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# Announcements, expectations, and stock returns with asymmetric information☆

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ABSTRACT

Revisions of consensus macroeconomic and earnings forecasts positively predict announcement-day forecast errors, whereas stock market returns during forecast revision periods negatively predict announcement-day returns. A dynamic noisy rational expectations model with periodic announcements quantitatively accounts for these findings. Under asymmetric information, informed investors' forecast revisions positively predict forecast errors of the uninformed, causing average beliefs to underreact to new information and positively predict belief errors. Additionally, stock prices are partially driven by noise. Noise impact accumulates into stock prices during revision periods but gets corrected upon announcements. Therefore, revision period price changes negatively predict announcement-day returns.

## 1. Introduction

In representative agent rational expectations models, beliefs must be martingales, and errors in beliefs must be unpredictable. However, with the growing availability of data, an emerging literature often finds that survey-based measures of belief errors are predictable. For example, consensus forecast revisions are *positively* correlated with subsequent forecast errors — see Coibion and Gorodnichenko (2015) (henceforth, CG). I further document that stock market returns during forecast revision periods *negatively* predict returns on announcement days when forecast errors are realized. Both pieces of evidence present challenges to the representative agent full information rational expectations (RA-FIRE) hypothesis.[1] While the existing literature often attributes

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[1] For example, a growing literature examines CG tests across various variables and interprets the coefficient as reflecting behavioral biases in expectations formation, including influential works by Bordalo et al. (2019), Bouchaud et al. (2019), Bordalo et al. (2020), Bianchi et al. (2022), Banerjee et al. (2021), among others.

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these predictabilities to behavioral biases, this paper provides a novel explanation within the rational expectations framework. I demonstrate that the observed evidence can be reconciled by relaxing the representative agent assumption rather than deviating from rational expectations per se. I develop a dynamic noisy rational expectations model (NREE) with periodic announcements to both qualitatively and quantitatively provide a unified explanation for these empirical findings.

I first replicate the CG regression using GDP and unemployment forecasts. Consistent with CG, I find that revisions of consensus forecasts positively predict their errors, which is often interpreted as evidence of underreaction in consensus beliefs.[2] I also demonstrate the robustness of this finding using panel data of firm-level earnings forecasts. More importantly, I document a novel finding that aggregate stock market returns during the revision periods negatively predict macroeconomic announcement-day returns.[3] This pattern also holds true at the firm-analyst level: individual stock returns during each analyst's forecast revision period negatively predict the same stock's earnings announcement-day returns. These findings suggest that the stock market's responses to forecast revisions negatively predict its responses to forecast errors. In other words, the stock market overreacts to the same news during the forecast revision period.

Next, I document three additional stylized facts that motivate the development of a NREE model with asymmetric information. First, in the cross-section, I identify a significant pattern of heterogeneity: while the forecast revisions of informed forecasters positively predict the forecast errors of the uninformed, the forecast revisions of uninformed forecasters have no predictive power for the forecast errors of the informed. Second, in the time series, I demonstrate that stock returns exhibit more pronounced overreactions during high volatility periods, whereas they tend to underreact during periods of low economic volatility. Finally, I show that stock trading volume spikes at announcements and quickly reverts afterward.

The main contribution of this paper is to develop a dynamic NREE model (Wang, 1993) with periodic announcements to jointly account for the above documented facts: underreaction in consensus beliefs, overreaction in stock prices (and conditional on volatility), heterogeneity in cross-sectional forecasts, and the associated trading patterns. My model has three key elements. First, it features two types of investors: the informed and the uninformed. I assume that dividends are driven by a hidden Markov state variable, unobservable to both groups of investors. Informed investors observe a private signal about the hidden state, whereas the uninformed do not but can learn from equilibrium stock prices. Both groups of investors rationally revise their beliefs under their own information sets. Second, as in standard NREE models, the total supply of the stock is noisy, which prevents the price from fully revealing private information. Finally, pre-scheduled macroeconomic announcements fully reveal the true value of the latent fundamentals, thereby periodically resolving uncertainty.

In this model, investors have asymmetric information but are fully rational. All investors have Bayesian beliefs, but the average (consensus) of Bayesian beliefs does not satisfy Bayes' law. Specifically, I demonstrate that informed investors' forecast revisions, which contain their superior information, positively predict uninformed investors' forecast errors. In other words, uninformed investors underreact to the private information of the informed. However, uninformed investors' forecast revisions *do not* predict the forecast errors of the informed. As a result, the average forecast of the two groups underreacts to new information and positively predicts the average forecast errors revealed through announcements. This implication of my model is not only consistent with the result of the CG regression but also aligns with the cross-sectional heterogeneity in forecast error predictability between informed and uninformed forecasters that I document.

While consensus beliefs underreact to news, stock prices overreact in my model, consistent with empirical evidence. In the NREE model, the stock price not only is a function of investors' beliefs but also is driven by the impact of noise traders. Right after an announcement, as the fundamentals are fully revealed, the price is mainly determined by fundamentals, with the noisy supply having the minimal impact. Over time, as the fundamental state variable evolves and no one can observe the true state, investors update their beliefs based on noisy information. As a result, the uncertainty about the fundamentals accumulates, and so does the impact of the noisy supply. This noise impact on stock prices can only get corrected at the next announcement, when the uncertainty is resolved again. The accumulation of noise during the belief revision period and its correction upon announcements implies a negative predictability of announcement-day returns by revision period returns.

In addition, a unique implication of my model is that the negative return predictability is more pronounced during periods of high economic volatility but weakens or even turns positive during periods of low volatility. In the model, when there is an unexpected negative volatility shock, the uncertainty also drops. As prices become more informative, the noise impact begins to get partially corrected during revision periods but is fully corrected upon announcements. Consequently, past price corrections during revision periods positively predict further corrections upon announcements, consistent with the data.

Finally, my model also explains the spikes in trading volume observed upon announcements, as seen in the data.

[2] In the rest of the paper, I use the terminology "underreaction" and "overreaction" to refer to deviations from the RA-FIRE benchmark. Agents in my model are fully rational, and under- and overreactions occur due to asymmetric information.

[3] The consensus forecast is the average of survey forecasts, forecast revision is the change between current and previous forecasts, and forecast error is the difference between the true value and the latest forecast. Revision period returns are the cumulative returns between the last and current forecast submission dates, and announcement-day returns are 30-minute returns around announcements. The timeline and detailed definitions are provided in Table A.1 in Appendix A.1.

*Literature review.* This paper builds on the noisy rational expectations equilibrium literature, established by Grossman and Stiglitz (1980), Grossman (1981), Hellwig (1980), and Campbell et al. (1993). More recent contributions include He and Wang (1995), Breon-Drish (2015), Andrei and Cujean (2017), Banerjee and Green (2015), and Banerjee and Breon-Drish (2022), among others. My model extends the continuous-time setup of Wang (1993) by incorporating periodic macroeconomic announcements and time-varying uncertainty, which none of the above papers focus on. Closely related, Banerjee et al. (2009) demonstrate negative return predictability in a finite-horizon NREE setup. In their setup, the return reversal is driven by the assumption that noise trader supply vanishes at the terminal date, resulting in price overreactions exclusively. However, my infinite-horizon framework allows for both price overreactions and underreactions, contingent on endogenously generated time-varying uncertainty through periodic announcements and volatility regimes, which aligns with empirical evidence.

This paper also contributes to the literature on the impact of macroeconomic announcements on stock market returns. Empirical evidence in this literature highlights significant macroeconomic announcement premia (e.g., Savor and Wilson, 2013; Lucca and Moench, 2015; Cieslak et al., 2019; Hu et al., 2022). Ai and Bansal (2018) provide preference conditions under which macroeconomic announcement premia arise in equilibrium. However, none of the above papers focus on the belief formation process and its implications for the predictability of stock returns on macroeconomic announcement days as I do.

This paper further contributes to the literature on expectations formation using survey data. It builds on Coibion and Gorodnichenko (2012, 2015), who explain the underreaction in consensus forecasts through rational inattention or sticky information. Other studies employing similar CG regressions typically interpret the error predictabilities as deviations from rational expectations (e.g., Bordalo et al., 2019; Bouchaud et al., 2019; Bordalo et al., 2020; Bianchi et al., 2022; Banerjee et al., 2021). Evidence from Afrouzi et al. (2023) and Bordalo et al. (2019) show stronger overreaction in longer-horizon forecasts, while Bordalo et al. (2020) and Angeletos et al. (2021) find that individual forecasts overreact, with longer-horizon forecasts displaying even greater overreaction. Li et al. (2023) observe similar patterns in the housing market and explain them as a result of slow learning about the long-run mean. Guo (2022) finds return predictability over earnings announcement cycles, while Bordalo et al. (2024) show both forecast errors and return predictability using long-term expected earnings growth, with both papers attributing these patterns to behavioral biases. None of these studies offers a unified and rational explanation for both the underreaction in consensus beliefs and the overreaction in prices, at least in the short horizon, as this paper does.

This paper is broadly related to the literature on heterogeneous information and preferences, including differential information models (e.g., Hellwig, 1980; He and Wang, 1995; Allen et al., 2006; Banerjee et al., 2009, CG etc.), models with heterogeneous priors or "agree to disagree" (e.g., Kandel and Pearson, 1995; Bhamra and Uppal, 2014, etc.), and models with heterogeneous preferences (e.g., Bhamra and Uppal, 2009; Borovička, 2020, etc.). Within the above literature, Allen et al. (2006) point out that average beliefs are not Bayesian, a key insight shared with this paper. However, these existing models lack the feature of asymmetric hierarchical information present in this paper. As a result, while they can explain the underreaction observed in consensus beliefs, they do not account for the observed information asymmetry in the cross-section. Additionally, unlike differential information models where trading volume starts to increase *before* announcements, trading in this paper only spikes after the announcements, consistent with the data.[4]

The remainder of the paper is organized as follows. Section 2 presents the stylized facts. Section 3 develops a dynamic NREE model featuring periodic announcements. Section 4 conducts a quantitative analysis, demonstrating the model's ability to explain the empirical evidence discussed in Section 2. Finally, Section 5 concludes. Appendix A contains data, measurements, and robustness checks, while Appendix B includes proofs, derivations, a simplified two-period model, and details of the numerical solutions.

## 2. Stylized facts

In this section, I present several stylized facts about the expectation formation process for macroeconomic and financial variables and the corresponding financial market reactions. I summarize the empirical facts here, while further details on data construction, measurements, and robustness analysis are provided in Appendix A.

*1. Underreaction in consensus beliefs.* Revisions of consensus macroeconomic and earnings forecasts positively predict the errors of these forecasts realized on announcement days.

Panel A of Table 1 presents my replication of the CG regression at the consensus level for the real GDP growth rate and unemployment rate (UE). Following their methodology, I regress the consensus forecast errors on the consensus forecast revisions. Under the RA-FIRE hypothesis, the regression coefficient should not differ significantly from zero, as nothing should predict the error of a rational belief. However, the coefficients for both GDP and UE are significantly positive. In Table A.4 of Appendix A.2, I demonstrate the robustness of my findings using a panel regression on consensus forecasts of firm-level earnings per share (EPS).[5] The above evidence implies that the consensus forecast underreacts to new information relative to the RA-FIRE benchmark.

[4] Specifically, in He and Wang (1995), investors engage in speculative trading before announcements to bet on outcomes based on their differential information, where each investor possesses some information that others lack. Moreover, the finite-horizon setup prevents trading after the terminal date, resulting in increased trading volume before that date. Both factors contribute to a rise in trading volume in the periods leading up to announcements, as depicted in Figures 4 and 5 of their paper.

[5] The point estimate for the CG regression is 0.41 ($t$ = 11.14) at the firm level for consensus EPS forecasts.

**Table 1**
Forecast error predictability.

| | *A. Consensus* | | *B. Uninformed* | | *C. Informed* | |
|---|---|---|---|---|---|---|
| | GDP | UE | GDP | UE | GDP | UE |
| $\beta_F$ | 0.39 | 0.24 | 0.63 | 0.49 | 0.08 | –0.08 |
| | (2.29) | (6.84) | (4.13) | (3.83) | (0.85) | (–0.87) |

Panel A presents the CG coefficient from the regression:

$$Ferr_{t+1}\left(x_{t+1}\right) = \alpha + \beta_F Frev_t\left(x_{t+1}\right) + \varepsilon_{t+1}. \quad (1)$$

The consensus forecast revision is defined as $Frev_t\left(x_{t+1}\right) = \bar{\mathbb{E}}_t\left(x_{t+1}\right) - \bar{\mathbb{E}}_{t-1}\left(x_{t+1}\right)$, which is the difference between the consensus (average) forecast of $x$ submitted in the current quarter $t$ and that of the previous quarter $t-1$. At $t+1$, the true value of $x$ is eventually revealed through an announcement. The consensus forecast error is therefore defined as the difference between the realized value and its most recent consensus forecast: $Ferr_{t+1}\left(x_{t+1}\right) = x_{t+1} - \bar{\mathbb{E}}_t\left(x_{t+1}\right)$. Panel B presents the regression coefficients for predicting the uninformed group's forecast error using the informed group's forecast revision, while Panel C shows the coefficient for predicting the informed group's forecast error using the uninformed group's forecast revision. Both regressions control for the respective group's forecast revision. Forecasters in the top tercile of information precision, measured as the rolling average of their forecast accuracy (scaled mean-adjusted absolute forecast error) up to the previous quarter, are classified as the informed group, while those in the bottom tercile are classified as the uninformed group. The data for GDP and unemployment (UE) are sourced from the Survey of Professional Forecasters (SPF) and cover the period from 1968 to 2019. Newey–West $t$-statistics (with 5 lags) are reported in parentheses.

*2. Heterogeneity in cross-sectional forecasts: The role of asymmetric information.* Individual forecasts exhibit persistent errors.[6] Informed investors' forecast revisions positively predict uninformed investors' forecast errors, while the reverse is not true — uninformed investors' forecast revisions cannot predict informed investors' forecast errors.

I measure forecasters' information precision using the rolling average of their forecast accuracy up to the previous quarter.[7] Based on this measure, I classify the top tercile of forecasters with the highest information precision as the informed group and the bottom tercile with the lowest information precision as the uninformed group. Panel B of Table 1 reports the results of a predictive regression of the uninformed group's forecast error using the informed group's forecast revision. The regression coefficients are highly significant. In contrast, Panel C presents the results from regressing the informed group's forecast error on the uninformed group's forecast revision. Unlike Panel B, the forecast revisions of the uninformed group do not have predictive power over the forecast errors of the informed group, and none of the regression coefficients are significant. Appendix A.6 shows that the results remain robust to alternative measures of information precision and group classifications.

*3. Overreaction in stock prices.* A novel stylized fact established in this paper is that stock market returns during forecast revision periods negatively predict stock market returns on announcement days.[8]

My objective is to examine the stock market's responses to the same news that investors use to process information. To achieve this, I estimate a return predictability regression by regressing the high-frequency announcement-day aggregate stock market returns on the returns during forecast revision periods. As summarized in Panel A of Table 2, the estimated coefficient for GDP announcements is –0.075. That is, a one standard deviation increase in revision period returns is associated with a 7.5 basis points (bps) reduction in returns during the 30-minute window around the GDP announcement. Similarly, the same regression produces a coefficient of –0.082 for unemployment rate news releases. In Table A.6 of Appendix A.4, I show the robustness of my findings using a panel at the firm-analyst level — I regress stock return as of earnings announcement days on stock returns as of earnings revision days.[9] The granularity of this analysis provides higher statistical power and demonstrates significant return predictability. These results suggest that positive returns during revision periods predict negative returns on announcement days, which can be interpreted as stock market overreaction to new information.

*4. Overreaction conditional on volatility.* Overreaction in prices is stronger in periods with high economic volatility. However, during periods of low volatility, this effect can be insignificant or even of the opposite sign.

To understand the difference in announcement-day return predictability based on time-varying volatility, I split the sample into high- and low-volatility periods, defined as whether the mean realized volatility during the revision period is above or below its mean, and then re-estimate the announcement-day return predictability regression.[10] The results are presented in Panel B of Table 2. The regression coefficient $\beta_H$ measures the predictability of announcement-day returns by the cumulative return over revision periods when volatility is high, while $\beta_L$ measures the same for low-volatility periods. The $\beta_H$'s are significantly and consistently negative across all forecasts. Compared to Panel A, $\beta_H$'s are around 1.5 times larger than the unconditional $\beta_P$'s in the corresponding regressions. In contrast, the $\beta_L$'s are often insignificant or even positive, indicating weak or positive predictability during periods of

[6] In Table A.3.2 of Appendix A.3.2, I show that measurements of panelists' forecast accuracy are predictable using lagged values, ranging from one quarter to twenty quarters.

[7] Specifically, forecast accuracy for each forecaster in quarter $t$ is measured using the scaled mean-adjusted absolute forecast error, defined as the forecaster's absolute forecast error minus the mean absolute forecast error for all forecasters in that quarter, divided by the same mean. See Appendix A.3 for further details.

[8] This fact is related to the broader pattern of overreactions observed in long-term bonds (d'Arienzo, 2020; Wang, 2021), stocks (Greenwood and Shleifer, 2014; Bordalo et al., 2024), and other asset classes (Nagel and Xu, 2023).

[9] Specifically, a 1% increase in the three-day return around an analyst's forecast revision day is associated with a 1.4 bps decrease in the three-day return around the earnings announcement.

[10] In Appendix A.6, I show that the results remain robust when using the revision period VIX as an alternative measure of economic volatility.

**Table 2**
Announcement return predictability.

| | *CE* | | *SPF* | |
|---|---|---|---|---|
| | GDP | UE | GDP | UE |
| *Panel A. overreaction in prices* | | | | |
| $\beta_P$ | −0.075 | −0.082 | −0.071 | −0.088 |
| | (−2.21) | (−2.19) | (−2.20) | (−1.44) |
| $R^2(\%)$ | 7.82 | 3.97 | 7.19 | 4.19 |
| *Panel B. overreaction conditional on volatility* | | | | |
| $\beta_H$ | −0.098 | −0.131 | −0.143 | −0.183 |
| | (−3.26) | (−4.14) | (−4.60) | (−3.54) |
| $\beta_L$ | 0.059 | 0.073 | 0.056 | 0.011 |
| | (1.12) | (0.48) | (1.49) | (0.15) |

Panel A presents the coefficient in the stock market from the regression:

$$Rerr_{t+1} = \alpha + \beta_P Rrev_t + \varepsilon_{t+1}, \tag{2}$$

where the revision period return, $Rrev_t = (P_t - P_{t-1})/P_{t-1}$, is defined as the cumulative return from the stock price on the last quarter's forecast submission day $P_{t-1}$ to the price on the current quarter's submission day $P_t$, and $Rerr_{t+1} = (P_{t+1} - P^-_{t+1})/P^-_{t+1}$ is the high-frequency return upon the announcement, with the price change from $P^-_{t+1}$ (15 min before the announcement) to $P_{t+1}$(15 min after the announcement). Panel B splits the sample into high and low volatility periods, where $\beta_H$ ($\beta_L$) representing the regression coefficients when the realized volatility during forecast revision periods is below and above its mean, respectively. The realized volatility is calculated as the square root of the sum of squared daily returns over revision periods. GDP and UE data are sourced from the Survey of Professional Forecasters (SPF) and Consensus Economics (CE), while returns data are obtained from the S&P 500 ETF (SPY). The right-hand-side variables are normalized by their mean and standard deviation, with returns expressed in percentages. The dataset covers the period from 2003 to 2019. Newey–West $t$-statistics (with 5 lags) is reported in parentheses.

low volatility. This suggests that stock market overreacts to information when uncertainty is high and underreacts to information when uncertainty is low. As I will show in Section 4, this feature of the data is a unique implication of my model with time-varying volatility.

*5. Trading volume spikes.* Trading volume increases sharply upon announcements, followed by an immediate drop afterward. In Fig. 1, I plot the trading volume around GDP and unemployment announcements. Evidently, the announcement triggers a spike in trading. This evidence also uniquely supports my model with asymmetric information.

These findings, taken together, pose challenges to the representative agent rational expectations hypothesis. This paper demonstrates that a departure from the representative agent setup, rather than the rational expectations assumption, can reconcile the above evidence.

## 3. The dynamic model

In this section, I develop a continuous-time NREE model with periodic announcements to explain the above facts. The model is based on Wang (1993), except that here I incorporate periodic macroeconomic announcements following Ai and Bansal (2018). This dynamic setup allows me to study the predictability of forecast and pricing errors within a unified equilibrium framework and to calibrate the model to examine its quantitative implications.

### 3.1. Model setup

*Preference, endowment, and information.* There is a unit measure of investors who maximize CARA utilities represented by $\mathbb{E}\int_0^\infty -e^{-\rho t - C_t} dt$, where $C_t$ is consumption at time $t$ and $\rho$ is the subjective time discount rate. For simplicity, I assume that the absolute risk aversion is 1.

Two assets are available for trading: a stock and a risk-free bond. I assume that the risk-free return $r$ is constant. The stock is the claim to the following dividend process:

$$dD_t = \left(x_t - D_t\right) dt + \sigma_D dB_{D,t}, \tag{3}$$

where $D_t$ is the dividend flow, $x_t$ is the long-run trend for the dividend flow, $\sigma_D$ is the volatility of the dividend flow, and $dB_{D,t}$ is an i.i.d. shock to the dividend modeled as a standard Brownian motion. I model the expected dividend flow as $x_t - D_t$, so that the dividend process is stationary. The long-run trend of the dividend flow, $x_t$, is itself mean reverting, modeled as an Ornstein–Uhlenbeck process:

$$dx_t = b\left(\bar{x} - x_t\right) dt + \sigma_x dB_{x,t}, \tag{4}$$

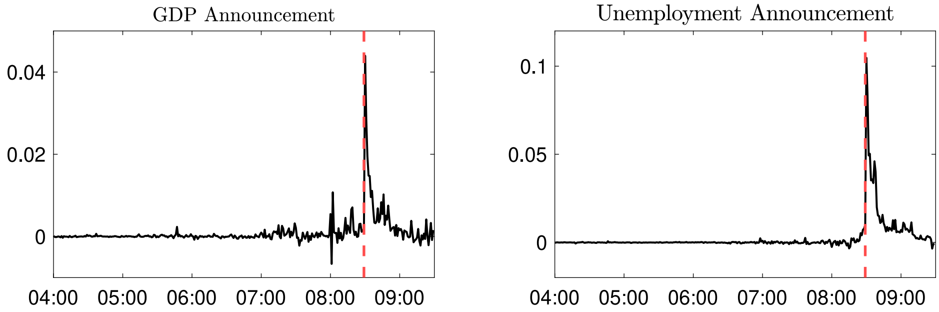


**Fig. 1.** Excessive trading volume around macroeconomic announcement.
This figure depicts excessive trading volume (in percentage) around GDP and unemployment announcements from 4:00 a.m. to 9:30 a.m. Excessive trading volume is defined as the turnover rate – calculated as the total shares traded in one minute divided by the total shares outstanding – relative to the past week's average turnover rate at the same time. The data are based on the S&P 500 ETF (SPY), averaged for each announcement from 2003 to 2019. The dashed red line indicates the announcement time at 8:30 a.m.

where $\bar{x}$ is the long-run mean, $b$ is the mean reversion rate, $\sigma_x$ is the volatility of the hidden state, and $B_{x,t}$ is a Brownian motion. Latent state $x_t$ is assumed to be unobservable to all investors but is periodically revealed through announcements.[11] In addition, as is standard in the NREE literature, I assume that the total equity supply is stochastic, denoted as $\theta_t$:

$$d\theta_t = -a\theta_t dt + \sigma_\theta d B_{\theta,t}. \tag{5}$$

In the above equation, $a$ is the rate of mean reversion and $\sigma_\theta$ is the noisy supply volatility. Assume that Brownian motions $B_{D,t}$, $B_{x,t}$, and $B_{\theta,t}$ are mutually independent. For tractability, I assume that the long-run average of $\theta_t$ is zero. Intuitively, $\theta_t$ can be interpreted as the noise traders' supply.

The dividend flow is observable to all investors. However, its long-run trend $x_t$ and the total risk asset supply $\theta_t$ are not. Assume that a fraction $(1-\omega)$ of investors are informed, meaning that they observe a common noisy signal about $x_t$, denoted as $s_t$:

$$ds_t = x_t dt + \sigma_s d B_{s,t}, \tag{6}$$

where $\sigma_s$ is the inverse of signal precision and $B_{s,t}$ is a Brownian motion independent of $B_{D,t}$, $B_{x,t}$, and $B_{\theta,t}$. The standard Kalman filter implies that the informed investor's belief about $x_t$ can be summarized by a posterior mean and a posterior variance, $\hat{x}_t \equiv \hat{\mathbb{E}}_t\left[x_t\right]$ and $\hat{q}(t) \equiv \hat{\mathbb{E}}_t\left[\left(\hat{x}_t - x_t\right)^2\right]$, respectively, where $\hat{\mathbb{E}}_t$ stands for the conditional expectation under the informed investor's information set at time $t$.

Uninformed investors do not observe the signal $s_t$ but can learn from the equilibrium price. Denote $\tilde{x}_t \equiv \tilde{\mathbb{E}}_t\left[\hat{x}_t\right]$ and $\tilde{q}(t) \equiv \tilde{\mathbb{E}}_t\left[\left(\tilde{x}_t - \hat{x}_t\right)^2\right]$ as the uninformed investor's posterior mean and variance of the informed investor's posterior belief about $x_t$, and $\tilde{\theta}_t \equiv \tilde{\mathbb{E}}_t\left[\theta_t\right]$ for their posterior mean of the total noisy supply.[12] From here on, denote $\tilde{\mathbb{E}}_t$ as the conditional expectation under the uninformed investor's information set at time $t$. I define *uncertainty* as the posterior variance $\hat{q}(t)$ and $\tilde{q}(t)$.

*Macroeconomic announcements.* At pre-scheduled times $t = nT$ for $n = 0, 1, 2, \ldots$, there is a periodic announcement that is assumed to fully reveal the true value of $x_t$. In between announcements, investors do not observe $x_t$ directly and must form Bayesian beliefs about $x_t$ based on all available information.[13]

*Learning from prices.* As in standard NREE models, informed investors observe more information than the uninformed and try to profit from it by trading competitively and non-strategically in the stock market. Because their trading affects asset demand and therefore the stock price, their information is reflected in the price. Because of the presence of the noisy supply $\theta_t$, the equilibrium price is not fully revealing and contains noisy information about the fundamentals, $x_t$. I conjecture and later verify that the equilibrium stock price takes the following linear form:

[11] Mapping back to the data, announcements provide information about economic quantities, such as GDP and EPS, represented as $D_t$, which forecasters aim to predict. In the model, the specification that announcements also reveal information about future levels of dividends ($D_s$ for $s > t$), captured by $x_t$, is motivated by the immediate response of forward-looking stock prices to these announcements.

[12] Appendix B.1 shows that learning about $\hat{x}_t$ is equivalent to learning about $x_t$, where the posterior mean is $\tilde{x}_t$ and the posterior variance is $\hat{q}(t) + \tilde{q}(t)$. This is intuitive because uninformed investors face higher estimation errors about $x_t$ than the informed because of the lack of private information.

[13] This setup is a parsimonious way of modeling announcements. Essentially, the dividend is assumed to have a predictable component, modeled by a Markov process $x_t$, and an unpredictable component, modeled by a Brownian motion $B_{D,t}$. Announcements periodically reveal the true value of the predictable component at pre-scheduled times. However, it is important to note that not all future uncertainty for stocks is resolved upon an announcement at time $t$. In particular, future growth uncertainty depends on both the future value of $x_s$ and the future value of $B_{D,s}$ for $s > t$.

$$P_t = \phi + \phi_D D_t - \phi_\theta(t)\theta_t + \phi_x(t)\hat{x}_t + \phi_\Delta(t)\tilde{x}_t \tag{7}$$
$$= \phi + \phi_D D_t - \phi_\theta(t)\tilde{\theta}_t + \bar{\phi}_x\tilde{x}_t, \tag{8}$$

where $\phi_\theta(t)$, $\phi_x(t)$, and $\phi_\Delta(t)$ are time-varying sensitivities of price to $\theta_t$, $\hat{x}_t$, and $\tilde{x}_t$, respectively. Intuitively, the coefficient $\phi_\theta(t) > 0$ characterizes the price impact of the noisy supply. A positive supply shock has a negative impact on the equilibrium price. Similarly, $\phi_x(t) > 0$ and $\phi_\Delta(t) > 0$ represent the price impact of informed investors and that of uninformed investors. As I guess and verify in Appendix B.1, the price coefficient on dividends $\phi_D$ is time invariant, and so is the total price impact of both investors' beliefs, denoted as $\bar{\phi}_x = \phi_x(t) + \phi_\Delta(t)$.

The informed investors observe the realizations of $D_t$, $s_t$, $P_t$, and the pre-scheduled announcements. Because of the asymmetric information, they can perfectly infer the posterior belief of the uninformed, $\tilde{x}_t$, and thus compute the total noisy supply $\theta_t$ from the equilibrium price (7). In this linear pricing framework, the private information of informed investors is completely summarized in their posterior mean, $\hat{x}_t$. The conditional expectation can therefore be summarized as $\hat{\mathbb{E}}_t \equiv \mathbb{E}\left[\cdot\, |\mathcal{F}_t^i\right]$, where the informed investors' information set $\mathcal{F}_t^i = \left\{D_t, s_t, P_t, \tilde{x}_t\right\}$, or equivalently, $\mathcal{F}_t^i = \left\{D_t, \theta_t, \hat{x}_t, \tilde{x}_t\right\}$.

On the other hand, the uninformed investors do not observe $s_t$. They observe $D_t$, $P_t$, and the announcements. Unlike the informed, observing the price only reveals a combination of $\hat{x}_t$ and $\theta_t$ to them.[14] The uninformed investors' learning problem can be simplified by defining $\xi_t = \phi_x(t)\hat{x}_t - \phi_\theta(t)\theta_t - \frac{\hat{q}(t)}{\sigma_D^2}\phi_x(t)D_t$, which captures the information content of the price. Appendix B.1 shows that $\xi_t$ is conditionally independent of $D_t$; therefore, observing $\xi_t$ and $D_t$ is equivalent to observing $P_t$ and $D_t$. The conditional expectation can now be defined in terms of the uninformed investors' information set as $\tilde{\mathbb{E}}_t \equiv \mathbb{E}\left[\cdot\, |\mathcal{F}_t^u\right]$, where $\mathcal{F}_t^u = \left\{D_t, \tilde{x}_t, P_t\right\}$, or equivalently, $\mathcal{F}_t^u = \left\{D_t, \tilde{x}_t, \xi_t\right\}$. This easily shows that the uninformed investors' information set is a subset of the informed investors' information: $\mathcal{F}_t^u \subseteq \mathcal{F}_t^i$. Therefore, uninformed investors' information represents *publicly available* information. Note that $\mathcal{F}_0^u = \mathcal{F}_0^i$; that is, informed and uninformed investors start with the same information set right after an announcement. However, between announcements, $\mathcal{F}_t^u \subset \mathcal{F}_t^i$ for all $t \in (0, T)$.

It is useful to define the difference in beliefs as $\Delta_t \equiv \hat{\mathbb{E}}_t\left[x_t\right] - \tilde{\mathbb{E}}_t\left[x_t\right] = \hat{x}_t - \tilde{x}_t$ to characterize the trading advantage of informed investors over the uninformed. The dynamic of $\Delta_t$ is provided in Appendix B.1. Using Eqs. (7) and (8), the difference in investors' beliefs about $\theta_t$ can be expressed as a function of $\Delta_t$:

$$\theta_t - \tilde{\theta}_t = \frac{\phi_x(t)}{\phi_\theta(t)}\Delta_t. \tag{9}$$

Intuitively, a negative noisy supply shock in $\theta_t$ increases the market price. Because uninformed investors do not observe $\hat{x}_t$ and $\theta_t$ separately, they rationally interpret the price increase as partially reflecting deteriorations in $\theta_t$ and partially as positive news about fundamentals $\hat{x}_t$. As a result, they upwardly revise their beliefs about $\hat{x}_t$ so that $\tilde{x}_t$ increases. The difference in beliefs about $\theta_t$ therefore translates into a difference in beliefs about $\hat{x}_t$.

*Dynamics of beliefs and time-varying uncertainty.* Informed and uninformed investors' posterior beliefs are computed using the standard Kalman filter. The following lemma summarizes their dynamics.

**Lemma 1.** *In the interior (between announcements), $t \in (0, T)$, the law of motion for the posterior mean and variance of informed investors satisfy*

$$d\hat{x}_t = b\left(\bar{x} - \hat{x}_t\right)dt + \frac{\hat{q}(t)}{\sigma_D}d\hat{B}_{D,t} + \frac{\hat{q}(t)}{\sigma_s}d\hat{B}_{s,t}, \tag{10}$$
$$d\hat{q}(t) = \left[\sigma_x^2 - 2b\hat{q}(t) - \left(\frac{1}{\sigma_D^2} + \frac{1}{\sigma_s^2}\right)\hat{q}^2(t)\right]dt, \tag{11}$$

*where $d\hat{B}_{D,t} = \frac{1}{\sigma_D}\left(dD_t - \hat{\mathbb{E}}_t\left[dD_t\right]\right)$ and $d\hat{B}_{s,t} = \frac{1}{\sigma_s}\left(ds_t - \hat{\mathbb{E}}_t\left[ds_t\right]\right)$ are innovations in the dividend flow and informed investors' signal process.*

*The law of motion for the posterior mean and variance of uninformed investors are*

$$d\tilde{x}_t = b\left(\bar{x} - \tilde{x}_t\right)dt + \frac{\hat{q}(t) + \tilde{q}(t)}{\sigma_D}d\tilde{B}_{D,t} + v(t)\sigma_\xi(t)\,d\tilde{B}_{\xi,t}, \tag{12}$$
$$d\tilde{q}(t) = \left[\left(\frac{1}{\sigma_D^2} + \frac{1}{\sigma_s^2}\right)\hat{q}^2(t) - 2b\tilde{q}(t) - \left(\frac{\hat{q}(t) + \tilde{q}(t)}{\sigma_D}\right)^2 - v^2(t)\sigma_\xi^2(t)\right]dt, \tag{13}$$

*where $d\tilde{B}_{D,t} = \frac{1}{\sigma_D}\left(dD_t - \tilde{\mathbb{E}}_t\left[dD_t\right]\right)$ and $d\tilde{B}_{\xi,t} = \frac{1}{\sigma_\xi(t)}\left(d\xi_t - \tilde{\mathbb{E}}_t\left[d\xi_t\right]\right)$ are innovations in the dividend flow and the information content of price. The function $v(t)$ is defined in equation (B.9), and the volatility of $\xi_t$, $\sigma_\xi(t)$ is defined in (B.8) in Appendix B.1.*

*At the boundary (announcement), $\hat{x}_T = \tilde{x}_T = x_T$ and $\hat{q}(T) = \tilde{q}(T) = 0$.*

[14] In general, since $x_t$, $\hat{x}_t$, and $\theta_t$ are unknown to the uninformed investors, one would need to characterize the posterior beliefs of all three variables to solve their optimization problem. However, in Appendix B.1, I show that characterizing the dynamics of $\tilde{x}_t$ and $\tilde{q}(t)$ is sufficient to compute the posteriors for all three.

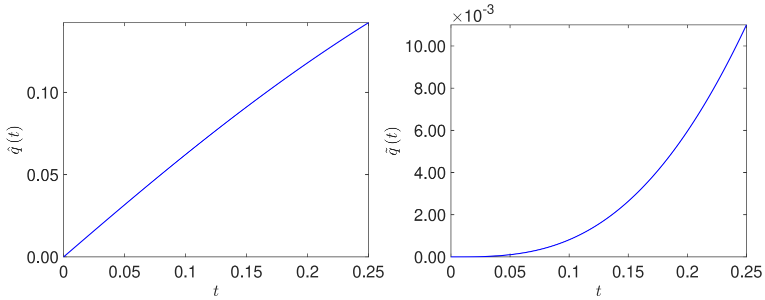


**Fig. 2.** Time-varying uncertainty.
This figure plots the time-varying uncertainty $\hat{q}(t)$ and $\tilde{q}(t)$ defined in Lemma 1 for one announcement cycle under the benchmark parameter values in Table 3. Here, $t = 0$ stands for the time right after an announcement.

**Proof.** See Appendix B.1 for the proof. □

Since the periodic announcement fully reveals the true value of $x_t$ at $t = nT$, investors' beliefs about $x_t$ instantaneously reset to its true value right after the announcement: $\hat{x}_{nT} = \tilde{x}_{nT} = x_{nT}$. Consequently, both $\hat{q}(t)$ and $\tilde{q}(t)$ drop to zero. After the announcement, information about $x_t$ starts to become imprecise, and both $\hat{x}_t$ and $\tilde{x}_t$ drift away from the true value of $x_t$ according to the law of motion (10) and (12) above. At the same time, uncertainties start to build up as the estimation errors $\hat{q}(t)$ and $\tilde{q}(t)$ accumulate over time. The monotonicity of $\hat{q}(t)$ and $\tilde{q}(t)$ is a consequence of these periodic announcements. They drop to zero at each announcement and then asymptotically converge to their respective steady states before the next announcement arrives, starting a new cycle.[15] This time-varying uncertainty is illustrated in Fig. 2.

For simplicity, I focus on the equilibrium in which all announcement cycles are identical. That is, the policy functions depend only on the time to the next announcement.[16] Under this assumption, I only need to characterize the time-varying coefficients on one representative announcement cycle, $[0, T]$. Without loss of generality, I use $T$ (or 0) to denote the moment just after the announcement, and $T^-$ for the moment right before the announcement.

*Underreaction in consensus beliefs — Predictability of consensus forecast errors.* Using the above formula, I can derive the optimal forecasts for both informed and uninformed investors. The consensus forecast at time $t$, as in the data, is defined as the weighed average of the informed and uninformed investors' forecasts about the true value of $x_T$, which is announced at time $T$. This is given by $(1-\omega)\hat{\mathbb{E}}_t\left[x_T\right] + \omega\tilde{\mathbb{E}}_t\left[x_T\right]$. The following proposition demonstrates that the consensus forecast underreacts to information relative to the RA-FIRE benchmark when asymmetric information is present.

**Proposition 1.** *Given the optimal filtering equations from Lemma 1, for all $t \in (0, T]$,*

$$Cov\Big(\underbrace{\hat{\mathbb{E}}_t\left[x_T\right] - \hat{\mathbb{E}}_0\left[x_T\right]}_{\text{informed's forecast revision}},\ \underbrace{x_T - \tilde{\mathbb{E}}_t\left[x_T\right]}_{\text{uninformed's forecast error}}\Big) > 0, \tag{14}$$

$$Cov\Big(\underbrace{\tilde{\mathbb{E}}_t\left[x_T\right] - \tilde{\mathbb{E}}_0\left[x_T\right]}_{\text{uninformed's forecast revision}},\ \underbrace{x_T - \hat{\mathbb{E}}_t\left[x_T\right]}_{\text{informed's forecast error}}\Big) = 0, \tag{15}$$

*and*

$$Cov\left(Frev_t\left(x_T\right), Ferr_T\left(x_T\right)\right) > 0, \tag{16}$$

*where $Frev_t\left(x_T\right) = (1-\omega)\left(\hat{\mathbb{E}}_t\left[x_T\right] - \hat{\mathbb{E}}_0\left[x_T\right]\right) + \omega\left(\tilde{\mathbb{E}}_t\left[x_T\right] - \tilde{\mathbb{E}}_0\left[x_T\right]\right)$ is the consensus forecast revision, and $Ferr_T\left(x_T\right) = (1-\omega)\left(x_T - \hat{\mathbb{E}}_t\left[x_T\right]\right) + \omega\left(x_T - \tilde{\mathbb{E}}_t\left[x_T\right]\right)$ represents the consensus forecast error.*

**Proof.** See Appendix B.1 for the proof. □

Since both $\hat{\mathbb{E}}_t\left[x_T\right]$ and $\tilde{\mathbb{E}}_t\left[x_T\right]$ are derived using the optimal Kalman filter based on each group's information set, rationality implies that their forecast revisions cannot predict their *own* forecast errors. Eq. (15) shows that uninformed investors, having less information, cannot predict the errors in informed investors' forecasts. However, informed investors, who possess superior private information, make revisions that are positively correlated with the true state $x_T$. This private information is absent from

[15] Consistent with the model's prediction, I document in Appendix A.5 that, on average, the VIX increases between announcements and is associated with drops upon the announcements. Therefore, using the VIX as a measure of uncertainty, I calibrate the model-implied variance reduction upon announcements in Section 4 to match the empirical moments observed in the data.

[16] Although policy functions are identical over different announcement cycles, the state variables are not. They depend on realizations of unpredictable Brownian motion shocks.

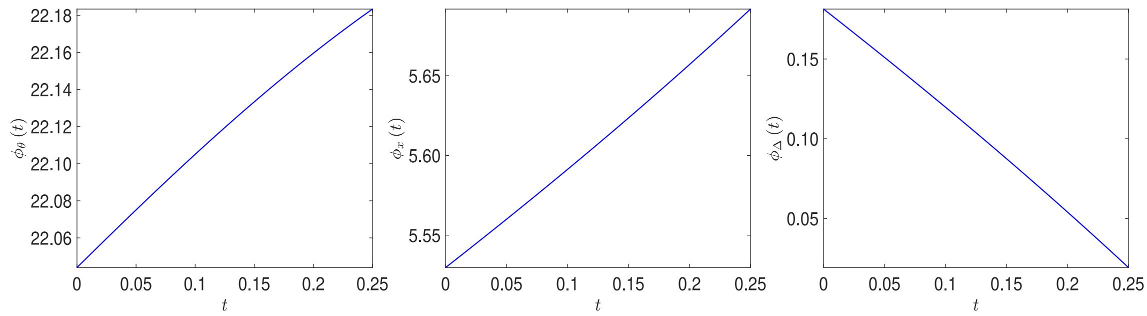


**Fig. 3.** Time-varying price sensitivities.
This figure plots the time-varying pricing function coefficients $\phi_\theta(t)$, $\phi_x(t)$, and $\phi_\Delta(t)$ for one announcement cycle under the benchmark parameter values in Table 3. Here, $t = 0$ stands for the time right after the announcements.

the uninformed investors' forecasts, resulting in their revisions positively predicting the uninformed investors' errors. The positive correlation in (14) arises from this information asymmetry. Intuitively, because only informed investors receive new information, the arrival of such information not only contributes to revisions in the informed investors' beliefs but also leads to errors in the uninformed investors' forecasts, as the latter group cannot update their beliefs accordingly.

In fact, the conclusion of the above proposition is more general than the specific learning setup of this paper. Under the assumption of rational expectations for both informed and uninformed groups, information asymmetry – specifically $\mathcal{F}_0^u = \mathcal{F}_0^i$ and $\mathcal{F}_t^u \subset \mathcal{F}_t^i$ – is sufficient to derive Eqs. (14) and (15). These two equations are crucial as they differentiate my model from others, such as differential information models. In Section 4, I present a quantitative analysis showing that the unique implications of the information asymmetry mechanism are consistent with the empirical evidence outlined in Section 2, compared to other models.

Finally, since the consensus forecast is an average of both groups' forecasts, its revision therefore positively predicts its error, as shown in Eq. (16). It is important to note that the consensus belief does not satisfy Bayes' law, as a Bayesian belief must be a martingale. Therefore, *heterogeneity*, in this context arising from the asymmetric information, is responsible for the underreaction of the consensus belief revision at time $t$.

### *3.2. Equilibrium*

Turning to the model solution, I follow the standard approach in the NREE literature. First, given the conjectured functional form of the stock price (7) and investors' beliefs in Lemma 1, I solve for their optimal portfolio choices. Then, I impose market clearing conditions to determine the conjectured coefficients in the pricing function and investors' value functions. In contrast to standard NREE models (e.g., Grossman and Stiglitz, 1980; Wang, 1993), the coefficients here are time varying, reflecting the time-varying information structure and price responses to uncertainty. This time variation in the price sensitivity to information is the key to explaining the predictability of announcement returns.

*Equilibrium pricing function.* Fig. 3 plots the pricing function coefficients $\phi_\theta(t)$, $\phi_x(t)$, and $\phi_\Delta(t)$ for one announcement cycle (recall Eqs. (7) and (8)). I make several observations on the properties of these pricing functions.

First, $\phi_\theta(t) > 0$; that is, increases in the aggregate equity supply $\theta_t$ lower the price for two reasons. First, increases in supply lower the equilibrium price because of a downward-sloping demand curve, as in standard equilibrium models. This effect does not depend on uncertainty or asymmetric information. Second, information asymmetry and learning from prices amplify the responses of price to supply shocks; therefore, an increase in $\theta_t$ further lowers the price. Because the uninformed investors only observe a noisy combination of $\theta_t$ and $x_t$, they rationally attribute part of the price drop as deteriorations in fundamentals and downwardly revise their beliefs about $x_t$. As a result, they reduce their holdings of the stock because of their pessimistic beliefs. This mechanism lowers the demand for the asset, and the equilibrium price has to drop further to clear the market.

Second, $\phi_\theta(t)$ is an increasing function of uncertainty. It monotonically increases over time in between announcements and jumps down discontinuously upon the announcement, thereby mimicking the pattern of time-varying uncertainty in Fig. 2. It is increasing from 0 to $T^-$ because the above discussed amplification effect of asymmetric information becomes stronger over time as uncertainty builds up. At time $t = 0$, right after an announcement, uninformed investors know the true value of $x_0$ and the information asymmetry is temporarily eliminated. As $t$ increases, $x_t$ moves away from its previous value, and the uninformed investors are more uncertain about it and start to learn from prices. As the uncertainty and information asymmetry about $x_t$ build up over time, changes in prices have increasingly stronger impacts on uninformed investors' beliefs. Therefore, prices become more sensitive to noise, i.e., $\phi_\theta(t)$ increases. At time $T$ when the next announcement approaches, the uncertainty about $x_T$ instantaneously resolves, the impact of the noisy supply on prices jumps down discontinuously from $\phi_\theta(T^-)$ to $\phi_\theta(T)$, and a new announcement cycle starts. As I will prove formally in Proposition 2 below, this pattern of monotonicity and discontinuity of the $\phi_\theta(t)$ function is the key to explaining the predictability of announcement returns.

Third, $\phi_x(t)$ is positive and increasing, and $\phi_\Delta(t)$ is positive and decreasing. As $t$ increases from 0 to $T^-$, the information advantage of informed investors rises, and uninformed investors are more uncertain about $x_t$ by comparison. As a result, uninformed investors become less aggressive in trading and their price impact, $\phi_\Delta(t)$, diminishes. Because the total price impact $\phi_x(t) + \phi_\Delta(t) = \bar{\phi}_x$ is a constant, the drop in $\phi_\Delta(t)$ must be accompanied by an increase in the price impact of informed investors, $\phi_x(t)$, as shown in Fig. 3.

*Optimal portfolio choices.* I guess and verify in Appendix B.2 that the informed investor's value function $J\left(t, W_t, \theta_t, \Delta_t\right)$ takes a quadratic form, where $W_t$ denotes the financial wealth. In the interior of $(0, T)$ between announcements, the informed investor's optimization problem is

$$J\left(t, W_t, \theta_t, \Delta_t\right) = \max_{\{\alpha_t, C_t\}} \hat{\mathbb{E}}_t\left[\int_0^{T^- - t} -e^{-\rho z - C_{t+z}} dz + e^{-\rho(T^- - t)} J\left(T^-, W_T^-, \theta_T^-, \Delta_T^-\right)\right], \tag{17}$$

$$\text{s.t. } dW_t = \left(W_t r - C_t\right) dt + \alpha_t\left[dP_t + \left(D_t - rP_t\right) dt\right], \tag{18}$$

where $r$ is the exogenous risk-free rate, $C_t$ denotes the consumption, and $\alpha_t$ is the portfolio holdings of the risky asset. According to my timing convention, $J\left(T^-, W_T^-, \theta_T^-, \Delta_T^-\right)$ is the value function at time $T^-$ right before the announcements.

At time $T^-$, however, the portfolio choice problem is different. Because the stock price jumps from $P_T^-$ to $P_T$, wealth jumps from $W_T^-$ to $W_T$ accordingly. The optimization problem of the informed investor at the instant of the announcement is

$$J\left(T^-, W_T^-, \theta_T^-, \Delta_T^-\right) = \max_{\alpha_T^-} \left\{\hat{\mathbb{E}}_{T^-}\left[J\left(0, W_T, \theta_T, 0\right)\right]\right\} \tag{19}$$

$$\text{s.t. } W_T = W_T^- + \alpha_T^-\left(P_T - P_T^-\right).$$

Because $\theta_t$ is a continuous process, it has the same value before and after announcements. The belief difference, $\Delta_t$, is set to 0 upon the announcement because the true value of $x_T$ is revealed so that both investors' beliefs converge.

The uninformed investor's optimization problem takes a similar form, except the state variables are $t$ and $\tilde{\theta}_t$. Denote $\beta_t$ as the uninformed investor's risky asset holdings. In Appendix B.2, I conjecture and prove the form of the uninformed investor's value function $V\left(t, W_t, \tilde{\theta}_t\right)$. The following lemma summarizes the investors' optimal portfolio decisions, which serves as a foundation for analyzing their trading behaviors discussed in Section 4.

**Lemma 2.** *The informed and uninformed investors' optimal risky asset holdings are*

$$\alpha_t = \alpha_\theta(t)\theta_t + \alpha_\Delta(t)\Delta_t, \tag{20}$$

$$\beta_t = \beta_\theta(t)\tilde{\theta}_t, \tag{21}$$

*where $\alpha_\theta(t)$, $\alpha_\Delta(t)$, and $\beta_\theta(t)$ are defined in Appendix B.2, with the boundary values $\alpha_\theta(T^-)$, $\alpha_\Delta(T^-)$, and $\beta_\theta(T^-)$ defined in Appendix B.3.*

**Proof.** See Appendixes B.2 and B.3 for the derivations. □

Note that the market clearing condition requires that the total risky asset demand equals the aggregate supply $\theta_t$, that is,

$$(1-\omega)\alpha_t + \omega\beta_t = \theta_t. \tag{22}$$

The investors' optimality problems, together with the above market clearing condition, jointly pin down the pricing functions $\phi_\theta(t)$, $\phi_x(t)$, and $\phi_\Delta(t)$.

*Overreaction in stock prices — Predictability of announcement returns.* While the predictability of consensus forecast errors is a property of heterogeneous beliefs and does not depend on the detailed functional form of equilibrium prices, the predictability of announcement returns is a unique implication of my model that depends crucially on the time variation in pricing coefficients resulting from periodic announcements. The following proposition provides a sufficient condition for the overreaction of prices.[17]

**Proposition 2.** *Suppose $\phi_\theta(t)$ is monotonically increasing in $t$ on $(0, T)$ and jumps at $T$, then*

$$\tilde{Cov}_t\left(\underbrace{P_{t+\delta} - P_t}_{\textit{revision return}}, \underbrace{P_T - P_T^-}_{\textit{announcement return}}\right) < 0, \tag{23}$$

*for small enough $\delta$ as long as the following condition holds,*

$$\phi_\theta^2(t)\sigma_\theta^2 > \phi_x(t)\tilde{q}(t)\left[\phi_D + \phi_x(t)(a-b) + \phi_x'(t) + \phi_\Delta(t)\frac{\hat{q}(t) + \tilde{q}(t)}{\sigma_D^2}\right], \tag{24}$$

*where $\tilde{Cov}_t$ is defined as the conditional covariance given public information.*

**Proof.** See Appendix B.4 for the proof. □

[17] Proposition 4 in Appendix B.7 presents a simplified two-period model that provides a necessary and sufficient condition for the same result, without relying on any parametric assumptions.

The above proposition implies that the two key features of the $\phi_\theta(t)$ function – the discontinuity at the announcements and the monotonicity between the announcements, as shown in Fig. 3 – jointly explain the negative announcement return predictability. First, consider the monotonicity. The price revision can be written as

$$\begin{aligned} P_{t+\delta} - P_t = {} & \phi_D \left[D_{t+\delta} - D_t\right] + \bar{\phi}_x \left[\tilde{x}_{t+\delta} - \tilde{x}_t\right] - \phi_\theta(t+\delta)\left[\tilde{\theta}_{t+\delta} - \tilde{\theta}_t\right] \\ & - \underbrace{\left[\phi_\theta(t+\delta) - \phi_\theta(t)\right]}_{>0} \tilde{\theta}_t. \end{aligned} \tag{25}$$

The first line of Eq. (25) is the price adjustment resulting from uninformed investors' belief revisions. The second line reflects the adjustment due to the changes in $\phi_\theta(t)$. Since $\phi_\theta(t)$ is increasing over revision periods, $\phi_\theta(t+\delta) - \phi_\theta(t) > 0$. The term $\left[\phi_\theta(t+\delta) - \phi_\theta(t)\right]\tilde{\theta}_t$ can be interpreted as the accumulation of noise in prices as uncertainty builds up over time.

Next, consider the discontinuity. At the announcements, the price adjusts immediately. The "pricing error" realized at the announcement can be written as

$$\begin{aligned} P_T - P_T^- = {} & \bar{\phi}_x \left[x_T - \tilde{x}_T^-\right] - \phi_\theta(T)\left[\theta_T - \tilde{\theta}_T^-\right] \\ & - \underbrace{\left[\phi_\theta(T) - \phi_\theta(T^-)\right]}_{<0} \tilde{\theta}_T^-, \end{aligned} \tag{26}$$

Note that the pricing error can be decomposed into two parts: the first line of (26) is errors of uninformed investors' Bayesian beliefs relative to true states and the second line represents the correction of noise at the announcements. Belief errors of rational uninformed investors cannot be predicted by $P_{t+\delta} - P_t$, which is publicly available information. As a result, the only predictable term is $\left[\phi_\theta(T) - \phi_\theta(T^-)\right]\tilde{\theta}_T^-$. Since uncertainty drops sharply at the announcement time $T$, so does the pricing coefficient, $\phi_\theta(T) - \phi_\theta(T^-) < 0$. Given that $\tilde{\theta}_t$ is a persistent process, the monotonicity and discontinuity of $\phi_\theta(t)$ imply that the last terms in (25) and (26) are negatively correlated, which gives rise to the negative predictability of announcement returns.[18]

In summary, the above-discussed negative predictability relies on two conditions. The first condition is that the noisy supply is persistent, as shown in Eq. (5). The second condition is that the impact of noise on prices, $\phi_\theta(t)$, is increasing in uncertainty. Intuitively, during forecast revision periods, equilibrium prices become increasingly sensitive to the noisy supply as uncertainty about fundamentals accumulates, leading to an overreaction to noise. However, upon announcements, when the true state is revealed and uncertainty is resolved, the market must correct itself to eliminate the accumulated noise.

Note that if $\phi_\theta(t)$ is continuous over time, then the second line of Eq. (26) disappears. In this case, announcement-day pricing errors are unpredictable by past returns. I summarize this observation in the following lemma.

**Lemma 3.** *Suppose $\phi_\theta(t)$ is continuous over time, then*

$$Cov\left(P_{t+\delta} - P_t, P_T - P_T^-\right) = 0. \tag{27}$$

**Proof.** See Appendix B.4 for the proof. □

In standard NREE models, such as Grossman and Stiglitz (1980) and Wang (1993) where pricing coefficients are continuous (and in fact, constant), returns may be predictable over *longer* horizons because dividends or noisy supply are mean-reverting. However, as shown in Lemma 3, pricing errors realized at a high frequency – for examples, in minutes around macroeconomic announcements – are not predictable.

*Overreaction conditional on volatility.* In the data, the negative predictability of announcement-day returns is strongest during periods of high fundamental volatility and becomes insignificant or even positive during periods of low volatility. In this section, I discuss the comparative statics of my model with respect to the fundamental volatility parameter $\sigma_x$. First, as shown in Fig. 4, as $\sigma_x$ monotonically decreases to zero, the negative regression coefficient of return predictability, $\beta_P$ in Eq. (2), also monotonically converges to zero. In my model, return predictability arises due to the presence of asymmetric information. As $\sigma_x$ vanishes, asymmetric information dissipates, and so does return predictability.[19]

Second, I show that when incorporating time-varying volatility, my model can generate a negative return predictability coefficient during high-volatility periods but a positive coefficient during low-volatility periods. When fundamental volatility is high, investors' uncertainty increases rapidly during revision periods. As a result, prices become more sensitive to the noisy supply. Upon the announcement, the reduction in uncertainty is more pronounced, as is the correction of noise, leading to stronger negative predictability of announcement returns. However, when an economy switches from high volatility to low volatility, the accumulated uncertainty starts to reduce over time and results in a lower impact of the noise on prices. The accumulated noise starts to be partially corrected on revision days but gets fully corrected upon announcements, generating a positive predictability of announcement returns.

[18] This mechanism, however, can be complicated by the correlation between $\left[\phi_\theta(T) - \phi_\theta(T^-)\right]\tilde{\theta}_T^-$ in (26) and $\phi_D\left[D_{t+\delta} - D_t\right] + \bar{\phi}_x\left[\tilde{x}_{t+\delta} - \tilde{x}_t\right] - \phi_\theta(t+\delta)\left[\tilde{\theta}_{t+\delta} - \tilde{\theta}_t\right]$ in (25). Assuming a small $\delta$ allows me to provide a simple sufficient condition, inequality (24), under which the effect from the monotonicity of $\phi_\theta(t)$ dominates and revision period returns negatively predict announcement returns. Intuitively, the left-hand side of (24) is the price impact of the noisy supply. Proposition 2 implies that as long as the volatility of the noisy supply is large enough, the impact of the monotonicity of $\phi_\theta(t)$ dominates and inequality (23) holds.

[19] Lemma 11 in Appendix B.7 presents the analytical result for the monotonicity of $\sigma_x$ using a simplified two-period model.

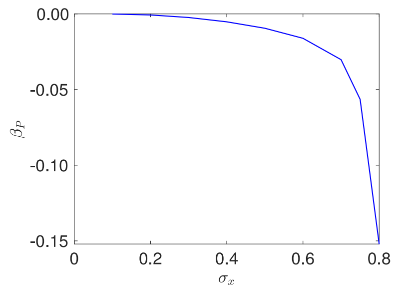


**Fig. 4.** Model-implied announcement return predictability.

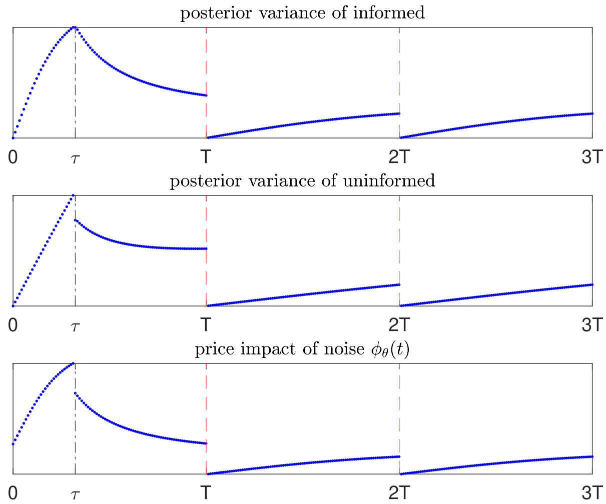


**Fig. 5.** Posterior variances and $\phi_\theta(t)$ over announcement cycles.
This figure plots the model-implied posterior variances of the informed investor $\hat{q}_t$ (top panel) and uninformed investor $\hat{q}_t + \tilde{q}_t$ (middle panel) and the price sensitivity to noise $\phi_\theta(t)$ (bottom panel) over three quarterly announcement cycles. At time $\tau$, there is an unexpectedly negative shock to the fundamental volatility $\sigma_x$.

In Fig. 5, I assume that there is an unexpected reduction in volatility $\sigma_x$ at time $\tau$ and plot the posterior variance about fundamentals $x_t$ for informed investors $\hat{q}_t$ (top panel), that for uninformed investors $\hat{q}_t + \tilde{q}_t$ (middle panel), and the price impact of noise, $\phi_\theta(t)$ (bottom panel), as functions of time. After the previous announcement at time 0, both posterior variances increase quickly until time $\tau$ when the economy suddenly transits into a low-volatility state. As a result, the posterior variances start to decrease. From 0 to $\tau$, $\phi_\theta(t)$ increases as uncertainty builds up but then declines after $\tau$ until the next announcement because of reductions in the accumulated uncertainty. Since $\phi_\theta(t)$ decreases from $\tau$ to $T^-$ but jumps further down from $T^-$ to $T$, returns during the forecast revision period positively predict announcement returns.

Intuitively, if the stock price is already "overheated", as the fundamental volatility drops, it starts to slowly and partially correct itself. At the announcement $T$, the true value of $x_T$ is revealed. The uncertainty drops further to zero, and the stock price fully corrects itself. Therefore, past price corrections over revision periods *positively* predict further corrections upon announcements. This can happen in my model when fundamental volatility is low.[20]

## 4. Quantitative results

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

*Numerical solution.* The equilibrium consists of a set of pricing functions $\{\phi_\theta(t), \phi_x(t), \phi_\Delta(t)\}$, the portfolio demand functions $\{\alpha_\theta(t), \alpha_\Delta(t), \beta_\theta(t)\}$, and the value functions of informed and uninformed investors. These functions must be jointly determined by the optimality and market clearing conditions. In Appendixes B.2 and B.3, I show that these conditions boil down to a system

[20] Incorporating time-varying volatility into the dynamic model would introduce an additional state variable and increase the complexity of the model solutions, without fundamentally changing the underlying intuition. Therefore, I leave this extension to future research.

**Table 3**
Parameters.

| Para. | Value | Description | Para. | Value | Description |
|---|---|---|---|---|---|
| $r$ | 0.03 | risk-free rate | $a$ | 0.007 | persistence of total equity supply |
| $\rho$ | 0.01 | time discount factor | $\sigma_D$ | 1.4 | level of dividend flow volatility |
| $\bar{x}$ | 9 | mean level of dividend flow | $\sigma_s$ | 0.4 | inverse of signal precision |
| $b$ | 0.14 | persistence of fundamental state | $\sigma_x$ | 0.8 | volatility of fundamental state |
| $\omega$ | 0.35 | fraction of uninformed investor | $\sigma_\theta$ | 0.58 | volatility of total equity supply |

This table displays annualized parameter values used in the simulations. The model is simulated at a daily frequency, and announcements are made at the end of each quarter.

of ODEs subject to boundary conditions at the announcements. I describe a recursive method that simultaneously solves the system of ODEs that characterize the equilibrium. Using these solutions, I simulate my model, compute relevant moments to calibrate my model, and replicate the regressions I conducted using the actual data. The numerical method is discussed in detail in Appendix B.8.

*Estimates.* Table 3 contains calibrated and estimated benchmark parameter values. All parameters are calibrated at an annual frequency, with $T = 1/4$ indicating quarterly announcements. First, I set the time preference parameter to $\rho = 0.01$. I choose the steady-state level of dividend, $\bar{x} = 9$, so that the implied relative risk aversion of both groups of investors is about 9 in the steady state. I set $\omega = 0.35$ so that 35% of the investors are uninformed and the rest are informed. This measure aims to approximately match the proportion of retail and institutional investors in the U.S.[21] Second, several parameters are calibrated to match outside data. The annual risk-free interest rate $r = 3\%$, the volatility of the fundamental state $\sigma_x = 0.8$, and the dividend persistence $b = 0.14$ are set to match the mean, volatility, and autocorrelation of the log price-to-dividend ratio, respectively.[22] The model produces an annualized mean of 3.46, a volatility of 0.46 and a first-order autocorrelation of 0.96 for the log price-to-dividend ratio, compared to 3.37, 0.43 and 0.94 in the data. The price-to-dividend ratio and dividend growth data are formulated from CRSP value-weighted NYSE/Amex/NASDAQ annual and monthly returns for the period 1926–2019.

I choose $\sigma_D = 1.4$ to match the volatility of the annual dividend growth rate, which is 10.34% from the model and 10.85% from the data. The volatility of total equity supply $\sigma_\theta = 0.58$ is chosen to match the annualized monthly realized return volatility from the CRSP value-weighted index. The model gives annual return volatility of 15.73%, which is close to 18.48% in the data. To capture the impact of time-varying uncertainty, I first calibrate the persistence of equity supply $a = 0.007$ to match the first-order autocorrelation of the daily option-implied variance VIX$^2$ from CBOE. The model produces an autocorrelation of 0.93 with the data counterpart of 0.97. Then I set the inverse of informed investors' signal precision $\sigma_s = 0.4$ to match the cumulative implied variance reduction on both GDP and unemployment announcement days each quarter for the period 1990–2019. The implied variance reduction is the difference between VIX$^2$ before and after announcement days, which measures the uncertainty reduction upon the announcements. In the data, the cumulative implied variance reduction is 1.97 (monthly percentage squared) and is significantly positive with a Newey–West $t$-statistic of 2.47. The mean implied variance reduction in the model is 2.48 in monthly percentage squared unit, close to the data. I provide details of the calculation of model-implied variance in Appendix B.6.

*Quantitative results.* I first construct the consensus forecast revision and consensus forecast error from the model. Note that announcements are made periodically at $nT$, where $n$ is an integer and $T = 1/4$ indicates quarterly announcements. For any announcement scheduled at $(n+1)T$, I assume that the first forecast is made right after the previous announcement at $nT$ and a revision of the forecast is made at $nT + \delta$, and I set $\delta = T/2$ so that revisions are made in the middle of two consecutive announcements, as in the actual data. Let $x$ be the forecast variable announced at time $(n+1)T$, the consensus forecast revision made at time $nT+\delta$ is defined as $Frev_{nT+\delta}(x) = \bar{\mathbb{E}}_{nT+\delta}(x) - \bar{\mathbb{E}}_{nT}(x)$, where $\bar{\mathbb{E}}_t[x] = (1-\omega)\hat{\mathbb{E}}_t[x] + \omega\tilde{\mathbb{E}}_t[x]$ is the weighted average forecast of informed and uninformed investors, and $\hat{\mathbb{E}}_t[x]$ and $\tilde{\mathbb{E}}_t[x]$ are shown in (B.49) and (B.48) in Appendix B.4. Similarly, the consensus forecast error of $x$ is defined as $Ferr_{(n+1)T}(x) = x - \bar{\mathbb{E}}_{nT+\delta}(x)$. My definitions of the consensus forecast revision and error are therefore identical to those in the empirical exercise I presented in Section 2.

As in the data, I define the returns during forecast revision periods as $Rrev_{nT+\delta} = \frac{P_{nT+\delta} - P_{nT}}{P_{nT}}$ and the high-frequency announcement-day return as $Rerr_{(n+1)T} = \frac{P_{(n+1)T} - P^-_{(n+1)T}}{P^-_{(n+1)T}}$, which are given in Eqs. (25) and (26). I regress the consensus forecast errors on consensus forecast revisions and regress announcement-day returns on returns during the revision periods, as specified in Eqs. (1) and (2) using the model-simulated data.

In the model, consensus forecast revisions positively predict their errors with a slope coefficient of $\beta_F = 0.46$, close to its empirical counterpart. As I explained in Section 3, the consensus forecast appears to underreact to new information because uninformed investors underreact to the private information perceived by informed investors.

[21] According to Federal Reserve's Financial Accounts of the United States, households own 35% of the total financial assets in 2019.

[22] In the model, the stationary price-to-dividend ratio can be directly calculated as follows: $\frac{\bar{P}}{\bar{D}} = \frac{\phi + (\phi_D + \bar{\phi}_x)\bar{x}}{\bar{x}} = \frac{1}{r}$, which is uniquely determined by the risk-free rate.

**Table 4**
Model implied forecast error predictability.

| | *Panel A. Data* | | | *Panel B. Model* | | | *Panel C. AMS/CG* | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) |
| $\beta_F$ | 0.32 | 0.56 | 0.00 | 0.46 | 0.93 | 0.00 | 0.82 | 0.91 | 0.89 |

This table reports forecast error predictability based on empirical data and model simulations. Column (1) presents the coefficient of consensus forecast revision predicting consensus forecast error, Column (2) shows the regression coefficient for predicting the uninformed group's forecast error using the informed group's forecast revision, and Column (3) provides the coefficient for predicting the informed group's forecast error using the uninformed group's forecast revision. Panel A uses empirical data from Table 1 with coefficients averaged for both GDP and UE. Panel B presents the moments implied by the model, while Panel C shows the same moments derived from a simulated model following AMS/CG, where forecasts from two independent informed investors are used to represent AMS/CG for ease of comparison.

The model-implied regression coefficient for returns is $\beta_P = -0.15$, indicating that returns over forecast revision periods negatively predict returns upon high-frequency announcements, consistent with the data counterpart of –0.16.[23] Economically, a model-implied one standard deviation increase in revision period returns is associated with a 15 bps reduction in returns on announcement days. In the model, prices overreact to new information due to the accumulated impact of the noisy supply, which gets corrected upon announcements, as illustrated in Section 3.2.

*Implications for asymmetric information.* In this section, I demonstrate that my model can quantitatively account for empirical facts related to asymmetric information, while other heterogeneous information models cannot. In particular, differential information models like Allen et al. (2006) (AMS), He and Wang (1995), and CG assume that investors receive independent signals, implying that one agent's revision must predict the other agent's error and vice versa. In Table 4, I compare the data (Panel A) with two simulated models: my model (Panel B) and a simulated model following AMS/CG assumptions (Panel C). Column (1) represents the coefficient of consensus forecast revision predicting consensus forecast error. Column (2) shows the coefficient of informed forecast revision predicting uninformed forecast error. Column (3) indicates the uninformed revision predicting informed error. These correspond to Eqs. (16), (14), and (15) in Proposition 1, respectively.

From Table 4, my model's implied moments closely match the data, particularly the absence of correlation between uninformed investors' forecast revision and informed investors' forecast error, as shown in column (3) of Panel B.[24] In contrast, AMS/CG can explain the underreaction in consensus forecast but cannot account for the information asymmetry. Specifically, columns (2) and (3) of Panel C are symmetric as one agent must underreact to the other's private information, which contradicts the data.

*Implications for trading volume.* The NREE model has implications not only for prices but also for trading dynamics around announcements. Empirical evidence shows that trading volume spikes sharply at the time of announcements, followed by a rapid decline afterward. This pattern in the data further supports the unique implications of my model. First, without heterogeneity, there will not be any trading. Second, trading volume only spikes at the time of announcements, as shown in Section 2. This evidence distinguishes my model from the differential information models such as He and Wang (1995) and Banerjee et al. (2009), where trading volume increases in the periods leading up to announcements due to a rise in disagreement-induced speculative trading incentives or a finite horizon setup.

The difficulty in defining trading volume in the continuous-time setup is that the optimal portfolio holdings of informed and uninformed investors are diffusion processes of infinite variations (see Eqs. (20) and (21)). However, their quadratic variations are finite and well-defined. This allows me to define the following notion of quadratic trading volume and compare the model with the data. Between announcements, the portfolio holding of an uninformed investor, $\beta_t$, follows a diffusion process of the form $d\beta_t = -a\beta_\theta(t)\,\tilde{\theta}_t dt + \chi_\beta(t)\, d\tilde{B}_t$, where $\tilde{B}_{D,t} = \left[\tilde{B}_{D,t}, \tilde{B}_{\xi,t}\right]$ is a vector of Brownian motions relative to uninformed investors' information set. I define the quadratic trading volume of the uninformed investor during an interval $[t, t+\tau]$ as

$$\tilde{M}(t, t+\tau) = \lim_{n\to\infty} \sum_{j=0}^{n-1} \left(\beta_{t+\frac{j+1}{n}\tau} - \beta_{t+\frac{j}{n}\tau}\right)^2 = \int_t^{t+\tau} \left[\chi_\beta(u)\right]^2 du + \sum_{nT\in(t,t+\tau)} \left[\beta_\theta(0)\,\theta_{nT} - \beta_\theta(T^-)\,\tilde{\theta}_{nT}^-\right]^2 . \tag{28}$$

The first equality is the definition of the quadratic variation of $\beta_t$, computed over a finite partition of $[t, t+\tau]$. This quantity can be constructed from high-frequency trading data. The second equality represents its continuous-time limit. The first term is the quadratic variation of the diffusion part of $\beta_t$. Since $\beta_t$ also jumps at announcement times $nT$, the second term captures the jump variation of $\beta_t$ at announcements. The trading volume for informed investors can be computed similarly. The details are described in Appendix B.5.

To evaluate the model's implications for trading volume changes around announcements, I calculate the average quadratic trading volume changes one day before and one day after the announcement, both in the data and in the model. In the data,

[23] The coefficient is obtained by regressing the cumulative returns of both GDP and unemployment announcement days on revision period returns. The coefficients are very similar, with values of –0.158 ($t$ = –2.28) and –0.156 ($t$ = –3.02) for the SPF and CE data, respectively.

[24] The model-implied correlation between informed investors' forecast revisions and uninformed investors' forecast errors is higher (0.93) than in the data (0.56) because $\omega$ is calibrated to match the fraction of institutional versus retail investors, unlike the professional forecasters in the survey data. Professional forecasters are more informed than retail investors, reducing information asymmetry in the data. In contrast, institutional investors are perceived to have greater private information, leading to higher asymmetry and a larger coefficient in the model.

this involves three steps. First, I compute the quadratic trading volume by summing the square of each minute's turnover rate over one day, where the turnover rate is defined as the total shares traded divided by the total shares outstanding. Second, I compute the cumulative quadratic volume for both GDP and unemployment on the announcement day in each quarter as $M(T^-, T)$, the day before both announcements as $M\left(T - \frac{1}{360}, T^-\right)$, and the day after both announcements as $M\left(T, T + \frac{1}{360}\right)$. Finally, I calculate the average percentage increase from the day before the announcement to the announcement day, given by $\frac{M(T^-,T)}{M\left(T-\frac{1}{360},T^-\right)} - 1$, and the average percentage decline from the announcement day to the day after, represented by $\frac{M(T^-,T)}{M\left(T,T+\frac{1}{360}\right)} - 1$. In the data, these changes are 0.75 and 0.43, both statistically significant with Newey–West $t$-statistics of 3.32 and 3.75, respectively. The model's point estimates are 0.31 and 0.36, which are fairly close to the corresponding moments in the data.

## 5. Conclusion

In this paper, I develop a noisy rational expectations model to simultaneously account for the positive predictability of consensus forecast errors and the negative predictability of pricing errors realized upon announcements. The predictability of announcement-day returns is more pronounced in periods of high economic volatility but becomes positive in low volatility periods. I emphasize that deviating from the representative agent framework, rather than challenging rational expectations itself, can reconcile these findings.

The key new ingredients in my model are periodic announcements and time-varying uncertainty. Under asymmetric information, informed investors' forecast revisions positively predict uninformed investors' forecast errors due to their superior information. However, the reverse relationship is not observed, consistent with empirical evidence. Consequently, the consensus belief underreacts to the private information of informed investors. The impact of the noisy supply on prices accumulates during revision periods when uncertainty increases but gets eliminated when uncertainty drops, either upon announcements or during low volatility periods. As a result, prices can either overreact or underreact to information, depending on the dynamics of time-varying uncertainty. A calibrated model can quantitatively reproduces key empirical findings, including the predictability of consensus forecast errors and announcement-day returns, the observed information asymmetry, and the trading volume around announcements.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jmoneco.2025.103751.

## Data availability

Data will be made available on request.

Codes for Model (Original data) (Mendeley Data)

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