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 Bloom (2009), a large literature shows that uncertainty shocks coincide with sizable declines in a broad range of activity indicators.[1] Yet an underappreciated regularity remains: although recessions almost always feature elevated uncertainty, many large uncertainty spikes are followed by little or no decline in real activity. The October 1987 stock market crash, the 1998 Russian crisis and near-collapse of Long-Term Capital Management, and the 2011 U.S. debt ceiling standoff each triggered marked increases in standard uncertainty indicators without producing a comparable recessionary response. Why some uncertainty episodes are contractionary while others are largely benign is a first-order question. We label uncertainty episodes as *agreed* when uncertainty rises while disagreement is low (broad consensus), and as *disagreed* when uncertainty rises while disagreement is high (dispersed views).

This paper argues that dispersion in consumers' views about the state of the economy, hereafter consumer disagreement, is a powerful conditioning variable for the real effects of uncertainty. We construct new indices of consumer disagreement from the Michigan Survey of Consumers and show that the macroeconomic consequences of uncertainty depend sharply on whether uncertainty coincides with high consumer agreement or high consumer disagreement. When uncertainty rises amid broad consensus (low disagreement), it triggers the familiar contractionary dynamics documented in Bloom (2009), Jurado et al. (2015), and Caldara et al. (2016). When uncertainty rises amid dispersed views (high disagreement), its effects on real activity are muted and statistically indistinguishable from zero. In short, uncertainty is contractionary only when households' views are aligned.

Our analysis proceeds in three steps: (i) we document new facts showing that disagreement conditions the uncertainty-activity relationship; (ii) we formalize agreed and disagreed uncertainty in a model of dispersed information and identify the two shocks in U.S. time series using sign restrictions; (iii) we provide complementary micro evidence using quasi-experimental variation in disagreement during an exogenous uncertainty episode.

We construct disagreement measures from the Michigan Survey of Consumers that capture dispersion in (i) signals about current business conditions, (ii) beliefs about future business conditions, and (iii) an aggregate factor summarizing both components. Disagreement is pervasive and the different indices move closely together. It is procyclical and negatively correlated with standard uncertainty measures: dispersion is higher in expansions, while downturns feature greater consensus. The key reduced-form fact is an asymmetry: when disagreement is high, the correlation between uncertainty and industrial production growth is small and statistically indistinguishable from zero; when disagreement is low, the correlation is negative and statistically significant. Regression

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

evidence confirms that higher disagreement attenuates the association between uncertainty, real activity, and recession probabilities.

Motivated by these patterns, we formalize the concepts of agreed and disagreed uncertainty in a parsimonious model with imperfect and dispersed information.[2] Agents observe noisy signals about an underlying fundamental shock and form forecasts by solving a signal-extraction problem. We define uncertainty as the conditional volatility of forecast errors (as in Jurado et al., 2015). Disagreement is either the cross-sectional dispersion in agents' signals or beliefs. The model shows that measured uncertainty reflects common fundamental volatility and greater dispersion in the information households receive. It also establishes a transparent mapping from volatility shocks to joint movements in uncertainty and disagreement: higher volatility of fundamental disturbances raises uncertainty while *compressing* disagreement (agreed uncertainty); higher volatility of noise raises both uncertainty *and* disagreement (disagreed uncertainty). We take these comovement predictions to the data as identifying restrictions in a Bayesian VAR to identify the dynamic effects of the two types of shocks in monthly U.S. data spanning 1978 to 2019.

The VAR results show a stark contrast in the impact of uncertainty. *Agreed uncertainty* shocks—those that raise uncertainty while lowering disagreement—are strongly contractionary, generating persistent declines in industrial production, employment, and consumption, consistent with the canonical uncertainty channel (e.g., Bloom, 2009; Jurado et al., 2015; Bloom et al., 2018; Ludvigson et al., 2021). *Disagreed uncertainty* shocks—those that raise both uncertainty and disagreement—generate increases in measured uncertainty of comparable size, yet the implied responses of real activity are muted, with uncertainty bands that include zero throughout. These differences are robust to alternative measures of disagreement and uncertainty.

We complement the structural time-series evidence with a distinct micro-survey approach using inflation expectations and consumer planned spending from the New York Fed Survey of Consumer Expectations (SCE). We use inflation expectations because the SCE provides daily fielding and both point forecasts and subjective uncertainty at the individual level, enabling a clean high-frequency design. We exploit (i) the exogenous uncertainty spike following Russia's invasion and (ii) the discrete release of forward-looking information in the March 16, 2022 Federal Reserve FOMC statement. The survey's daily fielding allows us to define an information-treated group (respondents interviewed after the statement) and a control group (respondents interviewed before). Treated respondents display a clear reduction in inflation forecast disagreement relative

[2]Models with sticky or noisy information rationalize information frictions and dispersed beliefs; see, among others, Mankiw and Reis (2002); Woodford (2003); Sims (2003); Mackowiak and Wiederholt (2009); Mankiw et al. (2004); Okuda et al. (2026). Empirically, expectation data support information rigidities and, in particular, noisy-information mechanisms; see Coibion and Gorodnichenko (2012, 2015) and the review in Coibion et al. (2018).

to the control group. Leveraging this quasi-experimental variation, we estimate panel regressions of planned spending on aggregate uncertainty interacted with treatment status. We find that uncertainty has a substantially larger negative effect on spending plans when disagreement is lower: a one standard deviation increase in uncertainty implies a 6.6 percentage point larger decline in planned spending for treated respondents relative to the control group. The micro evidence, thus, corroborates the time-series finding that uncertainty is contractionary when accompanied by low disagreement and largely benign when disagreement is high.

Our study contributes to the literature on the macroeconomic effects of uncertainty by showing that the real consequences of uncertainty depend systematically on consumer disagreement. A large body of work finds that uncertainty is typically contractionary, using a variety of macro and micro measures and identification strategies (e.g., Bloom, 2009; Bachmann et al., 2013; Jurado et al., 2015; Baker et al., 2016; Bloom et al., 2018; Ludvigson et al., 2021). Our results add a new dimension to this evidence by distinguishing between uncertainty episodes that coincide with broad agreement versus disagreement among consumers, and by demonstrating that this distinction is quantitatively and qualitatively important for real activity.[3] Our paper is related to Zohar (2024), who documents professional-forecast disagreement is procyclical while uncertainty is contractionary. We likewise find procyclical consumer disagreement, but our focus and evidence differ in three key ways. First, we study disagreement among households rather than professional forecasters or firms. Second, we treat disagreement as a state variable that shapes the real effects of uncertainty, not primarily as a cyclical outcome. Third, we pair model-based time-series identification with complementary micro-survey panel evidence, which directly supports the mechanism linking disagreement to the transmission of uncertainty.

Our paper is also related to Berger et al. (2020), who find that forward-looking uncertainty shocks have no significant real effects. That result concerns the temporal horizon of uncertainty—whether it is backward- or forward-looking—whereas our results concern the cross-sectional dispersion of beliefs at any given horizon. In our framework, the same measured uncertainty can be contractionary or benign depending not on when agents are uncertain, but on whether they are uncertain in the same direction. Unlike approaches that interpret benign uncertainty through the lens of news shocks or the composition of uncertainty innovations (Cascaldi-Garcia and Galvao, 2021), our analysis highlights a different channel: the dispersion of consumer beliefs.[4]

[3]Related work emphasizes that the effects of uncertainty are state-dependent along other dimensions, including financial conditions and the source of uncertainty (e.g., Caldara et al., 2016; Alessandri and Mumtaz, 2019; Fernàndez-Villaverde et al., 2011, 2015, 2025, 2021, 2023; Basu and Bundick, 2017; Cascaldi-Garcia et al., 2022). A complementary literature studies uncertainty and labor-market outcomes, including unemployment dynamics (e.g., Caggiano et al., 2014; Leduc and Liu, 2016; Theodoridis and Zanetti, 2016; Schaal, 2017).

[4]Related work distinguishes among types or states of uncertainty and finds heterogeneous effects (e.g., Segal et al., 2015; Korobilis and Schröder, 2022; Bijsterbosch and Guerin, 2013; Aastveit et al.,

The remainder of the paper is organized as follows. Section 2 introduces our measures of consumer disagreement and presents preliminary reduced-form evidence on the relationship between uncertainty and disagreement. Section 3 develops a stylized model to formalize the concepts of uncertainty and disagreement, and uses the model's predictions to analyze the dynamic effects of agreed and disagreed uncertainty via time-series VAR models. Section 4 complements the time-series analysis by providing evidence from micro-survey data on the effects of uncertainty on consumer spending plans. Section 5 concludes. The appendices contain robustness checks under alternative modeling assumptions and data specifications.

2 Consumer disagreement and preliminary evidence

In this section we construct three measures of consumer disagreement using the University of Michigan Survey of Consumers (UMSC). The indices capture the cross-sectional dispersion of households' views about current and future macroeconomic conditions across a small set of core questions. We develop a parsimonious aggregate index that summarizes disagreement about macroeconomic conditions in the UMSC, and two complementary measures that separately proxy disagreement about *signals* (information received about current conditions) and disagreement about *beliefs* (expectations about current and future conditions). We then document the cyclical behavior of these indices and their relationship with real activity and standard measures of uncertainty, providing preliminary evidence that disagreement is a key variable influencing the joint dynamics of uncertainty and economic activity consistently across the different measures.

2.1 Measuring disagreement

Consumer survey data. The UMSC is administered by the Survey Research Center at the University of Michigan and surveys a minimum of 500 U.S. households each month. Responses are aggregated into a set of monthly categorical time series that are designed to be representative of the U.S. population.[5] To construct our disagreement measures, we focus on five questions that capture households' assessments of recent changes in business conditions and their expectations about current and future conditions, summarized in Table 1.

2017; Ghironi and Ozhan, 2020). A separate literature studies the cyclical implications of *first-moment* noise/news shocks (e.g., Lorenzoni, 2009; Blanchard et al., 2013; Forni et al., 2017). Our contribution is to identify and quantify the cyclical role of second-moment noise shocks that raise uncertainty while simultaneously increasing disagreement.

[5]For details on survey design and administration, see: https://data.sca.isr.umich.edu/survey-info.php.

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 five years

NEWS captures information households report receiving about recent changes in economic conditions. BAGO captures assessments of current conditions relative to a year earlier, while BEXP, BUS12, and BUS5 capture expectations about future business conditions at different horizons. Responses are recorded in three qualitative categories (e.g., "better/about the same/worse"), and the published series report the monthly shares of respondents in each category.[6] We use monthly data for these five series over 1978M1-2019M12.

Construction of the disagreement indexes. We construct a benchmark measure of *tail disagreement*, which captures the divergence between the two extreme categories of survey responses. Specifically, this index reflects disagreement between the "better" and "worse" responses (or analogous polar categories, such as "good time/bad time" or "favorable/unfavorable"). Formally, the tail disagreement index for each survey question is defined as:

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

where $j \in \{\text{NEWS, BAGO, BEXP, BUS12, BUS5}\}$ indexes the five survey questions, $b_t^{(j)}$ is the percentage of respondents giving an optimistic answer ("better"), and $w_t^{(j)}$ is the percentage giving a pessimistic answer ("worse"). The disagreement index, $T_t^{(j)}$, has a theoretical range of $[0, 1]$. A value of $T_t^{(j)} = 0$ is never observed in practice, as it would require all respondents to be concentrated in a single tail category ("better"/"worse") with no responses in the middle category ("no change"). Values close to zero therefore signify high agreement. A value of $T_t^{(j)} = 1$ indicates maximal disagreement, where consumers are evenly split between the two polar responses. Note, however, that a value close to one can also arise if all respondents choose the middle category, since both tail shares would be near zero, yielding a small absolute difference. In the survey data, this scenario is unlikely, as the vast majority of respondents choose one of the two tail categories.[7]

[6] Depending on the question, categories may take forms such as "favorable/no mention/unfavorable" or "more/about the same/less."

[7] In Appendix D, we compute alternative measures of disagreement, including Shannon entropy (Shannon, 1948) and the dispersion index (Lacy, 2006), which incorporate all response categories, and

We then construct a total disagreement measure, DISAG-TOTAL, by summarizing the information in the five individual measures using principal component analysis (PCA). Following the approach in Stock and Watson (2002) for macroeconomic diffusion indices, we extract the first principal component from the five unnormalized tail disagreement series, $T_t^{(j)}$, to obtain a latent index of total consumer disagreement, DISAG-TOTAL. This index is a weighted average of the individual series, with the weights (loadings) chosen to maximize the variance explained across the five measures. By applying PCA to the unnormalized series, the resulting factor preserves the original scale of the disagreement indexes rather than imposing equal variability across questions. Appendix A.4 reports the loadings and compares the DISAG-TOTAL index with the individual series.

It is important to note that different survey questions convey distinct types of information. The variable NEWS captures the percentage of respondents who have received either positive or negative news about current economic conditions. As such, the index T_t^{NEWS}, which we refer to as DISAG-SIGNAL, measures *signal* disagreement—disagreement about the information received. In contrast, the remaining four variables reflect agents' beliefs about the present and future state of the economy, and the corresponding indexes measure *belief* disagreement. We summarize belief disagreement using the first principal component of the four unnormalized belief-related measures, denoted as DISAG-BELIEF. This distinction between signal and belief disagreement will be clarified conceptually in the theoretical model and time-series analysis presented in Section 3.

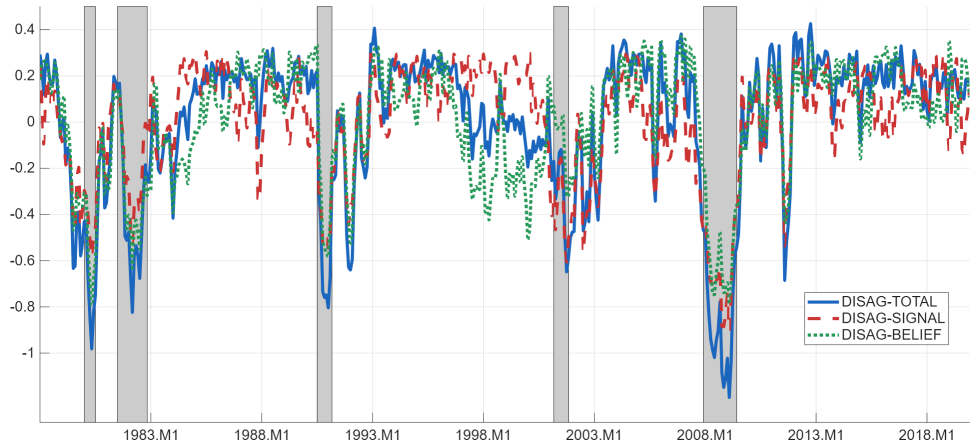


Figure 1: Disagreement Measures. The figure plots the total disagreement (blue solid line), signal disagreement (red dashed line), and belief disagreement (green dotted line). Gray shaded areas indicate NBER-dated recessions. All series are normalized to have mean zero.

Figure 1 shows the dynamics of total disagreement (DISAG-TOTAL), signal disagreement (DISAG-SIGNAL), and belief disagreement (DISAG-BELIEF). While all three core measures (total, signal, belief) generally exhibit similar trends, moving together during expansions and declining sharply during recessions, there are notable divergences at times, particularly in the mid-1980s and late 1990s. Table A.2 in the Appendix reports

show similar results.

the correlations between all measures of consumer disagreement. The correlation of DISAG-TOTAL with signal and belief disagreement is 0.88 and 0.90, respectively, while the correlation between signal and belief disagreement is 0.58, indicating substantial but not perfect overlap in their underlying dynamics.

Diagnostics of the disagreement index. Table 2 examines the cyclical properties of the disagreement indices by analyzing their comovement with three key measures of economic activity: monthly growth rates of industrial production, real personal consumption expenditure, and employment. All disagreement indices, except for T_t^{BEXP}, are procyclical. For instance, the correlation of the total disagreement index (DISAG-TOTAL) with industrial production growth is 0.37, with employment growth is 0.57, and with consumption growth is 0.15. Similar correlations are found for both belief and signal disagreement. These results suggest that consumers tend to agree more during recessions and less during expansions, which may reflect heightened media coverage during recessions and asymmetric response by the public, as documented by Soroka (2006).

Table 2: Correlation across Disagreement Indexes, Macro and Uncertainty Indicators

	DISAG-TOTAL	DISAG-SIGNAL	DISAG-BELIEF	T_t^{BAGO}	T_t^{BEXP}	T_t^{BUS12}	T_t^{BUS5}
IP Growth	0.37	0.36	0.29	0.31	-0.09	0.20	0.16
Emp. Growth	0.57	0.56	0.45	0.53	0.01	0.21	0.26
Cons. Growth	0.15	0.17	0.10	0.09	-0.02	0.07	0.15
JLN12 Macro	-0.63	-0.55	-0.56	-0.54	-0.15	-0.38	-0.47
JLN12 Fin	-0.59	-0.49	-0.55	-0.51	-0.10	-0.47	-0.37
JLN12 Real	-0.54	-0.51	-0.46	-0.43	-0.08	-0.31	-0.47
VIX	-0.27	-0.33	-0.16	-0.12	-0.01	-0.13	-0.24
EPU	-0.61	-0.56	-0.52	-0.51	-0.02	-0.43	-0.28

Notes: Pairwise correlations between the disagreement indices and selected macroeconomic and uncertainty indicators. Disagreement measures include the aggregate index (DISAG-TOTAL), signal disagreement (DISAG-SIGNAL), belief disagreement (DISAG-BELIEF), and the five individual tail disagreement series from the Michigan Survey of Consumers. Macroeconomic variables are year-on-year growth rates of industrial production (IP Growth), employment (Emp. Growth), and personal consumption expenditures (Cons. Growth). Uncertainty indicators include the 12-month-ahead macroeconomic, financial, and real uncertainty indices of Jurado et al. (2015) (JLN12 Macro, JLN12 Fin, JLN12 Real), the Economic Policy Uncertainty index of Baker et al. (2016) (EPU), and the CBOE Volatility Index (VIX). Sample: 1978M1-2019M12, monthly frequency.

Table 2 also reports the correlations between the disagreement indices and popular uncertainty measures. All disagreement measures are negatively correlated with the uncertainty indicators, suggesting that as uncertainty rises, disagreement tends to fall. Our disagreement measures differ from more traditional disagreement indicators, such

as cross-sectional standard deviations of numerical forecasts, which we cannot construct in this setting due to data limitations (the UMSC reports only categorical responses). Although our indexes cannot capture disagreement intensity within each category (e.g., "how much better" or "how much worse"), they exhibit similar cyclical properties to quantitative measures of disagreement. Our disagreement indexes are unconditionally procyclical, aligning with the findings of Zohar (2024) for professional forecasters and firm-level disagreement. Notably, our consumer disagreement measures are strongly negatively correlated with uncertainty, suggesting that disagreement plays a distinct role in economic dynamics.

2.2 Preliminary evidence

In this section, we present preliminary evidence on the role of consumer disagreement in the joint dynamics of uncertainty and real economic activity. Specifically, we examine whether and to what extent disagreement affects the relationship between uncertainty and economic activity.

Scatterplot evidence. We begin by examining the comovement between industrial production growth and uncertainty, conditioning on the level of disagreement. Using simple scatterplots, we present results for various disagreement indexes to assess the robustness of the findings across different measures.

Figure 2 shows the relationship between industrial production growth (IP growth) and uncertainty under high and low disagreement conditions. Each row corresponds to one of the disagreement measures: total (top panels), signal (middle panels), and belief (bottom panels). The solid red lines represent the linear regression fit, and the dotted red lines show the associated 95% confidence bands. In high-disagreement periods (left panels), the correlation between uncertainty and IP growth is close to zero and statistically insignificant. However, in low-disagreement periods (right panels), the linear regression fit shows a statistically significant negative correlation between uncertainty and IP growth across all disagreement measures.

This preliminary analysis provides *prima facie* evidence of systematically different comovements between uncertainty and economic activity depending on the level of disagreement. It suggests that the contractionary effect of uncertainty on economic activity is pronounced during periods of high uncertainty and low disagreement, but absent when disagreement is high.

Threshold VAR evidence. To complement the scatterplot evidence, we formally examine whether the impact of uncertainty on real economic activity varies with the level of disagreement. We estimate a bivariate Threshold VAR, where disagreement is used

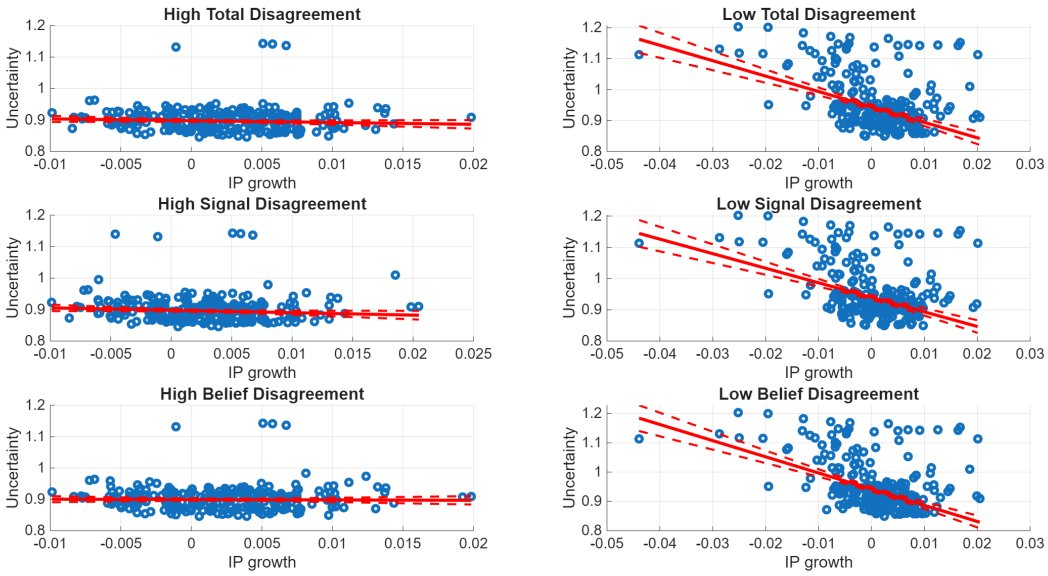


Figure 2: Scatterplots of Uncertainty vs. IP Growth Conditional on Disagreement. Each row corresponds to a different disagreement measure (total, signal, belief). Left panels show periods of high disagreement (above the sample median); right panels show periods of low disagreement (below the sample median). Uncertainty is measured by the 12-month-ahead Macroeconomic Uncertainty index of Jurado et al. (2015) (JLN12 Macro). Blue dots represent individual monthly observations. The red solid line denotes the OLS fitted line and the red dashed lines indicate the corresponding 95% confidence bands. The negative relationship between uncertainty and IP growth is pronounced and statistically significant only during low-disagreement periods, whereas in high-disagreement periods this relationship is weaker, statistically insignificant, or slightly positive.

as the conditioning variable.[8] The two variables in the VAR are the 12-month-ahead macroeconomic uncertainty index from Jurado et al. (2015) and industrial production growth, in that order. The threshold is set at the median value of disagreement, distinguishing between high and low disagreement regimes. The VAR includes six lags.[9] We identify the uncertainty shock using the standard Cholesky decomposition, where the first shock corresponds to the orthogonal innovation in uncertainty.

Figure 3 presents the results of the Threshold VAR analysis, using three different measures of disagreement: total (top panels), signal (middle panels), and belief (bottom panels). The left panels show the (level) response of industrial production (IP) to an uncertainty shock under high disagreement (above the sample median, red line) and low disagreement (below the sample median, blue line) regimes. The right panels display the *difference* in IP responses between low and high disagreement (green line).

The impulse responses consistently indicate that the contractionary effect of uncertainty on IP is significantly stronger when disagreement is low, across all measures of disagreement. This finding corroborates the scatterplot evidence, reinforcing the idea that the impact of uncertainty on real economic activity is dependent on the level of consumer disagreement.

[8] Appendix C.1 details the implementation of the threshold VAR model.

[9] The results are qualitatively similar with 8 and 12 lags. The VAR is estimated by OLS, with bootstrap procedures used to obtain confidence intervals.

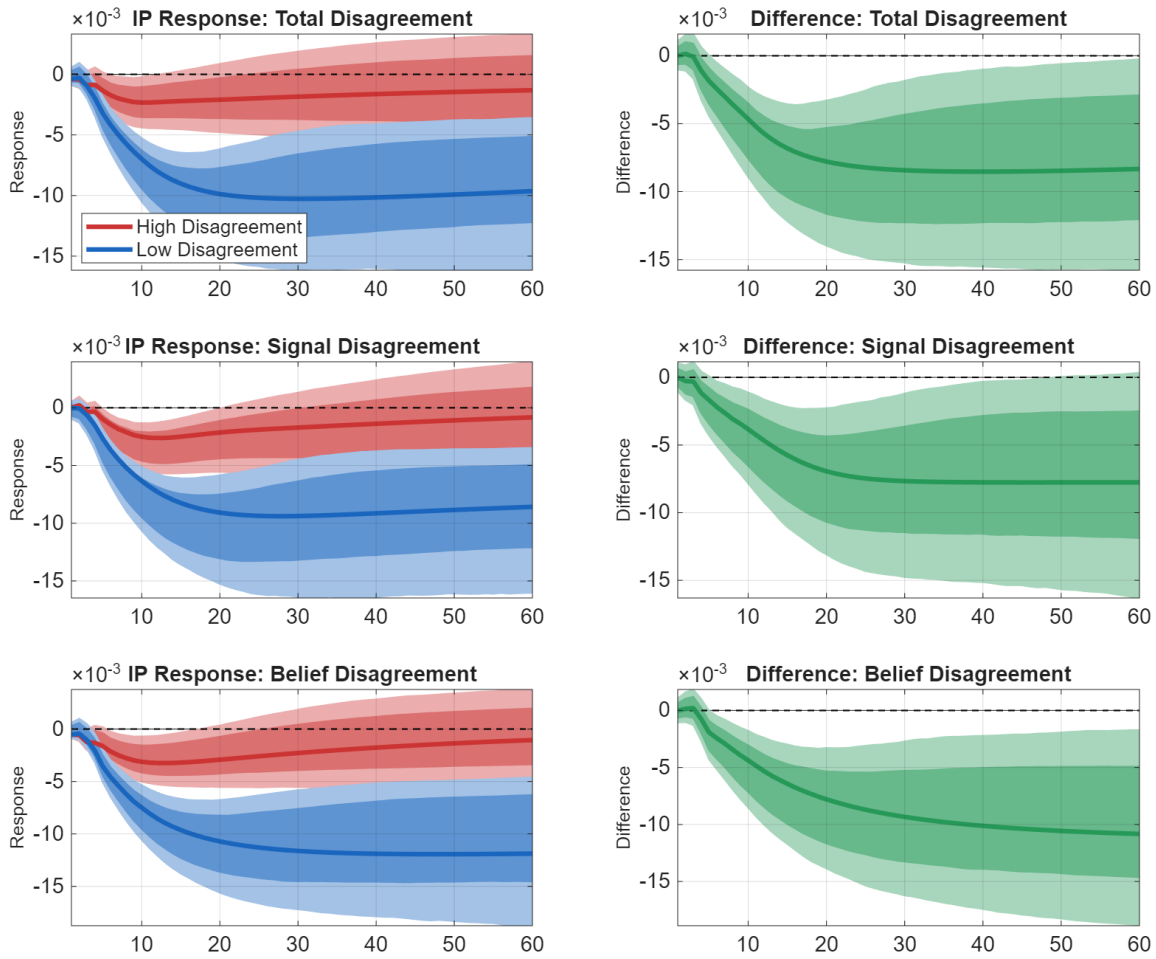


Figure 3: Threshold VAR Impulse Responses. Each row reports results for one disagreement measure (total, signal, belief). Uncertainty is the 12-month ahead Macroeconomic Uncertainty index (JLN12 Macro). The left panels display the response of industrial production (IP) to an uncertainty shock under high disagreement (red line with red shaded confidence bands) and low disagreement (blue line with blue shaded confidence bands) regimes. The right panels show the *difference* in responses (low minus high disagreement; green line with green shaded bands). Dark shading denotes 68% confidence intervals, while light shading denotes 90% intervals. Horizons are measured in months.

Evidence from simple linear regressions. We examine the role of consumer disagreement in the relationship between uncertainty and economic activity using a simple linear regression, following Caldara and Iacoviello (2022):

$$y_t = \alpha + \beta_1 \text{UNC}_t + \beta_2 \text{UNC}_t \times \text{DISAG}_t + \gamma_1 \Delta \log(\text{IP}_{t-1}) + \gamma_2 \Delta \log(\text{IP}_{t-2}) + \varepsilon_t, \quad (2)$$

where y_t is either industrial production growth (i.e., $\Delta \log(\text{IP}_t)$) or a recession indicator $D_t \in \{0, 1\}$ (equal to 1 during NBER-dated recessions, 0 otherwise). UNC_t is the JLN12 macroeconomic uncertainty measure, and DISAG_t refers to one of our three disagreement measures (total, signal, or belief disagreement). We control for the past two periods of industrial production growth to capture business cycle momentum. The key coefficients, β_1 and β_2, measure the impact of uncertainty and the interaction between uncertainty and disagreement, respectively.

Consistent with established uncertainty literature, we expect β_1 to be negative, indicating that increased uncertainty reduces economic activity and raises the likelihood of recessions. The sign and magnitude of β_2 reveal how disagreement affects this relationship. For instance, when we measure activity from IP growth a positive (negative) value of β_2 would suggest that higher disagreement weakens (strengthens) the negative impact of uncertainty. All regressions use heteroskedasticity-robust standard errors.

Table 3: Disagreement Measures, Uncertainty, and Economic Activity

	Dependent Variable: IP Growth			Dependent Variable: Recession Dummy		
	(1) TOTAL	(2) SIGNAL	(3) BELIEF	(4) TOTAL	(5) SIGNAL	(6) BELIEF
Constant	0.0165***	0.0160***	0.0181***	−0.620***	−0.538***	−1.031***
	(0.0052)	(0.0052)	(0.0049)	(0.107)	(0.100)	(0.125)
JLN12	−0.0169***	−0.0163***	−0.0185***	0.768***	0.664***	1.228***
	(0.0057)	(0.0056)	(0.0053)	(0.118)	(0.110)	(0.138)
Uncertainty×Disagreement:						
JLN12×DISAG-TOTAL	0.0029***			−0.250***		
	(0.0010)			(0.028)		
JLN12×DISAG-SIGNAL		0.0045***			−0.249***	
		(0.0012)			(0.031)	
JLN12×DISAG-BELIEF			0.0013			−0.212***
			(0.0012)			(0.036)
$\Delta \log(\text{IP}_{t-1})$	0.151***	0.135***	0.153***	−1.184*	−1.297**	−0.998
	(0.046)	(0.045)	(0.045)	(0.650)	(0.627)	(0.821)
$\Delta \log(\text{IP}_{t-2})$	0.157***	0.149***	0.187***	−1.482**	−1.173*	−2.877***
	(0.039)	(0.036)	(0.039)	(0.632)	(0.633)	(0.738)
Observations	501	501	501	501	501	501
R^2	0.189	0.232	0.183	0.297	0.268	0.257

Notes: The table reports estimates from linear regressions relating uncertainty, disagreement, and real economic activity. Columns (1)-(3) report results for industrial production (IP) growth, while Columns (4)-(6) report results for a recession indicator equal to one during NBER-dated recessions and zero otherwise. Uncertainty is measured by the 12-month-ahead macroeconomic uncertainty index (JLN12) of Jurado et al. (2015). Disagreement is measured using, respectively, the total disagreement index (DISAG-TOTAL), the signal disagreement index based on the NEWS question (DISAG-SIGNAL), and the belief disagreement index (DISAG-BELIEF). All specifications include two lags of IP growth as controls. Standard errors are heteroskedasticity-robust and reported in parentheses. The sample period is 1978M1-2019M12. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The results from Table 3 show that the coefficient of JLN12 is negative and statistically significant across all specifications, confirming that uncertainty has a contractionary effect on IP growth (columns 1-3) and increases the likelihood of a recession (columns 4-6). More importantly, the coefficients of the interaction terms reveal that disagreement moderates the effect of uncertainty: higher disagreement mitigates the negative impact of uncertainty on IP growth and reduces the likelihood of a recession, with all coefficients

highly significant except for belief disagreement in the IP growth regression.[10]

In summary, the linear regression results confirm that consumer disagreement plays a crucial role in shaping the joint dynamics of uncertainty and economic activity. While uncertainty generally dampens real activity and raises the probability of a recession, higher disagreement weakens these effects. The next section develops a theoretical framework to further explore the interplay between disagreement and uncertainty.

3 Structural time-series analysis

In this section, we conduct a structural VAR analysis aimed at identifying uncertainty shocks and examining their effects.

The evidence presented in Section 2 yields two main conclusions. First, the presence of disagreement about signals and expectations regarding *current* economic conditions indicates that agents' information is imperfect and heterogeneous, otherwise disagreement would be zero. Second, there is a significant interplay between uncertainty and disagreement. These findings motivate the development of a simple model with imperfect and dispersed information, which we use to derive identifying restrictions for the agreed and disagreed uncertainty shocks in a structural VAR model.

3.1 Identifying restrictions from a simple theoretical model

Economic fundamentals 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 $0 \leq |\lambda| < 1$, and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$ is a fundamental economic shock with variance σ_ε^2.[11] 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 $\psi_j = \lambda^j$, $j = 0, 1, 2, \ldots$.

We assume a continuum of agents in the economy. Agents have rational expectations

[10] Both lags of IP growth are positive and statistically significant in the IP growth regressions (0.135-0.153 for lag 1, 0.149-0.187 for lag 2), indicating persistence in economic activity. In the recession regressions, the lags are generally negative, suggesting that higher past IP growth lowers the probability of a current recession. The R^2 values show that the signal disagreement measure provides the best fit for the IP growth regression, while the total disagreement measure provides the best fit the recession indicator regression.

[11] 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 analytical simplicity but could be extended or modified.

but information is imperfect and dispersed. It is imperfect in the sense that, in period t, agents cannot observe the current value of the fundamental process a_t or the value of the current shock ε_t.[12] It is dispersed because each agent receives an individual noisy signal about the fundamental shock

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

where $v_{it} \sim N(0, \sigma^2_{v_i})$ is an individual specific noise shock with variance $\sigma^2_{v_i}$. The variance of the noise shock, $\sigma^2_{v_i}$, controls the degree of information dispersion. The higher the noise volatility $\sigma^2_{v_i}$, the larger the range of the signals s_{it} and the more dispersed the information across agents. For simplicity, we assume that the noise variance is the same across agents, $\sigma_{v_i} = \sigma_v$.

Thus, at time t, the information set of agent i is given by

$$\mathcal{I}_{it} \equiv \{a_{t-1-j}, \varepsilon_{t-1-j}, s_{it-j}\}_{j=0}^{\infty}.$$

Agents are also assumed to know the model equations, parameter values, and the distributions of the shocks.

Variance of the forecast error. Following an important strand of literature (see, for instance, Jurado et al., 2015), we define uncertainty as the variance of the forecast error associated with the forecast of real economic activity. In our framework, agents form forecasts of real economic activity, a_{t+h}, using rational expectations conditional on their information set. In Appendix B, we derive these individual expectations and aggregate them into a single expectation measure. Using this aggregate measure we then derive the variance of the forecast error:

$$FEV(k) = \psi_k^2 \left(\frac{\sigma_v^2}{\sigma_\varepsilon^2+\sigma_v^2}\right)^2 \sigma_\varepsilon^2 + \sum_{j=0}^{k-1} \psi_j^2 \sigma_\varepsilon^2 \quad \text{for } k \geq 1. \tag{6}$$

Equation (6) highlights a central implication of imperfect information models: the variance of the aggregate forecast error depends on both the variance of the fundamental shock (σ^2_ε) and the variance of the noise shock (σ^2_v). This contrasts sharply with perfect information models, where agents observe the true fundamental shock without error. In such models, $\sigma^2_v = 0$ and uncertainty depends solely on the variance of the fundamental shock. In contrast, in our model, there are two sources of variation in uncertainty, σ^2_ε and σ^2_v. The next proposition establishes that both of them have a positive impact effect on uncertainty.

[12] This information structure mirrors real-world scenarios, as the first release of a time series is typically available in $t+1$.

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 noise shock (σ_v^2) for all $k = 1, 2, ...$:*

$$\frac{\partial FEV(k)}{\partial \sigma_\varepsilon^2} > 0 \quad and \quad \frac{\partial FEV(k)}{\partial \sigma_v^2} > 0 \quad k = 1, 2, ...$$

Proof. See Appendix B.1. □

We next derive the theoretical counterparts of our empirical measures of disagreement, distinguishing between signal disagreement, arising from differences in the signals agents receive, and belief disagreement, arising from differences in the forecasts they form.

Signal disagreement. Recall that our main empirical disagreement variable is one minus the absolute difference between the fraction of individuals in the survey hearing good news and the fraction hearing bad news. Here we derive its theoretical counterpart. Conditional on the fundamental shock, the cross-sectional distribution of the signals is

$$s_{it} \mid \varepsilon_t \sim N(\varepsilon_t, \sigma_v^2).$$

Let $\Phi(\cdot)$ and $f(x)$ denote the corresponding CDF and PDF, respectively. The probability that the signal is negative is

$$\Pr(s_{it} < 0 | \varepsilon_t) = \Phi\left(\frac{0 - \varepsilon_t}{\sigma_v}\right) = \Phi\left(-\frac{\varepsilon_t}{\sigma_v}\right) = \int_{-\infty}^{0} f(x)dx.$$

Within a continuum-of-agents setting, this probability is the theoretical counterpart of the fraction of individuals hearing negative news in the empirical measure. The probability that the signal is positive, i.e. the theoretical counterpart of the fraction of agents hearing positive news, is

$$\Pr(s_{it} > 0 | \varepsilon_t) = 1 - \Phi\left(\frac{0 - \varepsilon_t}{\sigma_v}\right) = 1 - \Phi\left(-\frac{\varepsilon_t}{\sigma_v}\right) = \int_{0}^{\infty} f(x)dx.$$

The difference between these two probabilities,

$$\Pr(s_{it} > 0 | \varepsilon_t) - \Pr(s_{it} < 0 | \varepsilon_t) = 1 - 2\Phi\left(-\frac{\varepsilon_t}{\sigma_v}\right),$$

corresponds, in the model, to the fraction of observed positive signals minus the fraction of observed negative signals conditional on the economic fundamental shock ε_t. Therefore, we measure disagreement as

$$\mathcal{D}_S \quad = \quad 1 - \left| 1 - 2\Phi\left(-\frac{\varepsilon_t}{\sigma_v}\right) \right|. \tag{7}$$

Moreover, we focus on a "representative" (i.e. one standard deviation) fundamental shock. Alternatively, one could also consider the mean absolute shock $E|\varepsilon_t| = \sigma_\varepsilon\sqrt{\frac{2}{\pi}}$ and the results of Proposition 2 below would still hold true. Thus, evaluating $\mathcal{D}_S$ at $\varepsilon = \pm\sigma_\varepsilon$ yields

$$\mathcal{D}_S = \begin{cases} 1 - \left|1 - 2\Phi\left(-\frac{\sigma_\varepsilon}{\sigma_v}\right)\right| & \text{if } \varepsilon_t = \sigma_\varepsilon, \\ 1 - \left|1 - 2\Phi\left(\frac{\sigma_\varepsilon}{\sigma_v}\right)\right| & \text{if } \varepsilon_t = -\sigma_\varepsilon. \end{cases} \tag{8}$$

The disagreement index is defined as one minus the absolute difference between the mass of the signal distribution in the positive region and the mass in the negative region, and represents the theoretical counterpart of our empirical disagreement measure defined in equation (1).

Disagreement is maximal when $\Phi(\cdot) = 0.5$, i.e. when half of the agents observe positive signals and half negative signals. It is minimal when either $\Phi(\cdot) = 0$ (all agents observe a positive signal) or $\Phi(\cdot) = 1$ (all agents observe a negative signal).

We next investigate how disagreement depends on the variance of the fundamental and the noise shocks, as formalized in the following proposition.

Proposition 2. *The disagreement index (i) decreases with the variance of the fundamental shock, $\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon^2} < 0$, and (ii) increases with the variance of the noise shock, $\frac{\partial \mathcal{D}}{\partial \sigma_v^2} > 0$.*

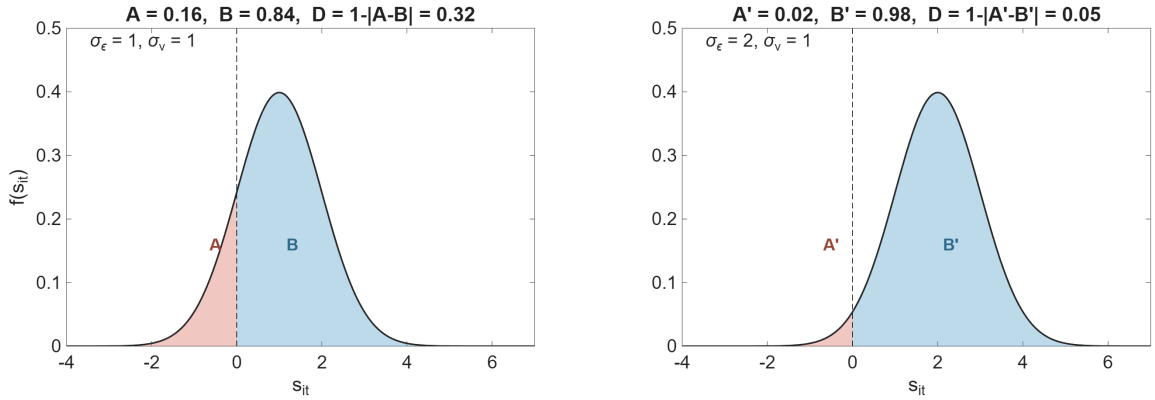
Proof. See Appendix B.2. □

Proposition 2 establishes two important results about the relationship between shock variances and the disagreement index: an increase in σ_ε^2 reduces disagreement, while an increase in σ_v^2 increases disagreement.

Figure 4 provides a graphical intuition of the results in Proposition 2 when $\varepsilon_t = \sigma_\varepsilon$ (the case $\varepsilon_t = -\sigma_\varepsilon$ is just symmetric). Panel (a) describes the effects of an increase in σ_ε^2. Subpanel (a.1) shows the cross-sectional signal density function when $\sigma_\varepsilon^2 = 1$ and $\sigma_v^2 = 1$. In this case, disagreement is $1 - |A - B| = 0.32$. Subpanel (a.2) shows the cross-sectional density when $\sigma_\varepsilon^2 = 4$ (four times larger) and $\sigma_v^2 = 1$. Higher σ_ε^2 implies a larger typical realization of the fundamental shock and the density shifts to the right. The density mass in the negative region is smaller, $A' < A$, while the density mass in the positive region is larger, $B' > B$, which implies a lower value of disagreement, $1 - |A' - B'| = 0.05$.

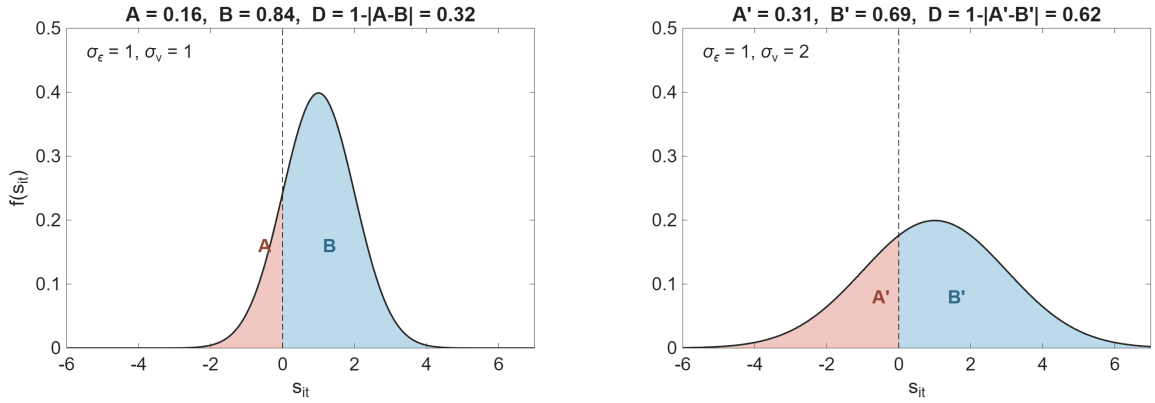
Panel (b) describes the effects of an increase in σ_v^2. Subpanel (b.1) is the same as subpanel (a.1) with disagreement $1 - |A - B| = 0.32$. Subpanel (b.2) depicts the cross-sectional density when $\sigma_\varepsilon^2 = 1$ and $\sigma_v^2 = 4$ (four times larger). A higher value of σ_v^2 implies higher dispersion with an unchanged mean. Consequently, the density mass in the negative region is higher, $A' > A$, while the mass in the positive region is lower, $B' < B$. This implies higher disagreement, $1 - |A' - B'| = 0.62$.

(a) Increasing σ_ε (fixed $\sigma_v = 1$)



(a.1) (a.2)

(b) Increasing σ_v (fixed $\sigma_\varepsilon = 1$)



(b.1) (b.2)

Figure 4: Visual illustration of Proposition 2. Each panel displays the cross-sectional distribution of signals $s_{it} \mid \varepsilon_t \sim N(\varepsilon_t, \sigma_v^2)$, evaluated at a representative positive shock $\varepsilon_t = \sigma_\varepsilon$. The red-shaded areas A and A' represent the fraction of agents receiving a negative signal, while the blue-shaded areas B and B' represent the fraction receiving a positive signal. Subpanel (a.1): disagreement is $\mathcal{D}_S = 1 - |A - B| = 0.32$. Subpanel (a.2): a larger σ_ε shifts the distribution further from zero, making the split more uneven (A' shrinks); disagreement is smaller than in (a.1), $\mathcal{D}_S = 1 - |A' - B'| = 0.05$. Subpanel (b.1): disagreement is $\mathcal{D}_S = 1 - |A - B| = 0.32$. Subpanel (b.2): a larger σ_v spreads the distribution, pushing more mass across zero (A' grows toward B'); disagreement is larger than in (b.1), $\mathcal{D}_S = 1 - |A' - B'| = 0.62$. The case $\varepsilon_t = -\sigma_\varepsilon < 0$ is symmetric: the distribution shifts to the left, but disagreement behaves identically.

Intuitively, an increase in σ_ε^2 (or a reduction of σ_v^2) makes the signal more informative about ε_t. Since ε_t is common to all individual signals, agents will tend to agree more about the sign of the signal. In the limit, as the variance of the fundamental shock approaches infinity (or the variance of the noise shock approaches zero), agents effectively observe the same signal. In this case, they perfectly agree and disagreement converges to zero.

Conversely, when the variance of the fundamental shock decreases (or the variance of the noise shock increases), the signal becomes less informative, the dispersion of the signals increases raising disagreement. In the limit, as the variance of the noise shock approaches infinity (or the variance of the fundamental shock approaches zero), disagreement will be maximal since the signal is entirely driven by noise and half of the agents will observe positive signals and half negative signals.

Restrictions. 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 noise shock (σ_v^2). Proposition 2 shows that our disagreement measure decreases with the variance of the fundamental shock (σ_ε^2) and increases with the variance of the noise shock (σ_v^2). These comovements provide a set of restrictions that identify the effects of changes in the variance of fundamental shocks (agreed uncertainty) and changes in the variance of noise shocks (disagreed uncertainty) in the structural VAR model of the next section.

Belief disagreement. We now turn to belief disagreement, denoted as $\mathcal{D}_B(k)$ where $k \geq 0$ refers to the forecast horizon. In the model, agents disagree about their forecasts solely because their information sets differ. As discussed in Section 2, the Michigan Survey contains questions about both current and future conditions. To be consistent with the empirical measure, we consider expectations of the form $E_{it}\left(a_{t+k} - a_{t-1}\right)$ for $k \geq 0$. When $k = 0$, beliefs are about current economic conditions; when $k > 0$, beliefs are about future economic conditions.

In the Appendix B, we derive the disagreement measure under two assumptions: (i) the signal is informative about the economic shock, $\gamma \neq 0$; (ii) a_t follows a random walk, obtained when $\lambda = 0$.[13] Under these assumptions, belief and signal disagreement coincide:

$$\mathcal{D}_B(k) = \mathcal{D}_S \quad \text{for} \quad k \geq 0,$$

and therefore the results of Proposition 2 hold for belief disagreement. In the more general case $\lambda \neq 0$, the relationship between shock variances and disagreement becomes

[13]When $\gamma = 0$—either because the variance of the fundamental shock is zero or the variance of the noise is infinite—the signals are completely uninformative, all individual forecasts equal zero, and disagreement is trivially zero. This is a degenerate case with no empirical relevance, which justifies the assumption $\gamma > 0$.

considerably more complex, and the results of Proposition 2 hold only for a subset of values of model parameters.

In the empirical analysis that follows, we use signal disagreement as the baseline disagreement measure because the identifying restrictions always hold for this variable, for any γ and λ. To assess the robustness of our results, we repeat the empirical analysis using the total disagreement measure (results reported in Appendix D.6).

3.2 Evidence from structural VAR models

This section quantifies the dynamic effects of the two uncertainty shocks implied by the model—a shock to the volatility of the fundamental disturbance, σ_ε^2, and a shock to the volatility of noise, σ_v^2—using a Bayesian VAR identified with sign restrictions. We first describe the identification strategy and VAR specification, and then present results for the benchmark model using our preferred measure of signal disagreement.

Identification. Our identification relies on the distinct impact comovements between observed uncertainty and disagreement, as characterized by Propositions 1 and 2. Table 4 summarizes the sign restrictions imposed on the impact responses of each variable. An innovation in σ_ε^2 raises observed uncertainty (measured by the variance of the forecast error) and lowers disagreement, corresponding to *agreed uncertainty*. An innovation in σ_v^2 raises both observed uncertainty and disagreement, corresponding to *disagreed uncertainty*. Beyond these sign restrictions, we additionally impose that real activity variables included in the VAR do not respond contemporaneously to either uncertainty shock.[14] Responses of all other variables are left unrestricted on impact.

Table 4: Identifying sign restrictions

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

Notes: Entries report the imposed *impact* responses of uncertainty (variance of the forecast error) and disagreement. No sign restrictions are imposed beyond the impact period.

We implement identification using the algorithm of Rubio-Ramírez et al. (2010). The sign restrictions are imposed only on impact (and not at longer horizons), following the principle of using the weakest set of restrictions consistent with the theoretical mapping

[14]This restriction is intended to mitigate concerns that high-frequency movements in uncertainty may reflect contemporaneous news about real activity rather than exogenous innovations to second moments.

(see also Mumtaz and Zanetti, 2012, 2015). Appendix C.3 reports the full set of restrictions for the benchmark model.

The benchmark VAR specification. We estimate a monthly U.S. Bayesian VAR, consistent with the frequency and specification choices in the uncertainty literature (e.g., Bloom, 2009; Jurado et al., 2015; Berger et al., 2020). The benchmark model includes eight variables: measured uncertainty, consumer disagreement, industrial production, inflation, consumption, employment, the S&P 500, and the federal funds rate. Uncertainty is measured by the 12-month-ahead macroeconomic uncertainty index of Jurado et al. (2015). Disagreement is measured by our signal disagreement index (DISAG-SIGNAL), constructed from the Michigan Survey of Consumers and described in Section 2.[15]

Both uncertainty and disagreement enter the VAR in levels. Industrial production, inflation, consumption, employment, and stock returns enter as month-on-month growth rates (first differences of logarithms), while the federal funds rate enters in levels since it is already expressed as a rate and requires no transformation. The sample spans January 1978 to December 2019. The start date is dictated by data availability for the Michigan Survey of Consumers series, and we end the sample prior to 2020 to avoid the extreme observations during the COVID-19 period. The benchmark VAR includes 13 lags, a standard choice for monthly data in this context. To address over-parameterization in a high-dimensional lag structure, we adopt the horseshoe prior following Korobilis (2022), which delivers a tuning-free method that achieves optimal shrinkage. Appendix C.2 provides details on the VAR specification, prior and estimation procedure.

[15]Appendix A reports detailed variable definitions and data sources.

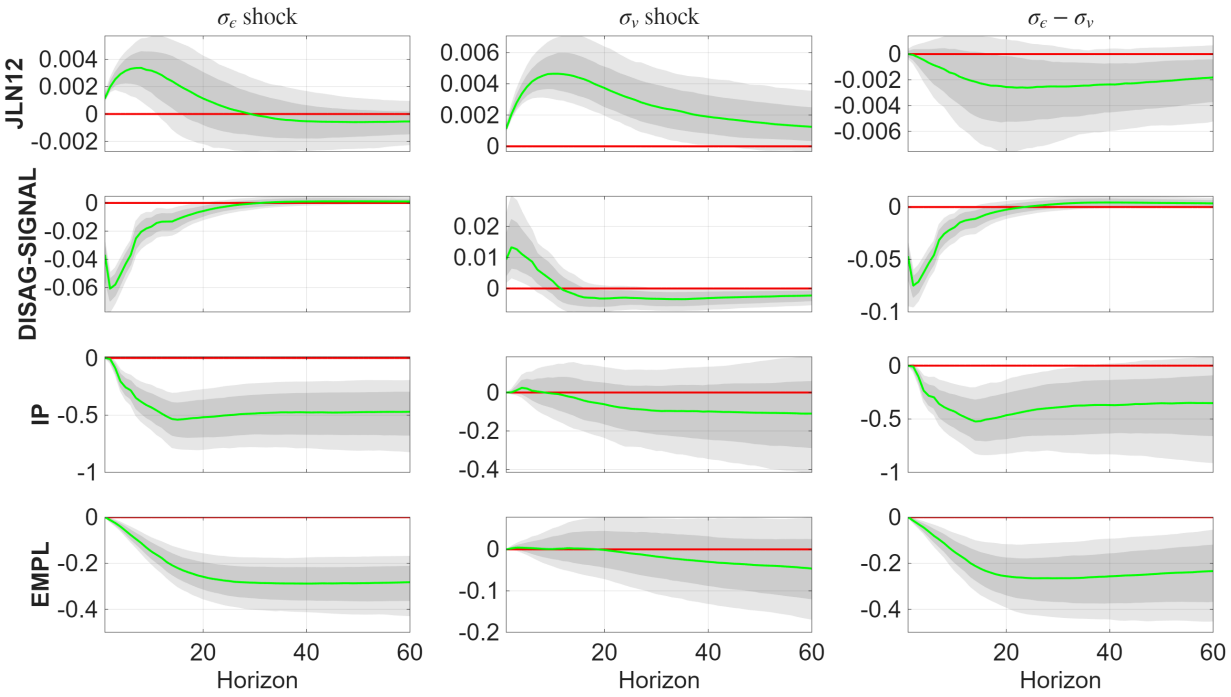


Figure 5: Impulse responses from the benchmark eight-variable Bayesian VAR: agreed versus disagreed uncertainty. Rows display responses of uncertainty (JLN12), signal disagreement (DISAG-SIGNAL), industrial production (IP), and employment (EMPL). The left column reports responses to an agreed uncertainty shock (σ_ε^2), the middle column to a disagreed uncertainty shock (σ_v^2), and the right column the difference between the two. Uncertainty is the 12-month-ahead macroeconomic uncertainty index of Jurado et al. (2015); disagreement is the signal disagreement index constructed in Section 2. The VAR also includes inflation (INFL), consumption (CONS), S&P 500 (SP500), and the federal funds rate (FFR); impulse responses for these variables are reported in Appendix D. Solid lines denote posterior means. Dark- and light-gray shaded areas denote 68% and 90% posterior credible bands, respectively.

Results. Figure 5 reports impulse responses from the benchmark eight-variable BVAR. The left column shows responses to an *agreed-uncertainty* shock (innovation to σ_ε^2), the middle column shows responses to a *disagreed-uncertainty* shock (innovation to σ_v^2), and the right column plots the difference between the two sets of responses.

Agreed uncertainty. A positive agreed-uncertainty shock produces the comovement between uncertainty and disagreement implied by the identification scheme: the JLN12 uncertainty measure rises sharply on impact and remains elevated for roughly two years, while DISAG-SIGNAL falls and stays depressed for an extended period. Real activity contracts: both industrial production and employment decline sharply from the first month onward and remain persistently negative over the subsequent months. Consumption exhibits similar depressing effects (shown in Appendix D). The responses are sizable and precisely estimated over a substantial portion of the horizon, as evidenced by the 68% and 90% credible bands. These dynamics align with the canonical evidence that uncertainty shocks are contractionary in aggregate time series (e.g., Jurado et al., 2015; Gilchrist et al., 2014; Ludvigson et al., 2021; Mumtaz and Zanetti, 2013).

Disagreed uncertainty. In contrast, a positive disagreed-uncertainty shock generates a rise in measured uncertainty that is similar in magnitude—and, if anything, slightly larger at

its peak—than under agreed uncertainty, while DISAG-SIGNAL increases on impact. This suggests that the two shocks contribute similarly to fluctuations in uncertainty. Despite the comparable increase in measured uncertainty, the responses of industrial production, employment, and consumption (shown in Appendix D) are close to zero, with the posterior credible bands encompassing zero throughout the horizon. Thus, conditional on the identifying restrictions, increases in uncertainty accompanied by higher disagreement do not generate the contractionary dynamics associated with agreed-uncertainty shocks.

Difference in responses. The right panel of Figure 5 reveals a pronounced asymmetry: agreed-uncertainty shocks produce markedly larger declines in industrial production and employment than disagreed-uncertainty shocks, with 68% and 90% credible bands for the difference excluding zero over the relevant horizons.

Appendix D presents the full set of impulse responses for all eight VAR variables together with a series of robustness checks to assess the sensitivity of our results to alternative measures of uncertainty and disagreement. These include: (i) results from a simple Cholesky decomposition with no sign restrictions, (ii) replacing the benchmark signal disagreement measure with the total disagreement index, (iii) the 12-month-ahead financial uncertainty index from Jurado et al. (2015) (JLNF-12), (iv) stock market volatility (VIX), (v) the Economic Policy Uncertainty index from Baker et al. (2016), (vi) the disagreement index from Lacy (2006), and (vii) Shannon entropy-based disagreement measures. The results from all alternative specifications align with our benchmark BVAR findings.[16]

In sum, agreed and disagreed uncertainty shocks have sharply different real effects. Agreed uncertainty is consistently contractionary, generating persistent declines in industrial production and employment. Disagreed uncertainty does not produce declines in real activity over short- and medium-term horizons. To our knowledge, this is the first paper to document-using consumer survey disagreement and time-series identification-that disagreement about current and future economic conditions materially dampens the macroeconomic effects of uncertainty.

4 Micro-survey data analysis

In this section, we complement the time-series analysis with micro-survey evidence that provides an alternative identification strategy for examining the effects of *agreed* and *disagreed* uncertainty. We focus on a sharp and plausibly exogenous uncertainty episode—Russia's invasion of Ukraine on February 24, 2022—and exploit the subsequent release of information by the Federal Reserve in the first FOMC statement following the invasion

[16]For consistency, we maintain the baseline assumption of zero impact responses of activity indicators to uncertainty shocks. This ensures that observed changes in activity are attributable to the uncertainty shocks, rather than endogenous feedback effects from economic activity.

(March 16, 2022). The key idea is that, during a common high-uncertainty episode, exposure to a salient and forward-looking policy communication can reduce dispersion in beliefs, allowing us to study whether uncertainty is more contractionary when disagreement is low.[17]

4.1 Empirical design and identification strategy

We use the New York Fed's Survey of Consumer Expectations (SCE), a nationally representative, internet-based rotating panel of roughly 1,300 U.S. household heads that has been conducted on a daily basis since 2013. The SCE includes questions measuring (i) inflation forecasts and (ii) spending plans.[18] Inflation expectations are used because SCE provides daily fielding and both a point forecast (for dispersion) and a subjective distribution (for uncertainty) at the individual level.

Our identification exploits the timing of interviews around the March 16, 2022 FOMC statement. Because interviews occur continuously, we can compare respondents surveyed shortly before versus shortly after the statement, within the same broader uncertainty episode. We treat interview timing relative to the announcement as quasi-experimental variation in exposure to the Fed's information: respondents interviewed after the statement are information-exposed (treated), while those interviewed before serve as a natural control group. We then test whether the relationship between spending plans and aggregate uncertainty differs across these groups, consistent with the hypothesis that lower disagreement amplifies the contractionary effects of uncertainty.

This design is motivated by a growing literature showing that central bank announcements generate sizable information effects that shape private-sector expectations, beyond the canonical policy-rate component.[19] Building on this evidence, we hypothesize that the March 2022 statement conveyed non-redundant information about the near-term outlook and policy path that households partially internalized, reducing dispersion in inflation beliefs. We operationalize this mechanism using the post-statement change in inflation-forecast disagreement and, leveraging the SCE panel structure, estimate how uncertainty affects spending plans for information-exposed versus non-exposed respondents.

[17] Several uncertainty measures spiked around the invasion. The global economic policy uncertainty index rose by 72%, the U.S. economic policy uncertainty index rose by 38% between February and March 2022, and the VIX increased by 66% between February 1 and March 7, 2022.

[18] Respondents participate for up to twelve months, with approximately equal inflows and outflows each month. The SCE elicits expectations on inflation, household finances, labor market conditions, and housing outcomes, and collects standard demographics including age, education, income, and location.

[19] The information-effect view originates in Romer and Romer (2000) and has been developed in, among others, Nakamura and Steinsson (2018), Melosi (2017) and Melosi et al. (2024). Related work highlights the informational content of FOMC communications about the state of the economy; see, e.g., Acosta (2023).

Survey data and information content in the FOMC statement. The March 16, 2022 FOMC statement plausibly conveyed salient information about the near-term outlook and the policy path in the immediate aftermath of Russia's invasion of Ukraine. It emphasized elevated uncertainty and its near-term implications for inflation and activity, noting that the invasion and related events were "likely to create additional upward pressure on inflation and weigh on economic activity." The Committee also raised the target range for the federal funds rate for the first time since the onset of the pandemic and signaled further policy tightening.[20] Consistent with broad public attention to the announcement, we document a sharp increase in Google Trends search intensity for "Federal Reserve" and "interest rate" on March 16 relative to March 15.

Respondents in the SCE are assigned to invitation windows spread across the month, and survey completion dates are correspondingly dispersed, providing high-frequency variation in interview timing.[21] Since the SCE records the day each questionnaire is completed, we can classify respondents interviewed shortly before versus shortly after the March 16, 2022 FOMC statement. The SCE's staggered fielding during March 2022 generates high-frequency variation in respondents' exposure to the March 16 FOMC statement. We classify respondents as information-exposed (treated) if they completed the survey on or after March 16 (March 16-31), and as a natural control group if they completed it prior to the statement (March 1-15). The identifying assumption is that, conditional on the SCE's invitation schedule and the narrow window around the announcement, survey completion timing is plausibly unrelated to respondents' preferences and contemporaneous economic circumstances. As a result, respondents completing the survey after March 16 are more likely to have been exposed to the Fed's communication than those completing it beforehand. In this sense, the design provides quasi-experimental variation in information exposure within a common uncertainty episode.

A potential threat to validity is non-random survey completion timing. We therefore test whether observable characteristics differ systematically between the pre- and post-statement groups. The SCE contains rich demographic and household measures that are time-invariant or slow-moving (e.g., age, education, household structure, numeracy), and imbalances could mechanically affect expectations and spending plans. Appendix E reports tests for nine observables. We find that the two groups are statistically similar along all dimensions except income.

The SCE elicits individual-level information on (i) expected inflation over the next 12 months (SCE question Q8v2part2),[22] (ii) inflation uncertainty over the next 12 months

[20] Full statement: `https://www.federalreserve.gov/newsevents/pressreleases/monetary20220316a.htm`.

[21] Each month, respondents are partitioned into three batches of roughly equal size and receive survey invitations around the 2nd, 11th, and 20th of the month; completed surveys are spread over the month. See Armantier et al. (2017) for details.

[22] Respondents report a point forecast of 12-month-ahead inflation (in percent) in response to: "What do you expect the rate of inflation (or deflation) to be over the next 12 months? Please give your best guess."

(SCE question Q9), and (iii) expected growth in total household spending over the next 12 months (SCE question Q26v2part2). We measure inflation forecast disagreement at the daily frequency as the cross-sectional interquartile range (IQR) of respondents' inflation forecasts, denoted $INF^{e}_{iqr,t}$.

The survey's subjective inflation uncertainty measure is elicited by asking respondents to allocate probabilities across a set of predefined, non-overlapping bins for possible inflation outcomes over the next 12 months, with probabilities summing to 100. Using each respondent's reported probability distribution, the SCE constructs and reports an individual-level measure of inflation uncertainty given by the interquartile range (IQR) of the implied subjective inflation distribution.

Finally, for spending plans, respondents report the expected percentage change in their total household spending (durables, nondurables, and services combined) over the next 12 months. This variable is our primary household-level outcome, capturing planned consumption spending over the coming year. The detailed questions are reported in Appendix E.1.

Inflation forecast disagreement and the March 2022 FOMC statement. Because the SCE is a rotating panel in which respondents are observed for up to twelve months, we can track the households who are *information-exposed* in March 2022 (i.e., those completing the survey between March 16 and March 31) back to their February 2022 interview. This enables a before-after comparison of inflation forecast disagreement for a *fixed set of respondents* surrounding the FOMC communication. Our working hypothesis is that the March 16 statement conveyed non-redundant information about the near-term outlook and the policy path, thereby reducing disagreement in inflation expectations within the information-exposed group.

To assess this hypothesis, we compute daily inflation forecast disagreement within this fixed respondent set and estimate the following regression:

$$INF^{e}{}_{iqr(treated),t} = \alpha + \beta_0 \, \mathbf{1}\{\text{Post-FOMC}_t\} + \varepsilon_t, \tag{9}$$

where $INF^{e}{}_{iqr(treated),t}$ denotes inflation forecast disagreement on day t, measured as the cross-sectional interquartile range of 12-month-ahead inflation point forecasts among respondents in the treated group who completed the survey on day t. The indicator $\mathbf{1}\{\text{Post-FOMC}_t\}$ equals one for post-statement survey completion days (March 16-31, 2022) and zero for the February 2022 interview days of the same respondent set. The coefficient β_0 therefore captures the change in disagreement for the information-exposed group in the post-statement period relative to February.

Table 5 reports the estimate of β_0. The coefficient is negative and statistically significant at the 5% level, indicating that inflation forecast disagreement is lower in

the post-statement period for the information-exposed group. Appendix E reports the analogous analysis for the pre-statement control group and finds no statistically significant change in disagreement over the same February-March comparison.

Table 5: Inflation forecast disagreement around the March 16, 2022 FOMC statement: information-exposed group

	Dependent variable: daily disagreement (IQR)
$\mathbf{1}\{\text{Post-FOMC}_t\}$	-0.10**
	(0.04)

Notes: The dependent variable is $INF^e{}_{iqr(treated),t}$, the cross-sectional interquartile range of 12-month-ahead inflation point forecasts among respondents in the information-exposed group who completed the survey on day t. The sample includes respondents who completed the survey between March 16 and 31, 2022 and who also completed the survey in February 2022; t indexes survey completion days in February and March. $\mathbf{1}\{\text{Post-FOMC}_t\}$ equals one for March 16-31 completion days and zero for February completion days. Standard errors are clustered by day. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2 Consumer spending plans and uncertainty

We construct a balanced panel of SCE respondents who complete the survey in both February and March 2022, drawing from both the information-exposed (treated) and pre-statement (control) groups. Each respondent is therefore observed twice (once per month), but survey completion dates are distributed across calendar days, which allows us to introduce a daily proxy for aggregate uncertainty. This panel structure allows us to include respondent fixed effects and compare changes in spending plans within the same household across months.

Our baseline specification relates planned spending growth to aggregate uncertainty and allows the sensitivity of spending plans to uncertainty to differ by treatment status and month, using the regression:

$$\begin{aligned} Q26_{it} = \alpha_i + \lambda_m + \beta_1 \, \mathbf{1}\{\text{Treated}_i\} \, \mathbf{1}\{\text{March}_m\} + \beta_2 \, VIX_{t-1} \\ + \beta_3 \, \mathbf{1}\{\text{Treated}_i\} \, VIX_{t-1} + \beta_4 \, \mathbf{1}\{\text{March}_m\} \, VIX_{t-1} \\ + \beta_5 \, \mathbf{1}\{\text{Treated}_i\} \, \mathbf{1}\{\text{March}_m\} \, VIX_{t-1} + \varepsilon_{it}, \end{aligned} \tag{10}$$

where $Q26_{it}$ is respondent i's expected percentage change in total household spending over the next 12 months. The fixed effect α_i absorbs all time-invariant respondent characteristics, and λ_m denotes month fixed effects, with $m \in \{\text{February}, \text{March}\}$. The indicator $\mathbf{1}\{\text{March}_m\}$ equals one for March interviews. The indicator $\mathbf{1}\{\text{Treated}_i\}$ equals one for respondents who complete their March interview on or after March 16, 2022 (information-exposed group) and zero for respondents who complete their March interview

prior to the statement (control group); it is constant across the respondent's February and March observations. The variable VIX_{t-1} denotes the CBOE Volatility Index lagged one trading day, where t indexes the calendar day of survey completion.[23] The coefficient of interest is β_5, which captures a difference-in-differences in the *slope* of spending plans with respect to uncertainty—that is, whether the marginal effect of VIX_{t-1} is more negative for treated versus control respondents in March relative to February. Essentially, β_5 answers: Does uncertainty become more contractionary after the information shock for those exposed to it? Formally, the coefficient β_5 is equal to

$$\beta_5 = \left[\frac{\partial \mathbb{E}[Q26_{it} \mid \text{Treated}_i = 1,\ \text{March}_m = 1]}{\partial VIX_{t-1}} - \frac{\partial \mathbb{E}[Q26_{it} \mid \text{Treated}_i = 0,\ \text{March}_m = 1]}{\partial VIX_{t-1}}\right] - \left[\frac{\partial \mathbb{E}[Q26_{it} \mid \text{Treated}_i = 1,\ \text{March}_m = 0]}{\partial VIX_{t-1}} - \frac{\partial \mathbb{E}[Q26_{it} \mid \text{Treated}_i = 0,\ \text{March}_m = 0]}{\partial VIX_{t-1}}\right].$$

Table 6 reports the estimates. The triple-interaction coefficient β_5 is negative and statistically significant at the 5% level, indicating that the treated-control difference in the sensitivity of spending plans to uncertainty becomes more negative in March relative to February. The implied treated-control slope difference in March is $\beta_3 + \beta_5$, which is negative in our estimates (-4.87; the null $\beta_3 + \beta_5 = 0$ is rejected at the 10% level), implying that uncertainty is more contractionary for treated than for control respondents in March. Quantitatively, a one-standard-deviation increase in the VIX is associated with a 6.6 percentage point *more negative* response of planned spending for treated respondents relative to control respondents in March, (*relative to the corresponding treated-control differential in February*). The magnitude is economically meaningful: this 6.6 percentage point differential decline is about 87% of the mean planned spending growth in the treated group in March (equal to 7.6 percentage points) and corresponds to 0.45 standard deviations of the treated group's distribution of expected spending changes (standard deviation of 14.7 percentage points).

This pattern is consistent with the mechanism emphasized in our analysis: following the FOMC communication, the treated group exhibits lower inflation forecast disagreement, and uncertainty is more contractionary for spending plans when disagreement is lower. Appendix E.4 reports robustness exercises using (i) individual-level inflation uncertainty constructed from Q9, (ii) alternative lags of the VIX (including a two-day lag), and (iii) an alternative uncertainty proxy, the U.S. equity market uncertainty index. The results are qualitatively similar to the baseline specification.

[23] The Jurado-Ludvigson-Ng uncertainty indices are not available at daily frequency required for this setting. Lagging the VIX ensures that the uncertainty measure reflects information available to respondents at the time they complete the survey on calendar day t.

Table 6: Panel evidence: February-March 2022 (balanced respondent panel)

Dependent variable: Spending plans ($Q26$)	
$\mathbf{1}\{\text{Treated}_i\} \times \mathbf{1}\{\text{March}_m\}$	-2.11
	(3.20)
VIX_{t-1}	-1.15
	(1.24)
$\mathbf{1}\{\text{Treated}_i\} \times VIX_{t-1}$	1.73
	(1.48)
$\mathbf{1}\{\text{March}_m\} \times VIX_{t-1}$	3.56
	(2.70)
$\mathbf{1}\{\text{Treated}_i\} \times \mathbf{1}\{\text{March}_m\} \times VIX_{t-1}$	-6.60**
	(3.29)
Month Fixed effects	Yes
Consumer Fixed effects	Yes
Adjusted R^2	0.55
N	1984

Notes: VIX is the CBOE volatility index standardized to have a mean of zero and standard deviation of one. Standard errors clustered at the respondent level are reported in parentheses. The regression includes the Aruoba-Diebold-Scotti (Aruoba et al., 2009) daily business conditions index as an additional control. This daily indicator is designed to track real business conditions at a high frequency. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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.

5 Conclusion

Uncertainty is not uniformly contractionary: its real effects depend on whether households' views are aligned or dispersed. We distinguish between agreed and disagreed uncertainty and show that shocks that raise uncertainty while disagreement is low (*agreed uncertainty*) lead to persistent declines in economic activity. In contrast, shocks that raise both uncertainty and disagreement (*disagreed uncertainty*) have muted effects on real activity over short- and medium-term horizons. This distinction helps explain why some large spikes in uncertainty coincide with recessions while others do not. These findings point to disagreement as a key state variable shaping the transmission of uncertainty. They are consistent with a mechanism in which uncertainty driven by common fundamental volatility induces coordinated pullbacks in spending, whereas uncertainty arising in environments with dispersed information and heterogeneous signals does not generate the same aggregate

response.

We rationalize these patterns in a stylized model with imperfect and dispersed information. Higher volatility of fundamental shocks raises uncertainty while compressing disagreement, whereas higher volatility of noise raises both uncertainty and disagreement. We exploit these comovement predictions to impose sign restrictions and identify agreed- and disagreed-uncertainty shocks in a monthly U.S. VAR. The results reveal a sharp asymmetry: agreed-uncertainty shocks generate large and persistent declines in industrial production, consumption, and employment, consistent with the canonical uncertainty channel; disagreed-uncertainty shocks raise measured uncertainty by a comparable amount but leave real activity largely unchanged.

We then provide complementary micro evidence on the mechanism. Using the New York Fed Survey of Consumer Expectations, we study the exogenous uncertainty episode following Russia's invasion of Ukraine (February 24, 2022) and exploit quasi-experimental variation in information exposure generated by the first post-invasion Federal Reserve FOMC statement. Because the survey is fielded daily, we compare respondents interviewed before versus after the statement. Information-exposed respondents display a marked decline in inflation-forecast disagreement relative to the pre-statement control group. Mirroring the time-series results, uncertainty is more contractionary when disagreement is lower: reported spending plans fall more steeply with uncertainty for the information-exposed group than for the control group.

Our results underscore the importance of distinguishing between sources of uncertainty when evaluating their macroeconomic consequences. More broadly, they point to a novel policy-relevant trade-off: communications that reduce disagreement by coordinating beliefs may strengthen the real effects of uncertainty episodes, even if they improve informational clarity. Two avenues for future work follow naturally. First, it would be valuable to study systematically how the information content of policy announcements affects disagreement and, in turn, the transmission of uncertainty to consumption and investment.[24] Second, understanding whether—and under what conditions—greater diversity of views can dampen aggregate responses to uncertainty remains an open question, with implications for the design of policy communication in volatile environments.

[24]See Li et al. (2026) for a study on information and monetary policy.

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Supplemental Appendices

Agreed and Disagreed Uncertainty

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A. Data

A.1. Data series

All core macro series and 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
INFL	PCEPI	Personal Consumption Expenditures (Price Index)	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
VIX	VIX	CBOE Volatility Index (VIX)	FRED	1
EPU	USEPUINDXM	Economic Policy Uncertainty Index for United States, Index, Monthly	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 four 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 oConsumers,s, https://data.sca.isr.umich.edu/), JLN (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). 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 on 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 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. Correlations among main tail disagreement indicators

Table A.2: Pairwise Correlations across Disagreement Indexes

	DISAG-TOTAL	DISAG-SIGNAL (T_t^{NEWS})	DISAG-BELIEF	T_t^{BAGO}	T_t^{BEXP}	T_t^{BUS12}	T_t^{BUS5}
DISAG-TOTAL	1.00	0.88	0.90	0.88	0.21	0.66	0.62
DISAG-SIGNAL (T_t^{NEWS})	0.88	1.00	0.58	0.60	0.07	0.32	0.49
DISAG-BELIEF	0.90	0.58	1.00	0.94	0.30	0.85	0.60
T_t^{BAGO}	0.88	0.60	0.94	1.00	0.27	0.64	0.39
T_t^{BEXP}	0.21	0.07	0.30	0.27	1.00	0.24	0.06
T_t^{BUS12}	0.66	0.32	0.85	0.64	0.24	1.00	0.57
T_t^{BUS5}	0.62	0.49	0.60	0.39	0.06	0.57	1.00

Notes: Pairwise correlations among the aggregate disagreement index (DISAG-TOTAL), signal disagreement (DISAG-SIGNAL, based on NEWS), belief disagreement (DISAG-BELIEF), and the four remaining (that is excluding, NEWS) individual tail disagreement series constructed from the Michigan Survey of Consumers. Sample: 1978M1-2019M12, monthly frequency.

A.3. Cross-correlation of disagreement with uncertainty and macroeconomic variables

Figure A.1 further studies the time series properties of disagreement by showing the cross-correlations of the DISAG-TOTAL index at time t with key uncertainty and macroeconomic variables, at various leads and lags. The panels show the cross-correlation between DISAG-TOTAL$_t$ and the variable x_{t+h} for lags $h = -12, ..., -1, 0, 1, ...12$. DISAG-TOTAL$_t$ is negatively correlated at several leads and lags with the JLN12 and JLNF12 uncertainty indexes, and the correlation coefficient never exceeds -0.6 (bottom panels), indicating that disagreement conveys sufficiently different information to uncertainty indicators. The DISAG-TOTAL index entails a low correlation with macroeconomic and financial variables. The correlation coefficient for IP, employment, consumption, and hours of work is within $\pm$ 0.3. Similarly, the correlation coefficient with inflation, the Federal Fund Rate, the SP&500 Index 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. The cross correlation of signal and belief disagreement indexes (not shown) with the same set of variables displayed below is nearly identical.

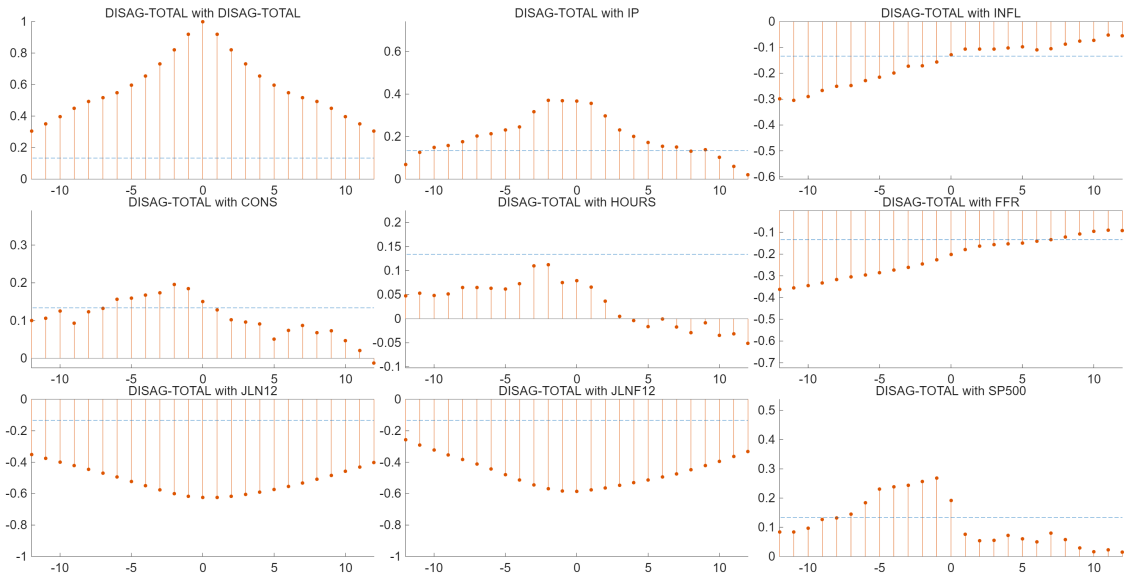


Figure A.1: Cross-correlations of total disagreement with uncertainty and macroeconomic variables at various leads and lags. *Notes*: In each of these plots, the y-axis shows the value of cross-correlation of DISAG with each of 8 macroeconomic, financial and uncertainty indicators, at 12 leads/lags. Negative values on the x-axes indicate the correlation between DISAG-TOTAL today and the value of each indicator h months in the past, $h = 1, ..., 12$. Positive values indicate the correlation between DISAG-TOTAL h months ago and the current value of each indicator. Zero values indicate contemporaneous correlations. All data and mnemonics are described in Appendix A, Table A.1.

A.4. Individual disagreement series, total disagreement (DISAG-TOTAL) and factor loadings

The top four panels and the bottom-left panel of Figure 2 show the estimate of the total 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.

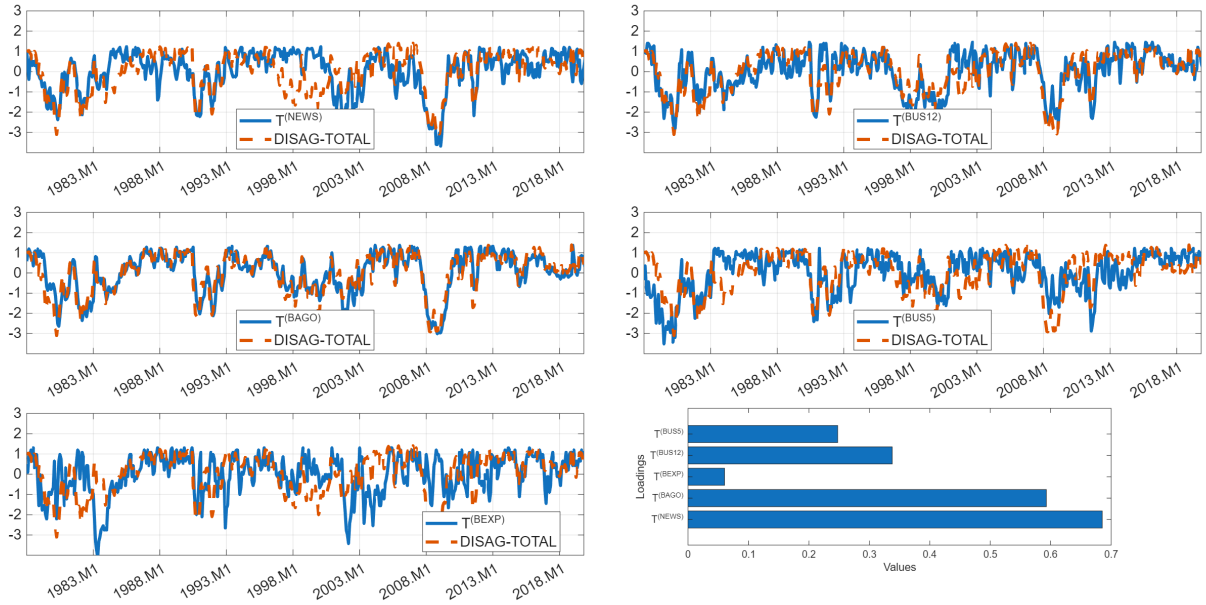


Figure A.2: Individual measures of disagreement versus their weighted average (factor). This figure displays the tails disagreement measure $T_t^j = 1 - |b_t^j - w_t^j|/100$ for each of the five Michigan Survey questions (blue solid lines) alongside the aggregate total disagreement factor (DISAG-TOTAL, orange dashed lines). The five panels show: NEWS (top left, $T^{(\text{NEWS})}$), BUS12 (top right, $T^{(\text{BUS12})}$), BUS5 (middle left, $T^{(\text{BUS5})}$), BAGO (middle right, $T^{(\text{BAGO})}$), and BEXP (bottom left, $T^{(\text{BEXP})}$). The bottom right panel shows the factor loadings, indicating the contribution of each question to the aggregate factor. All individual series exhibit substantial comovement with the aggregate factor, justifying the use of principal components to extract a common disagreement measure. Sample period: 1983M1-2018M1.

The figure shows that the correlation of the total disagreement index with each individual series is high. The bottom-right panel of Figure A.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. The loadings are fairly balanced across the five questions, with each contributing meaningfully to the aggregate factor. The NEWS question exhibits a relatively larger loading, motivating our preference for signal disagreement as the representative series for the disagreement measure, while BEXP has the smallest loading among the five series. The near-balanced pattern of loadings indicates that no single question dominates the aggregate factor, supporting the interpretation of the first principal component as a broad measure of consumer disagreement that captures common variation across all survey questions.

The strong comovement between individual series and the aggregate factor throughout the sample confirms that principal component analysis successfully extracts the common

disagreement component while filtering out idiosyncratic noise in individual questions. Notable features include:

- All five individual series track the aggregate factor closely, with similar peaks and troughs.
- The 2008-2009 financial crisis period shows a dramatic downward spike in disagreement across all questions.
- Earlier recession periods (1990-91, 2001) also feature spikes in disagreement although not as pronounced.
- The mid-1980s and late-1990s show interesting divergences between individual series, though the factor captures the dominant pattern.

A.5. Alternative disagreement indicators

The tails-based disagreement measure used in our benchmark specification is simple and intuitive, but it does not fully exploit the information contained in the MSC responses. Specifically, it considers only the two polar response categories (better/worse), while ignoring the middle category, which—depending on the question—corresponds to respondents indicating that conditions are either the "same" or "uncertain." For this reason, we recompute the disagreement index using two alternative measures: "entropy disagreement," based on Shannon's Shannon, 1948 entropy measure, and "Lacy disagreement," using the transformation proposed by Lacy (2006). Both measures exploit the full set of available response categories.

The entropy disagreement is defined as[1]

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

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.[2] 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 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

[1] This measure, which we refer to as disagreement, is known in ecology and related sciences as the "Shannon index" and is commonly used to quantify the diversity and distribution of species within a community; see Hill (1973).

[2] 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.

and the maximum indicate intermediate levels of dispersion.

Figure A.3 compares the entropy and Lacy disagreement measures with our disagreement measures described in Section 2. The panels in the top row compare our tail-based measure (blue solid line) with the entropy-based measure (red dashed line) for total disagreement (DISAG-TOTAL, left panel), signal disagreement (DISAG-SIGNAL, middle panel), and belief disagreement (DISAG-BELIEF, right panel). Similarly, the panels in the bottom row compare our tail-based measure (blue solid line) with the Lacy-based measure (red dashed line) for total disagreement (DISAG-TOTAL, left panel), signal disagreement (DISAG-SIGNAL, middle panel), and belief disagreement (DISAG-BELIEF, right panel).

The high degree of similarity and correlation among the tails, entropy, and Lacy measures confirms that our results are not driven by the specific functional form used to measure disagreement.

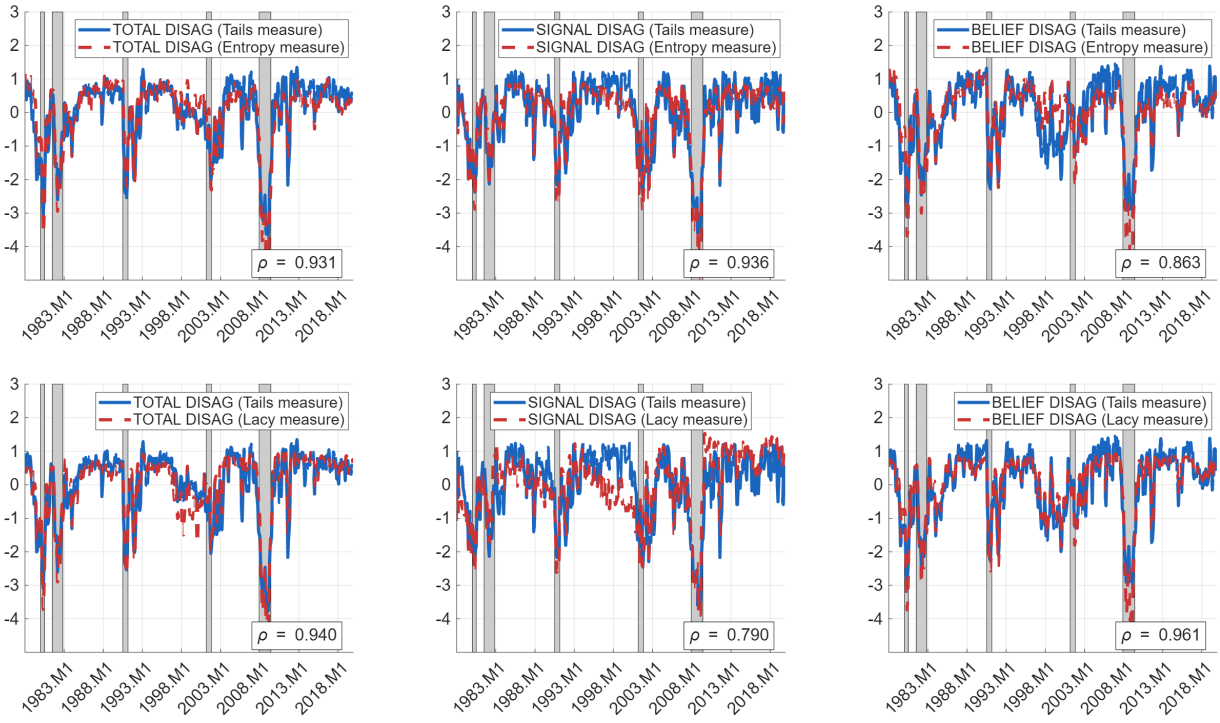


Figure A.3: Alternative disagreement measures: Tails vs. Entropy and Lacy. The six panels compare our baseline tails disagreement measures (blue solid line) with entropy-based measures (red dashed line, top row) and Lacy ordinal dispersion measures (red dashed line, bottom row) for total (DISAG-TOTAL, left column), signal (DISAG-SIGNAL, middle column), and belief (DISAG-BELIEF, right column) disagreement. Gray shaded areas denote NBER recessions. The correlation coefficient ρ reported in each panel measures the contemporaneous correlation between our baseline tail-based measure and the corresponding alternative measure. All series are normalized to facilitate comparison.

B. Model derivations and proof of propositions in Section 3

Derivation of the aggregate forecast error, equation (6). The forecast of agent i is

$$E_{it}\left(a_{t+k}-a_{t+k-1}\right)=\gamma\psi_k(\varepsilon_t+v_{it})+\sum_{j=1}^{\infty}\psi_{k+j}\varepsilon_{t-j},\quad \text{for}\quad k=1,2,..., \tag{B.1}$$

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 (B.1), the individual forecast depends on both the fundamental shock, ε_t, and the noise shock, v_{it}. By aggregating across agents we obtain

$$\int E_{it}(a_{t+k}-a_{t+k-1})di=\bar{E}_t(a_{t+k}-a_{t+k-1})=\gamma\psi_k\varepsilon_t+\sum_{j=1}^{\infty}\psi_{k+j}\varepsilon_{t-j} \tag{B.2}$$

The implied aggregate forecast error is

$$\left(a_{t+k}-a_{t+k-1}\right)-\bar{E}_t\left(a_{t+k}-a_{t+k-1}\right)=\ \textstyle\sum_{j=0}^{k-1}\psi_j\varepsilon_{t+k-j}+\psi_k(1-\gamma)\varepsilon_t\quad \text{for } k\geq 1. \tag{B.3}$$

The variance of the aggregate forecast error is equal to

$$FEV(k)=\ \psi_k^2\left(\tfrac{\sigma_v^2}{\sigma_\varepsilon^2+\sigma_v^2}\right)^2\sigma_\varepsilon^2+\textstyle\sum_{j=0}^{k-1}\psi_j^2\sigma_\varepsilon^2\quad \text{for } k\geq 1,$$

as equation (6) in the paper.

Derivation of belief disagreement Next, we describe the derivations for belief disagreement. For the sake of exposition, we derive disagreement under the simplifying assumption $\lambda=0$. When $\lambda=0$, the fundamental process evolves as a random walk

$$a_t=a_{t-1}+\varepsilon_t. \tag{B.4}$$

We have to decide which types of agents' beliefs to consider. Given that in the empirical measures we have both questions about current conditions and future conditions we consider the following expectations: $E_{it}\left(a_{t+k}-a_{t-1}\right)$ for $k\geq 0$. Using equation (B.4) we have

$$E_{it}\left(a_{t+k}-a_{t-1}\right)=\gamma(\varepsilon_t+v_{it}). \tag{B.5}$$

The cross-sectional distribution of beliefs is

$$E_{it}\left(a_{t+k}-a_{t-1}\right) \mid \varepsilon_t \sim N(\gamma\varepsilon_t, \gamma^2\sigma_v^2).$$

Notice that in this case, unlike for signal disagreement, the distribution depends on the parameter γ which represents the filter which agents use to produce expectations from the observed signal. The probability of having a negative expectation is

$$\Pr(E_{it}\left(a_{t+k}-a_{t-1}\right)<0|\varepsilon_t)=\Phi\left(\frac{0-\gamma\varepsilon_t}{\gamma\sigma_v}\right)=\Phi\left(-\frac{\varepsilon_t}{\sigma_v}\right),$$

and the probability of having a positive expectation is

$$\Pr(E_{it}\left(a_{t+k}-a_{t-1}\right)>0|\varepsilon_t)=1-\Phi\left(\frac{0-\gamma\varepsilon_t}{\gamma\sigma_v}\right)=1-\Phi\left(-\frac{\varepsilon_t}{\sigma_v}\right).$$

The two probabilities are exactly the same as those derived for signal disagreement, so that belief disagreement associated to the k- period ahead expected conditions, denoted by $\mathcal{D}_B(k)$, coincides with the signal disagreement. Notice that this is true provided that $\gamma \neq 0$. For $\gamma = 0$, we have a case where either the variance of the fundamental shock is zero or the variance of the noise is infinite. In this situation all the individual forecasts are zero, thus disagreement is zero, simply because the signal is uninformative. This is the main difference with respect to signal disagreement.[3] Therefore for $\gamma \neq 0$,

$$\mathcal{D}_B(k)=\mathcal{D}_S \text{ for } k\geq 0,$$

and the results of Proposition 2 hold for beliefs disagreement.

We next prove Propositions 1 and 2 in Section 3.

B.1. Proof of Proposition 1

Proof. Part (i). The partial derivative of $FEV(k)$ in equation (6) w.r.t. σ_ε^2 is:

$$\frac{\partial FEV(k)}{\partial\sigma_\varepsilon^2}=\psi_k^2\left(\frac{\sigma_v^2}{\sigma_v^2+\sigma_\varepsilon^2}\right)^2\left(\frac{\sigma_v^2-\sigma_\varepsilon^2}{\sigma_v^2+\sigma_\varepsilon^2}\right)+\sum_{j=0}^{k-1}\psi_j^2>0, \tag{B.6}$$

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.6) is positive.

[3] We thank an anonymous referee for pointing this out.

Part (ii). The partial derivative of $FEV(k)$ in equation (6) w.r.t. σ_v^2 is

$$\frac{\partial FEV(k)}{\partial \sigma_v^2} = 2\psi_k^2 \sigma_\varepsilon^2 \left(\frac{\sigma_v^2}{\sigma_\varepsilon^2 + \sigma_v^2} \right) \left(\frac{\sigma_\varepsilon^2}{(\sigma_\varepsilon^2 + \sigma_v^2)^2} \right) > 0, \tag{B.7}$$

since all the terms in equation (B.7) are positive. □

B.2. Proof of Proposition 2

Proof. Part (i).
We begin with the general chain rule identity

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} = \frac{\partial \mathcal{D}}{\partial u} \cdot \frac{\partial u}{\partial \sigma_\varepsilon},$$

where in our case $u(\sigma_\varepsilon) = \sigma_\varepsilon^2$. Hence,

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} = \frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon^2} \cdot 2\sigma_\varepsilon,$$

and for $\sigma_\varepsilon \neq 0$ we can equivalently write

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

Case 1: $\boldsymbol{\varepsilon_t = \sigma_\varepsilon}$ Since $\Phi(\cdot)$ denotes the CDF of a standard normal variable, we have $\Phi(-\sigma_\varepsilon/\sigma_v) < 0.5$. Therefore

$$1 - 2\Phi\left(-\frac{\sigma_\varepsilon}{\sigma_v} \right) > 0,$$

and $\mathcal{D}$ simplifies to

$$\mathcal{D} = 2\Phi\left(-\frac{\sigma_\varepsilon}{\sigma_v} \right). \tag{B.9}$$

Differentiating with respect to σ_ε gives:

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} = -\frac{2}{\sigma_v} \phi\left(-\frac{\sigma_\varepsilon}{\sigma_v} \right),$$

where $\phi(\cdot)$ is the standard normal pdf and we used the evenness of ϕ. Using (B.8) and noting that $\sigma_\varepsilon > 0$, we obtain:

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon^2} = -\frac{1}{\sigma_\varepsilon \sigma_v} \phi\left(-\frac{\sigma_\varepsilon}{\sigma_v} \right) < 0.$$

Case 2: $\boldsymbol{\varepsilon_t = -\sigma_\varepsilon}$ In this case, we have

$$\mathcal{D} = 2 - 2\Phi\left(\frac{\sigma_\varepsilon}{\sigma_v}\right). \tag{B.10}$$

Differentiating with respect to σ_ε gives:

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon} = -\frac{2}{\sigma_v}\phi\left(\frac{\sigma_\varepsilon}{\sigma_v}\right).$$

Using again (B.8) we have:

$$\frac{\partial \mathcal{D}}{\partial \sigma_\varepsilon^2} = -\frac{1}{\sigma_\varepsilon \sigma_v}\phi\left(\frac{\sigma_\varepsilon}{\sigma_v}\right) < 0.$$

Since in both cases the derivative with respect to σ_ε^2 is negative, we have proven part (i).

Part (ii).
We now compute the sign of $\frac{\partial \mathcal{D}}{\partial \sigma_v^2}$. By the same chain rule argument as before:

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

Case 1: $\boldsymbol{\varepsilon_t = \sigma_\varepsilon}$ Using (B.9), we get:

$$\frac{\partial \mathcal{D}}{\partial \sigma_v} = 2\phi\left(-\frac{\sigma_\varepsilon}{\sigma_v}\right) \cdot \frac{\sigma_\varepsilon}{\sigma_v^2}$$

Hence,

$$\frac{\partial \mathcal{D}}{\partial \sigma_v^2} = \frac{\sigma_\varepsilon}{\sigma_v^3}\phi\left(-\frac{\sigma_\varepsilon}{\sigma_v}\right) > 0.$$

Case 2: $\boldsymbol{\varepsilon_t = -\sigma_\varepsilon}$ Using (B.10), we analogously obtain:

$$\frac{\partial \mathcal{D}}{\partial \sigma_v} = \frac{2\sigma_\varepsilon}{\sigma_v^2}\phi\left(\frac{\sigma_\varepsilon}{\sigma_v}\right),$$

and therefore:

$$\frac{\partial \mathcal{D}}{\partial \sigma_v^2} = \frac{\sigma_\varepsilon}{\sigma_v^3}\phi\left(\frac{\sigma_\varepsilon}{\sigma_v}\right) > 0.$$

In both cases, we obtain $\frac{\partial \mathcal{D}}{\partial \sigma_v^2} > 0$, which proves part (ii). □

C. Econometric methodology

This appendix outlines the econometric specifications of (i) the threshold VAR model in Section 2.2; (ii) simple multivariate exercise using a VAR model that estimates orthogonalized shocks using the standard Cholesky decomposition; (iii) the BVAR model, and (iv) the sign restrictions used for identification in Section 3.2.

C.1. Threshold VAR model

The Threshold VAR extends the standard VAR by allowing parameters to switch between regimes based on an observable threshold variable. Our threshold variable is the disagreement measure (TOTAL, SIGNAL, or BELIEF). The model is:

$$\mathbf{y}_t = \begin{cases} \mathbf{c}_1 + \mathbf{B}_1^{(1)}\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p^{(1)}\mathbf{y}_{t-p} + \mathbf{u}_t^{(1)}, & \text{if DISAG}_t \leq \gamma \\ \mathbf{c}_2 + \mathbf{B}_1^{(2)}\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p^{(2)}\mathbf{y}_{t-p} + \mathbf{u}_t^{(2)}, & \text{if DISAG}_t > \gamma, \end{cases} \tag{B.1}$$

where $\mathbf{u}_t^{(j)} \sim N(\mathbf{0}, \mathbf{\Sigma}_j)$, and γ is the threshold parameter. We set γ equal to the sample median of each disagreement measure, yielding approximately equal-sized regimes.

Key features of the TVAR:

- **Regime-dependent dynamics**: Each regime has its own autoregressive coefficients $\mathbf{B}_i^{(j)}$, allowing the persistence and propagation of shocks to differ.
- **Regime-dependent shock variances**: The covariance matrices $\mathbf{\Sigma}_j$ can differ across regimes, so uncertainty shocks may have different magnitudes in high vs. low disagreement periods.
- **Estimation**: We estimate the model by OLS separately in each regime. Since the threshold variable (disagreement) is predetermined, this yields consistent estimates.
- **Inference**: We compute confidence bands via a regime-preserving bootstrap. In each bootstrap replication, we draw residuals from the appropriate regime, generate artificial data using the regime-switching structure, and re-estimate the TVAR.

The regime-specific impulse responses are computed analogously to the standard VAR but using regime-specific parameters. We focus on the response of IP growth to an uncertainty shock (the second variable's response to the first shock) in each regime. The *difference* in impulse responses between low and high disagreement regimes provides a direct measure of how disagreement moderates uncertainty's impact.

C.2. VAR model

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 multivariate regression form

$$\mathbf{y}_t = \mathbf{\Phi}\mathbf{x}_t + \boldsymbol{\varepsilon}_t, \tag{B.2}$$

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 $\boldsymbol{\varepsilon}_t$

$$\boldsymbol{\varepsilon}_t = \mathbf{\Lambda}\mathbf{f}_t + \mathbf{v}_t, \tag{B.3}$$

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 noise shocks with $\mathbf{\Sigma}$ an $n \times n$ diagonal matrix.

The rationale behind the VAR model in equations (B.2)-(B.3) is that the n-dimensional vector of VAR disturbances is decomposed into r common shocks $\mathbf{f}_t$ $(r < n)$ and n idiosyncratic noise shocks $\mathbf{v}_t$. Because $\mathbf{\Sigma}$ is diagonal, we consider only the r common shocks to be structural while the n idiosyncratic noise 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

$$\begin{aligned}
\mathbf{y}_t &= \mathbf{\Phi}\mathbf{x}_t + \mathbf{\Lambda}\mathbf{f}_t + \mathbf{v}_t && \text{(B.4)}\\
\left(\mathbf{\Lambda}'\mathbf{\Lambda}\right)^{-1}\mathbf{\Lambda}'\mathbf{y}_t &= \left(\mathbf{\Lambda}'\mathbf{\Lambda}\right)^{-1}\mathbf{\Lambda}'\mathbf{\Phi}\mathbf{x}_t + \mathbf{f}_t + \left(\mathbf{\Lambda}'\mathbf{\Lambda}\right)^{-1}\mathbf{\Lambda}'\mathbf{v}_t && \text{(B.5)}\\
\mathbf{A}_1\mathbf{y}_t &= \mathbf{B}_1\mathbf{x}_t + \mathbf{f}_t + \left(\mathbf{\Lambda}'\mathbf{\Lambda}\right)^{-1}\mathbf{\Lambda}'\mathbf{v}_t. && \text{(B.6)}
\end{aligned}$$

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.[4]

[4] 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.

Based on the model in equations (B.2)-(B.3) the joint likelihood function can be written as

$$(\boldsymbol{y}|\boldsymbol{x},\boldsymbol{\Phi},\boldsymbol{\Lambda},\boldsymbol{f},\boldsymbol{\Sigma}) \sim \prod_{t=1}^{T} N\left(\boldsymbol{\Phi}\mathbf{x}_t, \boldsymbol{\Lambda}\boldsymbol{\Lambda}' + \boldsymbol{\Sigma}\right) \tag{B.7}$$

and we define the following prior distributions

$$\begin{aligned}
\boldsymbol{\phi}_i \equiv vec\left(\boldsymbol{\Phi}_i\right) &\sim N_k\left(\mathbf{0}, \underline{\mathbf{V}}_i\right), && \text{(B.8)}\\
\underline{\mathbf{V}}_{i,(jj)} &= \sigma_i^2\tau_i^2\psi_{i,j}^2, && \text{(B.9)}\\
\psi_{i,j} &\sim Cauchy^{+}\left(0,1\right), && \text{(B.10)}\\
\tau_i &\sim Cauchy^{+}\left(0,1\right), && \text{(B.11)}\\
\mathbf{f}_t &\sim N_r\left(\mathbf{0},\mathbf{I}\right), && \text{(B.12)}\\
\boldsymbol{\Lambda}_{ij} &\sim \begin{cases} N\left(0,\underline{h}_{ij}\right) I(\Lambda_{ij}>0), & \text{if } S_{ij}=1,\\ N\left(0,\underline{h}_{ij}\right) I(\Lambda_{ij}<0), & \text{if } S_{ij}=-1,\\ \delta_0\left(\boldsymbol{\Lambda}_{ij}\right), & \text{if } S_{ij}=0,\\ N\left(0,\underline{h}_{ij}\right), & \text{otherwise,}\end{cases} && \text{(B.13)}\\
\sigma_i^2 &\sim inv-Gamma\left(\underline{\rho}_i,\underline{\kappa}_i\right), && \text{(B.14)}
\end{aligned}$$

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.13) and (B.14) become locally Uniform. Posterior computation and impulse response inference follow Korobilis (2022) and the reader should refer to this paper for technical details.

C.3. Sign restrictions for identification

We identify two structural shocks of interest—agreed uncertainty σ_ε and disagreed uncertainty σ_v—using sign restrictions on the impact responses consistent with our theoretical predictions from Section 3.2. Table B.1 reports the sign restrictions on the impact responses in the benchmark model.

Table B.1: Sign Restrictions on Impact Responses

Variable	Agreed Uncertainty (σ_ε)	Disagreed Uncertainty (σ_v)
Uncertainty indicator	+	+
Disagreement index	−	+
Industrial production	0	0
Inflation	unrestricted	unrestricted
Consumption	0	0
Employment	0	0
S&P 500	unrestricted	unrestricted
Federal funds rate	unrestricted	unrestricted

The key identifying restrictions are:

- **Agreed uncertainty** (σ_ε): Increases uncertainty (+) and decreases disagreement (−), consistent with a shock to fundamental uncertainty when information is uniform.
- **Disagreed uncertainty** (σ_v): Increases both uncertainty (+) and disagreement (+), consistent with a shock to idiosyncratic signal dispersion.
- **Zero impact restrictions**: We apply zero contemporaneous restrictions on real economic activity variables (IP, consumption, employment) to ensure they do not react immediately to the two uncertainty shocks. Orthogonalizing with respect to real economic activity is important to mitigate the concern of reverse causality: uncertainty can be endogenous and increase because of changes in economic activity.

D. Robustness analysis and additional VAR results

In this Appendix, we report a battery of robustness analyses for the benchmark VAR model developed in Section 3.2. Specifically, we present results from the following alternative VAR specifications. The uncertainty indicator is replaced with one of the following measures: the 12-month-ahead financial uncertainty indicator from Jurado et al. (2015) (hereafter JLNF-12), stock market volatility (VIX), or the economic policy uncertainty (EPU) index of Baker et al. (2016). The disagreement index is either the total or belief disagreement index constructed in Section 2, or alternative measures based on the Lacy index (Lacy, 2006) and Shannon entropy (Shannon, 1948).

D.1. Full set of IRFs from the benchmark VAR.

Figure D.1 below plots the IRFs for all variables in the benchmark VAR.

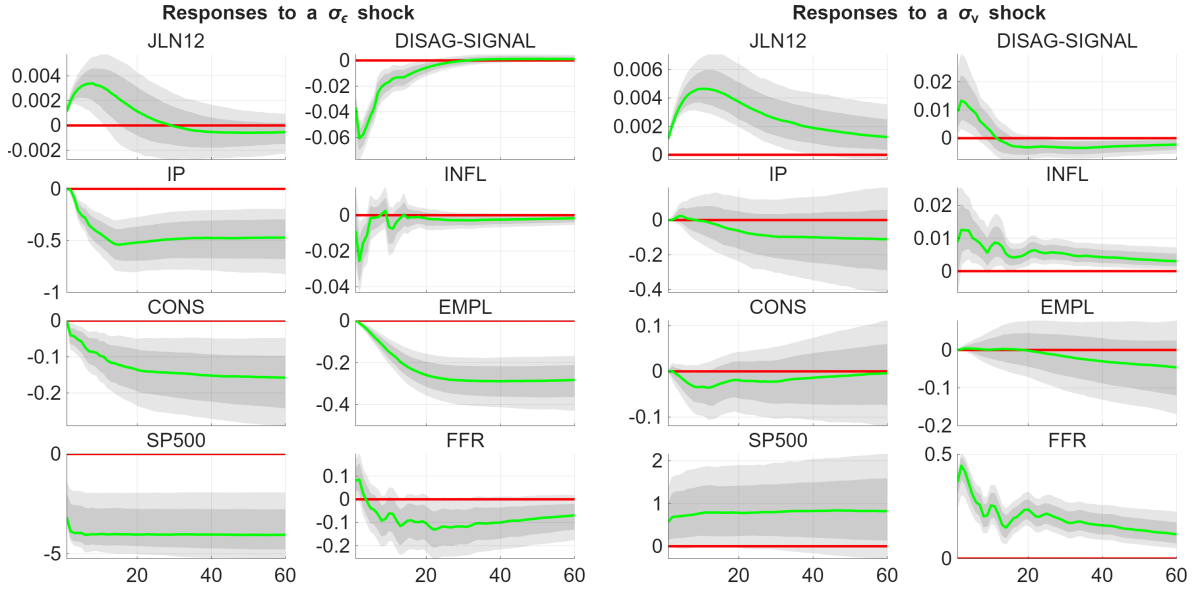


Figure D.1: Full impulse responses from the benchmark Bayesian VAR: agreed versus disagreed uncertainty. Rows display responses of all eight variables: uncertainty (JLN12), signal disagreement (DISAG-SIGNAL), industrial production (IP), inflation (INFL), consumption (CONS), employment (EMPL), S&P 500 (SP500), and the federal funds rate (FFR). The left column reports responses to an agreed uncertainty shock (σ_ε^2); the right column to a disagreed uncertainty shock (σ_v^2). Uncertainty is the 12-month-ahead macroeconomic uncertainty index of Jurado et al. (2015); disagreement is the signal disagreement index constructed in Section 2. Solid lines denote posterior means. Dark- and light-gray shaded areas denote 68% and 90% posterior credible bands, respectively.

D.2. Simple decomposition of reduced-form shocks based on a triangular VAR model

In this section we perform a simple multivariate exercise using a VAR model that estimates orthogonalized shocks using the standard Cholesky decomposition. It serves as a useful robustness check on the validity of the identification restrictions used in the benchmark

VAR. The variables in the VAR model are the 12-month-ahead macroeconomic uncertainty (JLN12) from Jurado et al. (2015), our index of signal disagreement (DISAG-SIGNAL), and the logarithm of real industrial production (IP). We estimate the VAR using an intercept and two lags.[5] 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 uncertainty (UNC) is placed first, followed by signal disagreement (DISAG-SIGNAL) and IP, and another where DISAG-SIGNAL is placed first, followed by uncertainty (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 D.2 shows the impulse responses (IRFs) to orthogonalized shocks under the two 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 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.

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

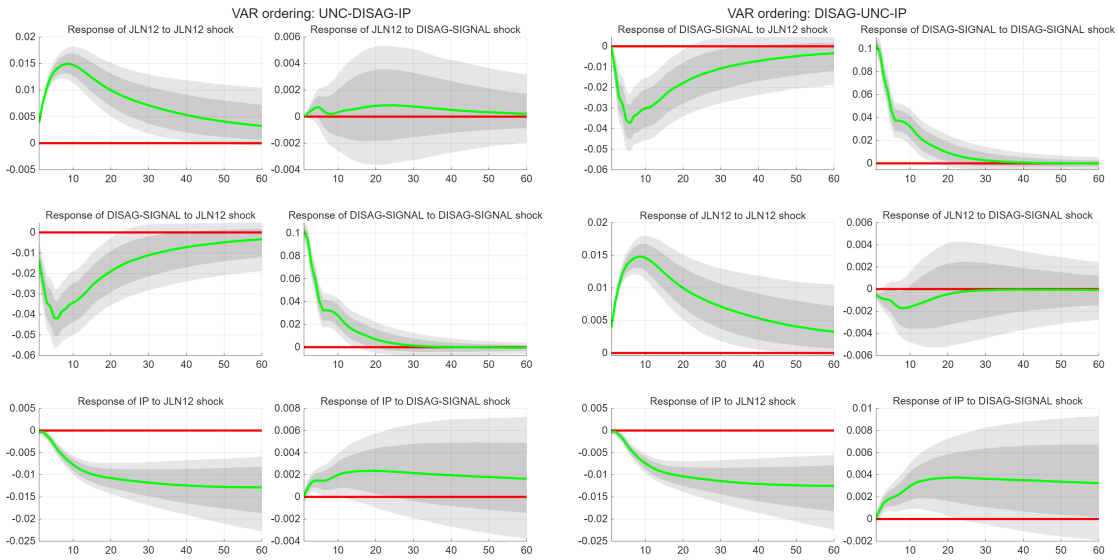


Figure D.2: Cholesky VAR: alternative orderings. The first two columns show IRFs under the ordering (UNC, DISAG-SIGNAL, IP); the last two columns show IRFs under the ordering (DISAG-SIGNAL, UNC, IP). Green lines denote median responses. Dark- and light-gray shaded areas denote 68% and 90% bootstrap confidence intervals, respectively.

The benchmark specification in Section 3.2 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 three alternative uncertainty measures used in earlier work. Jurado et al. (2015) developed the 12-month ahead financial uncertainty indicator (henceforth JLNF-12) using 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 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, and regulatory policy actions.

D.3. IRFs from VAR model with JLNF12

Figure D.3 shows the set of IRFs from the VAR specification that uses JLNF12 as the uncertainty indicator. These IRFs are broadly consistent with those reported in Figure 5 in Section 3.2. The left panel, which plots the responses to an agreed uncertainty shock, displays qualitatively similar contractionary effects on industrial production and employment compared with the estimates obtained when JLN12 is used as the uncertainty proxy. These contractionary effects on economic activity are consistent with the evidence

in Ludvigson et al. (2021), who also use JLNF12 as the uncertainty indicator in their empirical analysis.

The right panel reports the IRFs following an innovation to the disagreed uncertainty shock. Qualitatively, the estimated dynamic responses closely mirror those shown in Figure 5. Taken together, both the benchmark specification and this alternative specification indicate that innovations to disagreed uncertainty have a relatively benign effect on economic activity, which stands in sharp contrast to the pronounced contractionary effects associated with agreed uncertainty shocks.

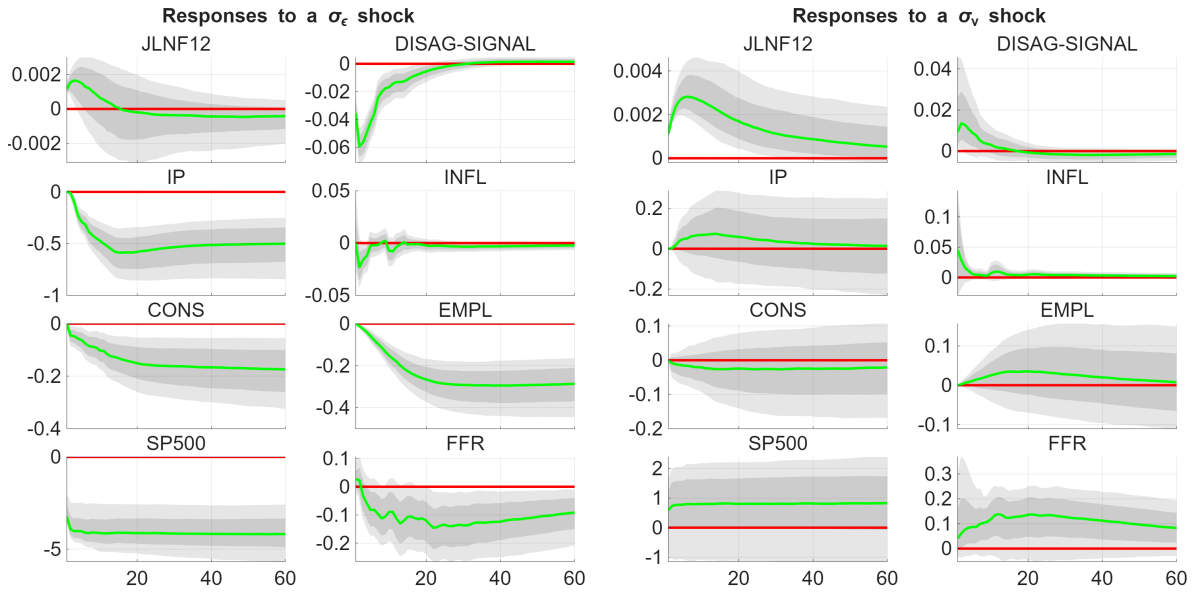


Figure D.3: Financial uncertainty (JLNF-12). Agreed σ_ε^2 (left) versus disagreed σ_v^2 (right) uncertainty. The figure shows impulse responses from the eight-variable Bayesian VAR. The VAR includes financial uncertainty (JLNF12), signal disagreement (DISAG-SIGNAL), industrial production (IP), inflation (INFL), consumption (CONS), employment (EMPL), S&P 500 (SP500), and the federal funds rate (FFR). Solid lines denote posterior means. Dark- and light-gray shaded areas denote 68% and 90% posterior credible bands, respectively.

D.4. IRFs from VAR model with VIX

Figure D.4 below displays the complete set of IRFs from the VAR specification with VIX used as the uncertainty indicator. The uncertainty response is sharp but short-lived. The IRFs to an agreed uncertainty innovation are consistent with a contractionary 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 stand in contrast with those described above. The posterior credible bands for industrial production, consumption, and employment encompass zero throughout the horizon, indicating, consistently with the benchmark specification, that a disagreed uncertainty shock does not exert a negative influence on activity indicators.

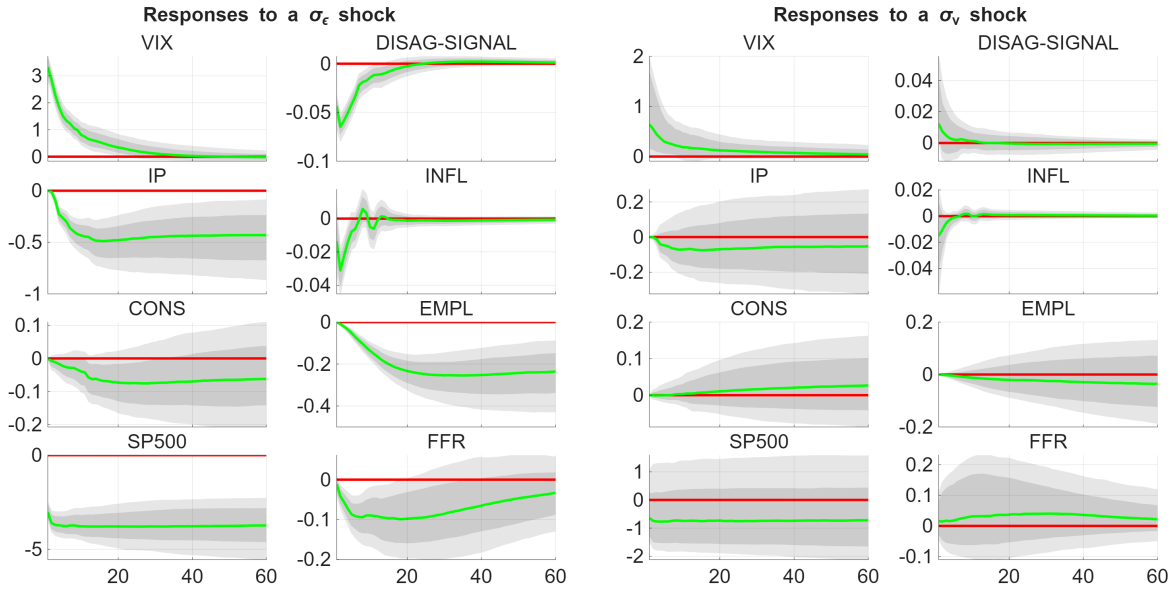


Figure D.4: Stock market volatility (VIX). Agreed σ_ε^2 (left) versus disagreed σ_v^2 (right) uncertainty. The figure shows impulse responses from the eight-variable Bayesian VAR. The VAR includes stock market volatility (VIX), signal disagreement (DISAG-SIGNAL), industrial production (IP), inflation (INFL), consumption (CONS), employment (EMPL), S&P 500 (SP500), and the federal funds rate (FFR). Solid lines denote posterior means. Dark- and light-gray shaded areas denote 68% and 90% posterior credible bands, respectively.

D.5. IRFs from VAR model with EPU

Figure D.5 displays the complete set of IRFs from the VAR specification using the Economic Policy Uncertainty (EPU) index as the uncertainty indicator. Two features distinguish EPU from the broad-based macroeconomic and financial uncertainty measures examined above. First, EPU captures uncertainty about economic policy rather than about aggregate economic or financial conditions, making the conceptual mapping to our theoretical framework less direct. Second, because our central measure of consumer disagreement refers to business conditions, the link between changes in information dispersion and the volatility of a text-based policy uncertainty indicator is less immediate. The sample period for this specification is 1985M1-2019M12, reflecting the availability of the EPU index. Despite these caveats, we estimate agreed and disagreed uncertainty shocks using the same identification scheme to assess whether the qualitative pattern documented in the benchmark specification carries over to this alternative measure. The results in Figure D.5 are broadly consistent with our main findings for the agreed uncertainty shock: both industrial production and employment display persistent contractionary responses. For the disagreed uncertainty shock, the point estimate of the industrial production response is negative but the 68% and 90% posterior credible intervals include zero throughout the horizon; the responses of employment and consumption are likewise indistinguishable from zero.

The weaker separation between the two shocks in this specification appears to reflect a difficulty in cleanly identifying the disagreed uncertainty shock. The positive sign

restriction on disagreement is satisfied on impact, but the response of the disagreement index is short-lived and imprecisely estimated, suggesting that the EPU-disagreement pairing does not generate as sharp an identification as the JLN-disagreement pairing used in the benchmark. Because our identification strategy imposes sign restrictions only on impact, additional restrictions may be needed to separate the two shocks more cleanly when using EPU. Nevertheless, the qualitative asymmetry remains: the real-activity responses to agreed uncertainty shocks are substantially larger in magnitude than those to disagreed uncertainty shocks, preserving the central result of the paper.

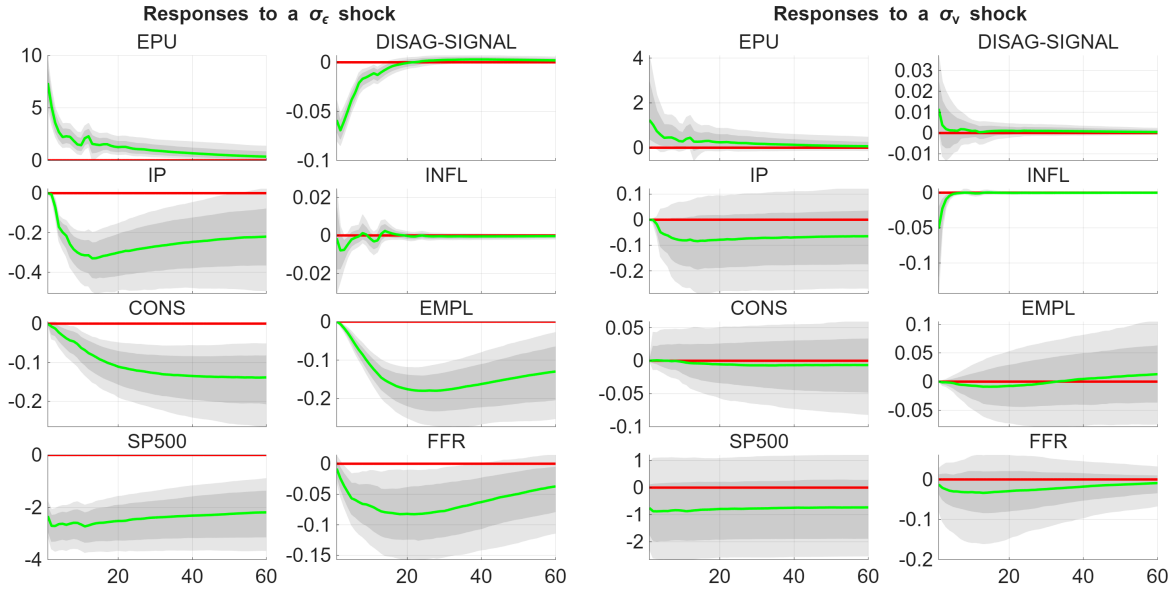


Figure D.5: Economic policy uncertainty (EPU). Agreed σ_ε^2 (left) versus disagreed σ_v^2 (right) uncertainty. The figure shows impulse responses from the eight-variable Bayesian VAR. The VAR includes economic policy uncertainty (EPU), signal disagreement (DISAG-SIGNAL), industrial production (IP), inflation (INFL), consumption (CONS), employment (EMPL), S&P 500 (SP500), and the federal funds rate (FFR). Solid lines denote posterior means. Dark- and light-gray shaded areas denote 68% and 90% posterior credible bands, respectively.

D.6. Total disagreement index (DISAG-TOTAL)

Our benchmark disagreement index is the signal disagreement measure (DISAG-SIGNAL), constructed using the disagreement index in equation (1) from the NEWS variable in the UMSC, as described in Section 2 (see Table 1). We assess the robustness of our findings by replacing DISAG-SIGNAL in the benchmark VAR with the total disagreement index (DISAG-TOTAL). Total disagreement is constructed as the first principal component of the five individual disagreement series. The IRFs estimated from the alternative specification are broadly similar to those from the benchmark model shown in Figure 5, and we therefore do not discuss them further. Importantly, the 68% and 90% credible bands for the difference between the responses of real activity indicators under agreed and disagreed uncertainty shocks exclude zero, confirming that the two shocks generate economically different dynamics.

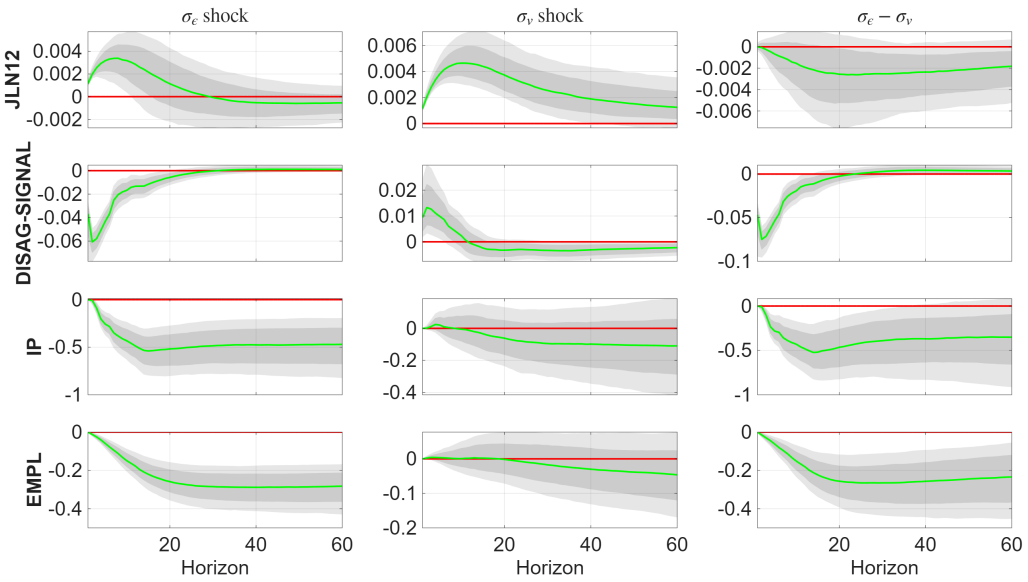


Figure D.6: Impulse responses from the eight-variable Bayesian VAR with total disagreement: agreed versus disagreed uncertainty. Rows display responses of uncertainty (JLN12), total disagreement (DISAG-TOTAL), industrial production (IP), and employment (EMPL). The left column reports responses to an agreed uncertainty shock (σ_ε^2), the middle column to a disagreed uncertainty shock (σ_v^2), and the right column the difference between the two. Uncertainty is the 12-month-ahead macroeconomic uncertainty index of Jurado et al. (2015); disagreement is the total disagreement index constructed in Section 2. The VAR also includes inflation (INFL), consumption (CONS), S&P 500 (SP500), and the federal funds rate (FFR). Solid lines denote posterior means. Dark- and light-gray shaded areas denote 68% and 90% posterior credible bands, respectively.

Below we plot the full set of IRFs from the specification that uses DISAG-TOTAL as the disagreement measure.

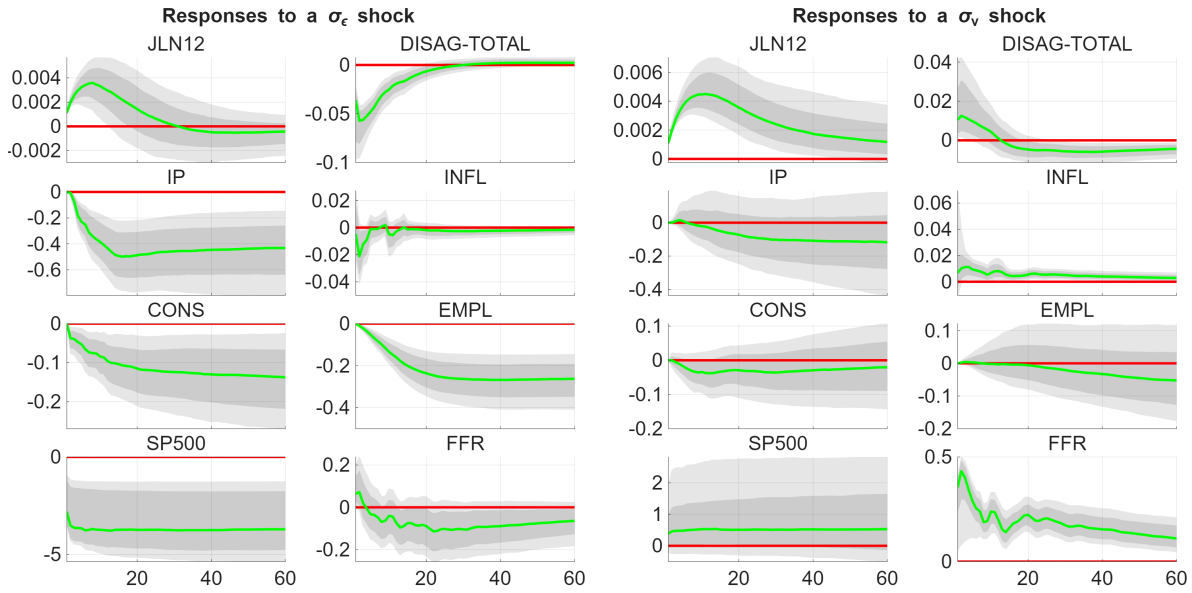


Figure D.7: Total disagreement (DISAG-TOTAL). Agreed σ_ε^2 (left) versus disagreed σ_v^2 (right) uncertainty. The figure shows impulse responses from the eight-variable Bayesian VAR. The VAR includes macroeconomic uncertainty (JLN12), total disagreement (DISAG-TOTAL), industrial production (IP), inflation (INFL), consumption (CONS), employment (EMPL), S&P 500 (SP500), and the federal funds rate (FFR). Solid lines denote posterior means. Dark- and light-gray shaded areas denote 68% and 90% posterior credible bands, respectively.

D.7. IRFs from VAR model with signal disagreement, entropy measure

Figure D.8 below displays the complete set of IRFs from the VAR specification with the entropy measure, DISAG-SIGNAL-E, used as the disagreement indicator. Overall, this exercise ensures that the DISAG-SIGNAL tails 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.

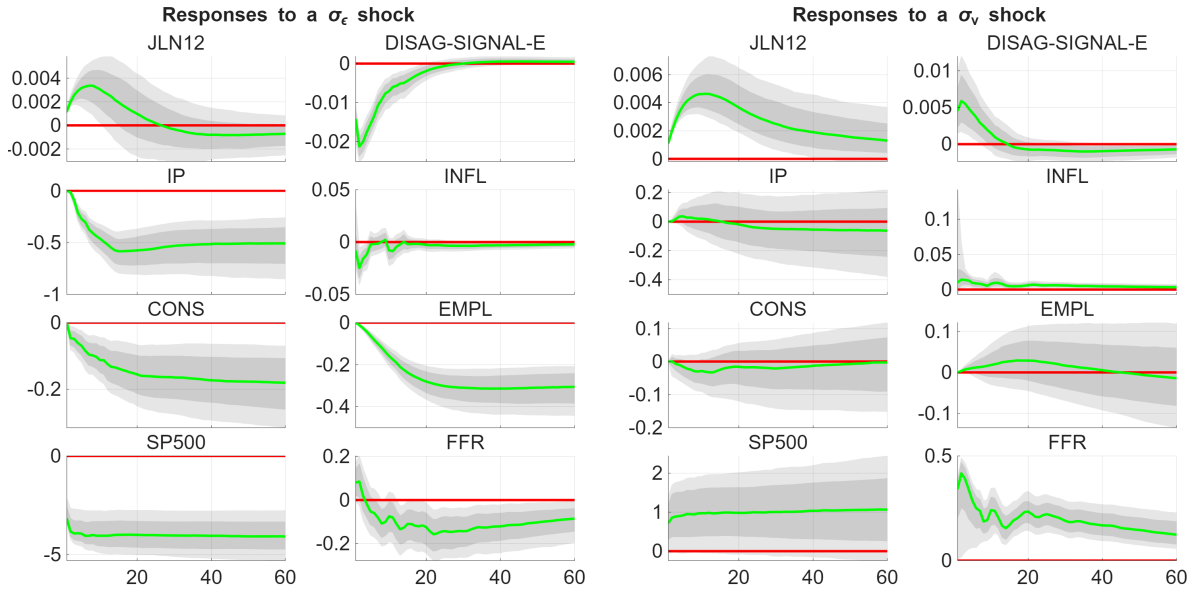


Figure D.8: Signal disagreement, entropy measure (DISAG-SIGNAL-E). Agreed σ_ε^2 (left) versus disagreed σ_v^2 (right) uncertainty. The figure shows impulse responses from the eight-variable Bayesian VAR. The VAR includes macroeconomic uncertainty (JLN12), signal disagreement based on Shannon entropy (DISAG-SIGNAL-E), industrial production (IP), inflation (INFL), consumption (CONS), employment (EMPL), S&P 500 (SP500), and the federal funds rate (FFR). Solid lines denote posterior means. Dark- and light-gray shaded areas denote 68% and 90% posterior credible bands, respectively.

D.8. IRFs from VAR model with signal disagreement, Lacy measure

Figure D.9 below displays the complete set of IRFs from the VAR specification with the Lacy measure, DISAG-SIGNAL-L, used as the disagreement indicator. Overall, this exercise ensures that the DISAG-SIGNAL tails 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.

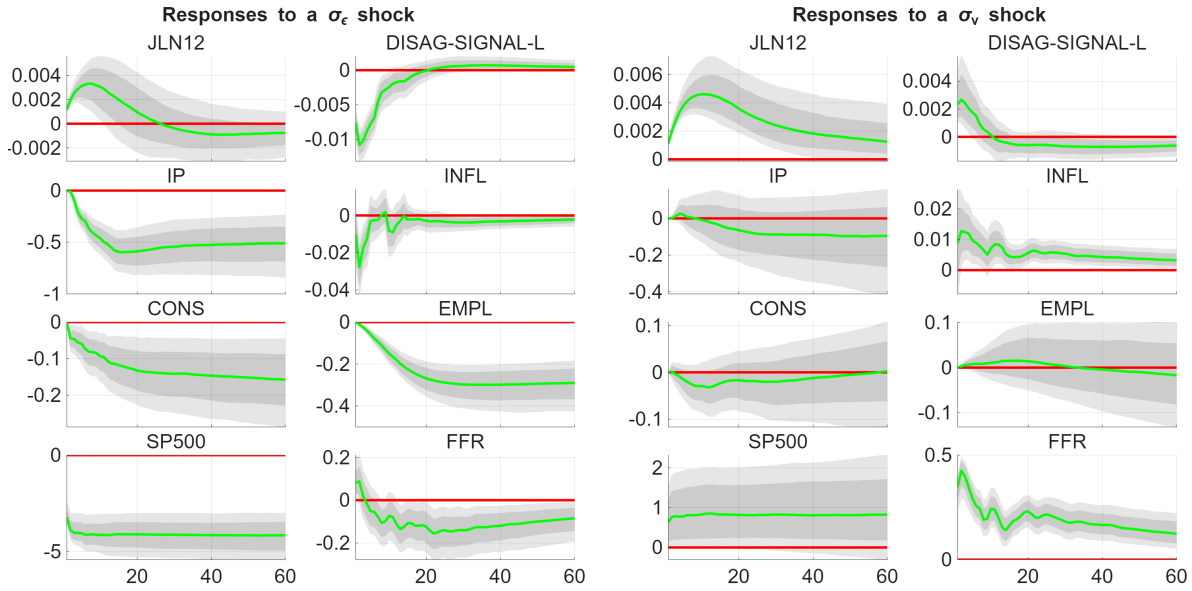


Figure D.9: Signal disagreement, Lacy measure (DISAG-SIGNAL-L). Agreed σ_ε^2 (left) versus disagreed σ_v^2 (right) uncertainty. The figure shows impulse responses from the eight-variable Bayesian VAR. The VAR includes macroeconomic uncertainty (JLN12), signal disagreement based on the Lacy index (DISAG-SIGNAL-L), industrial production (IP), inflation (INFL), consumption (CONS), employment (EMPL), S&P 500 (SP500), and the federal funds rate (FFR). Solid lines denote posterior means. Dark- and light-gray shaded areas denote 68% and 90% posterior credible bands, respectively.

E. Supporting evidence from micro-survey data

E.1. SCE variables description

Table E.1: SCE Questions about inflation and spending plans

SCE Question	Topic
Q8v2part2	Inflation forecasts over next 12 months
Q9	Inflation uncertainty over next 12 months
Q26v2part2	Household spending plans over next 12 months

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

E.2. Testing the random assignment of control and treated groups

Table E.2 reports and examines the differences in demographic and household characteristics provided in the survey between the information-treated and control groups: education, region of residency, numeracy, age, income, gender, commute, marital status or living with a 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 E.2 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 demographic characteristics lends support to the hypothesis that the information treatment experiment can be considered as random.

Table E.2: 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.

E.3. Estimating the change in inflation forecast disagreement for the control group

Using the sample that only includes 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 a similar regression equation (as in equation (9)). 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:

$$INF^{e}{}_{iqr(control),t} = \alpha + \beta_0 \mathbf{1}\{\text{Pre-FOMC}_t\} + \epsilon_t, \tag{E.1}$$

where $\mathbf{1}\{\text{Pre-FOMC}_t\}$ is an indicator variable which is equal to one for the days 1-15 March 2022 preceding the FOMC announcement and zero otherwise, and α is a constant.

Table E.3 reports the coefficient estimate of the dummy variable. In Table E.3, the estimated coefficient on the one-year-ahead inflation disagreement measure suggests that the latter exhibits no statistically significant change 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 E.3: Inflation forecast disagreement around the March 16, 2022 FOMC statement: control group

	$INF^e{}_{iqr(control),t} = \alpha + \beta_0 \mathbf{1}\{\text{Pre-FOMC}_t\} + \epsilon_t$
	Change in inflation forecast disagreement
pre FOMC time dummy	0.03
	(0.03)

Notes: The dependent variable is $INF^e{}_{iqr(control),t}$, the cross-sectional interquartile range of 12-month-ahead inflation point forecasts among respondents in the control group who completed the survey on day t. The sample includes respondents who completed the survey between March 1 and 15, 2022 and who also completed the survey in February 2022; t indexes survey completion days in February and March. $\mathbf{1}\{\text{Pre-FOMC}_t\}$ equals one for March 1-15 completion days and zero for February completion days. Standard errors are clustered by day. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

E.4. Estimating the panel regression with alternative uncertainty indicators

In this section we augment the baseline specification (10) by including a respondent-specific measure of inflation uncertainty, denoted, $INFLUNC_{it}$, constructed from survey question Q9, in which respondents allocate probabilities across inflation outcomes to form an individual-specific distribution.[6] This specification introduces several interaction terms and a proliferation of coefficients.

Table E.4 reports all the estimated coefficients from the augmented specification with respondent level inflation uncertainty. The coefficient on $\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times INFLUNC_{it}$ is estimated to be negative, indicating that the treated group reports a decline in spending plans (relative to the control group) in response to an increase in individual-specific inflation uncertainty; however, the effect is imprecisely estimated and therefore not statistically different from zero. Nonetheless, the estimated coefficient on the interaction between respondent-level inflation uncertainty, $INFLUNC_{it}$, and VIX is negative and statistically significant at the 5 percent level. Importantly, this estimate implies a 9.85-percentage-point decline in planned spending for the treated group relative to the control group. One way to interpret this finding is that high respondent level

[6]The augmented regression specification is: $Q26_{it} = \alpha_i + \lambda_t + \beta_1 \mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} + \beta_2 VIX_{t-1} + \beta_3 \mathbf{1}\{\text{Treat}_i\} \times VIX_{t-1} + \beta_4 \mathbf{1}\{\text{March}_m\} \times VIX_{t-1} + \beta_5 \mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times VIX_{t-1} + \beta_6 \mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times INFLUNC_{it} + \beta_7 \mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times INFLUNC_{it} \times VIX_{t-1} + \beta_8 INFLUNC_{it} + \beta_9 \mathbf{1}\{\text{Treat}_i\} \times INFLUNC_{it} + \beta_{10} \mathbf{1}\{\text{March}_m\} \times INFLUNC_{it} + \beta_{11} VIX_{t-1} \times INFLUNC_{it} + \beta_{12} \mathbf{1}\{\text{Treat}_i\} \times VIX_{t-1} \times INFLUNC_{it} + \beta_{13} \mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times VIX_{t-1} \times INFLUNC_{it} + \epsilon_{it}$.

inflation uncertainty amplifies the negative spending response to aggregate uncertainty by 3.25 percentage points relative to the estimate for $\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times VIX_{t-1}$ reported in the main body. This result suggests that spikes in aggregate uncertainty have a stronger negative impact on the spending plans of consumers who also expect high inflation uncertainty. In other words, aggregate and respondent-specific inflation uncertainty seem to reinforce each other.

Table E.4: Panel evidence: February-March 2022 (balanced respondent panel)

Dependent variable: Spending plans ($Q26$)	
$\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\}$	-3.17
	(3.16)
VIX_{t-1}	-0.98
	(1.25)
$\mathbf{1}\{\text{Treat}_i\} \times VIX_{t-1}$	1.74
	(1.40)
$\mathbf{1}\{\text{March }_m\} \times VIX_{t-1}$	2.25
	(2.79)
$\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times VIX_{t-1}$	-5.26
	(3.33)
$\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times INFLUNC_{it}$	-0.25
	(4.19)
$\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times VIX_{t-1} \times INFLUNC_{it}$	-9.85**
	(4.41)
$INFLUNC_{it}$	0.93
	(1.26)
$\mathbf{1}\{\text{Treat}_i\} \times INFLUNC_{it}$	-0.47
	(1.79)
$\mathbf{1}\{\text{March}_m\} \times INFLUNC_{it}$	-2.98
	(3.79)
$VIX_{t-1} \times INFLUNC_{it}$	-1.69
	(1.16)
$\mathbf{1}\{\text{Treat}_i\} \times VIX_{t-1} \times INFLUNC_{it}$	3.20 *
	(1.76)
$\mathbf{1}\{\text{March}_m\} \times VIX_{t-1} \times INFLUNC_{it}$	4.73
	(3.47)
Month Fixed effects	Yes
Consumer Fixed effects	Yes
N	1984

Notes: VIX is the CBOE volatility index standardized to have a mean of zero and standard deviation of one. Standard errors clustered at the respondent level are reported in parentheses. The regressions include the Aruoba-Diebold-Scotti (Aruoba et al., 2009) daily business conditions index as an additional control. This daily indicator is designed to track real business conditions at a high frequency. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Moreover, we report estimates of the panel regression of equation (10) in the main body where we replace VIX_{t-1} with either VIX_{t-2} or with an alternative proxy, the U.S. equity market uncertainty index, denoted as $UNCEQUITY$. Table E.5 reports the estimated coefficients from the specifications with VIX as the uncertainty proxy. Table E.6 reports the estimated coefficients from the specifications with $UNCEQUITY$ (with one or two day lags) as the uncertainty proxy.

Table E.5: Panel evidence: February-March 2022 (balanced respondent panel)

	Dependent variable: Spending plans ($Q26$)	
	(1)	(2)
$\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\}$	-1.41	-2.14
	(3.16)	(3.11)
VIX_{t-2}	-2.27	-1.96
	(1.44)	(1.51)
$\mathbf{1}\{\text{Treat}_i\} \times VIX_{t-2}$	2.88	2.72
	(1.64)	(1.62)
$\mathbf{1}\{\text{March}_m\} \times VIX_{t-2}$	4.46	3.25
	(3.01)	(3.21)
$\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times VIX_{t-2}$	-7.96**	-6.65*
	(3.38)	(3.48)
$\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times INFLUNC_{it}$		1.17
		(2.49)
$\mathbf{1}\{\text{Treat}_i\} \times \mathbf{1}\{\text{March}_m\} \times VIX_{t-2} \times INFLUNC_{it}$		-9.75**
		(3.77)
Month Fixed effects	Yes	Yes
Consumer Fixed effects	Yes	Yes
N	1838	1808

Notes: VIX is the CBOE volatility index standardized to have a mean of zero and standard deviation of one. Standard errors clustered at the respondent level are reported in parentheses. The regressions include the Aruoba-Diebold-Scotti (Aruoba et al., 2009) daily business conditions index as an additional control. This daily indicator is designed to track real business conditions at a high frequency. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table E.6: Panel evidence: February-March 2022 (balanced respondent panel)

	Dependent variable: Spending plans ($Q26$)			
	(1)	(2)	(3)	(4)
$\mathbf{1}\{\text{Treat}_i\}\times\mathbf{1}\{\text{March}_m\}$	-3.37*	-3.05*		
	(1.93)	(1.77)		
$UNCEQUITY_{t-1}$	-1.97**	-1.93**		
	(0.93)	(0.95)		
$\mathbf{1}\{\text{Treat}_i\}\times UNCEQUITY_{t-1}$	1.70	2.06		
	(1.39)	(1.28)		
$\mathbf{1}\{\text{March}_m\}\times UNCEQUITY_{t-1}$	2.97***	2.97***		
	(1.13)	(1.12)		
$\mathbf{1}\{\text{Treat}_i\}\times\mathbf{1}\{\text{March}_m\}\times UNCEQUITY_{t-1}$	-2.68*	-3.05**		
	(1.58)	(1.48)		
$\mathbf{1}\{\text{Treat}_i\}\times\mathbf{1}\{\text{March }_m\}\times INFLUNC_{it}$		0.30		
		(2.28)		
$\mathbf{1}\{\text{Treat}_i\}\times\mathbf{1}\{\text{March}_m\}\times UNCEQUITY_{t-1}\times INFLUNC_{it}$		-0.12		
		(1.94)		
$\mathbf{1}\{\text{Treat}_i\}\times\mathbf{1}\{\text{March}_m\}$			-1.48	-0.58
			(1.73)	(1.47)
$UNCEQUITY_{t-2}$			-0.64	-0.62
			(0.75)	(0.71)
$\mathbf{1}\{\text{Treat}_i\}\times UNCEQUITY_{t-2}$			1.07	0.98
			(1.12)	(1.02)
$\mathbf{1}\{\text{March}_m\}\times UNCEQUITY_{t-2}$			2.05	2.51*
			(1.40)	(1.44)
$\mathbf{1}\{\text{Treat}_i\}\times\mathbf{1}\{\text{March }_m\}\times UNCEQUITY_{t-2}$			-3.55*	-3.95**
			(2.02)	(2.00)
$\mathbf{1}\{\text{Treat}_i\}\times\mathbf{1}\{\text{March }_m\}\times INFLUNC_{it}$				-0.05
				(1.75)
$\mathbf{1}\{\text{Treat}_i\}\times\mathbf{1}\{\text{March}_m\}\times UNCEQUITY_{t-2}\times INFLUNC_{it}$				-3.48
				(2.27)
Month Fixed effects	Yes	Yes	Yes	Yes
Consumer Fixed effects	Yes	Yes	Yes	Yes
N	1984	1948	1838	1808

Notes: UNCEQUITY is the U.S. equity market uncertainty index standardized to have mean zero and unit variance. Standard errors clustered at the respondent level are reported in parentheses. The regressions include the Aruoba-Diebold-Scotti (Aruoba et al., 2009) daily business conditions index as an additional control. This daily indicator is designed to track real business conditions at a high frequency. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.