Journal of Monetary Economics xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Monetary Economics

journal homepage: www.elsevier.com/locate/jmoneco

The macroeconomic announcement premium and information environment☆

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A R T I C L E I N F O

Article history:
Received 1 September 2022
Revised 16 June 2023
Accepted 20 June 2023
Available online xxx

JEL classification:
G12
G14
D8

Keywords:
Macroeconomic news
Announcement premium
Risk reduction
Information quality
Business cycles

A B S T R A C T

The quality of information environment has impact on the market risk premium and the expected risk reduction on macroeconomic announcement days. The risk premium is high when the risk is high as in standard asset pricing models, while the risk premium is low when the prevailing information environment is poor. The same is true for the expected risk reduction. These effects extend to market factor premiums (i.e., the premium associated with market betas) on various sets of portfolios and have a connection with business cycles. The findings are consistent with the notion that poor information environment hampers the effectiveness of learning.

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1. Introduction

The central theme of asset pricing theories is that present values of assets are determined such that the expected future returns are compensation for bearing risk, conditioned on information available to investors at the time. Most existing theories model risk as stochastic volatility of economic fundamentals and empirical works focus on how various volatility measures predict future stock market returns. The impact of time-varying information environment on asset pricing, however, receives little attention. In this paper we examine how information environment affects the stock market index return on macroeconomic news announcement days.

The advantage of focusing on the macroeconomic news announcement days is that these are the days when the actions occur. Savor and Wilson (2013, 2014) show that, while there are less than 15% of the trading days during their sample period on which announcements about certain macroeconomic conditions are made, more than 2/3 of the cumulative returns

☆ We thank Hengjie Ai, Brandon Julio, Charles Martineau, Todd Milbourm, Jian Wang, Mungo Wilson, Jianfeng Yu, Guofu Zhou, Ti Zhou, Cai Zhu, and seminar participants at the 30th Annual Conference of Northern Finance Association, 25th Annual Conferrence of the Multinational Finance Society, Chinese University of Hong Kong in Shenzhen, Fudan University, Hong Kong University of Science and Technology, and Tongji University for their helpful comments on the paper. Yirong Luo provided excellent research assistance. All remaining errors are ours.

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https://doi.org/10.1016/j.jmoneco.2023.06.005
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on the stock index are generated during these days. We examine two determinants of the equity market risk premium (i.e., the expected excess return on the market portfolio) and the expected risk reduction on macroeconomic news announcement days. One is the usual measure of the risk of return and the other is a measure of information environment. The pre-announcement asset price is negatively related to risk and the expected announcement premium is positively related to the risk, as in standard asset pricing models. The arrival of a macroeconomic announcement about the future prospect of assets is expected to reduce the risk and therefore to cause asset price to rise. The expected risk reduction and announcement premium, however, depends on the information environment. When the information environment is poorer (better), less (more) effectively information is revealed from the announcements. The notion of a poor information environment is conceptually related to the noisiness of information discussed in the noisy-information model (e.g., Angeletos and La'O (2009); Lucas (1972); Morris and Shin (2002), and Coibion et al. (2021)). But the concept of a poor information environment goes beyond the noisiness or inaccuracy of the piece of information itself, it refers to the environment at the time of information arrival, in which the information is perceived, interpreted and digested. We build a model to illustrate the central theme of this paper that risk has a positive effect on the announcement premium and on the risk reduction, while poor information environment reduces the announcement premium and the risk reduction.

We choose the VIX index compiled by Chicago Board Options Exchange (CBOE) after 1990 and its sample version before 1990 as the measure of the risk perceived by investors conditional on current information. We adopt a set of macroeconomic forecast dispersion measures from the widely-cited Survey of Professional Forecasters and the well-established news-based U.S. Economic Policy Uncertainty index constructed by Baker et al. (2016) as the base of our information environment measure. When information environment is poorer, individual professional forecasters obtain noisier signals from their separate sources, which are less correlated, so their forecasts become more dispersed (e.g., Diamond and Verrecchia (1981)). The EPU index is also associated with poorer information environment, in that it is characterized by worse asymmetric information and reduced investors' reaction to information in both the stock market and the corporate bond market (e.g., Nagara et al. (2019) and Kaviani et al. (2020)). Macro announcement premium and expected risk reduction decrease in poor information environment because macroeconomic variables collected and aggregated in poor information environment tend to be less reliable, and/or government decisions made in poor environment carry less weight on investors' action. After all, there are two-way communications between the government and the private sector (e.g., Bauer and Swanson (2022)). Our Empirical results with the chosen measures of risk and information environment confirm the theoretical predictions. We show that poorer pre-announcement information environment predicts smaller announcement premium and risk reduction on the US stock market index, while higher pre-announcement risk predicts larger announcement premium and risk reduction. We also show that the empirical results obtained on stock market index extend to stock portfolios sorted by various criteria.

The intended contributions of the paper are as follows. First, the theoretical and empirical results extend the standard asset pricing models in which information environment does not explicitly appear in the conditional risk-return relationship. We emphasize that the risk-return relationship depends on the quality of value-relevant information available to the public. The risk-return relationship is clear when information environment is good and is blurred when information environment is poor. Beber and Brandt (2009) provide evidence that risk reduction on the macroeconomic news announcement days is higher when the macroeconomic risk is higher. Liu et al. (2022) present evidence of the time-varying announcement premium, using various variables representing macroeconomic risk. Our work in this paper contributes to this line of work by showing that, apart from the positive impact of risk on the announcement premium, noisy information environment hurts resolution of uncertainty and hence reduces the announcement premium. We find that during the periods of noisy information environment, the market return on the announcement days are not significantly different from non-announcement days on average.

Second, in the literature of macroeconomic news announcements, some authors have laid down the foundation for the announcement premium to be linked to resolution of uncertainty. Ai and Bansal (2018) show that a positive announcement premium is only possible under non-expected utility functions with certain conditions. The theoretically identified determinants of the magnitude of risk premium and risk reduction are the behavioral parameters, i.e., the inverse of the elasticity of intertemporal substitution relative to risk aversion. Watcher and Zhu (2022) propose a model with agents learning about a latent disaster probability from macroeconomic announcements to explain the announcement premium and the risk-return relationship. They attribute the variation of announcement premium to the time-varying disaster probability, another measure of risk. Our paper emphasizes that learning is limited by the quality of information revealed in the macroeconomic announcements, which is expected to reduce risk to the degree tied to the potentially time-varying quality of information environment.

Third, in the broader literature on the macroeconomic uncertainty, many authors have studied the effect of economic environment on learning about future prospect. Under the incomplete information setting, noisiness of the observed signal conveying information about the underlying macroeconomic activities is defined as information uncertainty (e.g., Angeletos and La'O (2009); Bansal and Shaliastovich (2010); Morris and Shin (2002); Veronesi (2000), and Coibion et al. (2021)). Van Nieuwerburgh and Veldkamp (2006) point out that recessions are periods with higher information uncertainty, which attributes to asymmetric phases of business cycles. Kozeniauskas et al. (2018) show that various measures of risk and uncertainty have different implications to different economic subjects although they are all counter-cyclical. Our work adds to this line of research in the case of macroeconomic news announcements by demonstrating that the announcement premium and the risk reduction are high when pre-announcement risk is high, but they are low when information environment is poor, albeit the asset return risk and information environment poorness are positively correlated. This leads to asymmetric patterns in the risk-return relationship.

There is a line of literature on the high frequency, pre-announcement returns. Lucca and Moench (2015) show that most of the announcement return occurs in a few hours before the announcement. Bernile et al. (2016) find evidence from derivative markets that there is informed trading due to information leakage. Hu et al. (2022) develop a two-risk model to explain the phenomenon of high mean-variance ratio in the pre-announcement returns and low mean-variance ratio of the announcement returns. We study more persistent, lower frequency return patterns in the sample period, where the state of the economy can be classified by the level of risk and noisiness of information environment. Interestingly however, the pre-announcement return patterns documented by the above-mentioned studies manifest mostly in the periods of high risk yet good information environment.[1]

2. A simple two-period model and its implications

We develop a highly stylized static production-based model to illustrate our idea in this paper and to make connection with the empirical methodology later.[2] In the static model, risk of return and poorness of information environment are modeled as parameters and comparative statics are used to establish the relationship between the expected announcement return and the expected risk reduction with these parameters.

2.1. The setting

In the model, there is one good which can be used for both consumption and investment. There are a large number, N, of identical economic agents. Each of them is endowed with W units of the good to begin with. There is a linear production process, in the form of $f(K) = AK$, which converts amount K of the good to amount AK over one unit of time, where $A > 0$ is a random variable. There are four relevant time points, labeled as time-0^-, time-0, time-0^+ and time-1. Time-0^- is the time a consumption-investment decision has to be made by the agents with the knowledge of a prior distribution about A. The investment is done by agents through purchasing shares of a firm which owns the production technology, using a portion of W, with the remaining C_0 for consumption *between* time-0 and time-1. Time-0 is the time when a signal is obtained by all agents, which provides additional information about A. Time-0^+ is the time when agents can adjust their consumption-investment decisions by trading their shares with each other upon receiving the signal. Time-1 is the time when A realizes and agents consume C_1 *afterwards* according to their share positions. Without loss of generality, assume the firm is divided into N shares. At times-0^-, 0^+ and 1, each share has a price of P_{0-}, P_{0+} and P_1 respectively. Note that, since agents are identical, they will end up not trading at all at time-0^+, so there is no need of separate notations for the consumptions at time-0^- and time-0^+. Nevertheless, a (shadow) price P_{0+} will be generated in the process, which can be different from P_{0-} due to potentially more precise information about the productivity A. There is no money in the economy. The firm value is in the unit of the good. There is no riskfree asset either.

For simplicity, the random payoff of the production process is assumed to take two values only: $\bar{A}e^{\nu}$ and $\bar{A}e^{-\nu}$ with half-and-half probabilities, where $\nu > 0$ is the standard deviation of $\log A$. The preference of the agents takes the form of two-period recursive utility function of Epstein and Zin (1989), which separates risk aversion from elasticity of intertemporal substitution, as follows.

$$\left(C_0^{1-\rho} + \beta\left(E_{0^-}C_1^{1-\gamma}\right)^{\frac{1-\rho}{1-\gamma}}\right)^{\frac{1}{1-\rho}}, \tag{1}$$

where $\gamma > 0$ is the constant relative risk aversion (CRRA), $\rho > 0$ is the inverse of the intertemporal elasticity of substitution (IES), $\beta > 0$ measures the importance of C_1 relative to C_0, and $E_{0^-}[\cdot]$ denotes expected value conditioned on the information at time-0^-. We will focus on the case of $\rho < 1 < \gamma$. Ai and Bansal (2018) show that $\rho < \gamma$ is a sufficient and necessary condition for positive announcement premiums which coincides with the condition for the preference for early resolution of uncertainty. The concept is developed to the property of generalized risk sensitivity in broader frameworks than (1) for positive announcement premiums. Ai et al. (2022) further show that the case $1 < \gamma$ exhibits strong general risk sensitivity, under which more informative announcements are associated with a higher announcement premium. Much empirical work also supports the parameter choice of $\rho < 1 < \gamma$. The equity premium puzzle raised by Mehra and Prescott (1985) requires a large risk aversion γ, while the riskfree rate puzzle raised by Weil (1989) requires a large intertemporal elasticity of substitution, or a small ρ. Bansal and Yaron (2004) advocate the case $\rho < 1 < \gamma$, which explains the observed negative correlation between consumption volatility and price-dividend ratio, among many other phenomena documented in the literature, in addition to the high equity premium and the low riskfree rate.[3]

[1] The results on this are presented in Appendix D of Online Appendix.

[2] The idea can also be illustrated in a pure exchange economy. The model in the exchange economy, however, does not offer much simplification. The detail is explained in Online Appendix.

[3] We acknowledge, however, that there are considerably mixed results from the literature regarding the values of the parameters. Even the interpretation of the parameters are restricted to the case of no labor income in the model (e.g. Swanson (2012, 2018)).

2.2. The consumption-investment decision at time-0^-

At time-0^-, given the price P_{0^-}, each agent maximizes (1) over C_0, under the constraint:

$$C_1 = [(W - C_0)/P_{0^-}]A\bar{K}, \tag{2}$$

where $W - C_0$ is the investment of a typical agent, $(W - C_0)/P_{0^-}$ is the number of shares the agent owns, and $\bar{K}$ is the average investment which each individual agent takes as given. This implies that $dC_1/dC_0 = -A\bar{K}/P_{0^-}$. The first order condition for the optimal C_0 is

$$C_0^{-\rho} - \beta(E_{0^-}C_1^{1-\gamma})^{\frac{\gamma-\rho}{1-\gamma}} E_{0^-}(C_1^{-\gamma}A\bar{K}/P_{0^-}) = 0. \tag{3}$$

For a given P_{0^-}, C_0 can be solved from the first order condition.

As a decision rule for an individual, C_0 is a function of P_{0^-} among other parameters: $C_0 = C_0(P_{0^-})$. While the closed form solution of this function is not available, Lemma 1 below shows that it is an increasing function. The proof is relegated to Online Appendix.

Lemma 1. *As a decision rule of individual agents,* $C_0(P_{0^-})$ *is an increasing function of* P_{0^-}*, starting at* $C_0(0) = 0$.

This is intuitive. The more expensive the share is, the less should be invested, and more should be consumed at time-0. This function, when aggregated over all agents, is the demand function for the shares.

Since agents are identical, $\bar{K} = W - C_0(P_{0^-})$ holds, the equilibrium requires that the total demand for shares, $N[W - C_0(P_{0^-})]/P_{0^-}$ be equal to the total supply N. That is,

$$P_{0^-} = W - C_0(P_{0^-}). \tag{4}$$

As such, each agent ends up owning one share. The first order condition (3) and the equilibrium condition (4) jointly determine the price and quantity. Since there is no closed-form solution of $C_0(P_{0^-})$, there is no closed-form solution for P_{0^-} either. However, we have the following result.

Lemma 2. *There is a unique solution of* (P_{0^-}, C_0) *that satisfies the first-order condition (3) and the equilibrium condition (4), with* $0 < P_{0^-} < W$ *and* $0 < C_0 < W$.

Noting that $C_0^{-\rho} = C_0^{\gamma-\rho}C_0^{-\gamma} = C_0^{(1-\gamma)\cdot\frac{\gamma-\rho}{1-\gamma}}C_0^{-\gamma}$, the first order condition can be rewritten as

$$P_{0^-} = \frac{\beta\left(E_{0^-}C_1^{1-\gamma}\right)^{\frac{\gamma-\rho}{1-\gamma}} E_{0^-}[C_1^{-\gamma}A\bar{K}]}{C_0^{-\rho}} = \beta\left(E_{0^-}(C_1/C_0)^{1-\gamma}\right)^{\frac{\gamma-\rho}{1-\gamma}} E_{0^-}[(C_1/C_0)^{-\gamma}A\bar{K}]. \tag{5}$$

When $\gamma = \rho$ in the case of expected utility, the first order condition takes a familiar form: $P_{0^-} = \beta E_{0^-}[(C_1/C_0)^{-\gamma}A\bar{K}]$. The multiplier $\left(E_{0^-}(C_1/C_0)^{1-\gamma}\right)^{\frac{\gamma-\rho}{1-\gamma}}$ shows how asset pricing under recursive utility is different from that under expected utility.

In equilibrium, $\bar{K} = (W - C_0)$ and $A\bar{K} = C_1$, so the time-0^- price can also be written from the first order condition as

$$P_{0^-} = \frac{\beta\left(E_{0^-}(C_1^{1-\gamma})\right)^{\frac{\gamma-\rho}{1-\gamma}} E_{0^-}(C_1^{1-\gamma})}{C_0^{-\rho}} = \frac{\beta\left(E_{0^-}(C_1^{1-\gamma})\right)^{\frac{1-\rho}{1-\gamma}}}{C_0^{-\rho}} = \frac{\beta\left(\frac{1}{2}C_{1H}^{1-\gamma} + \frac{1}{2}C_{1L}^{1-\gamma}\right)^{\frac{1-\rho}{1-\gamma}}}{C_0^{-\rho}}, \tag{6}$$

where $C_{1H} = (W - C_0)\bar{A}e^{v}$ and $C_{1L} = (W - C_0)\bar{A}e^{-v}$. Although this is not a closed form solution in terms of model parameters, the formula provides a sensible economic interpretation.

Since both the price and the quantities are functions of model parameters, we can perform comparative statics. The parameter v is of particular interest. First, from the equilibrium condition (4), $dP_{0^-}/dv = -dC_0/dv$ holds. That is, when v (or any other parameter except for W) varies, the equilibrium P_{0^-} and C_0 move in opposite directions. This is to be contrasted with the earlier statement regarding an increasing decision rule of an individual agent for choosing C_0 with a hypothesized P_{0^-}, holding v (and other parameters) constant. Next, from (6), the first order condition can be rewritten as

$$P_{0^-}C_0^{-\rho} = \beta\left(E_{0^-}C_1^{1-\gamma}\right)^{\frac{1-\rho}{1-\gamma}}. \tag{7}$$

This, together with $dP_{0^-}/dv = -dC_0/dv$, can be used to show the following lemma.

Lemma 3. *If* $\rho < 1$ *then* $dP_{0^-}/dv < 0$.

With risk aversion, a higher risk in future makes the future consumption less desirable, so the current consumption increases and the price of the share for future consumption decreases. The condition $\rho < 1$, i.e., the elasticity of intertemporal substitution is greater than one, makes sure that the substitution effect dominates the income effect given a change in risk. Since $\mathrm{Var}_{0^-}\log(P_1/P_{0^-}) = \mathrm{Var}_{0^-}\log A = v^2$, v is the pre-announcement risk at time-0^-.

2.3. The expected announcement return

At time-0, the agents receive a signal which tells time-1 state being $\bar{A}e^{-\nu}$, or $\bar{A}e^{\nu}$, with a probability u of being wrong, where u is a known number between 0 and 1/2. (There is no need to consider the case $u > 1/2$, as a signal of $\bar{A}e^{-\nu}$ with a probability $u > 1/2$ being wrong is the same as a signal of $\bar{A}e^{\nu}$ with the probability $1-u$ being wrong.) We refer to u, the probability that the signal is wrong, as the degree of poorness of information environment. When $u = 0$, the agents are certain about the revealed state by the announcement; when $u = 1/2$, uncertainty perceived by the agents about time-1 state reaches the highest level and the signal contains no information.

Suppose the signal indicates the high state $\bar{A}e^{\nu}$ and the price of the share changes to P^H_{0+}. An agent decides to adjust her consumption between time-0 and time-1 by buying Z/P^H_{0+} shares of the ownership and decreasing the time-0 consumption of amount Z (with negative Z for selling shares and increasing consumption at time-0) to maximizes the recursive utility based on the new information in the signal. Let E^H_{0+} be the conditional expectation based on a signal of the high state with the probabilities of $(u, 1-u)$ on $(\bar{A}e^{-\nu}, \bar{A}e^{\nu})$. The individual maximization problem is equivalent to

$$\max_Z \ (C_0 - Z)^{1-\rho} + \beta\left(E^H_{0+}[(1 + Z/P^H_{0+})C_1]^{1-\gamma}\right)^{\frac{1-\rho}{1-\gamma}}. \tag{8}$$

The first order condition for the optimal Z for a given P^H_{0+} is

$$-(C_0 - Z)^{-\rho} + \beta\left(E^H_{0+}[(1 + Z/P^H_{0+})C_1]^{1-\gamma}\right)^{\frac{1-\rho}{1-\gamma}-1} E^H_{0+}\left([(1 + Z/P^H_{0+})C_1]^{-\gamma}C_1/P^H_{0+}\right) = 0. \tag{9}$$

Since all agents are the same, the price P^H_{0+} must be adjusted to the level in equilibrium such that $Z = 0$. At equilibrium,

$$P^H_{0+} = \frac{\beta\left(E^H_{0+}C_1^{1-\gamma}\right)^{\frac{1-\rho}{1-\gamma}}}{C_0^{-\rho}} = \frac{\beta\left((1-u)C_{1H}^{1-\gamma} + uC_{1L}^{1-\gamma}\right)^{\frac{1-\rho}{1-\gamma}}}{C_0^{-\rho}}. \tag{10}$$

Similarly, if the signal indicates the low state $\bar{A}e^{-\nu}$ with an error probability of u, the post-signal price will be

$$P^L_{0+} = \frac{\beta\left(E^L_{0+}C_1^{1-\gamma}\right)^{\frac{1-\rho}{1-\gamma}}}{C_0^{-\rho}} = \frac{\beta\left(uC_{1H}^{1-\gamma} + (1-u)C_{1L}^{1-\gamma}\right)^{\frac{1-\rho}{1-\gamma}}}{C_0^{-\rho}}, \tag{11}$$

where E^L_{0+} is the conditional expectation based on a signal of the low state with the probabilities of $(1-u, u)$ on $(\bar{A}e^{-\nu}, \bar{A}e^{\nu})$. It is shown in Online Appendix that, if $\rho < 1$, then in equilibrium, $P^L_{0+} \le P_{0-} \le P^H_{0+}$ with the equality holding only when $u = 1/2$ or $\gamma = 1$.[4]

At time-0^- before the signal is released, the post-announcement price P_{0+} is a random variable taking two values P^L_{0+} and P^H_{0+} with half-and-half probabilities. The expected announcement return $\Lambda(u, \nu) \equiv E_{0-} \log[P_{0+}/P_{0-}]$ is a function of both ν and u in general. From (6), (10) and (11),

$$\begin{aligned}\Lambda(u, \nu) = \frac{1-\rho}{1-\gamma}\Big[&\frac{1}{2}\log\left(ue^{\nu(1-\gamma)} + (1-u)e^{-\nu(1-\gamma)}\right) + \frac{1}{2}\log\left((1-u)e^{\nu(1-\gamma)} + ue^{-\nu(1-\gamma)}\right) \\ &- \log\left(\frac{1}{2}e^{\nu(1-\gamma)} + \frac{1}{2}e^{-\nu(1-\gamma)}\right)\Big],\end{aligned} \tag{12}$$

after canceling out terms of C_0, $W - C_0$, β and $\bar{A}$.

We first consider the expected return as a function of u. Two cases with $u = 0$ and $u = 1/2$ are worth mentioning. If $u = 0$, the signal is perfect and all the uncertainty about the time-1 productivity is resolved with

$$\begin{aligned}\Lambda(0, \nu) &= \frac{1-\rho}{1-\gamma}\left[\left(\frac{1}{2}\log\left(e^{-\nu(1-\gamma)}\right) + \frac{1}{2}\log\left(e^{\nu(1-\gamma)}\right)\right) - \log\left(\frac{1}{2}e^{\nu(1-\gamma)} + \frac{1}{2}e^{-\nu(1-\gamma)}\right)\right] \\ &= -\frac{1-\rho}{1-\gamma}\log\left(\frac{1}{2}e^{\nu(1-\gamma)} + \frac{1}{2}e^{-\nu(1-\gamma)}\right) > 0,\end{aligned}$$

as $\rho < 1 < \gamma$. On the other hand, if $u = 1/2$, then the signal is useless and $P_{0+} = P_{0-}$, so $\Lambda(1/2, \nu) = 0$. This means $\Lambda(0, \nu) > \Lambda(1/2, \nu)$ for all $\nu > 0$. More generally, we have the following proposition. Proofs of all propositions are included in Online Appendix.

Proposition 1. *If $\rho < 1 < \gamma$, then $\partial\Lambda(u, \nu)/\partial u \le 0$ with equality if and only if $u = 1/2$ (or in the limiting case $\nu = 0$).*

Proposition 1 shows that the expected log return is monotonically decreasing in all u for $0 \le u \le 1/2$. This is a new point raised and verified in this paper. We have the following proposition regarding the effect of ν.

[4] This is intuitive. A signal of a high productivity makes the price higher and vice versa. However, a sufficient condition of $\rho < 1$, which means the elasticity of intertemporal substitution greater than one, is assumed. It can be shown that the condition is also necessary. On the other hand, the condition $\rho < \gamma$ is not required for these inequalities to hold.

Proposition 2. *If $\rho < 1 < \gamma$, then $\partial\Lambda(u, v)/\partial v \geq 0$ with equality if and only if $u = 1/2$ (or in the limiting case $v = 0$).*

The expected announcement return equals $E_{0-}[\log P_{0+}/P_{0-}] = \frac{1}{2}\log P^L_{0+} + \frac{1}{2}\log P^H_{0+} - \log P_{0-}$. As v increases, P_{0-} decreases and so is $\log P_{0-}$ as we mentioned before and proved in Online Appendix. As v increases, P^L_{0+} decreases too, more than P_{0-}. However, P^H_{0+} may decrease, but less than P_{0-}, or may even increase, if u is small. This is because when v is greater and the signal is more precise, $\bar{A}e^v$ is greater and investors are more certain about the high state. With large risk aversion γ, a greater discount of uncertainty is reflected in a lower P_{0-}. When the uncertainty gets partially resolved, the post-announcement price gets lifted on average. The proof in Online Appendix shows that the condition $\rho < 1$ is both sufficient and necessary, while the condition $\gamma > 1$ is sufficient, but not necessary. Moreover, we have the following proposition.

Proposition 3. *If $\rho < 1 < \gamma$, then $\partial^2\Lambda(u, v)/\partial u\partial v \leq 0$, with equality if and only if $u = 1/2$.*

The proposition implies that the effect of information environment on the expected announcement return is strong when risk is high, while the effect of risk on the expected announcement return is strong when information environment is good.

2.4. The resolution of uncertainty

At time-0^-, the variability or risk of the logarithm return $\log[P_1/P_{0-}]$ can be measured by its variance conditioned on the time-0^- information. After receiving the signal, the remaining variability can be measured by the variance of the same returns, but conditioned on time-0^+ information. The changes in the corresponding variances from time-0^- to time-0^+ should be negative, reflecting the partial resolution of uncertainty or reduction of risk. The resolution of uncertainty plays an important role in the analysis of expected announcement returns, as in Ai and Bansal (2018). In fact, the partial resolution of uncertainty or risk reduction is the main source of the positive expected announcement returns, in conjunction with the separation of risk premium and the reciprocal of elasticity of intertemporal substitution.

In the setting of the model, the changes in the conditional variance of the return are functions of v and u. How the variance changes depend on v and u is also a subject we investigate in this paper. Denote

$$\Delta(u, v) = -[\mathrm{Var}_{0^+}\log(P_1/P_{0-}) - \mathrm{Var}_{0^-}\log(P_1/P_{0-})] = [1 - 4u(1-u)]v^2. \tag{13}$$

Note that this is the negative change in the conditional variance of the same log return $\log(P_1/P_{0-})$ from time-0^- to time-0^+. We show in Online Appendix that $\Delta(u, v) \geq 0$ for all $v > 0$ and all $0 \leq u \leq 1/2$ with equality if and only if $u = 1/2$.

In the model, the variance of the return after announcement is always smaller than the one before announcement, unless the signal in the announcement contains no information. $\Delta(u, v)$ represents the magnitude of the reduction in the variance from before to after the announcement. The next three propositions pertain to the relation of $\Delta(u, v)$ with u and v.

Proposition 4. *$\partial\Delta(u, v)/\partial u \leq 0$ for all $v > 0$ and all $0 \leq u \leq 1/2$ with equality if and only if $u = 1/2$.*

Proposition 5. *$\partial\Delta(u, v)/\partial v \geq 0$ for all $v > 0$ and all $0 \leq u \leq 1/2$ with equality if and only if $u = 1/2$.*

Proposition 6. *$\partial^2\Delta(u, v)/\partial u\partial v \leq 0$ for all $v > 0$ and all $0 \leq u \leq 1/2$ with equality if and only if $u = 1/2$.*

Like the expected announcement return, the reduction in the variance of the return is also positively related to v and negatively related to u. In addition, the effect of information environment on the reduction is strong when risk is high, while the effect of risk on the reduction is strong when the information environment is good.

2.5. Discussion

The model presented above is highly simplified for the benefit of a clear illustration of the main ideas. The two main objects, poorness of information environment and risk, are treated as parameters. The model is directly applicable to a cross-country empirical studies if announcement data are available. However, to empirically verify the model implications for time-series data within a country, variations in risk and information environment measures are needed, so they should be thought as random variables, rather than fixed parameters. In addition, information environment is not directly observable. Proxies must be identified. Furthermore, the post-announcement variance of the announcement return in the model is non-stochastic, so the reduction in the variance is always positive. Empirically, however, the measure of the conditional variance is stochastic and may be affected by the directional effect of the news announcement, so the realized risk reduction is not guaranteed to be positive all the time, although the expected risk reduction associated with macroeconomic news announcements should be positive. For these reasons, the model should be viewed as one to convey the basic ideas and to provide interpretation of the empirical results.

3. Data and variable construction

This section provides data description on the risk and information environment measures and other related variables used in the main empirical tests. In addition, the construction and validity of the information environment measure are also discussed.

3.1. Data description

Following Savor and Wilson (2013, 2014), we choose Producer Price Index (PPI), employment report, and the Federal Open Market Committee's (FOMC) federal fund target rate announcements as the macroeconomic announcements to be studied in this paper. These news announcements are widely followed and regarded as the most important macroeconomic information sources (e.g., Bomfim (2003); Boyd et al. (2005); Gurkaynak et al. (2005); Lucca and Moench (2015)). We obtain PPI and employment report announcement dates from the Bureau of Labor Statistics website and the FOMC scheduled meeting dates from the Federal Reserve website.

Daily stock market returns are from the Center for Research in Security Prices (CRSP). We choose value-weighted NYSE/AMEX/NASDAQ index, including dividend distributions, for our main tests. Daily risk-free rates are from Kenneth French website. We denote the log (gross) return on the stock index in excess of the continuously compounded riskfree rate as R_t.

In addition, we calculate realized market factor premium on four sets of portfolios using an extended two-pass regression methodology originally developed by Fama and MacBeth (1973). The four sets of portfolios include 10 beta-sorted portfolios, 10 industry portfolios, 25 Fama-French size- and book-to-market-sorted portfolios, and the 45 combined portfolios. The 10 beta-sorted portfolios are formed by sorting common stocks in the universe of CRSP on their market betas, which are estimated at the end of every month over the past 12 months' daily returns (adjusted for delisting) and re-balanced every month. The portfolio returns are value-weighted average of individual stock returns. The ten industry portfolios and the 25 size- and book-to-market-sorted portfolios are constructed by Kenneth French. The combined portfolios consist of all the 45 portfolios mentioned above. On each trading day, we regress portfolios' daily returns on their corresponding pre-estimated market betas cross-sectionally to obtain the slope coefficient as the realized market factor premiums of the day. We denote them as λ_t^{beta} for the 10 beta-sorted portfolios, λ_t^{ind} for the 10 industry portfolios, λ_t^{ff} for the 25 Fama-French size- and book-to-market-sorted portfolios, and λ_t^{all} for the combined 45 portfolios. These realized market factor premium time-series will be used in a later section to establish the relationship of market factor premium with information environment and market return risk.

The option price implied market volatility, VIX, from the Chicago Board Options Exchange (CBOE) has been widely used in the literature for stock market risk. It is the market expectation of volatility over the next month, implied by prices of S&P 500 index options. Since it is derived from options prices, VIX is an *ex ante* measure of the future market volatility. Therefore, it is a natural choice for measuring the return risk in the model. The VIX time series, however, is available only from 1990. We use a linear function of the standard deviation of the one-minute returns on the S&P 500 index in the past 30 calendar days, denoted as $\widehat{\text{VIX}}_t$, to surrogate VIX over the period from Jan 2, 1985 to December 31, 1989. The parameters of the linear function are determined such that the same linear function can best fit VIX for the sample from January 2, 1990 to December 31, 2019. Thus, $V_t = \widehat{\text{VIX}}_t$ for 1985-1989 and $V_t = \text{VIX}_t$ for 1990-2019. We define the daily reduction of the risk as $D_t = -(V_t - V_{t-1})$. This construction corresponds well to that used in the simple model.[5]

We construct the measure of information environment from two sources. One is the Survey of Professional Forecasts (SPF), which is the oldest quarterly survey of macroeconomic forecasts, conducted by the American Statistical Association and the National Bureau of Economic Research from 1968 to 1990 and by the Federal Reserve Bank of Philadelphia from 1990 till now. There have been about 30 plus economists on average participating the survey in each quarter. We choose five variables which are most relevant to the macroeconomic announcements studied in this paper. They are the one-quarter-ahead forecasts for the unemployment rate (UR), GDP price index (Price), T-bill rate (TBill), the real GDP growth rate (GDP), and the estimated probability of a decline in real GDP in the next quarter, also known as anxiety index (AI). For each variable in each quarter, we calculate the mean and standard deviation of the forecasts made by different forecasters. We then regress the time-series of the standard deviations on the time-series of the means and use the time-series of the residuals as one component of the information environment measure.[6] The SPF survey results are usually released in late of the second month of each quarter with exact release dates unknown before 1990. To be on the conservative side, we convert quarterly dispersions to daily observations and set them to change their values at the end of these months and to remain constant for the next three months. Each of the time series is then standardized to have zero mean and unit standard deviation and is denoted as $\tilde{U}_t^{\text{UR}}$, $\tilde{U}_t^{\text{Price}}$, $\tilde{U}_t^{\text{TBill}}$, $\tilde{U}_t^{\text{GDP}}$ and $\tilde{U}_t^{\text{AI}}$ respectively.[7]

The other source of the information environment measure is the U.S. Economic Policy Uncertainty (EPU) index by Baker et al. (2016), computed mostly from newspaper archives of Access World News' NewsBank service, which covers ten major newspapers in the US. The index value rises when words like "economic uncertainty" show up more often in the social

[5] In the two-period model, Δ is defined as the reduction of conditional variance of the return. The conditional standard deviation of the return prior to the announcement equals the pre-announcement risk. There is a small difference here. In the model, Δ is the change in variance, but here we use D_t as change in VIX which is a standard deviation. This is of no consequence as Propositions 4 to 6 can be converted to those about standard deviation.

[6] The standard deviation itself represents dispersion among forecasters. But since the cross-sectional mean and standard deviation are correlated in time series and the mean contains directional information, its effect should be removed from the standard deviation. Another approach is to use standard deviation divided by the mean. Since the mean can be very close to zero at times, the regression residual is preferred.

[7] GDP and AI are weakly, negatively correlated. $\tilde{U}_t^{\text{GDP}}$ and $\tilde{U}_t^{\text{AI}}$ are modestly, positively correlated. These patterns show that the two variables related to real GDP growth contain non-overlapping information and neither of them is subsumed by the other.

media. It reflects perceived uncertainty by the public in the current information environment.[8] One of the advantages of including EPU index in the information environment measure is that the major component of EPU has daily frequency, while SPF dispersion is quarterly based. We use the 14-day moving average of the daily index over the window of day $t-13$ to t to calculate $\tilde{U}_t^{\mathrm{EPU}}$ as the information environment measure. The moving average removes potential noises and guarantees that the measure captures the information environment during a longer time period proceeding the day, rather than a surprise on the particular day. The sample period spans from January 1985 to December 2019.

3.2. The construction of the information environment measure

The combinational information environment measure $\tilde{U}_t^{\mathrm{Comb}}$ combines $\tilde{U}_t^{\mathrm{UR}}$, $\tilde{U}_t^{\mathrm{Price}}$, $\tilde{U}_t^{\mathrm{TBill}}$, $\tilde{U}_t^{\mathrm{GDP}}$, $\tilde{U}_t^{\mathrm{AI}}$, and $\tilde{U}_t^{\mathrm{EPU}}$ based on the discount mean square prediction error combining method of Stock and Watson (2004) and Rapach et al. (2010), where the combining weights formed on day t are functions of the past 12-month (up to day $t-1$) historical forecasting performance of the four information environment variables for the daily stock market excess return on announcement days. Details of the combination method are in Online Appendix. The method thus assigns greater weights to individual predictive regression model forecasts that have lower forecast errors over the past one year.

The fact that $\tilde{U}_t^{\mathrm{Comb}}$ is positively correlated with V_t makes the examination of their interactive effects difficult. To obtain clean interpretations of the results, we use the standardized residuals from regressing $\tilde{U}_t^{\mathrm{Comb}}$ on V_t to form the information environment measure, U_t, which is used for the empirical tests below. This will not affect the sign of the slope coefficients and the magnitude of their t-ratios of the information environment measure in the full model with the risk measure in the regression.[9]

The descriptive statistics of key variables for the main empirical tests are presented in Table B2 of Online Appendix. Fig. 1 presents time series plots of the information environment and the risk measures. The shaded areas are recessions. There are several episodes with noisy or poor information environment and low risk or vice versa, although all the time series are counter-cyclical, consistent with findings of previous studies (e.g., Baker et al. (2016) and Kozeniauskas et al. (2018)). We also note that, while the information environment is relatively poor and the risk tend to be high during recessions, there are periods of poor information environment and high risk that are not during recessions.

3.3. The validity of the information environment measure

Dispersion among forecasters can also be interpreted as disagreement among forecasters. There are two sources of potential disagreement. One is the differences in prior beliefs whose role diminishes as more information arrives. The second is the heterogeneity of information each forecaster receives, which is high when information environment is poor. In typical models of heterogeneous information, each agent receives a signal of the form $s_i = x + \varepsilon_i$ where x is the value of interest and ε_i is a noise with zero mean, standard deviation σ, and independent across agents. Obviously, σ characterizes the poorness of the information environment in this context. When the number of agents is large enough, the consensus forecast of x is close to x and the dispersion is close to σ. Therefore, disagreement is ultimately connected to poorness of information environment. Mean-adjusted dispersion has been used to measure various kinds of poorness of information environment in the literature (e.g., Kumar et al. (2008); Zhang (2006), and Falck et al. (2021)).

The textual analysis-based EPU index measures uncertainty about economic policy. It spikes around the black Monday in 1987, Gulf War in 1991, the Russian crisis/LTCM episode in 1998, the 2008 financial crisis, the 2011 debt ceiling dispute, and various presidential elections. Baker et al. (2016) find that the high value of EPU index can be associate with reduced investment and employment in policy-sensitive sectors like defense, health care, finance, and infrastructure construction. The EPU index is also correlated with general market uncertainty, and is widely adopted in the economics, finance and accounting literatures. Nagara et al. (2019) document that the EPU index is associated with increased stock market bid-ask spreads and decreased stock price reactions to earnings surprises and that firm managers respond to the index by increasing their voluntary disclosures, but these disclosures only partly mitigate the bid-ask spread increase. Kaviani et al. (2020) document that corporate bonds' credit spreads increase with the EPU index, which means bond prices tend to decrease or increase less with the EPU index. The impact is more pronounced for firms that operate in regulation-intensive industries, face high tax rates, or are dependent on government spending.

We provide direct evidence below that the information environment measure U_t serves our purpose. The central idea is that macroeconomic statistics announced by the government and forecasts made by professionals all tend to be less accurate when the information environment is poor. We present three sets of evidence. The first is the forecast errors of the SPF forecasts on the unemployment rate, GDP price index, T-bill rate, and the real GDP growth rate, which we use

[8] A second component of the index draws on reports by the Congressional Budget Office (CBO) that compile lists of temporary federal tax code provisions, scheduled to expire over the next 10 years, giving a measure of the level of uncertainty regarding the path that the federal tax code will take in the future. A third component of the index draws on the dispersion of SPF for the Consumer Price Index, Federal Expenditures, and State and Local Expenditures to construct indices of uncertainty about policy-related macroeconomic variables.

[9] As a result of this choice, the slope coefficients and their t-ratios of the risk would appear smaller. The results based on $\tilde{U}_t^{\mathrm{Comb}}$ are reported in Table C1 in Online Appendix.

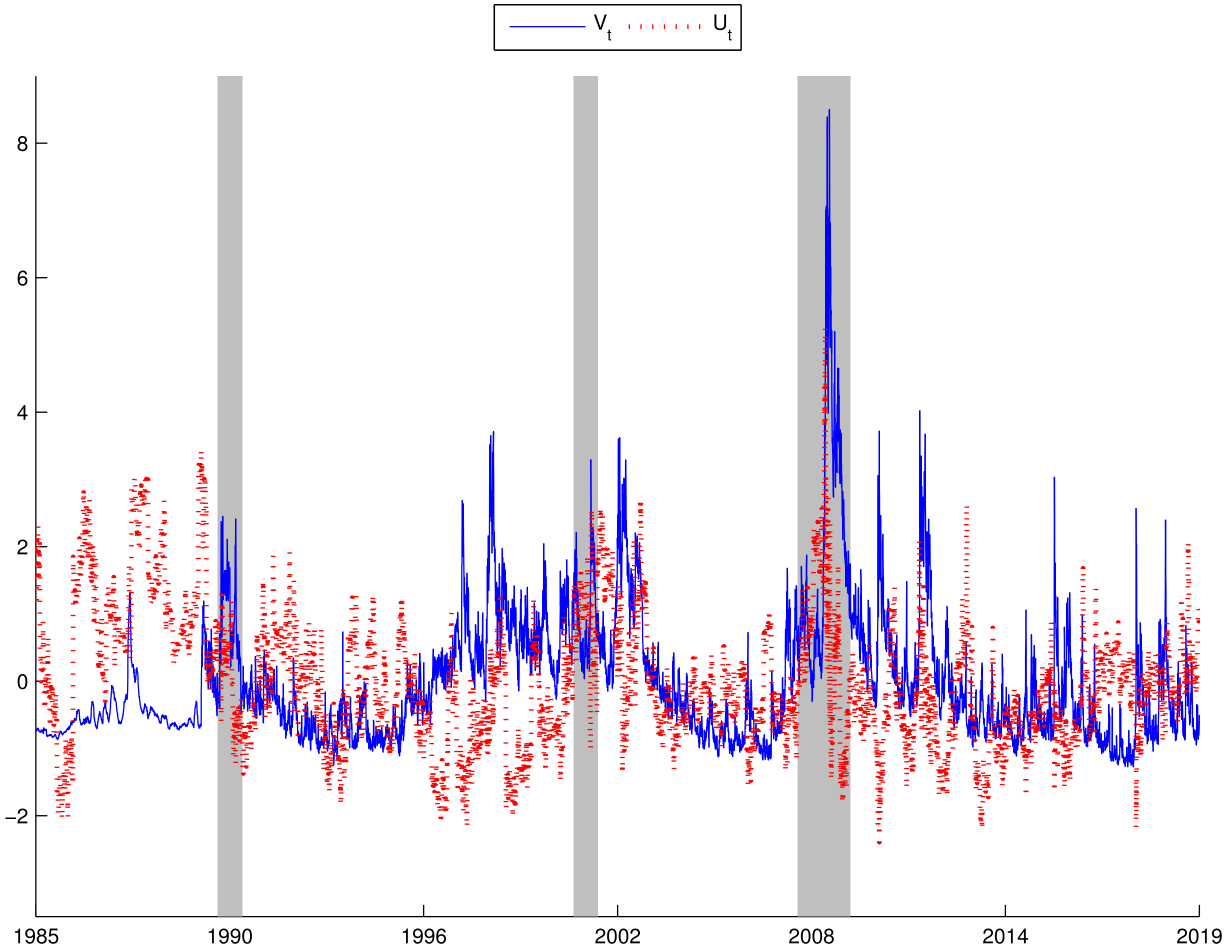

Fig. 1. The information environment and risk measures. The figure presents time series plots of the information environment measure U_t and the risk measure V_t over the sample period of 1985-2019. U_t is the information environment measure combining the forecast dispersions for the unemployment rate, GDP price index, T-bill rate, real GDP growth rate, and the anxiety indices from the Survey of Professional Forecasters (SPF) and the 14-day moving average of the daily news-based U.S. economic policy uncertainty index (EPU) from Baker et al. (2016) using the method in Stock and Watson (2004). V_t equals $\widehat{\text{VIX}}_t$ and VIX_t before and after January 1, 1990, respectively, where VIX_t is model-free implied volatility of S&P 500 index returns from CBOE and its sample spans from 1990 to 2019 and $\widehat{\text{VIX}}_t$ is the fitted VIX_t using high frequency returns during 1985-1989. For comparison, the variables are standardized with zero mean and unit variance. The shaded areas are recessions defined according to NBER business cycle dating committee.

for constructing U_t.[10] The second is the final revision of a set of 32 macroeconomic variables with respect to their initial vintages. The third is the security analysts' earnings forecast errors. The results are reported in Table 1.

Panel A of Table 1 presents the slope coefficients of U_t for forecast errors $y_{i,t+1}$ in quarterly panel regressions, where $y_{i,t+1}$ is the absolute value of the error of the median forecast with i being the unemployment rate, the year-on-year growth rate of GDP price index, or the T-bill rate and t being the quarter the forecasts is made by professional forecasters of SPF. A quarterly balanced panel from 1985.1 to 2019.4 of the three forecast errors is used in the study. The distribution of $y_{i,t+1}$ is right-skewed with a sample skewness of 1.60, with large outliers, so the transformed forecast errors $\log(1+y_{i,t+1})$ and $\log(1+10y_{i,t+1})$, which have skewness of 1.02 and 0.24 respectively, are also considered. The results show that the slope coefficients are significantly positive, especially for transformed forecast errors, indicating that the more foresters disagree, which cause U_t to be larger, the greater the error is for their consensus.

Panel B of Table 1 presents the slope coefficients of U_t for macroeconomic variable revisions $y_{i,t+k_i}$ in monthly panel regressions where i is a macroeconomic variable, t is the vintage announcement month-end of the latest value of the variable, and k_i is the number of months it takes for the variable to be finalized later. The revision $y_{i,t+k_i}$ is the absolute value of either the difference between the initial vintage value and its final revised value for a growth rate/ratio or the proportional difference for a level variable. The data for macroeconomic variables are taken from the St. Louis Fed website. After deleting variables that are never revised (such as interest rates, exchange rates, and stock market variables) and those are variations

[10] There is no realized value of the probability of a decline in real GDP, so the forecast error is not available for AI.

Table 1
The information environment measure. This table reports the slope coefficients of U_t in panel regressions of various dependent variables $y_{i,t+k}$ and its logarithmic transformations. The information environment measure, U_t, combines the latest available forecast dispersions of the unemployment rate, GDP price index, T-bill rate, real GDP growth rate, and the anxiety indices from the Survey of Professional Forecasters (SPF) as of day t and the moving average of the daily news-based U.S. economic policy uncertainty index (EPU) from Baker et al. (2016) over day $t-13$ to day t using the method in Stock and Watson (2004). In Panel A, $y_{i,t+k}$ is the error of the consensus forecast made by SPF forecasters for one-quarter ahead GDP price index, unemployment rate, t-bill rate, and real GDP, t is a quarter, $k=1$, and the panel is balanced quarterly data. In Panel B, $y_{i,t+k}$ is the revision of 32 macroeconomic variables with respect to their initial vintage of the announcements, where i is a variable, t is the month the announcement is made and $k=18$. The panel is unbalanced as the available initial vintage data varies with variables. In Panel C, $y_{i,t+k}$ is the error of the consensus forecasts of firm earnings per share (EPS), where i is one of the firms listed in NYSE, AMEX or NASDAQ covered by CRSP, COMPUSTAT and IBES, t is a month and $k=k_{i,t}$ is the number of months to the coming fiscal-year-end. In Panels A and B, $y_{i,t+k}$ is the absolute value of either the change if the variable is a growth rate or a ratio, or the relative change if the variable is a level variable. In Panel C, $y_{i,t+k}$ is the absolute value of the relative change. Detailed definitions of the variables are in Section 3. The sample period is 1985-2019.

A. SPF forecast errors									
	$y_{i,t+k}$			$\log(1+y_{i,t+k})$			$\log(1+10y_{i,t+k})$		
Coef. of U_t	0.036	0.035	0.035	0.028	0.027	0.027	0.100	0.098	0.098
t-stat	(1.73)	(2.00)	(1.51)	(2.20)	(2.60)	(1.97)	(2.72)	(3.22)	(2.58)
Seasonality Adj.	N	Y	Y	N	Y	Y	N	Y	Y
Variable FE	N	Y	Y	N	Y	Y	N	Y	Y
Cluster by quarter	N	N	Y	N	N	Y	N	N	Y
B. Macroeconomic variable revisions									
	$y_{i,t+k}$			$\log(1+y_{i,t+k})$			$\log(1+100y_{i,t+k})$		
Coef. of U_t	0.025	0.020	0.020	0.013	0.013	0.013	0.052	0.057	0.057
t-stat	(3.08)	(3.16)	(1.99)	(3.43)	(4.3)	(2.72)	(2.77)	(3.86)	(2.75)
Seasonality Adj.	N	Y	Y	N	Y	Y	N	Y	Y
Variable FE	N	Y	Y	N	Y	Y	N	Y	Y
Cluster by quarter	N	N	Y	N	N	Y	N	N	Y
C. Security analysts' forecast errors									
	$y_{i,t+k}$			$\log(1+y_{i,t+k})$			$\log(1+100y_{i,t+k})$		
Coef. of U_t	0.098	0.098	0.098	0.014	0.014	0.014	0.052	0.052	0.052
t-stat	(11.25)	(5.67)	(5.58)	(25.38)	(10.06)	(5.13)	(27.59)	(11.59)	(3.97)
Cluster by firm	N	Y	N	N	Y	N	N	Y	N
Cluster by month	N	N	Y	N	N	Y	N	N	Y
Coef. of U_t	0.098	0.048	0.062	0.014	0.004	0.006	0.052	0.005	0.017
t-stat	(9.73)	(5.21)	(4.11)	(23.35)	(6.95)	(3.54)	(26.81)	(2.77)	(2.73)
Control	N	Y	Y	N	Y	Y	N	Y	Y
Seasonality Adj.	N	Y	Y	N	Y	Y	N	Y	Y
Firm FE	N	N	Y	N	N	Y	N	N	Y
Cluster by firm	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster by month	Y	Y	Y	Y	Y	Y	Y	Y	Y

or subcategories of major variables, an unbalanced panel of 32 variables are selected for the study. The detail of the selection is relegated to Online Appendix. The distribution of $y_{i,t+k_i}$ is much right-skewed with a sample skewness of 4.32. The transformed revisions $\log(1+y_{i,t+k_i})$ and $\log(1+100y_{i,t+k_i})$ have skewness of 2.00 and -0.14 respectively. The revisions also exhibit strong seasonality, so monthly dummies are included in certain specifications. The results show that the slope coefficients of U_t are significantly positive.

Panel C of Table 1 presents the slope coefficients of U_t for security analysts' earnings forecast errors. We obtain the analysts' earnings forecast data from the Institutional Brokers' Estimate System (IBES) summary file. For each firm covered by the database, analysts make forecast of fiscal-year-end earnings per share (EPS) of the target firm roughly one year before the fiscal year-end and then keep revising the forecast if needed until the year-end. The summary statistics of the forecasts are then recorded in IBES on the monthly basis. We construct an unbalanced panels of forecast error $y_{i,t+k_{i,t}}$ where i is a firm and t is a month, and $k_{i,t}$ is the number of months from t to the fiscal-year-end for firm i. Since EPS is not comparable across firms, the absolute value of the proportional error is adopted for $y_{i,t+k_{i,t}}$. The distribution of $y_{i,t+k_{i,t}}$ is right-skewed with a sample skewness of 97.70, with large outliers, so the transformed forecast errors $\log(1+y_{i,t+k_{i,t}})$ and $\log(1+100y_{i,t+k_{i,t}})$, which have skewness of 4.19 and 0.72 respectively, are also considered. Moreover, earnings forecasts have been well studied in the literature with certain known predictors of the forecast errors (e.g., Zhang (2006)). We run regressions with and without these firm-specific predictors as control.[11] The forecast errors also exhibit seasonality, so monthly dummies are

[11] The sample firms are the ones whose common stocks were listed in NYSE, AMEX or NASDAQ covered by CRSP, COMPUSTAT and IBES from the period of 1985 to 2019, which leads to 663,818 firm-month observations. The details of control variables are discussed in Online Appendix.

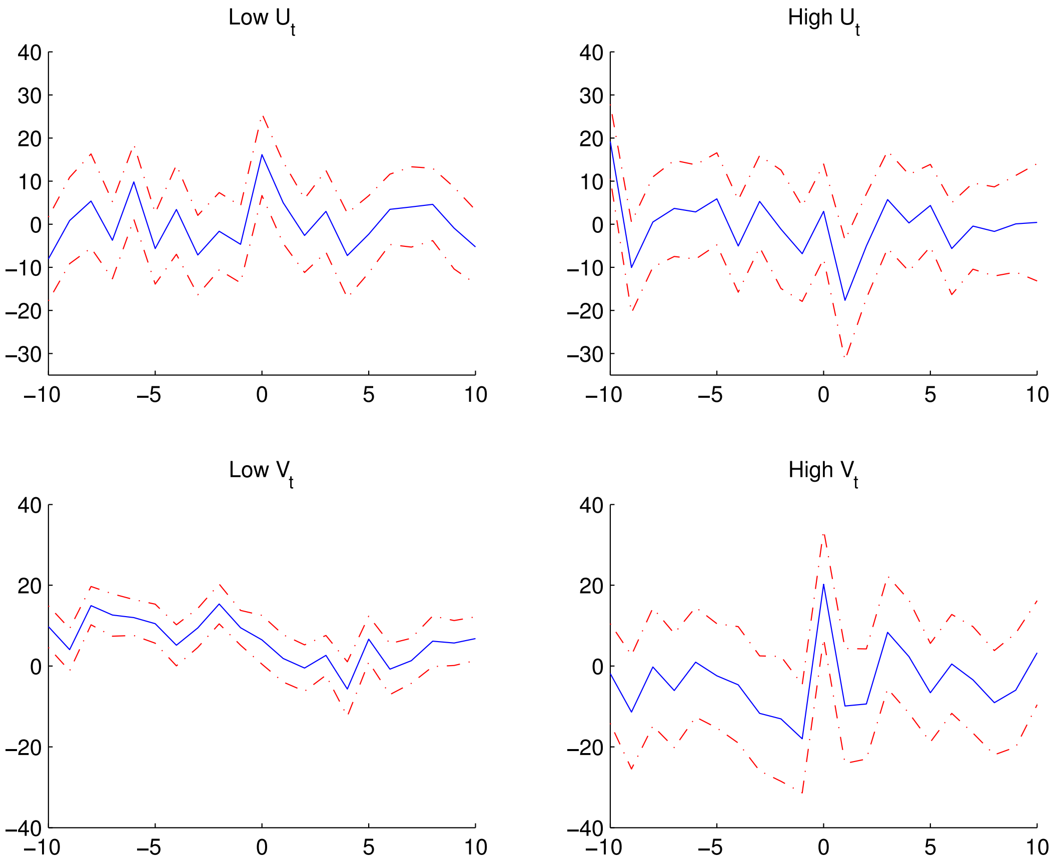

Fig. 2. The average daily excess returns of the stock market around the announcement day. The figure presents the time series average and its corresponding 90% confidence interval of the daily excess returns of the market value weighted portfolio of NYSE/AMEX/NASDAQ, R_t (in basis point), around the macroeconomic announcement days from day -10 to day +10 where day 0 is the announcement day during the low and high information environment and risk periods over the sample period of 1985-2019. The low and high information environment/risk periods are determined by the two tertiles of U_t and V_t respectively.

included in certain specifications. The results in the table show that the slope coefficients of U_t are positive and statistically significant across different regression specifications.

Overall, the evidence presented in Table 1 shows that the macroeconomic statistics collected and aggregated by government agencies tend to be less accurate and forecasts of both macroeconomic variables and firm level earnings made by professionals also tend to be less accurate when the information environment proxied by U_t is poor. While we do not claim that U_t is optimally constructed, the evidence supports the validity of the constructed U_t as a measure of the poorness of information environment.

4. Main empirical analysis

In this section, we empirically test how information environment affects the announcement premium and risk reduction based on the propositions developed in the model.

4.1. Announcement premium and risk reduction

To visualize the impact of the information environment on the announcement premium, we partition the whole sample period into high (poor), medium and low (good) information environment, equally numbered subsamples by the value of the information environment measure U_t, then plot the average daily excess returns on the value weighted stock market portfolio from ten days before announcements to ten days after announcements during low and high information environment subsamples in the top panels of Fig. 2.

As one can see, during the good information environment (low U_t) subsamples, the average daily excess returns of the stock market on announcement days are significantly higher than those on other days within the 21-day window around the announcement day, while during the poor information environment (high U_t) subsamples, there is no significant difference in the average daily market excess returns between the announcement day and the other days within the window.

Table 2
The market premium: regression analysis. This table presents the regression results of
$R_{t+1} = a_1 + a_2 U_t + a_3 V_t + a_4 V_t U_t + \varepsilon_{t+1}$,
$D_{t+1} = b_1 + b_2 U_t + b_3 V_t + b_4 V_t U_t + \varepsilon_{t+1}$,
where R_{t+1} (in basis point) is the stock market excess return calculated as the value weighted portfolio of NYSE/AMEX/NASDAQ minus the risk-free rate; $D_{t+1} = -(V_{t+1} - V_t)$ (in basis point) is the daily risk reduction, on announcement day $t+1$, U_t is the information environment measure and V_t is the risk measure. U_t and V_t are standardized to have zero mean and unit standard deviation. The regressions are run for announcement days where announcements are about unemployment, PPI, and FOMC Federal Fund target rate. All t-statistics are computed using Newey-West standard errors with one-day lag. The sample spans from 1985 to 2019.

	R_{t+1}					D_{t+1}				
Intercept	11.75	11.23	11.28	11.26	11.29	22.78	21.88	21.96	21.93	21.97
t-stat	(3.34)	(3.35)	(3.38)	(3.39)	(3.41)	(4.96)	(5.28)	(5.32)	(5.35)	(5.37)
U_t	-11.75		-11.87		-7.55	-15.39		-15.60		-9.50
t-stat	(-2.66)		(-2.58)		(-2.04)	(-2.42)		(-2.57)		(-2.54)
V_t		11.14	11.26	14.42	14.18		19.68	19.84	24.27	23.96
t-stat		(1.70)	(1.76)	(2.69)	(2.64)		(1.91)	(1.97)	(2.96)	(2.92)
$V_t U_t$				-14.95	-13.49				-20.89	-19.05
t-stat				(-2.14)	(-1.94)				(-1.90)	(-1.76)
Adj R^2	0.93%	0.87%	1.83%	3.53%	3.84%	1.01%	1.78%	2.82%	5.05%	5.36%
Obs	1109	1109	1109	1109	1109	1109	1109	1109	1109	1109

Similarly, the bottom panels plot the average market excess return for subsamples of high and low risk, where the high and the low are the top and bottom one-thirds of days ranked by the value of V_t. The figure shows that the average market excess return is low on low risk days and high on high risk days, consistent with Propositions 1 and 2 in the model.

To directly test the model implication on the joint effects of the information environment and the risk on the macroeconomic announcement premium, we run the following regressions:

$$R_{t+1} = a_1 + a_2 U_t + a_3 V_t + a_4 V_t U_t + \varepsilon_{t+1}, \tag{14}$$

where R_{t+1} is the daily stock market excess return (in basis point) on the announcement day $t+1$, and ε_{t+1} is a generic term for errors. Since U_t and V_t are all standardized, the coefficients can be interpreted as the effects of a one standard deviation increase in them. The regressions results of (14) are presented in Table 2.[12] Consistent with Savor and Wilson (2013, 2014), it shows that the average market excess return during the announcement days is significantly positive. Moreover, the coefficient of U_t is significantly negative, while the coefficient of V_t is significantly positive, well supporting Propositions 1 and 2 in the model. In addition, the significantly negative coefficient of the cross term $U_t V_t$, consistent with Proposition 3, indicates that the risk-return relationship on the announcement day can be hindered by low information quality. It at least partially explains why it is hard to empirically verify risk-return trade off in the financial market.

As argued by Ai and Bansal (2018) and also shown in the model of this paper, the announcement premium is associated with risk reduction. Let $D_{t+1} = -(V_{t+1} - V_t)$ be the daily risk reduction, we further test the theoretical implication. First, to visualize the daily risk reduction on the announcement day during poor and good information environment periods, we plot the average daily risk reduction from ten days before the announcements to ten days after the announcement days separately for good and poor information environment as well as low and high risk periods in Fig. 3. As one can see, during the periods of good information environment and high risk, the average daily reductions on the announcement days are significantly larger than the other days within the 21-day window around the announcement day, while during the periods of poor information environment and low risk, there is no significant difference in the average daily risk reduction between the announcement days and the other days within the 21-day window, consistent with Propositions 4 and 5 in the model.

We conduct the regression analysis on the daily risk reduction as

$$D_{t+1} = b_1 + b_2 U_t + b_3 V_t + b_4 V_t U_t + \varepsilon_t. \tag{15}$$

Table 2 also reports the results of (15). As shown in the table, the average daily risk reduction is significantly positive on the announcement days; U_t negatively affects the risk reduction on the announcement days while V_t positively predicts it. The results are consistent with Propositions 4 and 5 in the model that the poor information environment lowers the magnitude of risk reduction by the announcement while the risk increases the magnitude of the reduction. Moreover, the coefficient of the cross term $V_t U_t$ is also significantly negative, supporting Proposition 6.

4.2. Interaction

To better interpret the cross-product term in (14) and (15), we take an alternative approach to analyzing the impact of U_t and V_t on the announcement premium and risk reduction. Specifically, we examine the positive impact of the risk on the

[12] To focus on studying announcement premium, we only report the main empirical results on announcement days in the paper while the related results on none-announcement days are presented in Table C2-C6 of Online Appendix.

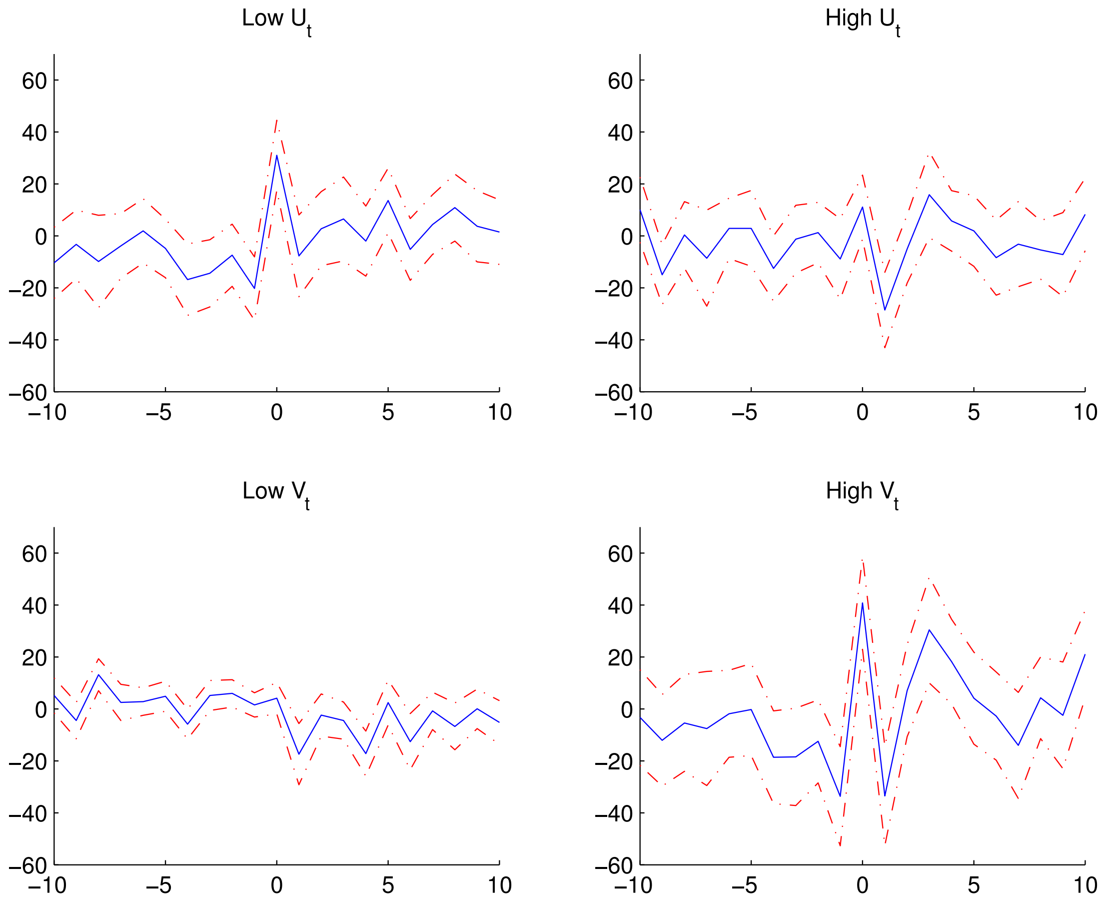

Fig. 3. The average daily risk reduction around the announcement day. The figure presents the time series average and its corresponding 90% confidence interval of the daily risk reductions, $D_{t+1} = -(V_{t+1} - V_t)$ (in basis point), around the macroeconomic announcement days from day -10 to day +10 where day 0 is the announcement day during the low and high information environment and risk periods over the sample period of 1985-2019. The low and high information environment/risk periods are determined by the two tertiles of U_t and V_t respectively.

announcement premium and risk reduction conditioned on different information environment and the negative impact of poorness of the information environment on the announcement premium and risk reduction conditioned on different levels of the risk. As implied by the result of the mixed second order derivative in Proposition 3 of the model, we expect to see a stronger risk-return relationship when the information environment is good and a stronger information environment effect when the risk is high.

We regress R_{t+1}, the daily stock market excess return on the announcement day $t+1$, on V_t for the low and high U_t subsamples, as well as on U_t for low and high V_t subsamples respectively. The low and high information environment (risk) periods are determined by the two tertiles of the information environment measures, U_t (the risk measure, V_t).[13] Table 3 presents the regressions results. As one can see that the positive effect of the risk on the announcement premium is more significant in the good information environment subsample than in the poor information environment subsample, while the impact of the information environment on the announcement premium is more significant in the high risk subsample than in the low risk subsamples. The empirical results well support Proposition 3 of the model.

We conduct the same exercise to test the impacts of the information environment and the risk on D_{t+1}, the risk reduction on the announcement day, under the high and low U_t, V_t conditions. The results are reported in Table 3 as well. Consistent with Proposition 6, the positive impact of the risk on D_{t+1} is stronger during the good information environment subsample than the poor one, while the impact of the information environment on D_{t+1} is stronger during the high risk subsample than the low one.

We also perform similar tests for market and portfolio excess returns and risk reductions on non-announcement days. The magnitude and significance of the slope coefficients of U_t are smaller than those for announcement days. The contrast indicates that it is the information potentially contained in the announcements that makes U_t useful in predicting market excess returns and reduction in risk. For saving space, these results are relegated to Appendix C in Online Appendix.

[13] The sorting variable is not included in the regression because it does not have much variation within the subsample.

Table 3
The market premium with high/low information environment and risk: subsample regression analysis. This table presents the regression result of
$R_{t+1} = a_1 + a_2U_t + a_3V_t + \varepsilon_{t+1}$,
$D_{t+1} = b_1 + b_2U_t + b_3V_t + \varepsilon_{t+1}$,
where R_{t+1} (in basis point) is the stock market excess return calculated as the value weighted portfolio of NYSE/AMEX/NASDAQ minus the risk-free rate; $D_{t+1} = -(V_{t+1} - V_t)$ (in basis point) is the daily risk reduction, on announcement day $t+1$. U_t is the information environment measure and V_t is the risk measure, standardized to have zero mean and unit variance. The low and high subsamples are determined by the two tertiles of U_t and V_t respectively. All t-statistics are computed using Newey-West standard errors with one-day lag. The sample spans from 1985 to 2019.

	R_{t+1}				D_{t+1}			
	Low U_t	High U_t	Low V_t	High V_t	Low U_t	High U_t	Low V_t	High V_t
Intercept	12.37	3.17	5.30	22.29	25.52	10.38	2.28	44.49
t-stat	(2.40)	(0.54)	(1.44)	(2.73)	(3.38)	(1.68)	(0.58)	(4.06)
U_t			0.82	-19.34			-0.15	-24.96
t-stat			(0.16)	(-2.38)			(-0.04)	(-2.01)
V_t	21.43	-2.39			28.81	3.09		
t-stat	(2.30)	(-0.21)			(2.47)	(0.15)		
Adj R^2	3.32%	-0.21%	-0.27%	1.62%	2.91%	-0.20%	-0.28%	1.48%
Obs	362	388	354	385	362	388	354	385

5. Extensions

In this section, we extend our analysis by studying the impacts of the information environment and the risk on the market factor premium on the macroeconomic announcement days; and study how the business cycle affects the announcement premium and risk reduction.

5.1. Market factor premium

Savor and Wilson (2014) show that, while the Capital Asset Pricing Model (CAPM) does not hold on average, it holds strongly on macroeconomic announcement days. The market factor premium estimated from market-beta sorted portfolios is significantly positive when estimated for macroeconomic announcement days. In this subsection, we examine how this result holds in relation to the information environment and risk discussed in this paper.

We construct four sets of portfolios described in the data section: 10 market-beta-sorted portfolios, 10 industry portfolios, 25 size- and book-to-market-sorted portfolios, and the 45 portfolios combined from the three sets. We run time-series regressions of daily portfolio returns on the daily market returns during the past year ending on day t to obtain the portfolio's conditional market beta at t. In Fig. 4, the portfolio returns averaged over the low U_t, low V_t, high U_t, and high V_t announcement days are plotted against the average conditional portfolio betas for the first three sets of portfolios. For the low U_t and high V_t subsamples, the portfolio returns are high and exhibit an increasing pattern over the portfolio betas. For the high U_t and low V_t subsamples, the portfolio returns are low and relatively flat with their betas.

We run cross-sectional regressions of the portfolio returns on their pre-estimated portfolio betas to obtain slope coefficients as their realized market factor premiums, λ^i_{t+1}, where $i =$ beta, ind, ff and all. Fama and MacBeth (1973) estimate market factor premium using the time-series average of λ^i_{t+1}. Savor and Wilson (2014) estimate market factor premiums conditional on announcement day and on non-announcement day using the time-series average of λ^i_{t+1} for the announcement-day subsample and the non-announcement-day subsample respectively and show their difference. We extend the methodology by running the following regressions,

$$\lambda^i_{t+1} = c_1 + c_2U_t + c_3V_t + c_4V_tU_t + \varepsilon_{t+1}. \tag{16}$$

Table 4 reports the regression results for announcement days $t+1$. All the test results in Table 4 confirm that the market factor premium is significantly positive on the announcement days. More importantly, both the information environment and the risk measures significantly predict the announcement-day market factor premium. In addition, it is indicated, by the significantly negative coefficient of the cross term V_tU_t across all the portfolios, that the positive impact of the risk on the announcement-day market factor premium can be substantially subdued in the poor information environment.

The interactive analysis similar to the one in Table 3 can also be applied to the realized market factor premium. The results are presented in Table 5. As one can see, across all the four sets of portfolios, during the high risk period, the impact of the information environment on the announcement-day market factor premium is more profound than the one during the low risk period, while the effect of the risk on the announcement-day market factor premium is more significant in the good information environment period than the poor one.

Another interesting observation is that the adjusted R^2 is the highest in the good information environment and high risk subsamples across all the portfolios tests. It is consistent with the implication of Proposition 3 that the announcement premium exhibits the largest variation when u is low and v is high. This set of regression analysis with the CAPM market

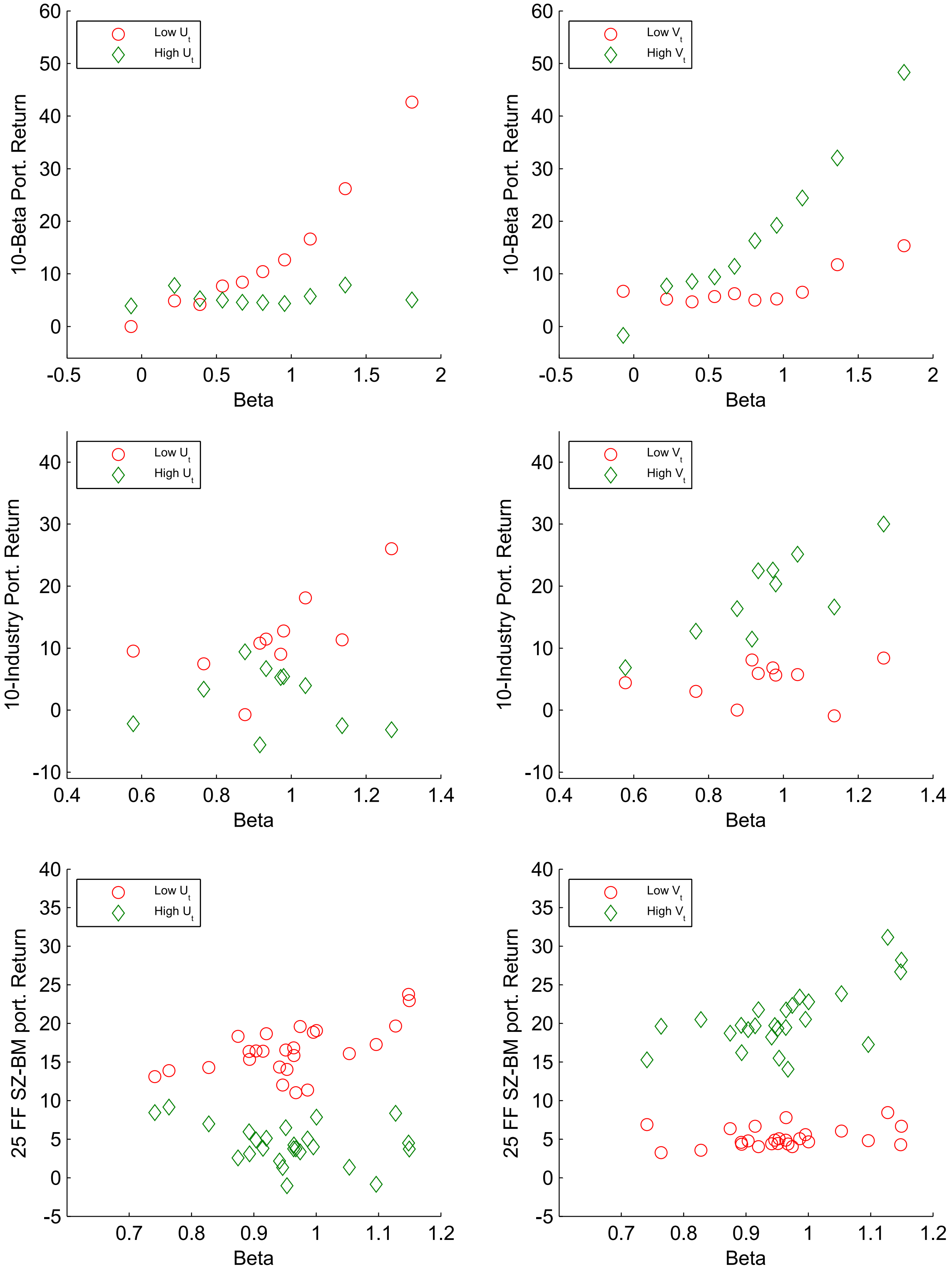

Fig. 4. Security Market Line during low and high information environment and risk periods. The figure presents the scatter plots of average excess returns (vertical axis) and corresponding market betas (horizontal axis) of three sets of portfolios: 10 beta portfolios in the top panel, 10 industry in the middle panel, and 25 Fama-French size and book-to-market portfolios in the bottom panel. In each sub-figure, portfolio excess returns are averaged over announcement days with low U_t, high U_t, low V_t and high V_t subperiods respectively, where low and high are determined by the two tertiles. The sample period spans from 1985 to 2019.

Table 4
The market factor premium: regression analysis on portfolios. This table presents the regression results of
$\lambda^i_{t+1} = c_1 + c_2 U_t + c_3 V_t + c_4 V_t U_t + \varepsilon_{t+1}$,
where λ^i_{t+1} (in basis point) is $\lambda^{\text{beta}}_{t+1}$, the CAPM market factor premium estimated using the Fama-MacBeth regression for the 10 beta portfolios; $\lambda^{\text{ind}}_{t+1}$, for the 10 industry portfolios; $\lambda^{\text{ff}}_{t+1}$, for the 25 Fama-French size and book-to-market portfolios; and $\lambda^{\text{all}}_{t+1}$, for the 45 combined portfolios, on announcement day $t+1$. U_t is the information environment measure and V_t is the risk measure, standardized to have zero mean and unit variance. The announcements are about unemployment, PPI, and FOMC Federal Fund target rate. All t-statistics are computed using Newey-West standard errors with one-day lag. The sample spans from 1985 to 2019.

	10-beta portfolios					10-ind portfolios				
Intercept	11.93	11.28	11.35	11.31	11.35	10.28	9.74	9.82	9.77	9.83
t-stat	(2.94)	(2.91)	(2.95)	(2.94)	(2.96)	(2.11)	(2.06)	(2.09)	(2.07)	(2.09)
U_t	-15.26		-15.41		-11.05	-16.33		-16.45		-12.89
t-stat	(-3.60)		(-3.36)		(-2.79)	(-3.24)		(-2.98)		(-2.41)
V_t		13.97	14.14	17.43	17.08		10.99	11.16	13.98	13.57
t-stat		(1.97)	(2.04)	(2.73)	(2.67)		(1.65)	(1.67)	(2.05)	(1.99)
V_tU_t				-15.75	-13.61				-13.62	-11.13
t-stat				(-2.54)	(-2.21)				(-2.98)	(-2.47)
Adj R^2	1.20%	1.04%	2.27%	3.23%	3.78%	0.94%	0.39%	1.35%	1.49%	2.00%
Obs	1109	1109	1109	1109	1109	1109	1109	1109	1109	1109
	25-ff portfolios					45-com portfolios				
Intercept	10.30	9.65	9.72	9.67	9.72	10.43	9.79	9.87	9.83	9.88
t-stat	(2.29)	(2.21)	(2.24)	(2.23)	(2.25)	(2.60)	(2.54)	(2.58)	(2.57)	(2.60)
U_t	-14.88		-15.03		-11.13	-15.79		-15.94		-11.60
t-stat	(-3.09)		(-2.85)		(-2.26)	(-3.73)		(-3.50)		(-2.81)
V_t		13.80	13.96	16.95	16.59		13.36	13.52	16.83	16.46
t-stat		(1.66)	(1.68)	(2.08)	(2.03)		(1.97)	(2.05)	(2.67)	(2.61)
V_tU_t				-14.33	-12.18				-15.80	-13.56
t-stat				(-2.88)	(-2.48)				(-3.27)	(-2.84)
Adj R^2	0.88%	0.78%	1.69%	2.19%	2.62%	1.32%	0.96%	2.31%	3.22%	3.85%
Obs	1109	1109	1109	1109	1109	1109	1109	1109	1109	1109

Table 5
The market factor premium with high/low information environment and risk: subsample regression analysis on portfolios. This table presents the regression result of
$\lambda^i_{t+1} = c_1 + c_2 U_t + c_3 V_t + \varepsilon_{t+1}$,
where λ^i_{t+1} (in basis point) is $\lambda^{\text{beta}}_{t+1}$, the CAPM market factor premium estimated using the Fama-MacBeth regression for the 10 beta portfolios; $\lambda^{\text{ind}}_{t+1}$, for the 10 industry portfolios; $\lambda^{\text{ff}}_{t+1}$, for the 25 Fama-French size and book-to-market portfolios; and $\lambda^{\text{all}}_{t+1}$, for the 45 combined portfolios, on the announcement day $t+1$. U_t is the information environment measure and V_t is the risk measure, standardized to have zero mean and unit variance. The low and high subsamples are determined by the two tertiles of U_t and V_t respectively. All t-statistics are computed using Newey-West standard errors with one-day lag. The sample spans from 1985 to 2019.

	10-beta portfolios				10-industry portfolios			
	Low U_t	High U_t	Low V_t	High V_t	Low U_t	High U_t	Low V_t	High V_t
Intercept	18.31	2.20	3.87	27.12	16.89	-2.57	1.73	22.60
t-stat	(2.97)	(0.33)	(0.93)	(2.85)	(2.04)	(-0.34)	(0.30)	(2.10)
U_t			0.08	-23.45			-1.00	-23.62
t-stat			(0.01)	(-3.02)			(-0.14)	(-2.81)
V_t	28.12	-1.77			23.53	-4.25		
t-stat	(2.74)	(-0.17)			(2.02)	(-0.46)		
Adj R^2	4.3%	-0.24%	-0.28%	1.76%	1.70%	-0.16%	-0.28%	1.34%
Obs	362	388	354	385	362	388	354	385
	25-ff portfolios				45-combined portfolios			
	Low U_t	High U_t	Low V_t	High V_t	Low U_t	High U_t	Low V_t	High V_t
Intercept	17.50	-0.47	3.83	29.97	17.67	-0.69	1.63	25.23
t-stat	(2.55)	(-0.06)	(0.72)	(2.92)	(2.82)	(-0.11)	(0.38)	(2.72)
U_t			3.80	-20.91			0.19	-23.84
t-stat			(0.48)	(-2.54)			(0.03)	(-3.30)
V_t	25.95	-1.63			27.81	-2.99		
t-stat	(2.31)	(-0.14)			(2.67)	(-0.31)		
Adj R^2	2.63%	-0.25%	-0.20%	1.12%	4.04%	-0.19%	-0.28%	1.93%
Obs	362	388	362	385	362	388	354	385

Table 6
The announcement premium over business cycles: regression analysis. This table presents the regression result of
$R_{t+1} = d_1 + d_2U_t + d_3V_t + d_4Rec_t + d_5V_tRec_t + d_6V_tU_t + \varepsilon_{t+1}$,
$D_{t+1} = e_1 + e_2U_t + e_3V_t + e_4Rec_t + e_5V_tRec_t + e_6V_tU_t + \varepsilon_{t+1}$,
where R_{t+1} (in basis point) is the stock market excess return calculated as the value weighted portfolio of NYSE/AMEX/NASDAQ minus the risk-free rate; $D_{t+1} = -(V_{t+1} - V_t)$ (in basis point) is the daily risk reduction, on announcement day $t+1$. U_t is the information environment measure and V_t is the risk measure, standardized to have zero mean and unit variance. Rec$_t$ is the recession dummy variable in the sample period from 1985 to 2019. Recessions are defined according to NBER business cycle dating committee. The regressions are run for announcement days where announcements are about unemployment, PPI, and FOMC Federal Fund target rate. All t-statistics are computed using Newey-West standard errors with one day lag.

	R_{t+1}				D_{t+1}			
Intercept	11.75	12.70	12.43	11.30	23.01	25.12	25.49	24.06
t-stat	(3.56)	(3.46)	(3.24)	(2.89)	(5.54)	(5.23)	(5.24)	(4.77)
U_t		-11.01	-11.18	-7.12		-13.69	-13.45	-8.33
t-stat		(-2.40)	(-2.45)	(-1.87)		(-2.07)	(-2.38)	(-2.21)
V_t		13.47	11.21	9.95		24.76	27.89	26.30
t-stat		(1.94)	(1.68)	(1.45)		(2.07)	(2.57)	(2.34)
Rec_t	-0.69	-16.46	-24.69	-28.21	-3.39	-36.63	-25.19	-29.63
t-stat	(-0.03)	(-0.85)	(-1.07)	(-1.32)	(-0.12)	(-1.34)	(-0.70)	(-0.89)
V_tRec_t			7.76	19.20			-10.77	3.64
t-stat			(0.44)	(1.42)			(-0.38)	(0.17)
V_tU_t				-14.89				-18.77
t-stat				(-2.20)				(-1.85)
Adj R^2	-0.09%	1.86%	1.85%	4.13%	-0.09%	3.12%	3.12%	5.38%
Obs	1109	1109	1109	1109	1109	1109	1109	1109

factor premium provides strong evidence further confirming that the information environment and the risk have significant impacts on the announcement premium.

5.2. Announcement premium over business cycles

How the risk premium varies over business cycles has always been an important topic studied in finance and economic literature (e.g., Fama and French (1989); Ferson and Harvey (1991); Lustig and Verdelhan (2012); Muir (2017), and Kroencke (2022)). In this subsection, we examine the impact of recession on the announcement premium and risk reduction, and how the recession effect interacts with information environment and risk. Theoretically, on the one hand, the economic growth rate is low in recessions and, inevitably, risk is high as we see from Fig. 1; on the other hand, recessions are the time when information is scarce and learning is difficult, as shown by Van Nieuwerburgh and Veldkamp (2006), and evidenced in Fig. 1 (the information environment is poor during recessions) as well. Empirically, the net effect of recession on the announcement premium and risk reduction should be jointly determined by these related factors. To test it, We run the following regressions:

$$R_{t+1} = d_1 + d_2U_t + d_3V_t + d_4Rec_t + d_5V_tRec_t + d_6V_tU_t + \varepsilon_{t+1}, \tag{17}$$

$$D_{t+1} = e_1 + e_2U_t + e_3V_t + e_4Rec_t + e_5V_tRec_t + e_6V_tU_t + \varepsilon_{t+1}, \tag{18}$$

where Rec$_t$ is the recession dummy variable. Table 6 presents the results for announcement days. Column (1) and (5) show that the slope coefficients of the recession dummy are negative for both R_{t+1} and D_{t+1}, though not statistically significant. After controlling for U_t and V_t, the coefficients of the recession dummy turn positive with insignificant t-statistics, while the slope coefficients of U_t remain significantly negative, indicating that among the predictors, the information environment measure, U_t, has the strongest predictive power on the announcement premium and risk reduction.

In addition, the slope coefficients of the cross term, V_tRec$_t$, for both R_{t+1} and D_{t+1}, are not statistically significant, with or without controlling for the cross term, V_tU_t. It indicates that recessions do not have significant impact on the risk-return relationship. Comparing to the recession dummy, the information environment measure can better capture informativeness of the announcement.

6. Conclusion

The risk-return relationship has been the central topic in asset pricing studies. Understanding how asset prices react to information based on the current level of risk and the uncertainty of the piece of information itself is essential to study the topic. We build a static model to illustrate the different roles of the return risk and the information environment. The pre-announcement risk is positively associated the announcement premium and the risk reduction due to the announcement, while noisiness of the prevailing information environment associated with informativeness of the upcoming announcement hinders the risk reduction and hence the announcement premium.

The evidence supports the theory. We examine the macroeconomic announcement premium documented by previous studies under different market conditions characterized by different levels of noisiness of the information environment and the risk measures. The results clearly shows that the announcements premium and the risk reduction are positively predicted by the level of the risk and negatively predicted by noisiness of the information environment. Furthermore, we find evidence that the impact of the information environment on the announcement premium and the risk reduction is strong when the risk is high, while the effect of the pre-announcement risk on the announcement premium and the risk reduction is strong when the information environment is good. We extend the results to the market factor premium on a few sets of stock portfolios.

We further demonstrate that the studies regarding learning asymmetries over business cycles have a bearing on the theory we presented in this paper. Our analysis shows that although recession is indeed the period when information environment is poor and learning is hard, the impact of recession on the risk-return relationship on the announcement day is much less significant than the impact of the information environment both statistically and economically.

Data availability

Data will be made available on request.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.06.005

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