The (Ir)relevance of Household Uncertainty in U.S. Business Cycles: Evidence from the Michigan Survey of Consumers

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Abstract

This paper introduces new measures of household uncertainty from the Michigan Survey of Consumers and new methods of identifying uncertainty shocks from qualitative survey data on sentiment using sign restrictions on impulse responses. Household uncertainty shocks explain almost none of the variance of measures of real activity in the U.S. Moreover, the endogenous response of household uncertainty is unimportant in the transmission of other macroeconomic shocks to the real economy. I conclude that household uncertainty plays essentially no role in U.S. business cycles. By contrast, I do find some evidence of more important roles for household confidence and firm uncertainty.

Keywords: Uncertainty, confidence, sign restrictions, business cycles.

JEL classification:

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1 Introduction

"Economic uncertainty," even when carefully defined, is almost impossible to measure objectively. Consequently, a considerable amount of empirical macroeconomic research in the decade and a half since Bloom (2009) has focused on finding proxies for uncertainty to answer the question "How can economists measure subjective uncertainty?" And since most of these proxies increase during economic downturns, a parallel line of research has examined the causal role of uncertainty in the business cycle to answer arguably more important questions like "Is uncertainty a cause of economic fluctuations?"[1] and "Is uncertainty an amplifier of other macroeconomic shocks?"

In this paper, I address each of these questions and contribute to each strand of the literature with respect to *household uncertainty*, in contrast to uncertainty faced, for example, by firms, market participants, or professional forecasters. First, building upon the work of Leduc and Liu (2016), I use the Michigan Survey of Consumers to construct new indices of household uncertainty. I then use these measures to study the role of household uncertainty in macroeconomic fluctuations. I introduce a novel identification of uncertainty shocks based on sign and size restrictions on impulse responses and conduct counterfactual exercises to assess the importance of uncertainty as a transmission mechanism for other shocks. I find that household uncertainty plays essentially no role in U.S. business cycles: shocks to it explain very little of the variance of output or unemployment, and its endogenous response to other shocks contributes almost nothing to the effect of those shocks on the economy.

These new measures of household uncertainty complement existing proxies. Other measures are based on stock market volatility, survey responses, newspaper text analysis, and forecast errors of large datasets; they aim at measuring uncertainty about macroeconomic conditions, financial markets, business outlooks, and policy decisions; and they differentiate among uncertainty as perceived by households, market participants, firms, and policymakers.[2] The measures I construct below—in addition to being obviously survey based and targeted at households—measure uncertainty about personal finances, broader economic conditions, and buying conditions in large, highly visible markets. One class of these new measures is based on the number of survey respondents who quite literally say they are uncertain or don't know when asked about certain economic conditions, while another measures

[1] Or, as in the titular question of Ludvigson, Ma and Ng (2021), is uncertainty an "exogenous impulse" or an "endogenous response" to other shocks?

[2] I discuss many of these in Section 2, but a complete overview is outside the scope of this paper. For an excellent overview of existing measures, see Cascaldi-Garcia et al. (2023).

disagreement among survey respondents, as in White (2018) and Pinto, Sarte and Sharp (2020).

Household uncertainty indices derived from the Michigan Survey of Consumers have several advantages over existing proxies. First, some of them are in a sense direct, in as much as they reflect respondents directly telling the surveyor that they are uncertain or don't know about various economic conditions. Second, they facilitate comparison with other measures of disagreement among survey respondents, another common proxy for uncertainty in the literature that has been used in the context of firms (Bachmann, Elstner and Sims (2013)) or professional forecasters (Coibion, Georgarakos, Gorodnichenko, Kenny and Weber (2022)). Third, they are publicly available and easy to track continually on a monthly basis. Finally, and important for estimating uncertainty's impact on the macroeconomy, they facilitate accounting for first-moment conditions like consumer confidence as recommended by Leduc and Liu (2016) and Coibion et al. (2022).[3]

As those authors and others have pointed out, changes in uncertainty might partly reflect endogenous responses to changes in confidence. In Section 3, I demonstrate that this problem is especially important to address in the context of survey-based measures of uncertainty. One simple approach to address this would be to include a measure of confidence ordered prior to a measure of uncertainty in a recursively identified (Cholesky) structural VAR as in Leduc and Liu (2016).[4] But that technique also implicitly imposes (implausibly) that shocks to confidence cannot effect uncertainty contemporaneously. Indeed, recent work by Ludvigson et al. (2021) provides strong evidence that rejects the zero contemporaneous response assumptions of uncertainty shocks identified in Cholesky VARs. Informed by these results, I take an "agnostic" approach as pioneered by Uhlig (2005) in the context of monetary policy. I construct a novel joint identification of shocks to confidence and uncertainty without imposing zero contemporaneous restrictions. I instead impose *sign* and *size* restrictions on survey responses to recover both types of sentiment shocks that orthogonal both to each other and to other identified macroeconomic shocks.

Specifically, the Michigan survey elicits favorable (e.g. "times are good") and unfavorable ("times are bad") responses on various questions. I specify that a confidence shock causes indices of favorable and unfavorable responses to move in opposite directions—more people think times are good and fewer think they are bad—while an uncertainty shock causes indices of favorable and unfavorable responses to move in the same direction—there is more

[3]Indeed, the Michigan Survey is the source of the most commonly used measures of consumer confidence. See, for example Barsky and Sims (2011) and Bachmann and Sims (2012).

[4]As a first pass, I do just this in Section 3.2.

disagreement. While this sign pattern is sufficient to separately identify these two sentiment shocks, additional information is required to separately identify them from other macroeconomic shocks. To that end, I further impose the size restriction that sentiment shocks have smaller effects in absolute value on unemployment than fundamental shocks on impact.[5]

I find household uncertainty shocks, whether identified in a simple Cholesky VAR or by this new application of sign and size restrictions, result in small and insignificant effects on measures of employment and output and explain less than 10 percent of their forecast error variances at all horizons. I conclude that household uncertainty shocks play essentially no role as a driving force of macroeconomic fluctuations in the U.S.

This result does *not* by itself mean that household uncertainty plays no role at all in the business cycle. Indeed, these new measures of uncertainty respond significantly to other macroeconomic shocks, just as Ludvigson et al. (2021) find with broader measures of macroeconomic uncertainty. It could well be that even though *shocks* to household uncertainty are unimportant, its endogenous response to other shocks could be a significant amplifier of the real effects of those shocks.[6] To assess this possibility, I adapt the methods of Sims and Zha (2006), Bernanke et al. (1997), and Bachmann and Sims (2012), to estimate counterfactual impulse responses; that is, I produce estimates that attempt to answer "How would shock X affect the economy if household uncertainty did *not* respond?" I find that household uncertainty is unimportant in the transmission of other shocks to the macroeconomy: impulse responses and forecast error variance decompositions are essentially unchanged when uncertainty does not respond to other shocks.

These results imply that household uncertainty is neither a driver of economic fluctuations, nor, despite its often large and significant systematic responses to them, is it an amplifier of other macroeconomic shocks. I conclude that household uncertainty plays essentially no role in U.S. business cycles.

In the sections below, I describe the Michigan Survey of Consumers and how to construct uncertainty measures from it, and I compare these indices with existing proxies for uncertainty; I show concretely the importance of accounting for first moments like consumer confidence when estimating the effects of uncertainty shocks; I describe my novel joint identification of first- and second-moment shocks, estimate impulse responses and variance de-

[5] This size restriction is similar to other methods of identifying sentiment or news shocks in contrast to fundamental shocks, as in Beaudry and Portier (2006), Beaudry and Lucke (2010), and Barsky and Sims (2011).

[6] An analogy: even though monetary policy shocks are typically found to have small effects, the endogenous response of monetary policy to other shocks is likely be critical to the transmission of those shocks to the macroeconomy, as Bernanke, Gertler and Watson (1997) find with oil price shocks.

compositions to these shocks, and compare the results to those from traditional recursively identified systems; I estimate the response of household uncertainty to other macroeconomic shocks and conduct counterfactual exercises to assess the importance of household uncertainty as a potential amplification mechanism; and I conclude.

2 New measures of household uncertainty

This section describes the Michigan Survey of Consumers and uncertainty indices that can be derived from it. In the first subsection below, I describe the Michigan Survey and the direct measures of uncertainty that I construct from it. I then discuss similar existing measures of uncertainty from survey data: Leduc and Liu's (2016) measure from the Michigan Survey and Bachmann et al.'s (2013) method of measuring survey response disagreement. The former measure potentially conflates confidence and uncertainty, as I discuss below. The latter method can be applied in a straightforward way to construct disagreement proxies for uncertainty from the Michigan Survey.

2.1 Uncertainty measures from the Michigan Survey

The Michigan Survey of Consumers is a monthly survey of individuals in the United States[7] conducted by the University of Michigan. Each month about 500 individuals are interviewed about their own individual financial situation and their views of the broader economy.[8] Data are available on a monthly basis since 1978 and quarterly since 1960.

Among the questions asked of survey respondents are ones about their personal finances, general business conditions, and whether now is a good time to purchase a house, a car, or large household durable goods. Importantly, all of these questions have separately coded answers for survey respondents who are "uncertain" or who "don't know," distinct from those whose responses are missing or who say that conditions are unchanged. These questions are:

> (Current Finances): *"We are interested in how people are getting along financially these days. Would you say that you are better off or worse off financially than you were a year ago?"*

> (Expected Finances): *"Now looking ahead—do you think that a year from now you will be better off financially, or worse off, or just about the same as now?"*

[7] Excluding Alaska and Hawaii.

[8] In the early years of the survey, often as many as 1400 individuals were interviewed. Since the late 1980s, however, the sample size has typically been between 500 and 600.

(1-year Business Conditions): *"Now turning to business conditions in the country as a whole—do you think that during the next 12 months we'll have good times financially, or bad times, or what?"*

(5-year Business Conditions): *"Looking ahead, which would you say is more likely – that in the country as a whole we'll have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression, or what?"*

(Durable Buying Conditions): *"Generally speaking, do you think now is a good or a bad time for people to buy major household items?"*

(House Buying Conditions): *"Generally speaking, do you think now is a good time or a bad time to buy a house?"*

(Car Buying Conditions): *"Speaking now of the automobile market—do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van, or sport utility vehicle?"*

Responses are coded into six categories for the questions on business conditions: Good times; good with qualifications; uncertain; bad with qualifications; bad times; or don't know. The buying conditions questions do not have "with qualifications" responses coded separately, but are otherwise the same as business conditions. Personal finances are coded as better, same, worse, or don't know.

What I use to construct measures of uncertainty is the number of respondents who are unable to decide one way or another on the questions above. A period in which many of those being surveyed respond that they are uncertain or that there are pros and cons or that they simply do not know is considered to be a period of high uncertainty. To assess the reasonableness of these measures as capturing household uncertainty about the macroeconomy, I examine the correlation of leads and lags of GDP growth with the share of favorable responses—that is that times are good, that buying conditions are good, or that personal finances are or are expected to be better—for each question. These correlations are displayed in Figure 1. Favorable answers to most of the questions are positively correlated with GDP, with the exceptions of buying conditions for houses and cars. Because of the strong correlation with GDP growth of favorable responses, answers to the first five questions listed above are well-suited as proxies for household uncertainty over macroeconomic conditions.

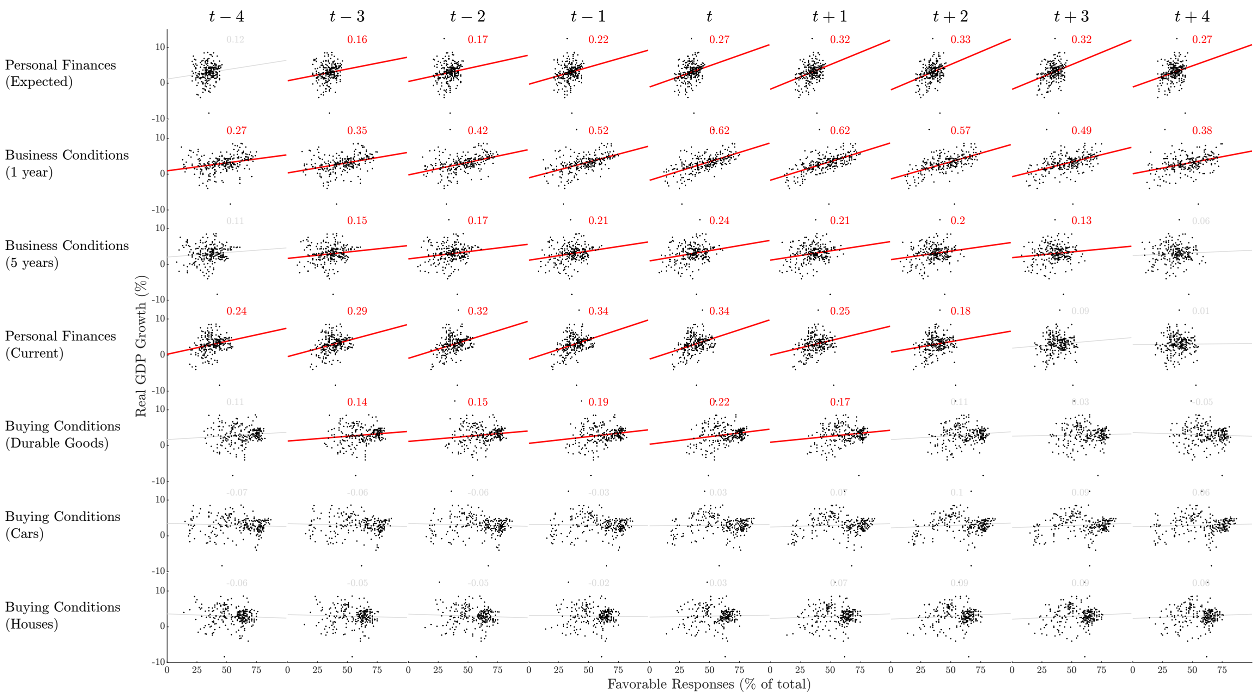

FIGURE 1: CORRELATION BETWEEN FAVORABLE RESPONSES AND REAL GDP GROWTH

Notes: Correlations of favorable responses to the indicated questions on the Michigan Survey of Consumers with leads and lags of annualized quarterly real GDP growth. Red lines and correlation coefficients denote significance at the 5% level. Faint gray lines and correlation coefficients are not significantly different from zero.

In most of what follows, I do not consider the questions about buying conditions for cars and houses.[9]

Another convenient reason for focusing on the first five series is that responses to those questions are the sources for popular measures of consumer sentiment from the Michigan Survey: the Index of Consumer Expectations (ICE) is constructed based on favorable and unfavorable responses to the questions about expected personal finances and one- and five-year business conditions; the Index of Consumer Sentiment (ICS) includes these in addition to current personal finances and buying conditions for durables. To construct indices of uncertainty over consumer expectations and consumer sentiment, I simply sum the measures of uncertainty for each component series and normalize it to equal 100 in the first year of the sample.[10]

[9]Cars and houses are two large and salient markets for households. Views about them may primarily reflect idiosyncratic factors in those markets rather than broader economic conditions.

[10]The headline first-moment indices are constructed in an analogous way, but instead sum the difference between favorable and unfavorable responses to the component questions.

The direct uncertainty indices and their components are plotted in the upper panel of Figure 2. They display some similarities and some differences from each other and from existing measures of uncertainty. For example, household uncertainty in these new measures has increased after recent presidential elections and during domestic and foreign financial and energy crises; however, there is little change across the series after the September 11 attacks, the "Black Monday" stock market crash, or at the onset of the COVID-19 pandemic, all of which are periods of high uncertainty as measured by the VXO/VIX. The uncertainty series that differs the most from the others is current personal finances: very few people respond that they "don't know" how their *current* personal finances compare to those from a year ago.

The consistency across the other measures, however, indicates that the new measures are detecting a similar phenomonenon: uncertainty about future events. Moreover, the differences between these and other measures like the VIX support the notion that household uncertainty actually is something different from uncertainty facing other economic actors; I return to this topic below.

2.2 Disagreement measures from the Michigan Survey

The qualitative nature of the responses in the Michigan Survey of Consumers is similar to the Federal Reserve Bank of Philadelphia's Business Outlook Survey (BOS), which Bachmann et al. (2013) use to construct an uncertainty proxy based on disagreement. Businesses in that survey are asked whether they think general business activity will increase, decrease, or stay the same. Importantly, the survey does *not* record mixed responses or any direct measure of uncertainty comparable to those I construct above. Bachmann et al. (2013) use the following measure of disagreement as a proxy for uncertainty:

$$\text{Disagreement}_t = \sqrt{\text{Favorable}_t + \text{Unfavorable}_t - (\text{Favorable}_t - \text{Unfavorable}_t)^2} \qquad (1)$$

where Favorable_t (Unfavorable_t) is the share of businesses in month t responding that general business activity will increase (decrease). It is straightforward to construct analogous measures of disagreement from the questions asked in the Michigan Survey on which the direct measures of uncertainty are based. This allows for a convenient comparison of direct uncertainty measures with disagreement-based proxies for households.

Disagreement indices and their components from the Michigan Survey are displayed in the lower panel of Figure 2. These series differ at times from the direct uncertainty measures

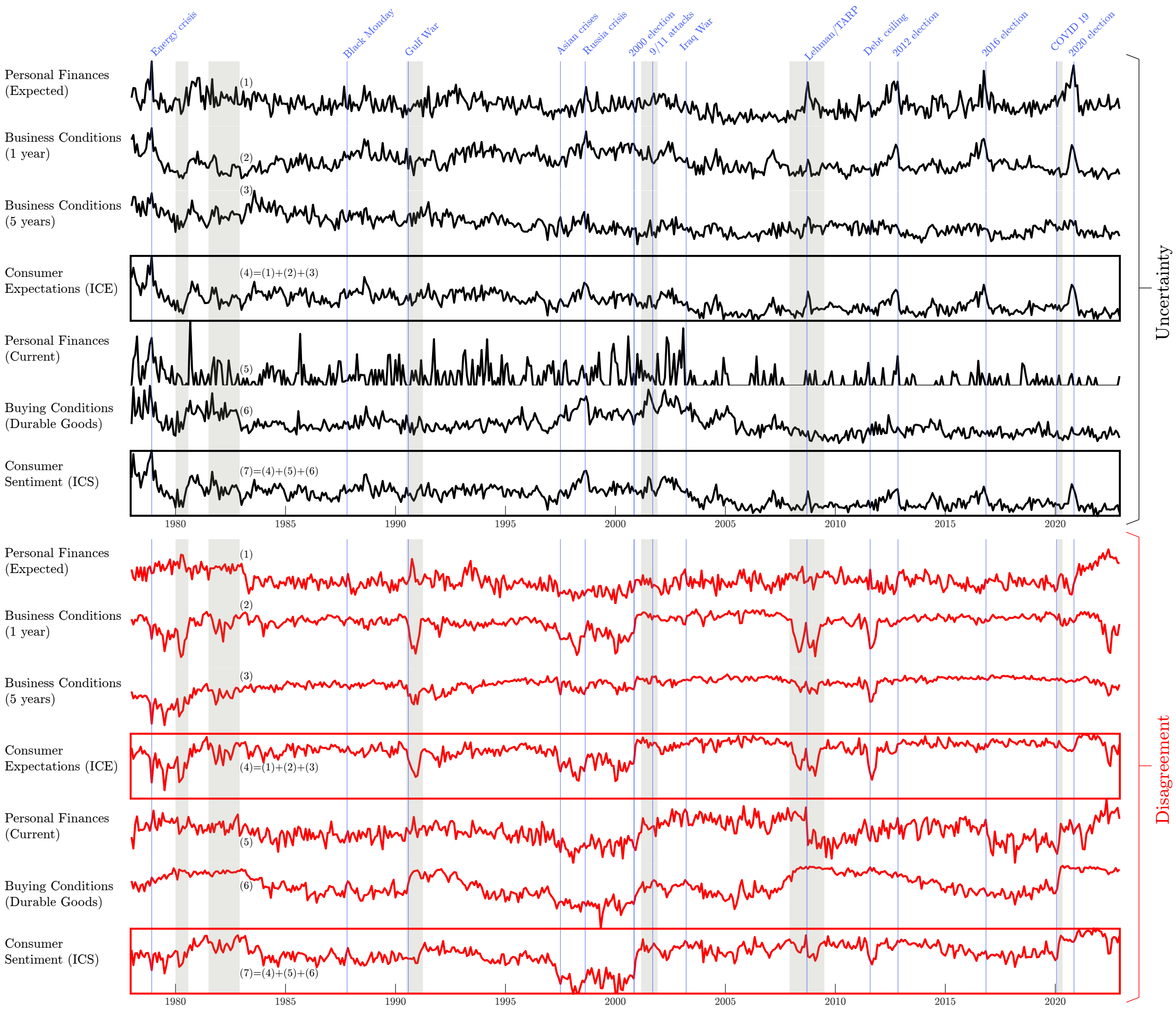

FIGURE 2: UNCERTAINTY AND DISAGREEMENT MEASURES FROM THE MICHIGAN SURVEY

Notes: Uncertainty (upper panel, black) and disagreement (lower panel, red) measures and indices from the Michigan Survey of Consumers, 1978–2022. Indices are normalized sums of the series indicated in each rectangle. See Section 2 for details. Vertical blue lines are selected events frequently associated with increased uncertainty. Gray bands are NBER recessions.

in the upper panel, and differ much more dramatically from each other. A few examples are worth highlighting. The first Gulf War is a period of high disagreement by some measures and low by others; September 2008, sees a spike in disagreement despite the 2007–2009 recession generally being a period of low disagreement; disagreement about current personal finances and buying conditions for durables increase and remain high throughout the pandemic; and the period immediately after the 2000 election is one of high disagreement by all measures.

2.3 Comparison with other measures

In this subsection, I describe Leduc and Liu's (2016) frequently cited measure of household uncertainty from the Michigan Survey and why it is probably better interpreted as a first-moment measure of confidence rather than a second-moment measure of uncertainty. I then compare the new indices described above to theirs and other measures of broader uncertainty.

2.3.1 Leduc and Liu's (2016) measure of uncertainty

After the questions about buying conditions, respondents are asked why they gave the answer they did. It is on this follow-up question to car buying conditions that Leduc and Liu (2016) base their measure of uncertainty. Table 38 of the Michigan Survey's time series data[11] lists twelve categories of responses, one of which is labeled as "Bad Time—Uncertain Future." Leduc and Liu (2016) use this as their measure of uncertainty, the share of survey participants responding that now is a bad time to buy a car because the future is uncertain. By estimating uncertainty using *only* a subset of respondents who have already said that it is a bad time to buy a car, their measure is almost ruling out the possibility that uncertainty could be associated with positive economic conditions.

But there is another problem with this measure of uncertainty. The response categories in this table on the Michigan Survey's public website, however, are not the same as the coded responses that survey conductors record. There are, in fact, 77 different coded responses to this follow-up question.[12] Many of the twelve categories in the table are "bins" of these underlying responses grouped together; others are simply labeled differently. The underlying response to which "Bad Time—Uncertain Future" corresponds is actually coded as "People should save money, bad times ahead." Such a response is clearly much more about a first moment (a bad future) than a second moment (an uncertain future).

Surveyors must necessarily exercise some judgment when coding interview responses. So, it's possible that Leduc and Liu's (2016) measure could indeed be capturing some aspect of household uncertainty. But it is at the very least equally plausible that it is instead measuring mostly bad news about the future, rather than uncertainty *per se*. It is perhaps not surprising, then, that shocks to this measure of "uncertainty" are strongly contractionary. The indices I construct above are arguably more reasonable measures of uncertainty, and I compare them with Leduc and Liu (2016) measure below.

[11] Available online at `https://data.sca.isr.umich.edu/data-archive/mine.php`.

[12] More detailed data from the survey beyond the headline time series can be accessed at `https://data.sca.isr.umich.edu/sda-public/`.

3 Quantifying the effects of household uncertainty

In the remainder of the paper, I attempt to answer the question "Does household uncertainty matter for the macroeconomy?" using the new measures described above. I follow most of the literature, and estimate the effects of uncertainty shocks on the macroeconomy using structural VARs, but I identify uncertainty shocks in a novel way, moving beyond the recursive identification schemes most of the literature relies on.

I first argue below in section 3.1 that appropriately controlling for first moments like consumer sentiment is crucial for identifying uncertainty shocks. Previous work has acknowledged this necessity, but I show below that it is especially important when using qualitative survey data like the uncertainty measures derived from the Michigan Survey of Consumers, the Business Outlook Survey, or other similar surveys.

The results from this first subsection support the inclusion of first moments in all VAR-based estimates of the effects of uncertainty shocks, especially for including the first-moment measure ordered prior to the uncertainty measure in Cholesky-identified VARs, a couple of which I estimate in Section 3.2. However, the argument in the next section primarily points the way toward a novel method of jointly identifying confidence and uncertainty shocks, which I describe in Sections 3.3 and 3.4.

3.1 The importance of controlling for first moments

As discussed in, for example, Bloom (2014), Leduc and Liu (2016), and Coibion et al. (2022), separately identifying first- and second-moment shocks is a major challenge unique to identification of uncertainty shocks as opposed to other macroeconomic shocks. Uncertainty often rises when first-moment sentiment measures like confidence are low; this could be due to a common cause of consumer confidence and uncertainty (the 9/11 attacks, for example) or a response of uncertainty directly to confidence or sentiment shocks. The latter case is particularly relevant in the context of qualitative survey responses like those in the Michigan Survey or the Business Outlook Survey.

To see why, consider the disagreement proxy from Section XY, expressed here slightly differently:

$$d^2 = g + b - (g - b)^2,$$

where d denotes disagreement, g denotes the fraction of favorable responses, and b denotes the fractions of unfavorable responses. Commonly used measures of confidence like the ICS

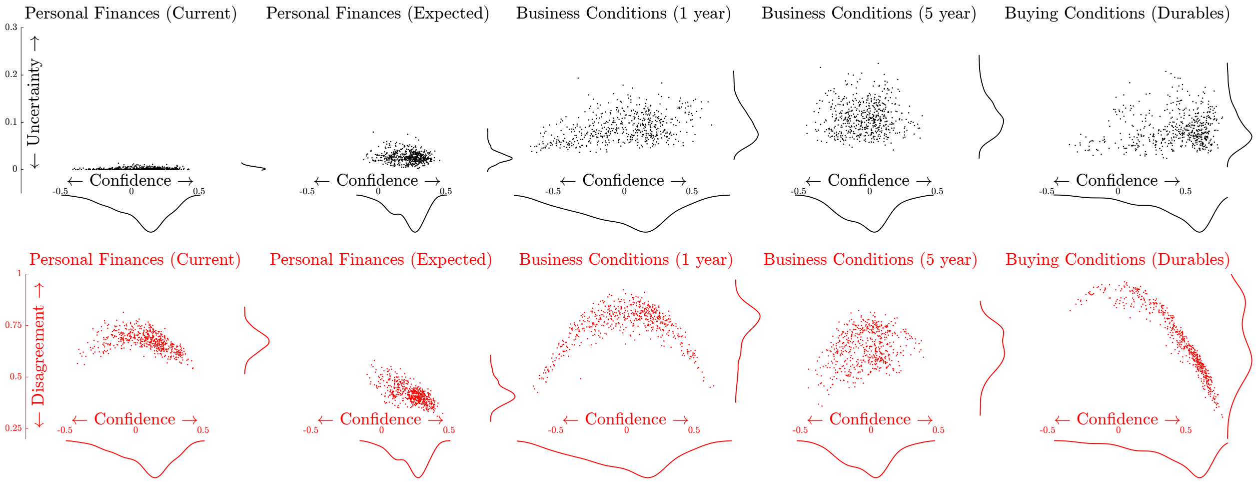

FIGURE 3: FIRST AND SECOND MOMENTS

Notes: Confidence and uncertainty (upper panel, black) and confidence and disagreement (lower panel, red), along with the marginal distributions of each uncertainty/disagreement and confidence measure. Marginal distributions from a kernel density estimation.

and ICE[13] from the Michigan survey, are normalized versions of the equation $c = g - b$. Clearly, $g - b$ appears directly in the expression for d above. This fact can induce an almost mechanical correlation between confidence and disagreement, which is evident in Figure 3. For nearly all measures of disagreement the negative correlation near the modal values of the marginal distributions is obvious at a quick glance.

To think about the importance of this idea in terms of shocks, note that any combination of g and b can be mapped to unique "iso-confidence" and "iso-disgreement" curves in (g, b) space, the first being the line where $g - b$ is constant and the second being a portion of the rotated parabola along which $g + b - (g - b)^2$ is constant. To a first approximation, uncertainty is given by $1 - n - (g + b)$, where n is the fraction of non-responses. Examples of these iso-quant curves are displayed in the leftmost panel of Figure 4. From the intersection point of the curves, the shaded areas illustrate the directions of change in g and b that result in higher or lower confidence or disagreement/uncertainty. If the pattern of favorable and unfavorable responses of each underlying question in the uncertainty or disagreement indices lie mostly within the shaded regions, then there will be negative correlation between first- and second-moment measures—that is, periods of high uncertainty/disagreement are those when confidence is low.

The scatter plots in the right panels of Figure 4 display the pattern of favorable and

[13] See, for example, Barsky and Sims (2011) and Bachmann and Sims (2012).

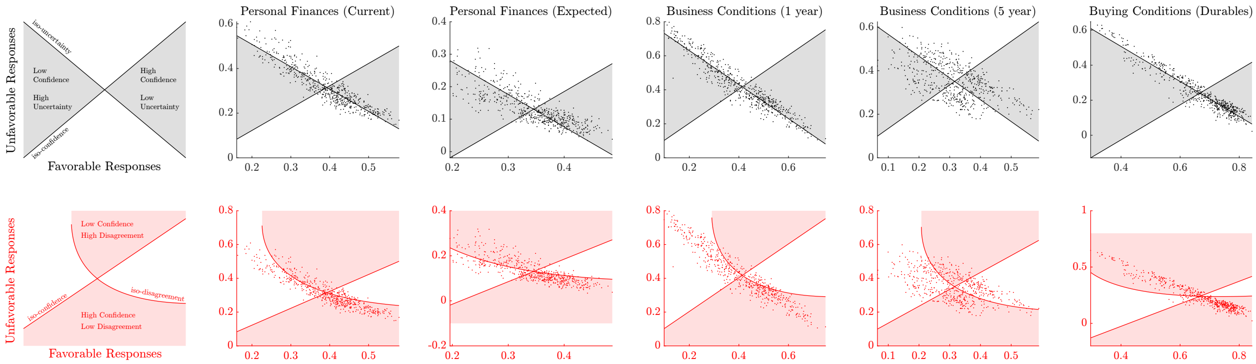

FIGURE 4: ISO-QUANT CURVES

Notes: Iso-confidence and iso-uncertainty (upper panel, black) and iso-confidence and iso-disagreement (lower panel, red), along with observed patterns of favorable and unfavorable responses. When points lie mostly in shaded regions, increases in uncertainty/disagreement are correlated with decreased confidence. Conceptually, appropriately accounting for a first moment like confidence holds the iso-confidence curve fixed and shifts the iso-uncertainty or -disagreement curves when estimating uncertainty shocks.

unfavorable responses to each question considered above, along with the iso-quant curves evaluated at the average $(\bar{g}, \bar{b})$ for each measure. In almost all cases, the largest mass of points is in the area with confidence and uncertainty/disagreement moving in opposite directions. It is most obvious in the disagreement panel for durable goods buying conditions. Figures 3 and 4 illustrate concretely the need to control for first moments like confidence to identifying uncertainty shocks. They also point toward a new way of jointly identifying confidence and uncertainty shocks, which I discuss in Section 3.3 below.

But before proceeding to that argument, note that Figure 4 gives a clear graphical intuition for what controlling for confidence in the estimation of uncertainty shocks does: it fixes the iso-confidence curve and shifts only the iso-uncertainty or iso-disagreement curve. This is exactly what including confidence ordered before uncertainty in a Cholesky-identified VAR does. I explore this in Section 3.2 and describe the new method of identification in Section 3.3.

3.2 Cholesky identification

Most estimates of uncertainty's effects on the macroeconomy identify uncertainty shocks using a recursive causal ordering: any variable in the system can only be affected contemporaneously by changes in those variables ordered prior to it. A structural VAR with one lag[14] can be represented by the following equation

$$B_0 y_t = B_1 y_{t-1} + \varepsilon_t,$$

where y_t is a $K \times 1$ vector of macroeconomic variables, the B_i are $K \times K$ matrices, and the mean-zero structural shocks ε_t are orthogonal with unit variance, i.e., $\mathbb{E}_t[\varepsilon_t \varepsilon_t'] = I_K$, where I_K is the K-dimensional identity matrix. If a recursive ordering is assumed, identification can be achieved if a unique lower triangular matrix B_0 can be recovered from the estimated reduced form regression of the vector of variables on its own lags:

$$y_t = A y_{t-1} + u_t,$$

where $A = B_0^{-1} B_1$ and $u_t = B_0^{-1} \varepsilon_t$. A lower-triangular Cholesky decomposition of the covariance matrix of reduced form residuals $\Sigma \equiv \mathbb{E}_t[u_t u_t']$ produces the (inverse of the) unique desired B_0.

A natural example to consider is Leduc and Liu's (2016) benchmark VAR, which includes (in this order) their measure of uncertainty, a measure of economic activity, inflation from the consumer price index (CPI), and the three-month Treasury rate. While this ordering places no restrictions on the contemporaneous effects of uncertainty shocks on the other variables, it also imposes the much less plausible assumption that only uncertainty shocks and no other macroeconomic shock can affect uncertainty contemporaneously.

The discussion in section 3.1 makes it clear that at a minimum this system should include a measure of consumer confidence.[15] As a first pass, I estimate similar Choleksy VARs that include, in order: a measure of consumer confidence, an index of uncertainty or disagreement described in Section 2.2, the unemployment rate or industrial production, CPI inflation, and the three-month Treasury rate. For each measure of uncertainty or disagreement I include the corresponding measure of confidence.[16] Confidence, uncertainty, and disagreement indices and industrial production are in logs, all others are in levels; I include a constant and 12 months of lags, using data from January 1978 to December 2019.

Impulse responses and the percent of forecast error variance attributable to uncertainty or disagreement shocks are displayed in Figure 5 (solid lines and shaded error bands). Impulse responses are to a one standard deviation shock that increases uncertainty/disagreement.

[14] Higher-order VARs can always be written in VAR(1) form using appropriately augmented matrices.

[15] Indeed, Leduc and Liu (2016) include the ICS in a slightly larger VAR as a robustness check.

[16] So, for example, when I estimate the effects of ICE uncertainty I include ICE confidence; when I estimate the effects of ICS disagreement, I include ICS confidence, etc.

Shocks to household uncertainty and disagreement have insignificant effects on unemployment and industrial production, with the exception of disagreement shocks, which are very mildly expansionary over short horizons. In no case does the shock to uncertainty or disagreement explain more than 5% of the forecast error variance of real activity.

By contrast, the dashed lines in Figure 5 show the responses of the same variables to shocks to confidence (one standard deviation *decrease*). Negative confidence shocks lead to large and significant increases in unemployment and decreases in industrial production. First-moment shocks to confidence explain up to 50% of the variance of real activity, an order of magnitude greater than second-moment shocks to uncertainty and disagreement. Of course, in Figure 4, one cannot simultaneously hold both iso-quant curves fixed and observe a change in favorable and unfavorable responses; the logic of controlling for first moments when estimating the effects of second-moment shocks applies equally in reverse: properly identifying first-moment shocks requires controlling for second moments.

The indices based on disagreement discussed in Section 2.2 can be extended back to 1960 on a quarterly basis.[17] While this allows for estimation based on a longer sample period, the overall sample size decreases and, more importantly, the identifying assumptions in a recursive system become even less credible. For example, if uncertainty is ordered first in a recursive system, an identifying assumption is that no other shocks affect uncertainty until at least three months after the shock.

The longer time series and quarterly availability of the data, nevertheless could add some useful information. First, broader measures available on a quarterly basis like GDP or consumption—arguably better measures of overall economic activity than industrial production—can be included in the quarterly VAR. Second, it is possible that the nature of uncertainty or confidence shocks that hit the economy prior to 1978 was different or that the typical response of the economy to uncertainty shocks changed like so many others did after the Great Moderation period, which makes up the vast majority of the post-1978 monthly sample.

The results, however, are mostly in line with the monthly estimates that begin in 1978. Figure 6 displays impulse responses and forecast error variance decompositions for unemployment, real GDP, consumption, and durable goods consumption to disagreement shocks. There is some evidence that unemployment rises very slightly, but statistically significantly, shortly after an uncertainty shock with a concurrent small decrease in aggregate consumption consistent with the findings of Coibion et al. (2022). Uncertainty shocks nevertheless

[17]Uncertainty indices cannot because a separate breakdown does not exist that differentiates respondents who directly say they are uncertain or don't know from those who refused to answer or whose response is missing.

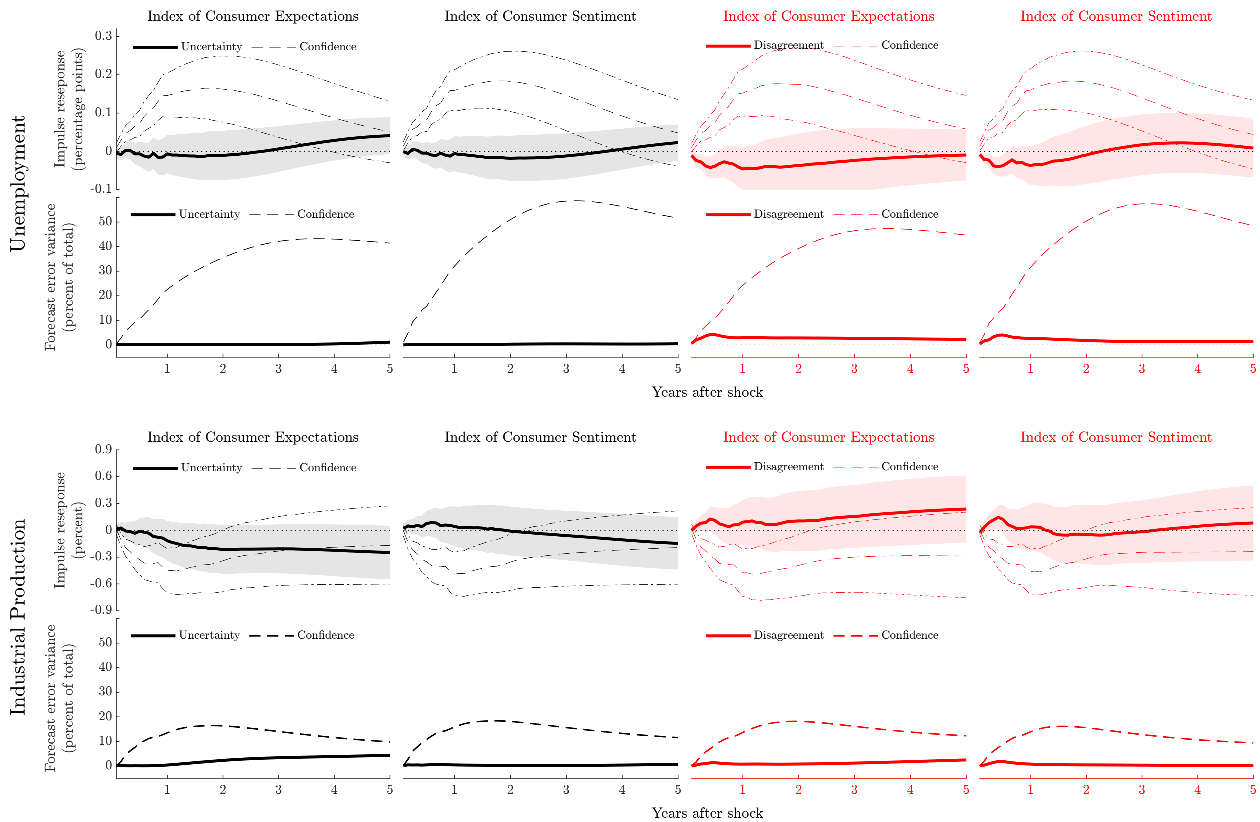

FIGURE 5: 1ST AND 2ND-MOMENT SHOCKS, CHOLESKY VARS: MONTHLY, 1978–2019

Notes: Impulse response functions with 90% confidence intervals and percentage of forecast error variance due to uncertainty, disagreement, and confidence shocks identified using a recursive ordering with confidence ordered first, followed by uncertainty or disagreement, and then all other variables. Responses to one-standard deviation shocks that increase uncertainty (left panel, black solid lines), increase disagreement (right panel, red solid lines), or decrease confidence (both panels, dashed lines) monthly indices from the Michigan Survey of Consumers, 1978–2019. Unemployment rate (upper panel), industrial production (lower panel). See section 3.2 for details.

still account for less than 5% of the forecast error variance at all horizons, and the statistical significance of the very small contractionary effect on unemployment and consumption is robust neither to the sample period nor the identification strategy. Confidence shocks, by contrast have large and significant effects and explain a large fraction of the variance of real activity.

Thus, the simplest and most common method of identifying uncertainty shocks in a structural VAR implies that household uncertainty shocks have at most very small effects on output, unemployment, and consumption, while confidence shocks have effects an order of magnitude larger. However, the identifying assumptions made in this section are not strongly defensible, especially when trying to jointly identify uncertainty and confidence shocks. To

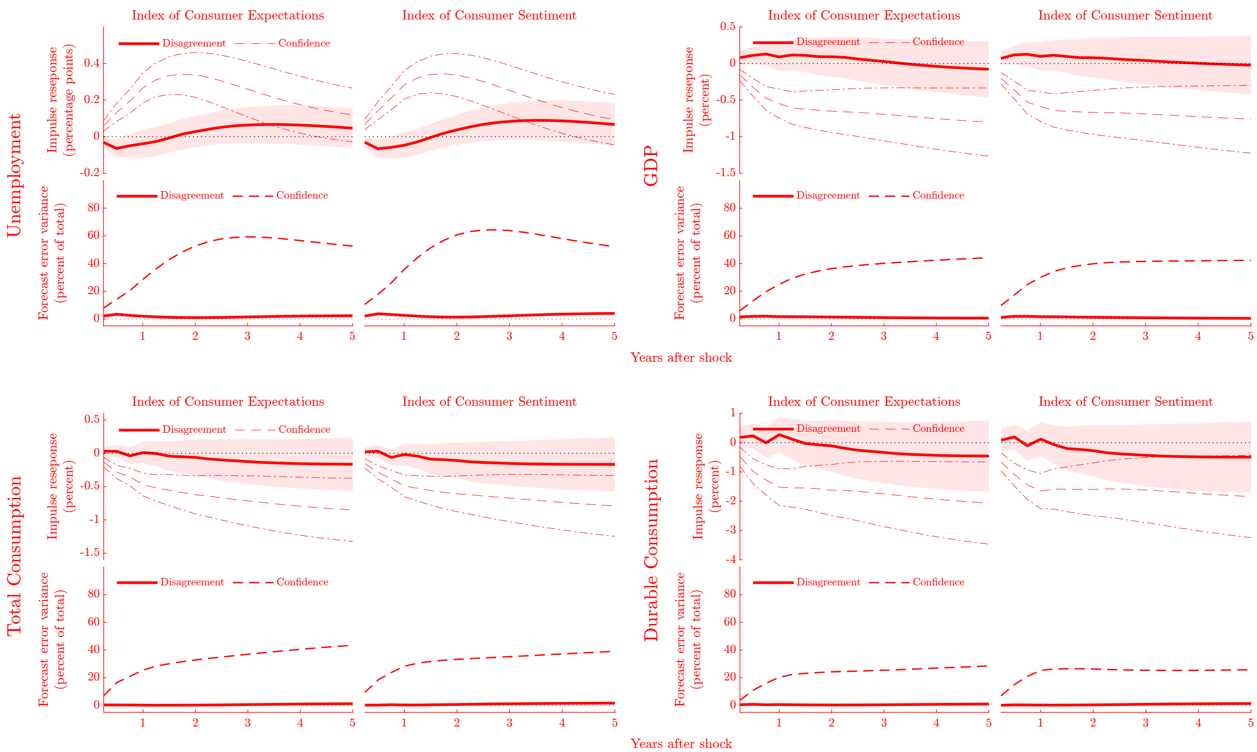

FIGURE 6: 1ST AND 2ND-MOMENT SHOCKS, CHOLESKY VARS: QUARTERLY, 1960–2019

Notes: Impulse response functions with 90% confidence intervals and percentage of forecast error variance due to disagreement and confidence shocks identified using a recursive ordering with confidence ordered first, followed by uncertainty or disagreement, and then all other variables. Responses to one-standard deviation shocks that increase disagreement (solid lines), or decrease confidence (dashed lines) quarterly indices from the Michigan Survey of Consumers, 1960–2019. Unemployment rate, real GDP, and real total and durable goods consumption. See section 3.2 for details.

see this last point, note that the argument in section 3.1 applies to both confidence and uncertainty/disagreement: identification of first-moment shocks require properly controlling for second-moments. In a recursively identified system, contemporaneous values of one of these can appear in the equation for the other, but not both. Graphically, one can't hold both the iso-quants curves in Figure 4 fixed: at least one curve has to shift if responses change.

Another potential issue regards the definition of disagreement. The expression in Equation 1 is the standard deviation of a random variable in which favorable responses are coded with a $+1$, unfavorable responses are coded as a -1, and neutral or missing responses are coded as a 0, and those outcomes obtain with probabilities g, b, and $1-g-b$, respectively. Because it is the standard deviation of a particularly defined random variable, Equation 1 is defensibly interpreted as a second moment measure. In fact, this definition is consistent with confidence being measured as $g - b$, which the Michigan Survey does. However, other numerical codings of the qualitative responses would imply different disagreement expression. For example, the Institute for Supply Management's indices of manufacturing activity code neutral responses as equal to $+\frac{1}{2}$; the resulting standard deviation of that random variable is different from the one in Equation 1. Thus differences in the somewhat arbitrarily chosen numerical coding of qualitative responses lead to different measures of disagreement. These differences are illustrated in the left two columns of Figure 7.

Thus one cannot simultaneously identifying confidence and uncertainty shocks in a Cholesky-identified VAR. Moreover, in any setting the "correct" measure of disagreement depends implicitly on an arbitrary choice for the numerical coding of qualitative survey responses.

These weaknesses motivate the next section, in which I propose a new method of jointly identifying confidence and disagreement shocks in a way that does *not* depend on the arbitrary numerical assignment described above. I use sign restrictions to separately identify first- and second-moment shocks and, in a larger system, combine them with size restrictions on impulse responses to separately identify these sentiment shocks from other fundamental macroeconomic shocks.

3.3 An agnostic approach

Uhlig (2005) proposed identifying monetary policy shocks by "agnostic" sign restrictions. In this section I extend this approach to identifying confidence and uncertainty (disagreement) shocks. Figure 3 makes it clear that commonly used disagreement measures are conditionally correlated with confidence measures. But Figure 4 makes clear that less restrictive measures of changes in confidence and disagreement can be constructed in a fairly straightforward way. Specifically, I specify that a positive "shock" to confidence involves an increase in g and a decrease in b, while a positive "shock" to disagreement involves an increase in both g and b. This flexible approach avoids the necessity of taking a stand on the right way to code numerically the qualitative survey responses. The right column of Figure 7 illustrates how this approach correctly identifies both confidence and disagreement shocks regardless of the details of how disagreement is measured.

To be concrete, suppose that we have in hand any of the survey measures discussed above. Suppose, for simplicity, that $x_t = [g_t, b_t]'$ follows a structural VAR(1) process, i.e.,

$$B_0 x_t = B_1 x_{t-1} + \varepsilon_t.$$

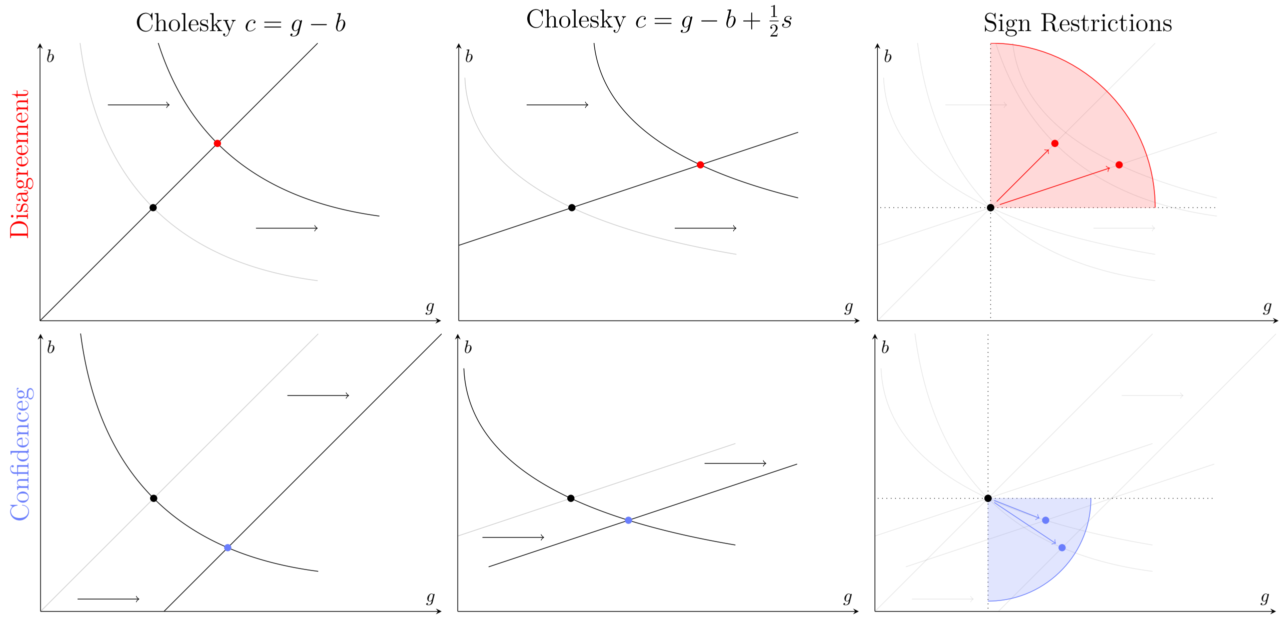

FIGURE 7: CHOLESKY VS. SIGN RESTRICTIONS FOR IDENTIFICATION

Notes: The upper panel illustrates a disagreement shock in the two-variable system consisting of favorable (g), unfavorable, (b), and neutral (s) responses; the lower panel shows the same for a confidence shock. The first two columns are identified by recursiveness assumptions (Cholesky), the left column assuming confidence as measured in the Michigan survey and the middle column assuming it is measured as in the ISM. The right column illustrates how sign restrictions classify the shocks as either uncertainty or confidence regardless of the particular assumptions made on how to measure confidence.

Estimates for the reduced-form VAR

$$x_t = Ax_{t-1} + u_t$$

are obtained, and we wish to the set of B_0 matrices consistent with the much weaker identification assumptions above, namely that the impact impulse responses satisfy the following sign restrictions:

$$\mathbf{IR}_0 = \begin{bmatrix} g_0 \\ b_0 \end{bmatrix} = \begin{array}{c} \\ g \\ b \end{array} \begin{array}{c} \begin{array}{cc} \text{Conf.} & \text{Dis.} \end{array} \\ \begin{bmatrix} + & + \\ - & + \end{bmatrix} \end{array}.$$

For now, I just impose these restrictions on the impact effect of the impulse responses. An estimate of reduced form parameters $\widehat{A}$ implies a set of admissible matrices $\left\{\widehat{B}_0\right\}$ that both satisfy the sign restrictions on impulse responses summarized above and imply that the estimated structural shocks $\widehat{\varepsilon}_t = \widehat{B}_0 \widehat{u}_t$ are mutually orthogonal.

To find this set of matrices, I use the algorithm described in Rubio-Ramírez, Waggoner and Zha (2010). Specifically, I begin with a matrix B that satisfies the orthogonality condition—for example, by taking a Cholesky factor of the estimated covariance matrix of reduced-form residuals. Let X be a a matrix with with each element independently drawn from the standard normal distribution, and let $X = QR$ be the QR decomposition of X, normalized such that the diagonal terms of R are positive. Then Q is a random orthogonal matrix, and so QB also satisfies the orthogonality condition. If impulse responses generated from $B_0 = QB$ satisfy the sign restrictions, keep the draw; if they do not, discard the draw; regardless of the outcome, return to step 1 and draw a random matrix X.

For each admissible draw, full-horizon impulse responses and forecast error variance decompositions can be computed; this leads to an identified set of IRFs and FEVDs in contrast to point estimates from the Cholesky VARs above. But to associate these estimated effects of favorable and unfavorable responses with macroeconomic "shocks," however, requires expanding the system to include macroeconomic variables and additional identifying assumptions. I do this in the next section.

3.4 A larger sign-identified system

The two variable system above describes the key novel sign restriction I use to identify confidence and disagreement shocks. But it excludes macroeconomic variables, estimating the effects on which is the whole reason for identifying these shocks. In this section, I incorporate the method of identifying confidence and uncertainty shocks described above into a slightly large VAR system that includes the same macroeconomic variables in the monthly specifications above: unemployment, inflation, and the three-month nominal Treasury rate.

In addition to the sign restrictions described above to identify confidence and uncertainty shocks, I identify monetary policy (MP), non-monetary aggregate demand (AD), and aggregate supply (AS) shocks also using sign restrictions. The sign pattern described below is consistent with most macroeconomic theories of short-run fluctuations, and follows Peersman (2005) and Fry and Pagan (2011):

$$\mathbf{IR}_0 = \begin{bmatrix} u_0 \\ \pi_0 \\ i_0 \end{bmatrix} = \begin{array}{c} \\ u \\ \pi \\ i \end{array} \begin{array}{c} \begin{array}{ccc} \text{AS} & \text{AD} & \text{MP} \end{array} \\ \begin{bmatrix} + & + & + \\ + & - & - \\ + & - & + \end{bmatrix} \end{array}.$$

So, AD shocks move inflation and unemployment in opposite directions and interest rates in the same direction as inflation; they are separately identifiable from MP shocks because in the latter nominal interest rates move in the opposite direction of inflation. AS shocks, by contrast, move unemployment and inflation in the same direction. Combined with the identifying assumptions from the previous section, the larger five-variable system is summarized by

$$
\mathbf{IR}_0 = \begin{bmatrix} g_0 \\ b_0 \\ u_0 \\ \pi_0 \\ i_0 \end{bmatrix} = \begin{array}{c} \\ g \\ b \\ u \\ \pi \\ i \end{array} \begin{array}{c} \begin{array}{ccccc} \text{Conf.} & \text{Dis.} & \text{AS} & \text{AD} & \text{MP} \end{array} \\ \begin{bmatrix} + & + & * & * & * \\ + & - & * & * & * \\ * & * & + & + & + \\ * & * & + & - & - \\ * & * & + & - & + \end{bmatrix} \end{array}.
$$

Some additional assumptions must be imposed in order to separately identify all five shocks. For example, if an expansionary AS shock increases favorable responses ($g \uparrow$) and decreases unfavorable responses ($b \downarrow$)—a likely outcome since both unemployment and inflation fall after this type of shock—then it will be indistinguishable from a confidence shock unless additional restrictions are imposed on either confidence shocks or AS shocks.

To this end, I follow much of the literature on shocks to economic sentiment (e.g., Bachmann and Sims (2012), Beaudry and Lucke (2010)) and assume that shocks to confidence or uncertainty have smaller impact effects on unemployment and inflation than AS or AD shocks and smaller impact effects on interest rates than monetary policy shocks. These additional inequality assumptions, in conjunction with the sign restrictions described above, are sufficient to separately identify all five shocks. Finally, in what I present below, I also assume that confidence and uncertainty shocks increase unemployment, but not until 6 months out. This assumption effectively "stacks the deck" in favor of finding larger effects of uncertainty shocks than would be the case if I didn't not impose any sign restrictions on them.

Nevertheless, shocks to household uncertainty have essentially no effect on unemployment. Impulse responses and forecast error decompositions are displayed in Figure XYZ. Uncertainty shocks have small and insignificant effects on unemployment. Moreover, they explain less than *five* percent of the variance of unemployment at all horizons. In the short run, unemployment is mostly explained by AD and MP shocks, while in the long run AS and to a slightly less extent confidence shocks explain most of unemployment variation. Variation in favorable and unfavorable responses is primarily explained by confidence shocks and AD

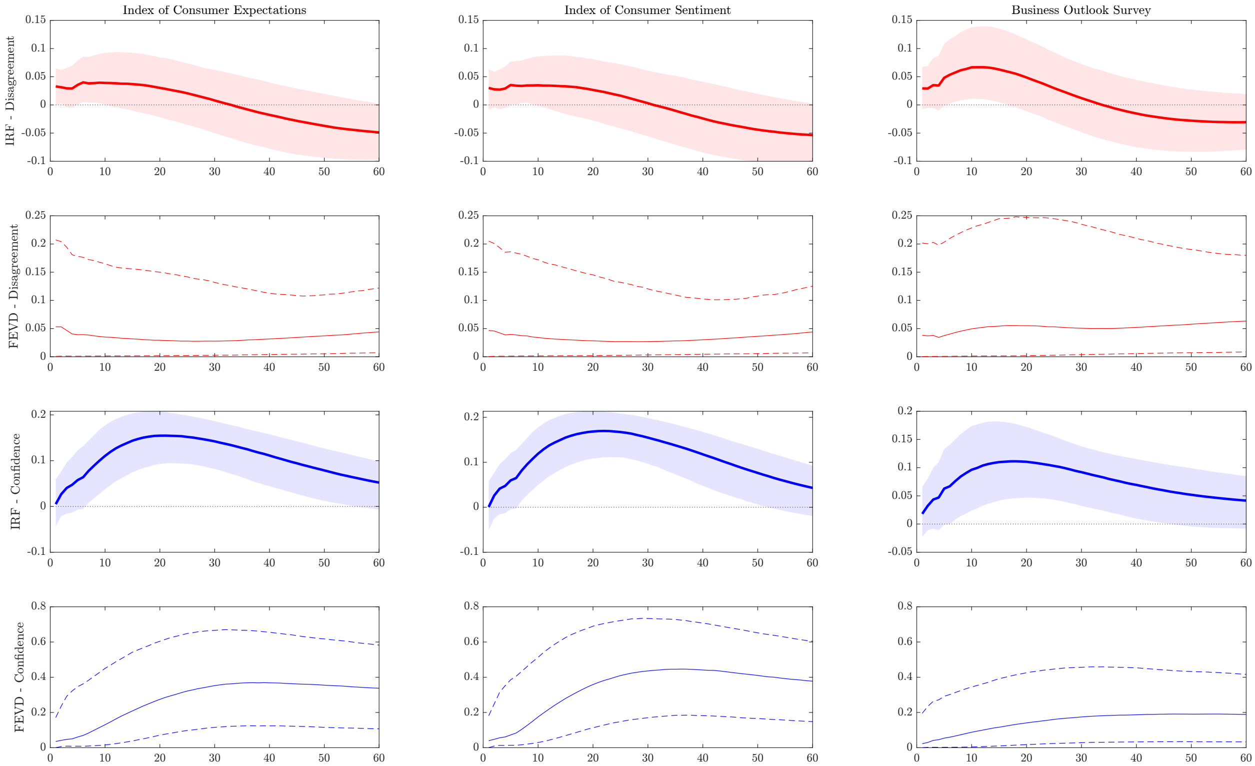

FIGURE 8: 1ST AND 2ND-MOMENT SHOCKS, SIGN AND SIZE RESTRICTIONS

Notes: Disagreement shocks (upper panel, red) and confidence shocks (lower panel, blue), identified by sign restrictions described in Section 3.4. Impulse responses and forecast error variance decompositions. Solid lines are median responses; shaded areas and dashed lines represent the 90% quantile of responses and forecast error variances.

and MP shocks.[18]

The novel joint identification of confidence and uncertainty shocks, despite being arguably more credible than the other strategies described above, nonetheless gives a result consistent with what was found above: household uncertainty shocks are not a source of economic fluctuations in the U.S.

4 Is uncertainty a transmission mechanism?

The last sentence of the previous section does *not* by itself imply that household uncertainty plays no role in U.S. business cycles. It could very well be the case that the "endogenous

[18]There are some differences between household and firm uncertainty and confidence shocks, which I describe in more detail in the appendix. Firm uncertainty shocks have somewhat larger effects than household uncertainty shocks, but household confidence shocks have much larger effects than firm confidence shocks.

response" (Ludvigson et al. (2021)) of household uncertainty to other macroeconomic shocks amplifies those shocks' effects.

To assess this possibility, I use the methods of Sims and Zha (2006), Bernanke et al. (1997), and Bachmann and Sims (2012) to assess the role of household uncertainty in the transmission of various other macroeconomic shocks. I describe the method in more detail in the appendix, but the idea is a simple one. A monetary policy shock, for example, might affect output indirectly through its effect on uncertainty. One way to assess the importance of this transmission channel is ask what the response of output to a monetary policy shock would be if uncertainty did not respond at all to monetary policy shocks. To do this in a VAR, first compute the responses of all endogenous variables to the shock in the standard way; then compute the response of output using the estimated coefficients of the model under the counterfactual assumption that the response of uncertainty to a monetary policy shock is exactly zero at all horizons. The standard method uses the actual values of the response of uncertainty; the counterfactual method replaces those actual values with zeros.

Although it is impossible to comprehensively assess this against all proposed shocks, I consider the following to be at least somewhat representative of the proposed major drivers of economic fluctuations in the U.S. from Ramey (2016):

- Total factor productivity (TFP) shocks from Francis, Owyang, Roush and DiCecio (2014).
- Unanticipated tax shocks from Romer and Romer (2010) and Mertens and Ravn (2012).
- Marginal efficiency of investment shocks from Justiniano, Primiceri and Tambalotti (2011).
- Three news shocks: to defense spending from Ben Zeev and Pappa (2017), future taxes from Leeper, Richter and Walker (2012), and investment specific technology (IST) from Ben Zeev and Khan (2015).
- Monetary policy shocks.

Where the last is associated with a shock to the Federal funds rate. The VAR is recursive, with all identified shocks except monetary policy ordered in the first block, followed by a measure of uncertainty, then real per capita GDP, per capita total hours worked, the log of a commodity price index, the log of the GDP deflator, and finally the Federal funds rate. Like Ramey (2016), I detrend the macro data using a quadratic polynomial.

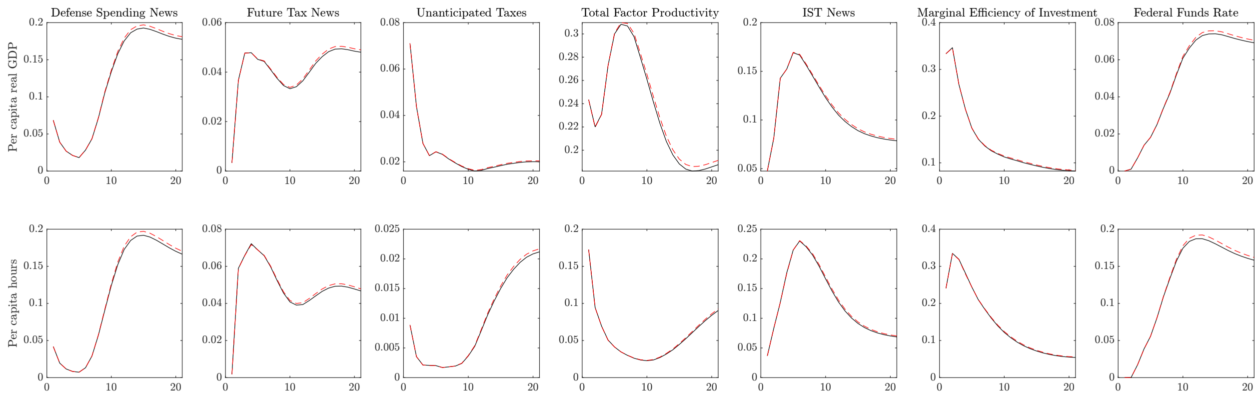

FIGURE 9: ACTUAL AND COUNTERFACTUAL FEVDS FROM RAMEY'S (2016) LARGE VAR

Notes: Fraction of forecast error variance of real per capita GDP and per capita hours to each shock in Ramey's (2016) representative VAR augmented with ICE disagreement index, quarterly 1960–2005. Black lines are actual values, dashed red lines are what obtains when uncertainty is counterfactually held constant. See Section 4.

The time period is 1960–2005, which starts later than Ramey (2016)'s estimates because of the availability of the unavailability of Michigan survey data prior to 1960.[19] Similar to Ramey (2016), the fiscal, technology, and monetary policy shocks account for between 63 and 73 percent of the variance of output and between 49 and 67 percent of hours at business cycle frequencies.

In the interest of space, I relegate the description of each individual shock to the appendix. But with any of these, the counterfactual considered is the following: "What would the response of GDP or hours be if uncertainty did *not* respond to the shock?"

The factual and counterfactual forecast error variance decompositions are displayed in Figure 9. I display results for the ICE disagreement index, but the results are almost identical for the other uncertainty indices. In no case does GDP or hours per capita respond differently when household uncertainty is counterfactually held constant throughout the full horizon. Counterfactual impulse repsonses (not displayed) similarly lie almost exactly on top of the actual values. I conclude that not only is household uncertainty not an important driver of macroeconomic fluctuations, neither is it an important amplifier of other macroeconomic shocks.

[19]For the business outlook survey, the sample period begins in the third quarter of 1968.

5 Conclusion

Survey-based measures of household uncertainty fluctuate significantly both independently of other macroeconomic variables and in response to other macroeconomic shocks. But the evidence presented above implies that shocks to household uncertainty are not a driver of macroeconomic fluctuations nor are the endogenous responses of household uncertainty to other shocks important propagation mechanisms.

These results are in marked contrast to household measures of confidence and differ somewhat from survey-based measures of *firm* uncertainty. Shocks to household confidence can explain 30 to 40 percent of the variance of unemployment, while firm uncertainty shocks explain both a larger share of the long-run variance of the unemployment rate and firm responses to outlook surveys.

The novel joint identification of confidence and uncertainty shocks by sign and size restrictions can be applied in and extended to different contexts. For example, the Michigan Survey also includes questions about future monetary policy and other government policies. It is straightforward to apply the same techniques to these questions to obtain measures of household-based measures monetary policy uncertainty and economic policy uncertainty. Since the focus of this paper is on uncertainty, the results described above do not separately identify components of confidence like news vs. pure sentiment shocks, an important exercise given the large effects I find of confidence. I leave these questions for future research.

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Appendix

5.1 Identification using short- and long-run restrictions

Ludvigson et al. (2021) argue convincingly that short-run restrictions are not convincing identifying assumptions: they are not based on theory and indeed can be rejected based on their identification procedure. However, their partially event-based procedure for identifying macroeconomic and financial uncertainty seems inappropriate in this context for two reasons. First, and most obviously, the measures constructed here do not explicitly distinguish between financial and macroeconomic uncertainty. Second, and perhaps less obvious, is the discussion about differences across household uncertainty measures and in comparison with other existing measures.

A quick examination of the time series in Figure 2 and the discussion in Section XYZ indicate that it seems inappropriate to assume *ex ante* that certain events are periods of elevated household uncertainty. For example, the first Gulf War was no high uncertainty, high disagreement by some measures, and low disagreement by others; the aftermath of the 2000 election was a high disagreement period, but low uncertainty period.

I am nevertheless sympathetic to their rejection of identification by short-run restrictions alone. I therefore propose an alternative structural VAR identification strategy below that mixes short- and long-run restrictions and allows for comparison of uncertainty shocks with news and technology shocks. The VAR systems I consider below similar to Beaudry and Lucke (2010) and Fisher (2006 and 2010).

Beaudry and Lucke (2010) identify total factor productivity (TFP) shocks, investment specific technology (IST) shocks, monetary policy shocks, preference shocks, news shocks in a baseline stuctural vector error correction model (VECM) consisting of measures of TFP, the relative price of investment, stock prices, hours worked, and a nominal interest rate. Their baseline identifying assumptions combine short- and long-run restrictions and are summarized in the left panel of Table 1.

The first column of the matrix in the left panel of Table 1 indicates that monetary policy shocks have no long run effect on TFP, and no contemporaneous effect on TFP, hours, or the relative price of investment; news shocks, on the other hand, can effect hours contemporaneously, but not TFP or the relative price of investment, and have long-run effects on both TFP and the relative price of investment. Beaudry and Lucke (2010) find a large role for news shocks in explaining movements in hours and TFP.

To build on their identification of news shocks to also identifying uncertainty shocks, five

Table 1: Identification by short- and long-run restrictions

Beaudry and Lucke's (2010) identification

$$
\begin{bmatrix} \mathbf{IR}_0 \\ \mathbf{IR}_\infty \end{bmatrix} =
\begin{array}{r}
 \\ \Delta tfp \\ \Delta q \\ \Delta sp \\ h \\ i \\ \Delta tfp \\ \Delta q \\ \Delta sp \\ h \\ i
\end{array}
\begin{array}{c}
\begin{array}{ccccc} \text{MP} & \text{Pref.} & \text{News} & \text{IST} & \text{TFP} \end{array} \\
\left[\begin{array}{ccccc}
0 & 0 & 0 & 0 & \times \\
0 & 0 & 0 & \times & \times \\
\times & \times & \times & \times & \times \\
0 & \times & \times & \times & \times \\
\times & \times & \times & \times & \times \\
\hdashline
0 & 0 & \times & \times & \times \\
\times & \times & \times & \times & \times \\
\times & \times & \times & \times & \times \\
\times & \times & \times & \times & \times \\
\times & \times & \times & \times & \times
\end{array}\right]
\end{array}
$$

Adding assumptions from Fisher (2006)

$$
\begin{bmatrix} \mathbf{IR}_0 \\ \mathbf{IR}_\infty \end{bmatrix} =
\begin{array}{r}
 \\ \Delta tfp \\ \Delta q \\ u \\ \Delta sp \\ h \\ i \\ \Delta tfp \\ \Delta q \\ u \\ \Delta sp \\ h \\ i
\end{array}
\begin{array}{c}
\begin{array}{cccccc} \text{MP} & \text{Pref.} & \text{News} & \text{U} & \text{TFP} & \text{IST} \end{array} \\
\left[\begin{array}{cccccc}
0 & 0 & 0 & 0 & \times & \times \\
0 & 0 & 0 & \times & \times & \times \\
\times & \times & \times & \times & \times & \times \\
\times & \times & \times & \times & \times & \times \\
0 & \times & \times & \times & \times & \times \\
\times & \times & \times & \times & \times & \times \\
\hdashline
0 & 0 & \times & \times & \times & \times \\
0 & 0 & 0 & 0 & 0 & \times \\
\times & \times & \times & \times & \times & \times \\
\times & \times & \times & \times & \times & \times \\
\times & \times & \times & \times & \times & \times \\
\times & \times & \times & \times & \times & \times
\end{array}\right]
\end{array}
$$

Notes: Identifying assumptions from Beaudry and Lucke (2010) (left panel): identified shocks are to monetary policy (MP), preferences (Pref.), news, investment-specific technology (IST), and total factor productivity (TFP); variables are first-differenced log TFP (Δtfp), first-differenced log relative price of investment (Δq), first-differenced log real S&P 500, log total per-capita hours, and the Federal funds rate; zeros indicated zero restrictions and $\times$ indicates no restrictions; upper matrix partition ($\mathbf{IR}_0$) summarizes short-run restrictions, and lower partition ($\mathbf{IR}_\infty$) summarizes long-run restrictions. To identify uncertainty shocks (U), the right panel includes a measure of uncertainty (u) and imposes the additional assumption from Fisher (2006) that only IST shocks affect the relative price of investment in the long-run.

additional assumptions must be made. To minimizes the changes from Beaudry and Lucke's (2010) identification of news shocks, I add additional long-run restrictions from Fisher (2006) to identifying IST shocks: specifically, that only IST shocks affect the relative price of investment in the long run. Because I add a measure of uncertainty, I maintain Beaudry and Lucke's (2010) assumption that only TFP shocks can affect TFP contemporaneously. In addition, I relax the assumption that IST shocks cannot affect TFP contemporaneously.[20]

I implement and estimate these combined short- and long-run restrictions using the algorithm of Rubio-Ramírez et al. (2010). The system as summarized in the right panel of Table 1 is globally identified, and is partially identified up to the uncertainty shock even with different assumptions on the TFP and IST shocks.

Disagreement shocks accounting for a meaningful share of the variance of per-capita hours, but not for unemployment or GDP growth. Moreover, the majority of the variance of disagreement/uncertainty is accounted for by news shocks. This is the rationale for the statement that uncertainty is mostly an endogenous response to other shocks. At short horizons less than a year, about 1/3 of the fluctuations in household uncertainty are attributable to uncertainty shocks. At horizons more than a few years, the majority of fluctuations in household uncertainty is due to first-moment news shocks.

[20] This additional assumption is innocuous in the partial identification of uncertainty shocks, although it does affect the relative importance of neutral versus investment-specific technology shocks.

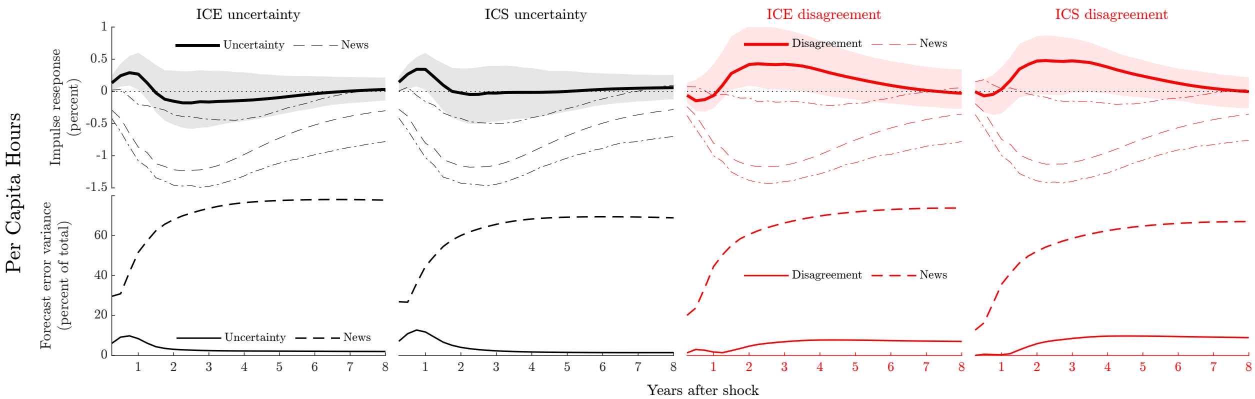

FIGURE 10: UNCERTAINTY AND NEWS SHOCKS: IRFS AND FEVDS

Notes: Impulse response functions with 90% pconfidence intervals and percentage of forecast error variance due to uncertainty (solid lines) and news shocks (dashed lines) with identifying assumptions summarized in Table 1. One-standard deviation shocks (increase for uncertainty, decrease for news) using ICE and ISC uncertainty and disagreement measures from the Michigan Survey fo Consumers, 1965–2019.

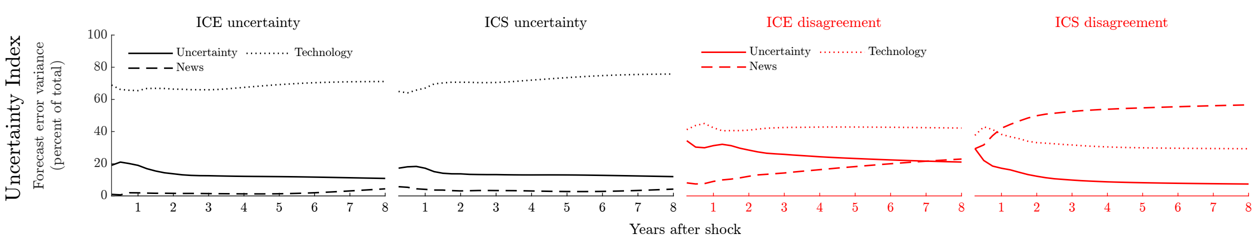

FIGURE 11: FORECAST ERROR VARIANCE DECOMPOSITION OF UNCERTAINTY MEASURES.

Notes: Percentage of forecast error variance of uncertainty/disagreement due to uncertainty, news, and neutral and investment-specific technology shocks with identifying assumptions summarized in Table 1, 1965–2019.