## Appendix A: Empirical Specifications

### *A.1. Timeline, Data and Measurements*

*Timeline.* Table A.1 below illustrates the timing of professional forecasts, announcements, and the associated stock prices.

Table A.1: Timeline

| Time | $t-1$ | $t$ | $t+1$ |
|---|---|---|---|
| Consensus forecast | $\bar{\mathbb{E}}_{t-1}(x_{t+1})$ | $\bar{\mathbb{E}}_t(x_{t+1})$ | $x_{t+1}$ |
| Stock price | $P_{t-1}$ | $P_t$ | $P^-_{t+1}$: 15 min before announcement |
| | | | $P_{t+1}$: 15 min after announcement |

This table shows the timing of professional forecasts, announcements, and the associated stock prices, where $t$ denotes one quarter. $\bar{\mathbb{E}}_t(x)$ is the consensus forecast of any variable $x$ made at time $t$, calculated as the cross-sectional average of all forecasts. $P_t$ denotes the stock price on the forecast revision day $t$. At $t+1$ (approximately one quarter later), the true value of $x$ is revealed through an announcement, during which forecast errors are revealed, and the stock price responds immediately from $P^-_{t+1}$ to $P_{t+1}$. The consensus forecast revision is defined as $Frev_t(x_{t+1}) = \bar{\mathbb{E}}_t(x_{t+1}) - \bar{\mathbb{E}}_{t-1}(x_{t+1})$, which is the difference between the average forecast of $x$ submitted in the current quarter $t$ and that of the previous quarter $t-1$. The consensus forecast error is defined as the difference between the realized value and its most recent consensus forecast: $Ferr_{t+1}(x_{t+1}) = x_{t+1} - \bar{\mathbb{E}}_t(x_{t+1})$. 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 announcement-day return, with the price change from $P^-_{t+1}$ (15 minutes before the announcement) to $P_{t+1}$(15 minutes after the announcement).

*Macroeconomic Forecasts.* I use historical survey data from the Survey of Professional Forecasters (SPF) (1968–2019) and Consensus Economics (CE) forecasts for the United States (1990–2019). The SPF and CE collect professional quarterly forecasts of macroeconomic variables — for example, GDP and unemployment — whereby panelists are asked to provide quarter-by-quarter forecasts over five horizons. The realizations of these macroeconomic variables are eventually announced by government agencies. For example, GDP is published by the Bureau of Economic Analysis (BEA), and the unemployment rate is announced by the Bureau of Labor Statistics (BLS).

I focus on forecasts of real GDP growth rate and the unemployment rate.[1] The SPF is a quarterly survey that includes approximately 40 professional forecasters each quarter,

[1] CG show that the predictability of consensus forecast errors applies to both datasets and various macro variables, including inflation rates and real consumption expenditures. My focus is on GDP, as it is released simultaneously with inflation rates (GDP/GNP deflator) and disposable personal income by the BEA. Similarly, non-farm payrolls and unemployment rates, which have longer survey periods, are announced together by the BLS. I do not include CPI announcements because the stock market's reaction to CPI is unclear; how the market perceives inflation as good or bad news is ambiguous.

beginning in 1968Q4. The data are reported at both the individual level and the consensus level, computed as the cross-sectional mean from the individual-level forecasts at a point in time. Since 1990Q2, the survey has been conducted in the second month of the quarter, and the deadline for submitting forecasts is around the middle of the survey month. The detailed deadline dates can be found at "Deadline and Release Dates for the Survey of Professional Forecasters," in "Dates of Previous Surveys." Similarly, CE conducts a survey of "Quarterly Consensus Forecasts" for many countries including the United States since 1989Q4. However, the survey submission dates are different from SPF — typically the second week of March, June, September, and December. The dates when survey responses are expected can be found at "Publication Schedules."

I assume the survey submission deadline is the date most panelists submit their forecasts for the following reasons. A special report of SPF conducted by the Philadelphia Fed (see page 15 of Stark (2010)) shows that a large number of survey responses arrive on the day of the deadline. CE panelists are contacted 2-3 business days before the "Survey Date" asking to receive their forecasts on the "Survey Date." Additionally, SPF surveys are published about a week after the deadline, and CE, two days later. Given my model's implication that price overreactions stem from asymmetric information, the most accurate measure of private information integration into prices is the forecast submission dates, when the information is available but not yet public.

*Macroeconomic Announcements.* I collect announcement dates for GDP from BEA's website and unemployment rate from the BLS. GDP announcements are made monthly, so each quarter contains three announcements: advance (first), second, and third estimate. I focus on the advance estimates for three reasons. First, the advance estimates are believed to reveal the most information, thus resolving most of the uncertainty. Second, the subsequent revisions may not reflect the initial reactions to the surprises in GDP growth rate announcements. Third, Gilbert (2011) shows that only the advance release has a significant impact on asset prices, whereas the final release has almost no price impact. While the monthly unemployment situation is released in the following month, quarterly realizations are released around January, April, July, and October, about one month after each quarter.

*Stock Market Returns.* First, I use realized close-to-close returns of the SPDR S&P 500 ETF (SPY) on adjacent survey submission days to measure the cumulative returns over the time that panelists revise their beliefs (i.e., $Rrev_t(x)$). This is because information arrives continuously, and beliefs are accordingly being continuously revised. I assume that revisions start right after the last survey submission day until the current submission day, so forecast revisions should reflect the cumulative revisions in response to newly obtained information between two adjacent forecast quarters. Therefore, the cumulative returns over the forecast revision periods reflect the stock market reactions to forecast revisions.

Second, I use returns on SPY over the 30-minute interval, 8:15 a.m. to 8:45 a.m. to measure the announcement-day returns, because GDP and the employment situation are all released at 8:30 a.m. before the stock market opens.[2] The high-frequency SPY is from the CRSP Millisecond Trade and Quote (TAQ) dataset, dating back to 2003Q3.[3] The high-frequency returns are chosen for accurate identification of announcement news content. Return predictability remains robust when using overnight returns but weakens with daily returns due to contamination with other information.

Table A.2 summarizes the data used in the empirical analysis. Note that the announcement returns earned in the 30-minute window are 1.2 and 3.6 bps for GDP and unemployment, respectively, and both are insignificantly different from zero. Additionally, one can see that professional forecasters do not have significant forecasting biases.[4]

[2] See Lou et al. (2019) and Hendershott et al. (2020) for how returns behave differently between daytime and overnight.

[3] I follow the standard procedure to clean TAQ data. Specifically, I drop negative prices, records where "TR_CORR" is zero, and trades with abnormal trading conditions ("TR_SCOND" = A, B, N, R, Z). I use the first price in each minute and sum the trading volume within each minute to calculate the minute-by-minute trading volume.

[4] Stark (2010) analyzes the accuracy of forecasts and finds that the SPF forecasts outperform benchmark projections from univariate autoregressive time-series models at short horizons. The special survey of analyzing the panelists' forecasting methods shows that "20 of 25 respondents said they use a combination of mathematical/computer models *plus* subjective adjustments to that model in reporting their projections."

Table A.2: Summary Statistics

| Variable | Mean | s.d. | Obs. | Variable | Mean | s.d. | Obs. |
|---|---|---|---|---|---|---|---|
| *Panel A: Returns on forecast revision periods* | | | | | | | |
| SPF | | | | CE | | | |
| $Rrev_t$ (%) | 1.739 | 7.080 | 58 | $Rrev_t$ (%) | 2.194 | 8.472 | 64 |
| *Panel B: Announcement-day returns, forecast revisions and forecast errors* | | | | | | | |
| Variable | Mean | s.d. | Obs. | Variable | Mean | s.d. | Obs. |
| GDP | | | | UE | | | |
| $Rerr_{t+1}$ (%) | 0.012 | 0.265 | 66 | $Rerr_{t+1}$ (%) | 0.036 | 0.453 | 62 |
| $Frev_t$ | –0.277 | 1.210 | 204 | $Frev_t$ | –0.014 | 0.269 | 204 |
| $Ferr_{t+1}$ | 0.091 | 1.797 | 204 | $Ferr_{t+1}$ | –0.043 | 0.155 | 205 |

This table reports summary statistics for the main variables used in the empirical tests. Panel A reports $Rrev_t$ (revision period returns) from SPF and CE surveys. Panel B displays the summary statistics for the real GDP growth rate and unemployment rate (UE). $Rerr_{t+1}$ is the announcement-day return, $Frev_t$ is the consensus forecast revision, and $Ferr_{t+1}$ is the consensus forecast error. All returns exclude observations on non-trading days. The data spans from 2003Q3 to 2019Q4 for returns and from 1968Q4 to 2019Q4 for forecasts.

*Earnings Forecasts and Earnings Announcements.* Earnings announcement data are sourced from I/B/E/S, which includes analyst forecasts of earnings per share (EPS) for individual firms. I collect both the mean forecasts for each firm in each quarter and the analyst-level forecasts, along with the realized EPS. Given that each analyst may submit multiple forecasts for the same quarter's EPS, I collect all forecast submission dates for each analyst, as well as the earnings announcement dates. Additionally, firm-level returns data are obtained from CRSP daily returns. The sample period extends from 1980 to 2019.

*Correlation between Revision Period Returns and Forecast Revisions.* Here, I show that the stock market is correlated with revisions in macroeconomic forecasts. I regress revision period returns $Rrev_t$ on consensus forecast revision $Frev_t$ directly. As shown in Table A.3, the contemporaneous correlation between the consensus forecast revision and stock market returns during revision periods is positive and statistically significant for GDP. For example, a one standard deviation positive forecast revision about GDP is associated with a 4.2% increase in revision period returns. When forecasters in the survey receive favorable news about GDP during forecast revision periods and revise their beliefs upward, the stock market moves in the same direction. This indicates that the forecasters in the survey are a good representative measure of investors who trade in the stock market, as their beliefs are reflected in the returns. Similarly, this contemporaneous relationship about unemployment is negative. Because a positive increase in the unemployment rate is treated as bad news for investors, an upward revision in the unemployment forecast must be associated with a drop in the stock market.

Table A.3: Correlation between Revision Period Returns and Forecast Revisions

| | *CE* | | *SPF* | |
|---|---|---|---|---|
| | GDP | UE | GDP | UE |
| $\beta$ | 4.20 | –1.97 | 4.54 | –3.26 |
| | (1.90) | (–1.62) | (2.75) | (–3.60) |
| $R^2$ | 0.15 | 0.04 | 0.25 | 0.16 |

This table reports the results for the regression $Rrev_t = \alpha + \beta Frev_t + \varepsilon_t$ for GDP and the unemployment rate (UE) using data from CE and SPF, respectively. I normalize the right-hand-side variables by the mean and standard deviation. Returns are in percentages. The data include the period 2003–2019. Newey-West $t$-statistics (with 10 lags) are in parentheses.

### *A.2. Underreaction in Consensus Forecasts for EPS*

To demonstrate the robustness of underreaction in consensus forecasts with respect to earnings forecasts, in this section, I examine the predictability of consensus forecasts for EPS at the firm level. I estimate the CG coefficient in a panel regression for EPS:

$$Ferr_{i,t+1}\left(x_{i,t+1}\right) = \alpha_i + \beta_F Frev_{i,t}\left(x_{i,t+1}\right) + \gamma_t + \varepsilon_{i,t+1}, \tag{A.1}$$

where $\alpha_i$ is the firm fixed effect and $\gamma_t$ is the quarter fixed effect. For each firm $i$, the consensus forecast revision, $Frev_{i,t}\left(x_{i,t+1}\right)$, is defined as the difference between the most recent and the initial consensus forecast of EPS for the current quarter $t$. At $t+1$, the actual firm-level EPS, $x_{i,t+t}$, is disclosed through the earnings announcement. Thus, the consensus forecast error for firm $i$, $Ferr_{i,t+1}\left(x_{i,t+1}\right)$, is defined as the difference between the realized EPS and its most recent consensus forecast. I exclude firms with only one estimate in the current quarter, as this eliminates cases without revisions, as well as firms with more than six estimates.

Column (1) in Table A.4 shows the results. The CG coefficient is significantly positive of 0.38 at the firm level, indicating that the consensus forecast underreacts to information for EPS. This exercise more precisely captures the formation of expectations because, unlike the SPF and CE data, there is no announcement during the forecast revision period, ensuring that the information remains uncontaminated by prior announcements. The results remain robust when including only firms with three and four monthly consensus estimates during the revision periods, as shown in columns (2) and (3), respectively, to ensure that forecast revisions are contained within a single quarter.

Table A.4: Consensus Forecast Error Predictability for EPS

| | (1) | (2) | (3) |
|---|---|---|---|
| $\beta_F$ | 0.41 | 0.45 | 0.47 |
| | (11.14) | (9.44) | (6.55) |
| Firm Quarter FE | Y | Y | Y |
| Firm clustering | Y | Y | Y |
| Obs. | 489,881 | 333,137 | 61,657 |
| $R^2$ | 0.175 | 0.178 | 0.299 |

This table presents the CG coefficient from the following panel regression: $Ferr_{i,t+1}(x_{i,t+1}) = \alpha_i + \beta_F Frev_{i,t}(x_{i,t+1}) + \gamma_t + \varepsilon_{i,t+1}$. For each firm $i$, the consensus forecast revision, $Frev_{i,t}(x_{i,t+1})$, is defined as the difference between the most recent and the initial consensus forecast of EPS for the current quarter $t$. At $t+1$, the actual EPS, $x_{i,t+1}$, is disclosed through the earnings announcement. The consensus forecast error for firm $i$ is therefore defined as the difference between the realized EPS and its most recent consensus forecast. Column (1) analyzes all data, while column (2) includes forecast revisions spanning 3 quarters and column (3) covers revisions spanning 4 quarters. All regressions include quarter and firm fixed effects, with standard errors clustered at the firm level and $t$-statistics in parentheses. All observations are winsorized at the top and bottom 1%. The data is from I/B/E/S and spans from 1980 to 2019.

### *A.3. Heterogeneity in Cross-Sectional Forecasts*

In this section, I provide details on Stylized Fact 2: heterogeneity in cross-sectional forecasts. The analysis proceeds in two steps. First, I construct a measure of information precision for individual panelists. Using this measure, I classify the top one-third of forecasters with the highest information precision as informed investors and the bottom one-third with the lowest information precision as uninformed investors. Second, I regress the forecast errors of each group on the forecast revisions of the other group to demonstrate the implication of Proposition 1: the forecast revision of the informed group positively predicts the forecast error of the uninformed group, while the forecast revision of the uninformed group does not predict the forecast error of the informed group.

To construct a measure of information precision for a panelist, I first develop a measure of forecast accuracy for each forecast made by the panelist. Information precision is then defined as the average forecast accuracy across all historical forecasts made by the panelist.

*A.3.1. Measurement of Forecast Accuracy*

I follow Harford et al. (2019) to construct a measure of forecast accuracy for each forecast by a panelist. My main measure of forecast accuracy, Scaled Mean-Adjusted Absolute Forecast Error ($smerr$), is constructed in three steps:

1. Absolute Forecast Error ($err$): The absolute forecast error for panelist $j$ in quarter $t$ is defined as the absolute value of their forecast error: $err_{j,t} = |Ferr_{j,t+1}| = |x_{t+1} - \mathbb{E}_{j,t}(x_{t+1})|$, where $x_{t+1}$ is the macroeconomic variable being forecasted in quarter $t$ (but announced in quarter $t+1$), and $\mathbb{E}_{j,t}(x_{t+1})$ is the forecast made by panelist $j$ in quarter $t$.[5]
2. Mean-Adjusted Absolute Forecast Error ($merr$): For panelist $j$ in quarter $t$, this is calculated by subtracting the mean absolute forecast error of all panelists in that quarter from the absolute forecast error of panelist $j$: $merr_{j,t} = |Ferr_{j,t+1}| - \frac{1}{J}\sum_{j=1}^{J}|Ferr_{j,t+1}|$, where $J$ is the total number of panelists in quarter $t$.
3. Scaled Mean-Adjusted Absolute Forecast Error ($smerr$): This is calculated by scaling the mean-adjusted absolute forecast error for panelist $j$ in quarter $t$ by the mean absolute forecast error for all panelists in that quarter: $smerr_{j,t} = \frac{|Ferr_{j,t+1}| - \frac{1}{J}\sum_{j=1}^{J}|Ferr_{j,t+1}|}{\frac{1}{J}\sum_{j=1}^{J}|Ferr_{j,t+1}|}$.

The key mechanism for forecast error predictability in my model is that informed investors' forecasts are more accurate than those of uninformed investors. Although I do not directly observe the forecasters' information sets in the data, I can infer their information precision by examining their historical forecast accuracy.

To avoid biasing my results due to a particular realization of a forecast, I use the average forecast accuracy, measured by $smerr_{j,t}$, across all forecasts made by a panelist as a measure of information precision. The effectiveness of this measure depends on the persistence of information precision as a characteristic of the panelist. When information precision is permanent or highly persistent, averaging historical forecast accuracy is an effective method for

[5] Note that the definition of $Ferr_{j,t+1}$ is the same as in equation (1) in the main text.

identifying panelist type. However, if information precision is transitory, averaging historical forecast accuracy provides little additional information about the panelist type.

### *A.3.2. Persistence of Forecast Accuracy*

To validate the average historical forecast accuracy as a measure of information precision, I first demonstrate that panelists' forecast accuracy is predictable over long horizons, up to twenty quarters. This predictability confirms the persistence of information precision and indicates that historical forecast accuracy can effectively identify an individual's information precision. To do this, I regress each of the three measures of forecast accuracy on its lagged value. For instance, for the absolute forecast error, I conduct the following predictability regression:

$$err_{j,t} = \alpha_j + \beta_h err_{j,t-h} + \gamma_t + \varepsilon_{j,t}, \tag{A.2}$$

where $h$ denotes the horizon for lags. Table A.5 displays the results for $\beta_h$ across all three measures for $h$ up to twenty quarters. The forecast accuracy is shown to be predictable over horizons as long as five years ahead. Having established the persistence of forecast accuracy, I will use the historical average of scaled mean-adjusted absolute forecast error ($smerr_{j,t}$) as a measure of information precision to classify forecasters into informed and uninformed groups. This classification will be used to test the key implications of Proposition 1.

### *A.3.3. Evidence for Asymmetric Information*

Every quarter, I calculate the rolling average of forecast accuracy (measured as the scaled mean-adjusted absolute forecast error) up to the previous quarter $t-1$ as a measure of information precision. Panelists are then sorted into three groups (terciles) based on this measurement: the informed group, whose rolling average *smerr* is in the bottom third, and the uninformed group, whose rolling average *smerr* is in the top third. I denote the informed group's average forecast revision and error as $\hat{\mathbb{E}}_t\left(x_{t+1}\right) - \hat{\mathbb{E}}_{t-1}\left(x_{t+1}\right)$ and $x_{t+1} - \hat{\mathbb{E}}_t\left(x_{t+1}\right)$, and the uninformed group's average forecast revision and error as $\tilde{\mathbb{E}}_t\left(x_{t+1}\right) - \tilde{\mathbb{E}}_{t-1}\left(x_{t+1}\right)$ and $x_{t+1} - \tilde{\mathbb{E}}_t\left(x_{t+1}\right)$. Based on this classification, I test the CG regression (1) across different groups. Specifically, I first regress the forecast error of the uninformed group on the forecast

Table A.5: Forecast Accuracy Predictability

| | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\beta_8$ | $\beta_{12}$ | $\beta_{16}$ | $\beta_{20}$ |
|---|---|---|---|---|---|---|---|---|
| *Panel A: GDP* | | | | | | | | |
| *err* | 0.103 | 0.089 | 0.097 | 0.138 | 0.097 | 0.099 | 0.126 | 0.045 |
| | (3.54) | (3.14) | (2.46) | (5.77) | (2.99) | (4.81) | (3.64) | (2.17) |
| *merr* | 0.103 | 0.089 | 0.097 | 0.138 | 0.097 | 0.099 | 0.126 | 0.045 |
| | (3.54) | (3.14) | (2.46) | (5.77) | (2.99) | (4.81) | (3.64) | (2.17) |
| *smerr* | 0.144 | 0.105 | 0.133 | 0.144 | 0.071 | 0.088 | 0.096 | 0.068 |
| | (5.25) | (4.67) | (4.20) | (5.15) | (4.10) | (4.34) | (3.87) | (4.06) |
| *Panel B: UE* | | | | | | | | |
| *err* | 0.126 | 0.119 | 0.113 | 0.109 | 0.072 | 0.078 | 0.030 | 0.035 |
| | (4.24) | (4.43) | (5.08) | (5.47) | (3.06) | (3.80) | (1.57) | (1.64) |
| *merr* | 0.126 | 0.119 | 0.113 | 0.109 | 0.072 | 0.078 | 0.030 | 0.035 |
| | (4.24) | (4.43) | (5.08) | (5.47) | (3.06) | (3.80) | (1.57) | (1.64) |
| *smerr* | 0.128 | 0.139 | 0.100 | 0.104 | 0.069 | 0.067 | 0.046 | 0.026 |
| | (5.57) | (7.43) | (5.25) | (6.46) | (2.98) | (5.30) | (2.08) | (0.96) |

This table shows forecast accuracy predictability across various horizons, from one quarter lagged to five years, with Panel A focusing on GDP and Panel B on UE. The coefficients are obtained by regressing the current quarter's individual-level forecast accuracy on their lagged values, where $\beta_h$ denotes the coefficient for $h$ lags (e.g., $\beta_4$ represents a lag of four quarters, or one year). The forecast accuracy is measured in three ways: *err* is the absolute forecast error for panelist $j$ in quarter $t$; *merr* is the mean-adjusted absolute forecast error, calculated as *err* minus the mean absolute forecast error for all panelists in the same quarter; and *smerr* is the scaled mean-adjusted absolute forecast error, calculated by scaling *merr* by the mean absolute forecast error in quarter $t$. All regressions incorporate quarter fixed effects. Standard errors are two-way clustered by analyst and quarter, with $t$-statistics reported in parentheses. The data is from SPF and spans from 1968Q1 to 2019Q4.

revision of the informed group. Then, I regress the forecast error of the informed group on the forecast revision of the uninformed group, while controlling for the respective group's own revision:

$$x_{t+1} - \tilde{\mathbb{E}}_t(x_{t+1}) = \beta_F \left( \hat{\mathbb{E}}_t(x_{t+1}) - \hat{\mathbb{E}}_{t-1}(x_{t+1}) \right) + \beta_C \left( \tilde{\mathbb{E}}_t(x_{t+1}) - \tilde{\mathbb{E}}_{t-1}(x_{t+1}) \right) + \varepsilon_{t+1}, \tag{A.3}$$

$$x_{t+1} - \hat{\mathbb{E}}_t(x_{t+1}) = \beta_F \left( \tilde{\mathbb{E}}_t(x_{t+1}) - \tilde{\mathbb{E}}_{t-1}(x_{t+1}) \right) + \beta_C \left( \hat{\mathbb{E}}_t(x_{t+1}) - \hat{\mathbb{E}}_{t-1}(x_{t+1}) \right) + \varepsilon_{t+1}. \tag{A.4}$$

The regression coefficients $\beta_F$ are displayed in Panel B and C of Table 1 in the main text.

In the above exercise, I use rolling average of historical forecast accuracy as a measure of information precision to avoid sorting based on ex-post realized forecast errors. Given the persistence of the forecast accuracy measure documented in Table A.5, using the average of all forecasts made by a panelist over the long sample period is likely a better measure of information precision. As I will show in Section A.6, my results are robust to alternative measures of information precision. Additionally, my findings are robust to alternative group classifications.

*A.4. Earnings Forecasts and Earnings Announcements*

*Overreaction in Stock Prices: Predictability of Earnings Announcement Returns.* In this section, I demonstrate the robustness of overreactions in stock prices by examining firm-level evidence. Table A.6 presents the results from a panel regression where I regress firm-level earnings announcement returns on analyst-level forecast revision period returns:

$$Rerr_{i,t+1} = \alpha_i + \beta_P Rrev_{i,j,\tau,t} + \gamma_{i,j,t} + \varepsilon_{i,j,t+1}, \tag{A.5}$$

where $Rerr_{i,t+1}$ is the earnings announcement return for firm $i$ that realized in quarter $t+1$, and $Rrev_{i,j,t}$ denotes the return over the most recent forecast revision period for each analyst $j$ associated with firm $i$, recorded on the revision date $\tau$ during quarter $t$. Note that each analyst can submit multiple revisions at time $\tau$ in one quarter. Both the announcement and revision periods are aligned and summarized across columns $[N,M]$, with the event window for earnings announcements and EPS revisions set at 0. For example, if the announcement return window is [–2, 2], that is, two days before and two days after the announcement, then the revision period also spans a [–2, 2] window, centered around the revision day. I exclude cases where the gap between the announcement and revision dates is 5 days to ensure there is no overlap between the revision period and the announcement. The results remain robust when changing this gap to 10 days or 20 days.

Table A.6 shows that the regression coefficients are significantly negative across various event windows. For example, Column (3) shows that a three-day window around an analyst's forecast revision can negatively predict a three-day window around earnings announcements. This suggests that earnings announcements respond negatively to analysts' forecast revision period returns. Specifically, a 1% increase in the revision period return is associated with approximately a 1 to 2 bps decrease in earnings announcement period return, indicating that firm-level stock prices overreact to information.

Table A.6: Earnings Announcement Return Predictability

| | [–2, 2] | [–1, 1] | [0, 2] | [0, 4] | [0, 0] |
|---|---|---|---|---|---|
| $\beta_P$ | –0.013 | –0.014 | –0.018 | –0.012 | –0.003 |
| | (–5.64) | (–5.89) | (–7.00) | (–4.92) | (–1.83) |
| Firm Analyst Quarter FE | Y | Y | Y | Y | Y |
| Firm Time clustering | Y | Y | Y | Y | Y |
| Obs. | 2,384,951 | 2,384,951 | 2,384,951 | 2,384,95 | 2,384,951 |
| $R^2$ | 0.074 | 0.062 | 0.062 | 0.073 | 0.050 |

This table presents the results for the following panel regression for firm-level earnings announcement return predictability: $Rerr_{i,t+1} = \alpha_i + \beta_P Rrev_{i,j,\tau,t} + \gamma_{i,j,t} + \varepsilon_{i,j,t+1}$. For each firm $i$, $Rerr_{i,t+1}$ is the earnings announcement return realized in quarter $t+1$, and $Rrev_{i,j,t}$ is the return over the most recent forecast revision period for each analyst $j$ associated with firm $i$, recorded on the revision date $\tau$, during quarter $t$. Both announcement and revision periods are aligned and summarized in $[N,M]$ across columns, with the event (earnings announcement or EPS revision) window set at 0. For example, Column (2) regresses the announcement return over [–2, 2] (five days around the announcement day 0) on the revision period return over [–2, 2] (five days centered around the revision day 0); and column (6) shows the coefficient from regressing the announcement day return on the revision day return. All regressions account for firm, analyst, and quarter fixed effects (FE). Standard errors are two-way clustered by firms and revision dates, with $t$-statistics reported in parentheses. All observations are winsorized at the top and bottom 1%. The data is from I/B/E/S and spans from 1980 to 2019.

The above analysis not only demonstrates the robustness of stock price overreaction to forecast revisions but also addresses two key limitations in the predictability of aggregate stock market returns on macroeconomic announcement days. First, revision period returns may predict announcement day returns because revisions are correlated with macroeconomic conditions, rather than because the information content of the revisions predicts announcement-day returns. Second, the return predictability may stem from other factors at the aggregate level, such as time-varying risk premiums.

The earnings announcement return predictability addresses the above limitations in three ways. First, all analysts can randomly submit their forecasts at any time, which means the timing of revision days is not correlated with macroeconomic conditions. Second, because analysts' revision days are clearly identified in the data, I can capture the return responses to revisions using shorter windows around the revision day. In fact, as shown in Table A.6, my results are robust to various definitions of the revision period. This approach provides a cleaner identification of revision period returns. Third, unlike macroeconomic forecasts, where all panelists submit revisions on the same day, EPS forecasts for each firm are submitted by many analysts on different dates. This setup mitigates the risk premium interpretation because the revision period return is at the analyst level and does not correlate with macroeconomic conditions or the dynamics of aggregate risk premiums.

*A.5. Time-varying Uncertainty*

My model predicts that an increase in uncertainty between announcements is associated with a drop in uncertainty upon the announcements, as illustrated in Figure 2. In this section, I verify the following two mechanisms of the model:

First, empirical evidence shows that uncertainty, on average, increases between announcements. To quantify this, I define the change in uncertainty between announcements as the 30-day implied variance change between one day before the current announcement and the previous announcement day: $\Delta IV_{t+1-T\to t} = \text{VIX}_t^2 - \text{VIX}_{t+1-T}^2$, where $T$ indicates the number of days between two announcements. On average, $\Delta IV_{t+1-T\to t}$ is 0.79 in monthly percentage squared units. This pattern also aligns with the observed dynamics of implied volatility using VIX futures around macroeconomic announcements, as documented by Hu et al. (2022).

Second, I define the actual uncertainty reduction on announcement days as the implied variance drop, calculated as the difference in $\text{VIX}^2$ between one day before the announcement and the announcement day itself: $\Delta IV_{t\to t+1} = \text{VIX}_t^2 - \text{VIX}_{t+1}^2$. I then regress the uncertainty reduction upon announcements on the uncertainty change between announcements:

$$\Delta IV_{t\to t+1} = \alpha + \beta \Delta IV_{t+1-T\to t} + \varepsilon_{t+1}, \tag{A.6}$$

The regression coefficient is 0.12, with a Newey-West $t$-statistic of 3.00 for a pooled regression of GDP and unemployment announcements. This result is consistent with the model's implication, suggesting that a greater rise in uncertainty between announcements is associated with a larger reduction in uncertainty upon announcements.

*A.6. Robustness Check*

In this section, I conduct robustness tests for the empirical results presented in the main text. First, I perform two robustness checks for the heterogeneity in cross-sectional forecasts

(Fact 2 in Section 2). The first check involves using alternative measurements for information precision, and the second is using alternative group classifications. The results are shown in Tables A.7 and A.8, respectively.

For the first robustness check, I introduce two additional measures of information precision. In Panel A of Table A.7, I use the absolute mean-adjusted forecast error over each panelist's entire available data from 1968 to 2019, excluding the current quarter $t$, as a measure of information precision. This approach is similar to the concept of a panelist fixed effect using a longer sample. In Panel B, I use a fixed two-year rolling window up to quarter $t-1$ to measure information precision.[6] For the second robustness check, instead of sorting panelists into three groups, I sort them into quintiles and deciles. In both cases, the informed (uninformed) group is defined as the group with the smallest (largest) scaled mean-adjusted absolute forecast error using the rolling window average up to quarter $t-1$, as in the benchmark specification in the main text. Columns (1) and (2) in Tables A.7 and A.8 display the regression results of equations (A.3) and (A.4), respectively. All results remain robust across different specifications.

Table A.7: Cross-Section Heterogeneity (Alternative Measurements)

| | *Panel A. Lifetime Horizon* | | | | *Panel B. Fixed 2-year Rolling Window* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Uninformed | | (2) Informed | | (1) Uninformed | | (2) Informed | |
| | GDP | UE | GDP | UE | GDP | UE | GDP | UE |
| $\beta_F$ | 0.57 | 0.47 | 0.03 | –0.08 | 0.58 | 0.43 | 0.06 | 0.01 |
| | (3.85) | (4.33) | (0.24) | (–0.74) | (4.59) | (4.47) | (0.58) | (0.09) |
| obs. | 201 | 204 | 201 | 204 | 195 | 197 | 195 | 197 |
| $R^2$ | 0.10 | 0.27 | 0.04 | 0.11 | 0.12 | 0.29 | 0.03 | 0.11 |

This table presents a robustness check for Panels B and C in Table 2. Panel A displays results where information precision is measured based on each panelist's lifetime forecast accuracy, excluding the current quarter $t$. Panel B shows results where information precision is measured by averaging over a fixed 2-year rolling window up to quarter $t-1$.

Second, I conduct a robustness check on the overreaction conditional on volatility (Fact 4 in Section 2). I use daily CBOE Volatility Index (VIX) as an alternative measure of time-varying volatility. Table A.9 presents the results. Additionally, in an unreported robustness

[6] In an unreported analysis, I show that the results remain robust when using a five or ten-year window.

Table A.8: Cross-Section Heterogeneity (Alternative Group Classifications)

| | *Panel A. Quintile* | | | | *Panel B. Deciles* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Uninformed | | (2) Informed | | (1) Uninformed | | (2) Informed | |
| | GDP | UE | GDP | UE | GDP | UE | GDP | UE |
| $\beta_F$ | 0.44 | 0.55 | 0.05 | –0.07 | 0.42 | 0.55 | 0.03 | –0.07 |
| | (2.20) | (4.85) | (0.56) | (–0.89) | (2.56) | (6.75) | (0.34) | (–1.66) |
| obs. | 201 | 204 | 201 | 204 | 194 | 194 | 194 | 194 |
| $R^2$ | 0.08 | 0.30 | 0.02 | 0.15 | 0.12 | 0.35 | 0.02 | 0.17 |

This table presents a robustness check for Panels B and C in Table 2. Panel A displays results where groups are characterized into quintiles, and Panel B shows results for groups characterized into deciles.

Table A.9: Announcement Return Predictability (Robustness Check)

| | *CE* | | *SPF* | |
|---|---|---|---|---|
| | GDP | UE | GDP | UE |
| $\beta_H$ | –0.097 | –0.116 | –0.129 | –0.169 |
| | (–3.18) | (–3.49) | (–3.14) | (–3.86) |
| $\beta_L$ | 0.079 | 0.051 | 0.052 | 0.041 |
| | (2.27) | (0.40) | (1.45) | (0.61) |

This table reports a robustness check for Panel B of Table 2, categorizing volatility as high or low based on whether the average VIX during the revision period is above or below the mean, respectively.

check, I confirm that the results remain robust when using the standard deviation of daily returns over the same period as a measure of fundamental volatility.

## Appendix B: Model Solutions

### *B.1. Investors' Learning Problems*

In this section, I compute both types of investors' optimal learning problems. First, I provide proof for Lemma 1, and subsequently, I prove Proposition 1, which summarizes the key results regarding underreaction in consensus belief and information asymmetry.

*Information Structure.* Here I show that characterizing the dynamics of $\tilde{x}_t$ and $\tilde{q}(t)$ is sufficient to compute the posteriors of $x_t$, $\hat{x}_t$, and $\theta_t$ of uninformed investors. To see this, first, $\tilde{\mathbb{E}}_t[x_t] = \tilde{\mathbb{E}}_t[\hat{x}_t]$, by the law of iterated expectations. Second, because uninformed investors observe the price, $P_t = \tilde{\mathbb{E}}_t[P_t]$ must hold. Computing the conditional expectation of price in (7) gives (8). Because the uninformed investor observes $P_t$ and $D_t$, given the pricing function (7), the posterior belief about $\theta_t$ can be computed as

$$\tilde{\theta}_t = \frac{1}{\phi_\theta(t)}\left(\phi + \phi_D D_t + \bar{\phi}_x \tilde{x}_t - P_t\right) = \theta_t - \frac{\phi_x(t)}{\phi_\theta(t)}(\hat{x}_t - \tilde{x}_t). \tag{B.1}$$

Third, as shown later in equation (B.13), the posterior variance-covariance matrix can be further inferred from the above equation.

*Proof for Lemma 1.* The optimal learning problem for the informed investor can be solved using a standard Kalman-Bucy filter. The unobserved state variable is given in equation (4), and the observed processes are (3), (5), and (6). By applying Theorem 10.3 from Liptser and Shiryaev (2001), it can be shown that the posterior mean and variance satisfy the law of motion given in (10) and (11), respectively. The innovation processes for (3) and (6) are given by

$$d\hat{B}_{D,t} = \frac{1}{\sigma_D}\left[dD_t - (\hat{x}_t - D_t)\,dt\right], \text{and } d\hat{B}_{s,t} = \frac{1}{\sigma_s}(ds_t - \hat{x}_t dt). \tag{B.2}$$

Now let's proceed to solve the uninformed investor's learning problem. Since the stock price depends on both $\hat{x}_t$ and $\theta_t$ (as shown in (7)), both of which are unobserved, the uninformed investors need to calculate the posterior distributions for both. Equation (B.1) implies that the posterior distribution of $\theta_t$ can be inferred from that of $\hat{x}_t$. Therefore, I focus on the learning problem for $\hat{x}_t$, whose law of motion is given by (10). Uninformed investors observe two sources of information for $\hat{x}_t$: the dividend process and the equilibrium price. Equation (3) can be expressed in terms of $d\hat{B}_{D,t}$ as follows:

$$dD_t = (\hat{x}_t - D_t)\, dt + \sigma_D d\hat{B}_{D,t}. \tag{B.3}$$

Note that observing the price is equivalent to observing $\zeta_t = \phi_x(t)\,\hat{x}_t - \phi_\theta(t)\,\theta_t$ because all other variables in (7) are known to the uninformed investors. Applying Ito's lemma, $\zeta_t$ can be represented as a Markov process given the state variables $\hat{x}_t$ and $\zeta_t$:

$$\begin{aligned} d\zeta_t \;&=\; \left[b\bar{x}\phi_x(t) + \left(\left(a - b - \frac{\phi_\theta'(t)}{\phi_\theta(t)}\right)\phi_x(t) + \phi_x'(t)\right)\hat{x}_t + \left(\frac{\phi_\theta'(t)}{\phi_\theta(t)} - a\right)\zeta_t\right] dt \\ &\quad + \frac{\hat{q}(t)}{\sigma_D}\phi_x(t)\, d\hat{B}_{D,t} + \frac{\hat{q}(t)}{\sigma_s}\phi_x(t)\, d\hat{B}_{s,t} - \sigma_\theta\phi_\theta(t)\, dB_{\theta,t}. \end{aligned} \tag{B.4}$$

It is useful to define $\xi_t \equiv \zeta_t - \frac{\hat{q}(t)}{\sigma_D^2}\phi_x(t)\, D_t$ so that $(\hat{x}_t, D_t, \xi_t)$ has a state space representation and the innovations of $dD_t$ and $d\xi_t$ are mutually independent. The dynamic of $\xi_t$ is

$$d\xi_t = \left[b\bar{x}\phi_x(t) + m_x(t)\,\hat{x}_t + \left(\frac{\phi_\theta'(t)}{\phi_\theta(t)} - a\right)\xi_t + m_D(t)\, D_t\right] dt + \frac{\hat{q}(t)}{\sigma_s}\phi_x(t)\, d\hat{B}_{s,t} - \sigma_\theta\phi_\theta(t)\, dB_{\theta,t}, \tag{B.5}$$

where the coefficients $m_x(t)$ and $m_D(t)$ are defined as

$$m_x(t) = \left(a - b - \frac{\phi_\theta'(t)}{\phi_\theta(t)} - \frac{\hat{q}(t)}{\sigma_D^2}\right)\phi_x(t) + \phi_x'(t)\,, \tag{B.6}$$

$$m_D(t) = \frac{1}{\sigma_D^2}\left[\hat{q}(t)\,\phi_x(t)\left(1 - a + \frac{\phi_\theta'(t)}{\phi_\theta(t)}\right) - \hat{q}'(t)\,\phi_x(t) - \hat{q}(t)\,\phi_x'(t)\right]. \tag{B.7}$$

It is convenient to define

$$\sigma_\xi(t) = \sqrt{\frac{\hat{q}^2(t)}{\sigma_s^2}\phi_x^2(t) + \sigma_\theta^2\phi_\theta^2(t)}, \tag{B.8}$$

as the volatility of $\xi_t$ and define

$$\nu(t) = \frac{1}{\sigma_\xi^2(t)} \left[ \frac{\phi_x(t)}{\sigma_s^2} \hat{q}^2(t) + m_x(t) \tilde{q}(t) \right]. \tag{B.9}$$

To solve the uninformed investor's learning problem using the Kalman-Bucy filter, I will consider (10) as the unobserved state variable and (B.3) and (B.5) as the observations. By applying Theorem 10.3 in Liptser and Shiryaev (2001), I can derive the filtering equation in (12) and the Ricatti equation in (13). The innovation processes are standard Brownian motions with respect to the uninformed investor's information set, which are defined as:

$$d\tilde{B}_{D,t} = \frac{1}{\sigma_D} \left[ dD_t - (\tilde{x}_t - D_t) dt \right], \tag{B.10}$$

$$d\tilde{B}_{\xi,t} = \frac{1}{\sigma_\xi(t)} \left[ d\xi_t - \left[ b\bar{x}\phi_x(t) + m_x(t)\tilde{x}_t + \left( \frac{\phi_\theta'(t)}{\phi_\theta(t)} - a \right) \xi_t + m_D(t) D_t \right] dt \right]. \tag{B.11}$$

Applying Ito's lemma to equation (B.1), the law of motion for $\tilde{\theta}_t$ is therefore derived as

$$d\tilde{\theta}_t = -a\tilde{\theta}_t dt + \frac{\phi_x(t)}{\phi_\theta(t)} \frac{\tilde{q}(t)}{\sigma_D} d\tilde{B}_{D,t} + \frac{1}{\phi_\theta(t)} \sigma_\xi(t) \left[ \nu(t) \phi_x(t) - 1 \right] d\tilde{B}_{\xi,t}. \tag{B.12}$$

Together with $\theta_t = \frac{1}{\phi_\theta(t)} (\zeta_t - \phi_x(t) \hat{x}_t)$, the following variances and covariances can be computed from the law of total covariance:

$$\begin{aligned}
\tilde{\mathrm{Var}}(x_t) &= \tilde{\mathbb{E}}[\hat{\mathrm{Var}}(x_t)] + \tilde{\mathrm{Var}}(\hat{\mathbb{E}}[x_t]) = \hat{q}_t + \tilde{q}_t, \text{ and } \tilde{\mathrm{Var}}(\theta_t) = \frac{\phi_{x,t}^2}{\phi_{\theta,t}^2} \tilde{q}_t, \\
\tilde{\mathrm{Cov}}(x_t, \hat{x}_t) &= \tilde{\mathbb{E}}[\hat{\mathrm{Cov}}(x_t, \hat{x}_t)] + \tilde{\mathrm{Cov}}(\hat{\mathbb{E}}[x_t], \hat{\mathbb{E}}[\hat{x}_t]) = \tilde{q}_t, \\
\tilde{\mathrm{Cov}}(x_t, \theta_t) &= \tilde{\mathrm{Cov}}[x_t, \frac{1}{\phi_{\theta,t}}(\phi_{x,t}\hat{x}_t - \zeta_t)] = \frac{\phi_{x,t}}{\phi_{\theta,t}} \tilde{q}_t, \text{ and } \tilde{\mathrm{Cov}}(\hat{x}_t, \theta_t) = \frac{\phi_{x,t}}{\phi_{\theta,t}} \tilde{q}_t.
\end{aligned} \tag{B.13}$$

*Difference in Beliefs.* Next, I characterize the dynamics of difference in beliefs $\Delta \equiv \hat{x}_t - \tilde{x}_t$. It's stochastic process can be derived by taking a difference between (10) and (12). Then equations (B.3) and (B.5) allow me to replace $dD_t$ and $d\xi_t$ in the definition of the innovation processes, (B.10) and (B.11), respectively, to write $d\Delta_t$ in terms of Brownian motions with respect to informed investors' information set, $\hat{B}_{D,t}$, $\hat{B}_{s,t}$, and $B_{\theta,t}$ as in (B.14). This yields:

$$d\Delta_t = -a_\Delta(t)\,\Delta_t dt - \sigma_{\Delta D}(t)\,d\hat{B}_{D,t} + \sigma_{\Delta s}(t)\,d\hat{B}_{s,t} + \sigma_{\Delta\theta}(t)\,dB_{\theta,t}, \tag{B.14}$$

where $a_\Delta(t) = b + \frac{\hat{q}(t)+\tilde{q}(t)}{\sigma_D^2} + m_x(t)\,\nu(t)$, $\sigma_{\Delta D}(t) = \frac{\tilde{q}(t)}{\sigma_D} > 0$, $\sigma_{\Delta s}(t) = \frac{\hat{q}(t)}{\sigma_s}[1 - \phi_x(t)\,\nu(t)]$, and $\sigma_{\Delta\theta}(t) = \sigma_\theta\phi_\theta(t)\,\nu(t)$ are strictly positive, and $\sigma_\xi(t)$ and $\nu(t)$ are defined in (B.8) and (B.9), respectively.

At the announcements, the true value of $x_t$ is revealed. As a result, $\hat{x}_t = \tilde{x}_t = x_t$, and $\Delta_t$ is set to zero. After the announcements, the uninformed investor observes less information than the informed, and their disagreement $\Delta_t$ evolves according to (B.14). Differences in beliefs are driven by several sources of information. First, $\Delta_t$ has a negative loading on dividend innovations: the uninformed responds more to $d\hat{B}_{D,t}$ than the informed. Comparing (12) with (10) shows that uninformed investors have a larger loading on $dD_t$, because they observe less information about $x_t$ and therefore rely more on learning from the dividend to update their beliefs. Second, $\sigma_{\Delta s}(t) > 0$; the uninformed investor's belief responds less to innovations in the informed investor's private signal $s_t$, which they only learn indirectly through prices. Finally, $\sigma_{\Delta\theta}(t) > 0$. Seeing that the informed perfectly knows $\theta_t$, a positive shock to $dB_{\theta,t}$ lowers the equilibrium price, and therefore the uninformed investor's belief $\tilde{x}_t$, without affecting the informed investor's belief $\hat{x}_t$.

*Proof for Proposition 1.* Now I provide a proof for Proposition 1. For simplicity, I focus on one representative announcement cycle. But the proof can be generalized to all the announcement cycles. Note that $\hat{\mathbb{E}}_t[x_T] - \hat{\mathbb{E}}_0[x_T]$ (or $\tilde{\mathbb{E}}_t[x_T] - \tilde{\mathbb{E}}_0[x_T]$) represents the revision of the informed (or uninformed) investor's forecast from time 0 to $t$, and $x_T - \hat{\mathbb{E}}_t[x_T]$ (or $x_T - \tilde{\mathbb{E}}_t[x_T]$) is the error of the informed (or uninformed) investor's forecast realized at the announcement at time $T$. As a result, the consensus forecast revision can be represented as

$$Frev_t(x_T) = (1-\omega)\left(\hat{\mathbb{E}}_t[x_T] - \hat{\mathbb{E}}_0[x_T]\right) + \omega\left(\tilde{\mathbb{E}}_t[x_T] - \tilde{\mathbb{E}}_0[x_T]\right), \tag{B.15}$$

and the consensus forecast error can be written as

$$Ferr_T\left(x_T\right)=(1-\omega)\left(x_T-\hat{\mathbb{E}}_t\left[x_T\right]\right)+\omega\left(x_T-\tilde{\mathbb{E}}_t\left[x_T\right]\right). \tag{B.16}$$

I first show that the forecast revision of informed investors cannot predict their own forecast errors, i.e., $\operatorname{Cov}\left(\hat{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right], x_T-\hat{\mathbb{E}}_t\left[x_T\right]\right)=0$.

$$\begin{aligned}
&\operatorname{Cov}\left(\hat{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right], x_T-\hat{\mathbb{E}}_t\left[x_T\right]\right) \\
=&\mathbb{E}\left[(\hat{\mathbb{E}}_t[x_T]-\hat{\mathbb{E}}_0[x_T])(x_T-\hat{\mathbb{E}}_t[x_T])\right]-\mathbb{E}\left[\hat{\mathbb{E}}_t[x_T]-\hat{\mathbb{E}}_0[x_T]\right]\mathbb{E}\left[x_T-\hat{\mathbb{E}}_t[x_T]\right] \\
=&\mathbb{E}\left\{\hat{\mathbb{E}}_t\left[(\hat{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right])(x_T-\hat{\mathbb{E}}_t\left[x_T\right])\right]\right\}=\mathbb{E}\left[(\hat{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right])(\hat{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_t\left[x_T\right])\right]=0.
\end{aligned}$$

where I used the law of iterated expectations. The proof for uninformed investors' follows the similar logic, which gives: $\operatorname{Cov}\left(\tilde{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_0\left[x_T\right], x_T-\tilde{\mathbb{E}}_t\left[x_T\right]\right)=0$. Then I establish equation (14) in Proposition 1 for all $t\in(0,T]$.

$$\begin{aligned}
&\operatorname{Cov}\left(\hat{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right], x_T-\tilde{\mathbb{E}}_t\left[x_T\right]\right)=\operatorname{Cov}\left(\hat{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right],(x_T-\hat{\mathbb{E}}_t\left[x_T\right])+(\hat{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_t\left[x_T\right])\right) \\
=&\operatorname{Cov}\left(\hat{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right], \hat{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_t\left[x_T\right]\right)=\operatorname{Cov}\left(\hat{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_t\left[x_T\right]+\tilde{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right], \hat{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_t\left[x_T\right]\right) \\
=&\operatorname{Var}\left(\hat{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_t\left[x_T\right]\right)+\operatorname{Cov}\left(\tilde{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right], \hat{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_t\left[x_T\right]\right)=\operatorname{Var}\left(\hat{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_t\left[x_T\right]\right)>0,
\end{aligned}$$

where the second equality comes from the rational belief of informed investors. To understand the last equality, note that

$$\begin{aligned}
0=&\operatorname{Cov}\left(\tilde{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_0\left[x_T\right], x_T-\tilde{\mathbb{E}}_t\left[x_T\right]\right) \\
=&\mathbb{E}\left[\left(\tilde{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_0\left[x_T\right]\right)\left(x_T-\tilde{\mathbb{E}}_t\left[x_T\right]\right)\right]-\mathbb{E}\left[\tilde{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_0\left[x_T\right]\right]\mathbb{E}\left[x_T-\tilde{\mathbb{E}}_t\left[x_T\right]\right] \\
=&\mathbb{E}\left[\left(\tilde{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right]\right)\left(x_T-\tilde{\mathbb{E}}_t\left[x_T\right]\right)\right]=\mathbb{E}\left[\hat{\mathbb{E}}_t\left(\tilde{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right]\right)\left(x_T-\tilde{\mathbb{E}}_t\left[x_T\right]\right)\right] \\
=&\mathbb{E}\left[\left(\tilde{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right]\right)\left(\hat{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_t\left[x_T\right]\right)\right]=\operatorname{Cov}\left(\tilde{\mathbb{E}}_t\left[x_T\right]-\hat{\mathbb{E}}_0\left[x_T\right], \hat{\mathbb{E}}_t\left[x_T\right]-\tilde{\mathbb{E}}_t\left[x_T\right]\right),
\end{aligned}$$

where the last equality is true because at time 0, both investors have the same belief about $x_T$ after the announcement, $\hat{\mathbb{E}}_0\left[x_T\right]=\tilde{\mathbb{E}}_0\left[x_T\right]$. Last, it is straightforward to show the consensus forecast revision positively predicts the consensus forecast error.

$$
\begin{aligned}
&\text{Cov}\left(Frev_t\left(x_T\right), Ferr_T\left(x_T\right)\right) \\
&= \left(1-\omega\right)^2 \text{Cov}\left(\hat{\mathbb{E}}_t\left[x_T\right] - \hat{\mathbb{E}}_0\left[x_T\right], x_T - \hat{\mathbb{E}}_t\left[x_T\right]\right) + \left(1-\omega\right)\omega \text{Cov}\left(\hat{\mathbb{E}}_t\left[x_T\right] - \hat{\mathbb{E}}_0\left[x_T\right], x_T - \tilde{\mathbb{E}}_t\left[x_T\right]\right) \\
&\quad + \left(1-\omega\right)\omega \text{Cov}\left(\tilde{\mathbb{E}}_t\left[x_T\right] - \tilde{\mathbb{E}}_0\left[x_T\right], x_T - \hat{\mathbb{E}}_t\left[x_T\right]\right) + \omega^2 \text{Cov}\left(\tilde{\mathbb{E}}_t\left[x_T\right] - \tilde{\mathbb{E}}_0\left[x_T\right], x_T - \tilde{\mathbb{E}}_t\left[x_T\right]\right) \\
&= \left(1-\omega\right)\omega \text{Cov}\left(\hat{\mathbb{E}}_t\left[x_T\right] - \hat{\mathbb{E}}_0\left[x_T\right], x_T - \tilde{\mathbb{E}}_t\left[x_T\right]\right) > 0.
\end{aligned}
$$

*Expected Returns.* To understand investors' portfolio allocations, it is useful to first compute expected returns for the informed and uninformed investors. Define the instantaneous excess return as $dQ_t = dP_t + D_t dt - rP_t dt$. Consider first the informed investor. Equations (B.3), (5), (10), and (B.14) represent the variables $D_t$, $\theta_t$, $\hat{x}_t$, and $\Delta_t$ in terms of Brownian motions with respect to their information set. These give

$$
\begin{aligned}
dQ_t = &\left\{\left[-r\phi + b\bar{x}\bar{\phi}_x\right] + \left[1 - \left(1+r\right)\phi_D\left(t\right)\right]D_t + e_\theta\left(t\right)\theta_t + \left[\phi_D - \left(b+r\right)\phi_x\right]\hat{x}_t + e_\Delta\left(t\right)\Delta_t\right\} dt \\
&+ \varrho_D\left(t\right) d\hat{B}_{D,t} + \varrho_s\left(t\right) d\hat{B}_{s,t} + \varrho_\theta\left(t\right) dB_{\theta,t},
\end{aligned}
\tag{B.17}
$$

where $e_\Delta\left(t\right) = \left[r + b + \frac{\hat{q}(t)+\tilde{q}(t)}{\sigma_D^2} + m_x\left(t\right)\nu\left(t\right)\right]\phi_\Delta\left(t\right) - \phi'_\Delta\left(t\right)$, and

$$
e_\theta\left(t\right) = \left(a+r\right)\phi_\theta\left(t\right) - \phi'_\theta\left(t\right),
\tag{B.18}
$$

and the diffusion coefficients are given by $\varrho_D\left(t\right) = \frac{1}{\sigma_D}\left[\phi_D\sigma_D^2 + \bar{\phi}_x\hat{q}\left(t\right) + \phi_\Delta\left(t\right)\tilde{q}\left(t\right)\right]$, $\varrho_s\left(t\right) = \left[1 + \phi_\Delta\left(t\right)\nu\left(t\right)\right]\phi_x\left(t\right)\frac{\hat{q}(t)}{\sigma_s}$, and $\varrho_\theta\left(t\right) = -\left[1 + \phi_\Delta\left(t\right)\nu\left(t\right)\right]\phi_\theta\left(t\right)\sigma_\theta$. Further define the variance of the excess return as

$$
\sigma_P\left(t\right) = \varrho_D^2\left(t\right) + \varrho_s^2\left(t\right) + \varrho_\theta^2\left(t\right).
\tag{B.19}
$$

The market clearing condition implies that the stock's expected return depends only on the total supply $\theta_t$ and not on $D_t$, $\hat{x}_t$, or the constant. Therefore, the coefficients on these variables in (B.17) must be equal to 0, implying

$$\phi_D = \frac{1}{1+r}, \ \bar{\phi}_x = \frac{\phi_D}{b+r}, \text{ and } \phi = \frac{b\bar{x}\bar{\phi}_x}{r}. \tag{B.20}$$

As a result, the excess return dynamic can be simplified as

$$dQ_t = \left[e_\theta(t)\,\theta_t + e_\Delta(t)\,\Delta_t\right]dt + \varrho_D(t)\,d\hat{B}_{D,t} + \varrho_s(t)\,d\hat{B}_{s,t} + \varrho_\theta(t)\,dB_{\theta,t}. \tag{B.21}$$

Similarly, I can use dynamics of $D_t$, $\tilde{\theta}_t$, and $\tilde{x}_t$ in (B.10), (B.12), and (12) to rewrite the excess return in terms of Brownian motions with respect to the uninformed investor's information set. This gives $dQ_t = e_\theta(t)\,\tilde{\theta}_t dt + \varrho_D(t)\,d\tilde{B}_{D,t} + \sigma_\xi(t)\left[1 + \phi_\Delta(t)\,\nu(t)\right]d\tilde{B}_{\xi,t}$.

Figure B.1: Time-Varying Expected Return Coefficients

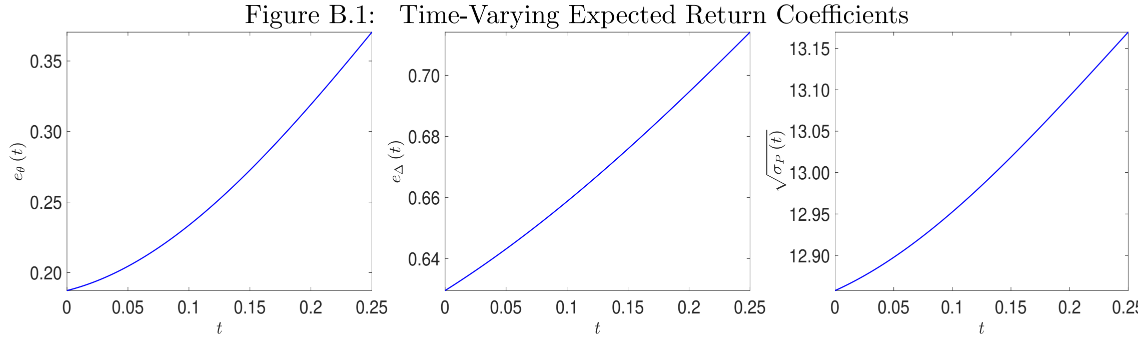


Figure B.1 plots $e_\theta(t)$, $e_\Delta(t)$, and the volatility of the excess return, $\sqrt{\sigma_P(t)}$, from the calibrated model. First, $e_\theta(t) > 0$ because $\theta_t$ is the total supply of the asset. The expected return must be an increasing function of $\theta_t$, because a higher expected return is needed to induce a higher demand to meet the market clearing condition. Second, $e_\Delta(t) > 0$. Note that $\tilde{\mathbb{E}}_t[dQ_t] = \left[e_\theta(t)\,\tilde{\theta}_t\right]dt = e_\theta(t)\left[\theta_t - \frac{\phi_x(t)}{\phi_\theta(t)}\Delta_t\right]dt$ by equation (9). That is, the expected return, and therefore the demand from the uninformed investors, are lower when they are more pessimistic. For markets to clear, the demand from informed investors must be increasing in $\Delta_t$. Therefore, the expected return from the informed investors' perspective must be an increasing function of $\Delta_t$. Last, $\sqrt{\sigma_P(t)}$ is increasing over time. As the posterior variances of $x_t$, $\hat{q}_t$, and $\tilde{q}_t$ rise from 0 to $T^-$, and so does the volatility of return.

*B.2. Solving for Optimization Problems in the Interior*

For illustration purposes, here I use the superscripts $i$ and $u$ to indicate variables for the informed and uninformed investors, respectively. For example, $W^i$ stands for the informed's wealth and $W^u$ is the uninformed's wealth. The following lemma summarizes the solutions to both types of investors' optimization problems. I drop the time scripts for simplicity.

**Lemma 4.** *In the interior* $(0, T)$ *between announcements, the informed and uninformed investor's value function takes the form of*

$$J\left(t, W^i, \theta, \Delta\right) = -e^{-rW^i - g(t,\theta,\Delta)}, \tag{B.22}$$

$$V\left(t, W^u, \tilde{\theta}\right) = -e^{-rW^u - f\left(t,\tilde{\theta}\right)}, \tag{B.23}$$

*respectively, where* $g(t, \theta, \Delta)$ *and* $f(t, \tilde{\theta})$ *have quadratic forms of*

$$g(t, \theta, \Delta) = g(t) + \frac{1}{2} g_{\theta\theta}(t)\, \theta_t^2 + \frac{1}{2} g_{\Delta\Delta}(t)\, \Delta_t^2 + g_{\theta\Delta}(t)\, \theta_t \Delta_t, \tag{B.24}$$

$$f\left(t, \tilde{\theta}\right) = f(t) + \frac{1}{2} f_{\theta\theta}(t)\, \tilde{\theta}_t^2, \tag{B.25}$$

*where the coefficients are time varying and satisfy the system of ODEs defined as follows:*

$$\begin{aligned}
g'(t) =& r - \rho - r\ln r + rg(t) - \frac{1}{2}\sigma_\theta^2 g_{\theta\theta}(t) - \frac{1}{2}\sigma_\Delta(t)\, g_{\Delta\Delta}(t) - \sigma_\theta \sigma_{\Delta\theta}(t)\, g_{\theta\Delta}(t), \\
g'_{\theta\theta}(t) =& (2a + r)\, g_{\theta\theta}(t) - r^2 \sigma_P(t)\, \alpha_\theta^2(t) + \sigma_\theta^2 g_{\theta\theta}^2(t) + \sigma_\Delta(t)\, g_{\theta\Delta}^2(t) + 2\sigma_\theta \sigma_{\Delta\theta}(t)\, g_{\theta\theta}(t)\, g_{\theta\Delta}(t), \\
g'_{\Delta\Delta}(t) =& rg_{\Delta\Delta}(t) - r^2 \sigma_P(t)\, \alpha_\Delta^2(t) + 2a_\Delta(t)\, g_{\Delta\Delta}(t) + \sigma_\theta^2 g_{\theta\Delta}^2(t) + \sigma_\Delta(t)\, g_{\Delta\Delta}^2(t) \\
& + 2\sigma_\theta \sigma_{\Delta\theta}(t)\, g_{\theta\Delta}(t)\, g_{\Delta\Delta}(t), \\
g'_{\theta\Delta}(t) =& rg_{\theta\Delta}(t) - r^2 \sigma_P(t)\, \alpha_\theta(t)\, \alpha_\Delta(t) + ag_{\theta\Delta}(t) + a_\Delta(t)\, g_{\theta\Delta}(t) + \sigma_\theta^2 g_{\theta\theta}(t)\, g_{\theta\Delta}(t) \\
& + \sigma_\Delta(t)\, g_{\Delta\Delta}(t)\, g_{\theta\Delta}(t) + \sigma_\theta \sigma_{\Delta\theta}(t) \left[g_{\theta\theta}(t)\, g_{\Delta\Delta}(t) + g_{\theta\Delta}^2(t)\right];
\end{aligned} \tag{B.26}$$

$$\begin{aligned}
f'(t) =& r - \rho - r\ln r + rf(t) - \frac{1}{2}\sigma_{\theta\theta}(t)\, f_{\theta\theta}(t), \\
f'_{\theta\theta}(t) =& (2a + r)\, f_{\theta\theta}(t) - r^2 \sigma_P(t)\, \beta_\theta^2(t) + \sigma_{\theta\theta}(t)\, f_{\theta\theta}^2(t),
\end{aligned} \tag{B.27}$$

*where* $\sigma_{\Delta}(t) = \sigma^2_{\Delta D}(t) + \sigma^2_{\Delta s}(t) + \sigma^2_{\Delta\theta}(t)$ *and* $\sigma_{\theta\theta}(t) = \left[\frac{\phi_x(t)}{\phi_\theta(t)}\frac{\tilde{q}(t)}{\sigma_D}\right]^2 + \left[\frac{\sigma_\xi(t)}{\phi_\theta(t)}(\phi_x(t)\nu(t) - 1)\right]^2$.

*Proof.* Conjecture that the informed investor's value function takes the form of (B.22), where $g(t,\theta,\Delta)$ is of the form (B.24). Subsequently, I can derive a solution to the optimization problem of informed investors as formulated in equation (17) subject to constraints specified in (18), (B.21), (5) and (B.14). Using Ito's lemma, the HJB equation is

$$\rho J = -e^{-C^i} + J_t + J_W\left[rW^i - C^i + \alpha\left(e_\theta(t)\theta + e_\Delta(t)\Delta\right)\right] + \frac{1}{2}J_{WW}\alpha^2\sigma_P(t) + \alpha J_{W\theta}\sigma_\theta\varrho_\theta(t)$$
$$+\alpha J_{W\Delta}\sigma_{Q\Delta}(t) - J_\theta a\theta - J_\Delta a_\Delta(t)\Delta + \frac{1}{2}J_{\theta\theta}\sigma^2_\theta + \frac{1}{2}J_{\Delta\Delta}\sigma_\Delta(t) + J_{\theta\Delta}\sigma_\theta\sigma_{\Delta\theta}(t),$$

where $\sigma_\Delta(t) = \sigma^2_{\Delta D}(t) + \sigma^2_{\Delta s}(t) + \sigma^2_{\Delta\theta}(t)$ and

$$\sigma_{Q\Delta}(t) = -\varrho_D(t)\sigma_{\Delta D}(t) + \varrho_s(t)\sigma_{\Delta s}(t) + \varrho_\theta(t)\sigma_{\Delta\theta}(t). \tag{B.28}$$

The first-order condition (FOC) with respect to $C^i$ is: $e^{-C^i} = J_W$. Under the guessed value functional form,

$$C^i = rW^i - \ln r + g(t,\theta,\Delta).$$

The FOC with respect to $\alpha$ gives $\alpha = -\frac{J_W(e_\theta(t)\theta + e_\Delta(t)\Delta) + J_{W\theta}\sigma_\theta\varrho_\theta(t) + J_{W\Delta}\sigma_{Q\Delta}(t)}{J_{WW}\sigma_P(t)}$. Under the guessed form of the value function, $\alpha = \frac{e_\theta(t)\theta + e_\Delta(t)\Delta - \frac{\partial g}{\partial\theta}\varrho_\theta(t)\sigma_\theta - \frac{\partial g}{\partial\Delta}\sigma_{Q\Delta}(t)}{r\sigma_P(t)}$. Substituting expressions in (B.28) yields $\alpha_t = \alpha_\theta(t)\theta_t + \alpha_\Delta(t)\Delta_t$, where

$$\alpha_\theta(t) = \frac{1}{r\sigma_P(t)}\left[e_\theta(t) - \varrho_\theta(t)\sigma_\theta g_{\theta\theta}(t) - \sigma_{Q\Delta}(t)g_{\theta\Delta}(t)\right], \tag{B.29}$$
$$\alpha_\Delta(t) = \frac{1}{r\sigma_P(t)}\left[e_\Delta(t) - \varrho_\theta(t)\sigma_\theta g_{\theta\Delta}(t) - \sigma_{Q\Delta}(t)g_{\Delta\Delta}(t)\right]. \tag{B.30}$$

Similar to the informed investor's problem defined in (17), the uninformed investor's optimization problem is characterized as

$$V\left(t, W_t^u, \tilde{\theta}_t\right) = \max_{\{\beta_t, C_t^u\}} \tilde{\mathbb{E}}\left[\int_0^{T^- - t} -e^{-\rho s - C_{t+s}^u} ds + e^{-\rho\left(T^- - t\right)} V\left(T^-, W_{T^-}^u, \tilde{\theta}_T^-\right)\right], \tag{B.31}$$

$$s.t.\ dW_t^u = \left(W_t^u r - C_t^u\right) dt + \beta_t \left\{e_\theta\left(t\right) \tilde{\theta}_t dt + \varrho_D\left(t\right) d\tilde{B}_{D,t} + \sigma_\xi\left(t\right)\left[1 + \phi_\Delta\left(t\right)\nu\left(t\right)\right] d\tilde{B}_{\xi,t}\right\},$$

and the state variable $\tilde{\theta}_t$ satisfies (B.12). The HJB equation is

$$\rho V = -e^{-C^u} + V_t + V_W\left[rW^u - C^u + \beta e_\theta\left(t\right)\tilde{\theta}\right] + \frac{1}{2}V_{WW}\beta^2\sigma_P\left(t\right) + \beta V_{W\theta}\sigma_{Q\theta}\left(t\right) - V_\theta a\tilde{\theta} + \frac{1}{2}V_{\theta\theta}\sigma_{\theta\theta}\left(t\right),$$

where $\sigma_{Q\theta}\left(t\right) = \frac{\phi_x(t)}{\phi_\theta(t)}\frac{\tilde{q}(t)}{\sigma_D}\varrho_D\left(t\right) + \frac{\sigma_\xi^2(t)}{\phi_\theta(t)}\left(\phi_x\left(t\right)\nu\left(t\right) - 1\right)\left(1 + \phi_\Delta\left(t\right)\nu\left(t\right)\right)$ and $\sigma_{\theta\theta}\left(t\right) = \left[\frac{\phi_x(t)}{\phi_\theta(t)}\frac{\tilde{q}(t)}{\sigma_D}\right]^2 + \left[\frac{\sigma_\xi(t)}{\phi_\theta(t)}\left(\phi_x\left(t\right)\nu\left(t\right) - 1\right)\right]^2$. Furthermore, conjecture that the uninformed investor's value function would be of the form (B.23) , where $f\left(t, \tilde{\theta}\right)$ satisfies (B.25). Substituting the guessed forms into HJB, the FOC with respect to $C^u$ yields $C^u = rW^u - \ln r + f\left(t, \tilde{\theta}\right)$, and $\beta_t$ gives $\beta_t = \beta_\theta\left(t\right)\tilde{\theta}_t$, where

$$\beta_\theta\left(t\right) = \frac{1}{r\sigma_P\left(t\right)}\left[e_\theta\left(t\right) - \sigma_{Q\theta}\left(t\right) f_{\theta\theta}\left(t\right)\right]. \tag{B.32}$$

Finally, substituting the optimal policy functions back into the HJB equations, and matching the coefficients of the value functions would give the system of ODEs of the two types of investors' value function coefficients stated in Lemma 4. □

Using (9) to replace $\tilde{\theta}_t$, the market clear condition (22) implies two results:

$$\left(1 - \omega\right)\alpha_\theta\left(t\right) + \omega\beta_\theta\left(t\right) = 1, \tag{B.33}$$

$$\alpha_\Delta\left(t\right) = \frac{\omega}{1 - \omega}\beta_\theta\left(t\right)\frac{\phi_x\left(t\right)}{\phi_\theta\left(t\right)} \tag{B.34}$$

Equation (B.33) shows that informed and uninformed investors must hold the total supply of the equity $\theta_t$ together. The term $\alpha_\Delta\left(t\right)$ in (20) reflects the informed investors' portfolio holdings owing to their information advantage against the uninformed $\Delta_t$. In my model, $\alpha_\Delta\left(t\right) > 0$; that is, whenever informed investors are more optimistic about $x_t$, they purchase aggressively and hold a positive amount of the stock. Equation (B.34) says the market clearing requires that this additional amount must be supplied by the uninformed investors.

Substituting equations (B.29), (B.30), and (B.32) back into the market clearing conditions (B.33) and (B.34) yields the ODEs for the pricing coefficients $\phi_\theta(t)$ and $\phi_\Delta(t)$. The following lemma summarizes this result.

**Lemma 5.** *The ODEs for $\phi_\theta(t)$ and $\phi_\Delta(t)$ can be characterized as follows:*

$$\begin{aligned}
\phi_\theta'(t) &= (a+r)\phi_\theta(t) - r\sigma_P(t) - (1-\omega)\left[\varrho_\theta(t)\sigma_\theta g_{\theta\theta}(t) + \sigma_{Q\Delta}(t) g_{\theta\Delta}(t)\right] - \omega\sigma_{Q\theta}(t) f_{\theta\theta}(t),\\
\phi_\Delta'(t) &= (a_\Delta(t)+r)\phi_\Delta(t) - \varrho_\theta(t)\sigma_\theta g_{\theta\Delta}(t) - \sigma_{Q\Delta}(t) g_{\Delta\Delta}(t)\\
&\quad - \left[\frac{\omega}{1-\omega} r\sigma_P(t) + \omega\left[\varrho_\theta(t)\sigma_\theta g_{\theta\theta}(t) + \sigma_{Q\Delta}(t) g_{\theta\Delta}(t) - \sigma_{Q\theta}(t) f_{\theta\theta}(t)\right]\right]\frac{\phi_x(t)}{\phi_\theta(t)}, \quad \text{(B.35)}
\end{aligned}$$

*where $\sigma_{Q\Delta}(t) = -\varrho_D(t)\sigma_{\Delta D}(t) + \varrho_s(t)\sigma_{\Delta s}(t) + \varrho_\theta(t)\sigma_{\Delta\theta}(t)$, and $\sigma_{Q\theta}(t) = \frac{\phi_x(t)}{\phi_\theta(t)}\frac{\tilde{q}(t)}{\sigma_D}\varrho_D(t) + \frac{\sigma_\xi^2(t)}{\phi_\theta(t)}(\phi_x(t)\nu(t) - 1)(1+\phi_\Delta(t)\nu(t))$.*

*B.3. Proof for Equilibrium Conditions on the Boundary*

*Solving for Boundary Conditions for Value Function Coefficients.* The boundary conditions for value functions coefficients and price sensitivities can be summarized as follows:

**Lemma 6.** *At the predetermined announcement $T$, the boundary conditions for the informed investor's value function coefficients could be characterized by*

$$\begin{aligned}
g\left(T^-\right) - g(0) = 0, \quad g_{\theta\theta}\left(T^-\right) - g_{\theta\theta}(0) &= \frac{\left[\phi_\theta\left(T^-\right) - \phi_\theta(0)\right]^2}{\hat{q}_T^-\bar{\phi}_x^2},\\
g_{\Delta\Delta}\left(T^-\right) = \frac{\phi_\Delta^2\left(T^-\right)}{\hat{q}_T^-\bar{\phi}_x^2}, \quad g_{\theta\Delta}\left(T^-\right) &= \frac{\phi_\Delta\left(T^-\right)\left[\phi_\theta\left(T^-\right) - \phi_\theta(0)\right]}{\hat{q}_T^-\bar{\phi}_x^2}, \quad \text{(B.36)}
\end{aligned}$$

*and the boundary conditions for the uninformed investor's value function coefficients are*

$$\begin{aligned}
f\left(T^-\right) - f(0) &= \frac{1}{2} ln\left(1 + f_{\theta\theta}(0)\Omega\right),\\
f_{\theta\theta}\left(T^-\right) - f_{\theta\theta}(0) &= -\Gamma f_{\theta\theta}^2(0) + \frac{1}{\Lambda} m_\theta^2\left(T^-\right), \quad \text{(B.37)}
\end{aligned}$$

*where* $\Omega = \frac{\phi_x^2(T^-)}{\phi_\theta^2(T^-)}\tilde{q}_T^-$, $\Gamma = \frac{\Omega}{1+f_{\theta\theta}(0)\Omega}$, $\mu = \bar{\phi}_x \frac{\phi_\theta(T^-)}{\phi_x(T^-)} - \phi_\theta(0)$, $\Lambda = \bar{\phi}_x^2 \hat{q}_T^- + \Gamma\mu^2$, *and* $m_\theta = \phi_\theta(T^-) - \phi_\theta(0) - \Gamma\mu f_{\theta\theta}(0)$.

*Proof.* First, I derive the boundary conditions for the informed investor's value function coefficients. The informed investor's optimization problem at the boundary is

$$\begin{aligned} -e^{-rW_T^{i-} - g\left(T^-, \theta_T^-, \Delta_T^-\right)} &= \max_{\alpha_T}\left\{-\hat{\mathbb{E}}_{T^-}\left[e^{-rW_T^i - g(0,\theta_T,0)}\right]\right\} \\ &= e^{-rW_T^{i-}} \max_{\alpha_T^-}\left\{-\hat{\mathbb{E}}_{T^-}\left[e^{-r\alpha_T^-\left(P_T - P_T^-\right) - g(0,\theta_T,0)}\right]\right\}, \end{aligned} \tag{B.38}$$

where $x_T^- \sim \mathcal{N}\left(\hat{x}_T^-, \hat{q}_T^-\right)$. Solving the exponent part within the expectation operator yields $-r\alpha_T^-\left(P_T - P_T^-\right) - g(0,\theta_T,0) = -\Phi_0 - \Phi_1 x_T$, where $\Phi_0 = r\alpha_T^-\{-[\phi_\theta(0) - \phi_\theta(T^-)]\theta_T^- - \bar{\phi}_x \hat{x}_T^- + \phi_\Delta(T^-)\Delta_T^-\} + g(0) + \frac{1}{2}g_{\theta\theta}(0)\theta_T^2$, $\Phi_1 = r\alpha_T^-\bar{\phi}_x$. Then

$$\hat{\mathbb{E}}_T\left[e^{-r\alpha_T^-\left(P_T - P_T^-\right) - g(0,\theta_T,0)}\right] = e^{-\Phi_0 - \left(\Phi_1 \hat{x}_T - \frac{1}{2}\Phi_1^2 \hat{q}_T^-\right)} = e^{Term^i},$$

where $Term^i = -r\alpha_T^-\left\{-[\phi_\theta(0) - \phi_\theta(T^-)]\theta_T^- + \phi_\Delta(T^-)\Delta_T^-\right\} - g(0) - \frac{1}{2}g_{\theta\theta}(0)\theta_T^2 + \frac{1}{2}r^2\alpha_{T^-}^2\bar{\phi}_x^2\hat{q}_T^-$. FOC with respect to $\alpha_T^-$ implies

$$\alpha_T^- = \alpha_\theta\left(T^-\right)\theta_T^- + \alpha_\Delta\left(T^-\right)\Delta_T^-,$$

where

$$\alpha_\theta\left(T^-\right) = \frac{\phi_\theta(T^-) - \phi_\theta(0)}{r\bar{\phi}_x^2\hat{q}_T^-}, \text{ and } \alpha_\Delta\left(T^-\right) = \frac{\phi_\Delta(T^-)}{r\bar{\phi}_x^2\hat{q}_T^-}. \tag{B.39}$$

Therefore, $g\left(T^-, \theta_T^-, \Delta_T^-\right) = -Term^i$ gives

$$\begin{aligned} & g\left(T^-\right) + \frac{1}{2}g_{\theta\theta}\left(T^-\right)\theta_{T^-}^2 + \frac{1}{2}g_{\Delta\Delta}\left(T^-\right)\Delta_{T^-}^2 + g_{\theta\Delta}\left(T^-\right)\theta_T^-\Delta_T^- \\ = & \frac{\left[\phi_\Delta(T^-)\Delta_T^- + (\phi_\theta(T^-) - \phi_\theta(0))\theta_T^-\right]^2}{\hat{q}_T^-\bar{\phi}_x^2} + \frac{1}{2}g_{\theta\theta}(0)\theta_T^2 + g(0). \end{aligned}$$

Since $\theta_t$ is continuous and does not jump at the announcement, $\theta_T^- = \theta_T$. Matching the coefficients yields the boundary conditions for the uninformed investor's value function summarized in Lemma 6.

Second, I derive the boundary conditions for the uninformed investor's value function coefficients. Before solving the optimization problem, it is useful to define the following notations, as stated in Lemma 6:

$$\Omega \equiv \frac{\phi_x^2\left(T^-\right)}{\phi_\theta^2\left(T^-\right)}\tilde{q}_T^-,\ \Gamma \equiv \frac{\Omega}{1+f_{\theta\theta}\left(0\right)\Omega},\ \mu \equiv \bar{\phi}_x\frac{\phi_\theta\left(T^-\right)}{\phi_x\left(T^-\right)} - \phi_\theta\left(0\right),$$
$$\Lambda \equiv \bar{\phi}_x^2\hat{q}_T^- + \Gamma\mu^2,\ \text{and}\ m_\theta = \phi_\theta\left(T^-\right) - \phi_\theta\left(0\right) - \Gamma\mu f_{\theta\theta}\left(0\right). \tag{B.40}$$

Additionally, the following lemma for a log multivariate normal distribution will be used. □

**Lemma 7.** *Let $X \sim \mathcal{N}\left(0,\Omega\right)$, then*

$$\mathbb{E}\left[e^{-\frac{1}{2}aX^2+bX}\right] = \frac{1}{\sqrt{1+a\Omega}}e^{\frac{1}{2}\frac{b^2\Omega}{1+a\Omega}} = e^{\frac{1}{2}\left[\frac{b^2\Omega}{1+a\Omega}-\ln(1+a\Omega)\right]}.$$

At the boundary, the uninformed investor's optimization problem is:

$$\begin{aligned} -e^{-rW_T^{u-}-f\left(T^-,\tilde{\theta}_T^-\right)} &= \max_{\beta_T}\left\{\tilde{\mathbb{E}}_T^-\left[-e^{-rW_T^u-f(0,\theta_T)}\right]\right\} \\ &= e^{-rW_T^{u-}}\max_{\beta_T^-}\tilde{\mathbb{E}}_T^-\left[-e^{-r\beta_T^-\left(P_T-P_T^-\right)-f(0,\theta_T)}\right], \end{aligned} \tag{B.41}$$

where $\begin{pmatrix} x_T^- \\ \theta_T^- \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \tilde{x}_T^- \\ \tilde{\theta}_T^- \end{pmatrix}, \begin{pmatrix} \hat{q}_T^- + \tilde{q}_T^- & \frac{\phi_x\left(T^-\right)}{\phi_\theta\left(T^-\right)}\tilde{q}_T^- \\ \frac{\phi_x\left(T^-\right)}{\phi_\theta\left(T^-\right)}\tilde{q}_T^- & \Omega \end{pmatrix}\right)$, in which I use the variance-covariance relationship derived in equation (B.13). Note that $x_T$ does not jump the announcement, therefore $x_T^- = x_T$. To eliminate the covariance and simplify the calculations, it is helpful to decompose $x_T^- - \tilde{x}_T^- = \left(x_T - \hat{x}_T^-\right) + \left(\hat{x}_T^- - \tilde{x}_T^-\right)$ and use the identity (B.1) to rewrite $\hat{x}_T^- - \tilde{x}_T^-$ as a function of $\theta_T - \tilde{\theta}_T^-$. This yields $\hat{x}_T^- - \tilde{x}_T^- = \frac{\phi_\theta\left(T^-\right)}{\phi_x\left(T^-\right)}\left(\theta_T - \tilde{\theta}_T^-\right)$.

With this simplification, it is now easier to use the joint distribution, $\begin{pmatrix} x_T - \hat{x}_T^- \\ \theta_T - \tilde{\theta}_T^- \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \hat{q}_T^- & 0 \\ 0 & \Omega \end{pmatrix}\right)$, with zero covariance to write the price changes as: $P_T - P_T^- = -\left[\phi_\theta(0)\theta_T - \phi_\theta(T^-)\tilde{\theta}_T^-\right] + \bar{\phi}_x\left(x_T - \tilde{x}_T^-\right) = \mu\left(\theta_T - \tilde{\theta}_T^-\right) + \left(\phi_\theta(T^-) - \phi_\theta(0)\right)\tilde{\theta}_T^- + \bar{\phi}_x\left(x_T - \hat{x}_T^-\right)$. Also rewrite the value function coefficient $f(0,\theta_T) = f(0) + \frac{1}{2}f_{\theta\theta}(0)\theta_T^2 = F_0 + F_1\left(\theta_T - \tilde{\theta}_T^-\right) + \frac{1}{2}f_{\theta\theta}(0)\left(\theta_T - \tilde{\theta}_T^-\right)^2$, where $F_0 \equiv f(0) + \frac{1}{2}f_{\theta\theta}(0)\tilde{\theta}_T^2$, and $F_1 \equiv f_{\theta\theta}(0)\tilde{\theta}_T$. Consequently, the expectation can be computed as

$$\begin{aligned} & \tilde{\mathbb{E}}_{T^-}\left[e^{-r\beta_T^-\left(P_T - P_T^-\right) - f(0,\theta_T)}\right] \\ = \; & \tilde{\mathbb{E}}_{T^-}\left[e^{-\left(r\beta_T^-\mu + F_1\right)\left(\theta_T - \tilde{\theta}_T^-\right) - \frac{1}{2}f_{\theta\theta}(0)\left(\theta_T - \tilde{\theta}_T^-\right)^2}\right] e^{\left[-r\beta_T^-\left(\phi_\theta\left(T^-\right) - \phi_\theta(0)\right)\tilde{\theta}_T^- - F_0\right] + \frac{1}{2}\left(r\bar{\phi}_x\right)^2 \hat{q}_T^- \beta_{T^-}^2} \\ = \; & e^{\frac{\Omega\left(r\beta_T^-\mu + F_1\right)^2}{2(1+f_{\theta\theta}(0)\Omega)} - \frac{1}{2}\ln(1+f_{\theta\theta}(0)\Omega)}, e^{\left[-r\beta_T^-\left(\phi_\theta\left(T^-\right) - \phi_\theta(0)\right)\tilde{\theta}_T^- - F_0\right] + \frac{1}{2}\left(r\bar{\phi}_x\right)^2 \hat{q}_T^- \beta_{T^-}^2}, \end{aligned}$$

where the second equality comes from the log normal distribution of $x_T - \tilde{x}_T^-$, and the last equality applies Lemma 7. Define $\tilde{\mathbb{E}}_{T^-}\left[e^{-r\beta_T^-\left(P_T - P_T^-\right) - f(0,\theta_T)}\right] = e^{Term^u}$, where

$$Term^u = \frac{1}{2}r^2\Lambda\beta_{T^-}^2 - r\left[\left(\phi_\theta\left(T^-\right) - \phi_\theta(0)\right)\tilde{\theta}_T^- - \Gamma\mu F_1\right]\beta_T^- + \left[-F_0 + \frac{\Gamma}{2}F_1^2 - \frac{1}{2}\ln\left(1 + f_{\theta\theta}(0)\Omega\right)\right].$$

Taking the FOC with respect to $\beta_T^-$ gives

$$\beta_T^- \;=\; \beta_\theta\left(T^-\right)\tilde{\theta}_T^-, \text{ where } \beta_\theta\left(T^-\right) = \frac{m_\theta}{r\Lambda}. \tag{B.42}$$

Substituting $\beta_T^-$ back into the optimization problem, $f\left(T^-, \tilde{\theta}_T^-\right) = -Term^u$ yields

$$f\left(T^-\right) + \frac{1}{2}f_{\theta\theta}\left(T^-\right)\tilde{\theta}_{T^-}^2 = f(0) + \frac{1}{2}f_{\theta\theta}(0)\tilde{\theta}_T^2 - \frac{\Gamma}{2}\left[f_{\theta\theta}(0)\tilde{\theta}_T\right]^2 + \frac{1}{2}\ln\left(1 + f_{\theta\theta}(0)\Omega\right) + \frac{1}{2\Lambda}\left(m_\theta\tilde{\theta}_T\right)^2.$$

Matching the coefficients completes the proof of Lemma 6.

*Solving for Boundary Conditions for Time-Varying Price Sensitivities.* Note that market clearing requires $(1-\omega)\alpha_T^- + \omega\beta_T^- = \theta_T^-$ at the announcement. This implies

$$\begin{aligned}(1-\omega)\alpha_\Delta\left(T^-\right) - \omega\beta_\theta\left(T^-\right)\frac{\phi_x\left(T^-\right)}{\phi_\theta\left(T^-\right)} &= 0,\\ (1-\omega)\alpha_\theta\left(T^-\right) + \omega\beta_\theta\left(T^-\right) &= 1.\end{aligned}$$

By substituting expressions in (B.39) and (B.42), the boundary conditions for the pricing function coefficients can eventually be determined, as summarized in the following lemma.

**Lemma 8.** *At the predetermined announcement $T$, the equilibrium pricing function coefficients satisfy*

$$\phi_\theta\left(T^-\right) - \phi_\theta(0) = \frac{\bar{\phi}_x^2\hat{q}_T^-}{(1-\omega)\Lambda + \omega\bar{\phi}_x^2\hat{q}_T^-}\left[r\Lambda + \omega\Gamma\mu f_{\theta\theta}(0)\right] \tag{B.43}$$

$$\phi_\Delta\left(T^-\right) = \frac{\omega}{(1-\omega)\Lambda}\bar{\phi}_x^2\hat{q}_T^-\frac{\phi_x\left(T^-\right)}{\phi_\theta\left(T^-\right)}m_\theta. \tag{B.44}$$

*B.4. Proof for Pricing Error Predictability*

*Proof for Lemma 3 .* If $\phi_\theta(t)$ is continuous, then at the announcement $T$, $\phi_\theta(T^-) = \phi_\theta(T)$. Using (8), the pricing errors realized upon the announcement can be expressed as $P_T - P_T^- = \bar{\phi}_x\left(x_T - \tilde{x}_T^-\right) - \phi_\theta(T)\left(\theta_T - \tilde{\theta}_T^-\right)$. Here, both $x_T - \tilde{x}_T^-$ and $\theta_T - \tilde{\theta}_T^-$ represent errors in the rational Bayesian beliefs of the uninformed investors. Furthermore, the price reactions to revisions, $P_{t+\delta} - P_t = \phi_D\left(D_{t+\delta} - D_t\right) - \left(\phi_\theta(t+\delta)\tilde{\theta}_{t+\delta} - \phi_\theta(t)\tilde{\theta}_t\right) + \bar{\phi}_x\left(\tilde{x}_{t+\delta} - \tilde{x}_t\right)$, are adapted to the uninformed investor's information set (in terms of public information). Because the forecast errors of Bayesian beliefs cannot be predicted by any variable measurable with respect to its own information set, $\mathrm{Cov}_t(P_{t+\delta} - P_t, x_T - \tilde{x}_T^-) = 0$ and $\mathrm{Cov}_t(P_{t+\delta} - P_t, \theta_T - \tilde{\theta}_T^-) = 0$.

*Proof for Proposition 2.* In equation (26), the terms $x_T - \tilde{x}_T^-$ and $\theta_T - \tilde{\theta}_T^-$ represent errors of Bayesian forecasts and are therefore unpredictable by any variable adapted to uninformed investors' information set, including $P_{t+\delta} - P_t$. However, the term $\left[\phi_\theta(T^-) - \phi_\theta(T)\right]\tilde{\theta}_T^-$ is predictable. Under my notation convention, $\phi_\theta(T^-) - \phi_\theta(T) = \phi_\theta(T^-) - \phi_\theta(0) > 0$, because of the assumed monotonicity of the $\phi_\theta(t)$ function. Therefore, equation (23) is equivalent to $\tilde{\text{Cov}}_t\left(P_{t+\delta} - P_t, \tilde{\theta}_T^-\right) < 0$, which is also equivalent to showing that $\tilde{\text{Cov}}_t\left(P_{t+\delta}, \tilde{\theta}_{t+\delta}\right) < 0$ so that $\tilde{\text{Cov}}_t\left(P_{t+\delta} - \tilde{\mathbb{E}}_t\left[P_{t+\delta}\right], \tilde{\theta}_{t+\delta} - \tilde{\mathbb{E}}_t\left[\tilde{\theta}_{t+\delta}\right]\right) < 0$. Here, $\tilde{\text{Cov}}_t$ is defined as the covariance conditioned on public information at time $t$, or equivalently, covariance conditioned on uninformed investors' information set.

An explicit computation of the term $\tilde{\text{Cov}}_t\left(P_{t+\delta} - \tilde{\mathbb{E}}_t\left[P_{t+\delta}\right], \tilde{\theta}_{t+\delta} - \tilde{\mathbb{E}}_t\left[\tilde{\theta}_{t+\delta}\right]\right)$ can be performed in several steps. First, $\tilde{x}_t$, $\tilde{\theta}_t$, and $D_t$ can be written as integrals of Brownian motions by applying stochastic integration using equations (12), (B.12), and (B.10):

$$\tilde{x}_{t+\delta} = e^{-b\delta}\tilde{x}_t + \left(1 - e^{-b\delta}\right)\bar{x} + \int_0^\delta e^{-b(\delta-z)}\left(\frac{\hat{q}_{t+z} + \tilde{q}_{t+z}}{\sigma_D} d\tilde{B}_{D,t+z} + \nu_{t+z}\sigma_{\xi,t+z} d\tilde{B}_{\xi,t+z}\right), \quad \text{(B.45)}$$

$$\tilde{\theta}_{t+\delta} = e^{-a\delta}\tilde{\theta}_t + \int_0^\delta e^{-a(\delta-z)}\left(\frac{\phi_{x,t+z}}{\phi_{\theta,t+z}}\frac{\tilde{q}_{t+z}}{\sigma_D} d\tilde{B}_{D,t+z} + \frac{1}{\phi_{\theta,t+z}}\sigma_{\xi,t+z}\left(\nu_{t+z}\phi_{x,t+z} - 1\right) d\tilde{B}_{\xi,t+z}\right), \quad \text{(B.46)}$$

$$D_{t+\delta} = e^{-\delta}\left[D_t + \int_0^\delta e^z \tilde{x}_{t+z} dz + \int_0^\delta e^z \sigma_D d\tilde{B}_{D,t+z}\right]. \quad \text{(B.47)}$$

The model-implied uninformed investor's forecast of $x_T$ at time $t$ can be obtained immediately as

$$\tilde{\mathbb{E}}_t\left[x_T\right] = \left(1 - e^{-b(T-t)}\right)\bar{x} + e^{-b(T-t)}\tilde{x}_t. \quad \text{(B.48)}$$

Similarly, the informed investors' forecast of $x_T$ at time $t$ can be expressed as

$$\hat{\mathbb{E}}_t\left[x_T\right] = \left(1 - e^{-b(T-t)}\right)\bar{x} + e^{-b(T-t)}\hat{x}_t. \quad \text{(B.49)}$$

To solve for $D_{t+\delta}$, I substitute the expression for $\tilde{x}_{t+\delta}$ into $\int_0^\delta e^z \tilde{x}_{t+z} dz$ in (B.47), which gives

$$\int_0^\delta e^z \tilde{x}_{t+z} dz = X + \int_0^\delta e^s \int_0^s e^{-b(s-z)}\frac{\hat{q}_{t+z} + \tilde{q}_{t+z}}{\sigma_D} d\tilde{B}_{D,t+z} ds + \int_0^\delta e^s \int_0^s e^{-b(s-z)}\nu_{t+z}\sigma_{\xi,t+z} d\tilde{B}_{\xi,t+z} ds, \quad \text{(B.50)}$$

where $X = \int_0^\delta e^z\left(e^{-bz}\tilde{x}_t + \left(1 - e^{-bz}\right)\bar{x}\right) dz$ is measurable with respect to date-$t$ information.

Applying Fubini's theorem, the second term of the above equation can be written as

$$\begin{aligned}\int_0^\delta e^s \left(\int_0^s e^{-b(s-z)} \frac{\hat{q}_{t+z}+\tilde{q}_{t+z}}{\sigma_D} d\tilde{B}_{D,t+z}\right) ds &= \int_0^\delta e^{bz} \left(\int_z^\delta e^{(1-b)s} \frac{\hat{q}_{t+z}+\tilde{q}_{t+z}}{\sigma_D} ds\right) d\tilde{B}_{D,t+z} \\ &= \int_0^\delta e^z \tau_D(t,z)\, d\tilde{B}_{D,t+z},\end{aligned}$$

where $\tau_D(t,z) = \frac{\hat{q}_{t+z}+\tilde{q}_{t+z}}{\sigma_D} \frac{1}{1-b}\left(e^{(1-b)(\delta-z)}-1\right)$. Similarly, the last term in equation (B.50) can be written as

$$\begin{aligned}\int_0^\delta e^s \left(\int_0^s e^{-b(s-z)} \nu_{t+z}\sigma_{\xi,t+z} d\tilde{B}_{\xi,t+z}\right) ds &= \int_0^\delta e^{bz} \left(\int_z^\delta e^{(1-b)s} \nu_{t+z}\sigma_{\xi,t+z} ds\right) d\tilde{B}_{\xi,t+z} \\ &= \int_0^\delta e^z \tau_\xi(t,z)\, d\tilde{B}_{\xi,t+z},\end{aligned}$$

where $\tau_\xi(t,z) = \nu_{t+z}\sigma_{\xi,t+z}\frac{1}{1-b}\left(e^{(1-b)(\delta-z)}-1\right)$. Using expression (B.47) and noting that $X$ is $\mathcal{F}_t^u$ measurable,

$$D_{t+\delta} = \tilde{\mathbb{E}}_t[D_{t+\delta}] + e^{-\delta}\int_0^\delta e^z\left[\sigma_D + \tau_D(t,z)\right] d\tilde{B}_{D,t+z} + e^{-\delta}\int_0^\delta e^z \tau_\xi(t,z)\, d\tilde{B}_{\xi,t+z}. \tag{B.51}$$

With the expressions (B.45), (B.46), and (B.51), in the second step, $P_{t+\delta} - \tilde{\mathbb{E}}_t[P_{t+\delta}]$ can be written as

$$\begin{aligned}P_{t+\delta} - \tilde{\mathbb{E}}_t[P_{t+\delta}] &= \phi_D\left(D_{t+\delta} - \tilde{\mathbb{E}}_t[D_{t+\delta}]\right) + \bar{\phi}_x\left(\tilde{x}_{t+\delta} - \tilde{\mathbb{E}}_t[\tilde{x}_{t+\delta}]\right) - \phi_\theta(t+\delta)\left(\tilde{\theta}_{t+\delta} - \tilde{\mathbb{E}}_t\left[\tilde{\theta}_{t+\delta}\right]\right) \\ &= \int_0^\delta \sigma_{P,D}(t,z)\, d\tilde{B}_{D,t+z} + \int_0^\delta \sigma_{P,\xi}(t,z)\, d\tilde{B}_{\xi,t+z},\end{aligned} \tag{B.52}$$

where the following shorthand notations are used:

$$\begin{aligned}\sigma_{P,D}(t,z) &= e^{-(\delta-z)}\phi_D(\sigma_D + \tau_D(t,z)) + e^{-b(\delta-z)}\bar{\phi}_x \frac{\hat{q}_{t+z}+\tilde{q}_{t+z}}{\sigma_D} - e^{-a(\delta-z)}\phi_\theta(t+\delta)\frac{\phi_{x,t+z}}{\phi_{\theta,t+z}}\frac{\tilde{q}_{t+z}}{\sigma_D}, \\ \sigma_{P,\xi}(t,z) &= \phi_D e^{-(\delta-z)}\tau_\xi(t,z) + e^{-b(\delta-z)}\bar{\phi}_x \nu_{t+z}\sigma_{\xi,t+z} - e^{-a(\delta-z)}\phi_\theta(t+\delta)\frac{1}{\phi_{\theta,t+z}}\sigma_{\xi,t+z}\left(\nu_{t+z}\phi_{x,t+z}-1\right).\end{aligned}$$

In addition, equation (B.46) implies that

$$\tilde{\theta}_{t+\delta} - \tilde{\mathbb{E}}_t\left[\tilde{\theta}_{t+\delta}\right] = \int_0^\delta e^{-a(\delta-z)}\left(\frac{\phi_{x,t+z}}{\phi_{\theta,t+z}}\frac{\tilde{q}_{t+z}}{\sigma_D}d\tilde{B}_{D,t+z} + \frac{\sigma_{\xi,t+z}}{\phi_{\theta,t+z}}\left(\nu_{t+z}\phi_{x,t+z} - 1\right)d\tilde{B}_{\xi,t+z}\right). \tag{B.53}$$

Third, using (B.52) and (B.53),

$$\begin{aligned} &\tilde{\text{Cov}}_t\left(P_{t+\delta} - \tilde{\mathbb{E}}_t\left[P_{t+\delta}\right], \tilde{\theta}_{t+\delta} - \tilde{\mathbb{E}}_t\left[\tilde{\theta}_{t+\delta}\right]\right) \\ = &\int_0^\delta e^{-a(\delta-z)}\left[\sigma_{P,D}(t,z)\frac{\phi_{x,t+z}}{\phi_{\theta,t+z}}\frac{\tilde{q}_{t+z}}{\sigma_D} + \sigma_{P,\xi}(t,z)\frac{\sigma_{\xi,t+z}}{\phi_{\theta,t+z}}\left(\nu_{t+z}\phi_{x,t+z} - 1\right)\right]dz. \end{aligned}$$

Denote $\Gamma(t,z,\delta) = \sigma_{P,D}(t,z)\left[e^{-a(\delta-z)}\frac{\phi_{x,t+z}}{\phi_{\theta,t+z}}\frac{\tilde{q}_{t+z}}{\sigma_D}\right] + \sigma_{P,\xi}(t,z)\left[e^{-a(\delta-z)}\frac{\sigma_{\xi,t+z}}{\phi_{\theta,t+z}}\left(\nu_{t+z}\phi_{x,t+z} - 1\right)\right]$. To establish $\tilde{\text{Cov}}_t\left(P_{t+\delta} - \tilde{\mathbb{E}}_t\left[P_{t+\delta}\right], \tilde{\theta}_{t+\delta} - \tilde{\mathbb{E}}_t\left[\tilde{\theta}_{t+\delta}\right]\right) < 0$, it is enough to establish that

$$\Gamma(t,z,\delta) < 0 \tag{B.54}$$

for all $z \in [0,\delta]$. The following lemma establishes (B.54) for $\delta$ small enough. Note that as $\delta \to 0$, for all $z \in [0,\delta]$, $\Phi(t,z,\delta) \to \Phi(t)$, where

$$\begin{aligned} \Gamma(t) &= \left(\phi_D\sigma_D + \bar{\phi}_x\frac{\hat{q}_t + \tilde{q}_t}{\sigma_D} - \phi_{x,t}\frac{\tilde{q}_t}{\sigma_D}\right)\frac{\phi_{x,t}}{\phi_{\theta,t}}\frac{\tilde{q}_t}{\sigma_D} + \left[\bar{\phi}_x\nu_t\sigma_{\xi,t} - \sigma_{\xi,t}\left(\nu_t\phi_{x,t} - 1\right)\right]\frac{\sigma_{\xi,t}}{\phi_{\theta,t}}\left(\nu_t\phi_{x,t} - 1\right) \\ &= \frac{\phi_{x,t}}{\phi_{\theta,t}}\frac{\tilde{q}_t}{\sigma_D}\left(\phi_D\sigma_D + \bar{\phi}_x\frac{\hat{q}_t}{\sigma_D} + \phi_{\Delta,t}\frac{\tilde{q}_t}{\sigma_D}\right) + \left(1 + \phi_{\Delta,t}\nu_t\right)\frac{\sigma_{\xi,t}^2}{\phi_{\theta,t}}\left(\phi_{x,t}\nu_t - 1\right). \end{aligned} \tag{B.55}$$

**Lemma 9.** *Under condition (24), $\Gamma(t) < 0$ for all $t$.*

*Proof.* Because $\phi_{\Delta,t}\nu_t > 0$, to show $\Gamma(t) < 0$, it is enough to prove that

$$\left(1 - \phi_{x,t}\nu_t\right)\sigma_{\xi,t}^2 > \phi_{x,t}\frac{\tilde{q}_t}{\sigma_D}\left(\phi_D\sigma_D + \bar{\phi}_x\frac{\hat{q}_t}{\sigma_D} + \phi_{\Delta,t}\frac{\tilde{q}_t}{\sigma_D}\right). \tag{B.56}$$

Using the definitions of $\sigma_{\xi,t}$ in (B.8), $\nu_t$ in (B.9), and $m_x(t)$ in (B.6), equation (B.56) is equivalent to the following condition:

$$\phi_{\theta}^{2}(t)\,\sigma_{\theta}^{2} > \phi_{x}(t)\,\tilde{q}_{t}\left[\phi_{D} + \left(a - b - \frac{\phi_{\theta}'(t)}{\phi_{\theta}(t)}\right)\phi_{x}(t) + \phi_{x}'(t) + \frac{\phi_{\Delta}(t)}{\sigma_{D}^{2}}\left(\hat{q}_{t} + \tilde{q}_{t}\right)\right].$$

Because $\phi_{\theta}'(t) > 0$, condition (24) is a sufficient condition for the above inequality. □

*B.5. Trading Volume*

Here, I provide the detailed definitions and numerical calculations for the quadratic trading volume. The portfolio holdings for informed and uninformed investors are given in equations (20) and (21). Using the dynamics of $d\theta_t$, $d\Delta_t$, and $d\tilde{\theta}_t$, within the interior $(0, T)$, the portfolio holdings are modeled as diffusion processes:

$$\begin{aligned}
d\alpha_t &= -\left(a\alpha_{\theta}(t)\,\theta_t + a_{\Delta}(t)\,\alpha_{\Delta}(t)\,\Delta_t\right)dt + \left(\alpha_{\theta}(t)\,\sigma_{\theta} + \alpha_{\Delta}(t)\,\sigma_{\Delta\theta}(t)\right)dB_{\theta,t} \\
&\quad -\alpha_{\Delta}(t)\,\sigma_{\Delta D}(t)\,d\hat{B}_{D,t} + \alpha_{\Delta}(t)\,\sigma_{\Delta s}(t)\,d\hat{B}_{s,t} \\
d\beta_t &= \beta_{\theta}(t)\left(-a\tilde{\theta}_t dt + \frac{\phi_x(t)}{\phi_{\theta}(t)}\frac{\tilde{q}(t)}{\sigma_D}d\tilde{B}_{D,t} + \frac{1}{\phi_{\theta}(t)}\sigma_{\xi}(t)\left[\nu(t)\,\phi_x(t) - 1\right]d\tilde{B}_{\xi,t}\right).
\end{aligned}$$

On the boundary, $\alpha_T^-$ and $\beta_T^-$ jump to $\alpha_T = \alpha_{\theta}(0)\,\theta_T$ and $\beta_T = \beta_{\theta}(0)\,\theta_T$, respectively.

The quadratic trading volume for informed and uninformed investors over any interval $(t, t+\tau)$ in the interior between announcements is defined, respectively, as

$$\begin{aligned}
\hat{M}(t, t+\tau) &= \int_t^{t+\tau}\left[\alpha_{\theta}(u)\,\sigma_{\theta} + \alpha_{\Delta}(u)\,\sigma_{\Delta\theta}(u)\right]^2 du + \int_t^{t+\tau}\left[\alpha_{\Delta}(u)\,\sigma_{\Delta D}(u)\right]^2 du \\
&\quad + \int_t^{t+\tau}\left[\alpha_{\Delta}(u)\,\sigma_{\Delta s}(u)\right]^2 du, \\
\tilde{M}(t, t+\tau) &= \int_t^{t+\tau}\left[\beta_{\theta}(u)\frac{\phi_x(u)}{\phi_{\theta}(u)}\frac{\tilde{q}(u)}{\sigma_D}\right]^2 du + \int_t^{t+\tau}\left[\frac{\beta_{\theta}(u)}{\phi_{\theta}(u)}\sigma_{\xi}(u)\left[\nu(u)\,\phi_x(u) - 1\right]\right]^2 du.
\end{aligned}$$

Upon the announcement, quadratic trading volumes are computed as

$$\hat{M}\left(T^-, T\right) = \left[\alpha_{\theta}(0)\,\theta_T - \alpha_{\theta}\left(T^-\right)\theta_T^- - \alpha_{\Delta}\left(T^-\right)\Delta_T^-\right]^2 \tag{B.57}$$

$$\tilde{M}\left(T^-, T\right) = \left[\beta_{\theta}(0)\,\theta_T - \beta_{\theta}\left(T^-\right)\tilde{\theta}_T^-\right]^2. \tag{B.58}$$

Numerically, the trading volume in the interior can be computed and approximated as

$$\begin{aligned}
\hat{M}(t,t+\tau) &= \lim_{n\to\infty}\sum_{j=0}^{n-1}\left(\alpha_{t+\frac{j+1}{n}\tau}-\alpha_{t+\frac{j}{n}\tau}\right)^2 \\
&\approx \left[(\alpha_\theta(t)\sigma_\theta+\alpha_\Delta(t)\sigma_{\Delta\theta}(t))^2+(\alpha_\Delta(t)\sigma_{\Delta D}(t))^2+(\alpha_\Delta(t)\sigma_{\Delta s}(t))^2\right]\tau \\
\tilde{M}(t,t+\tau) &= \lim_{n\to\infty}\sum_{j=0}^{n-1}\left(\beta_{t+\frac{j+1}{n}\tau}-\beta_{t+\frac{j}{n}\tau}\right)^2 \\
&\approx \beta_\theta^2(t)\left[\left(\frac{\phi_x(t)}{\phi_\theta(t)}\frac{\tilde{q}(t)}{\sigma_D}\right)^2+\left(\frac{1}{\phi_\theta(t)}\sigma_\xi(t)\left[\nu(t)\phi_x(t)-1\right]\right)^2\right]\tau.
\end{aligned}$$

Therefore, the quadratic trading volume after the announcement for a small time interval $\tau$ can be computed as

$$\begin{aligned}
\hat{M}(T,T+\tau) =& \Big[(\alpha_\theta(T)\sigma_\theta+\alpha_\Delta(T)\sigma_{\Delta\theta}(T))^2+(\alpha_\Delta(T)\sigma_{\Delta D}(T))^2 \\
&+(\alpha_\Delta(T)\sigma_{\Delta s}(T))^2\Big]\tau \qquad \text{(B.59)}\\
\tilde{M}(T,T+\tau) =& \left[\left(\beta_\theta(T)\frac{\phi_x(T)}{\phi_\theta(T)}\frac{\tilde{q}_T}{\sigma_D}\right)^2+\left(\frac{\beta_\theta(T)}{\phi_\theta(T)}\sigma_\xi(T)\left[\nu(T)\phi_x(T)-1\right]\right)^2\right]\tau. \qquad \text{(B.60)}
\end{aligned}$$

Similarly, the quadratic trading volume before the announcement for an interval $\tau$ is

$$\begin{aligned}
\hat{M}\left(T-\tau,T^-\right) =& \Big[\left(\alpha_\theta\left(T^-\right)\sigma_\theta+\alpha_\Delta\left(T^-\right)\sigma_{\Delta\theta}\left(T^-\right)\right)^2+\left(\alpha_\Delta\left(T^-\right)\sigma_{\Delta D}\left(T^-\right)\right)^2 \\
&+\left(\alpha_\Delta\left(T^-\right)\sigma_{\Delta s}\left(T^-\right)\right)^2\Big]\tau \qquad \text{(B.61)}\\
\tilde{M}\left(T-\tau,T^-\right) =& \left[\left(\beta_\theta\left(T^-\right)\frac{\phi_x\left(T^-\right)}{\phi_\theta\left(T^-\right)}\frac{\tilde{q}_T^-}{\sigma_D}\right)^2+\left(\frac{\beta_\theta\left(T^-\right)}{\phi_\theta\left(T^-\right)}\sigma_\xi\left(T^-\right)\left[\nu\left(T^-\right)\phi_x\left(T^-\right)-1\right]\right)^2\right]\tau. \qquad \text{(B.62)}
\end{aligned}$$

Therefore, the total quadratic trading volume upon the announcement is:

$$M\left(T^-,T\right)=(1-\omega)\hat{M}\left(T^-,T\right)+\omega\tilde{M}\left(T^-,T\right), \qquad \text{(B.63)}$$

and the total quadratic volume one day after the announcement (where $\tau=1/360$) is:

$$M(T,T+\tau)=(1-\omega)\hat{M}(T,T+\tau)+\omega\tilde{M}(T,T+\tau). \qquad \text{(B.64)}$$

Similarly, the volume one day before the announcement is

$$M\left(T-\tau,T^{-}\right)=\left(1-\omega\right)\hat{M}\left(T-\tau,T^{-}\right)+\omega\tilde{M}\left(T-\tau,T^{-}\right). \tag{B.65}$$

Finally, the trading volume percentage increase from the day before the announcement to the announcement day and the percentage decrease from the announcement day to the next day are computed as: $\frac{M\left(T^{-},T\right)}{M(T-\tau,T^{-})}-1$ , and $\frac{M\left(T^{-},T\right)}{M(T,T+\tau)}-1$, respectively.

*B.6. Implied Variance*

In order to compute the forward looking implied variance $Var_0\left[P_t-P_0\right]=Var_0\left[P_t\right]$, I first consider the case in which $t<T$ and solve the three components in the pricing function separately. From equation (B.45), $\tilde{x}_t$ can be written as

$$\tilde{x}_t=\left(1-e^{-bt}\right)\bar{x}+e^{-bt}\int_0^t e^{bz}\left(\frac{\hat{q}_z+\tilde{q}_z}{\sigma_D}d\tilde{B}_{D,z}+\nu\left(z\right)\sigma_\xi\left(z\right)d\tilde{B}_{\xi,z}\right).$$

Therefore, with an abuse of notation, I use $\mathcal{D}\left[X\right]$ to denote the diffusion part of $X$,

$$\mathcal{D}\left[\tilde{x}_t\right]=\int_0^t e^{b(z-t)}\frac{\hat{q}_z+\tilde{q}_z}{\sigma_D}d\tilde{B}_{D,z}+\int_0^t e^{b(z-t)}\nu\left(z\right)\sigma_\xi\left(z\right)d\tilde{B}_{\xi,z}. \tag{B.66}$$

Secondly, from equation (B.47), $D_t$ can be solved as

$$D_t=e^{-t}\left(D_0+\int_0^t e^{z}\tilde{x}_z dz+\int_0^t e^{z}\sigma_D d\tilde{B}_{D,z}\right),$$

where the term $\int_0^t e^u\tilde{x}_u du=\int_0^t e^{(1-b)u}\int_0^u\left\{e^{bz}\left(b\bar{x}\right)dz+\int_0^u e^{bz}\frac{\hat{q}_z+\tilde{q}_z}{\sigma_D}d\tilde{B}_{D,z}+\int_0^u e^{bz}\nu\left(z\right)\sigma_\xi\left(z\right)d\tilde{B}_{\xi,z}\right\}du$, so that the diffusion part

$$\begin{aligned}\int_0^t\int_0^u e^{bz+(1-b)u}\frac{\hat{q}_z+\tilde{q}_z}{\sigma_D}d\tilde{B}_{D,z}du&=\int_0^t\int_z^t e^{bz+(1-b)u}\frac{\hat{q}_z+\tilde{q}_z}{\sigma_D}dud\tilde{B}_{D,z}\\&=\frac{1}{\left(1-b\right)\sigma_D}\int_0^t\left[e^{(1-b)t+bz}-e^{z}\right]\left(\hat{q}_z+\tilde{q}_z\right)d\tilde{B}_{D,z}.\end{aligned}$$

Similarly,

$$\int_0^t \int_0^u e^{bz+(1-b)u} \nu(z)\, \sigma_\xi(z)\, d\tilde{B}_{\xi,z} du = \frac{1}{(1-b)} \int_0^t \left[ e^{(1-b)t+bz} - e^z \right] \nu(z)\, \sigma_\xi(z)\, d\tilde{B}_{\xi,z}.$$

Therefore, the diffusion part of $D_t$ is

$$\mathcal{D}[D_t] = \int_0^t \left[ \left( e^{b(z-t)} - e^{z-t} \right) \frac{\hat{q}_z + \tilde{q}_z}{(1-b)\, \sigma_D} + e^{z-t} \sigma_D \right] d\tilde{B}_{D,z} + \int_0^t \left[ e^{b(z-t)} - e^{z-t} \right] \frac{\nu(z)\, \sigma_\xi(z)}{1-b} d\tilde{B}_{\xi,z} \tag{B.67}$$

Finally, from equation (B.46),

$$\mathcal{D}\left[\tilde{\theta}_t\right] = \int_0^t e^{a(z-t)} \frac{\phi_x(z)}{\phi_\theta(z)} \frac{\tilde{q}(z)}{\sigma_D} d\tilde{B}_{D,z} + \int_0^t e^{a(z-t)} \left[ \phi_x(z)\, \nu(z) - 1 \right] \frac{\sigma_\xi(z)}{\phi_\theta(z)} d\tilde{B}_{\xi,z}. \tag{B.68}$$

Summing up (B.66), (B.67), and (B.68), the price can be represented in the form of

$$\mathcal{D}[P_t] = \int_0^t X_D(z)\, d\tilde{B}_{D,z} + \int_0^t X_\xi(z)\, d\tilde{B}_{\xi,z},$$

where

$$X_D(z) = \phi_D \left[ \left( e^{b(z-t)} - e^{z-t} \right) \frac{\hat{q}_z + \tilde{q}_z}{(1-b)\, \sigma_D} + e^{z-t} \sigma_D \right] - \phi_\theta(t)\, e^{a(z-t)} \frac{\phi_x(z)}{\phi_\theta(z)} \frac{\tilde{q}_z}{\sigma_D} + \bar{\phi}_x e^{b(z-t)} \frac{\hat{q}_z + \tilde{q}_z}{\sigma_D}, \tag{B.69}$$

$$X_\xi(z) = \phi_D \left[ e^{b(z-t)} - e^{z-t} \right] \frac{\nu(z)\, \sigma_\xi(z)}{1-b} - \phi_\theta(t)\, e^{a(z-t)} \left[ \phi_x(z)\, \nu(z) - 1 \right] \frac{\sigma_\xi(z)}{\phi_\theta(z)} + \bar{\phi}_x e^{b(z-t)} \nu(z)\, \sigma_\xi(z). \tag{B.70}$$

The variance can be computed as:

$$Var_0[P_t] = \int_0^t X_D^2(z)\, dz + \int_0^t X_\xi^2(z)\, dz.$$

Next, consider the general case of $Var_t[P_{t+\tau}]$. If $t + \tau < T$, that is, if computing the implied variance within an announcement cycle, use the above formula. If $t+\tau>T$, first compute $Var_t\left[P_T^-\right]$ using the above formula and then compute $Var_{T^+}\left[P_{t+\tau}\right]$:

$$Var_t\left[P_{t+\tau}\right]=\int_t^{t+\tau}X_D^2(z)\,dz+\int_t^{t+\tau}X_\xi^2(z)\,dz.$$

Using equation (26), where $\begin{pmatrix} x_T \\ \theta_T \end{pmatrix}\sim\mathcal{N}\left(\begin{pmatrix} \tilde{x}_T^- \\ \tilde{\theta}_T^- \end{pmatrix},\begin{pmatrix} \hat{q}_T^-+\tilde{q}_T^- & \frac{\phi_x(T^-)}{\phi_\theta(T^-)}\tilde{q}_T^- \\ \frac{\phi_x(T^-)}{\phi_\theta(T^-)}\tilde{q}_T & \frac{\phi_x^2(T^-)}{\phi_\theta^2(T^-)}\tilde{q}_T^- \end{pmatrix}\right)$, the variance at the announcement $Var_{T^-}\left[P_T-P_T^-\right]$ can be computed as

$$Var_{T^-}\left[P_T-P_T^-\right] = \bar{\phi}_x^2\left(\hat{q}_T^-+\tilde{q}_T^-\right)+\phi_\theta^2(0)\frac{\phi_x^2(T^-)}{\phi_\theta^2(T^-)}\tilde{q}_T^- - 2\bar{\phi}_x\phi_\theta(0)\frac{\phi_x(T^-)}{\phi_\theta(T^-)}\tilde{q}_T^-, \quad \text{(B.71)}$$

where $P_T-P_T^-$ comes from equation (26). Therefore, the total implied variance of return from $t$ to $\tau$ is obtained by

$$\begin{aligned} IV_{t,\tau} &= \underbrace{Var_t\left[P_T\right]/P_t^2}_{\text{IV before announcement}}+\underbrace{Var_{T^-}\left[P_T-P_T^-\right]/P_T^{-2}}_{\text{IV at announcement}}+\underbrace{Var_T\left[P_{t+\tau}\right]/P_T^2}_{\text{IV after announcement}} \\ &= \frac{1}{P_t^2}\left(\int_t^{T^-}X_D^2(z)\,dz+\int_t^{T^-}X_\xi^2(z)\,dz\right)+\frac{1}{P_T^2}\left(\int_T^{t+\tau}X_D^2(z)\,dz+\int_T^{t+\tau}X_\xi^2(z)\,dz\right) \\ &\quad+\frac{1}{P_T^{-2}}\left[\bar{\phi}_x^2\left(\hat{q}_T^-+\tilde{q}_T^-\right)+\phi_\theta^2(0)\frac{\phi_x^2(T^-)}{\phi_\theta^2(T^-)}\tilde{q}_T^- - 2\bar{\phi}_x\phi_\theta(0)\frac{\phi_x(T^-)}{\phi_\theta(T^-)}\tilde{q}_T^-\right]. \end{aligned} \quad \text{(B.72)}$$

The implied variance reduction upon the announcements is therefore defined as

$$\Delta IV_T^- = IV_{T^-,\tau}-IV_{T,\tau}. \quad \text{(B.73)}$$

*B.7. A Two-Period Model*

In this section, I present a two-period NREE model to illustrate the paper's two main economic mechanisms, which account for the empirical facts on the predictability of forecast errors and the stock market's reaction to them. First, I show that in the presence of the asymmetric information, revisions of the average forecast of both groups of investors positively predict errors of the average forecast. Intuitively, the predictability of the errors of the consensus (average) forecast comes from the predictability of the errors of the uninformed investor by the private information of the informed investor. Because the informed investor has superior information, his forecast revisions positively predict the forecast errors of the uninformed. Second, the revision period returns negatively predict the announcement-day returns.

*Model Setup.* Consider an economy with two groups of investors, the informed and uninformed. Both live for only two periods and maximize expected utility with identical CARA preferences: $u(C) = -e^{-C}$, where $C$ denotes consumption. For simplicity, the time discount factor and risk aversion are assumed to be 1. There are two types of securities, a risk-free bond with the price normalized to one and a risky asset with endogenous market price $P$. Each investor $j$ is endowed with $e_j$ units of a Lucas tree that pays $(x_0, x)$ on dates 0 and 1. All investors have a common prior about $x$, which is normally distributed with mean $\bar{x}$ and volatility $\sigma_x > 0$, i.e., $x \sim \mathcal{N}(\bar{x}, \sigma_x^2)$. The total endowment in the economy is $\theta$. As is common in the NREE literature, to prevent equilibrium prices from being fully revealing, I assume $\theta$ is a random variable and that all investors have a common prior for $\theta$, which is normally distributed with mean 0 and volatility $\sigma_\theta > 0$, $\theta \sim \mathcal{N}(0, \sigma_\theta^2)$. $\theta$ can represent noise, liquidity traders, asset supply shocks, or higher order uncertainties. I simply refer to it as total risky asset supply, as in Grossman and Stiglitz (1980).

The informed investor observes a *private* (but noisy) signal $s$ about $x$, whereas the uninformed does not. The informed investor's signal is of the form

$$s = x + \varepsilon,\ \varepsilon \sim \mathcal{N}\left(0, \sigma_s^2\right),$$

where $\varepsilon$ is normally distributed with mean 0 and variance $\sigma_s^2$. Assume that $\sigma_s > 0$, so that the informed investor cannot perfectly observe the true value of $x$. Both investors have rational expectations and update their beliefs using Bayes' rule, based on their individual signals. Since investors only care about the fundamental cash flow $x$ and the equilibrium price contains information about it, investors also learn from the observed price $P$. As a result, the information sets for the informed and uninformed investor are $\mathcal{F}^i = \{s, P\}$ and $\mathcal{F}^u = \{P\}$, respectively. Furthermore, since price does not convey any supplementary information to the informed, it can be concluded that $\mathcal{F}^i = \{s\}$.

As in standard NREE models, I focus on equilibriums in which prices are linear functions of fundamentals.

$$P = \phi_0 \bar{x} + \phi_s s - \phi_\theta \theta, \tag{B.74}$$

where $\phi_0$, $\phi_s$, and $\phi_\theta$ are yet to be determined.

The optimization problem for each investor $j = \{i, u\}$ can be characterized as

$$\max_{C_{j,0}, C_{j,1}, \alpha_j, B_j} u\left(C_{j,0}\right) + \mathbb{E}\left[u\left(C_{j,1}\right) \mid \mathcal{F}^j\right] \tag{B.75}$$

$$s.t.\ C_{j,0} + B_j + \alpha_j P = e_j\left(x_0 + P\right)$$

$$C_{j,1} = \alpha_j x + B_j,$$

where $C_{j,0}, C_{j,1}$ denote consumption at dates 0 and 1, and $B_j$ and $\alpha_j$ are the portfolio shares that investor $j$ holds in risk-free bonds and risky assets, respectively. The initial wealth is the product of the initial endowment $e_j$ and the initial value of the risky asset, $x_0 + P$.

The market clearing condition takes the form

$$\alpha_i + \alpha_u = \theta. \tag{B.76}$$

That is, the aggregate risky demand equals the total noisy supply.

The optimal solution yields investor $j$'s demand function for risky assets

$$\alpha_j = \frac{\mathbb{E}\left(x \mid \mathcal{F}^j\right) - P}{\mathrm{Var}\left(x \mid \mathcal{F}^j\right)},$$

where the posterior distributions for both groups of investors can be written as

$$\begin{aligned}\hat{\mathbb{E}}\left[x\right] &= \left(1-\lambda\right)\bar{x}+\lambda s,\\ \tilde{\mathbb{E}}\left[x\right] &= \left(1-\tau\right)\bar{x}+\tau P,\end{aligned}$$

and where $\hat{\mathbb{E}} \equiv \mathbb{E}\left[\centerdot \mid \mathcal{F}^{i}\right]$ and $\tilde{\mathbb{E}} \equiv \mathbb{E}\left[\centerdot \mid \mathcal{F}^{u}\right]$ are conditional expectations of informed and uninformed investors; $\lambda = \frac{\mathrm{Cov}(x,s)}{\mathrm{Var}(s)} = \frac{\sigma_x^2}{\sigma_s^2+\sigma_x^2}$ and $\tau = \frac{\mathrm{Cov}(x,P)}{\mathrm{Var}(P)} = \frac{\phi_s\sigma_x^2}{\phi_s^2(\sigma_s^2+\sigma_x^2)+\phi_\theta^2\sigma_\theta^2}$ are the weights that informed and uninformed put on the signals. And the conditional variances are

$$\begin{aligned}\hat{\mathrm{Var}}\left(x\right)=\mathrm{Var}\left(x\right)-\frac{\mathrm{Cov}^2\left(x,s\right)}{\mathrm{Var}\left(s\right)} &\equiv \varrho_i=\frac{\sigma_s^2\sigma_x^2}{\sigma_s^2+\sigma_x^2},\\ \tilde{\mathrm{Var}}\left(x\right)=\mathrm{Var}\left(x\right)-\frac{\mathrm{Cov}^2\left(x,P\right)}{\mathrm{Var}\left(P\right)} &\equiv \varrho_u=\frac{\left(\phi_s^2\sigma_s^2+\phi_\theta^2\sigma_\theta^2\right)\sigma_x^2}{\phi_s^2\left(\sigma_s^2+\sigma_x^2\right)+\phi_\theta^2\sigma_\theta^2}.\end{aligned}$$

Investor $j$'s demand function for risky assets can then be derived as

$$\alpha_i = \frac{\hat{\mathbb{E}}\left(x\right)-P}{\hat{\mathrm{Var}}\left(x\right)} = \frac{\left(1-\lambda\right)\bar{x}+\lambda s-P}{\varrho_i}, \tag{B.77}$$

$$\alpha_u = \frac{\tilde{\mathbb{E}}\left(x\right)-P}{\tilde{\mathrm{Var}}\left(x\right)} = \frac{\left(1-\tau\right)\left(\bar{x}-P\right)}{\varrho_u}. \tag{B.78}$$

Using the market clearing condition (B.76), the price can be derived accordingly as

$$P=\frac{\varrho_u\left(1-\lambda\right)+\varrho_i\left(1-\tau\right)}{\varrho_u+\varrho_i\left(1-\tau\right)}\bar{x}+\frac{\varrho_u\lambda}{\varrho_u+\varrho_i\left(1-\tau\right)}s-\frac{\varrho_u\varrho_i}{\varrho_u+\varrho_i\left(1-\tau\right)}\theta.$$

Rational expectations imply that the price coefficients are the same as in (B.74). Hence, by matching the coefficients, $\phi_0$, $\phi_s$, and $\phi_\theta$ can finally be determined accordingly,

$$\phi_\theta=\frac{\sigma_s^2\sigma_x^2\left(\sigma_\theta^2\sigma_s^2+2\right)}{2\sigma_\theta^2\sigma_s^4+2\sigma_s^2+\sigma_\theta^2\sigma_s^2\sigma_x^2+2\sigma_x^2},\ \phi_s=\frac{\phi_\theta}{\sigma_s^2},\ \phi_0=1-\phi_s.$$

*Consensus Forecast Error Predictability.* This section uses the above model to rationally explain why consensus forecast revisions positively predict consensus forecast errors.

The forecast revision of the informed investor is calculated as the difference between the posterior and the prior belief about the fundamental $x$, that is, $(\hat{\mathbb{E}}[x]-\bar{x})$; and forecast error can be calculated as the difference between the realization and posterior belief about $x$, (i.e., $x-\hat{\mathbb{E}}[x]$). A similar argument applies to the uninformed investor. Since both types of investors are updating beliefs based on Bayes' rule, $\hat{\mathbb{E}}[x]$ and $\tilde{\mathbb{E}}[x]$ are derived optimally with respect to their own information set. Hence, forecast revisions of informed and uninformed investors cannot predict their *own* forecast errors, that is,

$$\begin{aligned}
\mathrm{Cov}\left(\hat{\mathbb{E}}[x]-\bar{x},x-\hat{\mathbb{E}}[x]\right) &= \lambda(1-\lambda)\sigma_x^2-\lambda^2\sigma_s^2=0\\
\mathrm{Cov}\left(\tilde{\mathbb{E}}[x]-\bar{x},x-\tilde{\mathbb{E}}[x]\right) &= \tau\phi_s(1-\tau\phi_s)\sigma_x^2-(\tau\phi_s)^2\sigma_s^2-(\tau\phi_\theta)^2\sigma_\theta^2=0.
\end{aligned}$$

However, since the informed investors observes an additional private signal, his or her belief revision can positively predict the forecast error of the uninformed. The intuition is simple because the informed knows whatever the uninformed knows and therefore can predict the belief error of the uninformed. That is,

$$\mathrm{Cov}\left(\hat{\mathbb{E}}[x]-\bar{x},x-\tilde{\mathbb{E}}[x]\right)=\lambda(1-\tau\phi_s)\sigma_x^2-\lambda\tau\phi_s\sigma_s^2=\frac{\sigma_\theta^2\sigma_s^4\sigma_x^4}{(\sigma_s^2+\sigma_x^2)(\sigma_\theta^2\sigma_s^4+\sigma_s^2+\sigma_x^2)}>0$$

However, the uninformed investor's forecast revision cannot predict the informed investor's forecast error:

$$\mathrm{Cov}\left(\tilde{\mathbb{E}}[x]-\bar{x},x-\hat{\mathbb{E}}[x]\right)=(1-\lambda)\tau\phi_s\sigma_x^2-\lambda\tau\phi_s\sigma_s^2=0.$$

The following lemma summarizes the result.

**Lemma 10.** *The informed investor's forecast revision positively predicts the uninformed investor's forecast error, but not vice versa, that is,*

$$Cov\left(\hat{\mathbb{E}}[x]-\bar{x},x-\tilde{\mathbb{E}}[x]\right)>0,\ \ and\ Cov\left(\tilde{\mathbb{E}}[x]-\bar{x},x-\hat{\mathbb{E}}[x]\right)=0 \tag{B.79}$$

This result further implies that the consensus forecast revision can predict the consensus forecast error, where all predictability comes from the predictability of the uninformed investor's forecast error from the informed. Define the consensus posterior belief as

$$\bar{\mathbb{E}}[x] \equiv \frac{1}{2}\left(\hat{\mathbb{E}}[x] + \tilde{\mathbb{E}}[x]\right),$$

where $\bar{\mathbb{E}}$ is the *average* expectation operator. Similarly, the consensus forecast revision could be calculated as the average difference between investors' posterior and prior beliefs, (i.e., $\bar{\mathbb{E}}[x] - \bar{x}$), and the consensus forecast error can be calculated as the difference between the realization and average posterior belief, (i.e., $x - \bar{\mathbb{E}}[x]$). Therefore,

$$\begin{aligned}
\mathrm{Cov}\left(\bar{\mathbb{E}}[x] - \bar{x}, x - \bar{\mathbb{E}}[x]\right) &= \frac{1}{2}(\lambda + \tau\phi_s)\,\sigma_x^2 - \frac{1}{4}(\lambda + \tau\phi_s)^2\left(\sigma_s^2 + \sigma_x^2\right) - \frac{1}{4}(\tau\phi_\theta)^2\sigma_\theta^2 \\
&= \frac{\sigma_\theta^2\sigma_s^4\sigma_x^4}{4\left(\sigma_s^2 + \sigma_x^2\right)\left(\sigma_\theta^2\sigma_s^4 + \sigma_s^2 + \sigma_x^2\right)} > 0
\end{aligned}$$

The following proposition summarizes the result.

**Proposition 3.** *Consensus forecast revisions positively predict consensus forecast errors, that is,*

$$Cov\left(\bar{\mathbb{E}}[x] - \bar{x}, x - \bar{\mathbb{E}}[x]\right) > 0. \tag{B.80}$$

Therefore, consensus forecast revisions positively predict consensus forecast errors with asymmetric information. The intuition is as follows. The average of individuals' rational beliefs is not Bayesian — it puts too much weight on the prior and therefore underweights new information relative to the representative agent rational expectations benchmark (herein the informed investor).[1] Although each investor rationally updates his or her belief using his or her own information set, the uninformed investor cannot observe the informed investor's

[1] This result is consistent with Jouini and Napp (2007), who show that the consensus belief violates the law of iterated expectations. But the main difference lies in the fact that my model incorporates prices and announcements as public information and, more importantly, connects to the predictability of consensus belief errors in the data.

private signal. Aggregating over all the investors underweights the unobserved private signals due to the incomplete and asymmetric information. It is also important to notice that the consensus belief cannot be captured by any representative agent's belief, since a Bayesian investor's belief is a martingale. Consequently, *heterogeneity*, in this context arising from asymmetric information, is crucial under this rational framework to generate the observed empirics. Clearly, if the price is fully revealing ($\sigma_\theta = 0$ or $\sigma_s = 0$), the model collapses to a representative agent rational expectations benchmark. In this case, forecast revisions cannot predict forecast errors.

*Predictability of Announcement Returns.* In period 1, because the terminal value of the cash flow is fully revealed, the price of the asset $P_1 = x$. We assume that the price in period $-1$ is just equal to the unconditional expectation of the value of the asset: $P_{-1} = \mathbb{E}[x] = \bar{x}$. Then the covariance between the revision period return and announcement-day return can be written as

$$\begin{aligned} \mathrm{Cov}\left(P_1 - P_0, P_0 - P_{-1}\right) &= \mathrm{Cov}\left(x - P, P - \bar{x}\right) = \left(1 - \phi_s\right)\phi_s \sigma_x^2 - \phi_s^2 \sigma_s^2 - \phi_\theta^2 \sigma_\theta^2 \\ &= -\frac{\sigma_\theta^2 \sigma_s^4 \sigma_x^4 \left(\sigma_\theta^4 \sigma_s^4 + 3\sigma_\theta^2 \sigma_s^2 + 2\right)}{\left(\sigma_s^2 \left(\sigma_\theta^2 \left(2\sigma_s^2 + \sigma_x^2\right) + 2\right) + 2\sigma_x^2\right)^2} < 0 \end{aligned}$$

The following proposition characterizes the results.

**Proposition 4.** *Price changes over forecast revision periods negatively predict price changes upon announcements:*

$$Cov\left(P_1 - P_0, P_0 - P_{-1}\right) < 0. \tag{B.81}$$

*Overreaction Conditional Volatility.* It is straightforward to show that the negative predictability is monotonically decreasing in $\sigma_x$, since $\frac{\partial \mathrm{Cov}(P_1 - P_0, P_0 - P_{-1})}{\partial \sigma_x} = -\frac{8\sigma_s^6 \sigma_x^3 \left(\sigma_\theta^2 \sigma_s^2 + 2\right)\left(\sigma_\theta + \sigma_\theta^3 \sigma_s^2\right)^2}{\left(\sigma_s^2\left(\sigma_\theta^2 (2\sigma_s^2 + \sigma_x^2) + 2\right) + 2\sigma_x^2\right)^3} < 0$. The following lemma summarizes this result.

**Lemma 11.** *The negative predictability is stronger when $\sigma_x$ is higher, that is,*

$$\frac{\partial Cov(P_1 - P_0, P_0 - P_{-1})}{\partial \sigma_x} < 0. \tag{B.82}$$

Obviously, when $\sigma_x$ converges to zero, return predictability disappears.

*Comparisons with Other Heterogeneous Agent Models.* In this section, I will compare this model with other rational expectations models featuring heterogeneous agents, specifically He and Wang (1995), AMS, and CG. Unlike this paper, which assumes asymmetric information where informed investors have superior information compared to uninformed investors, these models assume that two agents receive independent noisy signals, implying differential information among investors. I will show that, despite the observations made by AMS and CG that average beliefs are not Bayesian and underreact to new information, these models are inconsistent with the empirical fact that uninformed investors' forecast revisions cannot predict forecast errors of the informed.

Here, I follow the approach of the above papers by assuming that two agents receive independent noisy signals. For simplicity, I assume $\bar{x} = 0$, $\sigma_x = 1$, and $\sigma_s = 1$. Investor $i$'s signal is of the form $s_i = x + \varepsilon_i$, where $\varepsilon_1$ and $\varepsilon_2$ are i.i.d and mutually independent. Therefore, the forecast of each agent is $\mathbb{E}_i[x] = \frac{1}{2}s_i$. Forecast revision is $\mathbb{E}_i[x] - \bar{x} = \frac{1}{2}s_i$, and forecast error is $x - \mathbb{E}_i[x] = \frac{1}{2}x - \frac{1}{2}\varepsilon_i$. It is straightforward to show that

$$\text{Cov}\left(\mathbb{E}_1[x] - \bar{x}, x - \mathbb{E}_2[x]\right) = \frac{1}{4} > 0, \tag{B.83}$$

$$\text{and Cov}\left(\mathbb{E}_2[x] - \bar{x}, x - \mathbb{E}_1[x]\right) = \frac{1}{4} > 0. \tag{B.84}$$

In other words, the forecast revision of one agent must positively predict the other agent's forecast error. Since this model deviates from the representative agent model, the consensus forecast revision must positively predict the consensus forecast error. This intuition is consistent with AMS and CG:

$$\text{Cov}\left(\frac{1}{2}\mathbb{E}_1\left[x\right]+\frac{1}{2}\mathbb{E}_2\left[x\right],x-\frac{1}{2}\mathbb{E}_1\left[x\right]-\frac{1}{2}\mathbb{E}_2\left[x\right]\right)=\frac{1}{8}>0.$$

Therefore, this type of model, without hierarchical information, although it can explain the underreaction of consensus belief since it deviates from the representative agent, fails to explain why uninformed investors' forecast revisions have no predictive power for informed investors' forecast errors, as shown in the data.

*Discussion of Static versus Dynamic Models.* The two-period model outlined above effectively illustrates the basic intuition of my paper, but it also has clear limitations. Firstly, it does not explicitly model the equilibrium in period $-1$ and assumes that $P_{-1}$ equals the unconditional mean of $x$. Secondly, in period 1, the price must equal the value of the current dividend, as it is the last period of the model, causing the price impact of the noisy supply $\phi_\theta$ to go to zero upon announcement. In contrast, a fully dynamic model allows the perceived present value of all future dividends to determine prices, depending on investor beliefs. This implies that the price impact of the noisy supply $\phi_\theta$ will not be zero and will be endogenously determined as an equilibrium object.

Most importantly, the two-period model cannot incorporate time-varying volatility, a crucial factor in accounting for the empirical observation that prices overreact when fundamental volatility is high and underreact when it is low. The full model, presented in the main text of the paper, addresses all these limitations, providing a more comprehensive understanding of the dynamic behavior of prices and investor beliefs in the presence of time-varying volatility.

### *B.8. Numerical Solutions*

The Wang (1993) paper has closed-form solutions, but my model does not due to time-varying uncertainty. The numerical solution is challenging because the first welfare theorem does not hold in the presence of asymmetric information, and the equilibrium does not have a social planner's representation. In my model, the equilibrium is characterized by a system of 10 ODEs that jointly determine the pricing functions, portfolio holdings, and value functions. The ODEs are defined in equations (11), (13), (B.26), (B.27), and (B.35) with the boundary conditions $\hat{q}(0) = 0$ and $\tilde{q}(0) = 0$, while the remaining boundary conditions are given in (B.36), (B.37), (B.44), and (B.43).

In this section, I develop a recursive method to solve the system jointly. The basic procedure of the recursive method is as follows: first, I use the pricing functions, portfolio holdings, and value functions from the initial guess to solve the system of ODEs backward until the previous announcement. This step has the interpretation that I am solving the equilibrium of an economy in which asymmetric information lasts only for one period. Next, I update the boundary conditions and iterate the above process until convergence. My numerical procedure has the interpretation of solving the equilibrium of an economy in which asymmetric information lasts for a finite number of periods. When the number of periods approaches infinity, I obtain the equilibrium in my model.

1. Start from the complete information economy where $x_t$ is perfectly observed by both groups of investors, and solve for the pricing functions and value functions to obtain the steady-state values of $\phi_\theta^{ss}$, $f_{\theta\theta}^{ss}$, and $f_0^{ss}$.
2. Denote $y(t) = \{\phi_\theta(t), \phi_\Delta(t); f(t), f_{\theta\theta}(t), g(t), g_{\theta\theta}(t), g_{\Delta\Delta}(t), g_{\theta\Delta}(t)\}$ as the equilibrium functions. The steady state solution allows us to obtain an initial guess for the equilibrium functions, $y^0(t)$. That is, for $t \in [0, T]$, $\phi_\theta^0(t) = \phi_\theta^{ss}$, $\phi_\Delta^0(t) = 0$, $\phi_x^0(t) = \bar{\phi}_x$, $f^0(t) = g^0(t) = f_0^{ss}$, $f_{\theta\theta}^0(t) = g_{\theta\theta}^0(t) = f_{\theta\theta}^{ss}$, $g_{\Delta\Delta}^0(t) = 0$, $g_{\theta\Delta}^0(t) = 0$. The initial guesses for the first-order derivatives of the pricing functions are $\phi_\theta'^0(t) = 0$, $\phi_\Delta'^0(t) = 0$, $\phi_x'^0(t) = -\phi_\Delta'^0(t) = 0$.
3. The ODE for $\hat{q}(t)$ in equation (11) is deterministic of time and does not depend on the equilibrium functionals. The general closed-form solution for $\hat{q}(t)$ is: $\hat{q}(t) = \frac{\sigma_x^2\left(1-e^{-2\hat{b}t}\right)}{\left(\hat{b}-b\right)e^{-2\hat{b}t}+b+\hat{b}}$, where $\hat{b} = \sqrt{b^2 + \sigma_x^2\left(\frac{1}{\sigma_D^2} + \frac{1}{\sigma_s^2}\right)}$ given the initial condition $\hat{q}(0) = 0$.
4. Starting from the guess for the value and pricing functions in the *nth* round, denoted

with a superscript $n$, update the value and pricing functions using equilibrium conditions. Solve for functionals related to equilibrium beliefs first. The functions $m_x^n(t)$ and $\sigma_\xi^n(t)$ can be obtained using $m_x^n(t) = \left(a - b - \frac{(\phi_\theta^n(t))'}{\phi_\theta^n(t)} - \frac{\hat{q}(t)}{\sigma_D^2}\right)\phi_x^n(t) + (\phi_x^n(t))'$, and $\sigma_\xi^n(t) = \sqrt{\frac{\hat{q}^2(t)}{\sigma_s^2}[\phi_x^n(t)]^2 + \sigma_\theta^2[\phi_\theta^n(t)]^2}$. Use these to calculate the function $\tilde{q}^n(t)$ for $t \in [0,T]$ with the initial condition $\tilde{q}^n(0) = 0$ and the ODE in equation (13), substituting (B.9), to get:

$$d\tilde{q}^n(t) = \left[\left(\frac{1}{\sigma_D^2} + \frac{1}{\sigma_s^2}\right)\hat{q}_t^2 - 2b\tilde{q}_t^n - \frac{(\hat{q}_t + \tilde{q}_t^n)^2}{\sigma_D^2} - \left(\frac{m_x^n(t)\tilde{q}_t^n + \frac{\phi_x^n(t)\hat{q}_t^2}{\sigma_s^2}}{\sigma_\xi^n(t)}\right)^2\right]dt$$

5. Given the above pricing functions and investors' beliefs, first update the pricing functions on the boundary: $\left\{\phi^{n+1}(T^-), \phi_\theta^{n+1}(T^-), \phi_\Delta^{n+1}(T^-)\right\}$. For simplicity, denote $\Omega^n = \left[\frac{\phi_x^n(T^-)}{\phi_\theta^n(T^-)}\right]^2 \tilde{q}^n(T^-)$, $\Gamma^n \equiv \frac{\Omega^n}{1+f_{\theta\theta}^n(0)\Omega^n}$, $\mu^n = \bar{\phi}_x\frac{\phi_\theta^n(T^-)}{\phi_x^n(T^-)} - \phi_\theta^n(0)$, $\Lambda^n \equiv \bar{\phi}_x^2\hat{q}_T^- + \Gamma^n(\mu^n)^2$, and $m_\theta^{n+1} = \phi_\theta^{n+1}(T^-) - \phi_\theta^n(0) - \Gamma^n\mu^n f_{\theta\theta}^n(0)$. Use the market clearing condition to update the boundary conditions of the pricing functions:

$$\phi_\theta^{n+1}(T^-) = \phi_\theta^n(0) + \frac{\Lambda^n\bar{\phi}_x^2\hat{q}_T^-}{(1-\omega)\Lambda^n + \omega\bar{\phi}_x^2\hat{q}_T^-}\left[r + \omega\frac{\Gamma^n}{\Lambda^n}\mu^n f_{\theta\theta}^n(0)\right].$$

Having solved $\phi_\theta^{n+1}(T^-)$, set

$$\phi_\Delta^{n+1}(T^-) = \frac{\omega}{(1-\omega)\Lambda^n}\bar{\phi}_x^2\hat{q}_T^-\frac{\phi_x^n(T^-)}{\phi_\theta^n(T^-)}m_\theta^{n+1}.$$

6. The updated pricing functions can now be used to construct the value functions on the boundary:

$$\begin{aligned}
f^{n+1}(T^-) &= f^n(0) + \frac{1}{2}\ln(1 + f_{\theta\theta}^n(0)\Omega^n) \\
f_{\theta\theta}^{n+1}(T^-) &= f_{\theta\theta}^n(0) - \Gamma^n[f_{\theta\theta}^n(0)]^2 + \frac{1}{\Lambda^n}\left(m_\theta^{n+1}\right)^2 \\
g^{n+1}(T^-) &= g^n(0),\ g_{\theta\theta}^{n+1}(T^-) = g_{\theta\theta}^n(0) + \frac{\left[\phi_\theta^{n+1}(T^-) - \phi_\theta^n(0)\right]^2}{\hat{q}_T^-\bar{\phi}_x^2}, \\
g_{\Delta\Delta}^{n+1}(T^-) &= \frac{\left[\phi_\Delta^{n+1}(T^-)\right]^2}{\hat{q}_T^-\bar{\phi}_x^2},\ g_{\theta\Delta}^{n+1}(T^-) = \frac{\phi_\Delta^{n+1}(T^-)\left[\phi_\theta^{n+1}(T^-) - \phi_\theta^n(0)\right]}{\hat{q}_T^-\bar{\phi}_x^2}.
\end{aligned}$$

Here, the boundary conditions for all pricing and value functions can be obtained.

7. With the boundary conditions at time $T^-$ obtained above (i.e., $y(T^-)$), use the ODEs of equations (B.26), (B.27), and (B.35) to update backward to obtain $y(0)$.
8. Having obtained the equilibrium functionals $y^{n+1}(t)$, return to Step 4 and iterate until convergence.

It is easy to generate simulated time paths using the dynamic general equilibrium model. I use the simulation-based estimation methodology of indirect inference to calibrate the parameter values. Essentially, I calculate the model-implied unconditional moments based on simulated sample paths, and evaluate the model based on how closely the averaged estimated moments match the actual data. The minimum distance/weighting matrix is used to test the null that the structural model is correctly specified. In this paper, the distance is defined simply as $distance = \sum_{i=1}^{n}\left(\frac{z_{i,simulated}-z_{i,data}}{z_{i,data}}\right)^2$, where $z_{i,simulated}$ denotes the simulated moment and $z_{i,data}$ are the actual data. The calibrated parameters and their targets are illustrated in Section 4.

For each candidate parameter set, I simulate 20,000 years and use the final 18,000 years to compute population moments and regression coefficients. The simulation results are robust even when varying the simulation years or seeds used to generate random variables. Then, I compute the distance based on the time path and update the parameters accordingly. Finally, the calibrated values in Table 3 give the minimum distance.

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