Forecast Dispersion and the Price Impact of Macroeconomic News

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Abstract

While a large literature in macro-finance examines how financial markets respond to macroeconomic news, little is known about how the composition of the forecaster pool shapes these responses. Using data on 25 major U.S. macroeconomic announcements, I document that forecast dispersion has a strong negative effect on market reactions, challenging the conventional interpretation of dispersion as a proxy for uncertainty. To reconcile this puzzle, I develop a noisy rational expectations model in which the informational content of dispersion depends on the share of experienced analysts. When the forecaster pool is primarily experienced, low dispersion indicates precise pre-announcement information, reducing the announcement's price impact. Conversely, when the pool is inexperienced, low dispersion reflects shrinkage toward noisy common information, increasing price impact. Using lagged analyst experience as an instrument, I confirm that the relationship between dispersion and price impact switches sign depending on the share of experienced analysts. These findings reveal an important channel through which analyst heterogeneity affects price discovery.

Keywords: Macroeconomic announcements, forecast dispersion, uncertainty, analyst heterogeneity, price impact.

JEL Classification: D83, E44, G12, G14

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1 Introduction

Financial markets react strongly to macroeconomic news releases. A substantial body of research has documented how these price impacts vary with market conditions (Boyd et al., 2005) and announcement types (Gilbert et al., 2017). However, less attention has been paid to the composition of the forecaster pool and how it affects market reactions to news. This paper explores how forecast dispersion, driven by forecaster heterogeneity rather than underlying uncertainty, shapes price discovery around macroeconomic announcements. I address this question both empirically, using a comprehensive dataset of forecasts for U.S. macroeconomic indicators, and theoretically, using a noisy rational expectations framework in which investors infer information quality from forecast dispersion and the composition of the forecaster pool.

I document a surprising empirical result that challenges the conventional view that dispersion primarily reflects uncertainty: markets react less strongly to news when analysts disagree more. If dispersion merely proxied for uncertainty, we would expect the magnitude of price responses to be increasing in dispersion.[1] To explain this finding, I develop a stylized noisy rational expectations model in which the informational content of dispersion depends on the composition of the forecaster pool. Low dispersion among experienced analysts reflects precise private information about the upcoming release, reducing the announcement's price impact. Conversely, when inexperienced analysts dominate, low dispersion arises from shrinkage toward noisy public signals, amplifying the announcement's price impact. Thus, the puzzling negative relationship between dispersion and price impact emerges because the average forecaster pool is dominated by inexperienced analysts. I test these predictions using twelve-month lagged analyst experience as an instrument for current forecaster pool composition and find that dispersion reduces price reactions when the forecaster pool is less experienced but increases them when it is more experienced.

Specifically, using data from Bloomberg on 25 major U.S. macroeconomic indicators, I measure forecast dispersion as the cross-sectional standard deviation of forecasts and

[1] Ai and Bansal (2018) link uncertainty resolution to price responses in a revealed preference framework where a non-negative premium is realized on announcement days if investors have generalized risk sensitivity, i.e., a preference property where they demand compensation for holding assets exposed to future economic uncertainty.

news surprise as the difference between the release and the consensus forecast. I find that, on average, a one standard deviation increase in dispersion reduces the price impact of surprises by about 15%–20% in the equity and treasury bond markets.

To explain this finding, I propose a model in which forecast dispersion depends on the composition of the forecaster pool. The model features two types of analysts, experienced and inexperienced, who share a common prior but differ in the precision of their private signals.[2] Experienced analysts have more informative signals and therefore place less weight on public information, whereas inexperienced analysts rely more heavily on it. This creates a fundamental trade-off: experienced analysts form more precise beliefs, which tends to reduce dispersion, but they shrink less toward the common prior (or the consensus forecast in the model extension), which increases dispersion. As a result, forecast dispersion depends non-monotonically on the share of experienced analysts: when this share is low, an increase in experienced analysts reduces shrinkage toward noisy public information and raises dispersion; but as this share becomes larger, the precision effect dominates the shrinkage effect, reducing dispersion.

Note that these predictions are not specific to Bloomberg but also apply to other surveys in which analysts can revise their multi-period-ahead forecasts over consecutive survey rounds.[3] Nonetheless, what is specific to Bloomberg is that it allows linking forecast dispersion to the actual price impact of macroeconomic announcements in real time. In particular, the main question is: when does greater forecast dispersion lead to smaller price responses?

I address this question by extending the asset pricing framework of Benamar et al. (2021) to incorporate analyst forecast consensus and dispersion as publicly observable metrics. The key insight is that the interpretation of dispersion depends on analyst composition: when experienced analysts dominate and dispersion is low, investors infer that the consensus reflects precise private information, which increases price informativeness ahead of the announcement and reduces the announcement's price impact. Conversely,

[2]Dispersion in expectations about macroeconomic outcomes has been commonly attributed to information differences (Mankiw and Reis, 2002; Mankiw et al., 2003; Reis, 2006; Coibion and Gorodnichenko, 2012).

[3]For instance, in the first quarter of year t, a Survey of Professional Forecasters (SPF) analyst can revise their forecasts for the current quarter (a nowcast) and for the next three quarters of year t based on existing public and private information. Appendix Section B confirms that while the average SPF analyst revises their forecast toward the consensus, experienced analysts revise significantly less for most indicators, as predicted by the model.

when inexperienced analysts dominate and dispersion is low, investors interpret this as shrinking toward a noisy common prior, which increases the importance of the announcement and its price impact. I also show in the model extension that this non-monotonicity persists even when investors endogenously acquire costly private information on top of the public forecasts. This framework provides a theoretical illustration of how forecast dispersion influences price formation, conditional on the composition of the analyst pool.

The model implies that the negative relationship between dispersion and price impact arises because the forecaster pool is typically dominated by inexperienced analysts. I confirm this pattern empirically across most indicators. The underlying mechanism rests on the assumption that experienced analysts possess more precise private signals and therefore place greater weight on them. I provide empirical support for this assumption through three complementary tests. First, I document that experienced analysts produce significantly more accurate forecasts across most indicators. Second, experienced analysts issue forecasts with longer lead times (i.e., earlier relative to announcement dates), consistent with the model's prediction that they rely less on late-arriving noisy public information, including forecasts by other analysts. Third, SPF data confirms that experienced analysts revise their forecasts less toward the consensus. These results provide direct validation of the shrinkage-versus-precision mechanism and highlight that the composition of the forecaster pool is a key determinant of forecast quality and the informativeness of survey expectations.

To test the model's predictions about how forecaster heterogeneity shapes price discovery, I exploit the relatively stable composition of the analyst pool over time. This stability implies that the share of experienced analysts in releases from the past year is a strong predictor of current forecaster pool composition, while remaining plausibly exogenous to contemporaneous macroeconomic uncertainty. Using the twelve-month lagged share of experienced analysts as an instrument for current composition, I document a hump-shaped relationship between dispersion and the share of experienced analysts: dispersion initially rises with experienced analysts as they shrink less toward public signals, then falls as their precision advantage dominates, with the turning point at approximately 60% share of experienced analysts.

I also confirm the model's prediction that the effect of dispersion on price impact depends on forecaster pool composition: the 2SLS estimation suggests that a one standard deviation drop in dispersion *reduces* the price impact of macroeconomic surprises by 24% in equities and 18% in treasuries when all analysts are experienced (consistent with the precision effect dominating). In contrast, when all analysts are inexperienced, the same drop in dispersion *increases* price impact by 27% in equities and 15% in long-term treasuries (consistent with the shrinkage effect dominating).

The main results are robust to multiple specifications and subsamples. These include alternative measures of forecast dispersion (coefficient of variation, interquartile range, and mean absolute deviation) and analyst experience (participation over different time windows and coverage of high-uncertainty releases), controls for macroeconomic uncertainty (VIX and the economic policy uncertainty index of Baker et al. (2016)), and controls for the number of forecasting analysts. The findings also hold when excluding FOMC announcements, high-frequency initial jobless claims releases, and crisis periods (the 2008-2009 financial crisis and COVID-19), addressing concerns about structural breaks during periods of elevated uncertainty.

Overall, this paper makes three main contributions. First, it provides systematic evidence that forecast dispersion reduces announcement price impact across 25 major U.S. indicators and multiple asset classes, revealing that the cross-sectional distribution of forecasts conveys information beyond underlying uncertainty. Second, it develops a theoretical framework that links forecaster heterogeneity, information quality, and market responses. This framework provides a microfoundation for how the composition of the forecaster pool shapes price discovery. Third, it provides empirical support for the mechanism using lagged analyst experience as an instrument for current forecaster composition. These findings have direct implications for interpreting survey-based expectations: the composition of the forecaster pool matters as much as the distribution of forecasts themselves, and understanding analyst heterogeneity is essential for assessing forecast informativeness and price discovery.

This paper relates to four strands of the literature. First, it contributes to the broad literature on the price impact of macroeconomic news. For instance, Gilbert et al. (2017) examine the impact of various economic indicators on treasury yields, while Badidi et al. (2022) use these price impacts to identify the type of news driving announcement risk premia, and finds that it is mostly discount rate news. The relationship between uncertainty and price impact has also been widely documented for scheduled macroeconomic announcements (Ederington and Lee, 1996; Beber and Brandt, 2006; Jiang et al., 2012; Bauer et al., 2022), finding that uncertainty resolution typically explains price reaction to these releases. I add to this literature by showing empirically and theoretically how forecast dispersion, arising from analyst heterogeneity rather than fundamental uncertainty, explains variation in the price impact of news across multiple asset classes, including equities and treasury bonds.[4]

Second, this paper relates to the literature on measuring uncertainty. Various uncertainty measures have been introduced in the literature, including consumption growth volatility (Bansal et al., 2005), investor demand for information (Benamar et al., 2021), news coverage frequency (Baker et al., 2016), and the common volatility component of forecast errors (Jurado et al., 2015). In addition, analyst forecast dispersion has been widely used as a proxy for uncertainty in various contexts: inflation expectations (Bomberger, 1996; Giordani and Söderlind, 2003), modeling uncertainty shocks (Bachmann et al., 2013; Ilut and Schneider, 2014), and asset pricing (Sadka and Scherbina, 2007; Anderson et al., 2009; Drechsler, 2013). I contribute to this literature by showing that forecast dispersion reflects not only underlying uncertainty but also forecaster heterogeneity. This heterogeneity affects price reactions to news, highlighting the importance of controlling for forecaster-specific factors when using survey-based measures of uncertainty to study asset prices.

Third, this paper is related to the literature on belief heterogeneity and information aggregation in financial markets. One strand of this literature, based on the noisy rational expectations framework of Grossman and Stiglitz (1980), studies how asymmetric information acquisition generates belief dispersion and affects asset prices. For example, Ai et al. (2021) and Cocoma (2025) apply this framework to explain the pre-FOMC announcement drift through strategic information acquisition by investors. A second strand focuses on belief heterogeneity among professional forecasters, which may arise from differences in analyst experience, information sets, or career concerns (Stickel, 1992; Ottaviani and Sørensen, 2006; Hilary and Hsu, 2013; Félix et al., 2021; Kumar et al.,

[4]Born et al. (2023) recently document a negative relationship between dispersion and stock returns for a small set of indicators, interpreting dispersion as investor disagreement. I contribute by providing a broader and more systematic empirical test across a comprehensive set of major U.S. indicators and multiple asset classes. More importantly, I introduce a new mechanism that distinguishes between analysts, who generate forecasts, and investors, who interpret and trade on them. This distinction highlights forecaster composition as a key determinant of the informational content of dispersion and shapes the relationship between dispersion and price impact.

2022). I contribute to both strands by modeling how belief precision varies across analyst types and by showing that this heterogeneity generates endogenous shrinkage toward public information by inexperienced analysts. Specifically, I show that the informativeness of publicly observable forecast metrics depends on forecaster pool composition, emphasizing that effective price discovery requires understanding not just *what* is forecasted, but also *who* is forecasting.

Fourth, this paper contributes to research on how survey expectations influence financial markets. The predictive power of survey expectations for asset returns and macroeconomic outcomes has been well documented. For instance, Givoly and Lakonishok (1979) show that stock prices react to revisions in analysts' consensus earnings forecasts, while Fried and Givoly (1982) find that analysts' forecast errors are more closely associated with price movements than model-generated forecasts. Kothari et al. (2016) provide a comprehensive review of the asset pricing implications of sell-side analysts' forecasts. I contribute to this literature by focusing on analyst heterogeneity. By studying how the cross-sectional distribution of forecasts and the composition of the pool of forecasters shape market reactions, I show that survey data contain valuable information beyond the consensus. Understanding the role of forecaster composition can also help policymakers interpret survey data, communicate macroeconomic information more effectively, and design survey panels that improve information aggregation.

The remainder of the paper proceeds as follows. Section 2 describes the data and presents baseline evidence on the relationship between dispersion and price impact. Section 3 develops a noisy rational expectations model that microfounds this relationship conditional on the composition of the forecaster pool. Section 4 validates the model's assumptions and tests its predictions empirically. Section 5 concludes.

2 Empirical Analysis

2.1 Macroeconomic Announcements and Analyst Forecasts

To construct my primary measures of forecast dispersion and announcement surprise, I use Bloomberg analyst forecasts for US macroeconomic indicators from August 1997 to November 2021. In addition to macroeconomic releases, the platform provides detailed data on the cross-section of forecasters for each announcement, including the date of their latest submission, name, and affiliation. These forecasters represent a group of economists and market professionals, surveyed starting approximately one month before each announcement date. Participants can update their forecasts at any time after their initial submission. Figure 2 shows that, on average, around 85% of forecasts are released or revised in the five days leading up to the announcement, ensuring that they reflect the most recent market expectations. For a comprehensive overview of Bloomberg's survey methodology, see Chen et al. (2013).[5]

I focus on 25 macroeconomic announcements with the largest Bloomberg relevance scores, which reflect the relative frequency of active alerts set by Bloomberg users for each indicator compared to all US economic calendar events. I construct the surprise in an announcement n on a day d as the release minus the consensus forecast,[6] divided by the differences' standard deviation (σ_{S_n}) for comparability across announcement types:[7]

$$S_{n,d} = \frac{\text{Release}_{n,d} - \text{Median}(\mathbf{f}_{n,d})}{\sigma_{S_n}}. \tag{1}$$

FOMC surprises are treated differently due to their unique impact on financial markets, which extends beyond changes in target rates to include information about the future path of monetary policy (i.e., Fed speak). Specifically, I identify FOMC surprises using high-frequency data in narrow windows around releases, focusing on two factors: the target factor (30-minute change in the current month's Fed Funds futures)[8] and the path factor (the second principal component of changes in Fed Funds and Euro-Dollar futures with maturities up to one year).[9] I exclude the target factor surprise during the zero lower bound period from July 2008 to February 2015 because analysts often correctly anticipated changes in target rates. Table 1 provides an overview of the 25

[5]I drop releases with less than 20 analysts, which typically occurs at the start of the forecasting sample. The average number of forecasters per announcement type in my sample ranges from 36 to 81, with an overall average of 62 forecasters per release.

[6]Following the literature, I use the median to measure the consensus forecast. I obtain similar results using the mean.

[7]σ_{S_n} is computed over the full sample for each announcement type, as is standard in the literature (Gilbert et al., 2017). While this may introduce a small degree of look-ahead bias in the pooled tests, it does not affect tests conducted at the announcement-type level and ensures consistent scaling across the sample period. Using a rolling window or expanding window estimate yields similar results, although with reduced sample size.

[8]To account for the timing of the announcement within the month, the 30-minute change is scaled by the ratio of total days in the month to the number of days remaining between the announcement date and the end of the month. For announcements released within the last week of the month, the 30-minute change in the following month's Fed Funds futures is used instead.

[9]I thank Acosta (2023) for publishing the updated FOMC surprise data.

macroeconomic indicators.

I measure dispersion as the cross-sectional standard deviation of the forecasts ($\sigma(\mathbf{f}_{n,d})$), divided by its time series standard deviation (σ_{Disp_n}) for comparability across announcement types:

$$\text{Disp}_{n,d} = \frac{\sigma(\mathbf{f}_{n,d})}{\sigma_{\text{Disp}_n}}. \tag{2}$$

As robustness checks, I also consider alternative measures of dispersion, including the coefficient of variation (the cross-sectional standard deviation divided by the cross-sectional mean), the interquartile range (the difference between the 75th and 25th percentiles of forecasts), and the mean absolute deviation of forecasts (the average absolute distance between individual forecasts and the cross-sectional mean).

Table C.1 reports summary statistics for the main variables used in the empirical analysis. The sample covers 25 major U.S. macroeconomic announcements from August 1997 to November 2021, yielding 5,806 announcement-day observations. Surprise and dispersion are standardized within each announcement type, with means close to zero and standard deviations close to one.[10] On an average announcement day, economic releases are covered by around 62 analysts, ranging from 38 at the 10th percentile to 80 at the 90th percentile. The large number of analysts covering each release suggests that forecast dispersion is unlikely to be driven by a small number of outlier forecasters. The share of experienced analysts, described in detail in Section 4.2.1, averages 39% across announcement days, indicating that on average a relatively small fraction of analysts covering a given release have a long track record of forecasting that indicator.

Daily equity returns average around 6.5 bps on announcement days, approximately double the unconditional daily average of around 3.1 bps over the same sample period,

[10] Appendix Table C.2 reports summary statistics of unstandardized (raw) surprise and dispersion across announcement types. While absolute average surprises are usually small relative to the actual mean release, suggesting that forecasts are unbiased on average, the table reveals significant heterogeneity in volatility and forecast dispersion. For instance, labor market indicators such as Nonfarm Payrolls and ADP Employment are highly volatile, with standard deviations roughly 2.45 (290.59/118.44) and 2.18 (341.82/156.95) times the mean of the actual release values, and average forecast dispersion equal to 52% (61.29/118.44) and 47% (74.48/156.95) of the mean actual value. In contrast, FOMC announcement forecasts exhibit very low dispersion (<1.7% of the mean actual value), consistent with analysts' ability to anticipate target rate decisions. Similarly, sentiment indicators such as the Conference Board consumer confidence index and the University of Michigan sentiment survey display low volatility (<0.3 of the mean actual value) and dispersion (<2.0%). GDP estimates follow a predictable revision pattern, with advance reports showing significantly higher dispersion (26.6% of the mean actual value) than final estimates (6.2%). These results highlight the importance of accounting for announcement type heterogeneity.

while volatility is similar or slightly lower (1.1% vs. 1.25% unconditionally), consistent with the well-documented announcement day equity premium (Savor and Wilson, 2013; Ai and Bansal, 2018). Treasury yield changes are centered around zero on average, with standard deviations ranging from 2.8 bps for the 6-month treasury bill to 5.9 bps for the 5-year treasury note. The alternative uncertainty measures, the VIX and the EPU of Baker et al. (2016), average 19.46 and 118.13 respectively in the five days before announcement days, close to their long-run historical averages of around 20 and 100, suggesting that the sample is not systematically biased toward high or low uncertainty periods. At the same time, both measures display substantial time-series variation motivating their inclusion as controls for macroeconomic uncertainty in the empirical analysis.

2.2 Price Impacts

I study the announcement-day impact of macroeconomic announcements on three asset classes: the aggregate stock market, S&P 500 futures, and U.S. treasury yields with maturities ranging from 6 months to 10 years. The aggregate stock market is from Kenneth French's website and is measured as the value-weighted return of all CRSP firms with share codes 10 or 11 that are listed on the NYSE, AMEX, or NASDAQ. I obtain nearest-to-maturity S&P 500 futures data from Bloomberg and treasury yield data from FRED.

These asset classes offer complementary insights into how different financial instruments process macroeconomic news. Treasury yields are known to respond directly to changes in expected monetary policy and risk-free rates (Balduzzi et al., 2001; Kuttner, 2001; Gilbert et al., 2017), while the effect on equity prices can be more ambiguous, as it reflects a combination of discount rate and cash flow effects (Campbell and Vuolteenaho, 2004; Boyd et al., 2005; Badidi et al., 2022). S&P 500 futures, although closely linked to equity returns, attract a more institutional investor base that may process macroeconomic information more efficiently and tend to lead spot markets in price discovery, potentially affecting the timing and efficiency of price discovery around news releases (Frino et al., 2000; Hasbrouck, 2003; Lin et al., 2018).

For each macroeconomic announcement type n, I estimate the unconditional price impact of surprises in the announcement on a specific asset class k using the regression:

$$R_{k,n,d} = \alpha_{k,n} + \beta_{k,n} S_{n,d} + \epsilon_{k,n,d}, \tag{3}$$

where $R_{k,n,d}$ represents returns (or changes in yields) of asset class k on day d with announcement type n, $S_{n,d}$ denotes the surprise component of the announcement, and $\beta_{k,n}$ captures the price impact coefficient. This specification allows me to assess how different asset classes respond to unexpected macroeconomic news across announcement types.

Appendix Table C.3 reports estimated price impacts across announcement types and asset classes. Consistent with Gilbert et al. (2017) and Badidi et al. (2022), I find that asset classes respond differently to macroeconomic news. For instance, a positive one-standard-deviation increase in the FOMC target surprise has the largest negative impact on the stock market and S&P 500 futures, around 28 basis points. Whereas, an increase in the FOMC path factor has a strong positive impact on treasury yields of all maturities, ranging from 1.8 to 3.5 basis points. The sign and magnitude of these impacts align with Gürkaynak et al. (2005), who argue that most of the variation in interest rates is due to news about the path factor, i.e., the future path of monetary policy. Indeed, the FOMC target factor only has a large and statistically significant price impact on short-term treasury yields with maturities of up to 2 years. Next, I interact the surprise with forecast dispersion to better understand the drivers of these price impacts.

2.3 Price Impacts and Forecast Dispersion

The effect of dispersion on the price impact of news is an empirical question. If dispersion primarily reflects underlying uncertainty about the release, then greater dispersion implies more uncertainty ex-ante, and prices should react more strongly when this uncertainty is resolved on the announcement day (Ai and Bansal, 2018). Alternatively, if dispersion arises from differences in analysts' information or signal precision, then higher dispersion may indicate that some forecasters rely more on private information and shrink less toward noisy public signals. In this case, greater dispersion can imply that market participants are already better informed before the release, leading to a smaller price reaction. I formalize this mechanism in Section 3, where I show how dispersion reflects the informational structure of the forecaster pool.

To test these competing predictions, I estimate the regression:

$$R_{k,n,d} = \alpha_{k,n} + \beta_{k,n} S_{n,d} + \gamma_{k,n} \text{Disp}_{n,d} + \delta_{k,n} S_{n,d} \times \text{Disp}_{n,d} + \epsilon_{k,n,d}, \tag{4}$$

where $\text{Disp}_{n,d}$ captures dispersion, defined as in Equation (2) (the standardized cross-sectional standard deviation of forecasts on day d). For easier interpretability and comparison across announcement types, I restrict each coefficient $\hat{\beta}_{k,n}$ to be positive by multiplying the surprise series (S_n) by -1 when $\hat{\beta}_{k,n}$ is negative.

Figure 3 displays estimated coefficients $\hat{\beta}_{n,k}$ and $\hat{\delta}_{n,k}$ for the stock and two-year treasury note markets. It reveals that announcements with the largest price impacts (significant $\hat{\beta}_{n,k}$); such as the FOMC target, ISM Manufacturing, and Housing Starts in the stock market (Panel A), and Nonfarm Payrolls, Advance GDP, ISM Manufacturing, and Advance Retail Sales in two-year treasury yields (Panel B); exhibit significantly negative interaction term coefficients $\hat{\delta}_{n,k}$.[11] This result suggests that greater forecast dispersion systematically dampens the market response to surprises. For example, a one-standard-deviation surprise in the FOMC target factor changes stock prices by roughly 1%, but this effect is reduced by more than 30% when dispersion increases by one standard deviation. Similarly, a one standard deviation surprise in Nonfarm Payrolls affects two-year treasury yields by about 6 basis points, but this impact is reduced by over 14% with a one standard deviation increase in dispersion.

Appendix Table C.4 presents the full set of coefficient estimates $\hat{\beta}_{n,k}$ and $\hat{\delta}_{n,k}$ across asset classes, including the stock market, S&P 500 futures, and treasuries with maturities from six months to ten years. A consistent pattern emerges: forecast dispersion attenuates the price impact of the most influential indicators. In fact, correlations between $\hat{\beta}_{n,k}$ and $\hat{\delta}_{n,k}$ coefficients range from a significant -45% to -87%. These findings highlight the role of forecast dispersion in shaping how macroeconomic news is priced across financial markets.

For easier interpretability and comparison across asset classes, I also conduct this

[11] The effect of the FOMC path factor in treasuries is an exception: although the coefficient on the interaction term is positive, it is both economically and statistically insignificant. This supports the intuition that the resolution of uncertainty channel may play a bigger role in the treasury bond market.

analysis using a pooled regression over all announcement types n:

$$R_{k,d} = \alpha_k + \beta_k S_{n,d} + \gamma_k \text{Disp}_{n,d} + \delta_k S_{n,d} \times \text{Disp}_{n,d} + \omega_n + \epsilon_{k,d}, \tag{5}$$

with announcement type fixed effects (ω_n).

Table 2 reports the pooled regression coefficients. Coefficients $\hat{\beta}_k$ are consistently large and significant across all asset classes, confirming that the surprise in the average announcement moves prices. Coefficients $\hat{\delta}_k$ are consistently negative and significant, supporting the initial finding that high forecast dispersion reduces the price impact of news. Comparing the magnitudes of coefficients $\hat{\beta}_k$ and $\hat{\delta}_k$, the reduction in these price impacts with a one standard deviation increase in dispersion ranges from 12% for 10-year treasury notes to 23% for S&P 500 futures. The smaller effect in the treasury bond market relative to equities is consistent with the idea that the resolution of uncertainty from announcements is stronger in the bond market (Andersen et al., 2007; Beber and Brandt, 2008).

I also study the robustness of these results to different specifications and controls. First, Appendix Table C.5 reports coefficient estimates using alternative measures of forecast dispersion: (i) the coefficient of variation, (ii) the interquartile range, and (iii) the mean absolute deviation of the forecasts. The table shows that the coefficient $\hat{\delta}_k$ remains negative and significant across all these alternative measures. Second, Appendix Table C.6 shows that this result is also robust to controlling for time fixed effects, the number of forecasting analysts, and common measures of uncertainty, including the economic policy uncertainty index of Baker et al. (2016) (EPU) and the VIX in the week preceding the release.[12] Third, Appendix Table C.7 shows that this result is robust to excluding (i) the FOMC target and path factors; (ii) initial jobless claims announcements, given their weekly frequency; and (iii) the financial crisis (September 2008 to June 2009) and COVID period (February 2020 to November 2021), to address concerns about structural breaks in the price impact of macroeconomic news during these high uncertainty episodes.

This consistently negative relationship between forecast dispersion and price impact

[12]The coefficient on the interaction between the surprise and the number of analysts in Panel B of Appendix Table C.6 is mostly negative, suggesting that surprises have smaller price impacts when more analysts provide forecasts, possibly because: (i) a larger analyst pool improves price discovery, or (ii) fewer analysts tend to forecast during high uncertainty periods when announcements are more informative.

suggests that dispersion contains valuable information beyond underlying macroeconomic uncertainty. But when and why does dispersion reduce the price impact of news? I address this question both theoretically using a noisy rational expectations model where dispersion captures analyst-specific noise (Section 3), and empirically by controlling for the composition of the forecaster pool (Section 4).

3 Conceptual Framework

I model a pure exchange economy with an infinite number of investors, noise traders, and two assets: a riskless bond with a return $R_f = 0$ and a risky asset with a random payoff $V = \mu + Z$, where μ is known and $Z \sim \mathcal{N}(0, \sigma_Z^2)$ is unknown until the liquidation date (see the timeline in Figure 1). There is a continuum of analysts making forecasts about a public announcement A that reveals information about the asset's payoff, where $A = Z + \epsilon$ and $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$. The noise ϵ reflects the announcement's informativeness about the asset's payoff.[13] All noise terms are mutually independent.

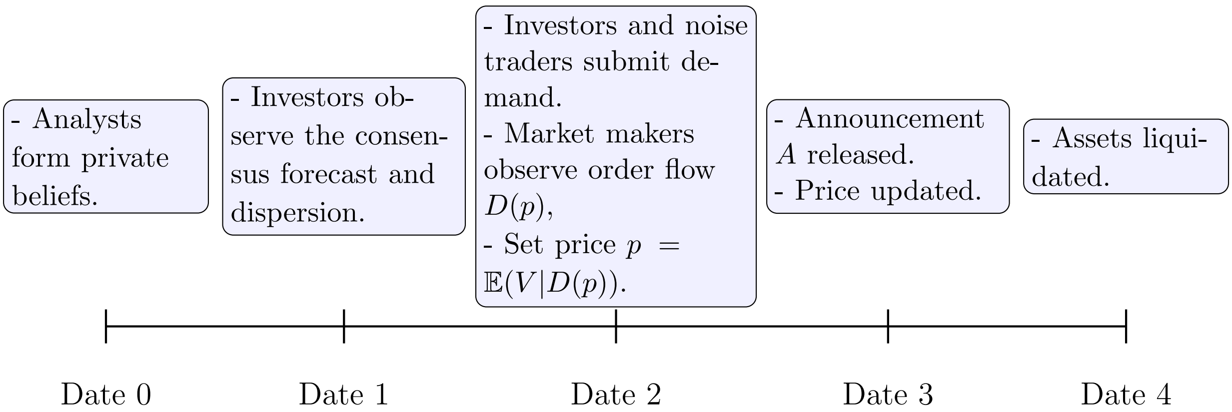

Figure 1: Model Timeline

3.1 Analyst Forecasts

There is a fraction $0 < \theta < 1$ of experienced analysts (E_i) and $1 - \theta$ of inexperienced analysts (N_i). Similar to Ottaviani and Sørensen (2006), I assume that analysts hold a common prior about the announcement A at date 0: $F_0 = A + e_{F_0}$, where $e_{F_0} \sim$

[13]Empirically, σ_ϵ^2 is likely smaller for treasuries than for equities, as economic indicators (e.g., monetary policy, inflation, and employment) tend to provide more direct and precise information about yields. In contrast, equities are subject to more complex dynamics.

$\mathcal{N}(0, \sigma^2_{F_0})$ represents common noise. Intuitively, this common prior can be interpreted as available public news observed through the previous month by market participants. Analysts also receive private information about A: Experienced analysts receive the signal $S_{E_i} = A + e_{E_i}$, with $e_{E_i} \sim \mathcal{N}(0, \sigma^2_E)$, while inexperienced analysts receive $S_{N_i} = A + e_{N_i}$, where $e_{N_i} \sim \mathcal{N}(0, \sigma^2_N)$. Beliefs are assumed to be unbiased to focus on forecast dispersion rather than systematic bias. In addition, experienced analysts have more precise private information: $\sigma^2_E < \sigma^2_{F_0} < \sigma^2_N$.

At date 1, analysts release their forecasts that optimally combine their prior with their private signal:[14]

$$\begin{aligned} f_{E_i} &= A + (1 - w_E)e_{E_i} + w_E e_{F_0}, \\ f_{N_i} &= A + (1 - w_N)e_{N_i} + w_N e_{F_0}, \end{aligned} \tag{6}$$

where $w_E = \frac{\sigma^2_E}{\sigma^2_{F_0} + \sigma^2_E}$ and $w_N = \frac{\sigma^2_N}{\sigma^2_{F_0} + \sigma^2_N}$ are the Bayesian weights on the public signal for experienced and inexperienced analysts, respectively. The difference $w_N - w_E > 0$ is the differential shrinkage intensity, i.e., the additional weight inexperienced analysts place on the public signal compared to experienced ones. This asymmetry arises because experienced analysts, having more precise beliefs ($\sigma^2_E < \sigma^2_{F_0} < \sigma^2_N$), underweigh noisy public information.[15].

3.1.1 Informativeness of the Consensus Forecast

The consensus forecast at date 1 satisfies:

$$F = A + \bar{w} e_{F_0}, \tag{7}$$

which aggregates out analyst-specific noise and reflects only the noise in the common prior e_{F_0}, weighted by the average shrinkage intensity $\bar{w} \equiv \theta w_E + (1 - \theta) w_N$. Since

[14]For tractability, the baseline model assumes that analysts do not internalize or revise toward the consensus. Appendix Section A.1 shows that the main dynamics remain unchanged when this assumption is relaxed.

[15]Shrinkage refers to the rational convergence of forecasts toward the common prior (or the consensus in the extension in Appendix Section A.1), which emerges from optimal Bayesian updating given analysts' information structure. This differs from behavioral herding driven by reputational concerns, career incentives, or psychological biases (Hong et al., 2000; Lamont, 2002; Clement and Tse, 2005). The model dynamics would still hold under these behavioral incentives, as this literature typically documents stronger herding among inexperienced analysts.

experienced analysts shrink less ($w_E < w_N$), $\bar{w}$ decreases with θ. Thus, the variance of the consensus satisfies:

$$\mathrm{Var}(F) = \underbrace{\sigma_Z^2}_{\text{Fundamental Uncertainty}} + \underbrace{\sigma_\epsilon^2}_{\text{Announcement Noise}} + \underbrace{\bar{w}^2\sigma_{F_0}^2}_{\text{Forecaster Noise}}. \tag{8}$$

Equation (8) decomposes this variance into: (i) fundamental uncertainty about the asset payoff σ_Z^2; (ii) announcement-specific noise σ_ϵ^2; and (iii) forecaster noise, $\mathrm{Var}(F|A) = \bar{w}^2\sigma_{F_0}^2$, which captures the effect of shrinkage to the noisy common prior on the informativeness of the consensus.

Since average shrinkage ($\bar{w}$) is strictly decreasing in the share of experienced analysts (θ), the forecaster noise component ($\mathrm{Var}(F|A) = \bar{w}^2\sigma_{F_0}^2$) also decreases in θ. This highlights how analyst composition affects the quality of the consensus forecast: as the share of experienced analysts rises, the consensus places more weight on precise private information and less on the noisy common prior, reducing forecaster noise and increasing informativeness (see Panel A of Figure 4).

3.1.2 Forecast Dispersion

Forecast dispersion (Disp), measured as the cross-sectional standard deviation of analysts' forecasts, satisfies:

$$\begin{aligned}
\mathrm{Disp}^2 &\equiv \mathbb{E}[\mathrm{Var}(f_i)] - \mathbb{E}[\mathrm{Cov}(f_i, f_q)]; \quad q \neq i \\
&= \underbrace{\theta\mathrm{Var}(f_{E_i}) + (1-\theta)\mathrm{Var}(f_{N_i})}_{\text{Variance term } \equiv \bar{w}\sigma_{F_0}^2} - \underbrace{\left[\theta^2\mathrm{Cov}(f_{E_i}, f_{E_q}) + (1-\theta)^2\mathrm{Cov}(f_{N_i}, f_{N_q}) + 2\theta(1-\theta)\mathrm{Cov}(f_{E_i}, f_{N_q})\right]}_{\text{Shrinkage term } \equiv \bar{w}^2\sigma_{F_0}^2} \\
&= \bar{w}(1-\bar{w})\sigma_{F_0}^2.
\end{aligned} \tag{9}$$

The second equality follows directly by substituting expressions: $\sigma_E^2 = \frac{w_E}{1-w_E}\sigma_{F_0}^2$ and $\sigma_N^2 = \frac{w_N}{1-w_N}\sigma_{F_0}^2$, and taking the average shrinkage intensity $\bar{w} \equiv \theta w_E + (1-\theta)w_N$. This simple expression reveals three key insights.

First, forecast dispersion does not depend on uncertainty about fundamentals ($\sigma_A^2 = \sigma_Z^2 + \sigma_\epsilon^2$), but on the precision of the common prior ($\sigma_{F_0}^2$) and how heavily analysts weight it ($\bar{w}$), challenging the interpretation of dispersion as a proxy for underlying uncertainty.

Second, analyst composition determines the interpretation of dispersion through $\bar{w}$.

Since experienced analysts place less weight on the common prior ($w_E < w_N$), the share of experienced analysts (θ) governs whether the forecast distribution shrinks toward public information or relies on heterogeneous private signals.

Third, dispersion is a non-monotonic function of the share of experienced analysts, reflecting two opposing forces. On the one hand, as θ increases, analysts rely less on the noisy common prior and more on idiosyncratic private signals, which reduces the shrinkage term in Equation (9), increasing forecast dispersion. On the other hand, an increase in θ also implies an increase in private signals precision, reducing idiosyncratic noise in analysts' forecasts and the variance term in Equation (9), reducing forecast dispersion. As a result, the relationship between dispersion and the share of experienced analysts is hump-shaped. When inexperienced analysts dominate ($\bar{w} > \frac{1}{2} \Leftrightarrow \theta < \theta^*$, where $\theta^* \equiv \frac{w_N - \frac{1}{2}}{w_N - w_E}$), dispersion increases with experience as shrinkage weakens. But once experienced analysts dominate ($\bar{w} < \frac{1}{2} \Leftrightarrow \theta > \theta^*$), dispersion starts to decrease with experience as forecast precision improves. The threshold θ^*, thus, marks the point at which the market transitions from being shrinkage-dominated to precision-dominated.

Testable Prediction 1. *Forecast dispersion is hump-shaped in the share of experienced analysts.*

Panel B of Figure 4 illustrates this hump-shape for different values of the precision ratio $\frac{\sigma_E^2}{\sigma_N^2}$. When experienced analysts have a strong informational advantage (low $\frac{\sigma_E^2}{\sigma_N^2}$), dispersion first increases with θ due to weaker shrinkage, but eventually declines as improvements in average forecast precision dominate. In contrast, when the informational advantage of experienced analysts is weak (high $\frac{\sigma_E^2}{\sigma_N^2}$), changes in θ have little effect on average shrinkage intensity or aggregate precision. Thus, while the model predicts a hump-shaped pattern under plausible parameter values, the strength and slope of this relationship are ultimately empirical questions, which I address in Section 4.

To formalize the relationship between forecast dispersion and consensus noise, conditional on the composition of the analyst pool, I derive the sensitivity of both measures to the share of experienced analysts θ. Using the corresponding expressions in Equations

(8) and (9), I get that:

$$\begin{aligned}\frac{d\,\mathrm{Var}(F|A)}{d\,\theta} &= 2(w_E - w_N)\bar{w}\sigma_{F_0}^2 \quad (<0),\\ \frac{d\,\mathrm{Disp}^2}{d\,\theta} &= (w_E - w_N)(1-2\bar{w})\sigma_{F_0}^2 \quad (>0 \text{ if } \bar{w} > \frac{1}{2} \Leftrightarrow \theta < \theta^*).\end{aligned} \tag{10}$$

These sensitivities suggest that the equilibrium relationship between consensus noise and forecast dispersion is non-monotonic in analyst experience. In markets with a high share of experienced analysts, low dispersion is a positive signal of consensus precision, as forecasts are based on precise private signals. Conversely, in markets dominated by inexperienced analysts, low dispersion signals shrinkage and consensus noise. Thus, the interpretation of forecast dispersion as a signal of consensus forecast precision depends on the composition of the forecaster pool.

3.1.3 Extension: Shrinking to the Consensus Forecast

Appendix Section A.1 shows that the main dynamics of the model continue to hold when analysts are allowed to revise their forecasts after observing the initial consensus. Specifically, inexperienced analysts overshrink to the consensus, while experienced analysts, having more precise private information, optimally revise to the consensus but always place positive weight on their private signals. This asymmetric revision behavior implies that low forecast dispersion reflects shrinkage (when inexperienced analysts dominate) or high precision (when experienced ones dominate). The non-monotonic relationship between analyst composition and dispersion is illustrated in Panel D of Figure C.1.

3.2 Asset Pricing Implications

Having established the relationship between forecast dispersion and the precision of the consensus, I now explore the implications for investor beliefs and asset prices. I treat the consensus forecast as a public signal that investors use to make trading decisions, adopting the asset pricing framework of Benamar et al. (2021).[16]

[16]While Benamar et al. (2021) proposes a model of private information acquisition by investors, I endogenize the formation of analyst forecasts as a source of public information. Nonetheless, Appendix Section A.4 shows that the asset pricing implications derived in this section also hold in environments where investors acquire additional costly private signals.

3.2.1 Investor Beliefs

At date 1, each investor $j \in (0,1)$ receives the consensus forecast:

$$F = Z + \zeta_F, \quad \zeta_F \sim \mathcal{N}(0, \sigma_\epsilon^2 + \bar{w}^2 \sigma_{F_0}^2), \tag{11}$$

where ζ_F represents the total noise in the public forecast, and its precision is given by $\phi_F = \left(\sigma_\epsilon^2 + \bar{w}^2\sigma_{F_0}^2\right)^{-1}$, combining announcement noise (σ_ϵ^2) and forecaster noise ($\bar{w}^2\sigma_{F_0}^2$). While investors observe the cross-sectional dispersion of forecasts (Disp^2), they cannot directly observe the precision of the consensus (ϕ_F). This is consistent with empirical practice, where, on platforms like Bloomberg or in the Survey of Professional Forecasters, users first see the consensus (mean or median) and dispersion (cross-sectional standard deviation).

In addition, investors know the structural parameters $\sigma_{F_0}^2$, σ_ϵ^2, and the share of experienced analysts θ, for example, from previous releases of the same indicator. Using Equation (9), they infer average shrinkage intensity $\bar{w}$ from Disp^2 as:

$$\bar{w} = \frac{1}{2} + \kappa\sqrt{\frac{1}{4} - \frac{\text{Disp}^2}{\sigma_{F_0}^2}}, \tag{12}$$

where κ equals 1 when $\theta < \theta^*$, and equals -1 otherwise. The precision of the consensus signal is then:

$$\phi_F = \left(\sigma_\epsilon^2 + \left(\frac{1}{2} + \kappa\sqrt{\frac{1}{4} - \frac{\text{Disp}^2}{\sigma_{F_0}^2}}\right)^2 \sigma_{F_0}^2\right)^{-1}. \tag{13}$$

This setup implies that dispersion serves as a signal of consensus quality, conditional on the share of experienced analysts: when θ is high, low dispersion indicates precise private information; otherwise, low dispersion reflects shrinkage and low consensus precision.

3.2.2 Asset Demand

At date 2, competitive risk-neutral dealers set the price of the asset p. Investors submit their demand functions for the risky asset $x_j(F, p)$, whereas noise traders have an inelastic demand $u \sim \mathcal{N}(0, \sigma_u^2)$. Dealers observe the aggregate demand for the risky asset:

$$D(p) = \int_j x_j(F, p)dj + u, \tag{14}$$

and set the price p such that their expected profit is zero: $p = \mu + \mathbb{E}(Z|D(p))$. This aggregate demand reveals a signal S_D about the payoff of the risky asset.

Given that investors have mean-variance preferences and their terminal wealth is equal to $W_j = (\mu + Z - p)x_j(F, p)$, they choose their demand $x_j(F, p)$ to maximize their expected terminal utility:

$$\mathbb{E}(U_j(W_j)|F, p) = \mathbb{E}(W_j|F, p) - \frac{1}{2}\gamma \mathrm{Var}(W_j|F, p), \tag{15}$$

Solving the investors' optimization problem and using Bayesian updating (see Appendix Section A.2 for detailed derivation), aggregate demand is equal to:

$$D(p) = \frac{\phi_F}{\gamma}(Z - p + \mu) + \frac{\phi_F}{\gamma}\zeta_F + u. \tag{16}$$

Therefore, observing the order flow conveys a signal $S_D = Z + \zeta_D$ about the asset's payoff, where $\zeta_D = \frac{\gamma}{\phi_F}u + \zeta_F$.[17] Here, ϕ_F enters the expression for ζ_D because forecasts increase the precision of investors' information, which reduces the weight of noise trader demand u in ζ_D and makes prices more informative. However, since F is an imperfect signal of Z, it introduces a second source of noise, ζ_F, which is the noise in the consensus forecast.

3.2.3 Price Impact of the Announcement

At date 3, the public announcement $A = Z + \epsilon$ is released. Dealers update prices $p_A = \mu + \mathbb{E}(Z|D(p), A)$, given the observable aggregate demand and public announcement.[18] This implies a post-announcement price:

$$p_A = \mu + \mathbb{E}(Z|S_D, A) = \underbrace{\mu + \mathbb{E}(Z|S_D)}_{p} + \underbrace{\frac{\mathrm{Cov}(Z, A|S_D)}{\mathrm{Var}(A|S_D)}}_{\beta} \underbrace{(A - \mathbb{E}(A|S_D))}_{\text{Surprise}}, \tag{17}$$

[17] Aggregate demand becomes less informative when investors' risk-aversion γ is high because they trade less aggressively on their private information.

[18] For tractability, trading is not allowed at this stage. Prices still react to the public signal A because the competitive and risk-neutral dealers set the price equal to the updated expected payoff.

where, taking the posterior variance of the asset's payoff, $\mathrm{Var}(Z|S_D) = \left(\frac{1}{\sigma_Z^2} + \frac{\phi_F^2}{\gamma^2\sigma_u^2+\phi_F}\right)^{-1}$, the price impact of the announcement[19] satisfies:

$$\beta = \left(1 + \frac{\sigma_\epsilon^2}{\sigma_Z^2} + \frac{\sigma_\epsilon^2\phi_F^2}{\gamma^2\sigma_u^2 + \phi_F}\right)^{-1}. \tag{18}$$

The expression for β shows that the price impact of the announcement increases with underlying uncertainty (σ_Z^2) and with the announcement's informativeness ($\frac{1}{\sigma_\epsilon^2}$) about the asset's payoff. The latter suggests a stronger price impact of macroeconomic announcements on treasuries relative to equities, consistent with the relatively larger R^2 in the price impact regressions for treasuries in Appendix Table C.3.

The effect of forecast precision (ϕ_F) on price impact (β) can be expressed as:

$$\frac{d\beta}{d\phi_F} = -\frac{\sigma_\epsilon^2\phi_F(2\gamma^2\sigma_u^2 + \phi_F)}{\left((1+\frac{\sigma_\epsilon^2}{\sigma_Z^2})(\gamma^2\sigma_u^2 + \phi_F) + \sigma_\epsilon^2\phi_F^2\right)^2} < 0. \tag{19}$$

Equation (19) formalizes the idea that an increase in consensus forecast precision (ϕ_F) reduces the price impact of news (β) because more precise information is incorporated into prices before the release of the announcement.

To derive the effect of forecast dispersion on the price impact of the announcement, I use the chain rule:

$$\frac{d\beta}{d\mathrm{Disp}^2} = \underbrace{\frac{d\beta}{d\phi_F}}_{(<0)} \times \underbrace{\frac{d\phi_F}{d\theta} \times \left(\frac{d\mathrm{Disp}^2}{d\theta}\right)^{-1}}_{=\frac{-2\phi_F^2\bar{w}}{1-2\bar{w}},\ (<0 \text{ if } \bar{w}<\frac{1}{2} \Leftrightarrow \theta>\theta^*)} \tag{20}$$

Since average shrinkage intensity ($\bar{w} \equiv \theta w_E + (1-\theta)w_N$) reflects the composition of the forecaster pool, the sign of this derivative depends on the share of experienced analysts (θ). When experienced analysts dominate ($\bar{w} < \frac{1}{2} \Leftrightarrow \theta > \theta^*$), the sensitivity $\frac{d\beta}{d\mathrm{Disp}^2}$ is positive, as low dispersion indicates high forecast precision, increasing investors' informativeness ahead of the announcement, and reducing the announcements' price impact. Conversely, when inexperienced analysts dominate ($\bar{w} > \frac{1}{2} \Leftrightarrow \theta < \theta^*$), the sensitivity $\frac{d\beta}{d\mathrm{Disp}^2}$ is negative, as low dispersion reflects high shrinkage to noisy common information,

[19] Appendix Section A.3 derives the formal link between the theoretical surprise ($A - \mathbb{E}(A|S_D)$) and its empirical counterpart ($A - F$), and shows that, under the model assumptions, the consensus-based measure is an unbiased proxy for the theoretical surprise. This proxy is also standard in the literature (e.g., Gilbert et al. (2017); Benamar et al. (2021); Gardner et al. (2022)).

increasing the announcement's importance and price impact.

Testable Prediction 2. *The effect of forecast dispersion on price impact depends on the composition of the forecaster pool: dispersion reduces (increases) price impact when the share of experienced analysts is low (high).*

3.2.4 Extension: Private Information Acquisition

Appendix Section A.4 derives the asset pricing implications when investors endogenously acquire additional private information. Because acquiring private information is costly, this decision depends on the precision of publicly available information (the consensus forecast). Specifically, when analyst forecasts are less precise, investors have stronger incentives to acquire costly private signals about the asset's payoff. This endogenous information acquisition creates an indirect effect that partially offsets the changes in announcement price impact driven by forecast dispersion and the composition of the forecaster pool, though it does not reverse the overall relationship.

These results summarize the conditions under which dispersion negatively predicts price impact, consistent with the empirical patterns discussed in Section 2. Next, I provide additional empirical evidence supporting the role of analyst composition in explaining the relationship between forecast dispersion and the price impact of news.

4 Empirical Tests of the Model

The model generates two key testable predictions about how analyst heterogeneity shapes price discovery. First, forecast dispersion is hump-shaped in the share of experienced analysts ($TP1$), reflecting the tradeoff between shrinkage intensity (which decreases with experience) and signal precision (which increases with experience). Second, the effect of dispersion on price impact depends on analyst composition ($TP2$): when inexperienced analysts dominate, low dispersion signals shrinkage toward noisy information, amplifying the announcement's price impact; when experienced analysts dominate, low dispersion indicates forecast precision, reducing price impact. I begin by validating the model's core assumption about analyst information quality, then test both predictions in turn.

4.1 Analyst Experience and Information Quality

The key assumption that drives the shrinkage versus precision mechanism of the model is that experienced analysts receive more precise private signals. I validate this assumption by testing whether experience predicts forecast accuracy and information processing behavior.

4.1.1 Analyst Experience and Forecast Precision

For each announcement type n and day d in month $t(d)$, I regress the mean absolute percentage error ($\text{MAPE}_{n,i,t(d):t(d)+11}$) of analyst i in year $t(d){:}t(d)+11$ on the number of announcements forecasted by the same analyst over the previous year ($\text{Exp}_{n,i,t(d)-12:t(d)-1}$):

$$\text{MAPE}_{n,i,t(d):t(d)+11} = a_n^e + b_n^e \text{Exp}_{n,i,t(d)-12:t(d)-1} + e_{n,i,t(d):t(d)+11}, \tag{21}$$

where each analyst's MAPE is constructed as:

$$\text{MAPE}_{n,i,t(d):t(d)+11} = \frac{1}{N_{n,t(d):t(d)+11}} \sum_{u=1}^{N_{n,t(d):t(d)+11}} \left| \frac{\text{Actual}_{n,u} - \text{Forecast}_{n,i,u}}{\text{Actual}_{n,u}} \right|,$$

and $N_{n,t(d):t(d)+11}$ is the number of releases of announcement type n in year $t(d){:}t(d)+11$. A negative coefficient $\hat{b}_n^e$ indicates that experience analysts produce more accurate forecasts, consistent with the model's assumption. I also run this regression in a pool, controlling for announcement-type fixed effects.

Table 3 reports coefficient estimates from the announcement-type regressions (Panel A) and the pooled regression (Panel B). The results strongly support the model's assumption that experienced analysts issue more precise forecasts. For example, for Nonfarm Payrolls, each additional forecast in the previous year is associated with a reduction in the MAPE of about 6.73% ($t = -5.55$), corresponding to a 0.07 standard deviation reduction in MAPE for a one standard deviation increase in experience.[20] ADP Employment also shows a strong effect of -1.87% ($t = -3.32$), corresponding to a 0.12 standard deviation reduction in MAPE. Other announcements with statistically and economically significant effects include Advance Retail Sales (-0.79%, $t = -2.49$; -0.05 standard deviations) and CPI (-0.76%, $t = -7.68$; -0.09 standard deviations). The only indicator with a positive

[20] Appendix Table C.2 reports these standard deviations.

and statistically significant coefficient $\hat{b}_n^e$ is Housing Starts. However, the effect is economically small at 0.02% ($t = 2.23$; 0.03 standard deviations), and switches sign for other housing market indicators, such as New Home Sales (-0.05%, $t = -3.55$; -0.06 standard deviations) and Existing Home Sales (-0.03%, $t = -4.55$; -0.07 standard deviations). In the pooled regression across all announcement types, the experience coefficient remains negative and significant (-0.17%, $t = -6.98$).

These results are robust to alternative measures of forecast accuracy. Appendix Table C.9 reports results using the mean squared error (MSE; Panel A) and the mean absolute error (MAE; Panel B). The findings consistently support the model's key assumption that experienced analysts generally produce more precise forecasts of macroeconomic announcements.

4.1.2 Analyst Experience and Forecast Timing

The model predicts that experienced analysts place less weight on noisy common information (Equations (6) and (A.4)). However, because the Bloomberg panel records only the latest forecast for each analyst per release, I cannot distinguish between initial releases and revisions to directly measure how much analysts shrink their forecasts. To address this limitation, I proxy for shrinkage using forecast lead time, defined as the number of business days between the forecast date and the release date. As illustrated in Figure 2, forecasts are heavily clustered in the few days before announcements, so variation in lead time captures analysts' reliance on late-arriving public signals, including forecasts by other analysts. Therefore, if experienced analysts indeed revise less toward noisy public information, they should issue forecasts with longer lead times.

To test this hypothesis, for each announcement type n and day d in month $t(d)$, I estimate the regression:

$$\text{LeadTime}_{n,i,t(d):t(d)+11} = a_n^{LT} + b_n^{LT}\text{Exp}_{n,i,t(d)-12:t(d)-1} + e_{n,i,t(d):t(d)+11}, \tag{22}$$

where $\text{LeadTime}_{n,i,t(d):t(d)+11}$ is the average forecast lead time of analyst i for announcement type n in year $t(d){:}t(d) + 11$. A positive coefficient $\hat{b}_n^{LT}$ indicates that more experienced analysts issue their forecasts earlier. I also run this regression in a pool, controlling for announcement-type fixed effects.

Table 4 reports regression estimates for the announcement-type specifications (Panel A) and the pooled specification (Panel B). Across most announcement types, coefficient $\hat{b}_n^{LT}$ is positive and statistically significant, consistent with the prediction that experienced analysts issue forecasts earlier. For example, one additional Nonfarm Payrolls forecast in the previous year is associated with an increase in forecast lead time of 0.10 days ($t = 14.47$). This implies that an analyst who has forecasted all twelve releases in the previous year issues their forecast 1.2 days earlier than an inexperienced analyst. Similar positive effects are documented across all other announcement types, except for FOMC announcements, where experience is associated with later forecasts.[21] The pooled regression in Panel B confirms the overall positive pattern, with an estimated coefficient $\hat{b}^{LT}$ of 0.03 ($t = 9.46$).

While forecast lead time provides an indirect proxy for shrinkage behavior in the Bloomberg sample, I can directly observe forecast revisions using the Survey of Professional Forecasters (SPF). Because the SPF collects forecasts for the same target quarter over multiple releases, it allows me to directly measure how much analysts revise their forecasts toward the consensus.[22] Appendix B shows that experienced analysts produce more accurate forecasts and revise less toward the consensus, providing direct validation of the model's precision versus shrinkage mechanism.

4.2 Analyst Composition, Forecast Dispersion, and Price Impact

To study the effects of analyst composition as predicted by the model, I construct the share of experienced analysts for each announcement type and examine the effect of this composition measure on dispersion and the price impact of macroeconomic news.

4.2.1 Measuring the Share of Experienced Analysts

I construct the empirical counterpart of the share of experienced analysts (θ) for each announcement type n and day d in month $t(d)$ as the as the fraction of analysts issuing

[21]This likely reflects the information sensitivity of monetary policy, with experienced analysts strategically delaying forecasts to incorporate Fed signals and data released close to the meeting.

[22]The main analysis relies on Bloomberg forecasts because they are submitted close to the announcement release (as illustrated in Figure 2), capturing the information available to market participants immediately before releases and making them directly relevant for asset pricing tests.

a forecast in month $t(d)$ who had also covered all (or the maximum number of) releases for indicator n over the previous twelve months:[23]

$$\text{ExpShare}_{n,t(d)} = \frac{\sum_i \mathbf{1}_{\text{Analyst } i \text{ issued forecasts in } t(d) \text{ and } t(d)-12:t(d)-1}}{\sum_i \mathbf{1}_{\text{Analyst } i \text{ issued forecasts in } t(d)}}, \tag{23}$$

Appendix Table C.2 reports the mean and standard deviation of $\text{ExpShare}_{n,t(d)}$ across announcement types and highlights clear differences in the typical forecaster pool for each indicator. For instance, Nonfarm Payrolls, which is the most closely followed indicator by relevance score, has the largest share of experienced analysts (around 55%), suggesting that a stable group of seasoned forecasters consistently covers this indicator. In contrast, indicators such as Initial Jobless Claims and FOMC announcements are typically covered by less experienced analysts (below 20%). Across all indicators, the average share of experienced analysts is approximately 40%, indicating that most macroeconomic releases are forecasted by relatively inexperienced analysts. This aggregate composition is consistent with the model's interpretation of the negative relation between dispersion and price impact: when the forecaster pool is relatively inexperienced, low dispersion reflects shrinkage toward noisy public information and therefore leads to stronger price reactions. I test this prediction by first studying the relationship between dispersion and the share of experienced analysts, then examining the impact on asset prices.

4.2.2 Dispersion and the Share of Experienced Analysts (*TP*1)

To test the first prediction about the relationship between forecast dispersion and the share of experienced analysts, I estimate the panel regression:

$$\text{Disp}_{n,d} = a + b_1 \text{ExpShare}_{n,t(d)} + b_2 \text{ExpShare}^2_{n,t(d)} + \mathbf{X}'_{n,d}\boldsymbol{c} + e_{n,d}, \tag{24}$$

where $\mathbf{X}_{n,d}$ includes controls for announcement type, month fixed effects, common uncertainty measures in the week before the release (VIX_{d-5} or EPU_{d-5}), and the number of analysts. A negative $\hat{b}_2$ with an interior turning point ($\widehat{\theta^*} \in (0,1)$) supports the hump-shaped relationship, in which case $\widehat{\theta^*}$ marks the point at which the forecaster pool

[23] I also consider alternative measures of the share of experienced analysts, defining experience as (i) coverage over 24-month windows instead of 12 months, or (ii) participation in high-uncertainty releases (VIX larger than 95th or 90th percentile) over the past 60 months.

transitions from shrinkage-dominated to precision-dominated.[24]

Table 5 reports the regression estimates. Across all specifications, the coefficient on the square term is negative, indicating concavity in the relationship between forecast dispersion and the share of experienced analysts. After controlling for month fixed effects and additional covariates (Specifications (2) to (6)),[25] both the linear and quadratic coefficients become statistically significant. The implied threshold $\widehat{\theta^*}$ ranges from 0.68 to 0.74, indicating that forecast dispersion first increases with the share of experienced analysts but declines once this share becomes sufficiently large. This pattern is consistent with the model's prediction that dispersion is initially driven by reduced shrinkage toward public information, but as the forecaster pool becomes more experienced, the precision effect dominates.

The hump-shaped pattern also holds under alternative definitions of analyst experience (Panel A of Appendix Table C.10): (i) experience defined over 24-month windows instead of 12 months, and (ii) participation in high-uncertainty releases (VIX larger than 95th or 90th percentile) over the past 60 months.

4.2.3 Price Impact, Dispersion, and the Share of Experienced Analysts (*TP*2)

To test the second prediction about the effect of forecaster pool composition on the relationship between dispersion and the price impact of news, for each asset class k, I estimate the panel regression:

$$R_{k,d} = \alpha_k + \beta_k S_{n,d} + \delta_{k,1} S_{n,d} \times \text{Disp}_{n,d} + \delta_{k,2} S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)} + \mathbf{X}'_{n,d}\boldsymbol{\lambda_k} + \epsilon_{k,d}. \tag{25}$$

$\mathbf{X}_{n,d}$ includes announcement-type fixed effects as well as all relevant single and double interaction terms (additional controls, such as month fixed effects, the number of analysts, and the VIX, are included in Appendix Table C.14). A negative $\delta_{k,1}$ and a positive $\delta_{k,1} + \delta_{k,2}$ support the model's prediction that low dispersion increases the price impact of news when $\text{ExpShare}_{n,t(d)}$ is low, but reduces it otherwise. This is because low dispersion in a

[24] To reduce multicollinearity between $\text{ExpShare}_{n,t(d)}$ and $\text{ExpShare}^2_{n,t(d)}$, this regression uses demeaned $\text{ExpShare}_{n,t(d)}$ at its sample mean ($\bar{\theta} \approx 0.39$). The threshold θ^* is reported in the original scale ($\in (0, 1)$) as $\widehat{\theta^*} = \bar{\theta} - \frac{\hat{b}_1}{2\hat{b}_2}$.

[25] While the VIX in the week preceding the announcement is positively related to dispersion (Specifications (4) and (6)), the EPU seems uncorrelated to dispersion over the same window (Specifications (5) and (6)). Thus, I focus on the VIX as the primary alternative proxy for fundamental uncertainty in the remaining tests.

market dominated by less experienced analysts signals shrinkage and low informativeness of the consensus forecast. Conversely, when the market is dominated by experienced analysts, low dispersion signals more precise beliefs and high quality of pre-announcement information, thus reducing the announcement's price impact.

The results in Table 6 provide strong empirical support for the model's prediction: the effect of forecast dispersion on the price impact of macroeconomic news depends on the composition of the analyst pool. Across all asset classes, the coefficient on the interaction between news surprise and forecast dispersion ($S_{n,d} \times \text{Disp}_{n,d}$) is negative and statistically significant, indicating that greater dispersion reduces the price impact of news. However, the positive and significant coefficient on the triple interaction term ($S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$) suggests that this effect reverses when the share of experienced analysts is sufficiently high, as low dispersion starts to reflect high consensus precision. Specifically, when the share of experienced analysts is zero, a one standard deviation increase in dispersion reduces the price impact of surprises by approximately 26% in equities and 14% in treasury yields. Conversely, when the share of experienced analysts is one, the same increase in dispersion raises the price impact by roughly 26% in equities and 6% in longer-term treasuries.[26] This pattern is consistent with the idea that low dispersion, in the presence of less experienced analysts, reflects shrinkage and reduces consensus informativeness.

In addition, the coefficient on the interaction between surprises and the share of experienced analysts is negative and highly significant across all specifications, consistent with the model's prediction that an increase in the proportion of experienced analysts increases the informativeness of the consensus forecast and the quality of pre-announcement information, thus reducing the announcement's price impact.

Panel A of Appendix Table C.14 confirms that these results are robust to controlling for month fixed effects, the number of analysts issuing forecasts, and the VIX, especially for treasury yields. Panels B to D of Appendix Table C.10 confirm robustness to alternative measures of experience. Overall, these results highlight that the information content of forecast dispersion extends beyond fundamental uncertainty.

[26]The smaller effect of analyst composition in short-term treasuries aligns with the idea that short-term yields respond more directly to macro news (Gilbert et al., 2017) and are, thus, less sensitive to changes in forecaster pool composition.

4.3 Addressing Endogeneity: Instrumental Variable Approach

My identification strategy faces an endogeneity concern: the share of experienced analysts may be endogenously driven by underlying uncertainty, for example, if less experienced analysts abstain from issuing forecasts during high uncertainty periods. To assess whether composition responds to uncertainty in this manner, I first examine the time-series dynamics of forecaster pools.

Figure 5 describes the time series variation in the composition of the forecaster pool across four key indicators: Nonfarm Payrolls, FOMC, GDP Advance, and CPI (Appendix Figure C.2 shows the decomposition for all 25 indicators). For each release, the number of analysts is decomposed into three groups: *experienced* analysts, who have forecasted all or the maximum number of releases for that indicator in the past year; intermittent analysts, who forecast irregularly; and entrants, who forecast the release for the first time. Intermittents and entrants make up the *inexperienced* analyst pool. The figure also plots retirees, who forecasted in the previous period but exit the sample thereafter; this group also includes analysts who switch firms and/or move to forecasting other indicators.

The time-series patterns reveal substantial heterogeneity in forecaster pool dynamics across indicators. FOMC releases exhibit the most volatile participation, with intermittent analysts dominating and frequent fluctuations in the total number of analysts. This instability is particularly pronounced during the zero lower bound period and features the largest surges in retirements during high-uncertainty periods. In contrast, GDP Advance displays the most stable composition, reaching a steady state around 2010. Nonfarm Payrolls and CPI show steady growth in experienced analysts until the mid-2010s, followed by a mild decline. Importantly, a common pattern across most indicators is that during high-uncertainty periods, the number of inexperienced analysts tends to contract more sharply than that of experienced ones, causing the forecaster pool to become temporarily more experienced on average. This endogenous selection during uncertain periods could bias the OLS estimates.

I address this concern in two ways. First, I control for month fixed effects, the number of analysts, and measures of macroeconomic uncertainty in Tables 5 and C.14. Second, because these measures capture aggregate uncertainty but may not fully account for time-varying, announcement-specific factors that affect analyst participation, I employ an instrumental variable approach. Specifically, I use one-year lagged share of experienced analysts ($\text{ExpShare}_{n,t(d)-12}$) as an instrument for the current share of experienced analysts ($\text{ExpShare}_{n,t(d)}$).

4.3.1 Instrumenting the Share of Experienced Analysts

Lagged average analyst experience is a valid instrument under two key conditions. *First*, lagged experience must be correlated with current experience. This condition is likely satisfied due to the relative stability of the forecaster pool over time. Appendix Figure C.4 shows that, for the average announcement type, a substantial proportion of forecasters remain active even over a twelve-month horizon, with 77% of analysts continuing to issue forecasts. Additionally, the autocorrelation coefficient of the share of experienced analysts over a twelve-month window is approximately 0.47. *Second*, the lagged share of experienced analysts must be exogenous to current underlying uncertainty, ensuring that it influences the price impact of announcements solely through its effect on current forecaster pool composition. The intuition is that any residual uncertainty about the macroeconomic indicator from earlier months is likely resolved over time, as additional announcements are released. Supporting this, the autocorrelation of the VIX declines to 0.20, and that of the economic policy uncertainty index of Baker et al. (2016) (EPU) falls to 0.14 over the same twelve-month window. I also control for these common uncertainty measures in the week preceding the release in the two-stage least squares (2SLS) regressions.[27]

4.3.2 Dispersion and the Share of Experienced Analysts (*TP*1)

Appendix Table C.12 reports 2SLS estimates for the relationship between dispersion and analyst composition. The first-stage regressions (Panels A and B) confirm that the lagged

[27]Appendix Table C.11 reports summary statistics from a double sort on forecast dispersion and the one-year lagged share of experienced analysts, and shows that the VIX and absolute surprises are significantly larger on high-dispersion periods regardless of the experience group. This result suggests that dispersion is associated with higher realized uncertainty, and thus, motivates the need to control for alternative uncertainty measures when estimating the effect of (forecaster-driven) dispersion on price impact. Importantly, the one-year lagged experience share used as an instrument is largely orthogonal to current uncertainty: within each dispersion group, the absolute surprise is similar across experience groups (differences of 0.01 and 0.02, both statistically insignificant), and the VIX is only marginally higher in low-experience states relative to high-experience states (differences of -1.5 and -1.0, the latter statistically insignificant), suggesting that lagged forecaster composition does not systematically co-move with contemporaneous macroeconomic uncertainty.

share of experienced analysts strongly predicts current composition, with Kleibergen-Paap Wald F-stats exceeding 18.5 across all specifications. The second stage estimates (Panel D) confirm the hump-shaped relationship documented in Table 5 and predicted by Equation (10) of the model. The coefficient on the instrumented share of experienced analysts ($\widehat{\text{ExpShare}}_{n,t(d)}$) is positive and statistically significant, while the coefficient on its square term is negative and significant across all specifications. The implied threshold, θ^*, at which the marginal effect becomes zero, ranges from 0.40 to 0.68, which is comparable to the OLS estimates and the theoretical prediction in Figure 4.[28] These results indicate that the non-monotonic relationship between dispersion and analyst composition is not merely driven by endogenous analyst selection during uncertain periods, but reflects the precision-versus-shrinkage mechanism predicted by the model.

4.3.3 Price Impact, Dispersion, and the Share of Experienced Analysts ($\boldsymbol{TP2}$)

I now apply the same instrumental variable strategy to test whether the effect of dispersion on price impact causally depends on forecaster composition ($TP2$). For each asset class k, I estimate the 2SLS analog of Equation (25), instrumenting the share of experienced analysts and all its interactions with the one-year lagged share and corresponding interaction terms.

Table 7 reports second-stage 2SLS estimates that provide strong causal evidence that analyst composition determines how dispersion affects price impact. [29] The coefficient on the interaction $S_{n,d} \times \text{Disp}_{n,d}$ remains negative and statistically significant across all asset classes, while the coefficient on the triple interaction $S_{n,d} \times \text{Disp}_{n,d} \times \widehat{\text{ExpShare}}_{n,t(d)}$) is positive and significant. The economic magnitudes are larger but comparable to the OLS estimates. Specifically, when the share of experienced analysts is zero, a one standard deviation increase in dispersion reduces the price impact of surprises by approximately 24% in equities and 16% in treasury yields. Conversely, when the share of experienced analysts is one, the same increase in dispersion raises the price impact by roughly 27% in equities and 15% in longer-term treasuries. The effect becomes approximately zero when the share of experienced analysts is around 0.6, precisely at the threshold where dispersion peaks (Appendix Table C.12). These results are robust to controlling for month fixed

[28] These 2SLS estimates are also robust to alternative definitions of analyst experience (Panel A of Appendix Table C.10).

[29] Appendix Table C.13 reports first-stage estimates of the 2SLS specifications.

effects, the number of analysts, and the VIX (Panel B of Appendix Table C.14) and alternative measures of experience (Panels B to D of Appendix Table C.10).

The larger 2SLS magnitudes for treasury yields align with the idea that the resolution of uncertainty channel plays a bigger role for treasury yields, reducing the effect of the composition of the forecaster pool on price impact. However, after controlling for this uncertainty channel, forecaster composition becomes more important in explaining treasuries' reaction to news.

These results provide causal evidence that analyst composition determines how markets interpret forecast dispersion beyond underlying uncertainty. The effect of dispersion on price impact reverses sign depending on whether inexperienced or experienced analysts dominate: low dispersion amplifies announcement reactions when the pool is inexperienced but dampens reactions when the pool is experienced.[30]

4.4 Pre-Announcement Trading Activity

The model predicts that if dispersion among experienced analysts signals forecast quality, the market should incorporate this information before the announcement, resulting in lower announcement-day price impact. Appendix Table C.16 provides additional supporting evidence for this mechanism by investigating pre-announcement trading activity conditional on dispersion and the share of experienced analysts. Specifications (1)-(3) show that abnormal trading volume in the days leading up to the announcement is higher when dispersion is low and experience share is high, consistent with informed trading ahead of the announcement. Specifications (4)-(6) show that the price response ratio of Weller (2018), defined as the ratio of cumulative returns in the ten days before the announcement to cumulative returns over the same period including the announcement day, is similarly higher on low-dispersion days with a high share of experienced analysts, indicating that this informed trading translates into greater pre-announcement price adjustment. These results support the model's prediction that forecast quality improves price informativeness ahead of the announcement.

[30]Appendix Section A.5 extends the baseline theoretical model in Section 3 to allow the share of experienced analysts to respond endogenously to underlying uncertainty, as suggested by the empirical patterns in Figure 5. This extension shows that OLS estimates of both the dispersion-experience threshold and the dispersion-price impact relationship are biased downward, consistent with the larger 2SLS estimates reported in Tables C.12 and 7.

4.5 Alternative Explanations

The forecaster composition channel explains why (i) forecast dispersion unconditionally reduces the price impact of macroeconomic news, and (ii) this relationship reverses sign depending on the share of experienced analysts. I now consider whether alternative mechanisms could explain these patterns.

First, if dispersion arises from *asymmetric loss functions*, where analysts face different costs for over- versus under-prediction (Capistrán and Timmermann, 2009), then dispersion would still increase with underlying uncertainty. This mechanism predicts a positive relationship between dispersion and price impact, as greater uncertainty should amplify announcement reactions. Moreover, it provides no role for forecaster composition, failing to explain why the dispersion-price impact relationship depends on analyst experience.

Second, under *diagnostic expectations* (Bordalo et al., 2020), analysts overreact to their own private signals, and when these signals are dispersed, the consensus forecast becomes less responsive to new information. This rigidity reduces the informativeness of the consensus forecast, which should increase the price impact of announcements when dispersion is high. However, this prediction contradicts the empirical finding that dispersion reduces price impact. Moreover, this mechanism predicts a uniformly positive relationship between dispersion and price impact, regardless of analyst experience, and therefore cannot explain the sign reversal documented in Tables 6 and 7.

Third, *gradual information diffusion* models (Hong and Stein, 1999) predict that when information spreads slowly across market participants, prices initially underreact to news, followed by continuation and eventual overreaction. High dispersion could proxy for slower information diffusion, generating smaller immediate price responses. However, this mechanism predicts that the muted initial reaction should be followed by larger price changes over subsequent days. To test this, I examine market reactions in one to five days after the release and find no evidence of delayed overreaction. Furthermore, this mechanism cannot explain why the relationship between dispersion and price impact depends on the composition of the forecaster pool.

Fourth, *differential interpretation* models (Banerjee and Kremer, 2010) suggest that when agents interpret public signals differently, this can lead to larger price reactions because of increased price uncertainty. This mechanism predicts a positive relationship between dispersion and price impact, contradicting the negative relationship documented in Table 2. Moreover, it provides no role for analyst heterogeneity in determining how dispersion affects prices.

In contrast to these alternative channels, the forecaster composition channel uniquely explains both empirical puzzles. When inexperienced analysts dominate the pool, low dispersion reflects shrinkage toward noisy common information, reducing consensus informativeness and amplifying the announcement's price impact. When experienced analysts dominate, low dispersion indicates precise private information, increasing consensus quality and dampening price impact. Moreover, the evidence that experienced analysts produce more accurate forecasts (Table 3), issue forecasts earlier (Table 4), and revise less toward the consensus (Appendix Section B) directly validates the model's core assumptions about analyst heterogeneity.

5 Conclusion

I study the relationship between analyst forecast dispersion and the price impact of macroeconomic news across various asset classes and show that greater dispersion reduces the price impact of news. This finding challenges the common interpretation of dispersion as solely a proxy for uncertainty and suggests that analyst heterogeneity contains valuable information that moves asset prices.

I propose an information-based explanation for the negative effect of dispersion on price impact, where this relationship is conditional on the composition of the forecaster pool. Specifically, I develop a noisy rational expectations model with two types of analysts, experienced and inexperienced, with different levels of informational advantage. I show that forecast dispersion is a non-monotonic function of the share of experienced analysts: when inexperienced analysts dominate the forecaster pool, low dispersion reflects shrinkage and low information quality, leading to a larger price impact upon the announcement's release. In contrast, when experienced analysts dominate, low dispersion signals more precise beliefs, resulting in more informative consensus forecasts and a smaller price response to the announcement.

To empirically test these predictions, I implement an instrumental variable approach using the lagged share of experienced analysts as an instrument for current forecaster composition. Consistent with the model, I find a concave relationship between dispersion and experience, and a sign reversal in the effect of dispersion on the price impact of news depending on the share of experienced analysts. The results are robust to controlling for proxies of time-varying macroeconomic uncertainty, confirming that dispersion captures more than just uncertainty about fundamentals. These results highlight the importance of controlling for the composition of the forecaster pool when using survey-based measures of dispersion in empirical tests of uncertainty. They also have practical relevance for policymakers and institutions that rely on survey data to assess expectations and uncertainty, highlighting the need to account for analyst heterogeneity when interpreting survey data and designing communication strategies.

In conclusion, this paper enhances our understanding of how survey expectations influence market efficiency and asset price movements, and opens new avenues for research in financial economics, particularly in understanding the interplay between analyst behavior, investor informedness, and market outcomes.

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Tables and Figures

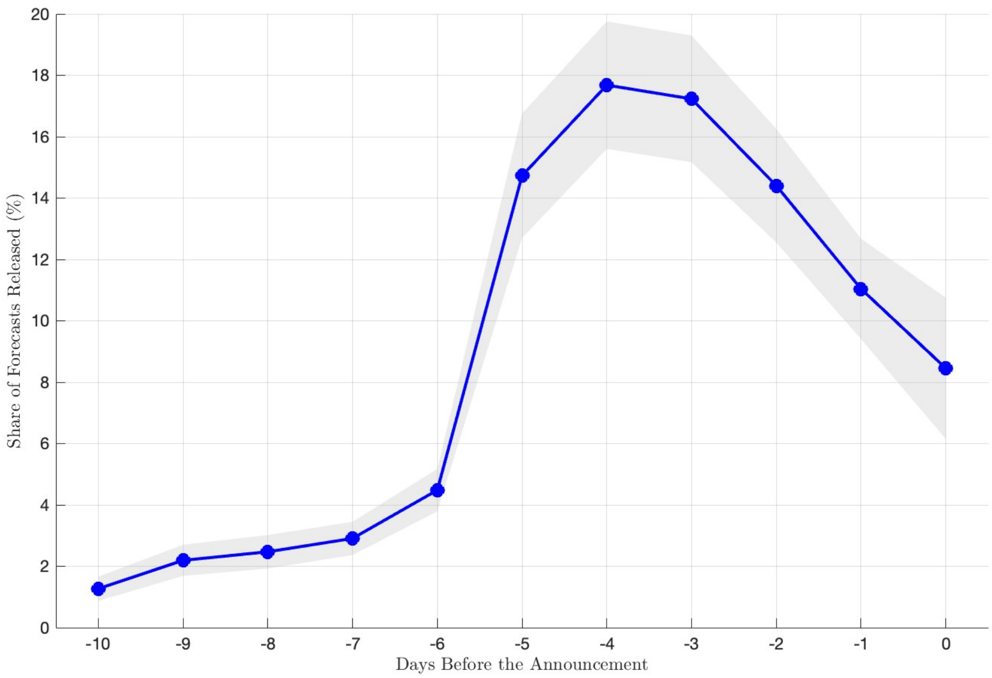

Figure 2: **Forecast Release Timing Relative to Announcement Days.** The figure plots the daily proportion of forecasts issued or revised during the 10-day window preceding announcement releases. The solid blue line represents the average percentage of forecasts released each day (relative to the total number of forecasts) across announcement types, with the gray shaded area indicating the 95% confidence interval.

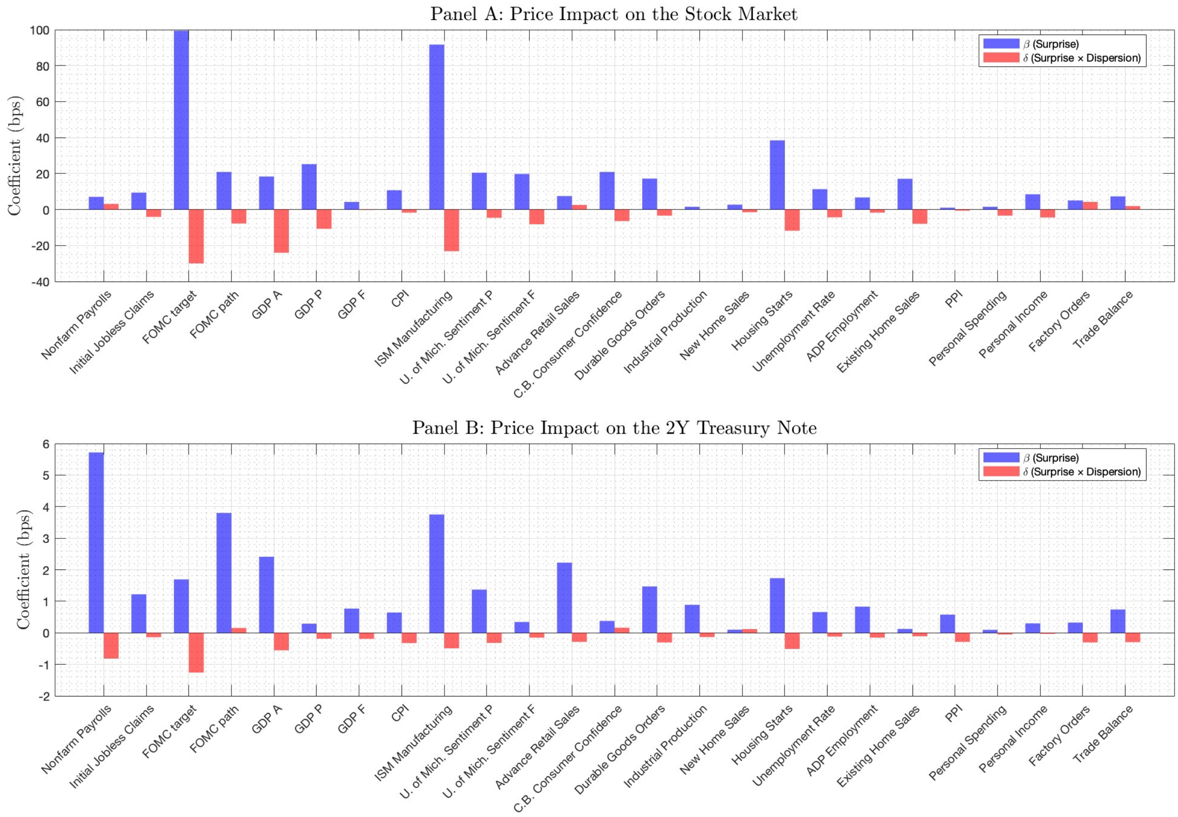

Figure 3: **Price Impact and Forecast Dispersion in the Stock and 2-Year Treasury Note Markets.** Panel A (Panel B) shows the estimated price impact of 25 U.S. macroeconomic announcements on the stock market (2-year treasury note) based on regression Equation (4). Blue bars represent coefficients on the surprises ($\hat{\beta}_{n,k}$), while red bars represent coefficients on the interaction between surprises and forecast dispersion ($\hat{\delta}_{n,k}$). For comparability across announcement types, Coefficients $\hat{\beta}_{n,k}$ are normalized to be positive by multiplying the surprise series (S_n) by -1 when $\hat{\beta}_{n,k}$ is negative. These estimates are also reported in Appendix Table C.4.

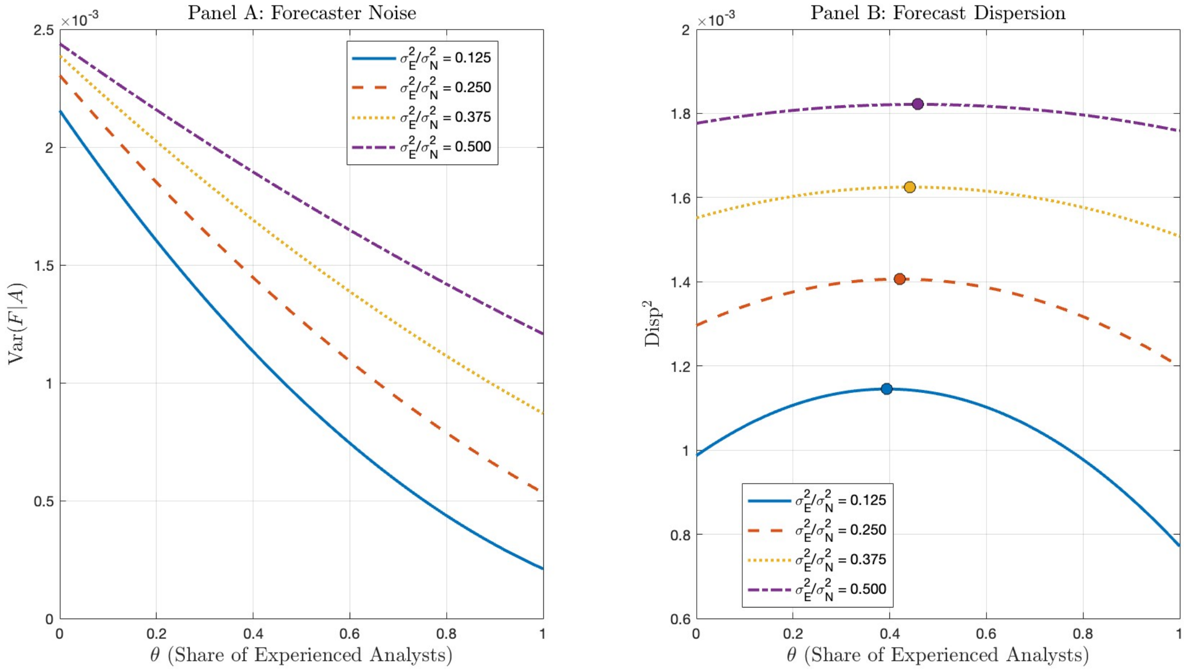

Figure 4: **Forecaster Noise and Forecast Dispersion vs. Share of Experienced Analysts.** Panel A (Panel B) plots the theoretical relationship between forecaster noise Var$(F|A)$ (forecast dispersion Disp^2) and the share of experienced analysts θ based on Equation (8) (Equation (9)) for different precision ratios σ_E^2/σ_N^2, with $\sigma_N = 0.10$ and $\sigma_F = \frac{\sigma_E+\sigma_N}{2}$.

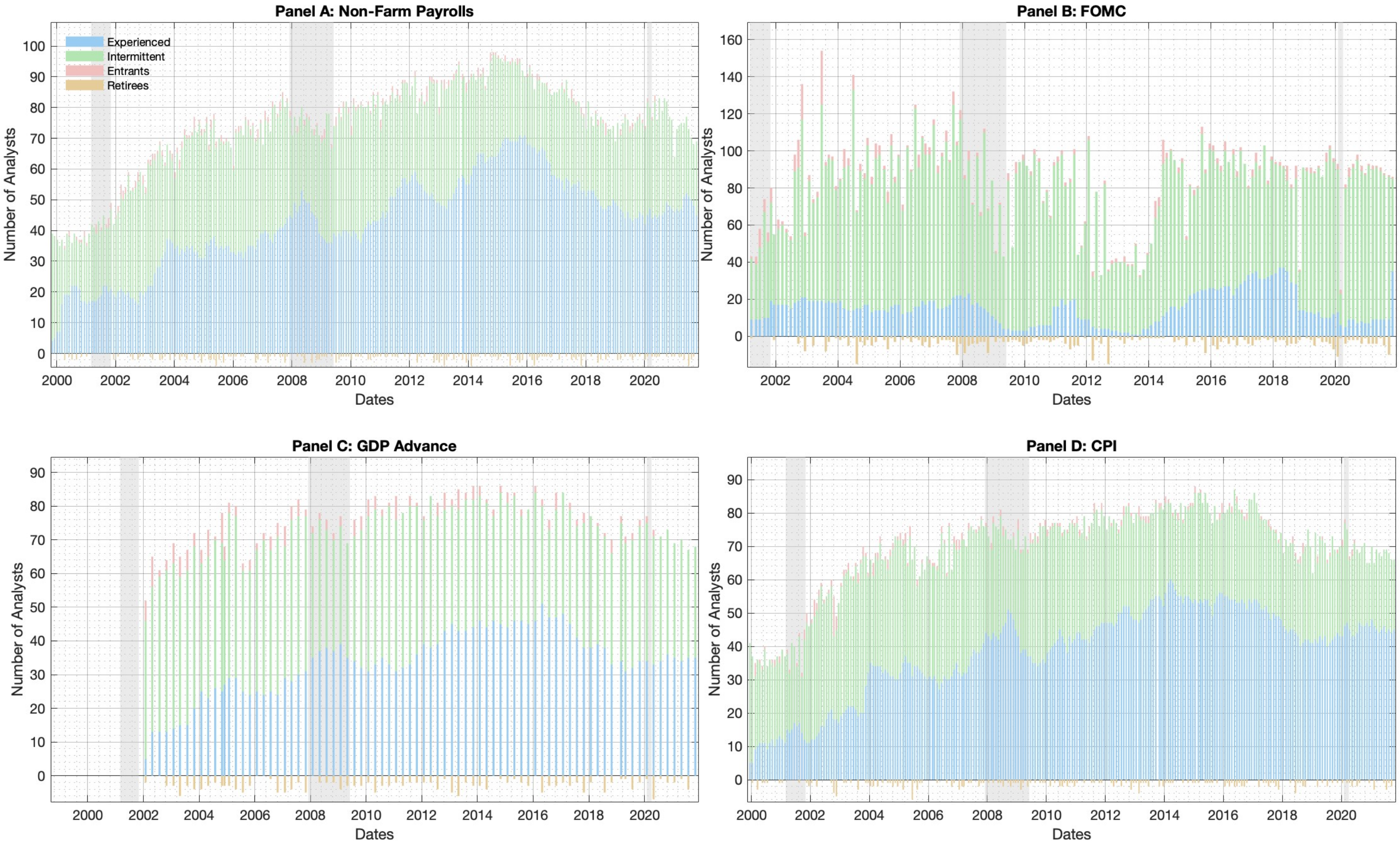

Figure 5: **Forecaster Pool Composition Over Time.** This figure plots the number of active analysts for four indicators: Nonfarm Payrolls (Panel A), FOMC (Panel B), GDP Advance (Panel C), and CPI (Panel D). For each release, the forecaster pool is decomposed into three categories: experienced analysts, who have issued forecasts for all or the maximum number of releases for that indicator in the past year; intermittent analysts, who have participated irregularly; and entrants, who are forecasting the indicator for the first time. The figure also plots (below zero) the number of retirees, who forecasted in the previous period but leave the sample thereafter; this group also includes analysts who switch firms and/or move to forecasting other indicators.

Table 1: **Macroeconomic Announcements.** This table describes the 25 macroeconomic indicators with the highest Bloomberg relevance score (as of November 2021). The last column reports the average number of forecasters on a particular announcement day. "A" stands for advance, "P" for preliminary, and "F" for final release. I exclude the zero lower bound period for the FOMC target announcement.

Ticker	Event	Score	Start Date	End Date	Obs.	Forecasters
NFP TCH Index	Nonfarm Payrolls	99.21	01/08/1997	08/10/2021	273	75
INJCJC Index	Initial Jobless Claims	98.43	18/03/1999	10/11/2021	1127	40
FDTR Index Target	FOMC Target	97.64	30/03/1999	03/11/2021	183	81
FDTR Index Path	FOMC Path	97.64	30/03/1999	03/11/2021	126	81
GDP CQOQ Index A	GDP A	96.85	26/03/1998	28/10/2021	95	72
GDP CQOQ Index P	GDP P	96.85	26/02/1999	26/08/2021	88	69
GDP CQOQ Index F	GDP F	96.85	24/09/1998	30/09/2021	93	65
CPI CHNG Index	CPI	96.06	19/02/1999	13/10/2021	273	70
NAPMPMI Index	ISM Manufacturing	95.28	01/03/1999	01/10/2021	272	67
CONSSENT Index P	U. of Mich. Sentiment P	94.49	16/06/2000	15/10/2021	251	58
CONSSENT Index F	U. of Mich. Sentiment F	94.49	28/05/1999	29/10/2021	251	52
RTSDCHNG Index	Advance Retail Sales	93.70	11/02/1999	16/11/2021	273	70
CONCCONF Index	Conf. Board Consumer Confidence	92.91	23/02/1999	28/09/2021	272	61
DGNOCHNG Index	Durable Goods Orders	92.13	25/02/1999	27/10/2021	273	66
IP CHNG Index	Industrial Production	91.34	17/02/1999	18/10/2021	273	69
NHSLTOT Index	New Home Sales	90.55	02/03/1999	26/10/2021	271	63
NHSPSTOT Index	Housing Starts	89.76	17/02/1999	19/10/2021	271	66
USURTOT Index	Unemployment Rate	89.29	02/07/1998	05/11/2021	275	72
ADP CHNG Index	ADP Employment	88.19	01/08/2007	03/11/2021	171	36
ETSLTOTL Index	Existing Home Sales	87.40	23/03/2005	21/10/2021	200	68
PPI CHNG Index	PPI	86.61	18/02/1999	10/09/2021	272	63
PCE CRCH Index	Personal Spending	85.83	01/03/1999	29/10/2021	270	65
PITLCHNG Index	Personal Income	85.83	01/03/1999	29/10/2021	271	63
TMNOCHNG Index	Factory Orders	85.04	04/03/1999	03/11/2021	271	54
USTBTOT Index	Trade Balance	84.25	19/02/1999	04/11/2021	273	61

Table 2: **Dispersion and Price Impact.** This table reports the coefficient estimates using the pooled regression (5) for each asset class k: aggregate stock market, S&P 500 futures, treasury yields with maturities of six months to ten years. t-statistics are in parentheses and based on daily clustered standard errors. Coefficients are in bps.

	Stock Market	S&P500 Futures	6M T. Bill	2Y T. Note	5Y T. Note	10Y T. Note
$S_{n,d}$	11.13***	10.93***	0.34***	0.99***	1.05***	0.93***
	(4.87)	(4.84)	(5.38)	(9.46)	(8.46)	(7.77)
$\text{Disp}_{n,d}$	2.89	2.55	−0.07*	-0.02	-0.04	-0.01
	(1.41)	(1.24)	(-1.82)	(-0.30)	(-0.54)	(-0.13)
$S_{n,d} \times \text{Disp}_{n,d}$	−2.36***	−2.48***	−0.06***	−0.15***	−0.15***	−0.11***
	(-3.63)	(-3.77)	(-4.16)	(-5.86)	(-4.46)	(-3.25)
cons	2.89	2.74	−0.20***	-0.10	0.03	0.03
	(0.84)	(0.80)	(-2.62)	(-0.72)	(0.20)	(0.16)
N	5,849	5,849	5,849	5,849	5,849	5,849
R^2	0.01	0.01	0.01	0.02	0.02	0.02
Announcement FEs	✓	✓	✓	✓	✓	✓

Table 3: **Experience and Forecast Error.** This table reports coefficient estimates from regressions of the mean absolute percentage error of analyst i in year t:$t+11$ on the number of announcements forecasted by the same analyst in the prior year $t-12$:$t-1$, following Equation (21). Panel A reports estimates at the individual announcement-type level. Panel B reports estimates from the pooled regression across announcement types, controlling for announcement-type fixed effects. Standard errors are clustered at the release-day level in the single-series regressions (Panel A) and at both the release-day and announcement-type levels in the pooled regression (Panel B). t-statistics are reported in parentheses. Coefficients are in percentage points.

Announcement Type	Cons.	t-stat	$\text{Exp}_{n,i,t(d)-12:t(d)-1}$	t-stat	R^2	N
			Panel A: Announcement Type Estimates			
Nonfarm Payrolls	205.72***	(9.14)	-6.73***	(-5.55)	0.48%	18,960
Initial Jobless Claims	4.53***	(51.95)	-0.01***	(-4.58)	0.30%	42,183
FOMC Target	2.78***	(7.27)	-0.06*	(-1.87)	0.13%	13,103
FOMC Path	2.78***	(7.27)	-0.06*	(-1.87)	0.13%	13,103
GDP A	70.28***	(8.58)	0.32	(0.79)	0.00%	5,450
GDP P	22.29***	(6.12)	-0.22	(-0.98)	0.09%	4,664
GDP F	11.75***	(17.64)	-0.03	(-0.82)	0.01%	4,753
CPI	55.10***	(42.58)	-0.76***	(-7.68)	0.84%	17,653
ISM Manufacturing	3.26***	(49.32)	-0.01**	(-2.56)	0.14%	16,974
U. of Mich. Sentiment P	4.11***	(57.62)	-0.02***	(-3.70)	0.22%	13,930
U. of Mich. Sentiment F	1.59***	(41.22)	0.00	(-1.18)	0.03%	12,224
Advance Retail Sales	113.46***	(28.04)	-0.79**	(-2.49)	0.24%	17,534
C.B. Consumer Confidence	5.53***	(25.69)	0.01	(0.72)	0.00%	15,270
Durable Goods Orders	138.57***	(21.61)	-0.27	(-0.49)	0.00%	16,683
Industrial Production	103.89***	(37.11)	-0.43**	(-2.32)	0.07%	17,291
New Home Sales	7.18***	(28.55)	-0.05***	(-3.55)	0.36%	15,550
Housing Starts	5.58***	(44.75)	0.02**	(2.23)	0.09%	16,374
Unemployment Rate	2.39***	(18.69)	0.00	(0.80)	0.00%	18,225
ADP Employment	73.56***	(8.17)	-1.87***	(-3.32)	1.35%	5,464
Existing Home Sales	3.35***	(24.62)	-0.03***	(-4.55)	0.43%	11,979
PPI	89.49***	(39.07)	-0.13	(-0.71)	0.01%	15,836
Personal Spending	50.56***	(32.29)	-0.04	(-0.52)	0.00%	15,981
Personal Income	55.65***	(33.91)	0.00	(0.04)	-0.01%	15,562
Factory Orders	87.37***	(23.21)	-0.48**	(-2.07)	0.08%	13,466
Trade Balance	6.00***	(37.65)	-0.02*	(-1.72)	0.05%	15,465
			Panel B: Pooled Estimates			
	7.52***	(26.18)	-0.17***	(-6.98)	28.76%	373,677

Table 4: **Experience and Forecast Timing.** This table reports regressions of forecast lead time on analyst experience, following Equation (22). Lead time is defined as the number of business days between the forecast date and the release date. Panel A presents estimates by announcement type. Panel B reports pooled estimates with announcement-type fixed effects. Standard errors are clustered at the release-day level in Panel A and two-way clustered by release day and announcement type in Panel B. t-statistics are in parentheses.

Announcement Type	Cons.	t-stat	$\text{Exp}_{n,i,t(d)-12:t(d)-1}$	t-stat	R^2	N
			Panel A: Announcement Type Estimates			
Nonfarm Payrolls	3.60***	(39.81)	0.10***	(14.47)	2.69%	18,960
Initial Jobless Claims	2.84***	(99.77)	0.01***	(17.91)	2.48%	42,183
FOMC Target	13.52***	(14.74)	-0.30***	(-3.69)	0.90%	13,103
FOMC Path	13.52***	(14.74)	-0.30***	(-3.69)	0.90%	13,103
GDP A	4.06***	(39.93)	0.05***	(6.85)	1.77%	5,450
GDP P	3.58***	(43.88)	0.05***	(5.72)	1.53%	4,664
GDP F	3.79***	(54.26)	0.07***	(12.08)	2.86%	4,753
CPI	3.62***	(16.35)	0.08***	(7.15)	0.24%	17,694
ISM Manufacturing	2.15***	(36.77)	0.07***	(15.20)	1.48%	16,974
U. of Mich. Sentiment P	4.35***	(14.20)	0.03	(1.26)	0.11%	13,930
U. of Mich. Sentiment F	3.80***	(39.62)	0.07***	(10.33)	4.15%	12,224
Advance Retail Sales	2.92***	(24.18)	0.12***	(9.28)	0.43%	17,540
C.B. Consumer Confidence	1.89***	(24.39)	0.09***	(15.29)	0.41%	15,270
Durable Goods Orders	3.66***	(10.20)	0.10***	(3.85)	0.08%	16,688
Industrial Production	3.64***	(12.06)	0.14***	(3.98)	0.05%	17,308
New Home Sales	2.95***	(37.05)	0.06***	(6.59)	0.89%	15,550
Housing Starts	2.39***	(30.83)	0.11***	(17.84)	2.80%	16,374
Unemployment Rate	3.76***	(39.28)	0.13***	(17.92)	3.49%	18,225
ADP Employment	2.92***	(61.42)	0.06***	(13.35)	2.54%	5,464
Existing Home Sales	2.53***	(39.35)	0.09***	(13.78)	1.83%	11,979
PPI	3.36***	(20.92)	0.09***	(10.38)	0.49%	15,861
Personal Spending	4.34***	(10.51)	0.18***	(4.76)	0.13%	15,995
Personal Income	3.52***	(9.94)	0.20***	(4.65)	0.13%	15,574
Factory Orders	2.77***	(45.70)	0.04***	(8.35)	0.98%	13,476
Trade Balance	2.89***	(36.29)	0.10***	(14.91)	3.57%	15,465
			Panel B: Pooled Estimates			
	3.59***	(70.84)	0.03***	(9.46)	5.22%	373,807

Table 5: **Dispersion and the Share of Experienced Analysts.** This table reports coefficient estimates from regressions of forecast dispersion on the share of experienced analysts and its square, as specified in Equation (24). Specifications (2) to (6) additionally control for month fixed effects, the number of analysts, and common uncertainty measures: EPU($\times$0.01) of Baker et al. (2016) and the VIX($\times$0.01). To reduce the multicollinearity between $\text{ExpShare}_{n,t(d)}$ and $\text{ExpShare}^2_{n,t(d)}$, the share of experienced analysts is demeaned using its full sample mean ($\bar{\theta} \approx 0.39$) in all specifications. $\widehat{\theta^*}$ denotes the implied threshold (in the original scale) at which the marginal effect of analyst experience on dispersion is zero ($\widehat{\theta^*} \equiv \bar{\theta} - \frac{\hat{b}_1}{2\hat{b}_2}$). $t-$statistics in parentheses are based on daily clustered standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{ExpShare}_{n,t(d)}$	-0.15	0.60***	0.58***	0.60***	0.61***	0.59***
	(-0.98)	(3.04)	(2.96)	(3.04)	(3.06)	(2.99)
$\text{ExpShare}^2_{n,t(d)}$	-0.75	-0.89*	-1.00**	-0.89*	-0.88*	-1.00**
	(-1.60)	(-1.73)	(-1.97)	(-1.73)	(-1.72)	(-1.96)
$\text{NumAnalysts}_{n,d}$			0.01***			0.01***
			(5.11)			(5.09)
EPU_{d-5}				0.01		0.01
				(0.31)		(0.25)
VIX_{d-5}					1.22**	1.14**
					(2.12)	(2.02)
N	5,849	5,848	5,848	5,848	5,848	5,848
R^2	0.43	0.66	0.66	0.66	0.66	0.66
Announcement FEs	✓	✓	✓	✓	✓	✓
Month FEs		✓	✓	✓	✓	✓
$\widehat{\theta^*}$	0.29	0.73	0.68	0.73	0.74	0.69

Table 6: **Price Impact, Dispersion, and the Share of Experienced Analysts.** This table reports estimates from the regression of asset returns (changes in yields) on macroeconomic news surprises and their interactions with forecast dispersion and analyst experience, as specified in Equation (25). $t-$statistics in parentheses are based on Newey-West standard errors with five-day lags. Coefficients are in basis points.

	Stock Market (1)	S&P500 F. (2)	6M T. B. (3)	2Y T. N. (4)	5Y T. N. (5)	10Y T. N. (6)
$S_{n,d}$	18.34***	18.86***	0.63***	1.64***	1.61***	1.29***
	(3.56)	(3.72)	(4.83)	(7.25)	(6.21)	(5.21)
$S_{n,d} \times \text{Disp}_{n,d}$	-4.81***	-5.36***	-0.09***	-0.20***	-0.20***	-0.18***
	(-3.20)	(-3.46)	(-3.29)	(-3.91)	(-3.24)	(-2.86)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$	9.65***	9.80***	0.11*	0.23**	0.28**	0.26*
	(2.62)	(2.64)	(1.88)	(2.08)	(1.98)	(1.78)
$\text{Disp}_{n,d}$	-0.91	-1.80	-0.12	0.03	0.01	-0.11
	(-0.23)	(-0.46)	(-1.25)	(0.21)	(0.08)	(-0.61)
$\text{ExpShare}_{n,t(d)}$	10.90	6.26	0.46	0.55	-0.15	-0.70
	(0.53)	(0.31)	(0.93)	(0.62)	(-0.15)	(-0.71)
$S_{n,d} \times \text{ExpShare}_{n,t(d)}$	-38.44***	-35.68***	-0.78***	-1.84***	-1.75***	-1.43**
	(-3.05)	(-2.89)	(-2.64)	(-3.65)	(-2.89)	(-2.41)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$	7.67	8.43	0.10	-0.12	-0.16	0.18
	(0.85)	(0.93)	(0.50)	(-0.38)	(-0.44)	(0.45)
R^2	0.00	0.00	0.00	0.02	0.01	0.01
N	5,848	5,848	5,848	5,848	5,848	5,848
Announcement FEs	✓	✓	✓	✓	✓	✓

Table 7: **Price Impact, Dispersion, and the Share of Experienced Analysts: 2SLS.** This table reports the second stage 2SLS estimates from the regression of asset returns (changes in yields) on macroeconomic news surprises and their interactions with forecast dispersion and analyst experience, using the one-year lagged share of experienced analysts ($\text{ExpShare}_{n,t(d)-12}$) as an instrument for current experience ($\text{ExpShare}_{n,t(d)}$). Appendix Table C.13 reports the first-stage estimates. $t-$statistics in parentheses are based on Newey-West standard errors with five-day lags. Coefficients are in basis points.

	Stock Market (1)	S&P500 F. (2)	6M T. B. (3)	2Y T. N. (4)	5Y T. N. (5)	10Y T. N. (6)
$S_{n,d}$	25.82***	26.80***	0.70***	1.84***	1.95***	1.65***
	(4.48)	(4.73)	(4.67)	(7.07)	(6.26)	(5.64)
$S_{n,d} \times \text{Disp}_{n,d}$	-5.93***	-6.35***	-0.12***	-0.28***	-0.31***	-0.30***
	(-3.59)	(-3.74)	(-3.89)	(-5.06)	(-4.30)	(-4.32)
$S_{n,d} \times \text{Disp}_{n,d} \times \widehat{\text{ExpShare}}_{n,t(d)}$	12.91***	12.82***	0.18***	0.41***	0.53***	0.54***
	(3.19)	(3.14)	(2.71)	(3.46)	(3.36)	(3.43)
$\text{Disp}_{n,d}$	0.68	0.12	-0.24	-0.18	-0.22	-0.40*
	(0.14)	(0.03)	(-2.00)	(-0.99)	(-0.99)	(-1.87)
$\widehat{\text{ExpShare}}_{n,t(d)}$	24.05	24.86	1.89**	3.06*	1.79	0.45
	(0.68)	(0.72)	(2.09)	(1.78)	(0.90)	(0.24)
$S_{n,d} \times \widehat{\text{ExpShare}}_{n,t(d)}$	-59.13***	-57.66***	-0.93***	-2.36***	-2.64***	-2.34***
	(-4.11)	(-4.09)	(-2.67)	(-3.95)	(-3.58)	(-3.33)
$\text{Disp}_{n,d} \times \widehat{\text{ExpShare}}_{n,t(d)}$	3.83	3.88	0.39	0.38	0.37	0.86*
	(0.35)	(0.36)	(1.55)	(0.96)	(0.76)	(1.74)
N	5,848	5,848	5,848	5,848	5,848	5,848
Announcement FEs	✓	✓	✓	✓	✓	✓

Internet Appendix

A Conceptual Framework Derivations and Extensions

A.1 Shrinking to the Consensus Forecast

If analysts update their forecasts in Equation 6 after observing the consensus at date 1, their revised forecasts take the form:

$$\begin{aligned} f^r_{E_i} &= A + (1-\lambda_E)\left[(1-w_E)e_{E_i} + w_E e_{F_0}\right] + \lambda_E \bar{w} e_{F_0}, \\ f^r_{N_i} &= A + (1-\lambda_N)\left[(1-w_N)e_{N_i} + w_N e_{F_0}\right] + \lambda_N \bar{w} e_{F_0}, \end{aligned} \tag{A.1}$$

where $w_E = \frac{\sigma_E^2}{\sigma_E^2+\sigma_{F_0}^2}$, $w_N = \frac{\sigma_N^2}{\sigma_N^2+\sigma_{F_0}^2}$, and $\bar{w} = \theta w_E + (1-\theta)w_N$. Using the Bayesian updating formula with correlated error terms:

$$\mathbb{E}[A|X_1, X_2] = (1-\lambda)X_1 + \lambda X_2, \quad \text{with } \lambda = \frac{\text{Var}(X_1 - A) - \text{Cov}(X_1 - A, X_2 - A)}{\text{Var}(X_1 - A) + \text{Var}(X_2 - A) - 2\text{Cov}(X_1 - A, X_2 - A)}.$$

The shrinkage intensity for experienced analysts satisfies:

$$\lambda_E = 1 - \frac{\bar{w}(\bar{w} - w_E)\sigma_{F_0}^2}{(1-w_E)^2\sigma_E^2 + (\bar{w} - w_E)^2\sigma_{F_0}^2}. \tag{A.2}$$

λ_E is strictly between 0 and 1 for all θ, and increases when the consensus is relatively more informative. Specifically, λ_E is larger when the average weight on public information $\bar{w}$ is low: that is, when the share of experienced analysts is high (large θ), as shown in Panel A of Figure C.1. The figure also shows that λ_E decreases in the precision advantage of experienced analysts. Intuitively, even experienced analysts find the consensus valuable when it provides information beyond their own initial forecast. However, they never fully shrink toward the consensus ($\lambda_E < 1$): since their private signals are relatively precise, they always place some weight on their initial forecast.

Similarly, for inexperienced analysts, the shrinkage intensity is given by:

$$\lambda_N = 1 - \frac{\bar{w}(\bar{w} - w_N)\sigma_{F_0}^2}{(1-w_N)^2\sigma_N^2 + (\bar{w} - w_N)^2\sigma_{F_0}^2}. \tag{A.3}$$

Since inexperienced analysts have less reliable private signals, the consensus provides valuable information beyond their own initial forecast. Given that $w_N > \bar{w}$, the optimal revision weight λ_N exceeds 1, meaning that inexperienced analysts overshrink by extrapolating from the consensus and placing negative weight on their private signal. Panel B of Figure C.1 shows that λ_N is strictly greater than 1 and is hump-shaped in θ, especially when the informational advantage of experienced analysts is large: as the share of experienced analysts increases, the consensus becomes more informative, and inexperienced analysts optimally place greater weight on it. However, as the consensus becomes more precise, the marginal benefit from further extrapolation declines, and λ_N gradually converges toward 1.

A.1.1 The Revised Consensus

Revised individual forecasts can be expressed as:

$$\begin{aligned} f^r_{E_i} &= A + (1-\lambda_E)(1-w_E)e_{E_i} + ((1-\lambda_E)w_E + \lambda_E\bar{w})\, e_{F_0}, \\ f^r_{N_i} &= A + (1-\lambda_N)(1-w_N)e_{N_i} + ((1-\lambda_N)w_N + \lambda_N\bar{w})\, e_{F_0}, \end{aligned} \tag{A.4}$$

and the consensus forecast simplifies to:

$$F^r = A + \underbrace{(\bar{w} - \theta(1-\theta)(w_N - w_E)(\lambda_N - \lambda_E))}_{\bar{w}^r}\, e_{F_0}. \tag{A.5}$$

$\bar{w}^r$ denotes the revised average weight on common information after forecast revision. Panel C of Figure C.1 shows that $\bar{w}^r$ is strictly decreasing in θ: as the share of experienced analysts increases, shrinkage toward common information declines because experienced analysts place a strictly positive weight on their private signals. As a result, the variance of the revised consensus, given by $\mathrm{Var}(F^r) = \sigma^2_Z + \sigma^2_\epsilon + (\bar{w}^r)^2\sigma^2_{F_0}$, falls with θ, consistent with the baseline model's prediction that a more experienced analyst pool improves the informativeness of the consensus forecast.

A.1.2 Forecast Dispersion

Dispersion of the revised forecasts, measured as the cross-sectional standard deviation of analysts' forecasts, satisfies:

$$\begin{aligned} (\mathrm{Disp}^r)^2 &\equiv \mathbb{E}[\mathrm{Var}(f^r_i)] - \mathbb{E}[\mathrm{Cov}(f^r_i, f^r_q)]; \quad q \neq i \\ &= \theta\mathrm{Var}(f^r_{E_i}) + (1-\theta)\mathrm{Var}(f^r_{N_i}) - \Big[\theta^2\mathrm{Cov}(f^r_{E_i}, f^r_{E_q}) + (1-\theta)^2\mathrm{Cov}(f^r_{N_i}, f^r_{N_q}) + 2\theta(1-\theta)\mathrm{Cov}(f^r_{E_i}, f^r_{N_q})\Big] \\ &= \theta(1-w_E)^2(1-\lambda_E)^2\sigma^2_E + (1-\theta)(1-w_N)^2(1-\lambda_N)^2\sigma^2_N + \theta(1-\theta)(w_N - w_E)^2(1-\theta\lambda_N - (1-\theta)\lambda_E)^2\sigma^2_{F_0}. \end{aligned} \tag{A.6}$$

Forecast dispersion decreases with both the shrinkage intensity of analysts (λ_E and λ_N) and their initial reliance on the common prior (w_E and w_N). Intuitively, as λ_E and λ_N increase, analysts place more weight on the consensus forecast and less on their private signals, leading to more homogenous forecasts and thus lower dispersion. Similarly, a higher w_E and w_N imply that analysts rely more on the common prior in forming their initial forecasts, reducing dispersion. In contrast, the overall effect of analyst composition (θ) on dispersion is ambiguous: increasing θ raises the share of experienced analysts who shrink less, but also improves consensus precision. I illustrate this non-monotonic relationship numerically in Panel D of Figure C.1. Similar to the baseline model in Section 3.1, increasing the share of experienced analysts initially raises dispersion (especially when experienced analysts have a strong informational advantage (i.e., $\sigma_E^2/\sigma_N^2 \downarrow$)) as they place less weight on the consensus. However, when experienced analysts dominate the market, increasing θ improves the precision of the consensus and reduces dispersion.

A.2 Derivation of Asset Demand

This appendix provides the detailed derivation of the aggregate demand function presented in equation (16). Given mean-variance preferences, investors choose their demand $x_j(F,p)$ to maximize their expected terminal utility:

$$\mathbb{E}(U_j(W_j)|F,p) = \mathbb{E}(W_j|F,p) - \frac{1}{2}\gamma \mathrm{Var}(W_j|F,p), \tag{A.7}$$

where $\mathbb{E}(W_j|F,p) = (\mu + \mathbb{E}(Z|F,p) - p)x_j(F,p)$ and $\mathrm{Var}(W_j|F,p) = x_j(F,p)^2\mathrm{Var}(Z|F,p)$. Investors' maximization problem is, thus, equivalent to

$$\arg\max_{x_j(F,p)} \quad (\mu + \mathbb{E}(Z|F,p) - p)x_j(F,p) - \frac{1}{2}\gamma x_j(F,p)^2\mathrm{Var}(Z|F,p). \tag{A.8}$$

Rearranging the first order condition, I get the demand function:

$$x_j(F,p) = \frac{\mu + \mathbb{E}(Z|F,p) - p}{\gamma \mathrm{Var}(Z|F,p)}. \tag{A.9}$$

Using Bayesian updating, $\mathbb{E}(Z|F,S_D) = \frac{\mathrm{Var}(Z|S_D)^{-1}\mathbb{E}(Z|S_D)+(\phi_F)F}{\mathrm{Var}(Z|S_D)^{-1}+\phi_F}$. Given that the posterior variance satisfies $\mathrm{Var}(Z|F,S_D) = \left(\mathrm{Var}(Z|S_D)^{-1} + \phi_F\right)^{-1}$, the posterior mean can be expressed as:

$$\mathbb{E}(Z|F,S_D) = \mathbb{E}(Z|S_D) + \phi_F \mathrm{Var}(Z|F,S_D)(F - \mathbb{E}(Z|S_D)), \tag{A.10}$$

where $\mathbb{E}(Z|S_D) = p - \mu$. Substituting in Equation (A.9), investor's demand satisfies:

$$x_j(F,p) = \frac{\phi_F}{\gamma}(F - p + \mu), \tag{A.11}$$

which is increasing in consensus precision (ϕ_F) and decreasing in investors' risk aversion (γ). Given that $F = Z + \zeta_F$, aggregate demand can be expressed as:

$$D(p) = \frac{\phi_F}{\gamma}(Z - p + \mu) + \frac{\phi_F}{\gamma}\zeta_F + u. \tag{A.12}$$

A.3 Theoretical vs. Empirical Surprise Measure

While the theoretical model assumes that the market's expectation is formed by a rational competitive dealer who observes the aggregate demand signal, the empirical analysis relies on the consensus forecast as a proxy for this expectation when constructing the surprise in Equation (1). This section derives the formal link between the theoretical surprise measure, $A - \mathbb{E}(A|S_D)$ in Equation (17), and its empirical counterpart, $A - F$, where F denotes the consensus forecast.

Since noise traders' demand u is inelastic and uninformative about the announcement, I can write

$$\mathbb{E}(A|S_D) = \mathbb{E}\left(A|F + \frac{\gamma}{\phi_F}u\right) = \mathbb{E}(A|F). \tag{A.13}$$

Taking $\mathbb{E}(A) = \mathbb{E}(F) = \mu$ and applying the Bayesian updating formula, I obtain

$$\begin{aligned} \mathbb{E}(A|F) &= \mu + \frac{\mathrm{Cov}(A,F)}{\mathrm{Var}(F)}(F - \mu) \\ &= F + \frac{\bar{w}^2\sigma_{F_0}^2}{\sigma_Z^2 + \sigma_\epsilon^2 + \bar{w}^2\sigma_{F_0}^2}(\mu - F), \end{aligned} \tag{A.14}$$

where the second equality follows by substituting the expression for $\mathrm{Var}(F)$ from Equation (8). Thus, the empirical surprise can be decomposed into

$$A - F = \underbrace{A - \mathbb{E}(A|S_D)}_{\text{True Surprise}} + \underbrace{\frac{\bar{w}^2\sigma_{F_0}^2}{\sigma_Z^2 + \sigma_\epsilon^2 + \bar{w}^2\sigma_{F_0}^2}(\mu - F)}_{\text{Bias}}. \tag{A.15}$$

Since the consensus forecast is assumed to be unbiased on average $\mathbb{E}(\mu - F) = 0$, then $A - F$ is an unbiased estimator of the true surprise. The assumption of unbiased forecasts is also supported by the data, as shown in Appendix Table C.8. Specifically, the mean forecast error ($\mathrm{Release}_{n,d} - \mathrm{Median}(\mathbf{f}_{n,d})$) is statistically insignificant for most announcement types. Only 3 out of 25 indicators reject unbiasedness at the 5% level (6 at the 10% level). Moreover, even for these indicators, the economic magnitude of the mean forecast error is small, ranging from less than 0.3% of the standard deviation of the actual release for FOMC announcements to 5.3% for Industrial Production announcements. Overall, this evidence suggests that systematic bias is not a general feature of macroeconomic forecasts.

A.4 Private Information Acquisition

Similar to Benamar et al. (2021), investors may pay a cost $c(\phi_j)$ to acquire an additional private signal[31] about the payoff of the risky asset $S_j^p = Z + \zeta_j^p$ at date 1; where the error terms $\zeta_j^p \sim N(0, \phi_j^{-1})$ are independent across investors and satisfy $\int_j \zeta_j^p = 0$. The aggregate demand for information is $\int_j \phi_j dj = \bar{\phi}$.

Investor j's total information can be expressed as the precision-weighted average of her private and public (the consensus forecast) information:

$$S_j = Z + \underbrace{\frac{\phi_j \zeta_j^p + \phi_F \zeta_F}{\phi_j + \phi_F}}_{\zeta_j \sim N(0, (\phi_j + \phi_F)^{-1})}, \tag{A.16}$$

and her optimal demand at date 2 becomes:

$$x_j(S_j, p) = \frac{\phi_j + \phi_F}{\gamma}(S_j - p + \mu). \tag{A.17}$$

Given that $\int_j S_j = Z + \frac{\phi_F}{(\phi) + \phi_F}\zeta_F$, aggregate demand is equal to:

$$D(p) = \frac{\bar{\phi} + \phi_F}{\gamma}(Z - p + \mu) + \frac{\phi_F}{\gamma}\zeta_F + u. \tag{A.18}$$

Observing this aggregate demand conveys a signal $S_D = Z + \zeta_D$ about the asset's payoff, where $\zeta_D = \frac{\gamma}{\bar{\phi} + \phi_F}u + \frac{\phi_F}{\bar{\phi} + \phi_F}\zeta_F$. The posterior variance satisfies $\mathrm{Var}(Z|S_D) = \left(\frac{1}{\sigma_Z^2} + \frac{(\bar{\phi} + \phi_F)^2}{\gamma^2 \sigma_u^2 + \phi_F}\right)^{-1}$.

A.4.1 Price Impact of the Announcement

At date 3, dealers update prices $p_A = \mu + \mathbb{E}(Z|D(p), A)$, given the observable aggregate demand and public announcement A. Parallel to Equation (18), the announcement's price impact satisfies:

$$\beta = \frac{\mathrm{Var}(Z|S_D)}{\mathrm{Var}(Z|S_D) + \sigma_\epsilon^2} = \left(1 + \frac{\sigma_\epsilon^2}{\sigma_Z^2} + \frac{(\bar{\phi} + \phi_F)^2 \sigma_\epsilon^2}{\gamma^2 \sigma_u^2 + \phi_F}\right)^{-1}. \tag{A.19}$$

In this case, the direct effects of aggregate information acquisition ($\bar{\phi}$) and forecast precision (ϕ_F) on price impact (β) can be expressed as:

$$\frac{\partial \beta}{\partial \bar{\phi}} = -\frac{2\sigma_\epsilon^2(\bar{\phi} + \phi_F)(\gamma^2 \sigma_u^2 + \phi_F)}{\left((1 + \frac{\sigma_\epsilon^2}{\sigma_Z^2})(\gamma^2 \sigma_u^2 + \phi_F) + \sigma_\epsilon^2(\bar{\phi} + \phi_F)^2\right)^2} < 0, \tag{A.20}$$

[31] The cost function $c(.)$ is increasing and strictly convex with $c(0) = 0$.

and

$$\frac{\partial \beta}{\partial \phi_F} = -\frac{\sigma_\epsilon^2(\bar{\phi}+\phi_F)(2\gamma^2\sigma_u^2+\phi_F-\bar{\phi})}{\left((1+\frac{\sigma_\epsilon^2}{\sigma_Z^2})(\gamma^2\sigma_u^2+\phi_F)+\sigma_\epsilon^2(\bar{\phi}+\phi_F)^2\right)^2} < 0, \text{ if } \phi_F > \bar{\phi}-2\gamma^2\sigma_u^2. \tag{A.21}$$

Equation A.20 shows that, in the case of exogenous private information acquisition, an increase in information acquisition ($\bar{\phi}\uparrow$) reduces the price impact of news because more information is incorporated into prices before the release of the announcement. Similarly, Equation A.21 implies that a reduction in forecast precision ($\phi_F\downarrow$), increases the price impact of news, as pre-announcement information is less informative.[32] However, under endogenous information acquisition, the equilibrium $\bar{\phi}$ is also a function of forecast precision, as a reduction in forecast precision may reduce the informedness of investors and results in more information acquisition ahead of the announcement. Next, I derive equilibrium quantities under endogenous information acquisition and the asset pricing implications.

A.4.2 Endogenous Information Acquisition

Each investor chooses the precision ϕ_j of her private signal S_j^p at date 1 to maximize her expected terminal wealth (or certainty equivalent): $\mathbb{E}(U_j(W_j)) = \mathbb{E}(\mathbb{E}(U_j(W_j)|S_j,p))$. Substituting the optimal demand function into Equation (A.8). Investors' maximization problem becomes:

$$\arg\max_{\phi_j}\ \Pi_j(\phi_j) = \frac{\mathbb{E}\left((\mathbb{E}(Z|S_j,p)-p+\mu)^2\right)}{2\gamma\text{Var}(Z|S_j,p)} - c(\phi_j), \tag{A.22}$$

where,

$$\begin{aligned}\frac{\mathbb{E}\left((\mathbb{E}(Z|S_j,p)-p+\mu)^2\right)}{\text{Var}(Z|S_j,p)} &= \frac{\text{Var}\left((\phi_j+\phi_F)(S_j-p+\mu)\right)}{\text{Var}(Z|S_D)^{-1}+\phi_j+\phi_F}\\ &= \frac{(\phi_j+\phi_F)^2(\text{Var}(Z|S_D)+(\phi_j+\phi_F)^{-1})}{\text{Var}(Z|S_D)^{-1}+\phi_j+\phi_F}\\ &= (\phi_j+\phi_F)\text{Var}(Z|S_D),\end{aligned} \tag{A.23}$$

where second equality follows from $\text{Var}(S_j-p+\mu) = \text{Var}(S_j-E(S_j|S_D)) = \text{Var}(S_j|S_D) = \text{Var}(Z|S_D) + (\phi_j+\phi_F)^{-1}$. Thus, investors' first-order condition satisfies:

$$\frac{\partial \Pi_j(\phi_j^*)}{\partial \phi_j^*} = \frac{Var(Z|S_D)}{2\gamma} - c'(\phi_j^*) = 0 \tag{A.24}$$

[32]This holds for values of ϕ_F that satisfy $\phi_F > \bar{\phi}-2\gamma^2\sigma_u^2$. Intuitively, this condition ensures that the precision of the public forecast (ϕ_F) is sufficiently high relative to the aggregate precision of private signals ($\bar{\phi}$), adjusted for the impact of noise trader activity ($2\gamma^2\sigma_u^2$). When this condition holds, the public forecast dominates the noise in the market, making prices more informative and ensuring that changes in forecast dispersion meaningfully influence the price impact of news.

In an interior symmetric equilibrium, with $\phi_j^* = \bar{\phi}^*$ and $Var(Z|S_D) = \left(\frac{1}{\sigma_Z^2} + \frac{(\bar{\phi}^*+\phi_F)^2}{\gamma^2\sigma_u^2+\phi_F}\right)^{-1}$, the first-order condition becomes:

$$\underbrace{1 - 2\gamma c'(\phi_j^*)\left(\frac{1}{\sigma_Z^2} + \frac{(\bar{\phi}^* + \phi_F)^2}{\gamma^2\sigma_u^2 + \phi_F}\right)}_{\equiv G(\bar{\phi}^*,\phi_F,\gamma,\sigma_Z^2,\sigma_u^2)} = 0. \tag{A.25}$$

Since $G(.)$ is a decreasing function of $\bar{\phi}^*$, the unique interior equilibrium with $\bar{\phi}^* > 0$ exists if and only if $c'(0) < \frac{1}{2\gamma\left(\frac{1}{\sigma_Z^2}+\frac{\phi_F^2}{\gamma^2\sigma_u^2+\phi_F}\right)}$. Otherwise, investors don't have an incentive to acquire private information and optimally choose $\bar{\phi}^* = 0$. Setting $G(\bar{\phi}^*, \phi_F, \gamma, \sigma_Z^2, \sigma_u^2) = 0$, I derive the sensitivities

$$\begin{aligned}\frac{\partial G}{\partial \bar{\phi}^*} &= -2\gamma\left(\frac{c''(\bar{\phi}^*)}{\sigma_Z^2} + \frac{c''(\bar{\phi}^*)(\bar{\phi}^* + \phi_F)^2 + 2c'(\bar{\phi}^*)(\bar{\phi}^* + \phi_F)}{\gamma^2\sigma_u^2 + \phi_F}\right) \text{ and}\\ \frac{\partial G}{\partial \phi_F} &= -2\gamma c'(\bar{\phi}^*)\frac{(\bar{\phi}^* + \phi_F)(2\gamma^2\sigma_u^2 + \phi_F - \bar{\phi}^*)}{(\gamma^2\sigma_u^2 + \phi_F)^2},\end{aligned} \tag{A.26}$$

and using the implicit function theorem, I obtain that:

$$\begin{aligned}\frac{d\bar{\phi}^*}{d\phi_F} &= -\frac{\frac{\partial G}{\partial \phi_F}}{\frac{\partial G}{\partial \bar{\phi}^*}}\\ &= -\frac{\sigma_Z^2 c'(\bar{\phi}^*)(\bar{\phi}^* + \phi_F)(2\gamma^2\sigma_u^2 + \phi_F - \bar{\phi}^*)}{c''(\bar{\phi}^*)(\gamma^2\sigma_u^2 + \phi_F)\left(\gamma^2\sigma_u^2 + \phi_F + \sigma_Z^2(\bar{\phi}^* + \phi_F)^2\right) + 2\sigma_Z^2 c'(\bar{\phi}^*)(\bar{\phi}^* + \phi_F)(\gamma^2\sigma_u^2 + \phi_F)}.\end{aligned} \tag{A.27}$$

This sensitivity is negative if and only if $\phi_F > \bar{\phi} - 2\gamma^2\sigma_u^2$ (see footnote 32). In this case, a drop in forecast precision ($\phi_F \downarrow$) makes the consensus less informative, leading to greater information acquisition by investors. Next, I derive the impact of this endogenous information acquisition on the relationship between forecast precision and the price impact of news (β).

A.4.3 The Effect on Price Impact

Using the chain rule and the expressions in Equations (A.20), (A.21), and (A.27), the sensitivity of the price impact (β) to forecast precision (ϕ_F) simplifies to:

$$\begin{aligned}\frac{d\beta}{d\phi_F} &= \overbrace{\frac{\partial \beta}{\partial \phi_F}}^{<0} + \overbrace{\frac{\partial \beta}{\partial \bar{\phi}^*}\frac{d\bar{\phi}^*}{d\phi_F}}^{>0}\\ &= \frac{-\sigma_\epsilon^2 c''(\bar{\phi}^*)(\bar{\phi} + \phi_F)(2\gamma^2\sigma_u^2 + \phi_F - \bar{\phi})\left(\gamma^2\sigma_u^2 + \phi_F + \sigma_Z^2(\bar{\phi}^* + \phi_F)^2\right)}{\left((1 + \frac{\sigma_\epsilon^2}{\sigma_Z^2})(\gamma^2\sigma_u^2 + \phi_F) + \sigma_\epsilon^2(\bar{\phi} + \phi_F)^2\right)^2\left(c''(\bar{\phi}^*)\left(\gamma^2\sigma_u^2 + \phi_F + \sigma_Z^2(\bar{\phi}^* + \phi_F)^2\right) + 2\sigma_Z^2 c'(\bar{\phi}^*)(\bar{\phi}^* + \phi_F)\right)}.\end{aligned} \tag{A.28}$$

Equation A.28 shows that the overall effect of forecast precision on the price impact of news remains negative (if $\phi_F > \bar{\phi} - 2\gamma^2\sigma_u^2$). Specifically, low forecast precision ($\phi_F \downarrow$) reduces the informativeness of public signals, incentivizing investors to acquire more private information ($\bar{\phi}^* \uparrow$). While this increased private information acquisition reduces price impact ($\beta \downarrow$), it is insufficient to fully offset the rise in β caused by noisy forecasts. This result implies that endogenous information acquisition dampens but does not reverse the effect of forecast precision on price impact.

In addition, the effect of forecast dispersion on announcement price impact under endogenous information acquisition follows from Equation (20). Specifically, when the analyst pool consists primarily of less experienced analysts ($\theta < \theta^*$), low forecast dispersion signals increased shrinkage toward noisy common information, reducing consensus forecast precision ($\phi_F \downarrow$) and incentivizing greater private information acquisition by investors ($\bar{\phi}^* \uparrow$). However, as shown in Equation (A.28), this private information acquisition is insufficient to fully offset the direct effect of low forecast precision, resulting in higher announcement price impact, though the magnitude is smaller than without endogenous information acquisition.

Conversely, when experienced analysts dominate ($\theta < \theta^*$), low forecast dispersion indicates precise analyst information and higher consensus forecast precision ($\phi_F \uparrow$), reducing investors' incentives for private information acquisition ($\bar{\phi}^* \downarrow$). The reduction in private information acquisition increases the importance of the actual announcement, but not sufficiently to reverse the overall decrease in price impact due to precise analyst forecasts. Therefore, endogenous information acquisition reduces the magnitude but preserves the direction of the relationship between forecast dispersion and announcement price impact.

A.5 Endogeneity of the Share of Experienced Analysts

In practice, the share of experienced analysts (θ) may respond to macroeconomic uncertainty (σ_Z^2). Specifically, the empirical patterns in Figure 5 suggest that during high-uncertainty periods, inexperienced analysts disproportionately exit the forecaster pool, generating a positive correlation between uncertainty and the share of experienced analysts. This behaviour could be explained, for example, by reputation and career concerns (Hong et al., 2000; Lamont, 2002; Clement and Tse, 2005). I plan to develop this extension in future work. For the purposes of this paper, I propose a reduced-form expression that captures the endogeneity of the share of experienced analysts to characterize the direction of the bias in the OLS estimates:

$$\theta = \bar{\theta} + \phi_Z \sigma_Z^2, \quad \phi_Z > 0, \tag{A.29}$$

where $\bar{\theta}$ is the baseline share of experienced analysts and $\phi_Z > 0$ captures the tendency of inexperienced analysts to disproportionately exit the forecaster pool when fundamental uncertainty is high. Average shrinkage, thus, becomes:

$$\bar{w} = (\bar{\theta} + \phi_Z \sigma_Z^2) w_E + (1 - \bar{\theta} - \phi_Z \sigma_Z^2) w_N = \bar{w}_0 - \phi_Z (w_N - w_E) \sigma_Z^2, \tag{A.30}$$

where $\bar{w}_0 = \bar{\theta} w_E + (1 - \bar{\theta}) w_N$ is baseline shrinkage. Since experienced analysts shrink less ($w_E < w_N$), average shrinkage is strictly decreasing in fundamental uncertainty (σ_Z^2). This implies that forecast precision $\phi_F = \left(\sigma_\epsilon^2 + \bar{w}^2 \sigma_{F_0}^2\right)^{-1}$ increases with uncertainty through the composition channel.

The threshold θ^* at which the market transitions from shrinkage-dominated to precision-dominated is defined by $\bar{w} = \frac{1}{2}$. Substituting Equation (A.30) and solving for $\bar{\theta}$ yields:

$$\bar{\theta}^* = \frac{w_N - \frac{1}{2} + \phi_Z (w_N - w_E) \sigma_Z^2}{w_N - w_E} > \theta^*, \tag{A.31}$$

where $\theta^* = \frac{w_N - \frac{1}{2}}{w_N - w_E}$ is the threshold in the baseline model with exogenous share of experienced analysts. Equation A.31 illustrates that when analyst composition responds endogenously to uncertainty, the true transition threshold is higher than the exogenous one, i.e., θ^*, because high-uncertainty mechanically attracts more (less) experienced (inexperienced) analysts, making the forecaster pool appear more experienced than it would be absent this selection effect. As a result, the OLS estimate of the threshold is biased upward. This is consistent with the drop in the estimated threshold from 0.69 in the most conservative OLS specification in Table 5 to 0.58 in the 2SLS estimation in Table C.12.

Fundamental uncertainty, thus, also drives dispersion through:

$$\frac{d\,\mathrm{Disp}^2}{d\sigma_Z^2} = \underbrace{(1-2\bar{w})\sigma_{F_0}^2}_{>0 \text{ if } \theta>\theta^*} \cdot \underbrace{(-\phi_Z(w_N - w_E))}_{<0}. \tag{A.32}$$

This implies that in the precision-dominated regime ($\theta > \theta^*$), higher fundamental uncertainty reduces dispersion through the composition channel: higher uncertainty attracts more experienced analysts, reducing average shrinkage and forecast dispersion. Higher fundamental uncertainty also increases the price impact of announcements through the standard uncertainty resolution channel ($\frac{\partial\beta}{\partial\sigma_Z^2} > 0$, Equation (18)). However, the true structural relationship between dispersion and price impact in this regime is positive: low dispersion signals precise private information, which increases pre-announcement price informativeness and reduces the announcement's price impact (Equation (20)). The same logic holds symmetrically in the shrinkage-dominated regime ($\theta < \theta^*$): lower fundamental uncertainty increases dispersion through the composition channel, while also reducing the price impact of the announcement; yet the true structural relationship between dispersion and price impact in this regime is negative, as low dispersion signals shrinkage toward noisy public information, amplifying the announcement's price impact. Therefore, in both regimes, OLS incorrectly attributes part of the uncertainty-driven variation in price impact to dispersion, biasing the estimated dispersion-price impact relationship downward. Consistent with this predicted direction of bias, the 2SLS estimates of $\hat{\delta}_{k,1}$ and $\hat{\delta}_{k,2}$ in Table 7 are both larger in magnitude than their OLS counterparts in Table 6 across all asset classes.

B Evidence from the Survey of Professional Forecasters (SPF)

This section provides complementary evidence on the model's precision versus shrinkage mechanism using data from the Survey of Professional Forecasters (SPF). The SPF collects multiple forecasts for the same target quarter across different survey rounds, allowing direct observation of analysts' forecast revisions and their convergence toward the consensus. This feature enables testing whether experienced analysts herd less toward the consensus, as predicted by the model.

The SPF dataset covers the period from 1971:Q4 to 2025:Q3 and is constructed following the methodology of Bordalo et al. (2020) for 15 macroeconomic indicators. For GDP, inflation, and other real activity indicators, I compute the implied annual growth rate from quarter $q-1$ to $q+3$ forecasted in quarter q. For unemployment and interest rates, I use the forecast level for quarter $q+3$. I winsorize quarterly forecasts by removing observations that lie more than five interquartile ranges away from the median, and I drop survey rounds with fewer than 20 analysts. Consensus forecasts are computed as the cross-sectional mean of individual forecasts in each round.

To test whether experienced analysts revise less toward the consensus, I construct two key measures for each analyst i and indicator n in quarter q. First, I measure the forecast revision as:

$$\text{Rev}_{i,n,q-1:q+3|q} = \text{Forecast}_{i,n,q-1:q+3|q} - \text{Forecast}_{i,n,q-1:q+3|q-1},$$

which represents how much analyst i updates their forecast for the same target period $q-1 : q+3$ between consecutive survey rounds. Second, I compute the distance from consensus in quarter $q-1$ as:

$$\text{Gap}_{i,n,q-1:q+3|q-1} = \text{Forecast}_{i,n,q-1:q+3|q-1} - \overline{\text{Forecast}}_{n,q-1:q+3|q-1},$$

which measures how far analyst i's forecast in quarter $q-1$ deviates from the consensus forecast. Then, for each indicator n, I estimate:

$$\begin{aligned}\text{Rev}_{i,n,q-1:q+3|q} = a_n^r + b_n^r \text{Exp}_{i,n,q-1} + c_n^r \text{Gap}_{i,n,q-1:q+3|q-1} \\ + d_n^r(\text{Exp}_{i,n,q-1} \times \text{Gap}_{i,n,q-1:q+3|q-1}) + \mu_i^r + \nu_q^r + e_{i,n,q-1:q+3|q},\end{aligned} \tag{B.33}$$

where $\text{Exp}_{i,n,q-1}$ is (log(1+)) the number of forecasts covered by analyst i in the previous 20 quarters. A positive interaction coefficient $\hat{d}_n^r$ indicates that, conditional on having issued a higher forecast than the consensus in the previous round ($\text{Gap}_{i,n,q-1:q+3|q-1} > 0$), experienced analysts further increase their distance from the consensus by revising upward, consistent with weaker shrinkage and greater reliance on private information.

Additionally, I test whether experienced analysts make more accurate forecasts by estimating the regression:

$$FE_{i,n,q-1:q+3|q} = a_n^{fe} + b_n^{fe}\text{Exp}_{i,n,q-1} + \mu_i^{fe} + \nu_q^{fe} + e_{i,n,q-1:q+3|q}^{fe}, \tag{B.34}$$

where $FE_{i,n,q-1:q+3|q} = |\text{Actual}_{n,q-1:q+3} - \text{Forecast}_{i,n,q-1:q+3|q}|$ is the absolute forecast error. A negative coefficient $\hat{b}_n^{fe}$ indicates that experienced analysts produce more accurate forecasts, potentially explaining why they rely less on the consensus and exhibit greater confidence in their own information.

Figure C.3 presents the indicator-level regression results. Panel A shows evidence that experienced analysts shrink less toward the consensus. Specifically, the coefficient on the distance from consensus ($\hat{c}_n^r$) is negative and significant across all indicators, indicating that analysts generally revise their forecasts toward the consensus. However, the interaction term ($\hat{d}_n^r$) is positive and statistically significant for most indicators, indicating that experienced analysts exhibit significantly weaker herding behavior. This pattern is particularly pronounced for GDP-related indicators (Nominal GDP, Real GDP, GDP Deflator) and inflation, where the interaction coefficient is large and highly statistically significant.

Panel B shows that experienced analysts produce more accurate forecasts across most indicators. The coefficient on experience ($\hat{b}_n^{fe}$) is negative for the majority of indicators, with particularly large and significant effects for consumption and federal and state/local government spending. These results align with the findings from the Bloomberg data (Table 3) and support the model's assumption that experienced analysts receive more precise private signals.

C Supplementary Tables and Figures

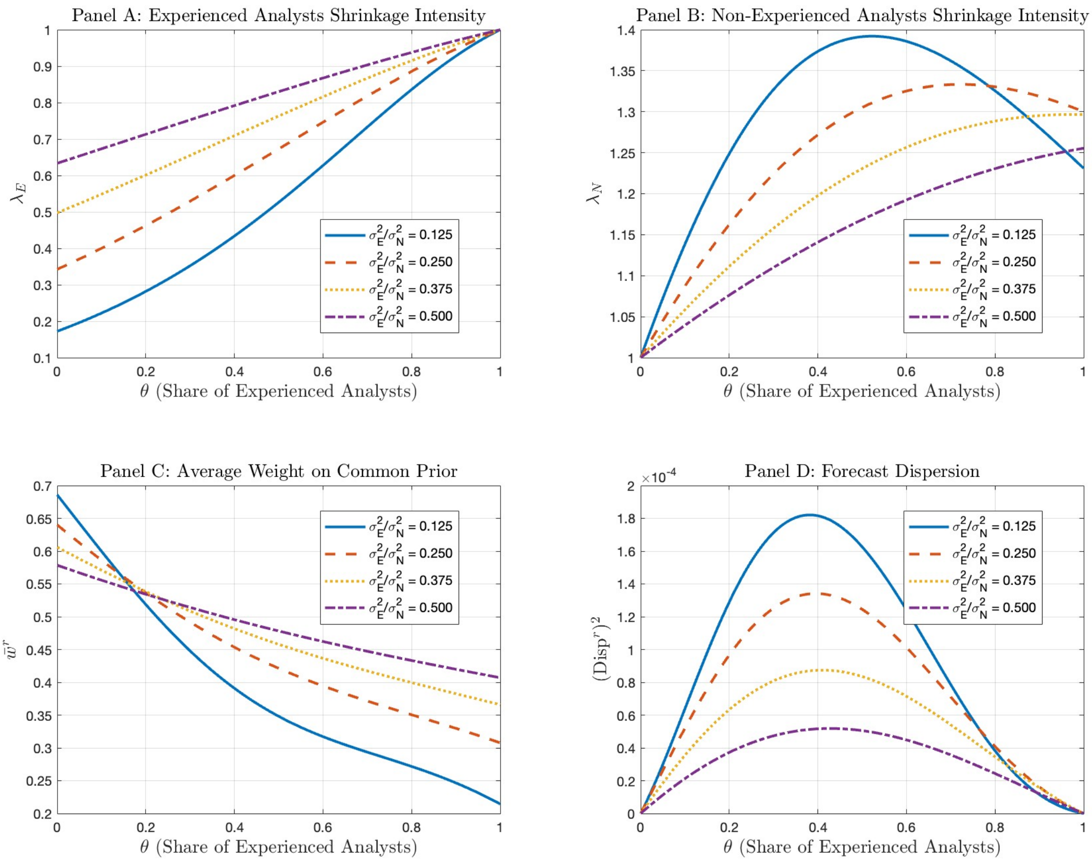

Figure C.1: **Shrinkage and Dispersion vs. Share of Experienced Analysts.** Panels A and B plot experienced and inexperienced analysts' shrinkage intensities λ_E and λ_N based on Equations (A.2) and (A.3), respectively. Panel C plots the revised average weight on common information $\bar{w}^r$ based on the expression in Equation (A.5). Panel D plots forecast dispersion $(\text{Disp}^r)^2$ based on Equation (A.6). All panels use different precision ratios σ_E^2/σ_N^2, with $\sigma_N = 0.10$ and $\sigma_F = \frac{\sigma_E+\sigma_N}{2}$.

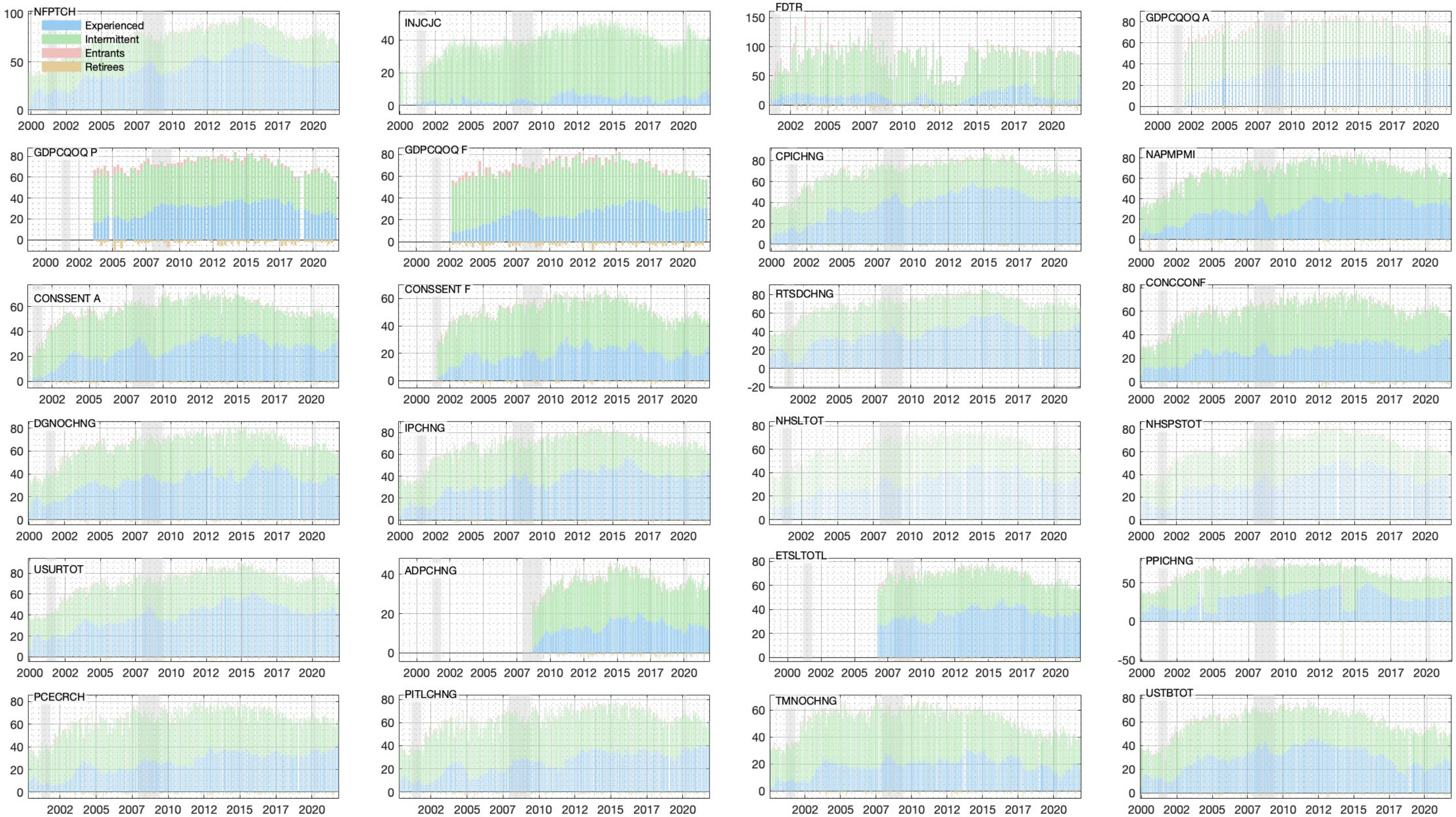

Figure C.2: **Forecaster Pool Composition Over Time.** This figure plots the number of active analysts for all indicators in my sample. For each release, the forecaster pool is decomposed into three categories: experienced analysts, who have issued forecasts for all or the maximum number of releases for that indicator in the past year; intermittent analysts, who have participated irregularly; and entrants, who are forecasting the indicator for the first time. The figure also plots (below zero) the number of retirees, who forecasted in the previous period but leave the sample thereafter; this group also includes analysts who switch firms and/or move to forecasting other indicators.

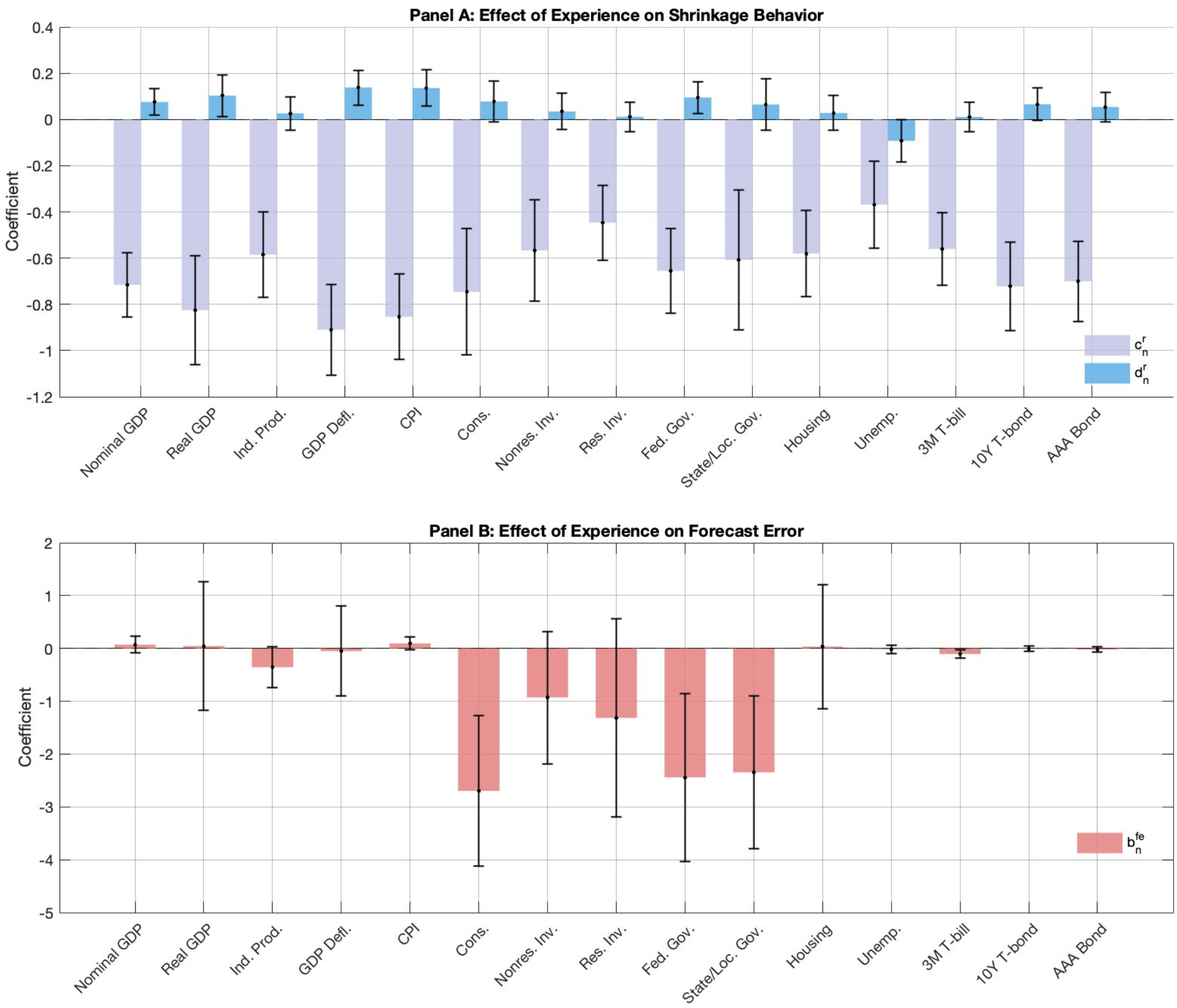

Figure C.3: **Experience, Shrinkage and Forecast Error in the SPF.** This figure plots indicator-level regression results using the Survey of Professional Forecasters (SPF). Panel A plots the estimated coefficients on the distance from the consensus forecast (Gap) and its interaction with analyst experience (Gap $\times$ Experience) from the forecast revision regression in Equation (B.33). Panel B plots the coefficient on analyst experience from the forecast error regression in Equation (B.34). Both regressions control for analyst and quarter fixed effects. Error bars denote 90% confidence intervals based on standard errors clustered by analyst and quarter.

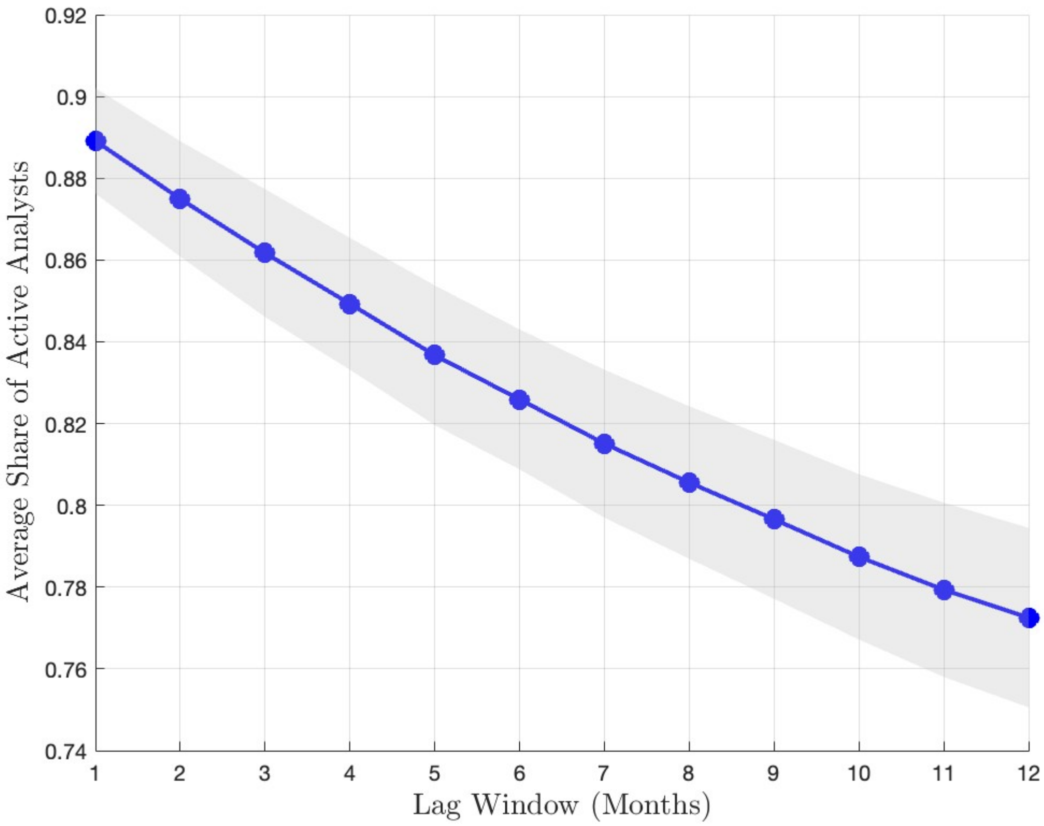

Figure C.4: **Average Share of Active Analysts Over Time.** This figure plots the average share of active analysts across one to twelve-month lag windows. The share of active analysts is calculated as the proportion of analysts who remain active (i.e., release forecasts) from month $t -$ window to month t out of active analysts in month $t -$ window, averaged across announcement types. The shaded region reflects the 95% confidence interval.

Table C.1: **Pooled Summary Statistics.** This table reports pooled summary statistics for the main variables used in the empirical analysis. The sample covers 25 major U.S. macroeconomic announcements from August 1997 to November 2021. Surprise and Dispersion are standardized within each announcement type (Table C.2 reports summary statistics for the raw variables). Daily stock market returns, S&P 500 futures returns, and treasury yield changes are in bps. VIX and the Economic Policy Uncertainty index of Baker et al. (2016) are measured five days before the release.

	Mean	S.D.	p(10)	p(25)	p(50)	p(75)	p(90)	N
Panel A: Forecast Variables								
Surprise	0.00	1.01	-1.10	-0.49	-0.01	0.49	1.06	5,806
Dispersion	0.01	1.02	-0.74	-0.42	-0.22	0.12	0.89	5,806
Experience Share	0.39	0.19	0.10	0.26	0.44	0.53	0.61	5,806
Number of Analysts	61.86	16.44	38	49	64	73	80	5,806
Panel B: Asset Returns (bps)								
Stock Market Return	6.85	108.48	-120	-44	10	62	130	5,806
S&P 500 Futures Return	6.16	106.77	-120	-42	8	60	124	5,806
Δ 6M T. Bill	-0.32	2.81	-3	-1	0	1	2	5,806
Δ 2Y T. Note	-0.15	4.89	-6	-2	0	2	5	5,806
Δ 5Y T. Note	-0.06	5.91	-7	-3	0	3	7	5,806
Δ 10Y T. Note	0.01	5.70	-7	-4	0	3	7	5,806
Panel C: Uncertainty Measures								
VIX	19.46	8.25	11.86	13.46	17.08	22.81	30.10	5,806
EPU	118.13	81.32	41.33	61.97	96.72	148.73	223.77	5,806

Table C.2: **Summary Statistics by Announcement Type.** This table reports the reporting units and number of observations for each macroeconomic indicator, along with the time-series mean and standard deviation of six key variables: (i) the actual release values; (ii) surprises, defined as the actual release minus the consensus (median) forecast; (iii) dispersion, defined as the cross-sectional standard deviation of forecasts; (iv) MAPE, defined as the mean absolute percentage forecast error of an analyst in a year (in %); (v) experience, defined as the number of releases forecasted by an analyst in a year; and (vi) experience share, defined as the proportion of analysts who issued forecasts for all releases in the previous year.

Announcement Type	Unit	Obs.	Actual		Surprise		Dispersion		MAPE		Experience		Exp. Share	
			Mean	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
Nonfarm Payrolls	Thousands	237	118.44	290.59	-1.65	171.72	61.29	170.05	136.70	292.84	10.25	3.03	0.55	0.12
Initial Jobless Claims	Thousands	1033	384.71	210.70	1.13	23.22	10.80	18.52	4.24	1.71	41.01	13.27	0.10	0.05
FOMC Target	%	97	2.03	1.61	0.01	1.12	0.03	0.05	2.29	6.41	7.77	3.79	0.22	0.08
FOMC Path	%	152	1.38	1.54	-0.04	0.86	0.02	0.04	2.29	6.41	7.77	3.79	0.18	0.09
GDP A	% Change	67	2.04	4.24	-0.05	0.67	0.54	0.53	73.11	88.70	8.90	3.94	0.43	0.11
GDP P	% Change	59	1.94	4.86	0.03	0.30	0.20	0.11	20.31	26.23	8.86	3.90	0.41	0.08
GDP F	% Change	64	2.11	4.57	-0.01	0.26	0.13	0.06	11.47	7.36	8.74	3.88	0.36	0.10
CPI	% Change	242	0.19	0.30	-0.00	0.13	0.09	0.03	47.34	24.64	10.23	2.99	0.53	0.13
ISM Manufacturing	Index	232	53.34	5.36	0.23	1.91	0.90	0.32	3.12	1.13	9.93	3.04	0.43	0.12
U. of Mich. Sentiment P	Index	223	83.64	11.86	-0.60	3.67	1.39	0.47	3.91	1.34	9.92	3.11	0.42	0.12
U. of Mich. Sentiment F	Index	226	83.71	11.53	0.24	1.25	0.85	0.37	1.56	0.66	10.42	3.70	0.36	0.09
Advance Retail Sales	% Change	233	0.31	1.35	0.03	0.77	0.30	0.28	105.45	48.20	10.18	3.07	0.52	0.12
C.B. Consumer Confidence	Index	249	91.11	25.41	0.33	5.23	1.88	0.78	5.63	3.25	9.85	3.13	0.41	0.08
Durable Goods Orders	% Change	247	0.24	3.76	0.04	2.37	1.18	0.53	135.80	92.81	10.16	3.01	0.50	0.09
Industrial Production	% Change	242	0.12	0.69	-0.06	0.42	0.24	0.18	99.52	46.56	10.12	2.99	0.49	0.12
New Home Sales	Thousands	238	693.48	306.18	4.61	57.93	19.06	10.55	6.65	2.66	10.39	3.17	0.48	0.10
Housing Starts	Thousands	239	1270.07	462.37	3.27	82.72	29.84	12.19	5.77	1.76	10.22	2.99	0.51	0.12
Unemployment Rate	%	237	5.99	1.85	-0.05	0.23	0.08	0.10	2.43	1.97	10.21	3.01	0.54	0.10
ADP Employment	Thousands	144	156.95	341.82	2.77	137.63	74.48	252.30	52.30	66.32	11.40	4.16	0.35	0.09
Existing Home Sales	Millions	168	5.21	0.51	0.00	0.18	0.09	0.06	3.00	1.42	10.36	2.81	0.53	0.07
PPI	% Change	234	0.22	0.69	0.03	0.43	0.18	0.09	88.20	34.31	9.95	3.17	0.47	0.15
Personal Spending	% Change	222	0.36	0.65	-0.02	0.19	0.18	0.28	50.02	23.03	12.33	4.08	0.39	0.11
Personal Income	% Change	224	0.30	1.25	0.04	0.35	0.20	0.34	55.71	28.38	12.29	4.10	0.39	0.12
Factory Orders	% Change	236	0.21	2.24	0.02	0.56	0.53	0.33	82.41	55.46	10.23	3.31	0.34	0.10
Trade Balance	$ Billions	247	-47.52	11.20	0.02	2.98	1.31	0.54	5.80	2.67	10.13	2.99	0.47	0.10

Table C.3: **Unconditional Price Impact.** This table reports price impacts (coefficient $\beta_{n,k}$ in Equation (3)) of the surprise S_n in various macroeconomic announcement types n on each asset class k: aggregate stock market, S&P 500 futures, treasury yields with maturities of six months to ten years. $t-$statistics in parentheses are based on Newey-West standard errors with five-day lags. Coefficients are in bps.

	Stock Market		S&P500 Futures		6M Treasury Bill		2Y Treasury Note		5Y Treasury Note		10Y Treasury Note	
Announcement Type	$\hat{\beta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	R^2
Nonfarm Payrolls	17.07 ***	0.02	16.47 ***	0.02	0.74	0.04	1.74 *	0.07	1.99 *	0.06	1.75 **	0.06
Initial Jobless Claims	0.39	0.00	0.56	0.00	-0.30 ***	0.01	-0.83 ***	0.03	-0.97 ***	0.03	-0.81 ***	0.02
FOMC Target	-25.74 **	0.05	-27.88 **	0.06	1.86 ***	0.22	1.39 **	0.04	1.15	0.02	0.23	-0.01
FOMC Path	-15.83	0.01	-16.07	0.02	1.47 ***	0.17	3.84 ***	0.43	3.56 ***	0.27	2.31 ***	0.15
GDP A	-11.70	0.00	-9.98	0.00	0.68 ***	0.04	1.55 ***	0.07	1.45 **	0.04	1.25 *	0.02
GDP P	4.09	-0.01	3.78	-0.01	0.26	0.00	0.20	-0.01	0.48	-0.01	0.15	-0.01
GDP F	-3.67	-0.01	-3.48	-0.01	-0.08	-0.01	0.23	-0.01	0.19	-0.01	-0.03	-0.01
CPI	-4.81	0.00	-6.55	0.00	0.19	0.00	0.47	0.01	0.81 *	0.02	0.60	0.01
ISM Manufacturing	17.21 *	0.02	14.76	0.01	0.91 ***	0.06	2.16 ***	0.16	2.37 ***	0.14	2.23 ***	0.13
U. of Mich. Sentiment P	-5.39	0.00	-1.63	0.00	0.04	0.00	0.33	0.00	0.77 **	0.01	0.84 ***	0.02
U. of Mich. Sentiment F	-1.48	0.00	-1.40	0.00	-0.08	0.00	-0.03	0.00	0.05	0.00	0.24	0.00
Advance Retail Sales	13.51 **	0.01	13.59 **	0.01	0.44 **	0.03	1.20 ***	0.05	1.39 ***	0.04	1.32 **	0.04
C.B. Consumer Confidence	4.98	0.00	1.93	0.00	0.57 ***	0.04	0.78 **	0.02	0.94 ***	0.02	0.92 ***	0.02
Durable Goods Orders	9.02	0.00	7.50	0.00	0.17	0.00	0.56	0.01	0.77 *	0.01	0.70 *	0.01
Industrial Production	-2.69	0.00	-0.87	0.00	0.20	0.00	0.52 *	0.01	0.71 **	0.01	0.57	0.01
New Home Sales	1.11	0.00	-0.87	0.00	0.15	0.00	0.40	0.00	0.68 **	0.01	0.84 ***	0.02
Housing Starts	4.14	0.00	3.01	0.00	-0.09	0.00	0.23	0.00	0.31	0.00	0.27	0.00
Unemployment Rate	-6.32	0.00	-5.44	0.00	-0.30	0.00	-0.45	0.00	-0.39	0.00	-0.50	0.00
ADP Employment	1.85	-0.01	0.23	-0.01	0.18 *	0.00	0.31	0.00	0.67 **	0.01	0.96 ***	0.03
Existing Home Sales	3.80	0.00	3.49	0.00	0.15	0.00	0.15	0.00	0.42	0.00	0.56	0.01
PPI	-0.90	0.00	-0.59	0.00	0.15	0.00	0.23	0.00	0.32	0.00	0.52	0.01
Personal Spending	5.59	0.00	5.67	0.00	0.17	0.00	0.01	0.00	0.04	0.00	0.19	0.00
Personal Income	-2.85	0.00	-5.73	0.00	-0.05	0.00	-0.19	0.00	-0.31	0.00	-0.45 *	0.00
Factory Orders	-13.35 **	0.01	-10.84 *	0.01	0.17	0.00	0.31	0.00	0.33	0.00	0.42	0.00
Trade Balance	12.36	0.01	11.79	0.01	-0.09	0.00	0.08	0.00	0.45	0.00	0.60 *	0.01

Table C.4: **Dispersion and Price Impact.** This table reports the price impact of the surprise and the coefficient on the interaction of the surprise and dispersion (Coefficients $\hat{\beta}_{n,k}$ and $\hat{\delta}_{n,k}$ in Equation (4) in various macroeconomic announcement types n on each asset class k: aggregate stock market, S&P 500 futures, treasury yields with maturities of six months to ten years. $t-$statistics in parentheses are based on Newey-West standard errors with five-day lags. The last row reports the correlations between coefficients $\hat{\beta}_{n,k}$ and $\hat{\delta}_{n,k}$ within each asset class. Coefficients are in bps.

	Stock Market			S&P500 Futures			6M Treasury Bill			2Y Treasury Note			5Y Treasury Note			10Y Treasury Note		
Announcement Type	$\hat{\beta}_{n,k}$	$\hat{\delta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	$\hat{\delta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	$\hat{\delta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	$\hat{\delta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	$\hat{\delta}_{n,k}$	R^2	$\hat{\beta}_{n,k}$	$\hat{\delta}_{n,k}$	R^2
Nonfarm Payrolls	7.03	3.10	0.01	4.11	3.43	0.01	2.65***	-0.41***	0.14	5.72***	-0.82***	0.19	6.38***	-0.94***	0.17	5.16***	-0.79***	0.13
Initial Jobless Claims	9.37**	-4.05***	0.01	9.85**	-4.36***	0.01	0.45***	-0.05***	0.01	1.22***	-0.14***	0.04	1.38***	-0.15***	0.03	1.18***	-0.14***	0.02
FOMC Target	99.43***	-29.93**	0.11	107.65***	-32.26**	0.13	0.13	0.65**	0.29	1.69	-1.26*	0.07	1.82	-1.22**	0.06	2.63**	-1.17***	0.04
FOMC Path	20.89*	-7.78	0.01	21.68**	-8.05	0.01	1.00***	0.37	0.28	3.80***	0.15	0.44	3.65***	-0.01	0.27	2.34***	0.03	0.14
GDP A	18.40	-23.98***	0.06	16.09	-21.22***	0.04	0.96**	-0.16	0.03	2.41***	-0.55**	0.07	2.34**	-0.62**	0.03	2.36***	-0.81***	0.03
GDP P	25.21	-10.68**	0.00	30.46	-12.48**	0.01	0.41	-0.05	-0.02	0.29	-0.19	-0.02	0.52	-0.37*	-0.02	0.15	-0.01	-0.03
GDP F	4.25	-0.23	-0.03	6.81	-1.21	-0.03	0.04	-0.04	-0.03	0.77	-0.19	-0.02	0.19	-0.14	-0.03	0.73	-0.25	-0.03
CPI	10.77	-1.74	0.00	22.06	-4.53	0.00	0.42	-0.18	0.00	0.64	-0.32	0.00	1.46	-0.66	0.03	1.91	-0.73	0.03
ISM Manufacturing	91.72***	-23.16***	0.08	86.57***	-22.32***	0.07	2.08***	-0.38**	0.07	3.75***	-0.49***	0.18	4.26***	-0.59***	0.15	4.53***	-0.71***	0.16
U. of Mich. Sentiment P	20.48	-4.60	0.00	3.54	-0.52	-0.01	0.97*	-0.29*	0.01	1.37*	-0.32	0.00	0.84	-0.02	0.01	0.60	0.08	0.01
U. of Mich. Sentiment F	19.77	-8.15	0.00	24.63*	-10.47*	0.01	0.15	-0.03	-0.01	0.35	-0.15	-0.01	0.34	-0.20	0.00	0.05	0.11	0.00
Advance Retail Sales	7.49	2.52	0.01	7.42	2.92	0.02	0.91***	-0.12**	0.04	2.22***	-0.29***	0.06	2.97***	-0.39***	0.08	2.84***	-0.36***	0.07
C.B. Consumer Confidence	20.83	-6.45	0.00	21.27	-7.87*	0.00	0.08	-0.27*	0.05	0.38	0.16	0.02	0.70	0.10	0.02	0.45	0.19	0.02
Durable Goods Orders	17.20	-3.41	0.01	16.83	-3.88	0.01	0.28	-0.03	0.00	1.47**	-0.31	0.02	1.70**	-0.31	0.02	1.54***	-0.29*	0.01
Industrial Production	1.50	0.04	-0.01	0.78	-0.34	-0.01	0.34	-0.05	0.00	0.89**	-0.14*	0.01	0.95*	-0.09	0.01	0.62	-0.03	0.00
New Home Sales	2.69	-1.51	-0.01	4.36	-1.39	-0.01	0.47	-0.13	0.00	0.10	0.12	0.00	0.13	0.22	0.01	0.43	0.16	0.02
Housing Starts	38.46**	-11.76**	0.00	34.13**	-10.66**	0.00	0.53	-0.21	0.00	1.73**	-0.51*	0.00	1.99**	-0.57*	0.00	1.51	-0.43	0.00
Unemployment Rate	11.31	-4.31	0.01	13.09	-4.33	0.01	0.60*	-0.13**	0.00	0.66	-0.12	0.00	0.35	-0.15	0.00	0.33	-0.17	0.00
ADP Employment	6.74	-1.77	-0.01	5.53	-1.74	-0.02	0.21	-0.02	-0.01	0.83**	-0.15**	0.00	1.37**	-0.22**	0.02	1.49**	-0.18*	0.03
Existing Home Sales	17.14	-7.96	0.00	18.03	-8.17	0.00	0.32	-0.06	-0.01	0.12	-0.11	-0.01	0.01	0.15	-0.01	0.06	0.18	0.00
PPI	1.02	-0.66	-0.01	14.17	-5.18	-0.01	0.01	-0.06	0.01	0.58	-0.28	0.00	1.09	-0.49	0.01	1.81**	-0.81***	0.04
Personal Spending	1.57	-3.43	0.00	2.07	-3.69	0.00	0.26	-0.06	-0.01	0.10	-0.05	-0.01	0.09	-0.09	-0.01	0.13	-0.03	-0.01
Personal Income	8.49	-4.40*	0.00	2.04	-2.96	0.00	0.06	-0.01	-0.01	0.30	-0.03	-0.01	0.21	0.01	-0.01	0.24	0.06	0.00
Factory Orders	5.07	4.19	0.01	6.00	2.35	0.00	0.01	-0.08	0.00	0.32	-0.31	0.01	0.28	-0.30	0.00	0.04	0.19	0.00
Trade Balance	7.31	1.93	0.00	6.07	2.17	0.00	0.18	-0.03	-0.01	0.74	-0.30	-0.01	0.21	-0.24	0.00	0.46	-0.39*	0.01
Correl($\hat{\beta}_{n,k}$, $\hat{\delta}_{n,k}$)	-0.84^{***}			-0.87^{***}			-0.45^{**}			-0.46^{**}			-0.58^{***}			-0.73^{***}		

Table C.5: **Dispersion and Price Impact: Alternative Measures of Dispersion.** This table is constructed similar to Table 2, but using alternative measures of dispersion. Panel A uses the coefficient of variation of the forecasts. Panel B uses the interquartile range. Panel C uses the mean absolute deviation of the forecasts. $t-$statistics in parentheses are based on daily clustered standard errors. Coefficients are in bps.

	Stock Market	S&P500 Futures	6M T. Bill	2Y T. Note	5Y T. Note	10Y T. Note
			Panel A: Coefficient of Variation			
$S_{n,d}$	11.69***	12.00***	0.36***	0.81***	0.94***	0.87***
	(5.46)	(5.62)	(6.50)	(8.87)	(8.91)	(8.63)
$\text{Disp}_{n,d}$	1.42	0.98	-0.03	0.06	0.03	0.01
	(0.75)	(0.52)	(-0.75)	(0.84)	(0.41)	(0.13)
$S_{n,d} \times \text{Disp}_{n,d}$	−4.09***	−4.12***	−0.03**	−0.09***	−0.11***	−0.11***
	(-4.77)	(-4.74)	(-2.05)	(-3.56)	(-3.43)	(-3.11)
cons	5.00*	4.93*	−0.27***	-0.21	-0.08	-0.01
	(1.70)	(1.69)	(-3.76)	(-1.64)	(-0.55)	(-0.04)
N	5,849	5,849	5,849	5,849	5,849	5,849
R^2	0.01	0.01	0.02	0.02	0.02	0.02
Announcement FEs	✓	✓	✓	✓	✓	✓
			Panel B: Interquartile Range			
$S_{n,d}$	10.25***	8.97***	0.40***	1.04***	1.05***	0.87***
	(4.25)	(3.86)	(7.23)	(10.51)	(8.68)	(7.77)
$\text{Disp}_{n,d}$	2.47	2.17	-0.05	0.04	0.05	0.07
	(1.26)	(1.07)	(-1.23)	(0.75)	(0.71)	(0.83)
$S_{n,d} \times \text{Disp}_{n,d}$	−2.49***	−2.52***	−0.05***	−0.15***	−0.13***	−0.09***
	(-3.52)	(-3.54)	(-4.42)	(-6.40)	(-4.35)	(-2.91)
cons	3.88	3.58	−0.24***	-0.18	-0.10	-0.09
	(1.24)	(1.14)	(-3.39)	(-1.48)	(-0.69)	(-0.60)
N	5,849	5,849	5,849	5,849	5,849	5,849
R^2	0.00	0.00	0.02	0.02	0.02	0.02
Announcement FEs	✓	✓	✓	✓	✓	✓
			Panel C: Mean Absolute Deviation			
$S_{n,d}$	11.26***	11.10***	0.32***	1.02***	1.02***	0.89***
	(4.79)	(4.87)	(5.09)	(9.62)	(8.20)	(7.44)
$\text{Disp}_{n,d}$	2.83	2.51	-0.06	0.00	-0.01	0.01
	(1.38)	(1.21)	(-1.57)	(0.08)	(-0.14)	(0.11)
$S_{n,d} \times \text{Disp}_{n,d}$	−2.38***	−2.51***	−0.06***	−0.15***	−0.15***	−0.10***
	(-3.67)	(-3.79)	(-4.03)	(-5.96)	(-4.46)	(-3.10)
cons	3.01	2.88	−0.21***	-0.13	-0.01	0.00
	(0.87)	(0.84)	(-2.78)	(-0.99)	(-0.06)	(0.00)
N	5,849	5,849	5,849	5,849	5,849	5,849
R^2	0.01	0.01	0.01	0.02	0.02	0.02
Announcement FEs	✓	✓	✓	✓	✓	✓

Table C.6: **Dispersion and Price Impact: Additional Controls.** This table reports coefficient estimates from alternative specifications of the pooled regression in Equation (5). Panel A includes month fixed effects. Panels B to D also control for the number of analysts, the EPU measure of Baker et al. (2016) ($\times 0.01$), and the VIX, respectively. $t-$statistics in parentheses are based on daily clustered standard errors. Coefficients are in bps.

	Stock Market	S&P500 Futures	6M T. Bill	2Y T. Note	5Y T. Note	10Y T. Note
			Panel A: Controlling for Month Fixed Effects			
$S_{n,d}$	10.78^{***}	10.46^{***}	0.33^{***}	0.91^{***}	0.98^{***}	0.91^{***}
	(4.79)	(4.75)	(5.88)	(9.12)	(8.19)	(7.73)
$\text{Disp}_{n,d}$	3.02	2.65	-0.04	0.04	-0.05	-0.00
	(1.30)	(1.15)	(-0.69)	(0.47)	(-0.49)	(0.00)
$S_{n,d} \times \text{Disp}_{n,d}$	-2.34^{***}	-2.44^{***}	-0.06^{***}	-0.14^{***}	-0.13^{***}	-0.10^{***}
	(-3.63)	(-3.77)	(-4.79)	(-5.77)	(-4.29)	(-3.18)
cons	2.68	2.59	-0.25^{***}	-0.18	0.04	0.01
	(0.66)	(0.65)	(-2.73)	(-1.22)	(0.23)	(0.05)
N	5,848	5,848	5,848	5,848	5,848	5,848
R^2	0.05	0.05	0.13	0.08	0.08	0.08
Announcement FEs	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓
			Panel B: Controlling for Month FE and the Number of Analysts			
$S_{n,d}$	13.94^{**}	11.61^{**}	0.92^{***}	1.23^{***}	1.27^{***}	1.21^{***}
	(2.29)	(1.96)	(4.31)	(4.24)	(3.92)	(4.09)
$\text{Disp}_{n,d}$	2.07	1.60	-0.02	0.04	-0.05	-0.01
	(0.92)	(0.73)	(-0.32)	(0.50)	(-0.51)	(-0.07)
$S_{n,d} \times \text{Disp}_{n,d}$	-2.25^{***}	-2.45^{***}	-0.04^{***}	-0.10^{***}	-0.11^{***}	-0.07^{***}
	(-3.06)	(-3.53)	(-2.91)	(-4.17)	(-3.30)	(-2.66)
$\text{NumAnalysts}_{n,d}$	0.01	0.00	-0.01	0.02	0.01	0.00
	(0.04)	(0.01)	(-1.20)	(1.03)	(0.70)	(0.26)
$S_{n,d} \times \text{NumAnalysts}_{n,d}$	-0.15^{*}	-0.11	-0.01^{***}	-0.01^{*}	-0.01	-0.01^{***}
	(-1.66)	(-1.20)	(-3.19)	(-1.90)	(-1.64)	(-2.57)
cons	3.17	3.69	0.49	-1.15	-0.68	-0.24
	(0.18)	(0.21)	(0.74)	(-1.23)	(-0.67)	(-0.25)
N	5,848	5,848	5,848	5,848	5,848	5,848
R^2	0.05	0.05	0.13	0.08	0.07	0.07
Announcement FEs	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓
			Panel C: Controlling for Month FE and the EPU			
$S_{n,d}$	11.59^{***}	11.36^{***}	0.32^{***}	0.89^{***}	0.97^{***}	0.87^{***}
	(4.66)	(4.66)	(5.02)	(7.98)	(7.29)	(6.71)
$\text{Disp}_{n,d}$	2.92	2.56	-0.04	0.04	-0.05	0.00
	(1.24)	(1.11)	(-0.70)	(0.48)	(-0.47)	(0.02)
$S_{n,d} \times \text{Disp}_{n,d}$	-1.97^{***}	-2.04^{***}	-0.06^{***}	-0.15^{***}	-0.14^{***}	-0.12^{***}
	(-2.59)	(-2.69)	(-3.64)	(-4.77)	(-3.72)	(-3.26)
$\text{EPU}_{n,d-5}$	-2.36	-2.71	0.16	-0.23	-0.24	-0.24
	(-0.46)	(-0.54)	(1.38)	(-1.24)	(-1.00)	(-1.04)
$S_{n,d} \times \text{EPU}_{n,d-5}$	-1.13	-1.24	0.02	0.03	0.02	0.06
	(-0.70)	(-0.79)	(0.44)	(0.45)	(0.28)	(0.82)
cons	5.58	5.89	-0.45^{***}	0.09	0.32	0.28
	(0.76)	(0.82)	(-2.65)	(0.36)	(0.94)	(0.85)
N	5,848	5,848	5,848	5,848	5,848	5,848
R^2	0.05	0.05	0.13	0.08	0.08	0.08
Announcement FEs	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓
			Panel C: Controlling for Month FE and the VIX			
$S_{n,d}$	10.40^{**}	12.01^{***}	0.44^{***}	0.89^{***}	1.05^{***}	0.93^{***}
	(2.25)	(2.66)	(4.96)	(6.21)	(5.66)	(5.25)
$\text{Disp}_{n,d}$	2.41	1.99	-0.05	0.02	-0.07	-0.02
	(1.03)	(0.86)	(-0.91)	(0.31)	(-0.68)	(-0.17)
$S_{n,d} \times \text{Disp}_{n,d}$	-2.24^{***}	-2.14^{***}	-0.05^{***}	-0.14^{***}	-0.13^{***}	-0.10^{***}
	(-2.87)	(-2.84)	(-3.00)	(-4.95)	(-3.33)	(-2.58)
$\text{VIX}_{n,d-5}$	5.41^{***}	5.41^{***}	0.08^{***}	0.11^{***}	0.15^{***}	0.15^{***}
	(4.29)	(4.35)	(3.14)	(2.72)	(2.95)	(3.00)
$S_{n,d} \times \text{VIX}_{n,d-5}$	0.01	-0.11	-0.01	0.00	-0.00	-0.00
	(0.03)	(-0.40)	(-1.21)	(0.13)	(-0.41)	(-0.13)
cons	-101.60^{***}	-101.60^{***}	-1.75^{***}	-2.34^{***}	-2.88^{***}	-2.87^{***}
	(-4.13)	(-4.21)	(-3.58)	(-2.91)	(-2.86)	(-2.93)
N	5,848	5,848	5,848	5,848	5,848	5,848
R^2	0.06	0.07	0.13	0.09	0.08	0.08
Announcement FEs	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓

Table C.7: **Dispersion and Price Impact: Subsample Analysis.** This table reports coefficient estimates from the pooled regression in Equation (5) for different subsamples: Panel A excludes FOMC target and path factors, Panel B excludes weekly initial jobless claims announcements, and Panel C excludes the financial crisis (September 2008 to June 2009) and the COVID period (February 2020 to November 2021). t-statistics in parentheses are based on daily clustered standard errors. Coefficients are in bps.

	Stock Market	S&P500 Futures	6M T. Bill	2Y T. Note	5Y T. Note	10Y T. Note
	Panel A: Dropping FOMC Announcements					
$S_{n,d}$	9.56***	9.28***	0.33***	0.86***	0.93***	0.86***
	(4.08)	(4.01)	(5.55)	(8.56)	(7.46)	(7.04)
$\text{Disp}_{n,d}$	2.38	2.15	-0.02	-0.04	-0.06	-0.02
	(1.17)	(1.05)	(-0.75)	(-0.74)	(-0.91)	(-0.30)
$S_{n,d} \times \text{Disp}_{n,d}$	-2.11***	-2.23***	-0.05***	-0.12***	-0.12***	-0.09***
	(-3.24)	(-3.37)	(-4.17)	(-5.19)	(-3.82)	(-2.81)
cons	2.62	2.46	-0.24***	-0.07	0.07	0.05
	(0.73)	(0.69)	(-3.19)	(-0.53)	(0.44)	(0.33)
N	5,598	5,598	5,598	5,598	5,598	5,598
R^2	0.00	0.00	0.01	0.02	0.02	0.02
Announcement FEs	✓	✓	✓	✓	✓	✓
	Panel B: Dropping Initial Jobless Claims					
$S_{n,d}$	11.29***	10.80***	0.31***	0.94***	0.96***	0.86***
	(4.31)	(4.16)	(4.20)	(7.53)	(6.53)	(6.00)
$\text{Disp}_{n,d}$	3.42	3.08	-0.09*	-0.00	-0.04	-0.00
	(1.54)	(1.38)	(-1.79)	(-0.05)	(-0.43)	(-0.03)
$S_{n,d} \times \text{Disp}_{n,d}$	-2.18***	-2.24***	-0.05***	-0.15***	-0.14***	-0.10**
	(-2.94)	(-3.03)	(-3.09)	(-4.65)	(-3.39)	(-2.33)
cons	1.80	1.70	-0.16*	-0.14	-0.00	-0.00
	(0.44)	(0.42)	(-1.71)	(-0.89)	(0.00)	(-0.02)
N	4,812	4,812	4,812	4,812	4,812	4,812
R^2	0.01	0.00	0.01	0.02	0.01	0.02
Announcement FEs	✓	✓	✓	✓	✓	✓
	Panel C: Dropping the Financial Crisis & COVID Period					
$S_{n,d}$	13.96***	13.27***	0.58***	1.54***	1.64***	1.42***
	(4.72)	(4.49)	(6.66)	(9.40)	(9.12)	(8.37)
$\text{Disp}_{n,d}$	4.27*	3.80	-0.10	0.10	0.16	0.19
	(1.72)	(1.51)	(-1.14)	(0.76)	(1.10)	(1.34)
$S_{n,d} \times \text{Disp}_{n,d}$	-3.50***	-3.26***	-0.16***	-0.36***	-0.37***	-0.30***
	(-2.93)	(-2.70)	(-4.01)	(-4.91)	(-4.71)	(-4.09)
cons	0.37	0.38	-0.12	-0.21	-0.24	-0.24
	(0.10)	(0.10)	(-1.09)	(-1.10)	(-1.10)	(-1.16)
N	5,083	5,083	5,083	5,083	5,083	5,083
R^2	0.01	0.01	0.02	0.03	0.02	0.02
Announcement FEs	✓	✓	✓	✓	✓	✓

Table C.8: **Mean Forecast Error.** This table reports mean forecast errors ($\text{Release}_{n,d} - \text{Median}(\mathbf{f}_{n,d})$) of the consensus forecast across announcement types n. $t-$statistics in parentheses are based on Newey-West standard errors.

Announcement Type	*Mean*	t-stat	N
Nonfarm Payrolls	29.17	(0.65)	282
Initial Jobless Claims	5.63	(1.12)	1219
FOMC Target	-0.01*	(-1.73)	184
FOMC Path	-0.01*	(-1.73)	184
GDP A	0.02	(0.28)	99
GDP P	0.04	(1.47)	89
GDP F	0.01	(0.50)	95
CPI	0.00	(-0.44)	281
ISM Manufacturing	0.17	(1.54)	281
U. of Mich. Sentiment P	-0.48**	(-2.44)	272
U. of Mich. Sentiment F	0.24***	(2.98)	264
Advance Retail Sales	0.04	(1.02)	278
C.B. Consumer Confidence	0.30	(1.08)	280
Durable Goods Orders	0.07	(0.63)	281
Industrial Production	-0.06**	(-2.47)	281
New Home Sales	5.04	(1.45)	279
Housing Starts	3.28	(0.83)	279
Unemployment Rate	-0.06*	(-1.91)	282
ADP Employment	30.70	(0.82)	184
Existing Home Sales	0.01	(0.62)	200
PPI	0.02	(1.09)	281
Personal Spending	-0.02	(-1.06)	279
Personal Income	0.10	(1.51)	280
Factory Orders	0.02	(0.59)	280
Trade Balance	-0.05	(-0.31)	281

Table C.9: **Experience and Forecast Error.** This table reports coefficient estimates from regressions of the mean squared error (MSE, Panel A) or the mean absolute error (MAE, Panel B) of analyst i in year $t(d){:}t(d)+11$ on the number of announcements forecasted by the same analyst in the prior year $t(d)-12{:}t(d)-1$. Standard errors are clustered at the release-day level, with t-statistics reported in parentheses. Coefficients are expressed in the announcement-type units reported in Table C.2; for announcements measured in % or %-change units, coefficients are multiplied by 100.

	Panel A: MSE					Panel B: MAE					
Announcement Type	Cons.	t-stat	$\text{Exp}_{n,i,t(d)-12:t(d)-1}$	t-stat	R^2	Cons.	t-stat	$\text{Exp}_{n,i,t(d)-12:t(d)-1}$	t-stat	R^2	N
Nonfarm Payrolls	537,555.08***	(2.79)	-7,173.34	(-0.68)	0.00%	135.85***	(6.23)	-0.99	(-0.92)	0.00%	18,960
Initial Jobless Claims	35,430.20***	(3.70)	-386.48**	(-2.04)	0.09%	31.94***	(8.43)	-0.18**	(-2.50)	0.15%	42,183
FOMC Target	0.88***	(6.94)	-0.04***	(-4.30)	1.34%	2.88***	(7.93)	-0.12***	(-4.50)	1.33%	13,103
FOMC Path	0.88***	(6.94)	-0.04***	(-4.30)	1.34%	2.88***	(7.93)	-0.12***	(-4.50)	1.33%	13,103
GDP A	66.21***	(19.20)	-0.08	(-0.15)	-0.02%	64.52***	(33.67)	-0.52***	(-3.55)	0.78%	5,450
GDP P	17.18***	(17.39)	-0.35***	(-5.35)	1.08%	30.51***	(35.98)	-0.30***	(-4.79)	1.09%	4,664
GDP F	9.73***	(14.21)	-0.02	(-0.34)	-0.02%	22.64***	(26.85)	-0.10	(-1.57)	0.13%	4,753
CPI	2.84***	(27.27)	-0.04***	(-3.58)	0.15%	12.54***	(49.47)	-0.16***	(-6.85)	0.80%	17,694
ISM Manufacturing	5.08***	(22.76)	-0.06***	(-3.08)	0.23%	1.73***	(55.77)	-0.01***	(-3.92)	0.30%	16,974
U. of Mich. Sentiment P	16.81***	(35.85)	-0.13***	(-3.62)	0.23%	3.33***	(63.68)	-0.02***	(-4.91)	0.49%	13,930
U. of Mich. Sentiment F	3.06***	(22.03)	-0.02	(-1.61)	0.03%	1.31***	(46.53)	-0.01***	(-2.86)	0.17%	12,224
Advance Retail Sales	46.11***	(3.21)	5.12**	(2.42)	0.25%	47.31***	(18.98)	0.23	(0.77)	0.02%	17,540
C.B. Consumer Confidence	29.51***	(27.79)	0.04	(0.53)	0.00%	4.27***	(53.89)	0.01	(1.48)	0.04%	15,270
Durable Goods Orders	981.38***	(16.13)	-16.88***	(-4.47)	0.35%	217.96***	(40.85)	-1.69***	(-4.44)	0.45%	16,688
Industrial Production	30.45***	(4.10)	-0.16	(-0.29)	0.00%	34.10***	(24.60)	0.13	(1.55)	0.03%	17,308
New Home Sales	4,781.77***	(13.88)	-107.33***	(-6.30)	0.72%	49.07***	(26.01)	-0.55***	(-5.87)	0.59%	15,550
Housing Starts	8,222.10***	(18.18)	-60.27**	(-2.18)	0.09%	70.26***	(34.85)	-0.34***	(-2.98)	0.15%	16,374
Unemployment Rate	22.02***	(3.33)	-0.07	(-0.22)	-0.01%	16.56***	(11.03)	-0.01	(-0.12)	-0.01%	18,225
ADP Employment	434,891.34***	(3.02)	-6,742.69	(-0.90)	0.02%	122.75***	(4.44)	-0.65	(-0.44)	-0.01%	5,464
Existing Home Sales	0.06***	(11.48)	0.00***	(-4.03)	0.39%	0.17***	(26.57)	-0.00***	(-5.13)	0.57%	11,979
PPI	25.73***	(14.18)	-0.38***	(-2.85)	0.31%	36.61***	(26.92)	-0.28***	(-2.67)	0.31%	15,861
Personal Spending	24.56***	(4.50)	-0.84***	(-3.44)	0.20%	21.43***	(13.88)	-0.33***	(-4.68)	0.77%	15,995
Personal Income	225.60***	(3.64)	-8.91***	(-3.24)	0.25%	36.88***	(7.65)	-0.87***	(-4.13)	0.59%	15,574
Factory Orders	92.67***	(22.48)	-1.23***	(-3.57)	0.14%	65.98***	(50.43)	-0.35***	(-3.20)	0.14%	13,476
Trade Balance	11.10***	(20.09)	0.08*	(1.68)	0.07%	2.53***	(38.05)	0.00	(0.33)	0.00%	15,465

Table C.10: **Robustness to Alternative Experience Measures.** This table reports robustness checks using alternative definitions of analyst experience: (1) participation in all releases in the previous 24 months, (2) participation in all high-uncertainty releases with VIX$>$ 95th percentile threshold in the previous 60 months, and (3) participation in all high-uncertainty releases with VIX$>$ 90th percentile threshold in the previous 60 months. Panel A reports OLS and 2SLS estimates from the regression of dispersion on experience share, similar to Tables 5 and C.12. Panels B to D report OLS and 2SLS estimates of price impact regressions on the stock market, 2-year treasury note, and 10-year treasury note, similar to Table 7. All specifications control for announcement type fixed effects. Specifications (1), (5), and (9) (Specifications (2), (6), and (10)) report baseline OLS (2SLS) estimates. Specifications (3), (7), and (11) (Specifications (4), (8), and (12)) report OLS (2SLS) estimates, including month fixed effects, the number of analysts, and the VIX.

	24 Months, All Releases				60 Months, VIX>95th pct				60 Months, VIX>90th pct			
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Dispersion and the Share of Experienced Analysts											
$\text{ExpShare}_{n,t(d)}$	1.91***	3.65**	3.52***	4.75***	0.29	1.11**	2.31***	3.13***	0.35	1.28	2.33***	3.18***
	(3.03)	(2.48)	(3.81)	(3.19)	(0.86)	(2.55)	(4.36)	(4.45)	(0.79)	(1.31)	(3.56)	(3.04)
$\text{ExpShare}^2_{n,t(d)}$	-3.76***	-6.42***	-4.09***	-4.98***	0.50	-0.65	-1.36***	-2.01***	0.37	-0.12	-1.38**	-2.30*
	(-4.46)	(-3.30)	(-3.57)	(-2.84)	(1.39)	(-1.35)	(-3.39)	(-3.74)	(0.74)	(-0.10)	(-2.11)	(-1.94)
R^2	0.41		0.65		0.42		0.65		0.41		0.65	
Kleibergen-Paap Wald F-stat		141.23		127.88		488.18		146.69		256.73		87.62
$\widehat{\theta}^*$	0.25	0.28	0.43	0.48	-0.29	0.86	0.85	0.78	-0.46	5.27	0.84	0.69
	Panel B: Price Impact on the Stock Market											
$S_{n,d}$	7.03	8.46	22.39**	22.93**	10.82	19.03**	19.82**	25.35**	11.31*	18.12**	18.86*	24.35**
	(1.38)	(1.56)	(2.43)	(2.47)	(1.54)	(2.21)	(1.98)	(2.38)	(1.82)	(2.53)	(1.92)	(2.37)
$S_{n,d} \times \text{Disp}_{n,d}$	-3.81**	-3.68**	-2.03	-1.97	-3.30*	-4.81**	-2.11	-3.71	-3.48*	-4.81**	-1.99	-3.71*
	(-2.46)	(-2.24)	(-1.16)	(-1.11)	(-1.68)	(-2.23)	(-0.97)	(-1.58)	(-1.94)	(-2.36)	(-0.97)	(-1.72)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$	8.66*	8.47*	6.23	6.28	4.43	7.88*	3.38	6.57	7.09	11.30**	5.35	10.22*
	(1.76)	(1.66)	(1.22)	(1.21)	(1.25)	(1.90)	(0.92)	(1.55)	(1.49)	(2.10)	(1.08)	(1.82)
R^2	0.00		0.05		0.00		0.04		0.00		0.04	
Kleibergen-Paap Wald F-stat		401.32		123.31		216.19		51.65		256.73		87.62
	Panel C: Price Impact on 2Y T. Note											
$S_{n,d}$	1.36***	1.60***	0.33	0.38	1.63***	2.24***	1.04***	1.42***	1.44***	2.09***	0.65*	0.91**
	(6.51)	(7.02)	(0.98)	(1.10)	(5.83)	(5.42)	(2.87)	(3.58)	(5.86)	(6.49)	(1.86)	(2.46)
$S_{n,d} \times \text{Disp}_{n,d}$	-0.19***	-0.24***	-0.17***	-0.20***	-0.20***	-0.33***	-0.19***	-0.29***	-0.16***	-0.32***	-0.15***	-0.25***
	(-4.43)	(-4.92)	(-3.34)	(-3.78)	(-3.56)	(-4.32)	(-3.14)	(-3.91)	(-3.08)	(-4.37)	(-2.68)	(-3.71)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$	0.28**	0.48***	0.17	0.33**	0.14	0.39***	0.15	0.34***	0.05	0.50***	0.05	0.32**
	(2.05)	(3.39)	(1.20)	(2.27)	(1.28)	(2.84)	(1.40)	(2.72)	(0.39)	(2.90)	(0.36)	(2.11)
R^2	0.02		0.10		0.02		0.09		0.02		0.09	
Kleibergen-Paap Wald F-stat		400.83		122.82		214.86		51.51		256.76		88.41
	Panel D: Price Impact on 10Y T. Note											
$S_{n,d}$	1.28***	1.35***	1.96***	1.91***	1.77***	2.60***	1.68***	2.10***	1.48***	2.12***	1.34***	1.68***
	(5.01)	(4.86)	(4.45)	(4.30)	(5.22)	(5.45)	(3.46)	(4.11)	(5.04)	(5.48)	(2.89)	(3.45)
$S_{n,d} \times \text{Disp}_{n,d}$	-0.16***	-0.16***	-0.12*	-0.11	-0.23***	-0.34***	-0.28**	-0.33***	-0.15**	-0.34***	-0.15**	-0.28***
	(-2.83)	(-2.60)	(-1.71)	(-1.57)	(-3.05)	(-4.07)	(-2.40)	(-3.11)	(-2.08)	(-3.62)	(-1.98)	(-3.08)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$	0.58***	0.56***	0.52**	0.52**	0.27*	0.59***	0.28*	0.49***	0.22	0.71***	0.32	0.56**
	(2.62)	(2.63)	(2.40)	(2.37)	(1.67)	(3.22)	(1.80)	(2.78)	(1.07)	(3.18)	(1.17)	(2.55)
R^2	0.01		0.08		0.01		0.07		0.01		0.07	
Kleibergen-Paap Wald F-stat		400.84		123.06		214.72		51.67		256.23		88.09
N	4084	4084	4078	4078	4084	4084	4078	4078	4084	4084	4078	4078
Announcement FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FEs			✓	✓			✓	✓			✓	✓
Controls			✓	✓			✓	✓			✓	✓

Table C.11: **Summary Statistics: Double Sort by Dispersion and Experience Share.** This table reports summary statistics for a double sort on forecast dispersion and (one-year lagged) experience share. Low (High) dispersion corresponds to announcement-days where dispersion is below (above) the sample median. Low (High) θ corresponds to announcement-days where the experience share is below (above) the sample median. The last two columns report the difference in means between high and low experience states within each dispersion group, and Panel C reports the difference in means between high and low dispersion states within each experience group. t-statistics are based on two-way clustered standard errors by announcement type and date.

	Low Exp. Share							High Exp. Share							High-Low	
	Mean	S.D.	p(10)	p(25)	p(50)	p(75)	p(90)	Mean	S.D.	p(10)	p(25)	p(50)	p(75)	p(90)	Diff	t-stat
Panel A: Low Dispersion																
Dispersion	-0.45	0.22	-0.74	-0.61	-0.37	-0.29	-0.25	-0.58	0.30	-1.03	-0.79	-0.51	-0.34	-0.26	-0.13	-1.91
|Surprise|	0.52	0.50	0.07	0.15	0.37	0.73	1.19	0.53	0.46	0.08	0.18	0.43	0.78	1.14	0.01	0.24
VIX	18.40	6.74	11.70	13.40	16.80	21.30	27.50	16.90	6.48	11.50	12.70	14.90	18.80	24.30	-1.50	-2.36
Exp. Share	0.22	0.13	0.05	0.11	0.20	0.35	0.40	0.54	0.08	0.44	0.48	0.53	0.59	0.65	0.32	6.07
Num. Analysts	55.01	18.00	36	40	51	67	78	69.68	9.98	56	64	71	76	81	14.67	2.31
Panel B: High Dispersion																
Dispersion	0.44	1.10	-0.19	-0.13	0.07	0.51	1.37	0.64	1.28	-0.19	-0.11	0.17	0.83	1.86	0.20	2.45
|Surprise|	0.86	0.87	0.10	0.24	0.60	1.13	1.95	0.88	0.88	0.09	0.25	0.66	1.19	1.92	0.02	0.52
VIX	21.74	8.93	12.50	15.10	19.60	25.70	33.60	20.77	9.52	12.00	13.60	17.70	24.80	33.40	-0.96	-1.60
Exp. Share	0.24	0.12	0.07	0.13	0.26	0.35	0.39	0.53	0.07	0.44	0.47	0.52	0.57	0.63	0.29	5.88
Num. Analysts	54.36	18.30	35	40	52	65	75	68.51	10.61	56	62	70	76	81	14.15	2.53
Panel C: High-Low (Dispersion)																
	Diff	t-stat						Diff	t-stat							
Dispersion	0.89	8.95						1.22	11.50							
|Surprise|	0.33	4.18						0.34	7.91							
VIX	3.34	4.27						3.88	5.24							
Exp. Share	0.02	2.83						-0.01	-1.79							
Num. Analysts	-0.65	-0.51						-1.17	-1.08							

Table C.12: **Dispersion and the Share of Experienced Analysts: 2SLS.** This table reports 2SLS estimates of the regression of dispersion on the share of experienced analysts, as described in Section 4.3.1. Panels A and B report first-stage coefficient estimates. Panel C reports Kleibergen-Paap Wald F-statistics. Panel D reports second-stage estimates. To reduce multicollinearity between $\text{ExpShare}_{n,t(d)}$ and $\text{ExpShare}^2_{n,t(d)}$, the share of experienced analysts is demeaned at its sample mean ($\bar{\theta} \approx 0.39$) in all specifications. The threshold $\widehat{\theta^*}$ is reported in the original scale as $\widehat{\theta^*} = \bar{\theta} - \frac{\hat{b}_1}{2\hat{b}_2}$. t-statistics in parentheses are based on daily clustered standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Instrumenting $\text{ExpShare}_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	0.45***	0.16***	0.16***	0.16***	0.16***	0.16***
	(28.62)	(8.81)	(8.70)	(8.81)	(8.80)	(8.69)
$\text{ExpShare}^2_{n,t(d)-12}$	0.44***	0.28***	0.28***	0.28***	0.28***	0.28***
	(8.85)	(6.88)	(6.88)	(6.89)	(6.88)	(6.89)
$\text{NumAnalysts}_{n,d}$			0.00			0.00
			(-0.19)			(-0.20)
EPU_{d-5}				0.00		0.00
				(-0.84)		(-0.78)
VIX_{d-5}					-0.02	-0.02
					(-0.59)	(-0.48)
R^2	0.80	0.88	0.88	0.88	0.88	0.88
Panel B: Instrumenting $\text{ExpShare}^2_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***
	(11.40)	(7.45)	(7.33)	(7.45)	(7.44)	(7.33)
$\text{ExpShare}^2_{n,t(d)-12}$	0.31***	0.32***	0.32***	0.32***	0.32***	0.32***
	(19.96)	(20.34)	(20.40)	(20.33)	(20.34)	(20.38)
$\text{NumAnalysts}_{n,d}$			0.00			0.00
			(0.62)			(0.61)
EPU_{d-5}				0.00		0.00
				(-0.50)		(-0.44)
VIX_{d-5}					0.00	0.00
					(-0.24)	(-0.21)
R^2	0.64	0.67	0.67	0.67	0.67	0.67
Panel C: Kleibergen-Paap Wald F-statistics						
Kleibergen-Paap Wald F-stat	95.73	18.57	18.90	18.54	18.54	18.86
Panel D: Second-Stage Estimates						
$\widehat{\text{ExpShare}}_{n,t(d)}$	0.15	2.79**	1.85*	2.78**	2.83***	1.89*
	(0.56)	(2.55)	(1.72)	(2.55)	(2.58)	(1.76)
$\widehat{\text{ExpShare}^2}_{n,t(d)}$	-12.00***	-4.91***	-4.94***	-4.92***	-4.91***	-4.95***
	(-9.03)	(-3.83)	(-3.92)	(-3.81)	(-3.84)	(-3.90)
$\text{NumAnalysts}_{n,d}$			0.01***			0.01***
			(4.92)			(4.90)
EPU_{d-5}				0.01		0.01
				(0.34)		(0.28)
VIX_{d-5}					1.22**	1.14**
					(2.11)	(2.01)
$\widehat{\theta^*}$	0.40	0.68	0.58	0.68	0.68	0.58
N	5,849	5,848	5,848	5,848	5,848	5,848
Announcement FEs	✓	✓	✓	✓	✓	✓
Month FEs		✓	✓	✓	✓	✓

Table C.13: **Price Impact, Dispersion, and the Share of Experienced Analysts: First Stage Estimates.** This table reports first-stage estimates of the 2SLS regressions of asset returns (changes in yields) on news surprises and their interactions with dispersion and analyst experience. One-year lagged share of experienced analysts ($\text{ExpShare}_{n,t(d)-12}$) is used as an instrument for current experience ($\text{ExpShare}_{n,t(d)}$). Panels A-D report first-stage regressions for the four endogenous variables: analyst experience ($\text{ExpShare}_{n,t(d)}$), its interaction with news surprises ($S_{n,d} \times \text{ExpShare}_{n,t(d)}$), its interaction with dispersion ($\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$), and the three-way interaction ($S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$). Each regression includes the same controls used in the second-stage estimation (Table 7, Panel B).

	Stock Market (1)	S&P500 F. (2)	6M T. B. (3)	2Y T. N. (4)	5Y T. N. (5)	10Y T. N. (6)
Panel A: Instrumenting $\text{ExpShare}_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	0.45***	0.45***	0.45***	0.45***	0.45***	0.45***
	(30.53)	(30.53)	(30.24)	(30.19)	(30.19)	(30.17)
$S_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.00	0.00	0.01	0.01	0.01	0.01
	(-0.18)	(-0.27)	(1.50)	(1.47)	(1.47)	(0.74)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.01**	0.01*	0.01**	0.01**	0.01**	0.01**
	(1.96)	(1.94)	(2.35)	(2.46)	(2.46)	(2.41)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.00	0.00	0.00**	0.00**	0.00**	0.00*
	(-0.13)	(-0.18)	(-2.33)	(-2.45)	(-2.45)	(-1.97)
$S_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.52)	(-0.44)	(-1.47)	(-1.50)	(-1.50)	(-1.05)
$\text{Disp}_{n,d}$	-0.01**	-0.01**	-0.01***	-0.01***	-0.01***	-0.01***
	(-2.48)	(-2.47)	(-2.60)	(-2.60)	(-2.60)	(-2.57)
$S_{n,d} \times \text{Disp}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(0.07)	(0.07)	(1.24)	(1.36)	(1.36)	(1.09)
R^2	0.23	0.23	0.23	0.23	0.23	0.23
Panel B: Instrumenting $S_{n,d} \times \text{ExpShare}_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	0.05**	0.05**	0.09***	0.10***	0.10***	0.09***
	(2.13)	(2.20)	(3.72)	(4.20)	(4.20)	(3.98)
$S_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.87***	0.87***	0.87***	0.86***	0.86***	0.87***
	(42.21)	(42.21)	(43.15)	(42.95)	(42.95)	(42.86)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	-0.03**	-0.03***	-0.05***	-0.06***	-0.06***	-0.06***
	(-2.46)	(-2.57)	(-4.19)	(-4.49)	(-4.49)	(-4.44)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.01	0.01	0.01	0.01*	0.01*	0.01*
	(1.17)	(1.15)	(1.62)	(1.78)	(1.78)	(1.69)
$S_{n,d}$	0.06***	0.06***	0.06***	0.06***	0.06***	0.06***
	(7.02)	(7.01)	(7.22)	(7.25)	(7.25)	(7.18)
$\text{Disp}_{n,d}$	0.01**	0.01**	0.02***	0.02***	0.02***	0.02***
	(2.45)	(2.49)	(3.29)	(3.30)	(3.30)	(3.45)
$S_{n,d} \times \text{Disp}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(-1.08)	(-1.07)	(-1.17)	(-1.24)	(-1.24)	(-1.15)
R^2	0.95	0.95	0.95	0.95	0.95	0.95
Panel C: Instrumenting $\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	-0.58***	-0.58***	-0.60***	-0.61***	-0.61***	-0.60***
	(-13.40)	(-13.35)	(-13.02)	(-13.43)	(-13.43)	(-13.25)
$S_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.02	0.02	0.04*	0.04**	0.04**	0.03
	(0.92)	(0.82)	(1.91)	(1.96)	(1.96)	(1.28)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.84***	0.84***	0.85***	0.86***	0.86***	0.86***
	(29.16)	(29.07)	(27.96)	(28.45)	(28.45)	(28.43)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	-0.03***	-0.03***	-0.04***	-0.04***	-0.04***	-0.04***
	(-2.78)	(-2.80)	(-3.87)	(-3.88)	(-3.88)	(-3.73)
$S_{n,d}$	-0.01	-0.01	-0.01**	-0.01*	-0.01*	-0.01*
	(-1.38)	(-1.29)	(-2.16)	(-1.93)	(-1.93)	(-1.84)
$\text{Disp}_{n,d}$	0.07***	0.07***	0.07***	0.07***	0.07***	0.07***
	(4.97)	(4.97)	(4.64)	(4.66)	(4.66)	(4.73)
$S_{n,d} \times \text{Disp}_{n,d}$	0.01***	0.01***	0.02***	0.01***	0.01***	0.02***
	(2.66)	(2.66)	(3.36)	(3.25)	(3.25)	(3.37)
R^2	0.86	0.86	0.86	0.86	0.86	0.86
Panel D: Instrumenting $S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	0.20**	0.21**	0.37***	0.40***	0.40***	0.39***
	(2.26)	(2.36)	(3.84)	(4.28)	(4.28)	(3.98)
$S_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	-0.17**	-0.17**	-0.21***	-0.22***	-0.22***	-0.21***
	(-2.23)	(-2.22)	(-2.95)	(-3.14)	(-3.14)	(-2.98)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	-0.15**	-0.15**	-0.29***	-0.31***	-0.31***	-0.31***
	(-2.42)	(-2.52)	(-4.18)	(-4.57)	(-4.57)	(-4.42)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.99***	0.99***	1.01***	1.01***	1.01***	1.01***
	(24.06)	(23.99)	(26.51)	(26.30)	(26.30)	(25.77)
$S_{n,d}$	0.09***	0.09***	0.10***	0.10***	0.10***	0.09***
	(3.87)	(3.86)	(4.31)	(4.37)	(4.37)	(4.14)
$\text{Disp}_{n,d}$	0.05**	0.05**	0.08***	0.08***	0.08***	0.09***
	(2.26)	(2.29)	(3.20)	(3.14)	(3.14)	(3.30)
$S_{n,d} \times \text{Disp}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(0.25)	(0.26)	(0.09)	(0.00)	(0.00)	(0.15)
R^2	0.97	0.97	0.97	0.97	0.97	0.97
Panel E: First-Stage F-statistics						
Kleibergen-Paap Wald F-stat	305.32	305.07	305.18	305.68	305.68	305.77

Table C.14: **Price Impact, Dispersion, and the Share of Experienced Analysts with Controls.** This table reports estimates from the regression of asset returns (changes in yields) on news surprises and their interactions with forecast dispersion and analyst experience, as specified in Equation (25). This extends the analysis in Table 7 by additionally controlling for month fixed effects, the number of analysts, and the VIX (both interacted with surprises). Panel A reports OLS estimates. Panel B reports 2SLS estimates, using one-year lagged share of experienced analysts ($\text{ExpShare}_{n,t(d)-12}$) as an instrument for current experience ($\text{ExpShare}_{n,t(d)}$). Table C.15 reports first-stage estimates. $t-$statistics in parentheses are based on Newey-West standard errors with five-day lags. Coefficients are in bps.

	Stock Market	S&P500 F.	6M T. B.	2Y T. N.	5Y T. N.	10Y T. N.
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: OLS Estimates			
$S_{n,d}$	25.98***	20.93**	0.49**	0.75*	0.91**	0.77*
	(3.08)	(2.45)	(2.08)	(1.87)	(2.34)	(1.89)
$S_{n,d} \times \text{Disp}_{n,d}$	-1.47	-2.35	-0.05*	-0.21***	-0.19***	-0.19***
	(-0.88)	(-1.38)	(-1.71)	(-3.15)	(-2.84)	(-2.89)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$	2.93	3.72	0.07	0.25*	0.31**	0.28**
	(0.80)	(1.00)	(1.26)	(1.81)	(2.17)	(2.00)
$\text{Disp}_{n,d}$	-0.89	-1.26	-0.05	-0.16	-0.21	-0.26
	(-0.21)	(-0.30)	(-0.54)	(-0.96)	(-1.25)	(-1.48)
$\text{ExpShare}_{n,t(d)}$	-7.17	-14.09	-0.25	-0.30	-0.24	-0.18
	(-0.29)	(-0.57)	(-0.41)	(-0.24)	(-0.20)	(-0.15)
$\text{NumAnalysts}_{n,d}$	-0.01	-0.03	-0.01*	0.01	0.00	0.00
	(-0.05)	(-0.11)	(-1.78)	(0.76)	(0.19)	(0.25)
VIX_{d-5}	5.41***	5.35***	0.08***	0.16***	0.15***	0.15***
	(6.03)	(6.03)	(4.41)	(4.37)	(4.30)	(4.18)
$S_{n,d} \times \text{ExpShare}_{n,t(d)}$	-20.97	-11.54	-1.53***	-2.92***	-2.72***	-1.47**
	(-1.56)	(-0.87)	(-4.44)	(-4.55)	(-4.41)	(-2.29)
$S_{n,d} \times \text{NumAnalysts}_{n,d}$	-0.06	-0.09	0.01**	0.02***	0.01**	0.01
	(-0.52)	(-0.81)	(2.27)	(3.06)	(1.98)	(1.11)
$S_{n,d} \times \text{VIX}_{d-5}$	-0.64**	-0.38	-0.01*	0.00	0.00	0.00
	(-2.32)	(-1.39)	(-1.66)	(0.25)	(-0.08)	(0.38)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$	7.33	6.70	0.03	0.19	0.44	0.50
	(0.81)	(0.74)	(0.16)	(0.55)	(1.22)	(1.39)
R^2	0.06	0.06	0.13	0.07	0.07	0.07
			Panel B: 2SLS Estimates			
$S_{n,d}$	29.40***	25.92***	0.55**	1.12***	1.27***	1.10**
	(3.37)	(2.95)	(2.36)	(2.61)	(3.06)	(2.51)
$S_{n,d} \times \text{Disp}_{n,d}$	-2.56	-3.64*	-0.07**	-0.29***	-0.26***	-0.31***
	(-1.37)	(-1.95)	(-2.00)	(-3.88)	(-3.59)	(-3.94)
$S_{n,d} \times \text{Disp}_{n,d} \times \widehat{\text{ExpShare}}_{n,t(d)}$	5.61	7.28*	0.11*	0.51***	0.54***	0.58***
	(1.34)	(1.73)	(1.78)	(3.19)	(3.43)	(3.52)
$\text{Disp}_{n,d}$	0.18	0.18	-0.09	-0.35	-0.41*	-0.53**
	(0.03)	(0.04)	(-0.86)	(-1.53)	(-1.86)	(-2.30)
$\widehat{\text{ExpShare}}_{n,t(d)}$	144.71	120.80	2.80	10.38	8.97	10.43
	(1.16)	(0.99)	(0.90)	(1.49)	(1.37)	(1.59)
$\text{NumAnalysts}_{n,d}$	-0.06	-0.07	-0.01*	0.01	0.00	0.00
	(-0.26)	(-0.31)	(-1.82)	(0.67)	(0.15)	(0.21)
VIX_{d-5}	5.45***	5.39***	0.08***	0.16***	0.15***	0.15***
	(6.03)	(6.03)	(4.47)	(4.47)	(4.40)	(4.22)
$S_{n,d} \times \widehat{\text{ExpShare}}_{n,t(d)}$	-35.93**	-35.72**	-1.83***	-4.61***	-4.65***	-2.58***
	(-2.16)	(-2.18)	(-4.43)	(-5.30)	(-5.67)	(-3.12)
$S_{n,d} \times \text{NumAnalysts}_{n,d}$	-0.02	-0.01	0.01**	0.02***	0.02***	0.01
	(-0.12)	(-0.11)	(2.42)	(3.43)	(2.85)	(1.27)
$S_{n,d} \times \text{VIX}_{d-5}$	-0.65**	-0.41	-0.01*	0.00	-0.01	0.00
	(-2.35)	(-1.49)	(-1.88)	(-0.21)	(-0.65)	(0.28)
$\text{Disp}_{n,d} \times \widehat{\text{ExpShare}}_{n,t(d)}$	3.07	1.80	0.11	0.52	0.81*	1.01**
	(0.27)	(0.16)	(0.48)	(1.06)	(1.66)	(2.00)
N	5,849	5,849	5,849	5,849	5,849	5,849
Announcement FEs	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓

Table C.15: **Price Impact, Dispersion, and the Share of Experienced Analysts with Controls: First Stage Estimates.** This table reports first-stage estimates of the 2SLS regressions of asset returns (changes in yields) on surprises and their interactions with dispersion and analyst experience. One-year lagged share of experienced analysts ($\text{ExpShare}_{n,t(d)-12}$) is used as an instrument for current experience ($\text{ExpShare}_{n,t(d)}$). Panels A-D report first-stage regressions for the endogenous variables: analyst experience ($\text{ExpShare}_{n,t(d)}$), its interaction with news surprises ($S_{n,d} \times \text{ExpShare}_{n,t(d)}$), its interaction with dispersion ($\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$), and the three-way interaction ($S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$). Each regression includes the same controls used in the second-stage estimation (Table C.14, Panel B).

	Stock Market	S&P500 F.	6M T. B.	2Y T. N.	5Y T. N.	10Y T. N.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Instrumenting $\text{ExpShare}_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	0.16***	0.16***	0.16***	0.15***	0.15***	0.15***
	(8.85)	(8.85)	(8.76)	(8.62)	(8.65)	(8.62)
$S_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.00	0.00	0.00	0.00	0.01	0.00
	(-0.07)	(-0.24)	(0.63)	(0.32)	(0.70)	(0.57)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.00	0.00	0.00	0.01	0.00	0.01
	(0.91)	(1.10)	(1.00)	(1.31)	(1.17)	(1.48)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.00	0.00	0.00**	0.00**	0.00**	-0.01***
	(0.76)	(0.40)	(-2.22)	(-2.35)	(-2.42)	(-3.85)
$S_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(0.65)	(1.10)	(-0.22)	(-0.09)	(0.56)	(-0.79)
$\text{Disp}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(1.08)	(0.96)	(1.14)	(0.88)	(0.99)	(1.02)
$S_{n,d} \times \text{Disp}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00***
	(0.89)	(0.83)	(1.17)	(0.95)	(1.31)	(2.71)
$\text{NumAnalysts}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.30)	(-0.31)	(-0.25)	(-0.21)	(-0.21)	(-0.22)
$\text{VIX}_{n,d-5}$	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-0.70)	(-0.74)	(-0.62)	(-0.60)	(-0.63)	(-0.61)
$S_{n,d} \times \text{NumAnalysts}_{n,d}$	0.00	0.00*	0.00	0.00	0.00	0.00
	(-1.62)	(-1.68)	(-0.37)	(-0.39)	(-1.30)	(0.53)
$S_{n,d} \times \text{VIX}_{n,d-5}$	0.00	0.00	0.01	0.01	0.01	0.00
	(0.36)	(-0.24)	(1.17)	(1.07)	(0.86)	(-0.12)
R^2	0.56	0.56	0.56	0.56	0.56	0.56
Panel B: Instrumenting $S_{n,d} \times \text{ExpShare}_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	0.02	0.02	0.04	0.04	0.03	0.13***
	(0.71)	(0.75)	(1.40)	(1.37)	(1.10)	(4.25)
$S_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.82***	0.82***	0.82***	0.81***	0.81***	0.80***
	(27.38)	(27.14)	(27.01)	(26.64)	(26.61)	(26.32)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	-0.01	-0.02	-0.04***	-0.05***	-0.04***	-0.06***
	(-0.99)	(-1.33)	(-3.22)	(-3.53)	(-3.17)	(-4.35)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.00	0.00	0.00	0.01	0.01	0.01
	(0.47)	(0.69)	(0.50)	(1.14)	(1.01)	(1.42)
$S_{n,d}$	0.03*	0.03*	0.04**	0.04**	0.03*	0.04**
	(1.78)	(1.89)	(2.11)	(2.03)	(1.95)	(2.19)
$\text{Disp}_{n,d}$	0.01**	0.01*	0.02***	0.02***	0.02***	0.02***
	(2.21)	(1.92)	(3.15)	(3.08)	(2.93)	(3.20)
$S_{n,d} \times \text{Disp}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(0.51)	(0.26)	(0.58)	(-0.10)	(-0.01)	(-0.03)
$\text{NumAnalysts}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(0.10)	(-0.02)	(-0.56)	(-0.57)	(-0.83)	(-0.53)
$\text{VIX}_{n,d-5}$	0.13***	0.09*	0.09*	0.08*	0.07	-0.03
	(2.61)	(1.76)	(1.84)	(1.71)	(1.36)	(-0.68)
$S_{n,d} \times \text{NumAnalysts}_{n,d}$	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(2.76)	(2.71)	(2.80)	(2.88)	(2.89)	(2.77)
$S_{n,d} \times \text{VIX}_{n,d-5}$	-0.13***	-0.13***	-0.14***	-0.13***	-0.12***	-0.13***
	(-3.67)	(-3.63)	(-3.80)	(-3.52)	(-3.46)	(-3.65)
R^2	0.95	0.95	0.95	0.95	0.95	0.95
Panel C: Instrumenting $\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	-0.99***	-1.00***	-1.00***	-1.01***	-1.00***	-1.03***
	(-18.46)	(-18.82)	(-18.10)	(-18.54)	(-18.12)	(-19.36)
$S_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.01	0.00	0.01	0.00	0.01	0.02
	(0.26)	(0.09)	(0.31)	(0.00)	(0.56)	(0.71)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.82***	0.83***	0.83***	0.83***	0.83***	0.84***
	(26.70)	(27.32)	(25.97)	(26.80)	(25.95)	(27.82)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	-0.02*	-0.02*	-0.03***	-0.03***	-0.03***	-0.04***
	(-1.70)	(-1.86)	(-3.02)	(-3.11)	(-3.25)	(-3.91)
$S_{n,d}$	0.00	0.00	-0.01	-0.02	-0.01	-0.01
	(-0.04)	(0.01)	(-0.71)	(-1.21)	(-0.83)	(-0.80)
$\text{Disp}_{n,d}$	0.08***	0.08***	0.09***	0.08***	0.09***	0.08***
	(5.70)	(5.70)	(5.57)	(5.54)	(5.55)	(5.63)
$S_{n,d} \times \text{Disp}_{n,d}$	0.01***	0.01**	0.02***	0.01***	0.02***	0.02***
	(2.62)	(2.29)	(2.99)	(2.77)	(3.16)	(3.47)
$\text{NumAnalysts}_{n,d}$	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**
	(-2.36)	(-2.35)	(-2.28)	(-2.18)	(-2.22)	(-2.18)
$\text{VIX}_{n,d-5}$	-0.08	-0.08	-0.08	-0.07	-0.07	-0.07
	(-0.90)	(-0.91)	(-0.88)	(-0.81)	(-0.81)	(-0.78)
$S_{n,d} \times \text{NumAnalysts}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(-1.30)	(-1.23)	(0.42)	(0.70)	(-0.15)	(0.44)
$S_{n,d} \times \text{VIX}_{n,d-5}$	0.03	0.04	0.00	0.03	0.03	-0.01
	(0.88)	(1.04)	(0.02)	(0.72)	(0.74)	(-0.29)
R^2	0.89	0.89	0.89	0.89	0.89	0.89
Panel D: Instrumenting $S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)}$: First-Stage Estimates						
$\text{ExpShare}_{n,t(d)-12}$	0.16	0.15	0.23**	0.20*	0.19*	0.44***
	(1.50)	(1.46)	(2.05)	(1.91)	(1.66)	(3.97)
$S_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	-0.29***	-0.30***	-0.32***	-0.36***	-0.35***	-0.39***
	(-2.62)	(-2.66)	(-2.70)	(-3.12)	(-2.99)	(-3.22)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	-0.05	-0.07	-0.23***	-0.24***	-0.24***	-0.32***
	(-0.73)	(-1.00)	(-2.98)	(-3.24)	(-3.06)	(-4.26)
$S_{n,d} \times \text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	0.97***	0.98***	0.98***	1.00***	1.00***	1.01***
	(24.90)	(24.17)	(22.40)	(24.09)	(23.58)	(24.02)
$S_{n,d}$	0.03	0.05	0.06	0.06	0.05	0.07
	(0.53)	(0.72)	(0.98)	(0.92)	(0.77)	(1.09)
$\text{Disp}_{n,d}$	0.06**	0.05**	0.09***	0.08***	0.09***	0.08***
	(2.33)	(2.01)	(3.08)	(3.11)	(3.03)	(2.99)
$S_{n,d} \times \text{Disp}_{n,d}$	0.02	0.02	0.02	0.01	0.01	0.01
	(1.41)	(1.10)	(1.13)	(0.48)	(0.59)	(0.58)
$\text{NumAnalysts}_{n,d}$	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.06)	(-0.18)	(-0.81)	(-0.79)	(-1.29)	(-0.76)
$\text{VIX}_{n,d-5}$	0.48**	0.42**	0.22	0.24	0.09	-0.18
	(2.35)	(1.98)	(1.08)	(1.20)	(0.44)	(-0.98)
$S_{n,d} \times \text{NumAnalysts}_{n,d}$	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
	(1.83)	(1.74)	(1.78)	(1.90)	(1.91)	(1.79)
$S_{n,d} \times \text{VIX}_{n,d-5}$	-0.42***	-0.41***	-0.43***	-0.38**	-0.35**	-0.41***
	(-2.70)	(-2.61)	(-2.79)	(-2.46)	(-2.30)	(-2.67)
R^2	0.97	0.97	0.97	0.97	0.97	0.97
Panel E: First-Stage F-statistics						
Kleibergen-Paap Wald F-stat	23.51	23.70	23.47	23.17	23.17	23.33

Table C.16: **Forecast Dispersion and Pre-Announcement Price Movements.** This table reports estimates from the reduced form regression of measures of pre-announcement trading activity on forecast dispersion, the (lagged) experience share, and their interaction. The dependent variable in columns (1)-(3) is abnormal trading volume of Campbell et al. (1993), defined as the cumulative sum of daily volume deviations from a 252-day moving average over the five days prior to the announcement (days $d-5$ to $d-1$). The dependent variable in columns (4)-(6) is the price ratio of Weller (2018), defined as the ratio of cumulative returns in the ten days before the announcement to cumulative returns over the same period, including the announcement day. All specifications include announcement-type fixed effects. Columns (2) and (5) additionally include month fixed effects, and columns (3) and (6) further control for the number of analysts and the VIX. t-statistics reported in parentheses are based on two-way clustered standard errors by announcement type and date.

	Trading Volume			Price Response Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Disp}_{n,d}$	0.31	0.08	0.00	0.05	0.06	0.06
	(5.25)	(1.88)	(-0.02)	(3.47)	(3.25)	(3.11)
$\text{ExpShare}_{n,t(d)-12}$	-1.50	-0.12	-0.16	0.00	-0.06	-0.05
	(-3.33)	(-0.26)	(-0.36)	(0.03)	(-0.34)	(-0.28)
$\text{Disp}_{n,d} \times \text{ExpShare}_{n,t(d)-12}$	-0.35	-0.19	-0.07	-0.10	-0.12	-0.12
	(-2.32)	(-2.08)	(-0.96)	(-2.25)	(-2.71)	(-2.58)
$\text{NumAnalysts}_{n,d}$			0.01			0.00
			(1.19)			(-0.17)
$\text{VIX}_{n,d-5}$			19.98			1.46
			(17.01)			(2.90)
Announcement FEs	✓	✓	✓	✓	✓	✓
Month FE		✓	✓		✓	✓
N	5,791	5,790	5,790	5,806	5,805	5,805
R^2	0.05	0.46	0.50	0.00	0.06	0.06