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Disagreement over the Nature of Macroeconomic Shocks

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JEL Classification

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Disagreement over the nature of macroeconomic shocks☆

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Abstract

We document that the majority of professional forecasters exhibit rationality in directional forecast revisions of key macroeconomic variables. Exploiting this property, we use the forecast revisions to construct a novel measure of disagreement over whether shocks to aggregate demand or aggregate supply are dominating in a given period of time. Unlike disagreement in terms of numerical values of forecasts, disagreement over which shocks are prevailing is procyclical, falling significantly during recessions. This disagreement can be useful to explain cross-sectional extreme forecasts, with forecasters who disagree with the consensus about the dominant type of shock having worse nowcasts for inflation. Our findings suggest that the qualitative disagreement over the nature of macroeconomic shocks contains distinct information from quantitative disagreement in terms of numerical forecasts of macroeconomic variables and from the overall level of macroeconomic uncertainty.

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1. Introduction

Economic modelling and policy analysis often involves uncovering and understanding the underlying nature of shocks. Macroeconometricians have long employed sign restrictions to separately identify shocks to aggregate demand versus aggregate supply (for a recent example, see Giannone & Primiceri, 2024). Meanwhile, the transmission of shocks ultimately

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depends on how they influence the expectations and decisions of economic agents. Recent research by Andre et al. (2022) provides insightful cross-sectional evidence showing that agents' beliefs about the effects of shocks are shaped, in part, by their interpretation of a shock, including whether it operates through demand- or supply-side channels. However, understanding of how individuals identify types of shocks is more limited.

This paper provides new insights into professional forecasters' perceptions about the nature of macroeconomic shocks. Exploiting the panel dimension of the U.S. Survey of Professional Forecasters (SPF) for multiple key macroeconomic indicators, we identify an individual forecaster's perceived dominant type of shock prevailing in a given period based on the sign of their latest forecast revisions – defined as the difference between the current nowcast and the one-quarter-ahead forecast from the previous quarter – for inflation and real economic activity. Simultaneous revisions in the same direction for both inflation and real activity are interpreted as a belief that shocks to aggregate demand are dominating, whereas revisions in opposite directions are interpreted as a belief that shocks to aggregate supply are dominating. To ensure the quality of the forecasts in terms of revision directions, we propose a novel rationality test based on the consistency of the revision direction with the sign of forecast errors made previously. We show that the latest forecast revisions made by the majority of individual professional forecasters are rational when directions of forecast revisions, rather than their numerical values, are considered.

A key aspect of our analysis is to explore heterogeneity in individual professional forecasters' perceptions of macroeconomic shocks. Building on our identification of the perceived nature of shocks and following Whitworth (2007), we construct a novel measure of disagreement over the prevailing dominant type of shock (henceforth 'shock disagreement'). We show that this measure exhibits a pro-cyclical pattern, with shock disagreement declining during recessions, even as the level of disagreement over numerical forecast values (henceforth 'forecast disagreement') rises. The negative relationship between shock disagreement and forecast disagreement holds across the business cycle, not just during downturns. One possible explanation for our results is that time-varying macroeconomic volatility is countercyclical, increasing the difficulty of forecasting the levels of macroeconomic variables during recessions, while at the same time facilitating the identification of types of shock through a form of "identification via heteroskedasticity" (Rigobon, 2003). We also find that shock disagreement is negatively correlated with standard measures of macroeconomic uncertainty, suggesting that differences in perceived types of shocks do not magnify uncertainty. Finally, our results show that forecasters whose perceived dominant type of shock deviates from the consensus perform worse in terms of inflation nowcast accuracy relative to those aligned with the consensus.

Our paper broadly contributes to three strands of literature. The first concern the rationality of macroeconomic forecasts made by professional forecasters. Since Muth's (1961) rational expectation hypothesis posits that agents fully incorporate available information when forming expectations about future events, rational expectation has become a crucial assumption for many macroeconomic models and policy evaluation. The availability of survey forecasts such as SPF provides an opportunity for researchers to empirically test the rationality of macroeconomic forecasts. Most of the existing literature focuses on evaluating point forecasts of conditional means and applies testing methods targeting different types of rationality, for example, unbiasedness and/or efficiency (Zarnowitz, 1985; Keane & Runkle, 1990; Davies & Lahiri, 1995; Clements & Taylor, 2001; Coibion & Gorodnichenko, 2015; Rossi & Sekhposyan, 2016), and internal consistency (Patton & Timmermann, 2012; Lahiri, 2012). In general, there is strong evidence that professional point forecasts of macroeconomic variables often deviate from rationality. However, a recent study by Eo & Morley (2023) shows that, despite their inaccuracy and bias, SPF forecasts of real GDP can predict the nature of recovery from recessions. Our paper contributes to this literature by showing that SPF forecasts are more rational in their revision directions than in their point forecasts, supporting the potential value of qualitative versus quantitative information embedded in SPF forecast revisions.

We also contribute to the literature on forecast disagreement among professional forecasters. Forecast disagreement refers to the cross-sectional dispersion of forecast values. It may arise from heterogeneity in priors and in the use of information, more specifically, including differences in prior beliefs (Patton & Timmermann, 2010), information sets (Mankiw et al., 2004), news interpretations (Manzan, 2011, 2021; Lahiri & Sheng, 2008), perceptions of shock persistence (Clements, 2022), innate biases (Capistrán & Timmermann, 2009), forecasters judgment (Galvão et al., 2021), and forecasting ability (Hounyo & Lahiri, 2023). Forecast disagreement may also reflect forecasters' strategic behaviour, such as attempts to manipulate public perceptions of forecasting ability (Lamont, 2002), rational deviations from true expectations to signal performance (Laster et al., 1999), and strategic bias toward typical able forecasters (Ehrbeck & Waldmann, 1996). More broadly, monetary policy may also shape forecast disagreement: forecasts tend to be more anchored during periods of monetary tightening (Dahlhaus & Sekhposyan, 2024), and cross-country differences in monetary policy credibility help explain disagreement in inflation and GDP growth forecasts (Dovern et al., 2012). We contribute to this literature by documenting that disagreement among professional forecasters over the nature of macroeconomic shocks helps explain their forecast disagreement.

Our paper also relates more broadly to the literature on measuring macroeconomic uncertainty. Popular uncertainty measures include news-based measures such as the Economic Policy Uncertainty index (Baker et al., 2016) and forecast-based measures such as the time-varying variance of forecast errors from econometric models (Jurado et al., 2015) and market forecast errors from Bloomberg forecasts (Scotti, 2016). Many studies also use survey forecasts to construct uncertainty index for the advantages of their real-time nature and incorporation of subjective expectations formed using various data sources and models. Some of these studies rely on consensus point forecasts. For example, Jo & Sekkel (2019) estimate common uncertainties using the SPF consensus forecasts of multiple macroeconomic variables, while Rossi & Sekhposyan (2015, 2017) construct their measures by comparing realized SPF consensus forecast errors of a key business cycle indicator with the historical forecast error distribution of that variable. Other studies measure uncertainty using the dispersion of individual respondents' density forecasts (Zarnowitz & Lambros, 1987; Abel et al., 2016), whereas some utilize the cross-sectional dispersion of point forecasts made by all individual forecasters, referred to as forecast disagreement (Sheen & Wang, 2021).[1] We provide a novel measure of disagreement regarding the prevailing dominant type of macroeconomic shock and show that it is distinct from traditional forecast disagreement and other commonly used macroeconomic uncertainty measures. Specifically, our measure exhibits a pro-cyclical pattern, falling significantly during recessions, whereas both existing forecast disagreement and macroeconomic uncertainty measures are counter-cyclical, rising during economic downturns.

The rest of this paper is structured as follows. Section 2 describes the SPF forecast data. Section 3 provides evidence of rationality in directional forecast revisions. Section 4 presents our identification strategy for the perceived nature of macroeconomic shocks and details of our proposed measure of shock disagreement. Section 5 explores how shock disagreement relates to the business cycle and forecast disagreement. Section 6 concludes.

2. Data

The Survey of Professional Forecasters (SPF) is a quarterly survey of U.S. macroeconomic forecasts, currently conducted by the Federal Reserve Bank of Philadelphia. According to The Federal Reserve Bank of Philadelphia (2024), the survey is distributed at the end of the first month of each quarter, immediately following the release of the Bureau of Economic Analysis (BEA) advance report on estimated macroeconomic data for the previous quarter. The questionnaires include recent historical data from the BEA report and other government statistical agencies and are sent to registered professional forecasters. These forecasters provide expectations for macroeconomic variables covering the current quarter and up to four quarters ahead. Response deadlines typically fall in the late second to third week of the middle month of each quarter. Since the survey is conducted quarterly, forecasters revise their previously made forecasts for the same target quarter based on newly available information. This includes publicly released data, such as that provided in the survey questionnaires, and insights acquired through private channels.

We consider the SPF forecasts of CPI inflation, real GDP growth rate and the unemployment

[1] There is a substantial literature investigating the link between forecast disagreement and uncertainty. For example, Zarnowitz & Lambros (1987) and Giordani & Söderlind (2003) provide supportive evidence for forecast disagreement as a proxy for uncertainty, whereas Rich & Tracy (2010) and Abel et al. (2016) argue that the relationship is weak. Lahiri & Sheng (2010) decompose aggregate forecast uncertainty into disagreement and perceived future shock variability, and argue that disagreement is a good proxy for uncertainty when perceived shock volatility is small.

rate for 161 target quarters from 1981Q4 to 2021Q4.[2] There are a total of 230 registered professional forecasters who responded to the survey at least once during the sample period. Out of these forecasters, 47% are from financial service providers such as banks and funds, 45% are from non-financial sectors such as manufacturing firms, universities and consulting companies, and the remaining 8% have unknown industrial background.

Note that the number of forecasters who provide both 1-quarter ahead and the current quarter forecasts varies over time. Figure 1 illustrates the number of such forecasters for each target quarter over the sample period. It is observed that there were less than 10 respondents for both forecasts around 1989, while jumping to the highest number of 47 respondents in 2006. In the past decade, the number of respondents for both forecasts has remained relatively high, around 30 for each target quarter.

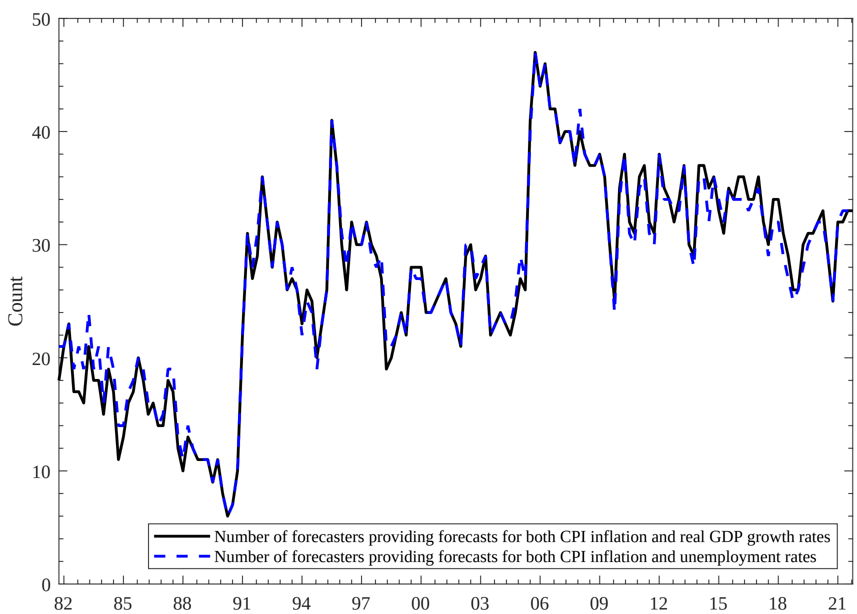

Figure 1: The number of forecasters providing both 1-quarter ahead and the current forecasts for the target quarters from 1981Q4 to 2021Q4

Let $F^j_{i,t|\tau}$ be a forecast made by an individual forecaster i in the quarter τ for the value of economic variable $j \in \{\pi, y, u\}$, which corresponds to CPI inflation, real GDP growth rate and the unemployment rate, respectively, for the target quarter $t = 1, 2, ..., 161$. The target quarter and the forecasting quarter satisfy $t \geq \tau$, with the forecasts made for the current

[2]Individual forecasts were downloaded from https://www.philadelphiafed.org/surveys-and-data/data-files

quarter ("nowcasts") given by $F^j_{i,t|t}$.

The Federal Reserve Bank of Philadelphia (2023) provides individual CPI inflation forecasts, $F^{\pi}_{i,t|\tau}$, and unemployment rate forecasts, $F^{u}_{i,t|\tau}$. Specifically, the quarterly CPI inflation forecasts are the annualized quarter-over-quarter percentage changes of the quarterly average of underlying monthly headline CPI. The quarterly unemployment rate forecasts are the quarterly average of underlying monthly levels of the unemployment rate. Since the SPF individual forecasts of real GDP are only provided in the level form, we convert them to the annualized quarter-over-quarter growth rate forecasts as $F^{y}_{i,t|\tau} = 100((F^{Y}_{i,t|\tau}/F^{Y}_{i,t|\tau-1})^4 - 1)$.

3. Testing for forecast revision rationality in terms of direction

Rational multi-horizon forecasts require not only forecast optimality in comparison with realized outcome at separate forecast horizons, but also internal consistency across forecast horizons. Patton & Timmermann (2012) propose a regression-based optimal revision test that imposes the restriction of internal consistency in a single regression. In this section, we develop a rational revision test in terms of *direction* based on the Patton & Timmermann (2012) rational revision test.

Consider forecasts made at two horizons, 1-quarter ahead and the current quarter:

$$A^j_t = \beta_0 + \beta_1 F^j_{i,t|t-1} + \beta_2 r^j_{i,t} + \varepsilon^j_{i,t}, \tag{1}$$

where A^j_t denotes the realized value of the target variable j and $r^j_{i,t} \equiv F^j_{i,t|t} - F^j_{i,t|t-1}$ denotes the forecast revision made by forecaster i for the target time t. Rational forecast revision requires that the coefficients satisfy $\beta_0 = 0$ and $\beta_1 = \beta_2 = 1$.

Equation (1) is a generalized version of the single-horizon Mincer-Zarnowitz (1969) test. Under the null hypothesis of $\beta_0 = 0$ and $\beta_1 = \beta_2 = 1$, forecaster i not only optimally revises their forecasts, but also makes an unbiased forecast $F^j_{i,t|t-1}$ at the longer horizon.

Subtracting $F^j_{i,t|t-1}$ from both sides of equation (1) produces forecast errors made in the previous quarter $e^j_{i,t|t-1} = A^j_t - F^j_{i,t|t-1}$, which will satisfy

$$e^j_{i,t|t-1} = r^j_{i,t} + \varepsilon^j_{i,t} \tag{2}$$

under optimal forecast revision where $\beta_0 = 0$ and $\beta_1 = \beta_2 = 1$. Equation (2) suggests that optimal revision made in the current quarter is equal to the expected forecast error made in the previous quarter. We consider this one-to-one quantitative relationship to be an overly strong requirement, particularly given that our shock identification strategy relies only on signs of forecast revisions.

3.1. Rationality test using direction of forecast revisions

We propose a directional rationality test based on the proportion of times when the direction of revisions is consistent with the sign of forecast errors made at the previous horizon. For a given forecaster and variable, suppose that the one-quarter-ahead forecast made at time $t-1$, $F_{t|t-1}$, exceeds the actual value A_t (for simplicity, we omit the superscripts i and j in this subsection). This over-prediction results in a negative one-quarter-ahead forecast error, $e_{t|t-1} < 0$. At time t, a rational forecaster would revise their forecast downward in response to new information and hence make a negative revision, $r_t < 0$. Therefore, a forecast revision is rational in direction if the signs of the revision and the preceding forecast error are the same.

We implement the non-parametric test proposed by Pesaran & Timmermann (1992) to test the directional consistency between revisions r_t and forecast errors $e_{t|t-1}$. Define the following binary indicators based on the signs of revision r_t and one-step ahead forecast errors $e_{t|t-1}$:

$$R_t = \begin{cases} 1, & \text{if } r_t > 0, \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

and $p_R = prob(r_t > 0)$,

$$E_{t|t-1} = \begin{cases} 1, & \text{if } e_{t|t-1} > 0, \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

and $p_E = prob(e_{t|t-1} > 0)$, and

$$Z_{t|t-1} = \begin{cases} 1, & \text{if } r_t e_{t|t-1} > 0, \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

and $p_Z = prob(r_t e_{t|t-1} > 0)$. For a sample of T observations, the sample estimates of the probabilities are then computed as

$$\hat{p}_R = 1/T \sum_t R_t, \quad \hat{p}_E = 1/T \sum_t E_{t|t-1}, \text{ and } \quad \hat{p}_Z = 1/T \sum_t Z_{t|t-1}.$$

Under the null hypothesis that forecast revisions r_t and one-step-ahead forecast errors $e_{t|t-1}$ are independent processes (i.e., irrational forecast revisions), $T\hat{p}_Z$ is binomial distributed with an expectation of $T\hat{p}^*$ where

$$\hat{p}^* = \hat{p}_R \hat{p}_E + (1 - \hat{p}_R)(1 - \hat{p}_E).$$

The test statistic against the alternative that r_t and $e_{t|t-1}$ are positively correlated is then constructed based on the difference between the sample estimate of the probability of observing consistent signs and the expected probability under the null hypothesis of independence between revisions and forecast errors, that is,

$$S = \frac{\hat{p}_Z - \hat{p}^*}{\left(v\hat{a}r(\hat{p}_Z) - v\hat{a}r(\hat{p}^*)\right)^{\frac{1}{2}}} \sim \boldsymbol{N}(0,1), \tag{6}$$

where $v\hat{a}r(\hat{p}_Z) = \frac{1}{T}\hat{p}^*(1-\hat{p}^*)$ and

$$v\hat{a}r(\hat{p}^*) = \frac{1}{T}\left(2\hat{p}_R - 1\right)^2 \hat{p}_R\left(1-\hat{p}_R\right) + \frac{1}{T}\left(2\hat{p}_E - 1\right)^2 \hat{p}_E\left(1-\hat{p}_E\right) + \frac{4}{T^2}\hat{p}_R\hat{p}_E\left(1-\hat{p}_R\right)\left(1-\hat{p}_E\right).$$

Note that we are investigating the relationship between the error of a previously made forecast and the subsequent revision. This differentiates us from the existing literature on rationality of fixed event forecasts where the rational forecasts are featured by the independence between a revision and the error of the revised forecast. For example, Ashiya (2003) studies the joint effect of optimism (pessimism) and the reaction of over (under) through the relationship between forecast revisions and consequent forecast errors.

3.2. Directional rationality test results

The directional rationality test builds on the consistency in the signs of 1-quarter ahead forecast error and the subsequent forecast revision. Figure 2 shows the percentage of forecasters whose 1-quarter ahead forecast error and subsequent forecast revision have the same sign at each quarter. Over the sample period from 1981Q4 to 2021Q4, the average observed probability of the same sign between the two series is around 67%, 76% and 65% for CPI inflation, the unemployment rate and real GDP, respectively. Comparing across the three targeted key macroeconomic variables, the time variation in percentage of forecasters who make directional rational revisions for the unemployment rate is the lowest, whereas the variation in percentage for real GDP growth is the highest. This suggests that making rational forecast revisions for real GDP growth rate is most challenging among all three targeted variables. The shaded bars mark the NBER recession dates during the sample period. Although we cannot observe a generalized pattern between recessions and properties of forecast revisions, it is clear that towards the end of the most recent recession associated with the COVID-19, every forecaster revises their previously made forecast in a rational direction.

We test for directional rationality of revisions made by individual forecasters. To ensure a reasonable sample size for testing, we only consider the forecasters who have reported both 1-quarter ahead and current quarter forecasts of all three macroeconomic variables for at least 30 targeted quarters. There are 54 forecasters in the sample who meet this requirement.

Table 1 reports the p-values of both directional rationality (DR) test and the optimal revision test (OR) for individual forecasters. The p-values of the DR test is calculated based on the test statistics presented in equation (6). For the OR test, the Wald test statistics under the null hypothesis of $\beta_0 = 0$ and $\beta_1 = \beta_2 = 1$ in equation (1) are calculated using the Newey-West adjusted variance-covariance estimator.

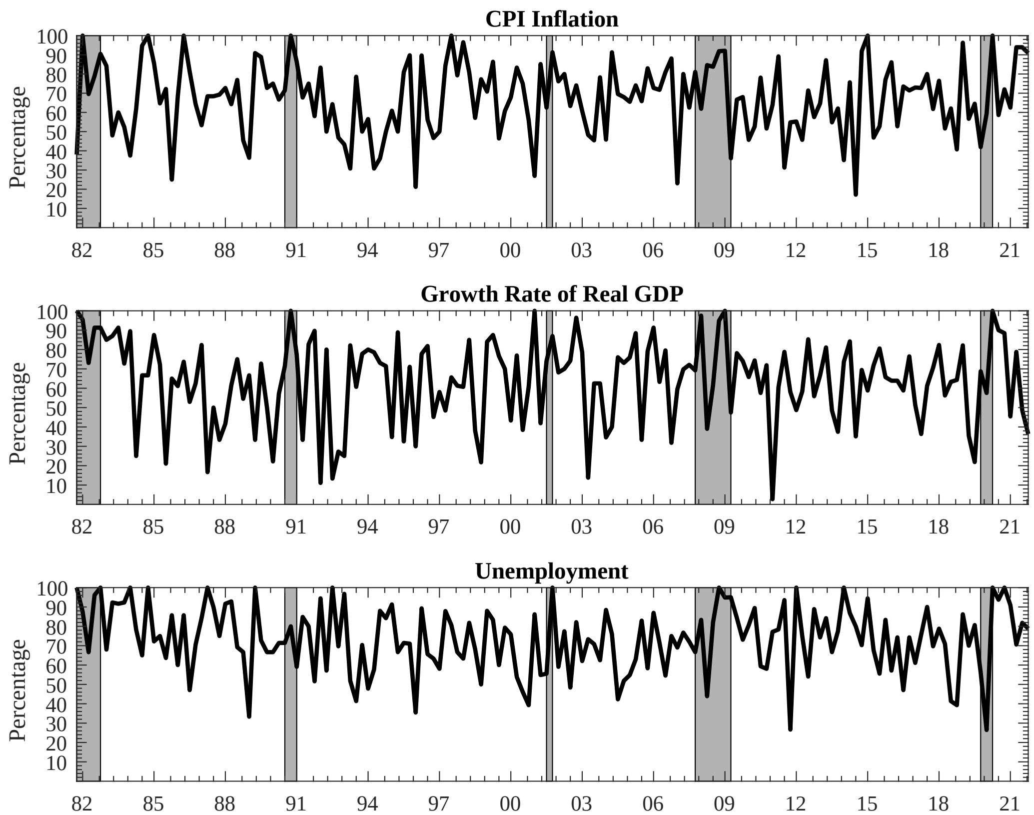

Figure 2: The percentage of forecasters whose 1-quarter ahead forecast and subsequent forecast revision have the same sign, for each target quarter ranging from 1981Q4 to 2021Q4. NBER recessions are shaded.

Table 1: Revision rationality test results for 54 individual forecasters for three macroeconomic variables from 1981Q4 to 2021Q4

Panel A: Rationality test for individual forecasters

	Inflation		Unemployment		GDP			Inflation		Unemployment		GDP	
	π		u		y			π		u		y	
ID	DR	OR	DR	OR	DR	OR	ID	DR	OR	DR	OR	DR	OR
20	0.00	0.08	0.40	0.00	0.19	0.00	484	0.27	0.52	0.38	0.00	0.01	0.01
35	0.24	0.00	0.00	0.03	0.04	0.08	504	0.00	0.00	0.00	0.00	0.00	0.00
40	0.00	0.00	0.00	0.00	0.00	0.03	506	0.00	0.00	0.02	0.00	0.00	0.01
60	0.12	0.16	0.00	0.00	0.02	0.00	507	0.00	0.69	0.00	0.03	0.02	0.00
62	0.00	0.01	0.00	0.00	0.00	0.00	508	0.08	0.00	0.00	0.02	0.00	0.28
65	0.01	0.00	0.26	0.00	0.08	0.00	510	0.28	0.50	0.00	0.28	0.19	0.00
70	0.00	0.00	0.00	0.23	0.01	0.01	512	0.05	0.09	0.02	0.00	0.45	0.06
84	0.09	0.13	0.00	0.73	0.01	0.03	516	0.00	0.00	0.00	0.52	0.06	0.34
94	0.02	0.01	0.01	0.35	0.05	0.00	518	0.00	0.13	0.00	0.00	0.05	0.04
99	0.18	0.42	0.00	0.02	0.00	0.01	520	0.45	0.19	0.01	0.00	0.00	0.06
407	0.01	0.18	0.00	0.01	0.25	0.03	524	0.03	0.00	0.01	0.07	0.04	0.00
411	0.00	0.04	0.00	0.00	0.00	0.49	527	0.00	0.24	0.35	0.00	0.15	0.62
420	0.16	0.00	0.01	0.00	0.04	0.14	528	0.00	0.00	0.03	0.00	0.28	0.00
421	0.18	0.45	0.00	0.00	0.01	0.00	535	0.00	0.00	0.01	0.00	0.40	0.00
422	0.06	0.04	0.00	0.00	0.08	0.00	542	0.00	0.03	0.00	0.00	0.00	0.00
424	0.00	0.03	0.05	0.18	0.00	0.00	546	0.06	0.02	0.00	0.00	0.01	0.08
426	0.24	0.00	0.06	0.05	0.00	0.00	548	0.04	0.01	0.08	0.00	0.32	0.00
428	0.02	0.01	0.00	0.00	0.00	0.00	549	0.00	0.01	0.00	0.00	0.00	0.08
429	0.00	0.02	0.00	0.00	0.02	0.00	553	0.09	0.00	0.00	0.00	0.15	0.00
431	0.00	0.46	0.01	0.14	0.06	0.00	555	0.00	0.17	0.06	0.00	0.07	0.00
433	0.00	0.01	0.01	0.00	0.00	0.00	556	0.00	0.06	0.00	0.09	0.05	0.02
439	0.36	0.00	0.28	0.00	0.01	0.00	557	0.00	0.00	0.01	0.00	0.03	0.00
446	0.12	0.03	0.00	0.00	0.00	0.01	563	0.07	0.00	0.17	0.00	0.37	0.00
456	0.00	0.48	0.00	0.00	0.09	0.00	568	0.00	0.01	0.00	0.00	0.01	0.00
463	0.00	0.43	0.00	0.01	0.00	0.02	570	0.00	0.37	0.26	0.00	0.00	0.00
472	0.00	0.03	0.00	0.00	0.00	0.08	572	0.17	0.00	0.05	0.00	0.00	0.05
483	0.13	0.02	0.03	0.14	0.00	0.00	574	0.33	0.29	0.01	0.00	0.05	0.00

Panel B: Proportion of rational forecasters – Directional rationality (DR) test:

Inflation(π)	62.9%	Unemployment(u)	79.6%	GDP(y)	68.5%

Panel C: Proportion of rational forecasters – Optimal Revision (OR) test:

Inflation(π)	27.8%	Unemployment(u)	13.0%	GDP(y)	11.1%

Notes: The results are based on 54 forecasters in the sample who have reported both 1-quarter ahead and current quarter forecasts for more than 30 target dates for all three macroeconomic variables. The DR test refers to the proposed directional rational revision test. The OR test refers to the optimal revision test of Patton & Timmermann (2010), where the null hypothesis is $\beta_0 = 0$ and $\beta_1 = \beta_2 = 1$ in a test regression $A_t^j = \beta_0 + \beta_1 F_{i,t|t-1}^j + \beta_2 r_{i,t}^j + \varepsilon_{i,t}^j$. Panel A reports the p-values of both DR and OR tests. Panel B summarizes the proportion of forecasters whose associated p-values are less than 10% in the DR test and hence revisions are considered rational in direction, while Panel C shows the proportion of forecasters whose associated p-values are higher than 10% in the OR test and hence revisions are considered rational in magnitude.

Panel B reports that 63.0%, 79.6% and 68.5% of the 54 forecasters test as making rational revisions in terms of directions for inflation, the unemployment rate and the real GDP growth rate, respectively, at a 10 percent level of significance. In contrast, the optimal revision test suggests much smaller proportions of forecasters make rational revisions. Panel C reports that only 27.8%, 13.0% and 11.1% of forecasters do not reject their tests for being rational in forecasting inflation, the unemployment rate and the real GDP growth rate, respectively.

We further test for rational revision in direction at an aggregate level. Specifically, the rationality test described above is employed to test for the directional consistency between the mean values of 1-quarter ahead forecast errors, $\bar{e}^j_{t|t-1}$, and the mean values of the current revisions, $\bar{r}^j_{t|t}$, for each target quarter t and variable j, where

$$\bar{e}^j_{t|t-1} = \frac{1}{N^j_t}\sum_{i=1}^{N^j_t} e^j_{i,t|t-1} \quad \text{and } \bar{r}^j_t = \frac{1}{N^j_t}\sum_{i=1}^{N^j_t} r^j_{i,t}.$$

Table 2 reports the p-values of the test with the null hypothesis that $\bar{e}^j_{t|t-1}$ and $\bar{r}^j_{t|t}$ are independent processes against the alternative that they are positively correlated, considering the full sample period from 1981Q4 to 2021Q4. It is evident that, at the aggregate level, the current revisions are rational in direction for all three variables. Since the proposed directional rationality test shows that the current forecast revisions are rational in direction for a majority of the forecasters, we will utilize the bivariate revision directions to identify the perceived types of shocks for the professional forecasters.

Table 2: Aggregate directional rationality test results for three macroeconomic variables from 1981Q4 to 2021Q4

	Inflation π	Unemployment u	GDP y
p-value	0.000	0.000	0.000

4. Disagreement over the prevailing dominant type of macroeconomic shock

4.1. Identification of perceived types of shocks

After the submission of forecasts in a previous quarter, forecasters receive new macroeconomic information that may not be anticipated previously. Based on their assessment of the nature of recent shocks, they update their multivariate forecasts for the current quarter. We identify forecasters' perceptions of the prevailing dominant type of shock by analyzing their forecast revisions for pairs of key macroeconomic variables: either CPI inflation and the real GDP growth rate or CPI inflation and the unemployment rate.

Specifically, if a forecaster revises both CPI inflation and real GDP growth (or CPI inflation and the unemployment rate) in the same direction (or in opposite directions), we interpret the perceived shocks hitting the macroeconomy as being predominantly aggregate demand in nature. Conversely, if the revisions for CPI inflation and real GDP growth (or CPI inflation and the unemployment rate) move in opposite directions (or in the same direction), the dominant shocks are interpreted as being aggregate supply in nature. If at least one of these forecasts remains unchanged, the perceived shock type cannot be determined.

Table 3 summarizes this identification strategy based on the signs of forecast revisions for the current quarter. The revision made by forecaster i for variable $j \in \{\pi, y, u\}$ at target quarter t is defined as the difference between the current forecast and the forecast made in the previous quarter:

$$r^j_{i,t} = F^j_{i,t|t} - F^j_{i,t|t-1}. \tag{7}$$

Table 3: Identification of the prevailing dominant type of shock

Revisions	$+r^y_{i,t}$	$-r^y_{i,t}$	$+r^u_{i,t}$	$-r^u_{i,t}$
$+r^\pi_{i,t}$	Demand	Supply	Supply	Demand
$-r^\pi_{i,t}$	Supply	Demand	Demand	Supply

For each quarter t, we select forecasters who have supplied bivariate forecasts for the target quarter t both in the previous quarter $t-1$ and in the current quarter t. Using the strategy discussed in Table 3, we identify individual forecasters' perceptions of the prevailing dominant type of shock: aggregate demand, aggregate supply or unidentified. Figure 3 depicts the percentage of forecasters who perceive a particular dominant type of shock, with the top figure showing the identification based on the forecast revisions of CPI inflation and real GDP growth and the bottom panel showing the identification based on the forecast revisions of CPI inflation and the unemployment rate. There are similar patterns in the changing dominance of aggregate demand and aggregate supply shocks when considering real GDP growth or the unemployment rate, although there are more unidentified shocks when considering the unemployment rate suggesting less of tendency for forecasters to change their forecasts of the unemployment rate given new information. This is consistent with a lagging nature of the unemployment rate's response to macroeconomic shocks compared to that for real GDP growth. Appendix A shows the decomposition of shocks into five categories: positive demand, positive supply, negative demand, negative supply and unidentified. Generally, forecasters who agree on the type of shock also agree on the sign, although there is more disagreement on the sign in the periods when there is also disagreement on the type.

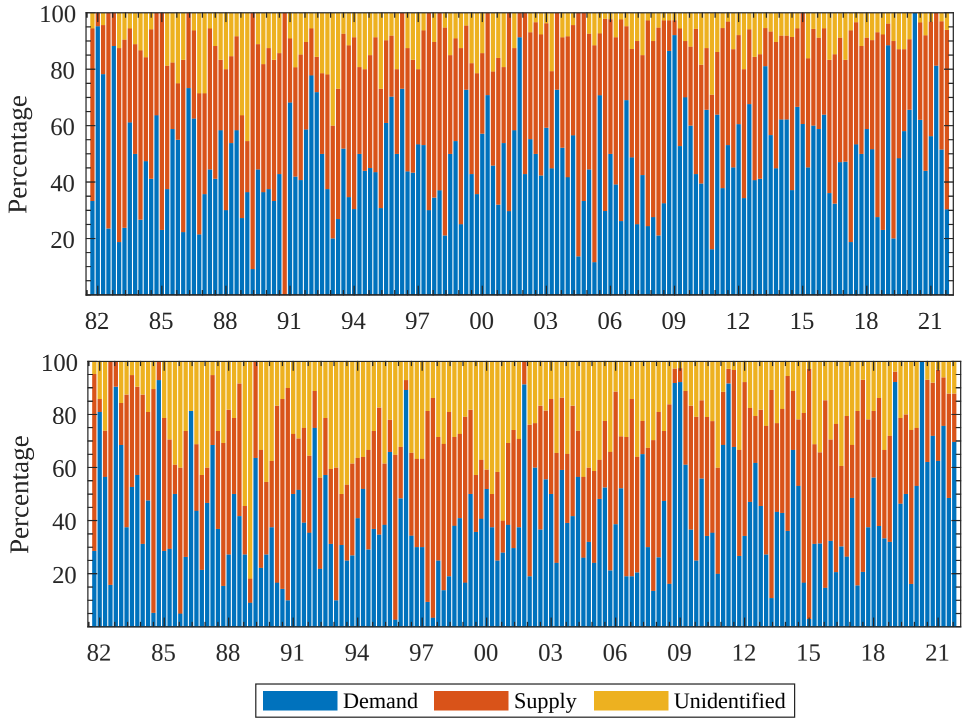

Figure 3: Proportions of forecasters whose perceived dominant type of shock is identified as aggregate demand, aggregate supply or unidentified from 1981Q4 to 2021Q4. Top panel presents the results using the current forecast revisions of CPI inflation and real GDP growth. The bottom panel presents the results using the current forecast revisions of CPI inflation and the unemployment rate.

4.2. Construction of the 'shock disagreement' measure

We propose to use a disagreement measure by Whitworth (2007) to assess the group disagreement level on the perceived dominant type of shock for each target quarter.

Consider that the number of forecasters who provide both current quarter forecasts and the previously made 1-quarter ahead forecasts for a target quarter t is denoted by N_t, where N_t takes different values across t as shown in Figure 1. We first compute the level of disagreement between a forecaster i and another forecaster k ($k \neq i$) in the group of N_t forecasters,

$$D_{i,t} = \frac{1}{N_t - 1} \sum_{k \neq i} d_{ik,t}, \tag{8}$$

where $d_{ik,t} = 1$ if the directions of CPI and real GDP growth forecast revisions for quarter t result in different perceived types of shock between the forecasters i and k, and $d_{ik,t} = 0$ otherwise.

The group disagreement is the average of the disagreement level for each forecaster within the group of N_t forecasters, that is,

$$D_t^G = \frac{1}{N_t} \sum_{i=1}^{N_t} D_{i,t}. \tag{9}$$

The theoretical range of D_t^G is in general between 0 and 1. A zero value indicates that every forecaster shares a common perception on shock types. A higher value of D_t^G suggests a higher level of group disagreement, but the theoretical maximum of unity is not feasible in our case because with three options for the shock types and more than three forecasters at every quarter, it is certain that some extent of agreement will exist. Whitworth (2007) suggests that the maximum disagreement is between 0.673 and 0.733 for the case of 3 options and the group size between 10 and 100.

Figure 4 shows the Whitworth measures of group disagreement for both identification strategies, $D_t^{G,\pi\&y}$ and $D_t^{G,\pi\&u}$, calculated using equations (8) and (9) at each quarter within the sample. The shaded areas indicate NBER recessions. It can be seen that disagreement over the perceived dominant shock type tends to drop to a very low level at the end of recessions. Furthermore, comparing between the two bivariate shock identifications, the associated group disagreement measures are moderately correlated (with a correlation coefficient of 0.618). The high similarity is especially prominent for major economic downturns such as the 2001 dot-com recession, the global financial crisis in 2008 and the recent COVID-19 recession. However, using forecast revisions of CPI inflation and the unemployment rate increases the number of quarters in which there is a substantial level of agreement on whether the shocks are primarily driven by aggregate demand or aggregate supply.

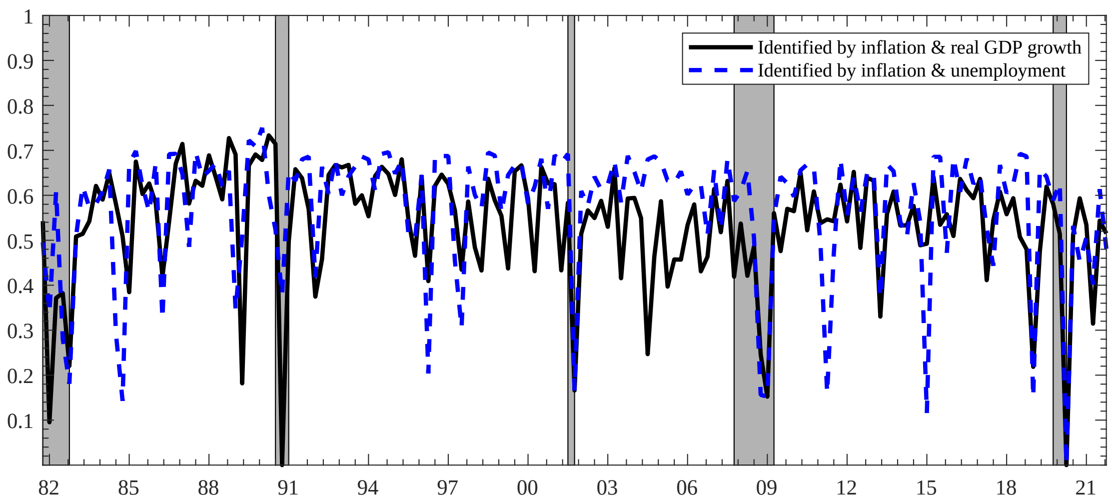

Figure 4: Whitworth measures of disagreement about the dominant type of shock for the target quarters from 1981Q4 to 2021Q4. NBER recessions are shaded.

5. Relating shock disagreement to the business cycle and forecast disagreement

5.1. Shock disagreement over the business cycle

The disagreement measures shown in Figure 4 typically fall during recessions. Does this pro-cyclical movement hold more generally over the business cycle? We test the significance of this relationship using the following regressions:

$$D_t^{G,\pi\&j} = \beta_0 + \beta_1 y_t^{YoY} + \nu_t \tag{10}$$

$$D_t^{G,\pi\&j} = \beta_0 + \beta_1 REC_t + \nu_t \tag{11}$$

$$D_t^{G,\pi\&j} = \beta_0 + \beta_1 REC_t + \beta_2 y_t^{YoY} + \nu_t, \tag{12}$$

where $j = y, u$ and the recession dummy variable $REC_t = 1$ if the associated quarter t is within the NBER dated recessionary periods and $REC_t = 0$ otherwise. The variable y_t^{YoY} is the Year-over-Year GDP growth rate in percentage. The estimation results are reported in Table 4.

Table 4: Estimation results for the relationship between shock disagreement and the business cycle from 1981Q4 to 2021Q4

	$D_t^{G,\pi\&y}$			$D_t^{G,\pi\&u}$		
Intercept	0.482***	0.560***	0.532***	0.528***	0.594***	0.570***
	(0.022)	(0.009)	(0.023)	(0.024)	(0.010)	(0.027)
y_t^{YoY}	0.021***		0.009	0.018**		0.008
	(0.007)		(0.007)	(0.008)		(0.009)
REC_t		−0.185***	−0.152***		−0.157***	−0.128***
		(0.028)	(0.037)		(0.037)	(0.044)
No. Obs	161	161	161	161	161	161
Adj. R^2	0.124	0.211	0.222	0.073	0.123	0.128

Notes: Estimates for $D_t^{G,\pi\&y}$ and $D_t^{G,\pi\&u}$ are for equations (10) to (12). The variable $REC_t = 1$ if the quarter t is within NBER dated recessionary period and $REC_t = 0$ otherwise and y_t^{YoY} is the Year-over-Year annual growth rate of real GDP at quarter t. Newey-West corrected standard errors are reported in parentheses. $**$ and $***$ indicate rejection of the null hypothesis of zero parameter value at the 5% and 1% test level, respectively.

Irrespective of how we measure disagreement, Table 4 shows disagreement over the dominant type of shock is indeed procyclical over the business cycle: when real GDP growth falls, shock disagreement tends to fall. The pro-cyclicality is disproportionally stronger during recessions; however, the sign of the conditional correlation with real GDP remains positive outside of recessions. One possible explanation for a greater consensus over the nature of shocks is that the onset of recessions is typically induced by a large economic shock that is better understood by forecasters, helping them with "identification via heteroskedasticity" (Rigobon, 2003). For example, the global financial crisis was triggered by a financial market meltdown in late 2007 and was apparently dominated by negative demand forces in terms of a credit freeze that stalled investment and consumption, leading to lower output growth, a higher unemployment rate and lower inflation. It is also clear that behavioural responses and lock-down policies around the world during the COVID-19 pandemic restricted global supply, therefore increasing inflation while many businesses contracted their workforce, leading to lower production and employment.

The procyclicality of the disagreement over the nature of shocks is in stark contract to numerical forecast disagreement, which tends to be counter-cyclical (for example, Bloom (2014), Dovern et al. (2012) and Sheen & Wang (2021)). This suggests that shock disagreement could contain distinct information over numerical forecast disagreement. To formally test the relationship between forecast disagreement and shock disagreement, we run the following

Table 5: Estimation results for the relationship between shock disagreement and forecast disagreement from 1981Q4 too 2021Q4

	$IQR^{\pi}_{t\|t}$		$IQR^{y}_{t\|t}$		$IQR^{u}_{t\|t}$	
Intercept	1.596***	1.516***	1.570**	1.271*	0.460***	0.411*
	(0.397)	(0.383)	(0.726)	(0.673)	(0.072)	(0.247)
$IQR^{\pi}_{t\|t-1}$	0.376***	0.281*				
	(0.122)	(0.158)				
$IQR^{y}_{t\|t-1}$			0.346***	0.343***		
			(0.031)	(0.026)		
$IQR^{u}_{t\|t-1}$					0.181***	0.183***
					(0.022)	(0.020)
$D^{G,\pi\&y}_t$	−1.592**	−1.361**	−1.666	−1.195		
	(0.618)	(0.642)	(1.233)	(1.164)		
$D^{G,\pi\&u}_t$					−0.608	−0.541
					(0.451)	(0.405)
REC_t		0.273		0.407**		0.081
		(0.216)		(0.194)		(0.074)
No. Obs	161	161	161	161	161	161
Adj. R^2	0.195	0.203	0.429	0.446	0.219	0.224

Notes: Estimates are for equations (13) and (14). Newey-West corrected standard errors are reported in parentheses below the estimated parameters. $*$, $**$ and $***$ indicate rejection of the null hypothesis of zero parameter value at the 10%, 5% and 1% test level, respectively.

regressions:

$$IQR_{t|t} = \beta_0 + \beta_1 IQR_{t|t-1} + \beta_2 D^G_t + \nu_t \tag{13}$$

$$IQR_{t|t} = \beta_0 + \beta_1 IQR_{t|t-1} + \beta_2 D^G_t + \beta_3 REC_t + \nu_t, \tag{14}$$

where $IQR_{t|t}$ and $IQR_{t|t-1}$ represent the interquartile range of nowcasts and the previously made 1-quarter ahead forecasts for a target variable, π, y or u, at time t. The estimation results for each target variable are reported in Table 5. As expected, the parameter β_1 is positive and significant across specifications and across different measures of forecast disagreement, indicating that a higher forecast disagreement in the previous quarter corresponds to a higher forecast disagreement in the current quarter. All estimates for β_2 are negative, indicating that an increase in disagreement over the nature of shock corresponds to less numerical forecast disagreement, and they are statistically significant for forecast disagreement over inflation. This suggests that forecasters can have more diverse numerical forecasts even when they agree more over the nature of shocks.

We can rationalise the arguably counterintuitive negative correlation between shock disagreement and forecast disagreement through the lens of a Bayesian learning process. If forecasters are Bayesian learners, they would update their expectations based on a prior belief and forms interpretation of newly arrived information (e.g. Kandel & Pearson (1995) and Manzan (2011)). When facing heightened uncertainty, a Bayesian learner would place a less weight on noisy new information and instead place a relatively higher weight on their heterogeneous prior beliefs, which gives rise to higher disagreement on the path to economic recovery. Indeed, as shown in Appendix B and Appendix C, while disagreement over the dominant nature of shocks is negatively correlated with popular measures of economic uncertainty, forecast disagreement is positively correlated with popular measures of macroeconomic uncertainty, not only during recessions, but more generally across time.[3] In fact, disagreement is closely linked with uncertainty (e.g. Lahiri & Sheng (2010)), with early literature on macroeconomic uncertainty sometimes relying on forecast disagreement measures (e.g. Bloom (2014)). In addition, different capacities in processing information and mental models can also dictate how forecasters interpret newly arrived information, even when they agree over the nature of shocks (Andre et al., 2022).

5.2. Shock disagreement and cross-sectional extreme forecasts

Does disagreement with the consensus dominant type of shock correlate with disagreement with the numerical consensus forecast? We measure the extent of the deviation of individual forecasts for the variable j from the consensus forecast made at time t by the absolute value of standardized difference between the individual forecast and the average forecast, that is,

$$\tilde{D}_{th}^{ij} = \left| \frac{F_{t+h|t}^{ij} - \bar{F}_{t+h|t}^{j}}{\hat{\sigma}_{F_{t+h|t}^{j}}} \right|, \tag{15}$$

where $j = \pi, u,$ and y representing inflation, the unemployment rate and GDP growth rate, respectively, and $\bar{F}_{t+h|t}^{j} = \frac{1}{N_t}\sum_{i=1}^{N_t} F_{i,t+h|t}^{j}$ and $\hat{\sigma}_{F_{t+h|t}^{j}}^{2} = \frac{1}{N_t-1}\sum_{i=1}^{N_t}\left(F_{i,t+h|t}^{j} - \bar{F}_{t+h|t}^{j}\right)^2$. To measure individual's disagreement with the consensus shock type, we construct a binary variable S_{it} for each individual forecaster $i \in (1, N_t)$ at time t. The value of S_{it} is equal to 1 if the perceived dominant shock type by forecaster i at time t is different from the consensus type and 0 otherwise. Appendix D shows that forecasters from the financial industry tend to have a highly likelihood of the consensus view on the nature of shocks compared to those from other industries.

We use the following panel regression to examine the relationship between $\tilde{D}_{th}^{ij}$ and S_{it} for

[3]These measures include the macroeconomic uncertainty indicator (JNL) of Jurado et al. (2015), the macroeconomic disagreement indicator (SW) by Sheen & Wang (2021), the VIX index and the economic policy uncertainty indictor (BBD) by Baker et al. (2016).

individual forecasters:

$$\tilde{D}^{j}_{ith} = \beta_1 + \beta_2 S_{it} + \beta_3 EX^{j}_{ith} + \beta_4 \left(S_{it} \times EX^{j}_{ith}\right) + \gamma_t + \alpha_i + \nu_{it}. \tag{16}$$

In equation (16), EX^{ij}_{th} is a binary variable that is used to differentiate forecasts within the interquartile range from those considered extreme. The value of EX^{ij}_{th} is set to one if the forecast for variable j over the horizon h that is made by forecaster i at time t is within the cross-sectional interquartile range and zero otherwise. The effect of shock disagreement on forecast disagreement is β_2 for forecasts within the cross-sectional interquartile range, while for those outside the cross-sectional interquartile range, the effect of shock type disagreement is $\beta_2 + \beta_4$.

In the regressions for inflation and real GDP growth ($j = \pi, y$), individual forecaster's shock disagreement indicator S_{it} is based on the directions of current forecast revisions for inflation and real GDP growth, while S_{it} in the regression for the unemployment rate forecasts ($j = u$) is based on the directions of current forecast revisions for inflation and the unemployment rate.

Table 6 reports the key estimation results of equations (16) for $\tilde{D}^{i,\pi}_{th}$, $\tilde{D}^{i,u}_{th}$ and $\tilde{D}^{i,y}_{th}$ with $t = 1, 2, ..., 161$ quarters ranging from 1981Q1 to 2021Q4 and forecast horizon $h = 0, 1, 2, 3$ and 4. Note that the forecasters included in the estimation for $\tilde{D}^{i,\pi}_{th}$ and $\tilde{D}^{i,y}_{th}$ are those who provided both current forecast revisions and h quarter ahead forecasts for inflation and real GDP growth at each t. Similarly, the estimations for $\tilde{D}^{i,u}_{th}$ include forecasters who provide current forecast revisions and h quarters ahead forecasts for inflation and the unemployment rate at t. This ensures that the same individual forecasters are used to construct both dependent and independent variables in each quarter. Because forecasters typically do not provide forecasts for all horizons every quarter, the resulting panel data set is unbalanced and missing observations are allowed when estimating equation (16). There are more forecasters who report current-quarter forecasts than those who also report future forecasts. All panel estimation includes both time and individual fixed-effects and White cross-section cluster standard errors are employed to account for potential serial correlation.

The results in Table 6 suggest that the effect of disagreeing with the consensus type of shock to the level of disagreement with the numerical consensus forecast can be different depending on whether the individual forecast is within or outside of the interquartile range. The difference is the most pronounced for the unemployment rate forecasts, where the estimated β_2 and β_4 are significant across all horizons. Specifically, the estimated β_2 are all negative, implying that when an individual's unemployment forecast is within the interquartile range, disagreeing with the consensus shock type reduces the disagreement with the average forecast. However, with estimated β_4 being positive and much higher than estimated β_2 in magnitude, estimated values of $\beta_2 + \beta_4$ are all positive, suggesting that perceiving a current dominant shock type different from the consensus raises the level of disagreement of current and future unemployment forecasts when they are considered very different from the majority. The small p-values for the null hypothesis of $\beta_2 + \beta_4 = 0$ provide evidence of a significant effect. This result is consistent with Andre et al. (2022) that different mental models in interpreting shocks can help explain forecast disagreement.

While Table 6 suggests that identifying the dominant nature of prevailing shocks differently from consensus leads extreme forecasts to be further away from the consensus forecasts in magnitude, the question remains whether these nonconformist forecasts are actually more accurate. We measure an individual forecaster's performance by the squared value of forecast errors, $\left(A_t^j - F_{i,t+h|t}^j\right)^2$, and consider the following panel regressions,

$$\left(A_t^j - F_{i,t+h|t}^j\right)^2 = \beta_1 + \beta_2 S_{it} + \beta_3 EX_{ith}^j + \beta_4 \left(S_{it} \times EX_{ith}^j\right) + \gamma_t + \alpha_i + \nu_{it}. \tag{17}$$

Similarly to equation (16), S_{it} indicates shock disagreement with the consensus type for individual forecasters, while EX_{ith} and its interaction with S_{it} allows different effects of individual shock disagreement to forecast performance between forecasts within and outside the interquartile range.

Table 7 reports the estimation results for inflation ($j = \pi$), the unemployment rate ($j = u$) and real GDP growth ($j = y$). Except for a few cases, the estimates of β_2 are positive across target variables and forecast horizons, implying that a different perception than consensus about the dominant type of prevailing shock leads to worsened numerical forecasting performance. The estimates of β_4 are positive for inflation, negative for the unemployment rate and real GDP growth, except for the nowcast of real GDP growth. However, the estimated disagreement effects are statistically significant only for the nowcast of inflation, with the estimate of $\beta_2 + \beta_4$ substantially exceeding that of β_2. This provides strong evidence that extreme nowcasts of inflation amplify the adverse impact of shock type disagreement on inflation nowcasting performance.

Table 6: Panel estimation results for the relationship between disagreement from consensus for dominant shock type and numerical forecasts from 1981Q4 to 2021Q4

Dependent Variable: $\tilde{D}_{th}^{i,\pi}$

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
β_2	0.010	-0.004	0.016	0.016	-0.004
	(0.014)	(0.010)	(0.010)	(0.011)	(0.010)
β_4	0.025	0.011	-0.008	-0.050	0.029
	(0.032)	(0.035)	(0.026)	(0.032)	(0.031)
$\beta_2 + \beta_4$	0.035	0.007	0.008	-0.034	0.025
p-value ($H_0 : \beta_2 + \beta_4 = 0$)	*0.269*	*0.823*	*0.771*	*0.244*	*0.389*
Time fixed-effect	Yes	Yes	Yes	Yes	Yes
Individual fixed-effect	Yes	Yes	Yes	Yes	Yes
R^2	0.593	0.602	0.595	0.597	0.582
(Unbalanced) Observations	4367	4257	4257	4257	4257

Dependent Variable: $\tilde{D}_{th}^{i,u}$

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
β_2	-0.030^{***}	-0.024^{**}	-0.037^{***}	-0.022^{*}	-0.027^{**}
	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)
β_4	0.097^{***}	0.109^{***}	0.144^{***}	0.134^{***}	0.083^{***}
	(0.033)	(0.028)	(0.026)	(0.025)	(0.026)
$\beta_2 + \beta_4$	0.067^{**}	0.085^{***}	0.107^{***}	0.112^{***}	0.056^{**}
p-value ($H_0 : \beta_2 + \beta_4 = 0$)	*0.025*	*0.002*	*0.000*	*0.000*	*0.022*
Time fixed-effect	Yes	Yes	Yes	Yes	Yes
Individual fixed-effect	Yes	Yes	Yes	Yes	Yes
R^2 0.642	0.663	0.655	0.661	0.673	
(Unbalanced) Observations	4387	4291	4291	4291	4291

Dependent Variable: $\tilde{D}_{th}^{i,y}$

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
β_2	-0.009	-0.010	-0.021^{*}	-0.006	-0.002
	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)
β_4	0.057^{**}	-0.019	-0.012	0.003	-0.004
	(0.029)	(0.033)	(0.033)	(0.032)	(0.034)
$\beta_2 + \beta_4$	0.048^{*}	-0.029	-0.033	-0.003	-0.006
p-value ($H_0 : \beta_2 + \beta_4 = 0$)	*0.064*	*0.340*	*0.289*	*0.905*	*0.856*
Time fixed-effect	Yes	Yes	Yes	Yes	Yes
Individual fixed-effect	Yes	Yes	Yes	Yes	Yes
R^2	0.550	0.568	0.559	0.544	0.534
(Unbalanced) Observations	4367	4253	4253	4253	4253

Notes: Estimates are for $\tilde{D}_{th}^{ij} = \beta_1 + \beta_2 S_{it} + \beta_3 EX_t^{ij} + \beta_4 \left(S_{it} \times EX_t^{ij}\right) + \gamma_t + \alpha_i + \nu_{it}$ for inflation (π), unemployment rate (u) and real GDP growth (y). The coefficient β_2 measures the effect of perceiving a current dominant shock type different from the consensus view on disagreement with the consensus current and future forecasts. This effect holds for forecasts that are within the cross-sectional interquartile range, whereas for forecasts outside this range, the effect is $\beta_2 + \beta_4$. Both time and individual fixed-effects are included in estimations. White cross-section cluster standard errors are reported in parentheses. $*$, $**$ and $***$ indicate rejection of the null hypothesis of zero parameter values at the 10%, 5% and 1% test level, respectively.

Table 7: Panel estimation results for the relationship between shock type disagreement with consensus and forecast performance from 1981Q4 to 2021Q4

Dependent Variable: $\left(A_t^{\pi} - F_{i,t+h|t}^{\pi}\right)^2$

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
β_2	0.305**	0.081	-0.034	-0.084	0.021
	(0.143)	(0.099)	(0.078)	(0.087)	(0.091)
β_4	0.747*	0.224	0.307	0.307	0.255
	(0.402)	(0.344)	(0.384)	(0.274)	(0.324)
$\beta_2+\beta_4$	1.052***	0.305	0.273	0.223	0.276
p-value ($H_0: \beta_2+\beta_4=0$)	*0.009*	*0.603*	*0.298*	*0.377*	*0.381*
Time fixed-effect	Yes	Yes	Yes	Yes	Yes
Individual fixed-effect	Yes	Yes	Yes	Yes	Yes
R^2	0.522	0.887	0.916	0.913	0.920
(Unbalanced) Observations	4367	4224	4192	4161	4130

Dependent Variable: $\left(A_t^{u} - F_{i,t+h|t}^{u}\right)^2$

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
β_2	0.034	0.194*	0.143	0.153	0.132
	(0.028)	(0.102)	(0.107)	(0.101)	(0.093)
β_4	-0.086	-0.428	-0.279	-0.208	-0.306
	(0.090)	(0.279)	(0.235)	(0.206)	(0.187)
$\beta_2+\beta_4$	-0.052	-0.234	-0.136	-0.055	-0.174
p-value ($H_0: \beta_2+\beta_4=0$)	*0.425*	*0.222*	*0.353*	*0.681*	*0.144*
Time fixed-effect	Yes	Yes	Yes	Yes	Yes
Individual fixed-effect	Yes	Yes	Yes	Yes	Yes
R^2	0.527	0.792	0.862	0.897	0.917
(Unbalanced) Observations	4387	4258	4225	4193	4162

Dependent Variable: $\left(A_t^{y} - F_{i,t+h|t}^{y}\right)^2$

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
β_2	0.695	0.885	0.452*	0.480*	-0.135
	(0.431)	(1.702)	(0.242)	(0.272)	(0.264)
β_4	0.479	-2.231	-1.267	-1.134	-0.208
	(1.223)	(3.354)	(0.831)	(0.784)	(0.581)
$\beta_2+\beta_4$	1.174	-1.347	-0.815	-0.654	-0.343
p-value ($H_0: \beta_2+\beta_4=0$)	*0.298*	*0.445*	*0.274*	*0.340*	*0.553*
Time fixed-effect	Yes	Yes	Yes	Yes	Yes
Individual fixed-effect	Yes	Yes	Yes	Yes	Yes
R^2	0.648	0.819	0.993	0.990	0.993
(Unbalanced) Observations	4367	4220	4187	4156	4126

Notes: Estimates are for $\left(A_t^j - F_{i,t+h|t}^j\right)^2 = \beta_1 + \beta_2 S_{it} + \beta_3 EX_{it}^j + \beta_4\left(S_{it} \times EX_{it}^j\right) + \gamma_t + \alpha_i + \nu_{it}$ for inflation (π), unemployment rate (u) and real GDP growth (y). Estimated values of β_2 indicate the effect of perceiving the dominant type of prevailing shocks different from the consensus view on forecast performance. This disagreement effect is for the forecasts that are within the cross-sectional interquartile range. For the forecasts that are outside of the interquartile range, the disagreement effect is $\beta_2+\beta_4$. Both time fixed-effect and individual fixed-effect are included in estimations. White cross-section cluster standard errors are included in parentheses. $*$, $**$ and $***$ indicate rejection of the null hypothesis of zero parameter value at the 10%, 5% and 1% test level, respectively.

6. Conclusion

We have provided new evidence that professional forecasters are largely rational in direction of their forecast revisions, suggesting they generally understand the dominant types of prevailing shocks hitting the macroeconomy. We develop a novel measure of shock disagreement to capture the extent to which forecasters differ in their perceived classification of predominant macroeconomic shocks as being either aggregate demand or aggregate supply in nature. We show that disagreement over the nature of shocks declines during recessions even when disagreement over numerical forecast values rises, and is negatively correlated with widely used measures of macroeconomic uncertainty. We find that forecasters whose perceived shock type deviates from the consensus and who make extreme forecasts tend to be associated with larger deviations from numerical consensus forecasts, and that these forecasters perform worse in nowcasting inflation. These findings highlight the qualitative informational value embedded in disagreement over the dominant nature of shocks and its relevance for understanding the formation of expectations and forecast performance.

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Appendix A. Identification of shock sign and type

Given the directional changes we are able to identify the perceived sign of the dominant type of shock:

Table A.1: Identification of shock sign and type

Revisions	$+r^y_{i,t}$	$-r^y_{i,t}$	$+r^u_{i,t}$	$-r^u_{i,t}$
$+r^\pi_{i,t}$	+Demand	−Supply	−Supply	+Demand
$-r^\pi_{i,t}$	+Supply	−Demand	−Demand	+Supply

Figures A.1 and A.2 report the proportion of forecasters with different perceived dominant type of shock over the sample period.

Figure A.1: Proportions of forecasters whose perceived dominant type of shock is identified using inflation and GDP growth revisions as positive demand, negative demand, positive supply or negative supply from 1981Q4 to 2021Q4. Top panel replicates the demand/supply shock types in the paper, while the bottom panel shows further decompositions.

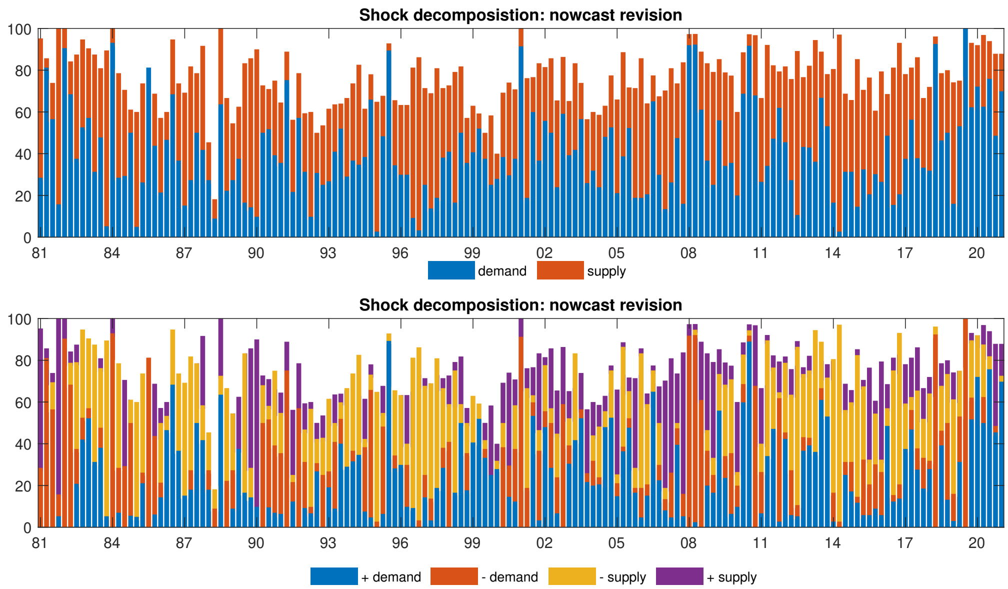

Figure A.2: Proportions of forecasters whose perceived dominant types of shock is identified using inflation and the unemployment rate revisions as positive demand, negative demand, positive supply or negative supply, from 1981Q4 to 2021Q4. Top panel replicates the demand/supply shock types in the paper, while the bottom panel shows further decompositions.

Appendix B. Disagreement over nature of shocks and uncertainty measures

Figures B.1 and B.2 show that our measures of disagreement over the nature of shocks are negatively correlated with popular measures of macroeconomic uncertainty.

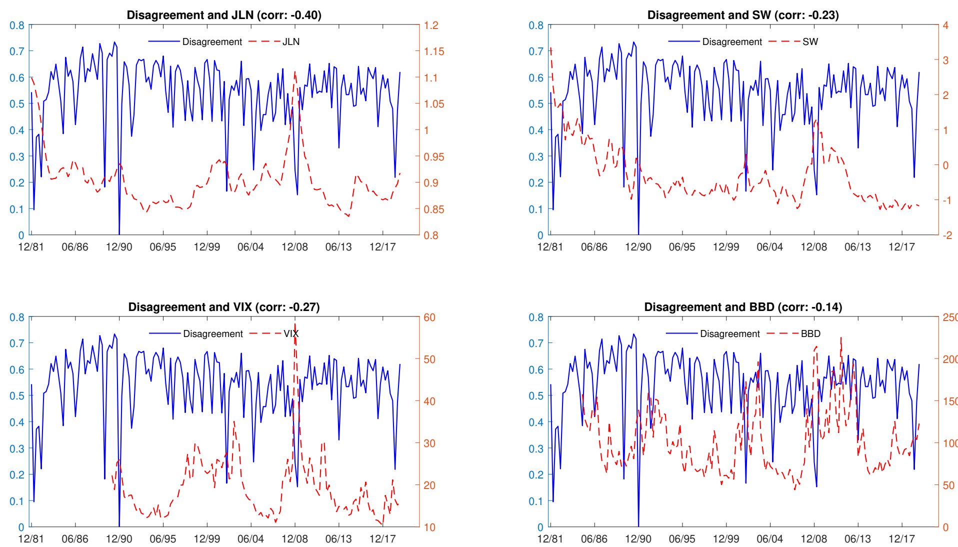

Figure B.1: Shock disagreement based on real GDP growth (left-axis) and macroeconomic uncertainty measures (right-axis). Uncertainty measures include the macroeconomic uncertainty indicator (JNL) of Jurado et al. (2015), the macroeconomic disagreement indicator (SW) by Sheen & Wang (2021), the VIX index and the economic policy uncertainty indictor (BBD) by Baker et al. (2016).

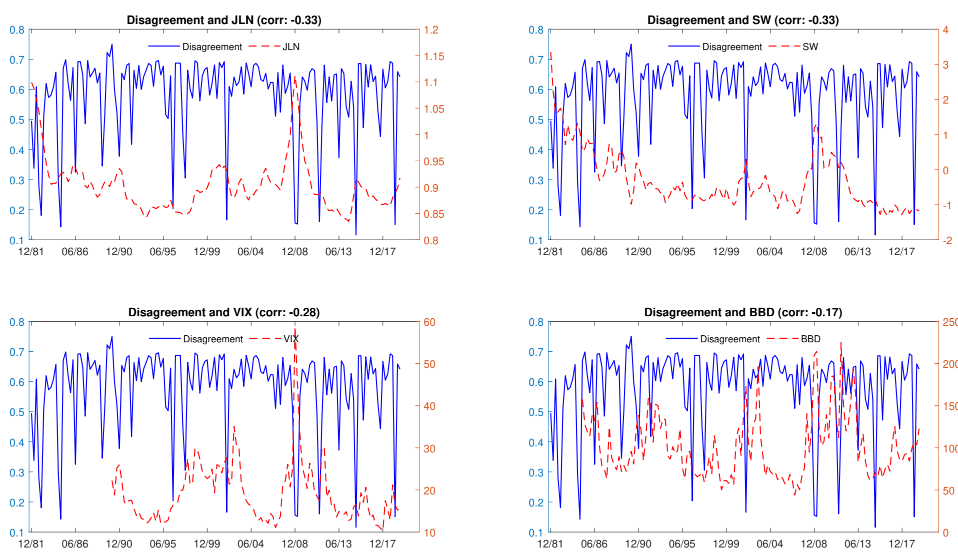

Figure B.2: Shock disagreement based on unemployment rate (left-axis) and macroeconomic uncertainty measures (right-axis). Uncertainty measures include the macroeconomic uncertainty indicator (JNL) of Jurado et al. (2015), the macroeconomic disagreement indicator (SW) by Sheen & Wang (2021),the VIX index and the economic policy uncertainty indictor (BBD) by Baker et al. (2016).

Appendix C. IQR and uncertainty measures

The time series presented in Figure C.1 reveal a moderately strong positive relationship between the interquartile range of current forecasts ($IQR^{\pi}_{t|t}$, $IQR^{y}_{t|t}$, and $IQR^{u}_{t|t}$) and the corresponding measures of economic uncertainty. Forecast disagreement tends to move with economic uncertainty in terms of long term pattern: when uncertainty escalates, disagreement about numerical forecast values tends to intensify; conversely, when uncertainty recedes, forecast disagreement typically declines.

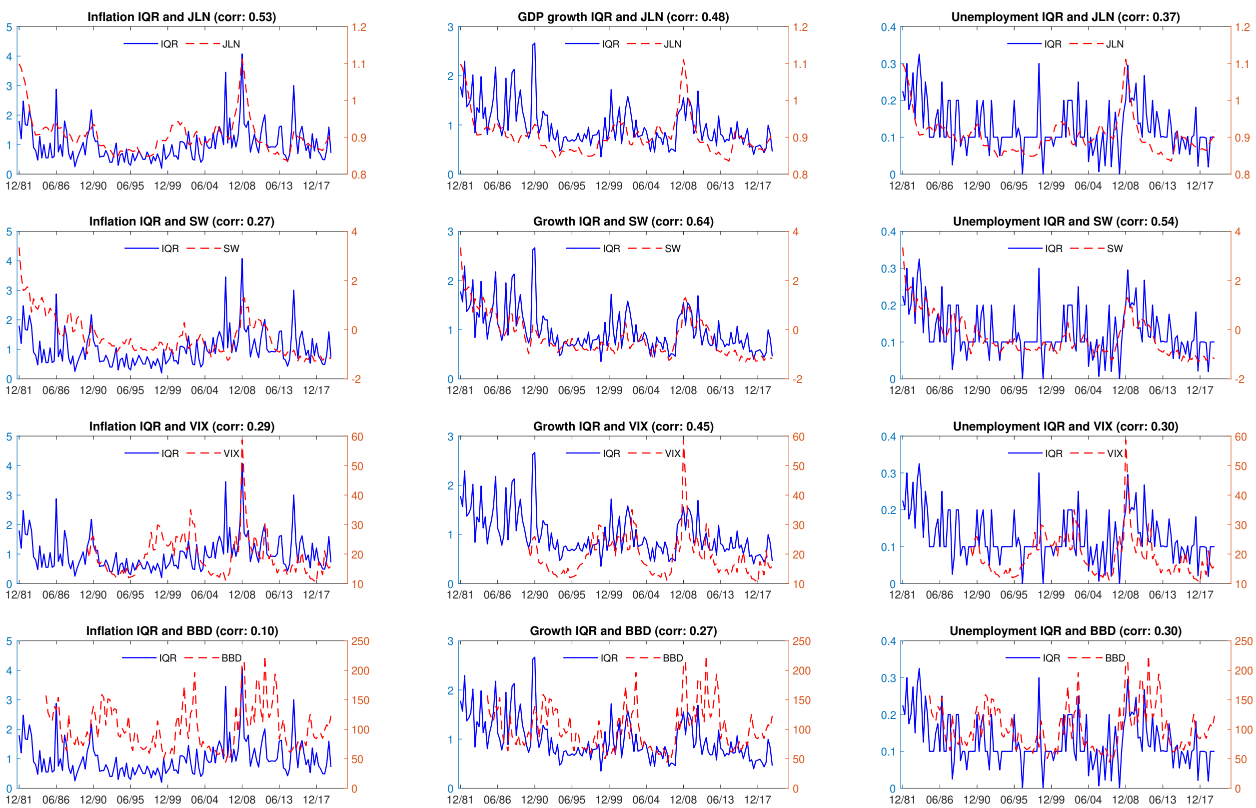

Figure C.1: Forecast disagreement (left-axis) and uncertainty measures (right-axis). Uncertainty measures include the macroeconomic uncertainty indicator (JNL) of Jurado et al. (2015), the macroeconomic disagreement indicator (SW) by Sheen & Wang (2021), the VIX index and the economic policy uncertainty indictor (BBD) by Baker et al. (2016).

Appendix D. Disagreement and industry classification

Since 1990Q2, each SPF survey records a broad industry classification for each forecaster depending on whether they work in a financial service provider such as investment banks, commercial banks and hedge funds, a non-financial service provider such as manufacturers, universities and consulting firms, or industry information is unknown.[4]

Out of these industries, it seems plausible that the financial service providers would be better informed in real-time on economic indicators compared to the others. We therefore generate a binary variable FIN_i for each forecaster i, where $FIN_i = 1$ if forecaster i works in a financial service provider and $FIN_i = 0$ otherwise. We also differentiate forecasters whose industry information is unknown using a binary variable UN_i where $UN_i = 1$ if no industry information and $UN_i = 0$ otherwise. We consider a panel regression for both shock identification strategies, given by

$$S_{it}^{\pi\&j} = \beta_0 + \beta_1 FIN_i + \gamma_t + \nu_{it},$$

where $j = y$ or u.

Table D.1: Estimation results of a panel regression $S_{it} = \beta_0 + \beta_1 FIN_i + \gamma_t + \nu_{it}$ for shocks types identified by bivariate forecast revisions for either inflation and real GDP growth ($\pi\&y$) or inflation and unemployment rate ($\pi\&u$) from 1992Q2 too 2021Q4

	$S_{it}^{\pi\&y}$	$S_{it}^{\pi\&u}$
Intercept	$0.428(0.008)^{***}$	$0.458(0.016)^{***}$
FIN_i	$-0.040(0.016)^{**}$	$-0.016(0.054)$
Time fixed-effect	Yes	Yes
(Unbalanced) No. Obs	3775	3752
R^2	0.070	0.092

Note: White cross-section cluster standard errors are reported in parentheses. $**$ and $***$ indicate rejection of the null hypothesis of zero parameter value at the 5% and 1% test level, respectively. The estimation is based on a subsample from 1992Q2 to 2021Q4 since the SPF industry classification of individual forecasters only becomes available from 1992Q2.

Table D.1 reports the estimation results for these regressions. We observe a negative and significant coefficient of FIN_i in the $S_{it}^{\pi\&y}$ column in Table D.1. This suggests that forecasters

[4] A detailed list of service provides under each classification code is provided in the SPF documentation at https://www.philadelphiafed.org/-/media/FRBP/Assets/Surveys-And-Data/survey-of-professional-forecasters/spf-documentation.pdf?sc_lang=en&hash=8408A4F1BF351A3C268B40F6BC7B95AA

from financial sector tend to agree more with the consensus view of the dominant type of shock when shocks are identified based on current forecast revisions for inflation and real GDP growth rates.