t}.
\]

Matching the drift and diffusion terms with equation (A.17), we can get (A.18) and (A.19).
The instantaneous risk premium \((A.20)\) can be obtained from
\[
\mu_i^R \cdot r (\hat{x}_t, t) = -Cov_t \left[ \frac{d \left[ p^i (\hat{x}_t, t) D_t \right]}{p^i (\hat{x}_t, t) D_t}, \frac{d \pi_t}{\pi_t} \right] = -\gamma \sigma - \frac{1}{\gamma H (\hat{x}_t, t) q_t} \left[ \eta_i \sigma + \frac{p^i (\hat{x}_t, t) q_t}{p^i (\hat{x}_t, t) \sigma} \right] = \gamma \eta_i \sigma^2 + \left[ \gamma \frac{p^i (\hat{x}_t, t)}{p^i (\hat{x}_t, t)} - \frac{1}{\gamma H (\hat{x}_t, t) q_t} \left[ \frac{1}{\gamma} - \frac{H_x (\hat{x}_t, t)}{H (\hat{x}_t, t)} q_t - \frac{1}{\gamma} - \frac{H_x (\hat{x}_t, t) p^i (\hat{x}_t, t) (q_t)^2}{1 - \gamma H (\hat{x}_t, t) p^i (\hat{x}_t, t)} \right] \right].
\]

\[\square\]

### A.3.3 Expected sensitivity

Guess the price-to-dividend ratio takes the exponential form: \(p (\hat{x}_t, t) = e^{A \hat{x}_t + g(t)}\). Substituting this into \((A.16)\) yields,
\[
e^{-A \hat{x}_t - g(t)} - \omega (\hat{x}_t, t) + g'(t) - A \omega (\hat{x}_t, t) + \frac{1}{2} A^2 \left( \frac{q_t}{\sigma} \right)^2 = 0.
\]

Use the Taylor expansion around \(\bar{x}\) (since \(\hat{x}_t\) is an OU process), \(e^{-A \hat{x}_t - g(t)} \approx \bar{p} - A \bar{p} (\hat{x}_t - \bar{x})\), where \(\bar{p}\) is the inverse of steady state price-to-dividend ratio. Match the coefficient of \(\hat{x}_t\) yields,
\[
A = \frac{\xi - \frac{1}{\bar{\psi}}}{a_x + \bar{p}}. \quad (A.21)
\]

Note that the sensitivity of each firm can be approximated as: \(p^i_x (\hat{x}_t, t) / p^i (\hat{x}_t, t) = \frac{\xi - \frac{1}{\bar{\psi}}}{a_x + \bar{p}}\).

### A.3.4 Implied variance reduction

In our model, all shocks are conditional normal, and the variance of the shocks are deterministic. Therefore, the return variance under the physical and risk neutral measure are the same. We only need to compute the variance under the physical measure. The implied variance before the
The implied variance after the announcement could be written as:

\[ \text{Var} \left[ \ln P(t) - \ln P(nT^-) | \hat{x}_{nT}^{-}, q_{nT}^- \right] = \text{Var} \left[ \ln P(t) - \ln P(nT^+) | \hat{x}_{nT}^{-}, q_{nT}^- \right] \]

Therefore, the implied variance reduction could be obtained immediately by taking the difference of the above two expressions:

\[ \Delta IV = \text{Var} \left[ \ln P(nT^+) - \ln P(nT^-) | \hat{x}_{nT}^{-}, q_{nT}^- \right] . \]

Because dividend is continuous upon announcements, we can get

\[ \Delta IV = \text{Var} \left[ \ln p(nT^+) - \ln p(nT^-) | \hat{x}_{nT}^{-}, q_{nT}^- \right] . \quad \text{(A.22)} \]

Therefore,

\[ \Delta IV_i = \left( \frac{\xi_i - \frac{1}{\psi}}{a_x + \hat{p}_i} \right)^2 \left( q_{nT}^- - q_{nT}^+ \right) = \left( \frac{\xi_i - \frac{1}{\psi}}{a_x + \hat{p}_i} \right)^2 \left( \frac{q_{nT}^-}{q_{nT}^{-2} + \sigma^2} \right) . \]

A.3.5 Numerical Solutions

To solve the PDE (A.16) with the boundary condition (15) for each firm \( i \), we consider the following auxiliary problem\(^6\):

\[ p(\hat{x}_t, t) = \mathbb{E} \left[ \int_t^T e^{-\int_t^s \varpi(\hat{x}_u, u) du} ds + e^{-\int_t^T \varpi(\hat{x}_u, u) du} p(\hat{x}_T, T) \right] , \quad \text{(A.23)} \]

\(^6\)We fix \((\xi_i, \eta_i)\) for each firm and calculate the firm-specific price-to-dividend \( p'(\hat{x}_t, t) \). 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

$$d\hat{x}_t = -\nu(\hat{x}_t, t)\, dt + \frac{q_t}{\sigma} dB_t. \quad (A.24)$$

Note that the solution to (A.23) and (15) satisfies the same PDE. Given an initial guess of the pre-announcement price-to-dividend ratio, we can solve (A.23) by the Markov chain approximation method (Kushner and Dupuis, 2001). The major steps are:

1. 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 (A.23) backwards recursively:

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

until we obtain $p(\hat{x}_t, 0)$.
3. Compute an updated pre-announcement price-to-dividend ratio function, $p(\hat{x}_T, T)$ using (15):

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

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

Now we talk about the numerical details. For simplicity, define log price-to-dividend ratio

$$\textit{We construct a locally consistent Markov chain approximation of the diffusion process (A.24) as follows. We choose a small } \delta x, \textit{let } Q = |\nu(\hat{x}, t)| \delta x + \left(\frac{q_t}{\sigma}\right)^2, \textit{and define the time increment } \Delta = \frac{2\delta x^2}{Q}, \textit{be a function of } \delta x. \textit{Define the following Markov chain on the space of } \hat{x}:$$

$$\Pr(\hat{x} + \delta \hat{x} \mid \hat{x}) = \frac{1}{Q} \left[-\nu(\hat{x}, t)^+ \delta \hat{x} + \frac{1}{2} \left(\frac{q_t}{\sigma}\right)^2\right],$$

$$\Pr(\hat{x} - \delta \hat{x} \mid \hat{x}) = \frac{1}{Q} \left[-\nu(\hat{x}, t)^- \delta \hat{x} + \frac{1}{2} \left(\frac{q_t}{\sigma}\right)^2\right].$$

One can verify that as $\delta x \to 0$, the above Markov chain converges to the diffusion process (A.24) (In the language of Kushner and Dupuis (2001), this is a Markov chain that is locally consistent with the diffusion process (A.24)).
\( \rho(\hat{x}_t, t) \equiv \ln p(\hat{x}_t, t) \), therefore,

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

\[
= \ln \left[ \Delta + e^{-\varpi(\hat{x}_t, t) \Delta} e^{\varphi(\hat{x}_t, t) \Delta} - \varpi(\hat{x}_t, t) \nu(\hat{x}_t, t) \Delta + \frac{1}{2} \Delta \varphi_x^2(\hat{x}_t, t) \left( \frac{\varpi}{\nu} \right)^2 \right]
\]

\[
= \ln \left[ \Delta + e^{\varphi(\hat{x}_t+\Delta, t)+\Delta} - [\varpi(\hat{x}_t, t) + \varpi(\hat{x}_t, t) \nu(\hat{x}_t, t)] \Delta + \frac{1}{2} \Delta \varphi_x^2(\hat{x}_t, t) \left( \frac{\varpi}{\nu} \right)^2 \right].
\]

At the announcement \( T \),

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

Approximate the expectation using two ways: First, if \( \hat{x} \) is in the interior \([\bar{x} - 5 \frac{a_x}{\sqrt{2a_x}} + \max (n), \bar{x} + 5 \frac{a_x}{\sqrt{2a_x}} + \max (n)]\), use Gaussian quadrature:

\[
\mathbb{E} \left[ e^{\frac{\psi - \gamma}{a_x + \rho} \hat{x}_T^+ + \varphi(\hat{x}_T^+, T^+)} \mid \hat{x}_T^-, q_T^- \right] = \omega^T e^{\frac{\psi - \gamma}{a_x + \rho} \hat{x}_T^+ + \varphi(\hat{x}_T^+, T^+)} \hat{x}_T^+ = \hat{x}_T^- + n.
\]

where nodes \( n \) and weights \( \omega \) are random variables generated from multivariate normal distribution.

Second, if \( \hat{x} \) is close to the boundary, use local approximation:

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