Agreed and Disagreed Uncertainty*

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Abstract

We formalize two novel concepts of uncertainty in a model of imperfect and dispersed information: *agreed* and *disagreed* uncertainty. We show that consumer disagreement significantly shapes the effect of uncertainty on economic activity. Episodes of elevated uncertainty accompanied by high consumer disagreement (*disagreed uncertainty*) do not exert negative effects on economic activity. In contrast, episodes of high uncertainty with low consumer disagreement (*agreed uncertainty*) lead to substantial economic contractions. These results challenge the conventional view that uncertainty invariably triggers recessions. We establish these findings using both time-series and micro-survey panel methods.

Keywords: Uncertainty, information frictions, disagreement, Bayesian vector autoregression (VAR), sign restrictions.

JEL Classification: E20, E32, E43, E52.

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1 Introduction

Since the seminal work of Bloom (2009), extensive research has shown that uncertainty exerts significant recessionary effects on economic activity.[1] However, while recessions almost always coincide with heightened uncertainty, prolonged uncertainty does not always lead to recessions. Figure 1 plots monthly indicators (dark solid line) for macroeconomic and financial uncertainty (top and bottom panels, respectively) from Jurado et al. (2015), alongside a widely monitored economic activity indicator, namely real industrial production (IP, gray dashed line). Shaded areas indicate periods of elevated uncertainty, differentiating between negative IP growth (gray areas) and positive IP growth (hatched areas). The top (bottom) panel shows that elevated macroeconomic (financial) uncertainty with negative IP growth occurs in 14.2% (17.3%) of the sample, while elevated uncertainty with positive IP growth occurs in 18.7% (31.3%) of the sample. This simple accounting exercise highlights that heightened uncertainty is more often associated with episodes of non-contractionary real activity than recessions, challenging the conventional view that uncertainty is predominantly a recessionary phenomenon.[2]

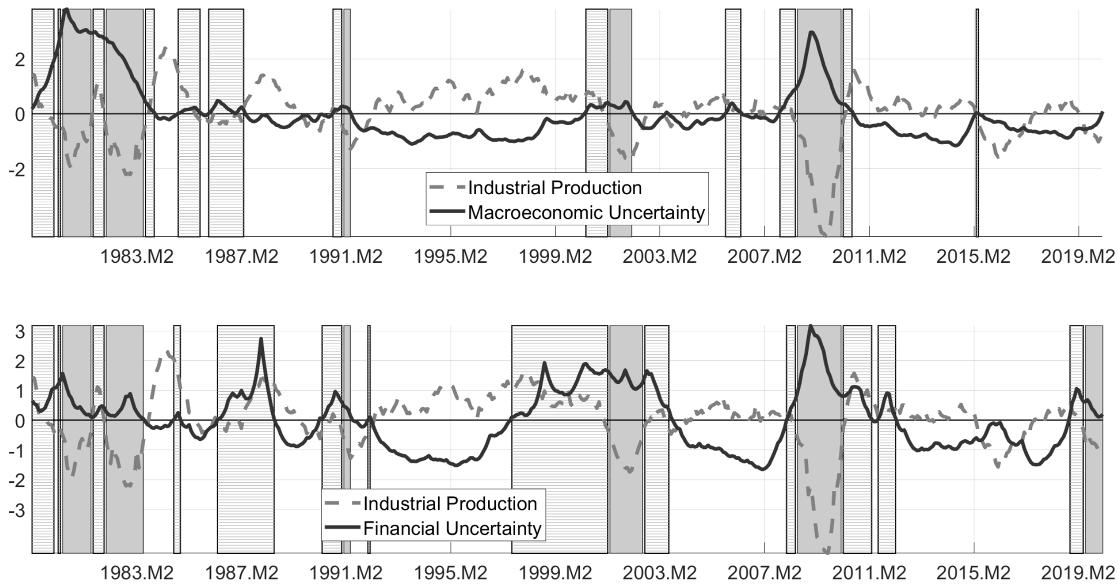

Figure 1: Uncertainty indicators and the growth rate of industrial production. Annual growth rate of industrial production (IP, gray-dashed line) and the index of macroeconomic (top panel) and financial (bottom panel) uncertainty (dark-solid line) from Jurado et al. (2015) normalized to have zero mean and unitary variance, for the period 1979.M1-2019.M12. Patched areas show periods when uncertainty was above its sample mean, differentiated between negative IP growth (gray-shaded area) and positive IP growth (horizontally-hatched area). Unshaded/unhatched areas show periods with uncertainty below the sample mean.

[1]See Bloom (2014) for a review.

[2]Distinctive episodes of elevated uncertainty with positive IP growth include the stock market crash of October 1987 and the September 1998 LTCM collapse, neither of which generated a broad-based contraction in real activity.

This paper argues that the dispersion in consumer views about the state of the economy (hereafter, consumer disagreement) conveys important information about the systematic effect of uncertainty on economic activity. By developing a new index of consumer disagreement from survey data, we show that elevated uncertainty during periods of high consumer agreement (*agreed uncertainty*) has the standard depressing effects on activity indicators documented in numerous studies (e.g., Bloom, 2009; Jurado et al., 2015; Caldara et al., 2016). By contrast, elevated uncertainty during periods of high consumer disagreement (*disagreed uncertainty*) has no discernible effect on economic activity.

The starting point of our analysis is new evidence on the prevalence of information dispersion and ensuing disagreement, captured by our new index measuring the disparity in consumers' opinions about economic conditions, constructed from the Michigan Survey of Consumers. We document several new findings showing that consumer disagreement is widespread, procyclical, and inversely correlated with economic uncertainty, resulting in a broader dispersion of opinions during economic expansions and greater consensus during downturns.

Using our newly constructed index of consumer disagreement, we begin by presenting reduced-form, non-causal evidence on the observed relationship between uncertainty and disagreement. We show that the comovement between uncertainty and real activity (measured by the growth of real industrial production) is non-negative when consumer disagreement is high. Simple regressions suggest that disagreement significantly attenuates the contractionary effects of uncertainty, and a simple Vector Autoregressive (VAR) model, identified using Cholesky ordering, indicates an insignificant response of real activity to uncertainty when disagreement is high. Building on this preliminary evidence, we develop the central results of our study.

We formalize the concepts of agreed and disagreed uncertainty in a simple model with imperfect and dispersed information.[3] In our model, agents receive idiosyncratic signals about a fundamental shock and form forecasts about its path by solving a signal extraction problem. Uncertainty is defined as the conditional volatility of the forecast error (the standard measure of uncertainty in Jurado et al., 2015 and several other studies). Disagreement arises from the difference in the mass of agents receiving a good signal versus those receiving a bad signal. An innovation in the volatility of fundamental disturbances increases uncertainty and reduces disagreement (agreed uncertainty). An innovation in the volatility of idiosyncratic disturbances increases both uncertainty and disagreement (disagreed uncertainty). These distinct comovements are used as sign restrictions in a small-scale Bayesian VAR model to identify the dynamic effects of agreed and disagreed

[3] Mankiw and Reis (2002), Woodford (2003), Sims (2003), Mackowiak and Wiederholt (2009), Mankiw et al. (2004), and Okuda et al. (2021) argue in favour of information frictions manifested in models of sticky and noisy information. Coibion and Gorodnichenko (2012, 2015) provide strong empirical evidence for information rigidities in agents' expectation formation, with most findings favoring noisy information models; see also Coibion et al. (2018) for a detailed review of these concepts.

uncertainty shocks in U.S. data from 1979 to 2019.

The key empirical results obtained from the VAR model can be summarized as follows. Agreed uncertainty shocks, characterized by a simultaneous decline in disagreement and an increase in uncertainty indicators, lead to substantial and prolonged declines in real activity indicators. These results are consistent with the well-established negative impact of economic uncertainty on real activity, as reported in seminal studies by Bloom (2009), Jurado et al. (2015), Bloom et al. (2018), and Ludvigson et al. (2021). Specifically, a positive innovation in agreed uncertainty is associated with significant and persistent declines in industrial production and employment.

In contrast, disagreed uncertainty shocks, identified by simultaneous increases in both disagreement and uncertainty indicators, exhibit qualitatively different dynamic effects. Although these shocks generate a strong, significant, and persistent rise in uncertainty–similar to agreed uncertainty shocks–economic activity indicators do not show any contractionary effects. A positive innovation in disagreed uncertainty generates a non-contractionary response of industrial production and employment, which is initially positive but statistically insignificant throughout the forecast horizon. The differing dynamic effects of agreed and disagreed uncertainty shocks are robust across various measures of consumer disagreement and uncertainty. These results hold across VAR models incorporating a broader range of macroeconomic activity indicators, as well as models that differentiate consumer disagreement by education and age cohorts.

Historical decompositions from our identified VAR model confirm the significance of disagreed uncertainty and provide a framework for assessing the relative importance of agreed versus disagreed uncertainty shocks in influencing economic activity over the sample period. Consistent with our theoretical predictions, disagreed (agreed) uncertainty shocks emerge as the primary drivers of heightened uncertainty during the majority of months with positive (negative) industrial production growth. The aforementioned decomposition reveals a striking fact: in 45% of the instances in the sample, heightened uncertainty –dominated by disagreed uncertainty shocks– bore no adverse impact on the economy.

In addition to the time-series evidence, we provide complementary evidence based on micro-survey data on consumer disagreement about inflation forecasts from the New York Fed Survey of Consumer Expectations. In this distinct empirical approach, we exploit: (i) the exogenous surge in uncertainty triggered by the Russian invasion of Ukraine and (ii) the release of information about future economic conditions contained in the first Federal Reserve FOMC statement several days after this geopolitical event. The daily collection of survey responses allows us to classify consumers into two distinct groups based on their exposure to Fed information: those who responded after the release of the FOMC statement (information-treated group) and those who responded before the release (control group). Exploiting the variation in inflation forecast disagreement between these two groups, we estimate the impact of uncertainty on household spending plans using panel regression analysis. The estimates indicate that spending plans in the information-treated group, which exhibited lower inflation forecast disagreement, contracted significantly more than in the control group, which lacked exposure to the policy information and showed no reduction in disagreement. In sum, our findings demonstrate that the contractionary impact of uncertainty on spending plans is stronger and of substantially greater magnitude for consumers with lower inflation forecast disagreement compared to the baseline impact effect, corroborating the evidence obtained from time-series methods.

Our study contributes to the growing literature on the macroeconomic implications of uncertainty and, to the best of our knowledge, it is the first to establish that consumer disagreement significantly shapes the macroeconomic effects of uncertainty. A large strand of the literature, including Bloom (2009), Bachmann et al. (2013), Jurado et al. (2015), Baker et al. (2016), Bloom et al. (2018), and Ludvigson et al. (2021), demonstrates–using a variety of macro and micro measures–the contractionary effect of uncertainty on economic activity. Our study adds a new dimension of disagreed uncertainty, which is benign for economic activity, highlighting that 45% of heightened U.S. uncertainty episodes are non-contractionary.[4]

Recent work also suggests that uncertainty may not have, as previously thought, adverse economic effects. Berger et al. (2020) separate contemporaneous shocks in realized stock market volatility from news shocks, which they interpret as forward-looking uncertainty, and find that these are benign for economic activity. In a similar vein, Cascaldi-Garcia and Galvao (2021) separate a "good financial uncertainty" component from technological news shocks, implying a positive impact of uncertainty on future productivity. Unlike these approaches, which link news shocks and uncertainty, our study emphasizes the role of dispersion in consumer beliefs in shaping the response of economic activity following uncertainty innovations.[5]

The remainder of the paper is organized as follows: Section 2 introduces the measure of

[4]Caldara et al. (2016) and Alessandri and Mumtaz (2019) stress the interaction between financial conditions and uncertainty, providing evidence that the negative impact of uncertainty shocks is amplified when financial conditions worsen. Fernàndez-Villaverde et al. (2011), Fernàndez-Villaverde et al. (2015), Fernàndez-Villaverde et al. (2025, 2021), Fernàndez-Villaverde et al. (2023), Mumtaz and Zanetti (2013), Born and Pfeifer (2014), Basu and Bundick (2017), Cascaldi-Garcia et al. (2022), Melosi et al. (2024), and several others show that uncertainty arising from different sources–such as fiscal and monetary policy, borrowing costs, and future perceived uncertainty–results in reduced economic activity. Caggiano et al. (2014), Leduc and Liu (2016), Theodoridis and Zanetti (2016), Schaal (2017) emphasize the contractionary effect of uncertainty on unemployment.

[5]Segal et al. (2015) distinguish between bad and good uncertainty, and their good uncertainty measure is benign for production and consumption. Using measures of low and high uncertainty from quantile factor models, Korobilis and Schröder (2022) show that only high-uncertainty shocks cause a significant fall in industrial production. Aastveit et al. (2017) shows that in periods of high uncertainty, the effects of monetary policy on output are dampened. Ghironi and Ozhan (2020) show that the impact of uncertainty in open economies with foreign direct investment depends on the design of monetary policy. Bijsterbosch and Guerin (2013) shows that only high uncertainty is contractionary. Finally, a different literature studies the cyclical effects of *first-moment* noise shocks (e.g., Lorenzoni, 2009; Blanchard et al., 2013; Forni et al., 2017). Our study contributes to this literature by identifying potential cyclical effects of second-moment idiosyncratic (noise) shocks.

consumer disagreement. Section 3 presents preliminary reduced-form, non-causal evidence on the observed relationship between uncertainty and disagreement. Section 4 develops a stylized model to formalize the new concepts of uncertainty. Section 5 uses predictions from the model to disentangle the dynamic effects of agreed and disagreed uncertainty. Section 6 utilizes micro-survey data to provide additional evidence on the effect of agreed and disagreed uncertainty on consumer spending plans. Section 7 concludes the paper. The appendices provide robustness checks of the empirical results under several alternative modeling assumptions and data specifications.

2 Measuring consumer disagreement

In this section, we construct a new index of consumer disagreement using the University of Michigan Survey of Consumers. We develop a parsimonious index that encapsulates the cross-sectional dispersion of consumer views from different survey questions, revealing consumers' information and beliefs about current and future economic conditions. We then study the cyclical properties of the disagreement index and focus on the link with economic activity and alternative measures of uncertainty.

2.1 Consumer survey data

The Michigan Survey of Consumers (hereafter MSC) is administered by the Survey Research Center at the University of Michigan. Each month, it conducts a minimum of 500 interviews, during which consumers answer a questionnaire containing 28 core questions and several subquestions. Survey responses are aggregated over respondents (consumers) to produce approximately 45 monthly and quarterly categorical time series.[6] To formulate our index, we select questions that capture consumers' views on current and future economic conditions, summarized in Table 1.

Table 1: Questions from the Michigan Survey of Consumers

Question	Mnemonic	Topic
Q23	NEWS	News Heard of Recent Changes in Business Conditions
Q25	BAGO	Current Business Conditions Compared with a Year Ago
Q26	BEXP	Expected Change in Business Conditions in a Year
Q28	BUS12	Business Conditions Expected During the Next Year
Q29	BUS5	Business Conditions Expected During the Next 5 Years

Consumer responses to the survey questions consist of three qualitative categories

[6] The samples for the Surveys of Consumers are statistically designed to be representative of all American households. For a detailed description of the survey, see: https://data.sca.isr.umich.edu/survey-info.php.

("better/about the same/worse"), and the associated time series measures the proportion of respondents in each category.[7] Our benchmark measure is an index of *tail disagreement*, which reflects disagreement between the two polar categories in the distribution of responses. Specifically, the *tail disagreement* index extracts disagreement from the "better/worse" (or "good time/bad time," or "favorable/unfavorable") responses. Formally, the definition of the disagreement index is:

$$T_t^{(j)} = 1 - \frac{|b_t^{(j)} - w_t^{(j)}|}{100}, \tag{1}$$

where $j \in$ {NEWS, BAGO, BEXP, BUS12, BUS5} indexes each of the five survey questions, $b_t^{(j)}$ is the percentage of respondents in question j with a positive/optimistic answer, and $w_t^{(j)}$ is the percentage of respondents with a negative/pessimistic answer. The disagreement index $T_t^{(j)}$ takes values between 0 and 1. A value equal to zero, which occurs if either $b_t^{(j)}$ or $w_t^{(j)}$ is equal to 100, indicates all respondents have the same opinion or view about the current or future economic outlook, and therefore no disagreement. Conversely, a value equal to 1 indicates that consumers are evenly split between the two polar responses, reflecting sharp differences in opinions and consequently maximal disagreement.

This indicator is intuitive but ignores information from the middle category of responses (e.g., "no mention," "same"). In Appendix D, we compute Shannon's entropy (Shannon, 1948) as a measure of disagreement, which considers both the polar and middle category responses.[8] We show that results are robust to this consideration. It is important to stress that the qualitative approach in reporting views suggests our measure of consumer disagreement refers to what we can loosely call "directional" disagreement. Thus, our concept of disagreement is different from disagreement among professional forecasters.[9] In other words, our index does not convey information about the intensity of the responses (e.g., how much better relative to how much worse). The index also cannot capture disagreement within the proportion of consumers that report better (or worse) economic prospects.

2.2 Construction of the consumer disagreement index

We use monthly data spanning the period 1978M1 to 2019M12 and derive distinct measures of disagreement by applying the formula in equation (1) to each of the five survey questions. We denote the singular disagreement measures related to each survey question in Table 1

[7] Depending on the question, these answers can also take the form "favorable/no mention/unfavorable," "good time/uncertain/bad time," or "more/about the same/less."

[8] Entropy can be interpreted as a measure of uncertainty: consumers are more uncertain about economic conditions when the middle category has a non-zero chance of occurring.

[9] The study of disagreement for professional forecasters is certainly a fruitful extension for future research.

by T^{NEWS}, T^{BAGO}, T^{BEXP}, T^{BUS12}, and T^{BUS5}. The measures of disagreement based on the mnemonics "NEWS" and "BAGO" in Table 1 (i.e., T^{NEWS} and T^{BAGO}, respectively) refer to *current* business conditions and thus directly relate to the information that consumers receive and process about past and present economic conditions.

To develop a parsimonious indicator of consumer disagreement, we summarize the information in the five different measures by formulating a single latent index using principal component analysis. In line with the literature on macroeconomic diffusion indexes (see, for example, Stock and Watson, 2002), our latent index is the first principal component of the five individual disagreement series. The first principal component is a weighted average of all five series, where the weights (loadings) are such that the latent index maximizes the variance explained for each series.[10] We refer to this latent index as DISAG, and use it as the benchmark measure of consumer disagreement for the rest of the analysis.

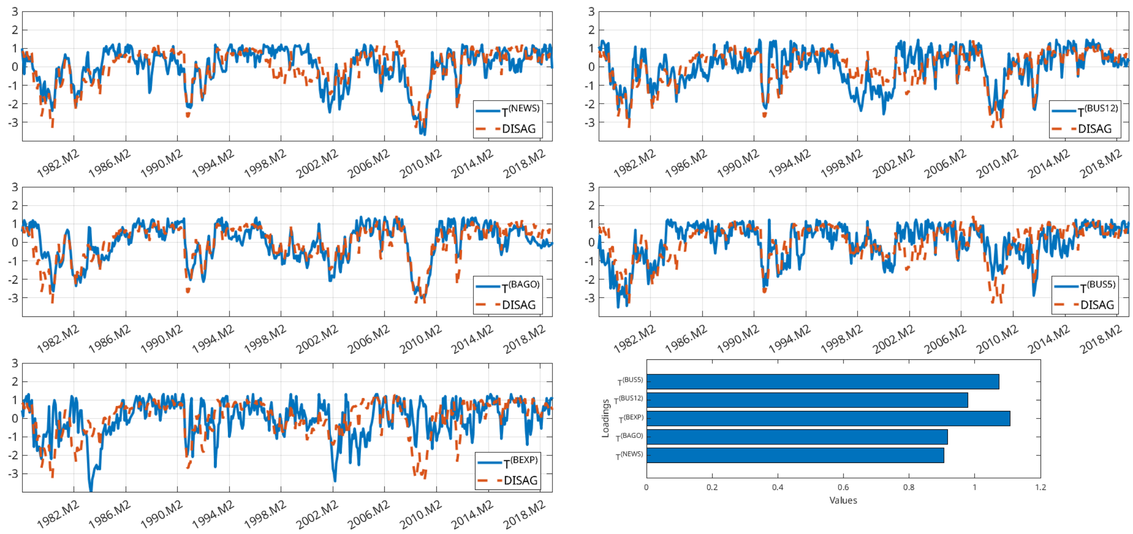

Figure 2: Individual measures of disagreement versus their weighted average (factor). The top four panels and the bottom-left panel display the time series of individual tail disagreement measures derived from the Michigan survey questions (solid line), alongside the aggregate index of consumer disagreement (DISAG, dashed line). For comparability, all series are standardized to have a mean of zero and a variance of one. The bottom-right panel presents the estimated weights (loadings) of each individual series on the aggregate disagreement index (principal component).

The top four panels and the bottom-left panel of Figure 2 show the estimate of the disagreement index (DISAG) against the individual measures of disagreement. A first finding is the large and significant time variation in the disagreement index that also characterizes the individual disagreement series.[11] The figure shows that the correlation

[10]To ensure that the first principal component describes the direction of maximum variance, we standardize the individual disagreement measures (and the index) to have a mean equal to zero and a variance equal to 1. This transformation does not affect the informational content of each series; rather, it affects the scale.

[11]The variability in consumer disagreement remains broadly unchanged across the full sample period, without displaying a reduction in volatility during the Great Moderation period of 1984-2007 that characterizes several macroeconomic activity indicators. See Liu et al. (2019) for a discussion of the

of the disagreement index with each individual series is high. The bottom-right panel of Figure 2 shows the loadings of each series on the principal component. The values in the figure are the weights with which each individual series contributes to the estimate of our latent disagreement index. These values show that the DISAG index is evenly and strongly correlated with the individual disagreement indexes NEWS, BAGO, BUS12, and BUS5, and it is less strongly correlated with the BEXP measure of disagreement.

2.3 Diagnostics of the disagreement index

Having constructed our new index of disagreement, we study its properties and compare it to other macroeconomic, financial and uncertainty indicators –they are described in Appendix A. Our benchmark measure of uncertainty (UNC) is the uncertainty index developed by Jurado et al. (2015).

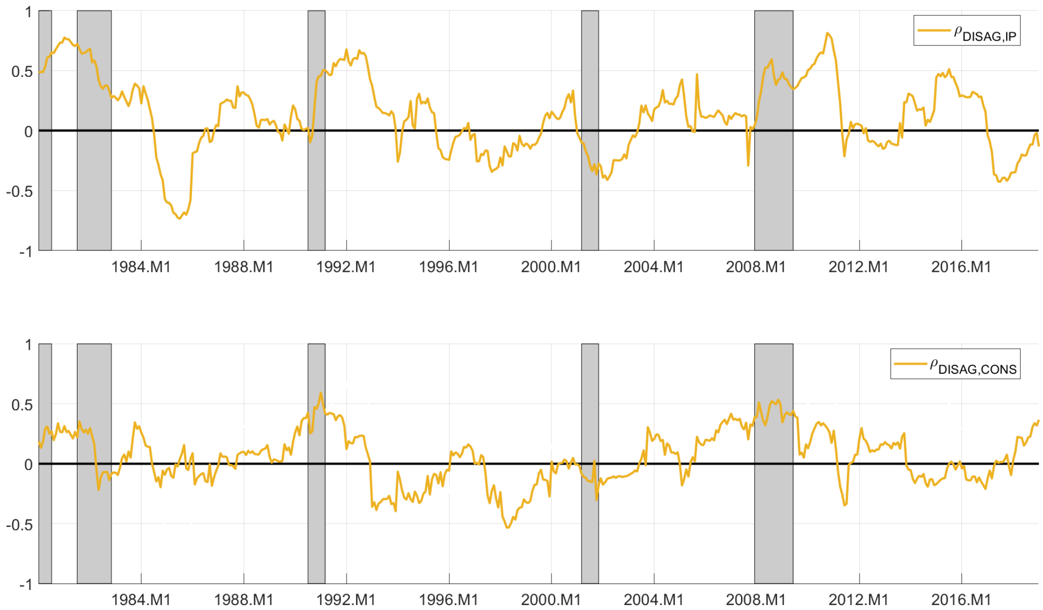

Figure 3: Time-varying correlations of DISAG with industrial production (IP) and real personal consumption (CONS) growth. These are calculated by estimating sample correlations in rolling windows of 24 months. The correlation at time t is computed over the period from $t-23$ to t, for all $t = 24, ..., T$. Shaded areas denote NBER-dated U.S. recessions.

We examine the cyclical properties of the disagreement index (DISAG) by analyzing its comovement with two key measures of economic activity: the monthly growth rates of industrial production (IP), and real personal consumption expenditure. Over the entire sample, DISAG shows a mild correlation with both industrial production growth (0.31) and real personal consumption growth (0.14). However, these correlations vary significantly over time. Figure 3 illustrates the time-varying correlations between DISAG

changes in time-series properties of macroeconomic variables since the 1960s.

and industrial production (top panel) and consumption growth (bottom panel). The estimates are based on sample correlations using a 24-month rolling window. These time-varying correlations range over the sample period from -0.74 to 0.85 for industrial production growth and -0.54 to 0.60 for consumption growth, highlighting the substantial fluctuation in the relationship between DISAG and these economic indicators.[12]

We next compare the disagreement index with empirical measures of uncertainty and measures of dispersion derived from business surveys. The top panel of Figure 4 displays our disagreement index (solid line) together with the Jurado et al. (2015) measure of macroeconomic uncertainty obtained from a 12-month forecast horizon and the Baker et al. (2016) economic policy uncertainty (JLN12 and EPU in dotted and dashed line, respectively). The JLN12 uncertainty indicator is highly countercyclical and exhibits a strong negative comovement with our index of disagreement with a contemporaneous correlation coefficient of -0.62. The EPU indicator, capturing a different dimension of uncertainty related to political risk, is also negatively –but not as strongly– correlated with our disagreement indicator with a correlation coefficient equal to -0.26.

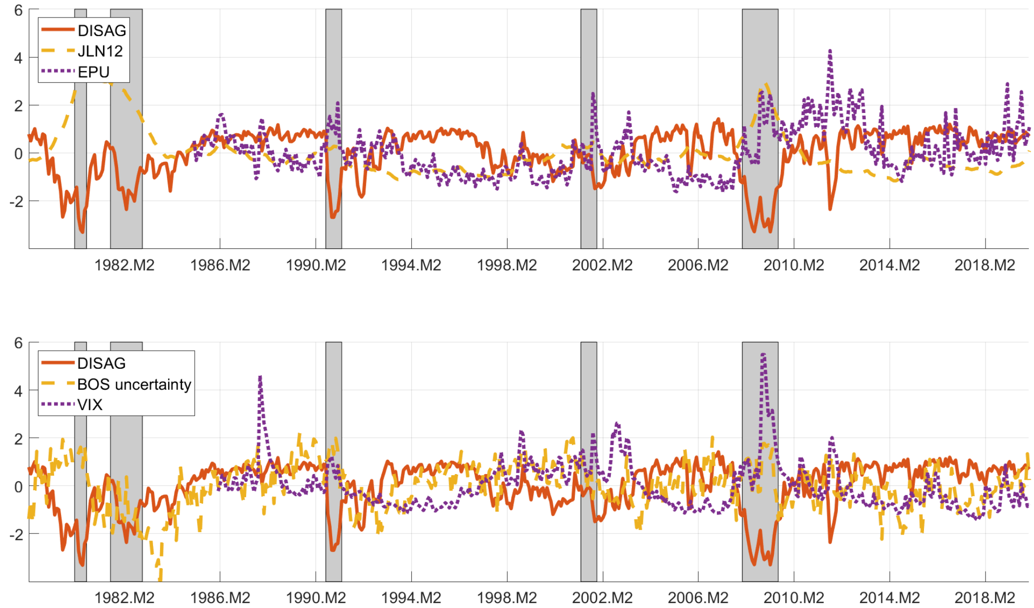

Figure 4: Index of consumer disagreement and uncertainty indicators. *Notes*: The top panel shows: consumer disagreement (DISAG) (solid red line) against the 12-month macroeconomic (JLN12) uncertainty indicator from Jurado et al. (2015) and the Economic Policy Uncertainty (EPU) constructed by Baker et al. (2016). The bottom panel shows: DISAG (solid red line) against the Business Forecast Dispersion Index (BOS) from Bachmann et al. (2013) (updated to 2019 by the authors) and stock market volatility (CBOE S&P 100 volatility index (VIX)). The series are standardized to have mean zero and unitary variance. Shaded areas denote NBER-dated U.S. recessions.

The bottom panel of Figure 4 compares our disagreement index with the business-

[12]The DISAG index has a skewness value of -1.23 and kurtosis value of 3.98.

level uncertainty index from the Philadelphia Fed Business Outlook Survey (BOS) that encapsulates the cross-sectional-forecast dispersion about six-month-ahead business activity in the manufacturing sector. Bachmann et al. (2013) shows that this index is a good proxy for uncertainty. The correlation of our index with the business dispersion index exhibits a negative yet weak correlation equal to -0.1.[13] The figure also compares our index with the CBOE S&P 100 volatility index (VIX) measure, the latter being used as a measure of uncertainty in many previous studies. VIX exhibits strong negative comovement with our disagreement index, with a correlation coefficient equal to -0.55. The key finding from these comparisons is the negative comovement of the different uncertainty indicators with consumer disagreement. In sum, consumer disagreement has fundamentally different cyclical properties compared to indicators of business-level uncertainty, stock market volatility, or uncertainty indicators from forecasts of financial and macroeconomic indicators and economic policy uncertainty.[14]

3 Preliminary reduced-form evidence

In this section, we provide preliminary evidence on the relationhip between economic activity, uncertainty and consumer disagreement.

First, we examine the comovement of industrial production and uncertainty during periods of elevated uncertainty and high disagreement with respect to the remaining periods in the sample. This simple approach enables us to identify, if any, systematic differences in those comovements by splitting the sample into periods of high and low disagreement. We refer to episodes of high disagreement and elevated uncertainty as disagreed uncertainty. Specifically, we define the sample of disagreed uncertainty as the monthly observations for which disagreement (DISAG) and uncertainty (UNC) indexes (12-month-ahead macroeconomic uncertainty from Jurado et al., 2015) are above their respective median values; 86 months in the sample correspond to jointly elevated uncertainty and high disagreement, while the remaining 429 months correspond to months with either elevated uncertainty and low disagreement or low uncertainty (with either high or low disagreement).[15]

Figure 5 shows the scatterplot of uncertainty and the monthly growth rate of industrial

[13]The survey question in the FED BOS is: *General Business Conditions: What is your evaluation of the level of general business activity six months from now vs. [CURRENT MONTH]: decrease, no change, increase?* To preserve comparability, we compute the BOS forecast dispersion index identically to Bachmann et al. (2013).

[14]In Appendix A, we report the cross-correlations (12 leads and lags) of consumer disagreement with uncertainty indicators and several macroeconomic indicators and show, consistent with our findings above, that disagreement is negatively correlated with uncertainty measures and is weakly correlated with macroeconomic indicators.

[15]Approximately 90% of the disagreed uncertainty sample defined above overlaps with the horizontally hatched gray area in the top panel of Figure 1 in the Introduction.

production (IP) with a fitted regression line (solid line) and 95% confidence intervals (dashed lines) for the disagreed uncertainty sample (left panel) and the remaining sample (right panel). The correlation between uncertainty and IP growth in the disagreed uncertainty sample is not significantly different from zero, while this correlation is negative and significant in the remainder of the sample, providing *prima facie* evidence of systematically different comovements of uncertainty and economic activity when disagreement is high compared to when it is low. This initial reduced-form result suggests that the contractionary effect of uncertainty on economic activity is pronounced during periods of high uncertainty combined with low disagreement but is absent when disagreement is high.

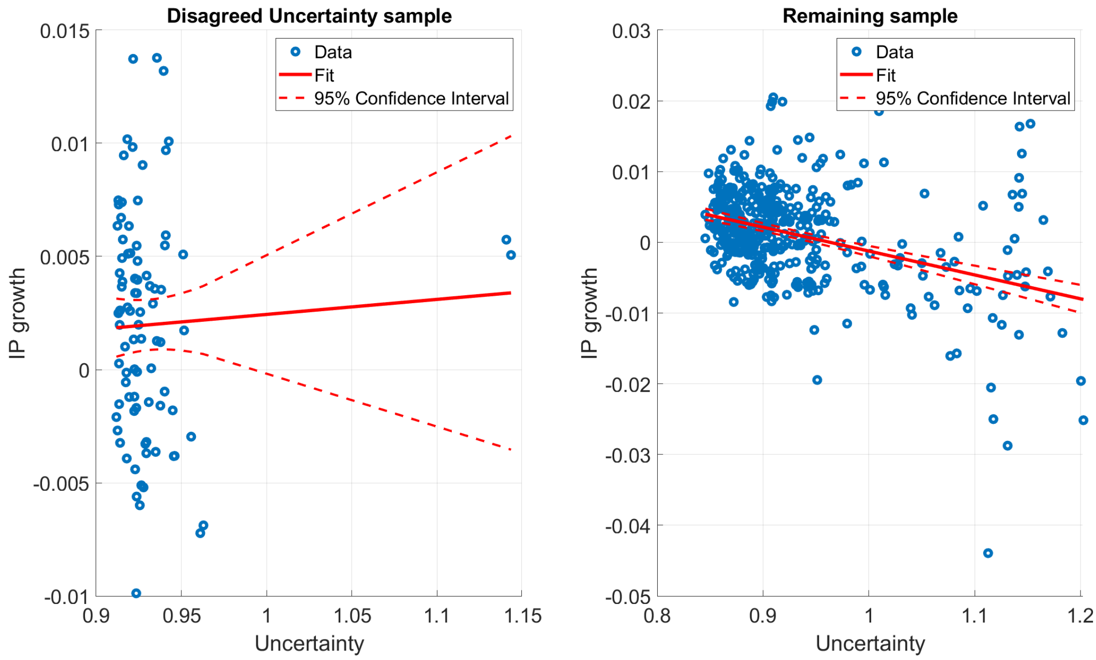

Figure 5: Uncertainty and the growth rate of industrial production. Scatterplot of uncertainty versus the growth rate of industrial production (IP), overlaid with a regression line (solid) and 95% confidence intervals (dashed). The left panel highlights periods where both uncertainty and disagreement are above their sample medians. The right panel includes periods with high uncertainty but low disagreement, as well as periods with low uncertainty regardless of disagreement levels.

Next, we examine the relationship between uncertainty and recessions using the following regression model:

$$D_t = \alpha + \beta_1 DISAG_t + \beta_2 UNC_t + \beta_3 DISAG_t \times UNC_t + \gamma Z_t + \varepsilon_t, \quad (2)$$

where D_t is a binary variable equal to one during NBER-dated recessions and zero otherwise, α is a constant term, $DISAG_t$ is our disagreement index, UNC_t is the uncertainty indicator as explained above, and $DISAG_t \times UNC_t$ is an interaction term intended to capture the joint effect of high uncertainty and high disagreement. The vector Z_t includes various sets of control variables. The coefficient of primary interest, β_3, reflects the interaction effect of uncertainty and disagreement on recessions. If uncertainty associated with high disagreement fails to have a recessionary impact, we expect β_3 to be either negative or zero. To simplify the interpretation of coefficients, we employ a linear probability model. Table 2 presents the estimation results for alternative specifications with different sets of controls.

Table 2: Uncertainty, disagreement and recessions

	Dependent variable: Recession, D_t			
	(1)	(2)	(3)	(4)
Constant	0.1218***	0.0910***	0.1226***	0.162***
	(0.0214)	(0.0287)	(0.0304)	(0.0273)
UNC_t	0.1242***	0.0822*	0.0759*	0.0043
	(0.0426)	(0.0472)	(0.0433)	(0.0515)
$DISAG_t$	−0.1259***	−0.1064***	−0.0984***	−0.0965***
	(0.0357)	(0.0358)	(0.0324)	(0.0329)
$UNC_t \times DISAG_t$		−0.0498***	−0.0319**	−0.0706***
		(0.0135)	(0.0135)	(0.0262)
IP_{t-1} growth			−7.9475***	
			(2.2458)	
IP_{t-2} growth			−5.8262***	
			(2.1054)	
Multiple controls	No	No	No	Yes(†)
Observations	502	502	502	502
$\overline{R}^2$	0.47	0.50	0.54	0.66
BIC	−0.61	−23.48	−50.28	−46.70

Notes: Standard errors in parentheses are heteroskedastic and autocorrelation consistent. The table shows the effects of disagreement (DISAG), uncertainty (UNC), and their interaction (product of UNC and DISAG). Uncertainty is the 12-month-ahead macroeconomic uncertainty from Jurado et al. (2015). To reduce multicollinearity and improve interpretability, both uncertainty and disagreement are standardized to have a mean of zero and a standard deviation of one. The interaction term is then computed using these standardized variables.
(†): The regression in column (4) is based on a two-step, post-Lasso procedure. First, we run regularized least squares (Lasso with 10-fold cross validation) on zero to 12 lags of a large set of predictors (UNC, DISAG, UNC*DISAG, IP, INF, FFR, HOURS, SP500) and we select those predictors whose coefficients were not penalized to be zero. Next, we run OLS with robust standard errors on the selected predictors.
Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In the benchmark specification (1), we estimate the model with a constant, uncertainty, and disagreement, excluding the interaction term and controls. In this specification, uncertainty has a statistically significant, positive effect on recessions, while disagreement is negatively correlated with recessions on average. In specification (2) which adds the interaction term to the regression, we observe a significantly negative coefficient, indicating that high uncertainty coupled with high disagreement correlates negatively with recessions.

Adding the interaction term does not reduce the significance of $DISAG_t$, although the coefficient of UNC_t remains significant only at the 10% level.

In specification (3), we introduce the first two lags of industrial production (IP) growth as control variables, finding that these are important recession predictors with a strong negative correlation. Including these controls reduces the magnitude of the coefficients on uncertainty, disagreement, and their interaction but does not alter their signs or diminish their statistical significance.

Specification (4) uses a highly parameterized model incorporating current values and up to 12 lags of UNC, $DISAG$, $UNC \times DISAG$, IP, inflation (INF), federal funds rate (FFR), hours worked (HOURS), and S&P 500 index (SP500). Due to the high dimensionality, we estimate the model using penalized regression (Lasso with 10-fold cross-validation) to shrink irrelevant coefficients to zero. The variables selected with non-zero coefficients are subsequently used as control variables (Z_t) in an unrestricted regression.[16] Column 4 in the table reports the least squares estimate of the interaction term, showing that it remains negative and significant.

A simple decomposition of reduced-form shocks based on a triangular VAR model. The evidence presented indicates that periods of elevated uncertainty and high disagreement are not systematically linked with declines in economic activity as conventionally thought. To study the impact of uncertainty in the presence of disagreement more formally, we perform a simple multivariate exercise using a VAR model that estimates orthogonalized shocks using the standard Cholesky decomposition. The variables in the VAR model are the 12-month-ahead macroeconomic uncertainty (UNC) from Jurado et al. (2015), our index of disagreement (DISAG), and the logarithm of real industrial production (IP). We estimate the VAR using an intercept and two lags.[17] Estimation via the Cholesky decomposition of the VAR covariance matrix corresponds to a triangular VAR model, in which the ordering of the variables may play a role. Therefore, we estimate the three-variable system using two different orderings: one where UNC is placed first, followed by DISAG and IP, and another where DISAG is placed first, followed by UNC and IP. The former ordering complies with Bloom (2009) and implies that uncertainty is exogenous to disagreement and economic activity. The second ordering implies that disagreement is exogenous to uncertainty. In both cases, industrial production is endogenous and responds contemporaneously to both uncertainty and disagreement orthogonalized shocks.

Figure 6 shows the impulse responses (IRFs) to orthogonalized shocks under the two

[16] In addition to UNC_t, $DISAG_t$, and $UNC_t \times DISAG_t$, whose coefficients are presented in Table 2, the variables selected by Lasso include: UNC_{t-6}, UNC_{t-12}, $DISAG_{t-8}$ through $DISAG_{t-12}$, $UNC_{t-9} \times DISAG_{t-9}$, IP_t through IP_{t-7}, INF_t, INF_{t-7}, FFR_{t-8}, $HOURS_{t-1}$, $HOURS_{t-10}$, $HOURS_{t-11}$, and $SP500_t$ through $SP500_{t-8}$.

[17] Results are qualitatively similar when using 12 lags. The VAR is estimated with OLS, and the bootstrap procedure is used to obtain confidence intervals.

different orderings. The first two columns display the IRFs of uncertainty and disagreement shocks for the VAR using the UNC-DISAG-IP ordering, while the third and fourth columns display the IRFs of the same shocks for the DISAG-UNC-IP ordering. In response to a positive uncertainty shock, both orderings indicate a statistically significant, delayed, and persistent rise in uncertainty, accompanied by a decline in disagreement and a contraction in industrial production. A positive shock to uncertainty leads to the notion of "agreed uncertainty," characterized by an increase in uncertainty and a fall in disagreement.

In contrast, a positive shock to disagreement leads to an increase in uncertainty under the first ordering (UNC-DISAG-IP), generating the occurrence of "disagreed uncertainty" (i.e., a contemporaneous increase in 12-month-ahead macroeconomic uncertainty and the disagreement index). The disagreed uncertainty shock results in a short-lived positive response in industrial production. Nevertheless, since the Cholesky VAR is not structural, it cannot be considered conclusive evidence for the effects of "disagreed uncertainty" shocks. This becomes apparent with the alternative ordering (DISAG-UNC-IP), where a disagreement shock causes an initial negative impact on uncertainty, with no significant subsequent response. This behavior arises because, in the second ordering, the response of uncertainty is estimated from the covariance matrix rather than being fixed to zero. Given the negative correlation between disagreement and uncertainty in the full data sample, a disagreement shock results in a negative initial response of uncertainty, followed by an insignificant response over the impulse response horizon.

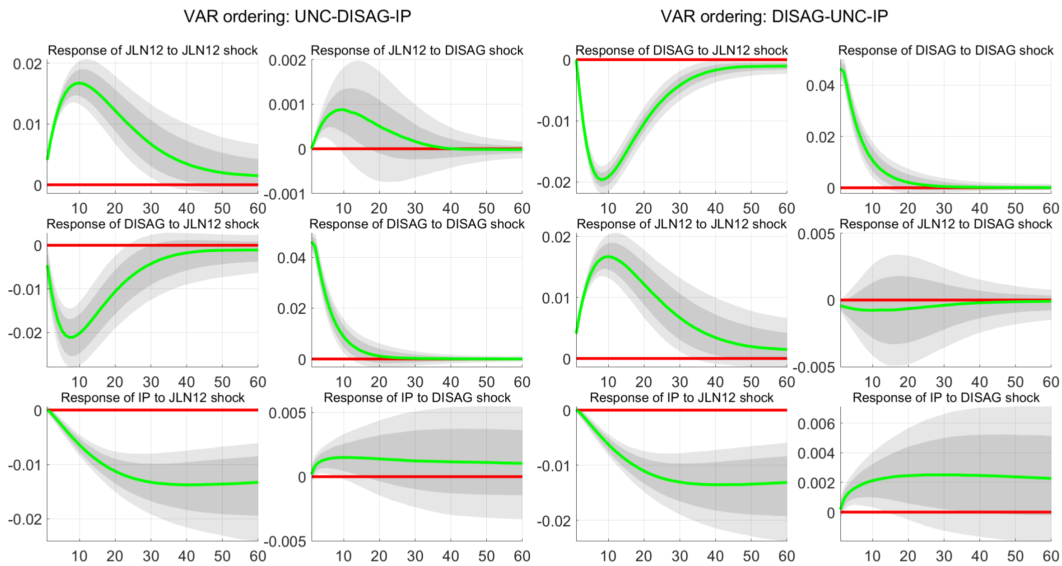

Figure 6: Impulse response functions from a simple recursive VAR on uncertainty, disagreement, and industrial production. The VAR is estimated with two lags using OLS and the Bootstrap. Each figure shows that mean response (solid line) and the 68% and 90% confidence bands in dark-gray and light-gray shaded areas, respectively.

The next section develops a theoretical framework to formalize the distinct notions of agreed and disagreed uncertainty.

4 A simple model of information dispersion

We develop a simple model with imperfect and dispersed information to derive the key theoretical implications that will be used in the main empirical analysis. In the model, we study how innovations in the variance of idiosyncratic shocks and innovations in the variance of fundamental shocks are linked to: (i) the variance of the forecast errors, the empirical proxy for uncertainty, and (ii) the model index of disagreement that is congruous with our empirical measure of disagreement. The simple model provides sign restrictions that formalize the concepts of agreed and disagreed uncertainty and enable the empirical identification of the impact of the different concepts of uncertainty on the economy.

4.1 Economic fundamental and signals

The fundamental process of the economy, TFP for instance, evolves according to

$$a_t = a_{t-1} + \rho_t, \tag{3}$$

where ρ_t is a stationary component modeled as an AR(1) process, $\rho_t = \lambda\rho_{t-1} + \varepsilon_t$ with $0 < |\lambda| < 1$, and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$ is a fundamental shock with known variance σ_ε^2.[18] The process can be rewritten as

$$a_t = a_{t-1} + \psi(L)\varepsilon_t, \tag{4}$$

where $\psi(L) = \psi_0 + \psi_1 L + \psi_2 L^2 + \ldots$, and $\psi_j = \lambda^j$, $j = 0, 1, 2, \ldots$.

Information is imperfect and dispersed. It is imperfect because agents in period t cannot observe the current value of the fundamental process a_t or the value of the current shock, ε_t. In period t, agents know the value of past fundamentals $\{a_{t-j}\}_{j=1}^{\infty}$ and shocks $\{\varepsilon_{t-j}\}_{j=1}^{\infty}$.[19]

Information is dispersed because there are N agents in the economy, and each agent receives an idiosyncratic signal about the fundamental shock. Formally, agent $i \in \{1, \ldots, N\}$ observes the signal

$$s_{it} = \varepsilon_t + v_{it}, \tag{5}$$

where $v_{it} \sim N(0, \sigma_{v_i}^2)$ is an idiosyncratic shock with known variance $\sigma_{v_i}^2$. The idiosyncratic shock controls the degree of information dispersion.

For simplicity, we assume that the variance of the noise is the same across agents,

[18]The fundamental process can adopt a variety of interpretations, e.g., productivity or demand shocks that are relevant sources of macroeconomic fluctuations. The specification is chosen for the sake of analytical simplicity but could be extended or modified.

[19]This information structure is close to real-world scenarios, as the first release of the series is typically available in $t + 1$.

$\sigma_{v_i} = \sigma_v$. Thus, the information set of agent i is given by $\mathcal{I}_{it} \equiv \{a_{t-1-j}, \varepsilon_{t-1-j}, s_{it-j}\}_{j=0}^{\infty}$.[20] Notice that this formulation implies that higher volatility of the idiosyncratic shock, $\sigma_{v_i}^2$, increases the range of signals and leads to greater dispersion of information across agents.

Agents solve a signal extraction problem to infer the fundamental shock from the signal s_{it}. At time t, each agent i solves this problem by conditioning on the information set $\mathcal{I}_{it} \equiv \{a_{t-1-j}, \varepsilon_{t-1-j}, s_{it-j}\}_{j=0}^{\infty}$, knowing the equations and parameters of the model and the distribution of the two shocks. In the rest of the analysis, without loss of generality, we simplify the analytical derivation of the system by assuming an identical variance of the idiosyncratic shock across agents (i.e., $\sigma_{v_i}^2 = \sigma_v^2$).

4.2 Variance of forecast error

Our definition of uncertainty is the variance of the forecast error k-periods ahead. The forecast of the i-th agent of the change in the fundamental process conditional on the information set is

$$E\left(a_{t+k} - a_{t+k-1} \mid \mathcal{I}_{it}\right) = \gamma\psi_k(\varepsilon_t + v_{it}) + \sum_{j=1}^{\infty} \psi_{k+j}\varepsilon_{t-j}, \tag{6}$$

where $\gamma = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_v^2}$ is the linear projection coefficient derived from the solution of the signal extraction problem (the same across individuals since the idiosyncratic variance is assumed to be identical). From equation (6), the individual forecast jointly depends on the fundamental shock, ε_t, and the idiosyncratic shock, v_{it}. The average forecast is obtained by averaging the expectations of individual agents in equation (6) across the N agents:

$$\begin{aligned} E_N(a_{t+k} - a_{t+k-1}) &= \frac{1}{N}\sum_{i=1}^{N} E\left(a_{t+k} - a_{t+k-1} \mid \mathcal{I}_{it}\right) \\ &= \gamma\psi_k\varepsilon_t + \gamma\psi_k\frac{1}{N}\sum_{i=1}^{N} v_{it} + \sum_{j=1}^{\infty}\psi_{k+j}\varepsilon_{t-j}. \end{aligned} \tag{7}$$

As N increases, the term $\frac{1}{N}\sum_{i=1}^{N} v_{it}$ vanishes in accordance with the law of large numbers. We define the aggregate average forecast with an infinite number of agents as the limit of E_N, for $N \to \infty$:

$$\begin{aligned} E_I(a_{t+k} - a_{t+k-1}) &= \lim_{N\to\infty} E_N(a_{t+k} - a_{t+k-1}) \\ &= \gamma\psi_k\varepsilon_t + \sum_{j=1}^{\infty}\psi_{k+j}\varepsilon_{t-j}, \end{aligned} \tag{8}$$

[20] Of course, all of the model equations and parameters are also known.

where the operator $E_I(\cdot)$ denotes the expectations across the distribution of individuals. Unlike individual forecasts in equation (7), the average forecast in equation (8) uniquely depends on the shock ε_t. The implied forecast error is

$$(a_{t+k} - a_{t+k-1}) - E_I\left(a_{t+k} - a_{t+k-1}\right) = \sum_{j=0}^{k-1} \psi_j \varepsilon_{t+k-j} + \psi_k (1-\gamma)\varepsilon_t, \tag{9}$$

and the variance of the forecast error is equal to

$$FEV(k) = \psi_k^2 \left(\frac{\sigma_v^2}{\sigma_\varepsilon^2 + \sigma_v^2}\right)^2 \sigma_\varepsilon^2 + \sum_{j=0}^{k-1} \psi_j^2 \sigma_\varepsilon^2. \tag{10}$$

Equation (10) shows that the variance of the forecast error jointly depends on the variances of the fundamental and idiosyncratic shocks, σ_ε^2 and σ_v^2, respectively. The next proposition establishes the relationship between the variances of the distinct shocks and the forecast error variance.

Proposition 1. *The variance of the forecast error increases with: (i) the variance of the fundamental shock (σ_ε^2), and (ii) the variance of the idiosyncratic shock (σ_v^2). Formally:*

$$\frac{\partial FEV(k)}{\partial \sigma_\varepsilon^2} > 0 \quad \textit{and} \quad \frac{\partial FEV(k)}{\partial \sigma_v^2} > 0 \quad . \tag{11}$$

Proof. See Appendix B.1. □

4.3 Disagreement index

In this section, we derive the theoretical measure of the disagreement index.

Consider the density of the signal conditional on a "representative" fundamental shock with the size of one standard deviation: $s_t \mid (\varepsilon_t = \sigma_\varepsilon) \sim N(\sigma_\varepsilon, \sigma_v^2)$.[21] The theoretical measure of the disagreement index consistent with the empirical measure is the following:

$$\begin{aligned} \mathcal{D} &= 1 - \left| \left[1 - \Phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right)\right] - \Phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) \right| \\ &= 1 - \left| 1 - 2\Phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) \right|, \end{aligned} \tag{12}$$

where $\Phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) = \int_{-\infty}^{0} f(x)dx$ is the cumulative distribution function (CDF) of a Normal random variable x with mean σ_ε and variance σ_v^2. The disagreement index is equal to

[21] In the exposition, we assume that the mean of the signal is positive and equal to σ_ε. Our results hold if we assume that the mean of the signal is negative and equal to $-\sigma_\varepsilon$, since the Normal distribution is symmetric, as we prove in Appendix B.2.

one minus the absolute value of the difference between the mass of the distribution in the positive region and that in the negative region. As in our empirical measure, the disagreement index is maximum and equal to one when half of the signals are negative and half are positive, and minimum and equal to zero when the signals are either all positive or all negative.

The following proposition establishes the relationship between the variances of the distinct shocks and the disagreement index.

Proposition 2. *The disagreement index: (i) decreases with the variance of the fundamental shock (σ_ε^2), and (ii) increases with the variance of the idiosyncratic shock (σ_v^2). Formally:*

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon^2} < 0 \quad \textit{and} \quad \frac{\partial \mathcal{D}}{\partial \sigma_v^2} > 0. \tag{13}$$

Proof. See Appendix B.2. □

Proposition 2 establishes two important results on the response of the disagreement index: an increase in σ_ε^2 reduces the disagreement index, while an increase in σ_v^2 increases the disagreement index. Intuitively, since the signal is conditional on the fundamental shock being proportional to the variability of the fundamental process, a higher variability of the fundamental process σ_ε^2 generates an average increase in the signal observed by agents, which reduces the disagreement index. An increase in the variance of σ_v^2 implies a wider spread in the signal received by agents, which increases the disagreement index.

To summarize, Proposition 1 shows that the variance of the forecast error (the empirical proxy for uncertainty) increases with the variance of the fundamental shock (σ_ε^2) and the variance of the idiosyncratic shock (σ_v^2). These comovements, together with those for the disagreement index from Proposition 2, allow us to disentangle innovations in the variance of fundamental shocks (agreed uncertainty) and innovations in the variance of idiosyncratic shocks (disagreed uncertainty), which we pursue in the next section.

5 Structural VAR evidence

VAR inference and shock identification. We employ the sign restrictions outlined in Propositions 1 and 2 within a Bayesian VAR (BVAR) model to disentangle the dynamic effects of agreed and disagreed uncertainty shocks.

Table 3: **Identifying sign restrictions**

Observed variable	Shock (1) σ_ε^2 Agreed Uncertainty	Shock (2) σ_v^2 Disagreed Uncertainty
Variance of the forecast error	+	+
Index of disagreement	−	+

Notes: The entries show the impact response of the variance of the forecast error and the index of disagreement to the shock to agreed uncertainty (column 1) and disagreed uncertainty (column 2).

Table 3 summarizes the sign restrictions, showing the response of the observed variables (i.e., uncertainty and disagreement) to agreed and disagreed uncertainty shocks, respectively. Column (1) in the table indicates that an innovation in the variance of the fundamental shock σ_ε^2 is associated with an increase in observed uncertainty (measured by the variance of the forecast error) and a decrease in the index of disagreement. This represents the concept of agreed uncertainty. Conversely, column (2) in the table indicates that an innovation in the variance of the idiosyncratic shock σ_v^2 is associated with a simultaneous increase in observed uncertainty and the index of disagreement. This represents the concept of disagreed uncertainty. Using these distinct comovements in observed uncertainty and the index of disagreement, the two distinct concepts of uncertainty shocks are identified in the data.

In the small-scale benchmark BVAR specifications described below, we apply the shock identification algorithm of Rubio-Ramírez et al. (2010) using the sign restrictions of Table 3. The sign restrictions are imposed exclusively on the impact period and not on subsequent periods following a shock, applying the most limited set of constraints to the data while remaining agnostic about the subsequent response of the variables, as in Mumtaz and Zanetti (2012). Appendix C describes the VAR model and the implementation of the estimation algorithms.

Benchmark BVAR specification. Since fluctuations in measures of uncertainty and disagreement are short-lived, the analysis uses monthly U.S. macroeconomic data, following Bloom (2009), Jurado et al. (2015), and Berger et al. (2020). The benchmark model is a parsimonious three-variable VAR estimated with data on uncertainty, disagreement, and industrial production, identical to the specification estimated in Section 3. Uncertainty is measured by the 12-month-ahead macroeconomic uncertainty in Jurado et al. (2015). Disagreement is measured by the tails disagreement factor, denoted as DISAG, and described in Section 2. Both uncertainty and disagreement indexes enter the BVAR in levels, while industrial production is converted into month-on-month growth rates (i.e., first differences of the logarithm). The sample period spans from January 1978 to December 2019, with the starting date determined by the availability of the MSC data and the endpoint set to avoid extreme outliers observed during the Covid-19 pandemic period that began in 2020. The estimated models include 13 lags, which several studies have shown to be an appropriate choice for monthly data. In Appendix C, we use the efficient algorithm for structural restrictions developed in Korobilis (2022) to test the robustness of the results using BVARs with a larger set of endogenous variables. Appendix D reports the full set of results.[22]

The top three panels in Figure 7 show IRFs to a positive innovation in the variance of the fundamental shock σ_ε^2 –agreed uncertainty– identified by imposing the impact sign restrictions in column (1) of Table 3. The JLN12 uncertainty indicator increases immediately upon impact and remains persistently elevated for approximately 25 months, while the DISAG indicator declines persistently in the short run and remains depressed for approximately 20 months. The response of industrial production is negative on impact, declines further until approximately month 15, and then becomes statistically significant and persistently depressed. These results on the dynamic effects of agreed uncertainty shocks echo recent findings in the literature (e.g., Jurado et al., 2015, Gilchrist et al., 2014, Ludvigson et al., 2021) using similar empirical methods, emphasizing a significant depressing effect of uncertainty on real activity indicators.

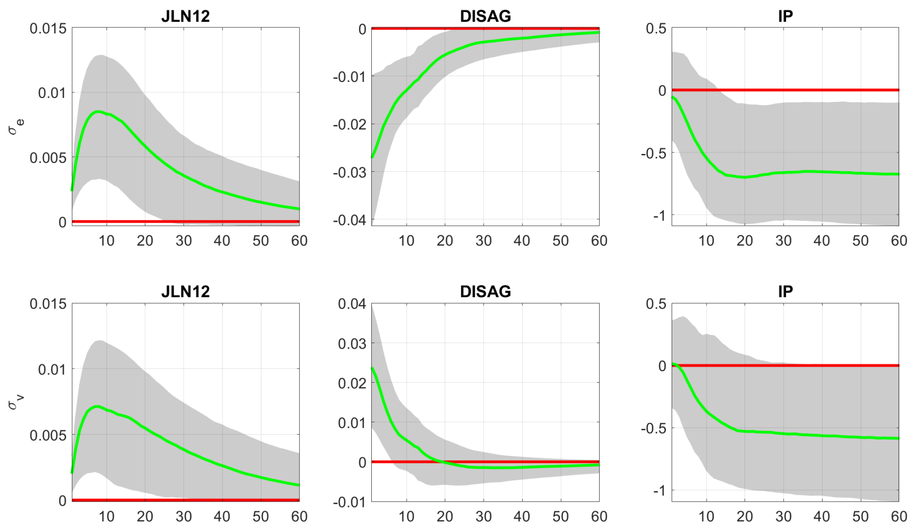

Figure 7: Benchmark model. Agreed σ_ε (top) versus disagreed σ_v (bottom) uncertainty. The figure shows impulse responses to the JLN 12-month-ahead macro uncertainty indicator (JLN12), the disagreement index (DISAG), and industrial production (IP), based on a VAR estimated on these three variables. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters.

The bottom three panels in Figure 7 show IRFs to a positive innovation in the variance of the idiosyncratic shock, σ_v^2 –disagreed uncertainty. This is identified by imposing the

[22]To address the issue of high dimensionality in the lag structure, we follow Korobilis (2022) and adopt the Horseshoe prior, a tuning-free method that achieves optimal shrinkage. Details of this approach are provided in Appendix C.

sign restrictions in column (2) of Table 3. The JLN12 uncertainty indicator displays an immediate and persistent rise, which is qualitatively and quantitatively very similar to the estimated response following an agreed uncertainty shock. Disagreement displays a short-lived increase. Crucially, and in contrast to the dynamic response in the top panel, the response of industrial production never becomes statistically significant across the entire forecast horizon, suggesting that economic activity does not decline following a disagreed uncertainty shock. To further scrutinize these different dynamic effects, we estimate the benchmark BVAR with an extended information set, including two additional activity indicators: total nonfarm employment and personal consumption expenditure.[23] To conserve space, the IRFs of four key variables from this specification are presented in Figure 8, and the complete set of results is reported in Appendix D.

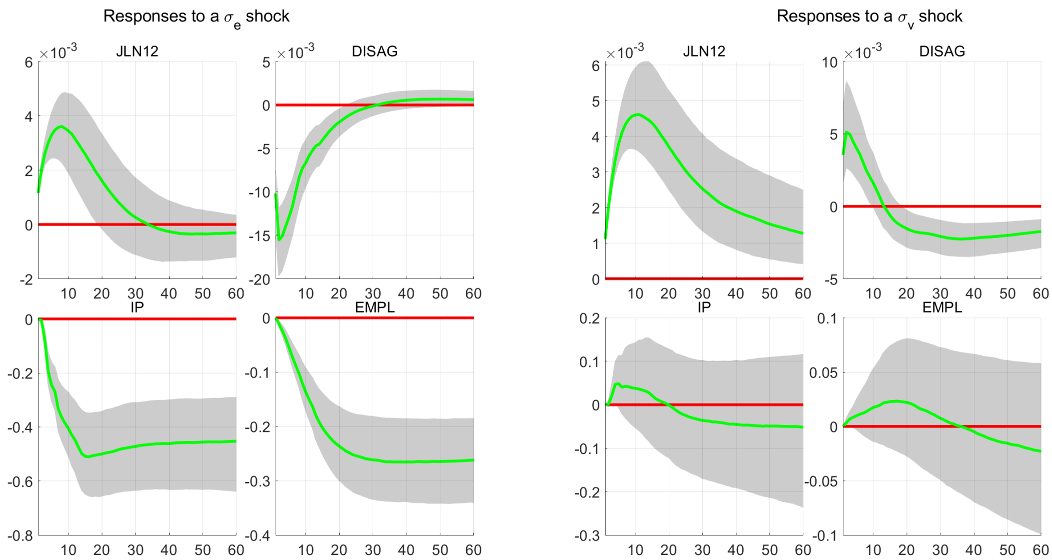

Figure 8: Extended Benchmark model. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses to the JLN 12-month-ahead macro uncertainty indicator (JLN12), the disagreement index (DISAG), industrial production (IP), and employment (EMPL) based on a VAR estimated on eight variables. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters.

The dynamic responses of the uncertainty and disagreement indicators are qualitatively similar to those estimated in Figure 7. Interestingly, the uncertainty indicator shows a stronger and more persistent response following a disagreed uncertainty shock (right panel) compared to an agreed uncertainty shock (left panel). Despite a stronger and more persistent rise in uncertainty, the responses of real activity indicators following a disagreed uncertainty shock (right panel) are qualitatively different from the responses

[23]The VAR specification contains the three variables of the benchmark BVAR and adds total nonfarm employment, personal consumption expenditure, the Fed Funds rate, the S&P 500 index, and inflation. In this specification, to rule out the autonomous effect of uncertainty shocks on economic activity that results in overstating the economic effects of agreed or disagreed uncertainty shocks, a zero-impact response of activity indicators to the identified shocks is imposed.

following an agreed uncertainty shock (left panel). Specifically, industrial production exhibits a small, positive, short-lived response until month 20 –though not estimated to be statistically significant– in contrast to the persistent negative response estimated following an agreed uncertainty shock (left panel). Similarly, employment exhibits a small, positive response until month 35 (not estimated to be statistically significant), in contrast to the negative and persistent response estimated following an agreed uncertainty shock (left panel).[24] Thus, disagreed uncertainty shocks are characterized by dynamic effects that are broadly benign for economic activity and qualitatively differ from the strong, adverse, and long-lasting effects on economic activity in the aftermath of shocks to agreed uncertainty.

To summarize, identified innovations agreed uncertainty and disagreed uncertainty display sharp qualitative differences in the dynamic responses of real activity indicators. Agreed uncertainty shocks are robustly contractionary and generate a sustained decline in industrial production and employment. In contrast, disagreed uncertainty shocks are broadly benign as they do not lead to declines in real activity in the short or medium term. This study is the first to demonstrate that consumer disagreement about current and future economic conditions, which characterizes disagreed uncertainty, is critical for the benign effects of uncertainty on real activity, while agreed uncertainty retains the standard adverse effect on real activity.

Appendix D undertakes a battery of robustness analyses. Specifically, the robustness is conducted with respect to alternative proxies for uncertainty used in related studies, where the benchmark uncertainty indicator is switched to one of the following: the Jurado et al. (2015) 12-month-ahead financial uncertainty indicator (henceforth JLNF-12), the business dispersion measure (BOS-dispersion) developed in Bachmann et al. (2013), stock market volatility (CBOE S&P 100 volatility index, VIX), or the Economic Policy Uncertainty index (EPU) developed by Baker et al. (2016). We also consider VAR specifications that: (i) estimate the dynamic effects of the two shocks on a broad spectrum of macroeconomic (including labor market) and survey indicators; (ii) replace the DISAG index with individual disagreement indices from specific survey questions; (iii) use alternative disagreement indicators that exploit the range of responses from consumers; and (iv) use disagreement based on different demographic characteristics of consumers, namely age and education.

Historical decompositions. Figure 9 shows the historical decomposition of uncertainty into each identified shock. To provide a comprehensive picture, historical decompositions are presented for both macroeconomic and financial uncertainty indicators (top and bottom panels, respectively) into estimated agreed and disagreed uncertainty shocks (and,

[24] In addition, as shown in Appendix D, the response of personal consumption displays a pattern consistent with the activity variables presented here, namely a strong, negative, and persistent response following an agreed uncertainty shock and a non-recessionary response following a disagreed uncertainty shock.

for completeness, an unidentified residual).[25] We obtain the contribution of each shock to the considered indicator of uncertainty using the benchmark three-variable BVAR specification estimated with the distinct uncertainty indicators. Consistent with Figure 1 in the introduction, each panel shows shaded areas that highlight periods of elevated uncertainty above its mean value, distinguishing between negative annualized IP growth (gray areas) and positive annualized IP growth (hatched areas).

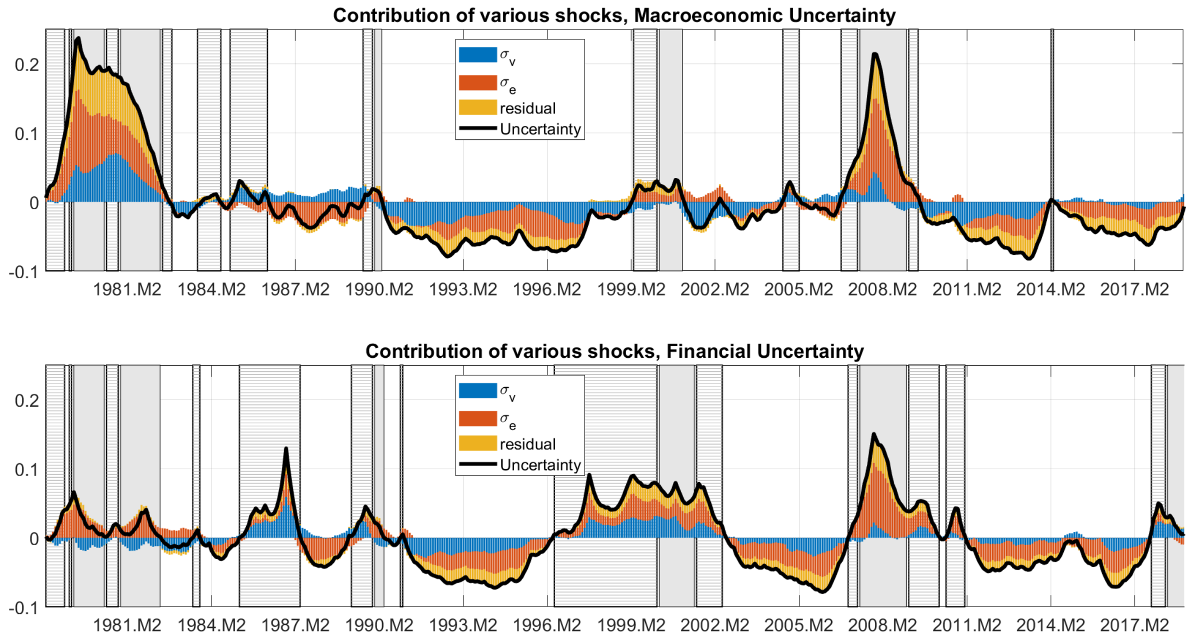

Figure 9: Benchmark model. Historical decomposition of macroeconomic and financial uncertainty. The figure presents the historical decomposition of uncertainty derived from macroeconomic indicators (top panel) and financial indicators (bottom panel). It breaks down uncertainty into contributions from the agreed uncertainty shock (σ_ε, red bars), the disagreed uncertainty shock (σ_v, blue bars), and the residual shock (yellow bars). These are plotted alongside the demeaned observed series of uncertainty (solid line), adjusted by subtracting the contributions of the constant term and initial conditions. Shaded regions indicate periods when uncertainty was above its sample mean. Gray-shaded areas correspond to periods of negative industrial production (IP) growth, while horizontally hatched areas represent periods of positive IP growth. Unshaded and unhatched regions denote periods when uncertainty was below the sample mean.

The total number of months with elevated uncertainty and positive industrial production (IP) growth (hatched areas) exceeds those with elevated uncertainty and negative IP growth (gray shaded areas). For macroeconomic uncertainty, 89 months exhibit above-mean uncertainty with positive IP growth, compared to 68 months with negative IP growth. For financial uncertainty, these figures are 152 and 82 months, respectively.

[25] Since the main focus is on identifying two uncertainty shocks, the three-variable BVAR specification contains a third residual that does not have a structural interpretation. Financial uncertainty is the 12-month-ahead financial uncertainty indicator derived from estimates of conditional volatilities of h-step-ahead forecast errors from 147 financial market variables. Ludvigson et al. (2021) suggest this indicator is less likely to be confounded by macroeconomic shocks and is hence more likely to represent an exogenous source of variation in uncertainty.

In most months with above-mean uncertainty and positive IP growth, disagreed uncertainty shocks (blue bars) dominate. For macroeconomic uncertainty, 53 out of 89 hatched-area months are dominated by disagreed uncertainty shocks, with an average contribution share of 46%.[26] Conversely, in 64 out of 68 gray-area months (negative IP growth), agreed uncertainty shocks dominate with an average share of 47%. This pattern suggests that our concepts of uncertainty successfully predict the direction of the impact of heightened uncertainty on real activity in 117 (53+64) out of 157 (89+68) months (i.e., approximately 75%) in the sample. Notably, in 45% $\left(\frac{53}{53+64}\right)$ of instances in the sample, heightened uncertainty –dominated by disagreed uncertainty shocks– bore no adverse impact on the economy. For financial uncertainty, applying the same metric, we can conclude that in 51% $\left(\frac{68}{68+65}\right)$ of instances in the sample, heightened uncertainty –dominated by disagreed uncertainty shocks– bore no adverse impact on the economy.

Historical episodes reinforce these findings. Periods such as August 1984–June 1985 and October 1985–February 1987 saw high macroeconomic uncertainty dominated by disagreed shocks, yet strong IP growth. Similarly, between February 1986 and April 1988 (encompassing Black Monday on October 19, 1987) financial uncertainty rose significantly but did not lead to an economic downturn. The 2008 Financial Crisis, however, saw uncertainty dominated by agreed uncertainty shocks, triggering an economic recession.

6 Complementary evidence with micro-survey data

In this section, we pursue an entirely different empirical strategy using micro-survey data. Specifically, we study an uncertainty episode prompted by a major geopolitical event –the Russian invasion of Ukraine on February 24, 2022– and leverage information provided by the Fed through an FOMC statement released shortly after this event to construct an alternative empirical identification of agreed and disagreed uncertainty.[27]

Identification strategy. Consumer responses from the New York Fed Survey of Consumer Expectations (henceforth SCE), collected shortly before and shortly after the FOMC statement –released by the Fed on March 16, 2022– are used to measure inflation forecast disagreement as well as consumer spending plans. The strategy exploits the varying exposure of consumers to economic information from the Fed's FOMC statement, resembling a randomized control trial, and examines how variation in forecast disagreement shapes the impact of uncertainty on consumers' spending plans.

[26] In the remaining 36 months, the contribution of disagreed uncertainty shocks averages a non-trivial share of 19%.

[27] Several indexes of uncertainty spiked around the time of the Russian invasion. The global economic policy uncertainty indicator increased by 72%, and the index of economic policy uncertainty in the U.S. increased by 38% between February and March 2022. The CBOE daily Volatility Index (VIX) jumped by 66% between February 1 and March 7, 2022.

Recent research shows that policy announcements by central banks entail a substantial information effect that is relevant for the formation of expectations.[28] Building on these results, the working hypothesis is that the FOMC statement reveals non-redundant information about the state of the U.S. economy that is internalized by consumers and attenuates the divergence in views about future inflation, potentially reducing disagreement.

In essence, we exploit the "Fed information effect" documented in Melosi (2017) and Nakamura and Steinsson (2018) to design an empirical framework-distinguishing between respondents treated and untreated with the information from the FOMC statement-to identify the impact of uncertainty on consumer spending plans using the panel data dimension from the SCE.

Survey data and information content in the FOMC statement. The SCE is a nationally representative, internet-based survey of a rotating panel of approximately 1,300 household heads, initiated in 2013. Respondents participate in the panel for up to twelve months, with a roughly equal number rotating in and out of the panel each month. The survey collects timely information on consumers' expectations on a variety of topics, including inflation, household finance, the labor market, and the housing market. It also collects data on household characteristics such as age, education, income level, and location.

An important feature of the SCE is the randomness of the assignment and completion of questionnaires. Respondents are randomly assigned to different periods within each month to complete and return the questionnaires.[29] The survey tracks the day each respondent completes the questionnaire, enabling the identification of consumers who completed it before and after the March 16, 2022, FOMC statement release.

In the aforementioned FOMC statement, the Fed provided substantial information about economic conditions, highlighting elevated uncertainty and offering useful signals about the likely path for economic activity and inflation: "The invasion of Ukraine by Russia is causing tremendous human and economic hardship. The implications for the U.S. economy are highly uncertain, but in the near term, the invasion and related events are

[28]The idea, originally pioneered by Romer and Romer (2000), has been revived by Nakamura and Steinsson (2018) and Melosi (2017). These studies use high-frequency movements in asset prices to show that a monetary tightening leads the private sector to update its beliefs and become more optimistic about the future course of policy and the economy. Similarly, Acosta (2023) decomposes FOMC statements into monetary policy news and news about demand and supply shocks and concludes that information provision is a key component of the Fed's communication policy. Melosi et al. (2024) show that fiscal policy also entails a strong signaling effect.

[29]The survey is sent to respondents in three batches throughout the month. Specifically, each month, the pool of respondents is partitioned into three batches of roughly equal size. In general, the first, second, and third batches receive an email invitation to fill out the survey on the second, eleventh, and twentieth of the month, respectively. Although not uniformly distributed, the completion of surveys is spread out throughout the month. See Armantier et al. (2017) for details on the design and administration of the survey.

likely to create additional upward pressure on inflation and weigh on economic activity." The Fed also communicated the decision to raise the policy rate for the first time since moving to the zero lower bound range in the immediate aftermath of the Covid-19 outbreak on March 15, 2020, and signaled likely future increases in the Fed Funds rate.[30] Evidence from Google Trends shows a surge in popularity for the search terms 'Federal Reserve' and 'interest rate' on March 16, 2022, compared to March 15, 2022, suggesting that the information contained in the statement reached the general public. The term 'Federal Reserve' ('interest rate') displayed an increase of over 100 (50) percent in search intensity. In fact, the term 'interest rate' reached maximum popularity (equal to 100) compared to all other search requests in Google in the U.S. on March 16, 2022.

The random assignment of the survey questionnaires splits an otherwise homogeneous population of respondents during March 2022 into two random groups that experience a different information treatment. Consumers who completed the survey on or after the release of the FOMC statement received a more precise signal about the future path of the economy, informed by the statement's details regarding the increase in the Federal Funds Rate and the in-depth review of economic and financial conditions, including an assessment of the future economic outlook and policy stance. The group of consumers who submitted answers within the period March 16-31, 2022, therefore constitutes the treatment group, as it was exposed to information not available to respondents who submitted answers before the FOMC statement, within the period March 1-15, 2022, which constitutes the control group.

Critical for the validity of this approach, the treatment of the "experiment" (i.e., the supply of information from the Fed) must be randomly assigned to respondents of the survey. In other words, the split of the two groups must be exogenous to preferences, economic conditions, and other factors that could directly predict different economic outcomes. This implies that the assignment of a respondent to the treatment or control group on the date of the FOMC meeting can be considered random, as in a randomized experiment. The survey collects a range of important information from respondents that rarely changes on a regular basis (e.g., family situation, education, numerical literacy). Differences in demographics and other characteristics could potentially affect responses to questionnaires. Therefore, we tested for differences in nine observable characteristics between the two groups of respondents (such as income, education, age, and health, among others). Appendix D shows that the differences in all characteristics (except income)

[30]Specifically, the statement read: "The Committee seeks to achieve maximum employment and inflation at the rate of 2 percent over the longer run. With appropriate firming in the stance of monetary policy, the Committee expects inflation to return to its 2 percent objective and the labor market to remain strong. In support of these goals, the Committee decided to raise the target range for the federal funds rate to 1/4 to 1/2 percent and anticipates that ongoing increases in the target range will be appropriate. In addition, the Committee expects to begin reducing its holdings of Treasury securities and agency debt and agency mortgage-backed securities at a coming meeting." The statement can be accessed at: `https://www.federalreserve.gov/newsevents/pressreleases/monetary20220316a.htm`.

between the treated and control groups are not statistically significant.

We obtain information on inflation forecasts (one- and three-year ahead) and household spending plans using the questions shown in Table 4. For the questions on inflation forecasts (one- and three-year ahead, coded Q9 and Q9c in the survey, respectively), respondents are presented with predefined, non-overlapping bins that define the range of values that inflation may take. Respondents are then asked to indicate the percent chance that inflation would take values in each of those intervals, with the reminder that the numbers need to add up to 100 percent.[31] The survey provides the interquartile range and standard deviation of inflation forecasts among respondents, supplying alternative measures for the cross-sectional dispersion of inflation forecasts that represent disagreement.

For the question on household spending plans (coded Q26v2part2 in the survey), respondents are asked to report the percent increase or decrease in total household spending (durable, nondurable, and services) they expect over the next twelve months.[32]

Table 4: SCE Questions about inflation and spending plans

SCE Question	Topic
Q9 and Q9c	Inflation forecasts 1 year and 3 years ahead
Q26v2part2	Household spending plans over next 12 months

Notes: Survey of Consumer Expectations, Federal Reserve Bank of New York.

Disagreement and FOMC statement. Since consumers stay in the survey for 12 months, respondents assigned to the information-treated group in February 2022 can be traced. This allows for the measurement of inflation forecast disagreement for the same respondents in the treated group across two consecutive months, namely February and March 2022. This setup enables the evaluation of the hypothesis that the information contained in the FOMC statement provides a more precise signal about the future path of the economy and, as a result, (significantly) reduces inflation forecast disagreement in the

[31] Q9 asks consumers the following: "Now we would like you to think about the different things that may happen to inflation over the next 12 months. We realize that this question may take a little more effort. In your view, what would you say is the percent chance that, over the next 12 months..." and the predefined bins are: the rate of inflation will be 12% or higher (bin 1); the rate of inflation will be between 8% and 12% (bin 2); the rate of inflation will be between 4% and 8% (bin 3); the rate of inflation will be between 2% and 4% (bin 4); the rate of inflation will be between 0% and 2% (bin 5); the rate of deflation (opposite of inflation) will be between 0% and 2% (bin 6); the rate of deflation (opposite of inflation) will be between 2% and 4% (bin 7); the rate of deflation (opposite of inflation) will be between 4% and 8% (bin 8); the rate of deflation (opposite of inflation) will be between 8% and 12% (bin 9); the rate of deflation (opposite of inflation) will be 12% or higher (bin 10).

[32] Q26v2part2 asks consumers the following: "Now think about your total household spending, including groceries, clothing, personal care, housing (such as rent, mortgage payments, utilities, maintenance, home improvements), medical expenses (including health insurance), transportation, recreation and entertainment, education, and any large items (such as home appliances, electronics, furniture, or car payments). By about what percent do you expect your total household spending to [increase/decrease] over the next twelve months? Please give your best guess." Consumers can provide a positive or negative percentage response.

treatment group between February and March. To test this hypothesis, we estimate the change in inflation forecast disagreement for the treated group between February (before being exposed to the information from the FOMC statement) and March (after receiving the information). Specifically, we estimate the following panel regression on the treated group:

$$DISAG_{it}^{INF} = \alpha_i + \beta_0 Post(FOMC)_t + \epsilon_{it}, \tag{14}$$

where $DISAG_{it}^{INF}$ is the inflation forecast disagreement reported by consumer i on day t, $Post(FOMC)_t$ is a time dummy variable equal to one for the days March 16-31, 2022, identifying the post-period following the release of information by the FOMC, and zero otherwise. The coefficient α_i denotes consumer fixed effects, controlling for time-invariant characteristics.[33] The coefficient β_0 measures the impact of the FOMC release of information on households' inflation forecast disagreement for the same respondents treated with FOMC information surveyed in February and March.

The following alternative inflation forecast disagreement measures are used, one at a time: (i) the interquartile range of the one-year-ahead inflation forecast, coded *Q9_iqr*; (ii) the standard deviation of the one-year-ahead inflation forecast, coded *Q9_std*; (iii) the interquartile range of the three-year-ahead inflation forecast, coded *Q9c_iqr*; and (iv) the standard deviation of the three-year-ahead inflation forecast, coded *Q9c_std*.[34]

Table 5: Change in forecast disagreement: information treated group

	Inflation forecast disagreement measures			
	(1) Q9iqr	(2) Q9std	(3) Q9ciqr	(4) Q9cstd
post FOMC time dummy	-0.61**	-0.36**	-0.63**	-0.40***
	(0.29)	(0.17)	(0.25)	(0.15)
Consumer Fixed effects	Yes	Yes	Yes	Yes
N	894	894	890	890

Notes: The February-March sample above contains all consumers who belong to the information treated group (those who submitted questionnaires between 16-31 March, 2022) who also completed the survey in February. *Q9iqr*, *Q9std*, *Q9ciqr*, *Q9cstd* denote one year ahead inflation forecast interquartile range, one year ahead inflation forecast standard deviation, three year ahead inflation forecast interquartile range, and three year ahead inflation forecast standard deviation respectively. Survey weights are employed to help ensure that the data are nationally representative. Standard errors clustered at consumer level are reported in the parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

[33]These include characteristics such as education, location, age, health, gender, and others.

[34]The standard measure of volatility is complemented with the IQR to proxy forecast uncertainty, as the IQR measure is less sensitive to small variations in the tails of the estimated density.

Table 5 presents the coefficient estimates across the alternative measures of forecast disagreement. In all four cases, the estimates are negative and statistically significant (at the 5% significance level), supporting the hypothesis that one-year-ahead (columns 1 and 2) and three-year-ahead inflation forecast disagreement (columns 3 and 4) decline significantly following the release of the March 16 FOMC statement. The magnitude of the coefficients is small but not trivial. For instance, in column (1), the coefficient estimate represents a reduction equivalent to one-eighth of the standard deviation of inflation forecast disagreement (and similarly for the other estimated coefficients). Appendix D presents a similar exercise for the control group, showing that the reduction in disagreement recorded by the treatment group is absent in the control group.

Consumer spending plans and uncertainty. We construct a balanced panel by tracking the consumer respondents who participated in the survey in both February and March 2022, belonging to either the treatment or control group. This setup allows the regression to include a full set of consumer fixed effects. Specifically, we estimate the following regression:

$$\begin{aligned} Q26_{it} &= \alpha_i + \lambda_t + \beta_1 DISAG_{it}^{INF} + \beta_2 VIX_t + \beta_3 DISAG_{it}^{INF} \times VIX_t + \beta_4 Post_t \\ &+ \beta_5 DISAG_{it}^{INF} \times Post_t + \beta_6 Post_t \times VIX_t + \beta_7 Post_t \times DISAG_{it}^{INF} \times VIX_t + \epsilon_{it}, \end{aligned} \tag{15}$$

where $Q26_{it}$ represents the consumer-reported twelve-month household spending plan, α_i denotes consumer fixed effects controlling for time-invariant characteristics, and λ_t denotes month fixed effects. $Post_t$ is a dummy variable equal to one if the survey responses were submitted between March 16-31, 2022 (inclusive) and zero otherwise. VIX_t represents the daily CBOE volatility index. Consistent with the previous analysis, each of the four alternative indicators of inflation forecast disagreement, denoted for brevity by $DISAG_{it}^{INF}$, is used one at a time. The coefficients β_2 and β_3 capture the impact of uncertainty and uncertainty interacted with inflation forecast disagreement on consumption plans, respectively, while β_6 and β_7 capture the impact of these variables for the group of respondents treated with the information from the FOMC announcement.

Table 6 presents the results. Columns (1) and (2) report the coefficient estimates based on the interquartile range of the inflation forecast for one and three years ahead, respectively, while columns (3) and (4) report the coefficient estimates based on the standard deviation of the inflation forecast for one and three years ahead, respectively.

We use the estimated coefficients from equation (15) to compute the baseline impact effect of uncertainty on household spending plans and the differential impact accounting for the post-FOMC announcement. These are respectively represented by the following expressions:

$$\text{Impact effect of uncertainty, baseline:} \quad \beta_2 + \beta_3 DISAG_{it}^{INF}, \tag{16}$$

$$\text{Impact effect of uncertainty, post FOMC:} \quad \beta_2+\beta_6+\beta_3 DISAG_{it}^{INF}+\beta_7 DISAG_{it}^{INF}. \tag{17}$$

Table 7 presents the results. Columns (1) and (2) of the table report the estimated baseline impact and post-FOMC impact effects of uncertainty on spending plans, respectively. The contractionary impact of uncertainty on household spending plans in the post-FOMC case is, across all alternative inflation forecast disagreement indicators, stronger and more precisely estimated compared to the baseline case.

For example, in the specification based on the one-year-ahead inflation forecast using the interquartile range (row 1 of Table 7), the post-FOMC negative impact effect is estimated at 0.37 percentage points, which is statistically significant at the five percent level, compared to a significantly smaller decline of 0.11 percentage points (statistically significant at the ten percent level) estimated for the baseline impact effect. In the specification based on the three-year-ahead inflation forecast interquartile range (row 2 of Table 7), the post-FOMC negative impact effect is estimated at 0.54 percentage points (statistically significant at the one percent level), compared to a statistically insignificant effect (equal to a decline of 0.09 percentage points) estimated for the baseline impact effect.

The last column of Table 7 reports the difference in the estimated impacts of uncertainty between the baseline and post-FOMC cases. It shows that this difference is statistically significant at the five percent significance level in two out of four cases. Appendix D reports results from a panel specification with an additional high-frequency control variable that tracks the daily business conditions developed by Aruoba et al. (2009). This index serves to control for economic developments that may potentially influence consumers' reported spending plans. The uncertainty impact effects estimated for the baseline and post-FOMC cases are quantitatively very similar to those discussed above, and the difference between the two impact effects is statistically significant in all examined cases.

To summarize, the results from the entirely different empirical strategy based on micro-survey panel data corroborate the time-series evidence and provide strong support for the idea that the impact effect of uncertainty on economic activity critically depends on disagreement. The impact effect of uncertainty on spending plans is more pronounced and an order of magnitude larger for consumers with smaller inflation forecast disagreement compared to the baseline impact effect.

Table 6: Panel evidence: daily observations, February-March 2022

	Dependent variable: Spending plans ($Q26$)			
	(1)	(2)	(3)	(4)
$Q9\_iqr$	0.0121			
	(0.0511)			
VIX	-0.0854**	-0.0825**	-0.0849**	-0.0821**
	(0.0407)	(0.0399)	(0.0406)	(0.0399)
$Q9\_iqr \times VIX$	-0.0270			
	(0.0328)			
$post$	-0.282**	-0.294**	-0.278**	-0.295**
	(0.1203)	(0.1178)	(0.1206)	(0.1185)
$post \times Q9\_iqr$	-0.246*			
	(0.1282)			
$post \times VIX$	-0.0322	-0.0633	-0.0312	-0.0657
	(0.0954)	(0.0963)	(0.0951)	(0.0964)
$post \times Q9\_iqr \times VIX$	-0.232*			
	(0.1362)			
$Q9c\_iqr$		-0.00301		
		(0.0509)		
$Q9c\_iqr \times VIX$		-0.00717		
		(0.0317)		
$post \times Q9c\_iqr$		-0.386***		
		(0.1295)		
$post \times Q9c\_iqr \times VIX$		-0.386***		
		(0.1365)		
$Q9\_std$			0.0224	
			(0.0505)	
$Q9\_std \times VIX$			-0.0327	
			(0.0304)	
$post \times Q9\_std$			-0.218*	
			(0.1304)	
$post \times Q9\_std \times VIX$			-0.200	
			(0.1314)	
$Q9c\_std$				0.00520
				(0.0508)
$Q9c\_std \times VIX$				-0.0150
				(0.0296)
$post \times Q9c\_std$				-0.360***
				(0.1287)
$post \times Q9c\_std \times VIX$				-0.345***
				(0.1302)
Month Fixed effects	Yes	Yes	Yes	Yes
Consumer Fixed effects	Yes	Yes	Yes	Yes
N	2102	2100	2102	2100

Notes: $Q9_{iqr}$, $Q9_{std}$, $Q9c_{iqr}$, $Q9c_{std}$, denote one year ahead inflation forecast interquartile range, one year ahead inflation standard deviation, three year ahead inflation forecast interquartile range, and three year ahead inflation standard deviation respectively. VIX is the CBOE volatility index. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7: Impact effect of uncertainty on spending plans

Estimated coefficients from Table 6	Baseline effect, equation (16) (1)	post FOMC effect, equation (17) (2)	Difference (2) - (1)
based on $Q9_{iqr}$	-0.11*	-0.37**	-0.26
	(0.06)	(0.17)	(0.18)
based on $Q9c_{iqr}$	-0.09	-0.54***	-0.45**
	(0.05)	(0.18)	(0.19)
based on $Q9_{std}$	-0.12**	-0.35**	-0.23
	(0.05)	(0.17)	(0.18)
based on $Q9c_{std}$	-0.09*	-0.51***	-0.41**
	(0.05)	(0.18)	(0.19)

Notes: Each row in the Table uses the estimates based on an alternative indicator of inflation forecast disagreement as reported in Table 6. To compute the expressions above we use the mean values for $DISAG^{INF}$ for each group. Standard error reported in brackets. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

7 Conclusion

In this paper, we establish two new concepts of uncertainty, namely, agreed and disagreed uncertainty. We demonstrate that the dispersion of consumer views about economic conditions, measured by consumer disagreement, plays a crucial role in shaping the effect of uncertainty on economic activity. Uncertainty episodes accompanied by high consumer disagreement –disagreed uncertainty– are not contractionary for economic activity, challenging the conventional view that uncertainty invariably triggers recessions.

We formalize the distinct concepts of uncertainty in an imperfect and dispersed information model. We use this model to formulate simple sign restrictions that disentangle the dynamic effects of innovations to agreed and disagreed uncertainty on U.S. economic indicators within a small-scale Bayesian VAR model. The findings indicate that innovations in agreed uncertainty (a joint increase in uncertainty and a decline in disagreement) predict significant and persistent depressing effects on economic activity, corroborating evidence from numerous studies. In contrast, innovations in disagreed uncertainty (a joint rise in uncertainty and consumer disagreement) are benign for economic activity. These results hold across a wide range of approaches and alternative economic and uncertainty indicators.

Finally, we provide complementary evidence using an empirical approach –resembling a randomized information treatment– that exploits variation in consumer inflation forecast disagreement around an exogenous uncertainty episode triggered by the Russian invasion of Ukraine in February 2022. We take advantage of consumers' differing exposure to information from the FOMC announcement shortly after the invasion to estimate the differential impact of uncertainty on consumption spending plans. Specifically, we compare consumers exposed to the FOMC announcement, who exhibit low inflation forecast disagreement, with those unexposed to the announcement, who display high disagreement. Our findings indicate that the contractionary impact of uncertainty on consumer spending plans is more pronounced among consumers with low disagreement, corroborating results from the time-series analysis.

Our study underscores the importance of distinguishing between the two types of uncertainty shocks when assessing the relationship between uncertainty and economic activity and opens several promising avenues for future research. First, an extension of our analysis would be to study how policy announcements that convey information about the economy may result in lower disagreement and exacerbate the negative effect of uncertainty. Second, it would be interesting to examine whether a strategic diffusion of information that preserves a broader range of views could mitigate or even counteract the adverse economic effects of uncertainty.

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Supplemental Appendices

Agreed and Disagreed Uncertainty

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Contents

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A. Data

A.1. Data series

All core macro series and all different measures of uncertainty and disagreement used throughout the paper, are presented in Table A.1.

Table A.1: Monthly dataset, 1978M1 - 2019M12

Mnemonic	FRED mnemonic	Description	Source	Tcode
		MACRO VARIABLES		
IP	INDPRO	Industrial Production: Total Index	FRED	5
EMPL	PAYEMS	All Employees, Total Nonfarm	FRED	5
CONS	DPCERA3M086SBEA	Real personal consumption expenditures (Quantity Index)	FRED	5
CONS DUR	DDURRA3M086SBEA	Real personal consumption expenditures: Durable goods (Quantity Index)	FRED	5
CONS NDUR	DNDGRA3M086SBEA	Real personal consumption expenditures: Nondurable goods (Quantity Index)	FRED	5
CONS SERV	DSERRA3M086SBEA	Real personal consumption expenditures: Services (Quantity Index)	FRED	5
INFL	PCEPI	Personal Consumption Expenditures (Price Index)	FRED	5
WAGES	AHETPI	Average Hourly Earnings of Production and Nonsupervisory Employees, Total Private	FRED	5
HOURS	AWHNONAG	Average Weekly Hours of Production and Nonsupervisory Employees, Total Private	FRED	5
FFR	FEDFUNDS	Federal Funds Effective Rate	FRED	1
SP500		S&P 500	Yahoo! Finance	5
Recession		NBER recession dummy for the US	NBER	1
		UNCERTAINTY MEASURES		
JNLN12		JLN Macroeconomic Uncertainty, 12 months	JLN	1
JLNF12		JLN Financial Uncertainty, 12 months	JLN	1
JLNR12		JLN Economic Real Uncertainty, 12 months	JLN	1
BOS uncertainty		Business Outlook Survey uncertainty index (expectations about shipments)	Philly Fed	1
VIX	VIX	CBOE Volatility Index (VIX)	FRED	1
EPU	USEPUINDXM	Economic Policy Uncertainty Index for United States, Index, Monthly, Not Seasonally Adjusted	FRED	1
		DISAGREEMENT MEASURES		
DISAG		Tails disagreement (Factor)	UofM	1
DISAG-E		Entropy disagreement (Factor)	UofM	1
DISAG-L		Lacy disagreement (Factor)	UofM	1
NEWS-T		Tails disagreement (NEWS)	UofM	1
BAGO-T		Tails disagreement (BAGO)	UofM	1
BEXP-T		Tails disagreement (BEXP)	UofM	1
BUS12-T		Tails disagreement (BUS12)	UofM	1
BUS5-T		Tails disagreement (BUS5)	UofM	1
DISAG-HS		Tails disagreement (Factor, Education High School)	UofM	1
DISAG-SC		Tails disagreement (Factor, Education Some College)	UofM	1
DISAG-CD		Tails disagreement (Factor, Education College Degree)	UofM	1
DISAG 18-34		Tails disagreement (Factor, Age 18-34)	UofM	1
DISAG 35-54		Tails disagreement (Factor, Age 35-54)	UofM	1
DISAG 55+		Tails disagreement (Factor, Age 55+)	UofM	1

There are five main data sources indicated in the fourth column of this table, FRED (Federal Reserve Economic Data, https://fred.stlouisfed.org/), UofM (University of Michigan Survey of consumers, https://data.sca.isr.umich.edu/), JLN2015 (data from Jurado et al. (2015), available at https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes), NBER (National Bureau of Economic Research, business cycle dating https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions), and Philly Fed (Federal Reserve Bank of Philadelphia, Business Outlook Survey, https://www.philadelphiafed.org/surveys-and-data/regional-economic-analysis/manufacturing-business-outlook-survey).[1] The name of each series is in the first column, while the second column of the table shows the mnemonic used by FRED (only relevant for those series downloaded from FRED). All data were downloaded in different dates throughout July 2021. The fifth column of Table A.1 shows the stationarity transformations applied to the series, where Tcode = 1 is for levels and Tcode = 5 is for

[1] The Business Outlook Survey (BOS) data are used to extract the uncertainty index of Bachmann et al. (2013) based on question 4 of the survey (expectations about shipments from six months from now). As the authors do not provide updates on this index, we use the raw BOS data and apply the transformation $FDISP_t$ (see Bachmann et al., 2013, page 7) to compute its values.

first differences of the natural logarithm. Series that are originally observed at daily or weekly frequencies (e.g. FEDFUNDS provided from FRED) are converted into monthly by taking simple arithmetic averages over the calendar month.

A.2. Cross-correlation of disagreement with uncertainty and macroeconomic variables

Figure B.1 further studies the time series properties of disagreement by showing the cross-correlations of the DISAG index at time t with key uncertainty and macroeconomic variables, at various leads and lags. The panels show the cross-correlation between $DISAG_t$ and the variable x_{t+h} for lags $h = -12, ..., -1, 0, 1, ...12$. Consistent with Figure 4, $DISAG_t$ is negatively correlated at several leads and lags with the JLN12 and VIX uncertainty indexes, and the correlation coefficient never exceeds -0.6 (bottom panels), indicating that disagreement conveys sufficiently different information to uncertainty indicators. The correlation between disagreement and BOS and EPU is weak and changes sign across leads and lags. The DISAG index entails a low correlation with macroeconomic and financial variables. The correlation coefficient for IP, employment, consumption (durables, non-durable and services), and hours of work is within $\pm$ 0.2. Similarly, the correlation coefficient with inflation, the Federal Fund Rate, the SP500 Index, and wages is within $\pm$ 0.3. Consistent with the analysis in Section 2, disagreement is negatively correlated with uncertainty measures and is weakly correlated with macroeconomic variables.

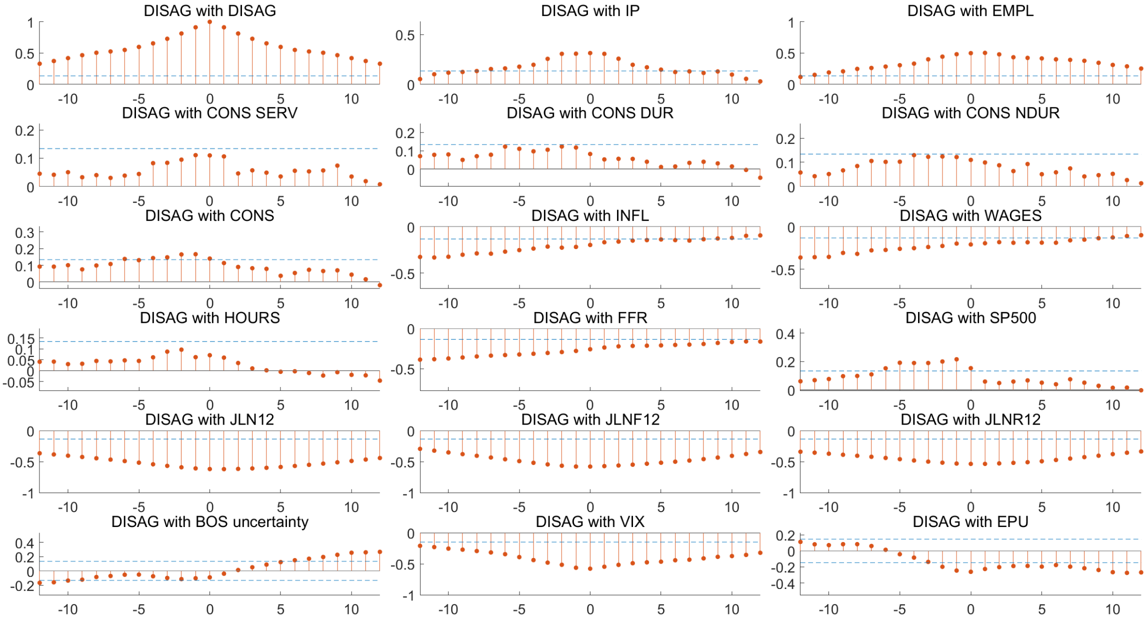

Figure B.1: Cross-correlations of disagreement with uncertainty and macroeconomic variables at various leads and lags. *Notes*: In each of these plots, the y-axis shows the value of cross-correlation of DISAG with each of 18 macroeconomic, financial and uncertainty indicators, at 12 leads/lags. Negative values on the x-axes indicate the correlation between DISAG today and the value of each indicator h months in the past, $h = 1, ..., 12$. Positive values indicate the correlation between DISAG h months ago and the current value of each indicator. Zero values indicate contemporaneous correlations. JLNF12 and JLNR12 are additional uncertainty measures developed by Jurado et al. (2015). All data and mnemonics are described in Appendix A, Table A.1.

B. Proof of propositions in Section 4

This appendix proves Propositions 1 and 2 in Section 4.

B.1. Proof of Proposition 1

Proof. Part (i). The partial derivative of $FEV(k)$ in equation (10) w.r.t. σ_ε^2 is:

$$\frac{\partial FEV(k)}{\partial \sigma_\varepsilon^2} = \psi_k^2 \left(\frac{\sigma_v^2}{\sigma_v^2 + \sigma_\varepsilon^2} \right)^2 \left(\frac{\sigma_v^2 - \sigma_\varepsilon^2}{\sigma_v^2 + \sigma_\varepsilon^2} \right) + \sum_{j=0}^{k-1} \psi_j^2 > 0, \tag{B.1}$$

since $\sum_{j=0}^{k-1} \psi_j^2 > \psi_0^2 = 1 > (\lambda^k)^2 = \psi_k^2$ and $\left| \left(\frac{\sigma_v^2}{\sigma_v^2+\sigma_\varepsilon^2} \right)^2 \left(\frac{\sigma_v^2-\sigma_\varepsilon^2}{\sigma_v^2+\sigma_\varepsilon^2} \right) \right| \leq 1$, then $\sum_{j=0}^{k-1} \psi_j^2 > \psi_k^2 \left(\frac{\sigma_v^2}{\sigma_v^2+\sigma_\varepsilon^2} \right)^2 \left(\frac{\sigma_v^2-\sigma_\varepsilon^2}{\sigma_v^2+\sigma_\varepsilon^2} \right)$, and therefore equation (B.1) is positive.

Part (ii). The partial derivative of $FEV(k)$ in equation (10) w.r.t. σ_v^2 is:

$$\frac{\partial FEV(k)}{\partial \sigma_v^2} = 2\psi_k^2 \sigma_\varepsilon^2 \left(\frac{\sigma_v^2}{\sigma_\varepsilon^2 + \sigma_v^2} \right) \left(\frac{\sigma_\varepsilon^2}{(\sigma_\varepsilon^2 + \sigma_v^2)^2} \right) > 0. \tag{B.2}$$

since all the terms in equation (B.2) are positive. □

B.2. Proof of Proposition 2

Proof. We prove parts (i) and (ii) of Proposition 2 starting for the case of a positive mean of the signal equal to σ_ε: $s_t|(\varepsilon_t = \sigma_\varepsilon) \sim N(\sigma_\varepsilon, \sigma_v^2)$.

Part (i). The partial derivative of the disagreement index ($\mathcal{D}$) w.r.t. σ_ε^2 is:

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon^2} = \frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} \cdot \frac{1}{2\sigma_\varepsilon}, \tag{B.3}$$

where from the definition of the disagreement index in equation (12):

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} = \underbrace{\frac{\partial \mathcal{D}}{\partial \Phi(\cdot)}}_{(+)} \cdot \underbrace{\frac{\partial \Phi(\cdot)}{\partial \sigma_\varepsilon}}_{(-)} < 0. \tag{B.4}$$

Since the mean of the Normal distribution is positive, then $\Phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) < 0.5$ and $\frac{\partial \mathcal{D}}{\partial \Phi(.)} > 0$. Since the derivative of the CDF of the standard normal distribution with respect to the positive mean is negative, then $\frac{\partial \Phi(\cdot)}{\partial \sigma_\varepsilon} < 0$.[2] Therefore, $\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} < 0$, and $\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon^2} < 0$.

Part (ii). The partial derivative of the disagreement index ($\mathcal{D}$) w.r.t. σ_v^2 is:

$$\frac{\partial \mathcal{D}}{\partial \sigma_v^2} = \frac{\partial \mathcal{D}}{\partial \sigma_v} \frac{1}{2\sigma_v}. \tag{B.5}$$

where from the definition of the disagreement index in equation (12):

$$\frac{\partial \mathcal{D}}{\partial \sigma_v} = \underbrace{\frac{\partial \mathcal{D}}{\partial \Phi(\cdot)}}_{(+)} \cdot \underbrace{\frac{\partial \Phi(\cdot)}{\partial \sigma_v}}_{(+)} > 0. \tag{B.6}$$

Since the mean of the Normal distribution is positive, then $\Phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) < 0.5$ and $\frac{\partial \mathcal{D}}{\partial \Phi(.)} > 0$. Since the derivative of the CDF of standard normal distribution with respect to the variance is positive, then $\frac{\partial \Phi(\cdot)}{\partial \sigma_v} > 0$.[3] Therefore, $\frac{\partial \mathcal{D}}{\partial \sigma_v} > 0$ and $\frac{\partial \mathcal{D}}{\partial \sigma_v^2} > 0$.

We now prove parts (i) and (ii) of Proposition 2 for the case of a negative mean of the signal equal to $-\sigma_\varepsilon$: $s_t|(\varepsilon_t = \sigma_\varepsilon) \sim N(-\sigma_\varepsilon, \sigma_v^2)$. The disagreement index is defined as:

$$\mathcal{D} = 1 - \left| 1 - 2\Phi\left(\frac{0+\sigma_\varepsilon}{\sigma_v}\right) \right|. \tag{B.7}$$

[2]The derivative of the CDF of the standard Normal distribution (mean μ and standard deviation σ) with respect to the positive mean is equal to: $\frac{d\Phi\left(\frac{x-\mu}{\sigma}\right)}{d\mu} = -\frac{1}{\sigma} \cdot \phi\left(\frac{x-\mu}{\sigma}\right)$, where $\phi(\cdot)$ is the density function of the Normal random variable. In our case, it is equal to $-\frac{1}{\sigma_v} \cdot \phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) < 0$.

[3]The derivative of the CDF of the standard Normal distribution (mean μ and standard deviation σ) with respect to the variance is equal to: $\frac{d\Phi\left(\frac{x-\mu}{\sigma}\right)}{d\sigma} = (-1) \cdot \phi\left(\frac{x-\mu}{\sigma}\right) \cdot \frac{(x-\mu)}{\sigma^2}$. In our case, it is equal to: $\frac{\partial \Phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right)}{\partial \sigma_v} = -2 \cdot \phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) \cdot \left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) > 0$ since $(0-\sigma_\varepsilon)/\sigma_v < 0$.

Part (i). When the mean of the distribution is negative, $\Phi\left(\frac{0+\sigma_\varepsilon}{\sigma_v}\right) > 0.5$ and $\frac{\partial \mathcal{D}}{\partial \Phi(.)} < 0$. The partial derivative of the disagreement index ($\mathcal{D}$) w.r.t. σ_ε^2 is as before:

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon^2} = \frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} \cdot \frac{1}{2\sigma_\varepsilon}, \tag{B.8}$$

where from the definition of the disagreement index in equation (B.7):

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} = \underbrace{\frac{\partial \mathcal{D}}{\partial \Phi(\cdot)}}_{(-)} \cdot \underbrace{\frac{\partial \Phi(\cdot)}{\partial \sigma_\varepsilon}}_{(+)} < 0. \tag{B.9}$$

Since the mean of the Normal distribution is positive, then $\Phi\left(\frac{0+\sigma_\varepsilon}{\sigma_v}\right) > 0.5$ and $\frac{\partial \mathcal{D}}{\partial \Phi(.)} < 0$. Since the derivative of the CDF of the standard normal distribution with respect to the negative mean is positive, then $\frac{\partial \Phi(\cdot)}{\partial \sigma_\varepsilon} > 0$.[4] Therefore, $\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} < 0$, and $\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon^2} < 0$.

Part (ii). The partial derivative of the disagreement index ($\mathcal{D}$) w.r.t. σ_v^2 is:

$$\frac{\partial \mathcal{D}}{\partial \sigma_v^2} = \frac{\partial \mathcal{D}}{\partial \sigma_v} \frac{1}{2\sigma_v}. \tag{B.10}$$

where from the definition of the disagreement index in equation (B.7):

$$\frac{\partial \mathcal{D}}{\partial \sigma_v} = \underbrace{\frac{\partial \mathcal{D}}{\partial \Phi(\cdot)}}_{(-)} \cdot \underbrace{\frac{\partial \Phi(\cdot)}{\partial \sigma_v}}_{(-)} > 0. \tag{B.11}$$

Since the mean of the Normal distribution is negative, then $\Phi\left(\frac{0+\sigma_\varepsilon}{\sigma_v}\right) > 0.5$ and $\frac{\partial \mathcal{D}}{\partial \Phi(.)} < 0$. Since the derivative of the CDF of a standard normal distribution with negative mean respect to the variance is negative, then $\frac{\partial \Phi(\cdot)}{\partial \sigma_\varepsilon} < 0$.[5] Therefore, $\frac{\partial \mathcal{D}}{\partial \sigma_v} > 0$, and $\frac{\partial \mathcal{D}}{\partial \sigma_v^2} > 0$.

$\square$

C. Econometric methodology

This appendix describes the structural vector autoregression methodology for identifying σ_ε^2 and σ_v^2 shocks via sign restrictions. The core VAR formulation follows Korobilis (2022), who develops an efficient algorithm for posterior inference in VARs with sign restrictions. This algorithm allows for estimating VARs of arbitrarily large dimensions, and is particularly suited for the monthly medium-scale VAR models with 13 lags we use in this paper. For the $n \times 1$ vector of time series variables $\boldsymbol{y}_t$ the VAR takes the

[4] In this case, the derivative of the CDF w.r.t. $-\sigma_\varepsilon$ it is equal to $\frac{1}{\sigma_v} \cdot \phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) < 0$.

[5] In this case case, it is equal to: $\frac{\partial \Phi\left(\frac{0+\sigma_\varepsilon}{\sigma_v}\right)}{\partial \sigma_v} = -2 \cdot \phi\left(\frac{0-\sigma_\varepsilon}{\sigma_v}\right) \cdot \left(\frac{0+\sigma_\varepsilon}{\sigma_v}\right) < 0$.

multivariate regression form

$$\mathbf{y}_t = \mathbf{\Phi}\mathbf{x}_t + \boldsymbol{\varepsilon}_t, \tag{B.1}$$

where $\mathbf{y}_t$ is a $(n \times 1)$ vector of observed variables, $\mathbf{x}_t = \left(1, \mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-p}\right)'$ a $(k \times 1)$ vector (with $k = np + 1$) containing a constant and p lags of $\mathbf{y}$, $\mathbf{\Phi}$ is an $(n \times k)$ matrix of coefficients, and $\boldsymbol{\varepsilon}_t$ a $(n \times 1)$ vector of disturbances distributed as $N\left(\mathbf{0}_{n\times 1}, \mathbf{\Omega}\right)$ with $\mathbf{\Omega}$ an $n \times n$ covariance matrix. We further assume the following factor decomposition of $\boldsymbol{\varepsilon}_t$

$$\boldsymbol{\varepsilon}_t = \mathbf{\Lambda}\mathbf{f}_t + \mathbf{v}_t, \tag{B.2}$$

where $\mathbf{\Lambda}$ is an $n \times r$ matrix of factor loadings, $\mathbf{f}_t \sim N(\mathbf{0}, \boldsymbol{I}_r)$ is an $r \times 1$ vector of factors, and $\mathbf{v}_t \sim N(\mathbf{0}, \mathbf{\Sigma})$ is an $n \times 1$ vector of idiosyncratic shocks with $\mathbf{\Sigma}$ an $n \times n$ diagonal matrix.

The rationale behind the VAR model in equations (B.1)-(B.2) is that the n-dimensional vector of VAR disturbances is decomposed into r common shocks $\mathbf{f}_t$ $(r < n)$ and n idiosyncratic shocks $\mathbf{v}_t$. Because $\mathbf{\Sigma}$ is diagonal, we consider only the r common shocks to be structural while the n idiosyncratic shocks can be considered as nuisance shocks e.g. due to measurement error or asymmetric information. Indeed, by left-multiplying the VAR using the generalized inverse of $\mathbf{\Lambda}$, the implied structural VAR form is

$$\begin{aligned} \mathbf{y}_t &= \mathbf{\Phi}\mathbf{x}_t + \mathbf{\Lambda}\mathbf{f}_t + \mathbf{v}_t && \text{(B.3)} \\ \left(\mathbf{\Lambda}'\mathbf{\Lambda}\right)^{-1}\mathbf{\Lambda}'\mathbf{y}_t &= \left(\mathbf{\Lambda}'\mathbf{\Lambda}\right)^{-1}\mathbf{\Lambda}'\mathbf{\Phi}\mathbf{x}_t + \mathbf{f}_t + \left(\mathbf{\Lambda}'\mathbf{\Lambda}\right)^{-1}\mathbf{\Lambda}'\mathbf{v}_t && \text{(B.4)} \\ \mathbf{A}_1\mathbf{y}_t &= \mathbf{B}_1\mathbf{x}_t + \mathbf{f}_t + \left(\mathbf{\Lambda}'\mathbf{\Lambda}\right)^{-1}\mathbf{\Lambda}'\mathbf{v}_t. && \text{(B.5)} \end{aligned}$$

As long as $\mathbf{\Sigma}$ is diagonal the term $\left(\mathbf{\Lambda}'\mathbf{\Lambda}\right)^{-1}\mathbf{\Lambda}'\mathbf{v}_t$ vanishes asymptotically, meaning that $\mathbf{f}_t$ retains the interpretation of structural shocks. Korobilis (2022) shows that structural identifying restrictions are identical to parametric restrictions on $\mathbf{\Lambda}$, and provides an efficient Markov chain Monte Carlo (MCMC) scheme for sampling such restrictions in high-dimensional VARs.[6]

Based on the model in equations (B.1)-(B.2) the joint likelihood function can be written as

$$(\boldsymbol{y}|\boldsymbol{x}, \mathbf{\Phi}, \mathbf{\Lambda}, \boldsymbol{f}, \mathbf{\Sigma}) \sim \prod_{t=1}^{T} N\left(\mathbf{\Phi}\mathbf{x}_t, \mathbf{\Lambda}\mathbf{\Lambda}' + \mathbf{\Sigma}\right) \tag{B.6}$$

[6]A VAR can be high-dimensional due to the large number of time series T, large number of endogenous variables n, large number of identified shocks r, large number of lags p, or combinations of these.

and we define the following prior distributions

$$
\begin{aligned}
\boldsymbol{\phi}_i \equiv vec\left(\boldsymbol{\Phi}_i\right) &\sim N_k\left(\mathbf{0}, \underline{\mathbf{V}}_i\right), && \text{(B.7)}\\
\underline{\mathbf{V}}_{i,(jj)} &= \sigma_i^2 \tau_i^2 \psi_{i,j}^2, && \text{(B.8)}\\
\psi_{i,j} &\sim Cauchy^+\left(0,1\right), && \text{(B.9)}\\
\tau_i &\sim Cauchy^+\left(0,1\right), && \text{(B.10)}\\
\mathbf{f}_t &\sim N_r\left(\mathbf{0}, \mathbf{I}\right), && \text{(B.11)}\\
\boldsymbol{\Lambda}_{ij} &\sim \begin{cases} N\left(0, \underline{h}_{ij}\right) I(\Lambda_{ij} > 0), & \text{if } S_{ij} = 1,\\ N\left(0, \underline{h}_{ij}\right) I(\Lambda_{ij} < 0), & \text{if } S_{ij} = -1,\\ \delta_0\left(\boldsymbol{\Lambda}_{ij}\right), & \text{if } S_{ij} = 0,\\ N\left(0, \underline{h}_{ij}\right), & \text{otherwise,} \end{cases} && \text{(B.12)}\\
\sigma_i^2 &\sim inv - Gamma\left(\underline{\rho}_i, \underline{\kappa}_i\right), && \text{(B.13)}
\end{aligned}
$$

for $i = 1, ..., n$, $j = 1, ..., r$, where $\boldsymbol{\Phi}_i$ is the i^{th} row of $\boldsymbol{\Phi}$, σ_i^2 is the i^{th} diagonal element of the matrix $\boldsymbol{\Sigma}$, and $\delta_0\left(\boldsymbol{\Lambda}_{ij}\right)$ is the Dirac delta function for $\boldsymbol{\Lambda}_{ij}$ at zero (i.e. a point mass function with all mass concentrated at zero). The hyperparameters $\psi_{i,j}$ and τ_i are components of a Horseshoe prior, which is a tuning-free shrinkage priors with excellent statistical properties (see Korobilis, 2022, for explanation and references to the statistics literature justifying the excellent theoretical properties of this prior). Therefore, we only need to select parameters with an underline, namely $\underline{h}_{ij}, \underline{\rho}_i, \underline{\kappa}_i$. As we typically do not have substantial prior information on these hyperparameters, it is fairly trivial to choose noninformative values. Following standard norms in Bayesian inference, we set $\underline{h}_{ij} = 10$ and $\underline{\rho}_i, \underline{\kappa}_i = 0.01$ such that the priors in equations (B.12) and (B.13) become locally Uniform. Posterior computation and impulse response inference follows Korobilis (2022) and the reader should refer to this paper for technical details.

D. Robustness analysis and additional results

In this Appendix we report i), the complete set of IRFs estimated from the VAR specifications in the main body of the paper and ii), results from VAR specifications that use various economic, financial, and survey indicators, iii), results from VAR specifications that use alternative proxies for uncertainty, iv) results from VAR specifications with disagreement indices derived from specific questions, v) results from VAR specifications with disagreement indices based on (Shannon, 1948) entropy measure, and (Lacy (2006)) measure, vi) results from VAR specifications with disagreement indices derived from consumers of different education and age groups. These VAR specifications serve to examine the robustness of the main finding in the main body of the paper, namely, the different dynamic effects of agreed and disagreed uncertainty shocks.

D.1. Complete IRFs from the extended benchmark model

Figure C.1 below displays the complete set of IRFs from the benchmark specification. Private consumption displays a negative effect following an agreed uncertainty innovation consistent with the negative responses estimated for industrial production and employment. Following a disagreed uncertainty innovation private consumption exhibits a small short run increase that is nevertheless not statistically significant. There are also systematic differences in the responses of S&P 500, Federal Funds rate and consumer price inflation following agreed and disagreed uncertainty innovations, suggesting that the qualitatively different dynamic responses following the two shocks are broad based.

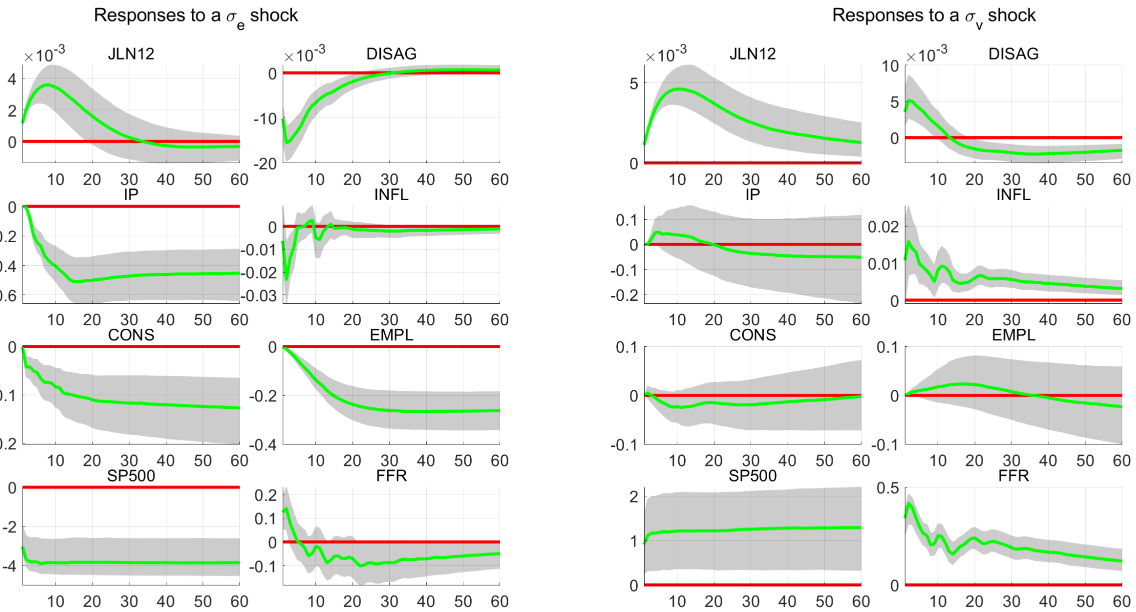

Figure C.1: Extended Benchmark model. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses from a eight-variable VAR system on JLN 12-month ahead uncertainty indicator (JLN12), disagreement index (DISAG), industrial production (IP), private consumption (CONS), Consumer price inflation (INFL), employment (EMPL), S&P 500 index (SP500), Federal funds rate (FEDFUNDS). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters.

Testing the statistical significance of the difference in the IRFs. Figure C.2 below plots the differences between the IFRs estimated for the agreed and disagreed uncertainty shocks for the macroeconomic indicators of interest in the extended benchmark specifiction. The figure suggests that the qualitatative different dynamic effects of agreed and disagreed uncertainty shocks are also statistically significantly different.

The benchmark specification in section 5 used the macro uncertainty measure (JLN-12) as the baseline measure of uncertainty. In this section we replace JLN-12 in the benchmark VAR with four alternative uncertainty measures used in earlier work. Jurado et al. (2015) developed the 12-month ahead financial uncertainty indicator (henceforth JLNF-12) using

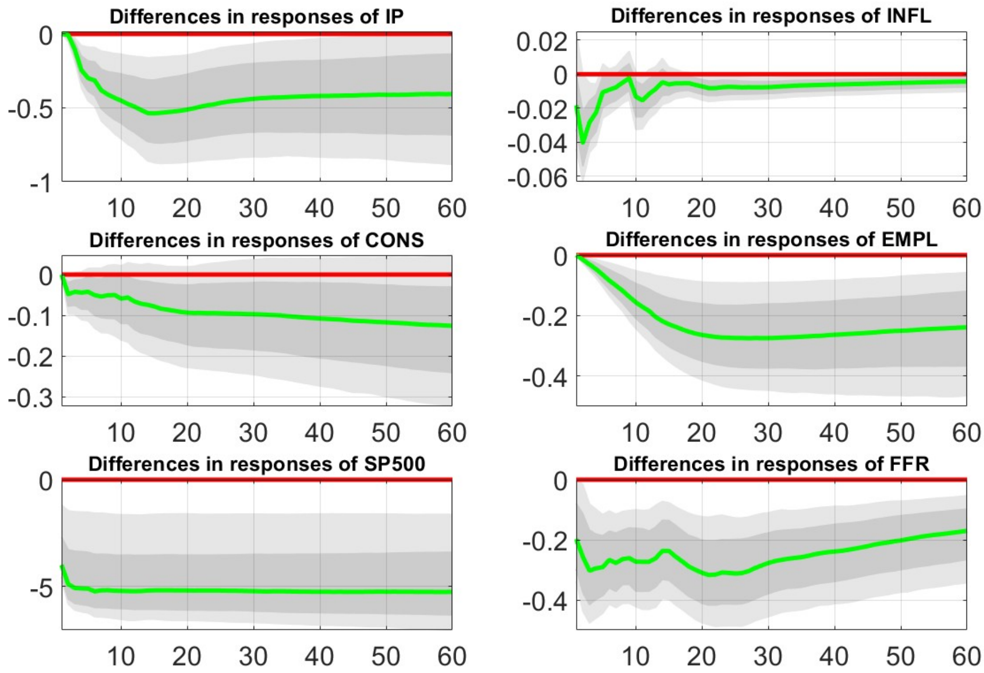

Figure C.2: Extended Benchmark model. Differences in IRFs between agreed and disagreed uncertainty shocks. The figure displays the posterior differences in the responses estimated for the agreed uncertainty and disagreed uncertainty shocks. These differences are computed from the posterior distribution of the VAR parameters. The dark-shaded (light-shaded) gray areas indicate 68% and 90% posterior confidence bands.

estimates of conditional volatilities of h-step ahead forecast errors from 147 financial time series. Ludvigson et al. (2021) suggest this indicator is a preferable measure of uncertainty as it is less likely to be confounded by exogenous shocks –and hence can be treated as an exogenous source of variation in uncertainty– in comparison to JLN-12. Beyond this measure we also use the business dispersion measure (BOS-dispersion), developed in Bachmann et al. (2013), and a popular measure of stock market volatility (CBOE S&P 100 volatility index VIX) used in several important studies as a proxy for uncertainty (Bloom, 2009, Gilchrist et al., 2014, Basu and Bundick, 2017). Finally, we use the Economic Policy Uncertainty index (EPU) developed by Baker et al. (2016). The latter is developed using text mining methods and captures uncertainty, broadly speaking, about future fiscal, monetary, trade, regulatory policy actions.

D.2. IRFs from VAR model with JLNF-12

Figure C.3 below displays the complete set of IRFs from the VAR specification with JLNF-12 used as the uncertainty indicator. The IRFs are broadly consistent with the IRFs displayed in the Figure C.1 above. The left panel which plots the IRFs to the agreed uncertainty shock displays very similar –qualitatively– depressing effects on industrial production and employment in comparison to the effects estimated when JLN12 is used as the uncertainty proxy. The depressive effects on economic activity are consistent with the evidence in Ludvigson et al. (2021) who also use JLNF-12 as the uncertainty indicator in their empirical analysis. The right panel displays the IRFs following an innovation to the disagreed uncertainty shock. Qualitatively the dynamic effects estimated are very much in line with those displayed in C.1. Thus, both the benchmark and this alternative specification suggest that innovations to disagreed uncertainty display a benign effect on economic activity, strikingly different from the strong depressing effect on activity estimated under agreed uncertainty innovations.

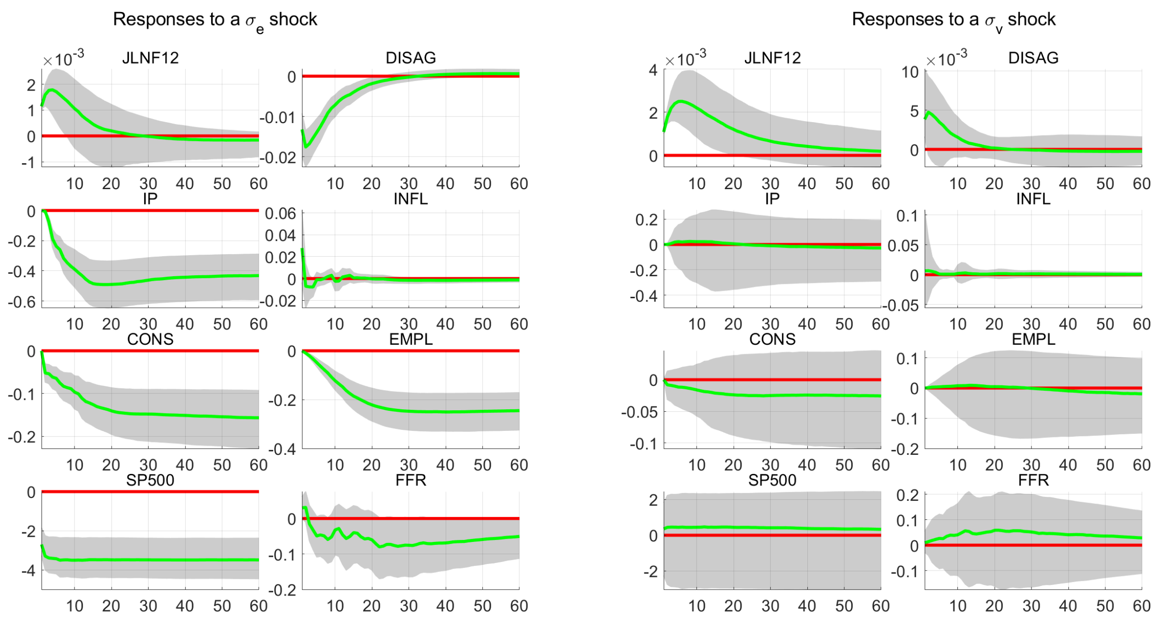

Figure C.3: JLNF-12 measure. Agreed σ_ε (left) versus disagreed σ_υ (right) uncertainty. The figure shows impulse responses from a eight-variable VAR system on JLNF 12-month ahead uncertainty indicator (JLNF12), disagreement index (DISAG), industrial production (IP), private consumption (CONS), Consumer price inflation (INFL), employment (EMPL), S&P 500 index (SP500), Federal funds rate (FEDFUNDS). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, while the horizontal axes reports time measured in months.

D.3. IRFs from VAR model with BOS-DISPERSION

Figure C.4 below displays the complete set of IRFs from a VAR specification with the BOS-DISPERSION used as the uncertainty indicator. A key difference in this Figure in comparison to Figure C.1 is the different dynamic response of uncertainty: while uncertainty rises under both agreed and disagreed shocks, the business dispersion measure displays more short-lived and non-persistence dynamics in comparison to JLN-12 or JLNF-12. This may not be surprising given this dispersion measure is based on a very different information set –firms in the manufacturing sector, in comparison to the broad spectrum of variables considered in JLN-12 aand JLNF-12. Nevertheless the dynamic effects following an agreed uncertainty shock identified from this alternative indicator suggest a strong and long lasting period of depressed activity, very much in line with conventional wisdom and our findings above. Focussing on the dynamic effects following a disagreed uncertainty shock, broadly speaking, real activity indicators do not respond in a statistically significant manner. If anything we note a small and statistical significant increase in consumption after about ten months following this shock. This suggests the response of real activity indicators is non-contractionary under disagreed uncertainty shocks, identified from this uncertainty proxy, and importantly there is a distinct quantitative difference between the dynamic effects estimated under disagreed and agreed uncertainty shocks.

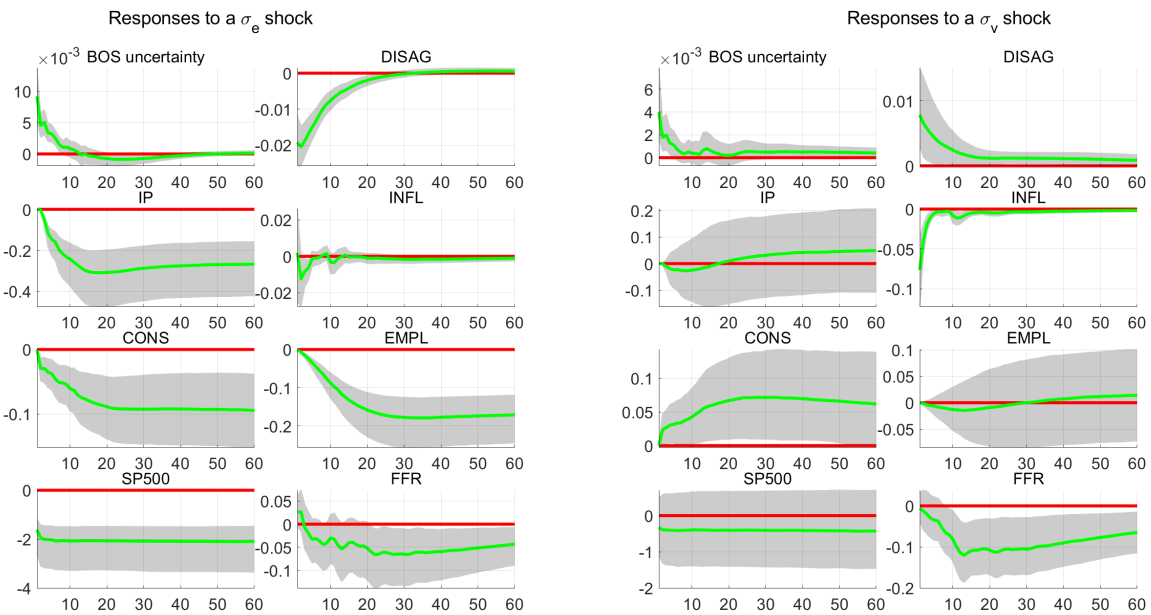

Figure C.4: Business Dispersion measure. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses from a eight-variable VAR system on Business dispersion indicator (BOS-DISPERSION), disagreement index (DISAG), industrial production (IP), private consumption (CONS), Consumer price inflation (INFL), employment (EMPL), S&P 500 index (SP500), Federal funds rate (FEDFUNDS). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, while the horizontal axes reports time measured in months.

D.4. IRFs from VAR model with VIX

Figure C.5 below displays the complete set of IRFs from the VAR specification with VIX used as the uncertainty indicator. Uncertainty responds sharply and it is short-lived. The IRFs to an agreed uncertainty innovation are consistent with a depressing and long lasting effect on real activity, very similar to what we have estimated in all other specifications. The dynamic effects estimated following a disagreed uncertainty shock are more mixed. Industrial production does not move initially but after the first few months displays a decline which is statistically significant until about month 40. However, the magitude of the response is significantly smaller compared to the response estimated following an agreed uncertainty innovation. The employment response suggests a very short statistically significant decline, while the consumption response is not statistically significant different from zero. We do however emphasize two important caveats with this specification. First, the sample period is different, due to the availability of the VIX indicator, beginning in 1986M1. Second, and more importantly the IRFs suggest that this specification may require more restrictions to properly identify the disagreed uncertainty shock. The positive sign restriction on disagreement that identifies this shock is satisfied on impact but the response is very short lived. Because we want to be as conservative as possible, our sign restrictions put very minimal constraints on the dynamics. This suggests that more identifying restrictions may be fruitful in order to clearly separate the two types of uncertainty shocks, when using this uncertainty indicator. Nevertheless, there are still significant qualitative differences in the responses of the real activity indicators; and the economic effects following this type of innovation are significantly smaller in magnitude in comparison to the economic effects estimated following an agreed uncertainty innovation.

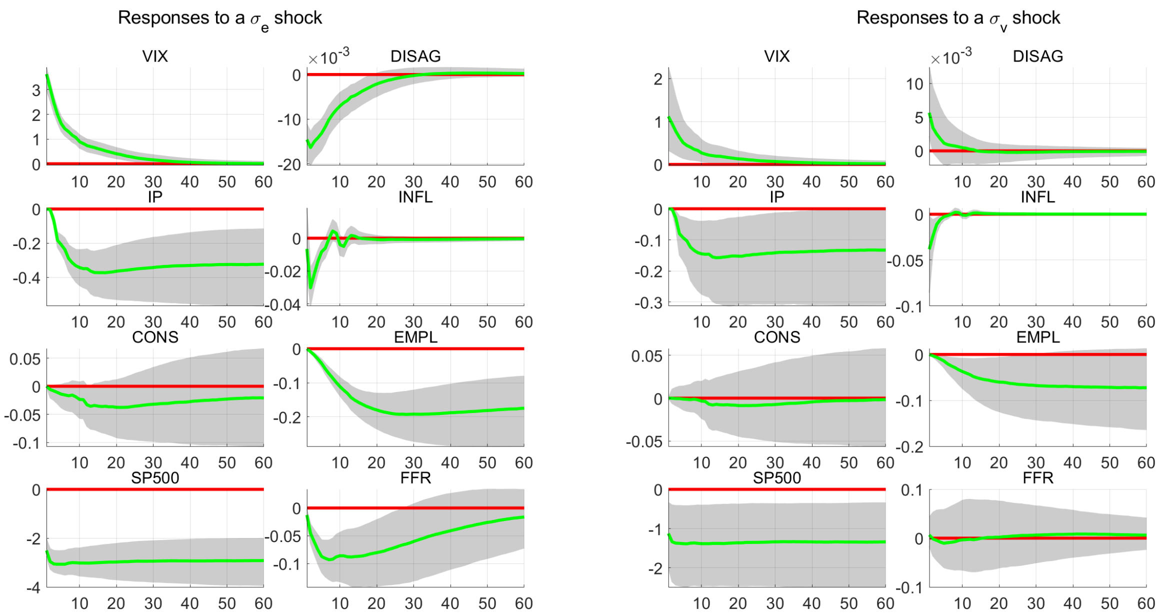

Figure C.5: Stock market implied volatility (VIX) measure. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses from a eight-variable VAR system on CBOE S&P 100 volatility index (VIX), disagreement index (DISAG), industrial production (IP), private consumption (CONS), Consumer price inflation (INFL), employment (EMPL), S&P 500 index (SP500), Federal funds rate (FEDFUNDS). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, while the horizontal axes reports time measured in months.

D.5. IRFs from VAR model with EPU

Figure C.6 below displays the complete set of IRFs from the VAR specification with EPU used as the uncertainty indicator. Its not straightforward to map the connection of this concept of uncertainty to the broad based macro or financial uncertainty indicators examined above. Moreover, the EPU indicator is not clearly related to our central measure of consumer disagreement as the latter refers to business conditions and the former is focussed on economic policy. Therefore its not straightforward to relate a change in information dispersion to the volatility of this indicator which is derived from text mining methods. The sample period, 1985M1 to 2020M12, for this specification is different to the benchmark due to the availability of the EPU index. We nevertheless wanted to examine the behavior of the real activity indicators using the concepts of agreed and disagreed uncertainty identified via this measure. Figure C.6 suggests a broad similarity to our findings when considering the dynamic effects following the agreed uncertainty shock –both industrial production and employment exhibit long lasting and depressing effects. While the response of industrial production is negative following both agreed and disagreed shocks, the response of employment is not statistically significant in the case of disagreed uncertainty shock (except for a brief period at the beginning of the forecast horizon). Moreover, the response of consumption is not statistically different from zero for the entire forecast horizon. We suggest this may be partly due to the fact that, similar to the VIX specification above, the identification of disagreed uncertainty shocks appears to be problematic since the disagreement index barely moves in a statistically significant manner in the case of the disagreed uncertainty shock.

D.6. Individual disagreement (BUS5 and NEWS)

Our benchmark DISAG index is the first principal component of the five individual disagreement series, described in section 2. We examine the robustness of our findings when we instead focus on individual disagreement indices. Figures C.7 and C.8 display complete set of IRFs estimated from two specifications where we replace the DISAG indicator in the benchmark VAR with disagreement about NEWS (*News Heard of Recent Changes in Business Conditions*) and BUS5 (*Business Conditions Expected During the Next 5 Years*), one at a time. The estimated IRFs from those specifications are broadly similar to the those from the benchmark and we do not discuss them further.

D.7. Disaggregated consumption

Our benchmark specification includes total private personal consumption. It is interesting to examine the dynamic responses of different consumption components. To this end we estimate a VAR specification where we introduce real consumption services, non-

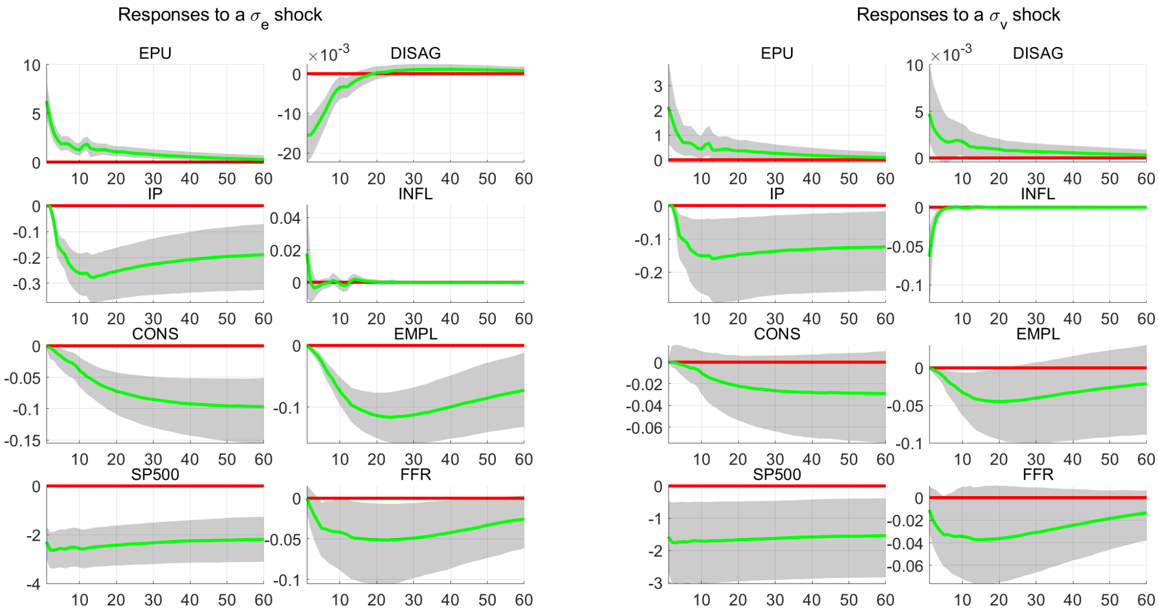

Figure C.6: EPU measure. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses from a eight-variable VAR system on economic policy uncertainty (EPU), disagreement index (DISAG), industrial production (IP), private consumption (CONS), consumer inflation (INFL), employment (EMPL), S&P 500 index (SP500), Federal funds rate (FEDFUNDS). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, while the horizontal axes reports time measured in months.

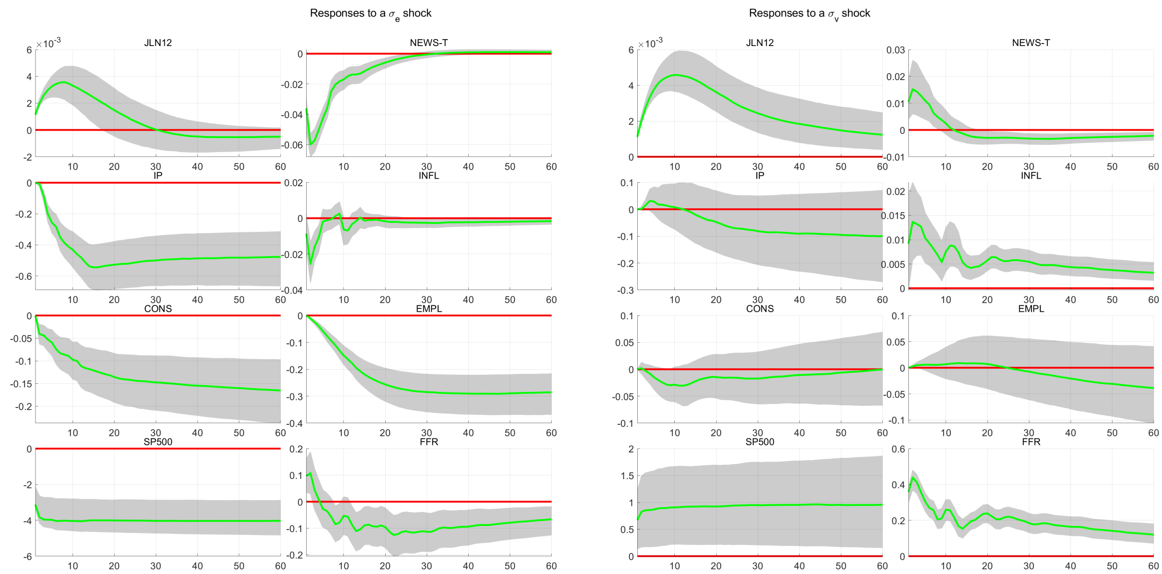

Figure C.7: Disagreement NEWS. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses from a eight-variable VAR system on JLN 12-month ahead uncertainty indicator (JLN12),disagreement index about NEWS (NEWS-T), industrial production (IP), private consumption (CONS), consumer price inflation (INFL), employment (EMPL), S&P 500 index (SP500), Federal funds rate (FEDFUNDS). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, while the horizontal axes reports time measured in months.

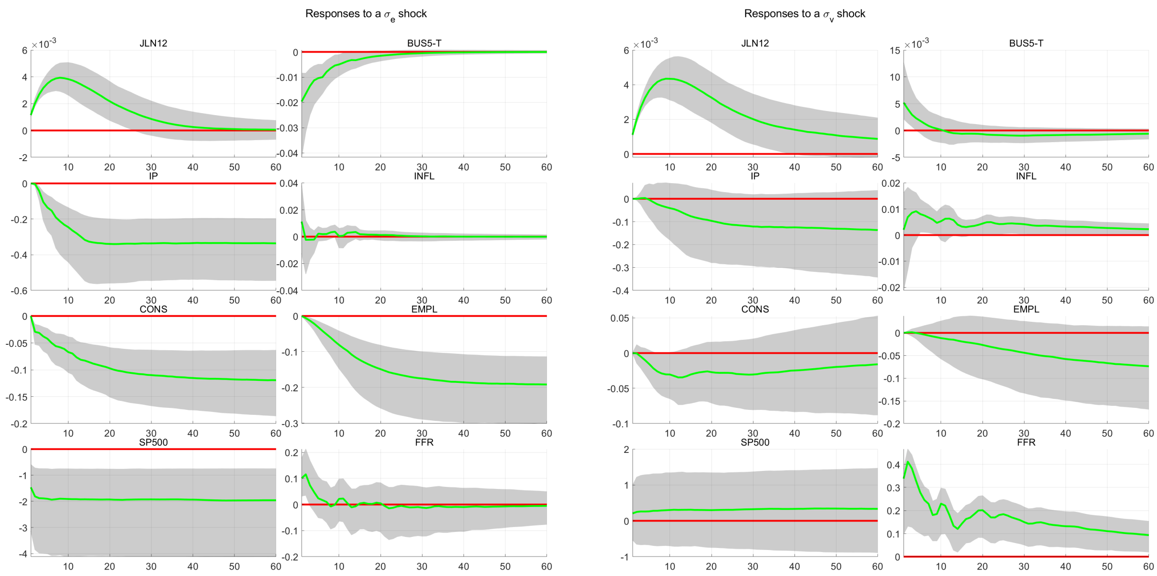

Figure C.8: Disagreement BUS5. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses from a eight-variable VAR system on JLN 12-month ahead uncertainty indicator (JLN12),disagreement index about BUS5 (BUS5-T), industrial production (IP), private consumption (CONS), consumer price inflation (INFL), employment (EMPL), S&P 500 index (SP500), Federal funds rate (FEDFUNDS). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, while the horizontal axes reports time measured in months.

durables and durables consumption. One would expect that uncertainty would mostly impact large durables purchases. For example, Eberly (1994) emphasizes the option to delay purchases of durable goods in an environment of elevated uncertainty, which in theory would depress durables spending, although the effects on non-durables and services might be weaker. Similarly, Bernanke (1983) and Romer (1990) show that uncertainty significantly delays consumer spending on durable purchases by increasing the option value of waiting. Bertola et al. (2005) provide extensive evidence on the sensitivity of durable goods spending to uncertainty. Figure C.9 displays the IRFs from this specification. Consumption non-durables, durables and services display a significant depressing effect following an innovation in agreed uncertainty. Consistent with theory, the response of durables consumption is stronger compared to the responses of non-durables and services consumption. By contrast following a disagreed uncertainty innovation the responses of the disaggregated consumption (with the exception of services consumption which displays a short-lived statistical significant decline) components are not statistically significant.

D.8. Alternative disagreement indicators

The tails disagreement employed in our benchmark specification is simple and intuitive, but does not fully utilize all the responses from MSC. Specifically, it only considers the two polar categories of responses (better/worse), while ignoring the middle category

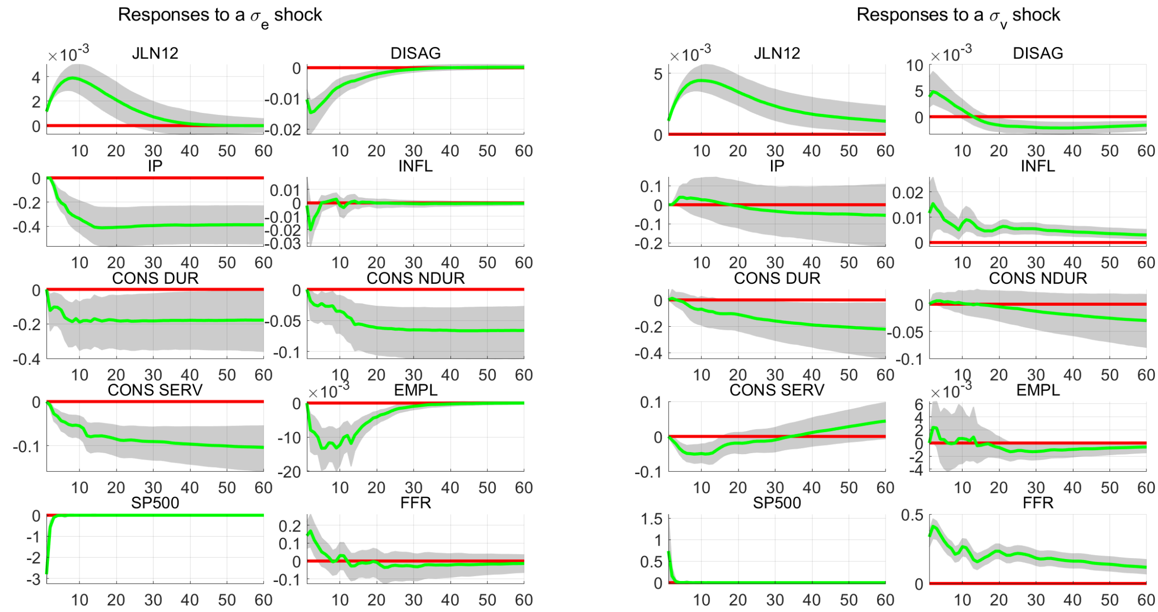

Figure C.9: Disaggregated consumption. Agreed σ_ε (left) versus disagreed σ_v(right) uncertainty. The figure shows impulse responses from a ten-variable VAR system on JLN 12-month ahead uncertainty indicator (JLN12), disagreement index (DISAG), industrial production (IP), consumption durables (CONS DUR), consumption non-durables (CONS NDUR), consumption services (CONS SERV), employment (EMPL), S&P500 stock index (SP500) and effective federal funds rate (FFR) . The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, while the horizontal axes reports time measured in months.

(depending on the question, this category relates to past/future conditions that are either the "same" or "uncertain"). For that reason we recompute the disagreement index using two alternative measures: "Entropy disagreement" using Shannon's (Shannon, 1948) entropy measure, and "Lacy disagreement" using the transformation proposed by Lacy (2006). These exploit all possible answers from consumers.

The entropy disagreement is defined as[7]

$$H_t^j = -\sum_{i=1}^{n} p(x_i^j) \log p(x_i^j)$$

where x_i^j is option i of n possible answers for question j, and $p(x_i^j)$ is the proportion of individuals answering x_i^j. This index gives a measure of the cross-sectional uncertainty of consumers about the possible business outcomes that may occur, where $p(x_i^j)$ has an interpretation of probabilities.[8] The higher the index the higher the uncertainty and the higher the disagreement. For example, if all consumers shared the same view about the prospects of the economy, the value of the index will be zero, which reflects a situation

[7]This measure we define as disagreement is called the "Shannon Index" in ecology and related sciences, and it is used to measure the diversity and distribution of types of species in a community; see Hill (1973).

[8]We assume that consumers who have the same view about business conditions do so because they also agree on the probabilities about observing a specific outcome.

of zero uncertainty and disagreement. By contrast if consumers are equally divided between the three outcome categories ("better," "worse," "same"), the value of the index attains the maximum value. The second alternative disagreement measure, from Lacy (2006), describes how dispersed or concentrated ordinal data is without requiring further assumptions about inter-category distances. The Lacy disagreement is defined using,

$$D_j^2 = \sum_{i=1}^{n-1} F_i \left(1 - F_i\right),$$

where F_i is the cumulative relative frequency for the ith category. Note that the sum excludes the last category, because F_n is always 1. This D_j^2 measure ranges from 0 to $(n-1)/4$. When the value of this measure is zero, all responses fall in the same category. The maximum value of $(n-1)/4$ denotes completely polarized distribution in which half of the responses are in category 1 and half are in category n. Values between the minimum and the maximum indicate intermediate levels of dispersion.

We re-estimate the VAR after replacing the disagreement indicator DISAG with the two alternative indicators one at a time, retaining all other variables in the extended benchmark specification. The results are reported in Figure C.10 below. First, we note that the median IRFs displayed following a shock to agreed uncertainty (left panel) and disagreed uncertainty (right panel) are qualitatively and quantitatively similar when we use either the Lacy (DISAG-L, dashed-green line) or Entropy (DISAG-E, dashed-blue line) concept of disagreement in the VAR, and they are broadly similar to the IRFs we estimate from the extended benchmark specification (also plotted in the same figure). This result shows that the different VAR specifications identify the same shocks to agreed and disagreed uncertainty. Moreover, the VAR specifications with the DISAG-L and DISAG-E indicators suggest that the short-run positive response of industrial production following an innovation to disagreed uncertainty are somewhat stronger in comparison to the responses in the same variables estimated in the benchmark specification. Overall, this exercise ensures that the DISAG indicator used in the benchmark VAR is robust to including information from those consumers that are more uncertain about the strength or weakness of current and future economic conditions.

D.9. IRFs from VAR model with DISAG-E

Figure C.11 below displays the complete set of IRFs from the VAR specification with the entropy measure, DISAG-E, used as the disagreement indicator.

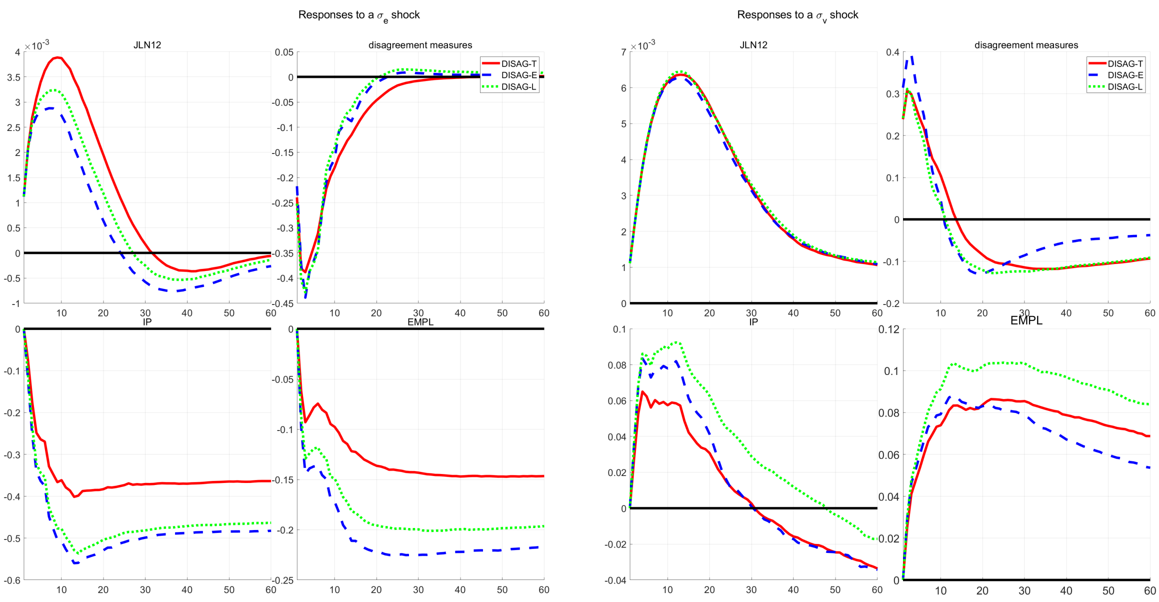

Figure C.10: Alternative disagreement indexes. Agreed (σ_ε, left) vs. disagreed σ_v (right) uncertainty. The figure shows (median) impulse responses for alternative disagreement indexes: Tail disagreement (DISAG-T) as used in the benchmark VAR, Entropy disagreement (DISAG-E), and Lacy disagreement (DISAG-L). The units of the vertical axes are percentage deviations, and the horizontal axes reports time measured in months.

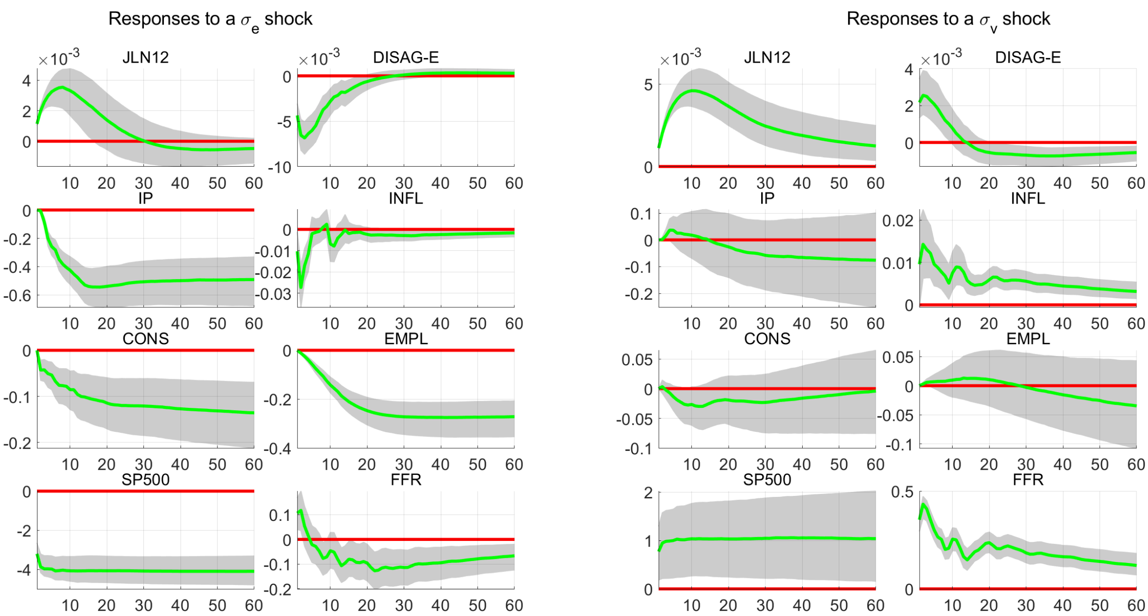

Figure C.11: Disagreement entropy measure. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses from a eight-variable VAR system on JLN 12-month ahead uncertainty indicator (JLN12), disagreement index (DISAG-E), industrial production (IP), private consumption (CONS), consumer price inflation (INFL), employment (EMPL), S&P 500 index (SP500), Federal funds rate (FEDFUNDS). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, while the horizontal axes reports time measured in months.

D.10. IRFs from VAR model with DISAG-L

Figure C.12 below displays the complete set of IRFs from the VAR specification with Lacy measure, DISAG-L, used as the disagreement indicator.

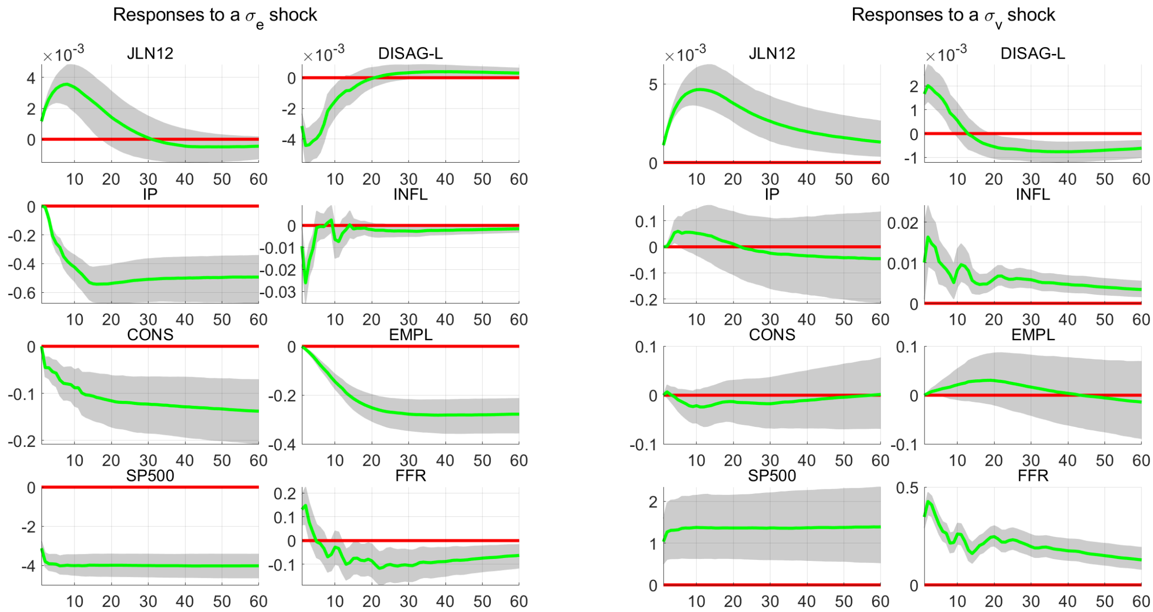

Figure C.12: Disagreement Lacy measure. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses from a eight-variable VAR system on JLN 12-month ahead uncertainty indicator (JLN12), disagreement index (DISAG-L), industrial production (IP), private consumption (CONS), consumer price inflation (INFL), employment (EMPL), S&P 500 index (SP500), Federal funds rate (FEDFUNDS). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, while the horizontal axes reports time measured in months.

D.11. Whose disagreement: Education and age

In addition to the overall aggregate response to the survey questions, the MSC collects demographic responses from consumers of different education and age status. They collect responses from three education categories, namely: *high-school*, *some college*, and *college degree*. They also collect responses from three age groups: 18-34, 35-54, and 55 and above. In this section we compute disagreement indicators for each of these education and age groups –six in total– using the tails concept of disagreement. We then, re-estimate the benchmark VAR using these indicators one at a time. Figures C.13, C.14, and C.15 display dynamic effects from the VARs that condition on the disagreement indicators based on the different education groups. The dynamic effects of agreed and disagreed uncertainty shocks, when we condition on disagreement according to education status, are very similar quantitatively to those dynamic effects reported for the extended benchmark specification. We report results from the VAR specifications conditioned on disagreement indicators based on the three age groups. When we condition the VAR on disagreement from the age groups, 18-34, and 55 and above age groups (see Figures C.16, C.18), the responses to industrial production and employment following agreed and disagreed uncertainty shocks are very similar qualitatively to the ones estimated from the extended benchmark model. By contrast, when we condition on disagreement of the 35-to-54 age group, the responses to the real activity indicators following agreed and disagreed uncertainty innovations (Figure C.18) display similar declines which are strong and statistically significant and they do not display the systematic differences we estimate in the benchmark specification. These results suggest that disagreement from the 18-34 and 55-and-over age groups appears to be the most relevant drivers behind our benchmark results, which are based on the aggregate responses.

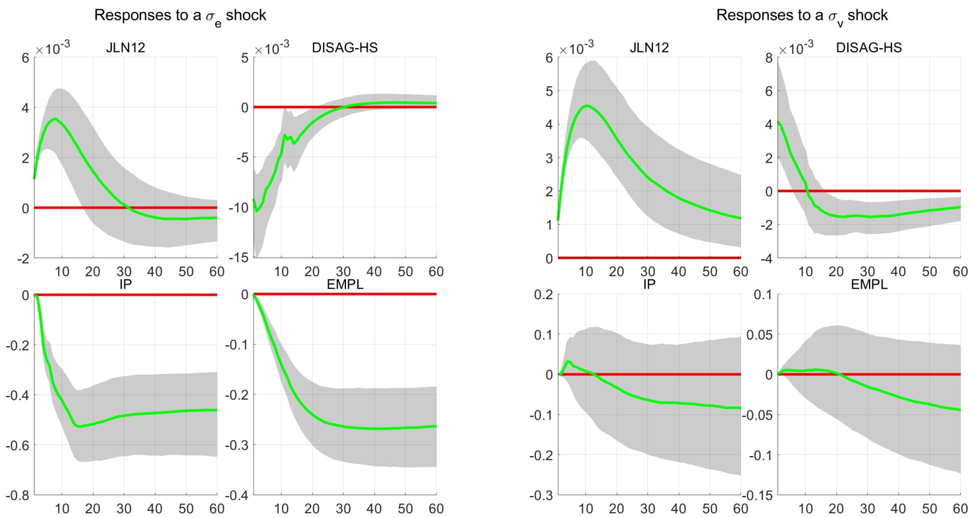

Figure C.13: Extended Benchmark model–education: High school. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses to the JLN 12-months-ahead uncertainty indicator (JLN12), the disagreement index for high school education level (DISAG-HS), industrial production (IP), and employment (EMPL). We compute IRFs from an eight-variable VAR system as described in the text. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, and the horizontal axes report time measured in months.

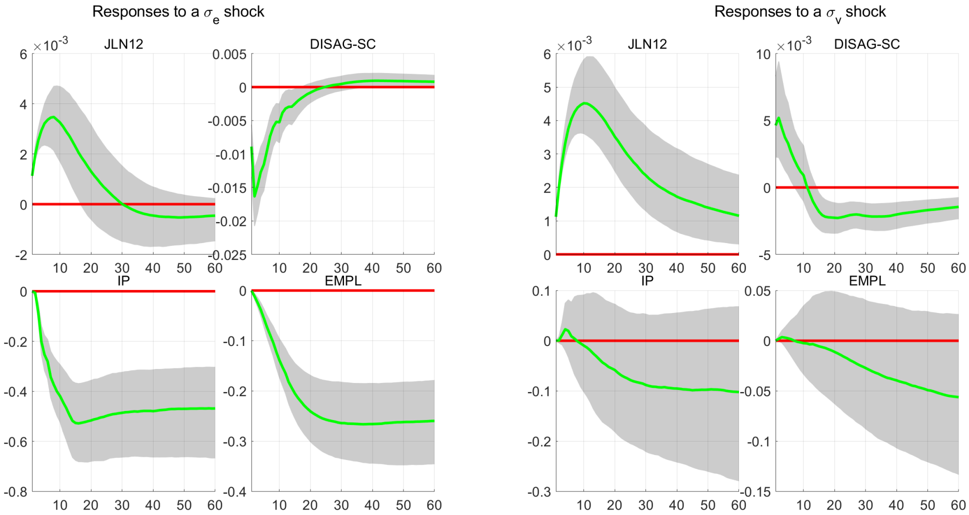

Figure C.14: Extended Benchmark model–education: some college. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses to the JLN 12-months-ahead uncertainty indicator (JLN12), the disagreement index for some college educational level (DISAG-SC), industrial production (IP), and employment (EMPL). We compute the IRFs from an eight-variable VAR system as described in the text. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, and the horizontal axes report time measured in months.

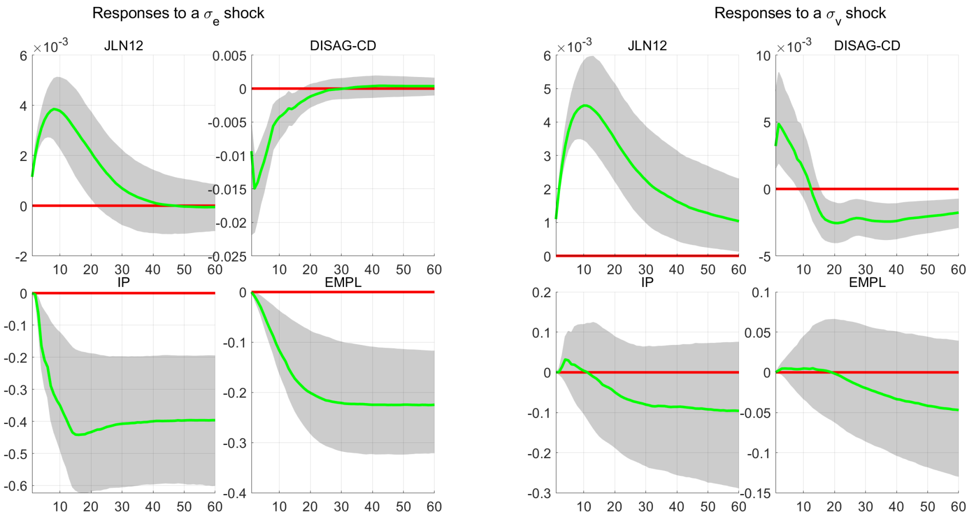

Figure C.15: Extended Benchmark model–education: College or higher. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses to the JLN 12-months-ahead uncertainty indicator (JLN12), the disagreement index for college-or-higher education level (DISAG-CD), industrial production (IP), and employment (EMPL). We compute IRFs from an eight-variable VAR system as described in the text. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, and the horizontal axes report time measured in months.

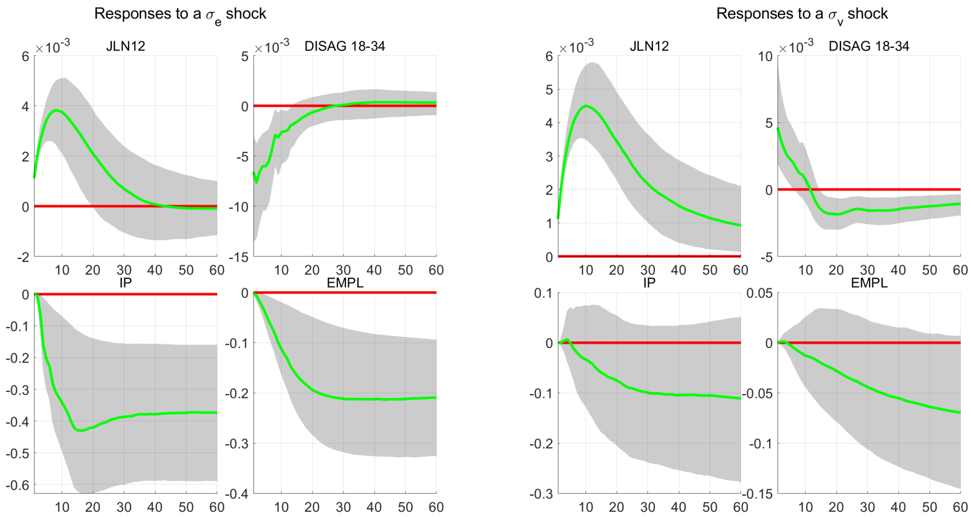

Figure C.16: Extended Benchmark model–age: 18-34. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses to the JLN 12-months-ahead uncertainty indicator (JLN12), the disagreement index for 18-34 age group (DISAG 18-34), industrial production (IP), and employment (EMPL). We compute IRFs from an eight-variable VAR system as described in the text. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, and the horizontal axes report time measured in months.

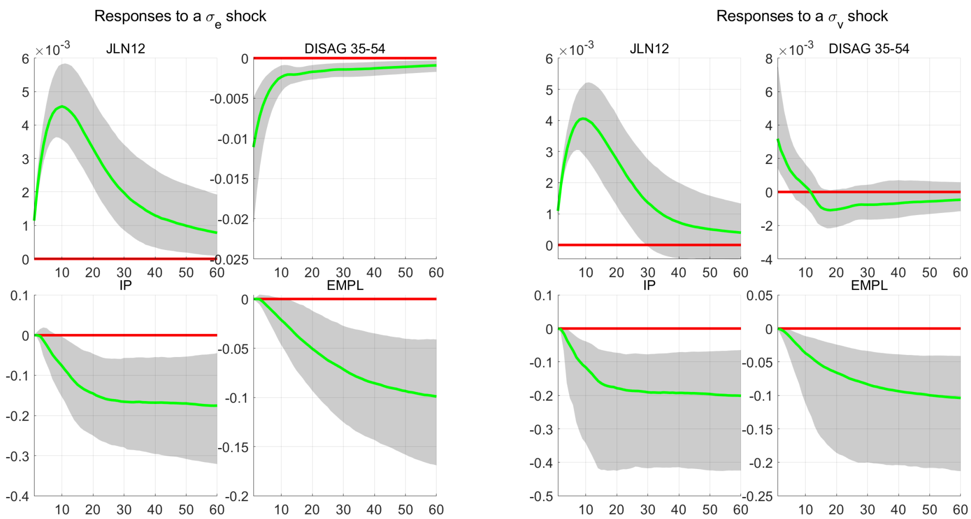

Figure C.17: Extended Benchmark model–age: 35-54. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses to the JLN 12-months-ahead uncertainty indicator (JLN12), the disagreement index for age 35-54 (DISAG 35-54), industrial production (IP), and employment (EMPL). We compute the IRFs from an eight-variable VAR system as described in the text. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, and the horizontal axes report time measured in months.

D.12. Supporting evidence from micro survey data: testing the random assignment of control and treated groups

Table C.1 reports and examines the differences in demographic and household characteristics provided in the survey between the information-treated and control groups:

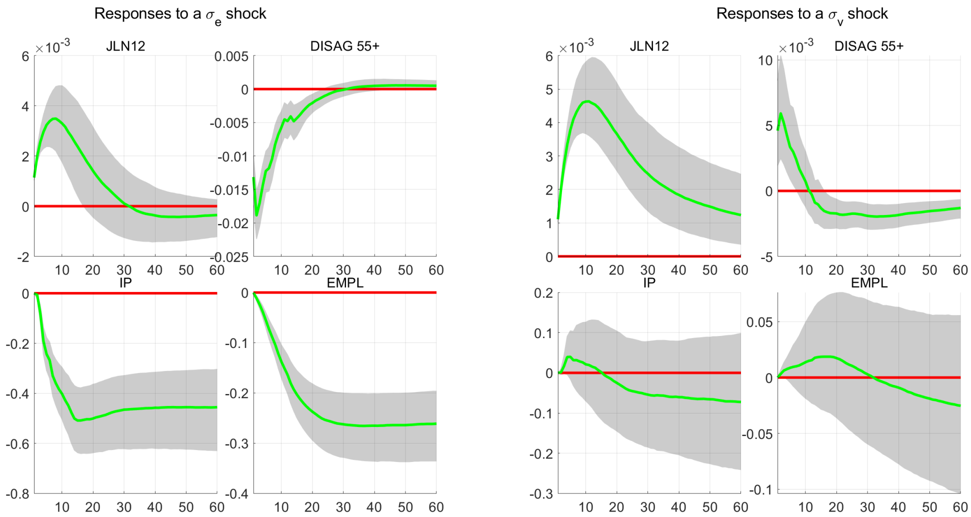

Figure C.18: Extended Benchmark model–age: 55 and above. Agreed σ_ε (left) versus disagreed σ_v (right) uncertainty. The figure shows impulse responses to the JLN 12-months-ahead uncertainty indicator (JLN12), the disagreement index for age 55 and above (DISAG 55+), industrial production (IP), and employment (EMPL). We compute the IRFs from an eight-variable VAR system as described in the text. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations, and the horizontal axes report time measured in months.

education, region of residency, numeracy, age, income, gender, commute, maried or living with partner, and health. The differences in those characteristics above between the two groups are not statistically significant for eight out of nine variables reported in Table C.1 below. For income, we can reject the null hypothesis of equality of income between the information-treated and control groups. Overall the comparison of the respondents' household and demographis characterics lends support to the hypothesis that the information treatment experiment can be considered as random.

Table C.1: Comparison of consumer characteristics between the information-treated and control group

	total sample	control group	treated group	difference	t-statistic (diff)
Education	0.874	0.885	0.864	0.021	0.845
No. of observations	741	381	360		
Region	2.536	2.567	2.503	0.0642	0.798
No. of observations	741	381	360		
Income	1.034	1.100	0.964	0.137	2.295
No. of observations	736	379	357		
Age	1.914	1.879	1.950	-0.071	-1.169
No. of observations	741	381	360		
Numeracy (high/low)	1.308	1.302	1.314	-0.012	-0.355
No. of observations	741	381	360		
Commuting	194.292	201.137	187.047	14.089	1.214
No. of Observations	741	381	360		
Gender	1.464	1.436	1.489	-0.053	-0.481
No. of Observations	84	39	45		
Married/ or living with partner	1.369	1.282	1.444	-0.162	-1.553
No. of Observations	84	39	45		
Health	0.512	0.590	0.444	0.145	1.328
No. of Observations	84	39	45		

Notes: Each characteristic in the table is reported as a categorical variable. Units displayed are mean values.

D.13. Supporting evidence from micro survey data: estimating the change in inflation forecast disagreement for the control group

Using the sample that only includes the consumers in the control group (who submitted the survey questionnaires in March before the FOMC statement release) for the months of February and March, we estimate the same regression in equation (14). By applying the same test to the control group, we establish whether the reduction in disagreement recorded by the information-treated group is absent in the control group, thus validating our working assumption that the FOMC announcement provides non-redundant information that *reduces* consumer disagreement. Specifically, we estimate the following regression for the control group:

$$DISAG_{it}^{INF} = \alpha_i + \beta_0 Pre(FOMC)_t + \epsilon_{it}, \tag{C.1}$$

where $Pre(FOMC)_t$ is a time dummy variable which is equal to one for the days 1-15 March 2022 preceding the FOMC announcement and zero otherwise, and α_i denote consumer fixed effects.

Table C.2 reports the coeficient estimate of the dummy variable. In columns 1 and 2 of Table C.2, the estimated coefficient on the one-year-ahead inflation disagreement measures suggests that the latter increased between February and March for the control group (at the ten percent significance level). In columns 3 and 4 the estimates on the three-year-ahead inflation disagreement suggest no statistically significant change in this measure between February and March for the control group. This second test shows that the control group who lacked exposure to Fed information experienced no significant change in disagreement between the two consecutive months of February and March 2022. These results corroborate the hypothesis that the FOMC announcement provides a useful signal about the state of the economy that results in a statistically significant reduction in disagreement that is absent in the control group.

Table C.2: Change in forecast disagreement: control group

	Inflation forecast disagreement measures			
	(1) Q9iqr	(2) Q9std	(3) Q9ciqr	(4) Q9cstd
pre FOMC time dummy	0.31*	0.19*	-0.24	-0.17
	(0.19)	(0.11)	(0.19)	(0.11)
Consumer Fixed effects	Yes	Yes	Yes	Yes
N	1208	1208	1210	1210

Notes: The February-March sample above contains all consumers who belong to the control group (those who submitted questionnaires between March 1-15, 2022) and also completed the survey in February. *Q9iqr*, *Q9std*, *Q9ciqr*, *Q9cstd* denote one year ahead inflation forecast interquartile range, one year ahead inflation forecast standard deviation, three year ahead inflation forecast interquartile range, and three year ahead inflation forecast standard deviation respectively. Survey weights are employed to help ensure that the data are nationally representative. Standard errors clustered at consumer level are reported in the parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

D.14. Supporting evidence from micro survey data: estimating the panel regression with a daily business conditions index

In this section we estimate the panel regression,

$$
\begin{aligned}
Q26_{it} &= \alpha_i + ADS_t + \beta_1 DISAG_{it}^{INF} + \beta_2 VIX_t + \beta_3 DISAG_{it}^{INF} \times VIX_t + \beta_4 Post_t \\
&+ \beta_5 DISAG_{it}^{INF} \times Post_t + \beta_6 Post_t \times VIX_t + \beta_7 Post_t \times DISAG_{it}^{INF} \times VIX_t + \epsilon_{it}
\end{aligned} \tag{C.2}
$$

where, as in the main body, $Q26_{it}$ is the consumer reported twelve-month household spending plan, α_i are consumer fixed effects controlling for time invariant characteristics, and ADS_t is the Aruoba-Diebold-Scotti (Aruoba et al., 2009) daily business conditions index available from the Philadelphia Fed. This daily indicator is designed to track real business conditions at a high frequency. Its underppined by (seasonally adjusted) economic indicators (weekly initial jobless claims; monthly payroll employment, monthly industrial production, monthly real personal income less transfer payments, monthly real manufacturing and trade sales; and quarterly real GDP) that blend high-frequency and low-frequency data. We include this to serve as a control for daily economic developments observed by consumers that may potentially influence their reported spending intentions. $Post_t$ is a dummy variable which is equal to one if the survey answers returned by respondents is on or after March 16, 2022 and zero otherwise. VIX_t is the daily CBOE VIX. Consistent with our analysis in the main body, we use, one at a time, the four alternative indicators of inflation forecast disagreement, denoted for brevity by $DISAG_{it}^{INF}$.

As in the main body we use coefficient estimates reported in Table C.3 to measure the impact effect of uncertainty on household spending plans. Specifically, from equation (C.2) we compute the partial derivatives:

$$\text{Impact effect of Uncertainty (baseline):} \quad \beta_2 + \beta_3 DISAG_{it}^{INF}, \tag{C.3}$$

$$\text{Impact effect of Uncertainty post FOMC:} \quad \beta_2 + \beta_6 + \beta_3 DISAG_{it}^{INF} + \beta_7 DISAG_{it}. \tag{C.4}$$

Table C.4 presents the results. Column 1 and column 2 of the table report the estimated baseline impact and post-FOMC impact effect of uncertainty on spending plans, respectively. The estimated impact effect of uncertainty on household spending plans is, across all alternative inflation forecast disagreement indicators, stronger and more precisely estimated for the post-FOMC impact effect compared to the baseline impact effect of uncertainty. The baseline impact effect is not statistically significant different from zero in all four cases. For example, in the specification based on the one-year-head inflation forecast using the interquartile range (row 1 of Table C.4), the post-FOMC impact effect is estimated at 0.34 percentage points, which is statistically significant at the five percent level, compared to an statistically insignificant effect estimated for the baseline impact effect. The last column of Table C.4 reports the difference in the estimated impacts of uncertainty between the baseline and post-FOMC cases. It shows that the difference between the baseline and post-FOMC effect statistically significant at conventional significance levels in all four four cases.

Table C.3: Panel evidence: daily observations, February-March 2022 (robustness with daily business conditions)

	Dependent variable: Spending expectations ($Q26$)			
	(1)	(2)	(3)	(4)
ADS	-0.0563*	-0.0487	-0.0561*	-0.0484
	(0.0308)	(0.0304)	(0.0308)	(0.0305)
$Q9\_iqr$	0.0135			
	(0.05107)			
VIX	0.0296	0.0267	0.0294	0.0268
	(0.0260)	(0.0254)	(0.0259)	(0.0254)
$Q9\_iqr \times VIX$	-0.0289			
	(0.0327)			
post	-0.154	-0.166*	-0.151	-0.167*
	(0.0981)	(0.0959)	(0.0985)	(0.0968)
$post \times Q9\_iqr$	-0.246*			
	(0.1289)			
$post \times VIX$	-0.116	-0.147*	-0.115	-0.149*
	(0.0869)	(0.0875)	(0.0867)	(0.0878)
$post \times Q9\_iqr \times VIX$	-0.226*			
	(0.1369)			
Q9c_iqr		-0.00760		
		(0.0506)		
$Q9c\_iqr \times VIX$		-0.00936		
		(0.0314)		
$post \times Q9c\_iqr$		-0.388***		
		(0.1298)		
$post \times Q9c\_iqr \times VIX$		-0.384***		
		(0.1373)		
Q9_std			0.0238	
			(0.0501)	
$Q9\_std \times VIX$			-0.0350	
			(0.0303)	
$post \times Q9\_std$			-0.218*	
			(0.1313)	
$post \times Q9\_std \times VIX$			-0.1930	
			(0.1321)	
Q9c_std				0.0006
				(0.0506)
$Q9c\_std \times VIX$				-0.0176
				(0.0294)
$post \times Q9c\_std$				-0.362***
				(0.1293)
$post \times Q9c\_std \times VIX$				-0.341***
				(0.1311)
Consumer Fixed effects	Yes	Yes	Yes	Yes
N	2102	2100	2102	2100

Notes: ADS is the Aruoba-Diebold-Scotti daily business conditions index. $Q9_{iqr}$, $Q9_{std}$, $Q9c_{iqr}$, $Q9c_{std}$, denote one year ahead inflation forecast interquartile range, one year ahead inflation standard deviation, three year ahead inflation forecast interquartile range, and three year ahead inflation standard deviation respectively. VIX is the CBOE volatility index. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table C.4: Impact effect of uncertainty on spending plans

Estimated coefficients from Table 6	Baseline effect, equation (16) (1)	post FOMC effect, equation (17) (2)	Difference (2) - (1)
based on $Q9_{iqr}$	0.00	-0.34**	-0.34*
	(0.05)	(0.18)	(0.19)
based on $Q9c_{iqr}$	0.02	-0.51***	-0.53**
	(0.04)	(0.19)	(0.19)
based on $Q9_{std}$	-0.01	-0.31*	-0.31*
	(0.05)	(0.17)	(0.18)
based on $Q9c_{std}$	0.00	-0.48***	-0.49**
	(0.04)	(0.18)	(0.19)

Notes: Each row in the Table uses the estimates based on an alternative indicator of inflation forecast disagreement as reported in Table 6. To compute the expressions above we use the mean values for $DISAG^{INF}$ for each group. Standard error reported in brackets. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.