The Role of Household Uncertainty in U.S. Business Cycles: Evidence from the Michigan Survey of Consumers

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Abstract

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

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

JEL classification: C32, C82, D80, E32.

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1 Introduction

Macroeconomic uncertainty even when carefully defined, is difficult to measure objectively. Consequently, a considerable amount of empirical 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 uncertainty?" And since most of these measures increase during economic downturns, a parallel line of research has examined the causal role of uncertainty in the business cycle to answer 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 a focus primarily on *household uncertainty*, in contrast to uncertainty faced, for example, by firms, stock 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 from qualitative survey data based on sign and size restrictions on impulse responses to estimate uncertainty's effects on unemployment and output, and I 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 and unemployment, and its endogenous response to other shocks contributes almost nothing to the effect of those shocks on the economy.

This conclusion is in marked contrast to some results that obtain when I instead consider *firm uncertainty.* The techniques developed here can easily be applied to other sources of qualitative data on sentiments; therefore, throughout the paper, I contrast results for household uncertainty from the Michigan Survey to those for firm uncertainty from a similar survey of businesses. I find a substantially larger role for firm uncertainty, a result that highlights the need to focus on just whose uncertainty matters for the macroeconomy.[2]

The household uncertainty indices I construct from the Michigan Survey measure uncertainty about personal finances, broader economic conditions, and buying conditions in large, highly visible markets. Survey responses are coded favorable ("times are good"), unfavor-

[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] This conclusion echoes that of Kehoe, Lopez, Midrigan and Pastorino (2020), for example, who conclude that firm-side credit constraints played a larger role in the Great Recession than did those of households.

able ("times are bad"), neutral, or a statement that the interviewee is uncertain or does not know, among others. I base one class of these new measures on the number of survey respondents who quite literally say they are uncertain or do not know when asked about economic conditions, while another is based on disagreement among survey respondents, as in Bachmann and Sims (2012), White (2018), and Pinto, Sarte and Sharp (2020).

These new measures complement existing proxies for uncertainty. Other measures of uncertainty are derived from a variety of sources. They frequently are based on stock market volatility, survey responses, newspaper text analysis, or forecast errors of large datasets; they aim at measuring uncertainty about the macroeconomy, financial markets, business conditions, or policy decisions; and they differentiate among uncertainty as perceived by households, market participants, professional forecasters, firms, and policymakers. I discuss many of these in Section 2, but a complete overview is outside the scope of this paper.[3]

Household uncertainty indices derived from the Michigan Survey of Consumers have several advantages over existing proxies. First, as mentioned above, 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)) and professional forecasters (Coibion, Georgarakos, Gorodnichenko, Kenny and Weber (2024)). 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 sentiments like consumer confidence, which might be correlated with uncertainty, as recommended by Leduc and Liu (2016) and Coibion et al. (2024). The Michigan Survey is the source of the most commonly used measures of consumer confidence,[4] so first- and second-moment sentiment measures can be constructed from the same survey and, indeed, responses to the exact same questions.

As many have pointed out, changes in uncertainty might partly reflect endogenous responses to changes in confidence or fundamental shocks. In Section 3.1, I demonstrate that it is especially important to account for first-moment sentiments in the context of survey-based measures of uncertainty. One simple approach to address this issue, if the goal is to identify an uncertainty shock, is to include a measure of confidence ordered prior to uncertainty in

[3]For an excellent overview of existing measures, see Cascaldi-Garcia et al. (2023).

[4]See, for example, Barsky and Sims (2011), Bachmann and Sims (2012), and Bolhuis, Cramer, Schulz and Summers (2024).

a recursively identified (Cholesky) structural VAR as in Leduc and Liu (2016).[5] But that technique also implicitly imposes—somewhat implausibly—that uncertainty cannot affect confidence contemporaneously, nor indeed can other variables ordered after uncertainty affect it contemporaneously. Recent work by Ludvigson et al. (2021) and Bernstein, Plante, Richter and Throckmorton (forthcoming) provides strong evidence that rejects the zero contemporaneous response assumptions of uncertainty shocks identified in Cholesky VARs.

Informed by these results, I take a more "agnostic" approach pioneered by Uhlig (2005) in the context of monetary policy to 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 first- and second-moment sentiment shocks that are orthogonal both to each other and to other identified macroeconomic shocks.

In particular, I specify that a confidence shock causes favorable and unfavorable responses to economic questions to move in opposite directions—more people think times are good and fewer think they are bad—while an uncertainty shock causes favorable and unfavorable responses to move in the same direction—there is more disagreement. Intuitively, a confidence shock affects the mean response, while an uncertainty shock increases the dispersion of responses. 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 impact effects in absolute value than fundamental shocks on certain variables.[6]

I find that 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 5 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.[7] To assess this possibility, I adapt the methods of Sims and Zha

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

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

[7] For example, even though monetary policy shocks are typically found to have fairly small effects, the

(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.

By contrast, I find a somewhat larger role for firm uncertainty—measured in a similar way using the Federal Reserve Bank of Philadelphia's Manufacturing Business Outlook Survey—as both a source of business cycle fluctuations and as an amplifier of other shocks. Firm uncertainty shocks lead, in some specifications, to large and signficant effects on output, unemployment, and investment and can explain between 10 and 15 percent of the forecast error variances of these variables. I also find that both household and firm confidence shocks play a larger role than uncertainty shocks, but household confidence shocks have larger effects than firm confidence shocks (30 to 40 percent, and 15 to 20 percent of the forecast error variance of unemployment, respectively).

These results imply that household uncertainty is neither a driver of economic fluctuations, nor, despite its often large and significant endogenous responses to them, is it an amplifier of other macroeconomic shocks.[8] I conclude that household uncertainty plays essentially no role in U.S. business cycles.

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

endogenous response of monetary policy to other shocks is likely critical to the transmission of those shocks to the macroeconomy, as Bernanke, Gertler and Watson (1997) find with oil price shocks.

[8]In some recent work, Bernstein et al. (forthcoming) show a similar result in a theoretical model—uncertainty arises as an endogenous response to unemployment fluctuations and has effects two orders of magnitude smaller than a first-moment level shock.

2 New measures of household uncertainty

In this section, I describe the Michigan Survey of Consumers and the uncertainty indices 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 for firms. The former measure potentially conflates confidence and uncertainty, as I discuss below, a distinction that is crucial for identification of causal effects. The latter method can be applied in a straightforward way to construct disagreement proxies for uncertainty from the Michigan Survey. I then compare these indices with other existing proxies for uncertainty.

2.1 Uncertainty measures from the Michigan Survey

The Michigan Survey of Consumers is a monthly survey of individuals in the United States[9] 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.[10] 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, who refused to answer, 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?"*
>
> (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?"*

[9] Excluding Alaska and Hawaii.

[10] 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.

(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 what I call *direct* 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. The logic is that a second-moment measure derived from these questions is likely to be more informative about macroeconomic uncertainty if that measure's first moment (favorable responses) is correlated with the broadest measure of the macroeconomy.

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

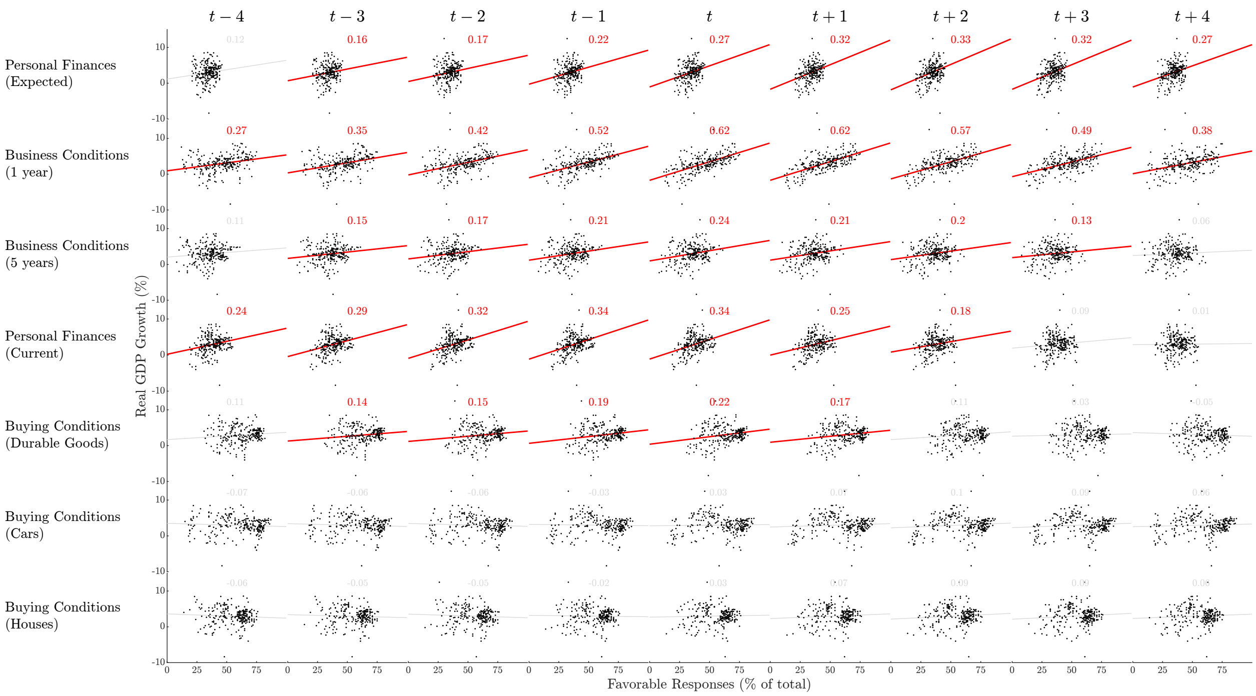

FIGURE 1: FAVORABLE RESPONSES AND REAL GDP GROWTH, 1960–2019

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.

macroeconomic conditions. In most of what follows, I do not consider the questions about buying conditions for cars and houses.[11]

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.[12]

[11] 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.

[12] The headline indices of consumer confidence are constructed in the same way, but instead sum the difference between favorable and unfavorable responses to the component questions. I discuss the importance of the assumptions that underlie this method in Section 3.1.

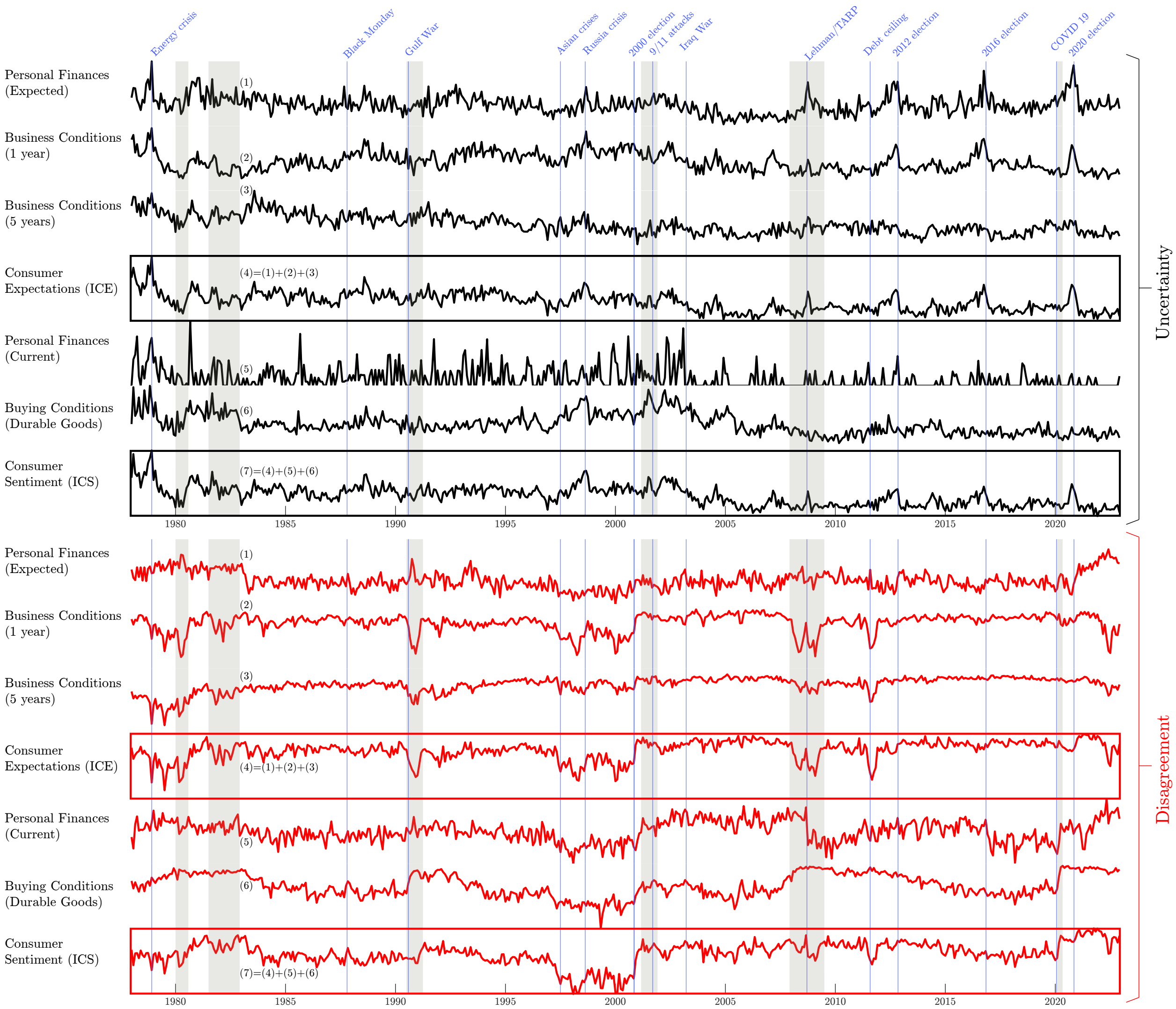

Figure 2: Uncertainty and disagreement measures from the Michigan Survey

Notes: Uncertainty (upper panel, black) and disagreement (lower panel, red) measures and indices from the Michigan Survey of Consumers, 1978–2022. ICE and ICS 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.

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 defined in Bloom (2009). 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 discussed below in Section 2.3 support the notion that household uncertainty actually is something different from uncertainty facing other economic agents.

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 Manufacturing Business Outlook Survey, which Bachmann et al. (2013) use to construct a proxy for firm uncertainty 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:

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

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 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) measure of household uncertainty from the Michigan Survey and why it is probably better interpreted as a first-moment measure of (low) confidence rather than a second-moment measure of uncertainty. I then compare the new indices described above to theirs and other measures of 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[13] 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.[14]

But there is another potentially more serious problem with this measure of uncertainty. The response categories in this table on the Michigan Survey's public website 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 about why it is a bad time to buy a car.[15] Many of the twelve categories in Table 38 of the public-facing site 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 seems much more about a first-moment sentiment (a bad future) than a second moment (an uncertain future).

Surveyors must necessarily exercise some judgment when coding qualitative interview responses. So, it is certainty 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*. Indeed, it is highly negatively correlated with the Index of Consumer Expectations

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

[14] The possibility of expansionary effects of uncertainty shocks is emphasized in Fernández-Villaverde and Guerrón-Quintana (2020).

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

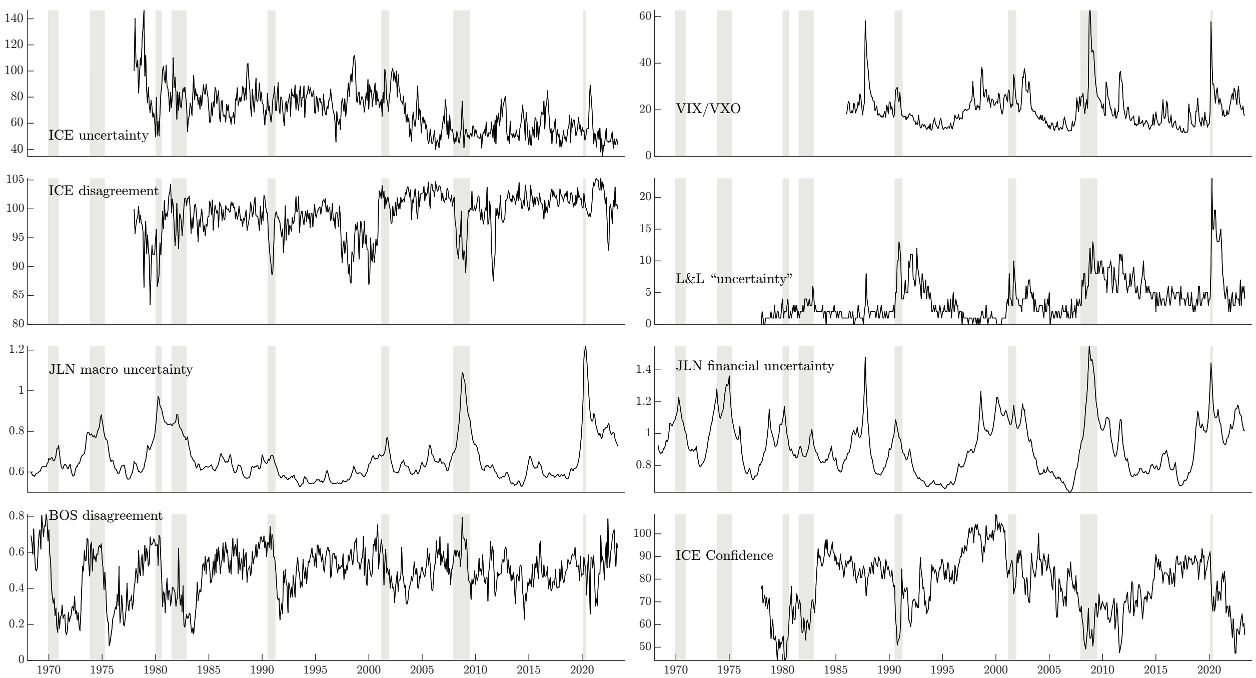

FIGURE 3: UNCERTAINTY AND CONFIDENCE MEASURES, 1968–2023.

Notes: Index of Consumer Expectations (ICE) measures as described in Section 2, Leduc and Liu's (2016) measure from the Michigan Survey (L&L), macroeconomic and financial uncertainty from Jurado et al. (2015) (JLN), disagreement from the Philadelphia Fed's Business Outlook Survey (BOS), and the volatility index (VIX) of the S&P 500 spliced with the implied volatility index (VXO) before 1990. Gray bands are NBER recessions.

confidence measure (see Figure 3). It is perhaps not surprising, then, that shocks to this measure of "uncertainty" are strongly contractionary, especially in light of the results for first-moment sentiment shocks I present below. The indices I construct above are arguably more reasonable measures of uncertainty, and I compare them with Leduc and Liu's (2016) and other existing measures below.[16]

2.3.2 Other types of uncertainty

As described in the introduction, a number of measures exist that describe uncertainty faced by firms, professional forecasters, market participants, and ones derived from large datasets of macroeconomic and financial data. Figure 3 displays the indices of consumer expecta-

[16]Leduc and Liu's (2016) primary contribution is theoretical, and the discussion above is in no way an attempt to invalidate that. The uncertainty that exists in their model is about aggregate total factor productivity, which most directly affects firm hiring decisions via a free-entry condition; the contractionary effects of uncertainty shocks in their model are arguably more analogous to the contractionary effects I find below of shocks to *firm* uncertainty.

tions[17]—direct uncertainty, disagreement proxy, and confidence—along with Leduc and Liu's (2016) measure from the Michigan survey, the VIX/VXO from Bloom (2009), Bachmann et al.'s (2013) measure of firm uncertainty (proxied by disagreement) from the Philadelphia Fed's Business Outlook survey (BOS), and macroeconomic and financial uncertainty from Jurado et al. (2015).

A few similarities and differences are worth pointing out. While the Great Recession was a period of high uncertainty by most other measures, it was a period of low uncertainty by these new household measures. But that is simply because it was a period extremely *low* confidence (see the bottom right panel of Figure 3). Few respondents in the Michigan Survey said directly that they were uncertain and there was little disagreement: most people said the future was looking unfavorable. Despite these low levels, a noticeable spike in both ICE disagreement and uncertainty measures in September 2008 at the height of the financial crisis. By contrast, the early 1990s recession was a period of low macroeconomic uncertainty by the Jurado et al. (2015) measure and low uncertainty by the ICE disagreement measure, although it was period of high financial uncertainty, high uncertainty as measured by Leduc and Liu (2016), and low household confidence.

These new measures do indeed seem to be capturing uncertainty given the patterns observed in Figure 2 and the alignment with other measures of uncertainty. Moreover, the comparisons discussed above and displayed in Figure 3 indicate that household uncertainty might be fundamentally different from other existing measures of uncertainty. Finally, the straightforward comparison with indices of a first-moment sentiment like confidence computed from the same set of responses to the same set of questions allows for an arguably cleaner identification of shocks to uncertainty. I discuss this issue in detail in the next sections.

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 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.

[17]The indices of consumer sentiment are nearly identical to those of consumer expectations, so I do not included them here.

I first argue below in Section 3.1 that appropriately controlling for first moments like consumer confidence 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 strongly support the inclusion of first-moment sentiment measures in all VAR-based estimates of the effects of uncertainty shocks, and especially for including the first-moment measure ordered prior to the uncertainty measure in Cholesky-identified VARs, some of which I estimate in Section 3.2. However, the discussion below 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 first moments

As discussed in, for example, Bloom (2014), Leduc and Liu (2016), and Coibion et al. (2024), separately identifying first- and second-moment shocks is a major challenge unique to the identification of uncertainty shocks and estimating their effects. 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 an endogenous response of uncertainty directly to a confidence shock. 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 2.2, expressed here slightly differently:

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

where d denotes disagreement, g ("good") denotes the fraction of favorable responses, and b ("bad") denotes the fraction of unfavorable responses. Commonly used measures of confidence like the ICS and ICE[18] from the Michigan Survey, are normalized versions of the equation $c = g - b$, where c denotes confidence.[19] Clearly, $g - b$ appears directly in the expression for d above. This fact can induce an almost mechanical correlation between

[18] See, for example, Barsky and Sims (2011), Bachmann and Sims (2012), and Bolhuis et al. (2024).

[19] These first- and second-moment expressions are the "correct" ones in that they correspond to the mean and variance if the responses to survey questions are modeled as multinomial random variables with favorable responses coded numerically as a 1 occurring with probability g, unfavorable responses as a -1 occurring with probability b, and neutral responses as a 0 occurring with probability $1 - g - b$. I discuss this in more detail in Section 3.2.

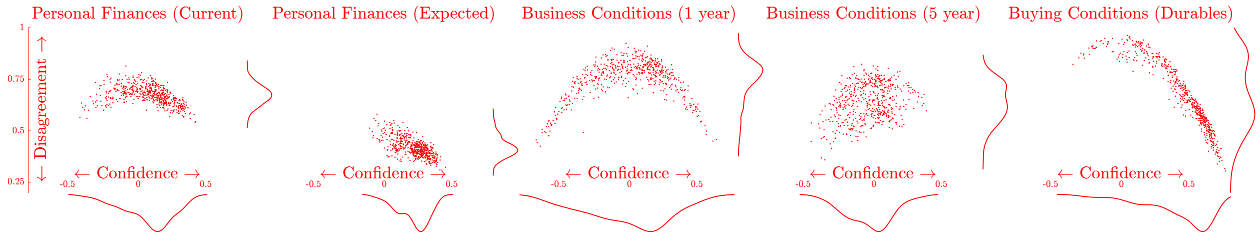

FIGURE 4: FIRST AND SECOND MOMENTS

Notes: Confidence and disagreement along with the marginal distributions of each measure. Marginal distributions from a kernel density estimation.

confidence and disagreement, which is evident in Figure 4, which plots disagreement and confidence along with marginal distributions from a kernel density estimation. For nearly all measures of disagreement the negative correlation near the modal values of the marginal distributions is obvious at a quick glance.

To see how this correlation relates to first- and second-moment *shocks*, note that any combination of g and b can be mapped to unique "iso-confidence" and "iso-uncertainty" curves in (g, b) space, the first being the line along which $g - b$ is constant and the second being a portion of the rotated parabola along which $g + b - (g - b)^2$ is constant. Examples of these iso-quant curves are displayed in the center panel of Figure 5. From the intersection point of the curves, the shaded areas illustrate the directions of changes in g and b that result in higher or lower confidence or uncertainty. If the pattern of favorable and unfavorable responses of each underlying question in the uncertainty indices lie mostly within the shaded regions, then there will be negative correlation between first- and second-moment shocks—that is, decreases in confidence will tend to be accompanied by increases in uncertainty, as measured by disagreement.

The scatter plots in the outer panels of Figure 5 display the pattern of favorable and 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 disagreement moving in opposite directions. It is most obvious for durable goods buying conditions. Figures 4 and 5 illustrate concretely the need to account for first moments like confidence to identifying uncertainty shocks: in any estimating equation that does not include confidence, uncertainty will be correlated with the error term. Figure 5 also points 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 5 gives a clear graphical inter-

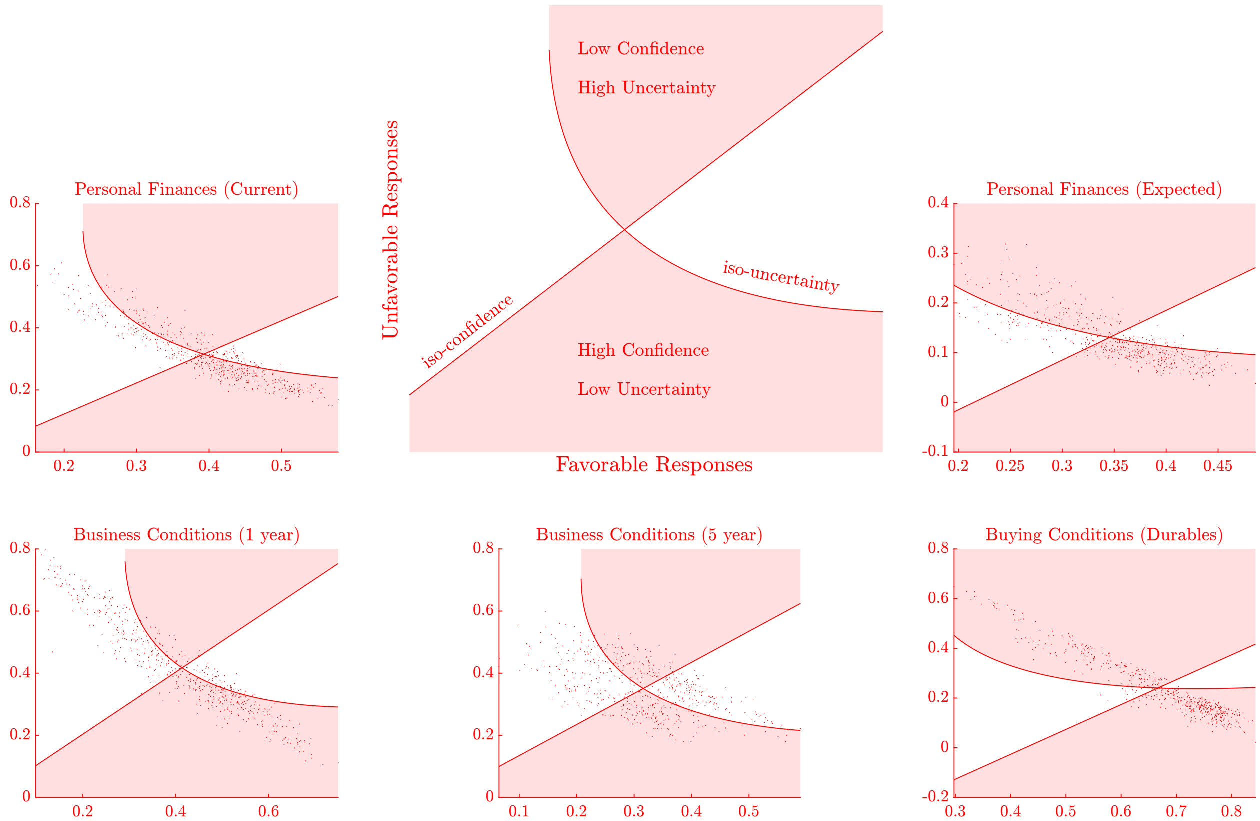

FIGURE 5: ISO-QUANT CURVES

Notes: Iso-confidence and iso-uncertainty along with observed patterns of favorable and unfavorable responses. When points lie mostly in shaded regions, increases in uncertainty tend to be accompanied by decreases in confidence. Conceptually, appropriately accounting for a first-moment sentiment holds the iso-confidence curve fixed and shifts the iso-disagreement curve when estimating uncertainty shocks.

pretation for what an uncertainty shock is: a shift in the iso-uncertainty curve holding the iso-confidence curve fixed. This is exactly what including confidence ordered before uncertainty in a Cholesky-identified VAR does. I explore this idea in Section 3.2 and describe the new method of jointly identifying confidence and uncertainty shocks 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[20] 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 assumption that only uncertainty shocks and no other 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.[21] 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 (log) industrial production, CPI inflation, and the three-month Treasury rate. For each measure of uncertainty or disagreement I include the corresponding measure of confidence.[22] All variables are in levels; I include a constant and 12 months of lags, using data from January 1978 to December 2019, and compute error bands using a standard nonparametric residual-based recursive-design bootstrap.[23]

Impulse responses and the percent of forecast error variance attributable to uncertainty

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

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

[22] 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.

[23] As described in, for example, Kilian (1998) and Kilian and Lütkepohl (2017).

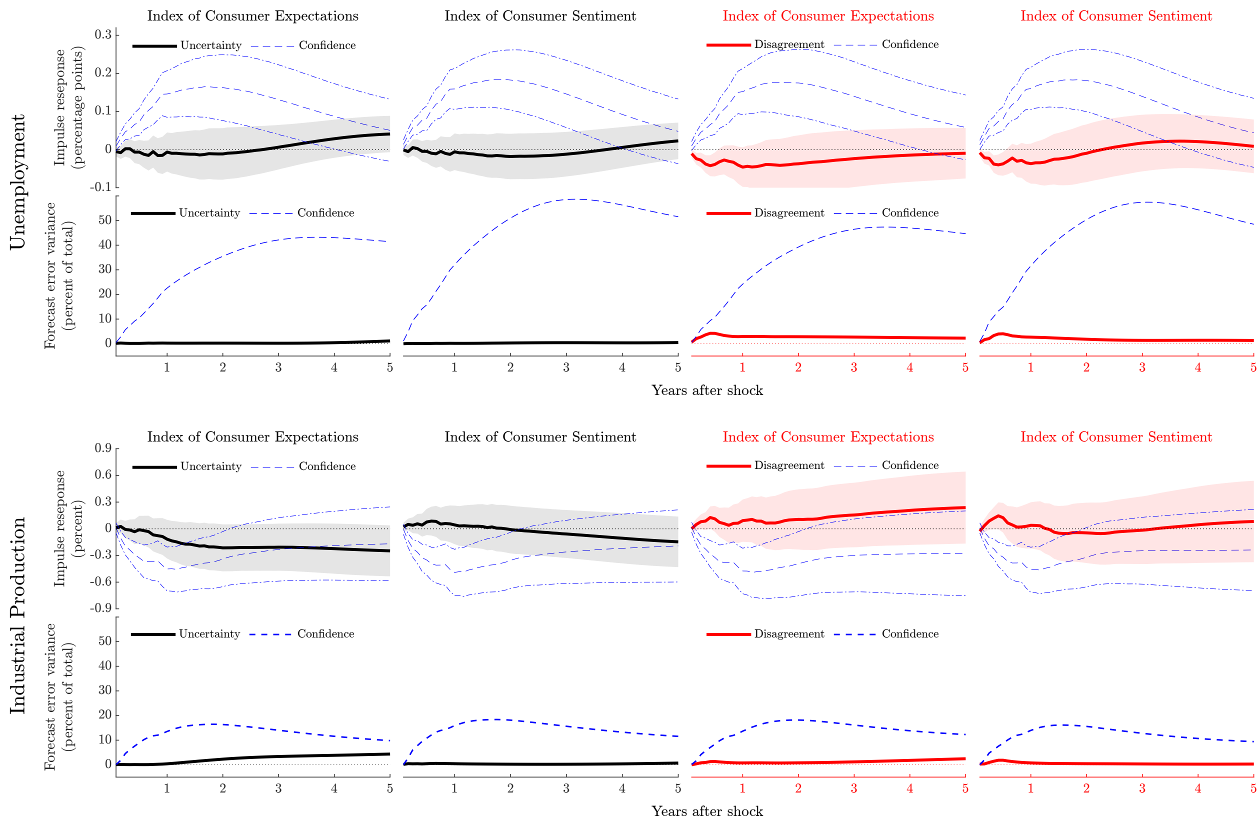

Figure 6: Household sentiment shocks, Cholesky VARs: monthly, 1978–2019

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.

shocks are displayed in Figure 6 (solid lines and shaded error bands). Impulse responses are to a one standard deviation shock that increases direct uncertainty or the disagreement proxy. Shocks to household uncertainty have insignificant effects on unemployment and industrial production, with the exception of shocks to disagreement proxies, which are very mildly expansionary over short horizons. In no case do uncertainty shocks explain more than 5 percent of the forecast error variance of real activity.

By contrast, the dashed lines in Figure 6 show the responses of the same variables to shocks to confidence (a *decrease* of one standard deviation). Negative confidence shocks lead to large and significant increases in unemployment and decreases in industrial production. These first-moment shocks to confidence explain up to 50 percent of the variance of real activity, an order of magnitude greater than second-moment shocks to uncertainty. Of course, referring back to Figure 5, 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: identifying a first-moment shock requires controlling for second moments, in this context by ordering uncertainty *before* confidence in a VAR. Therefore, a Cholesky VAR cannot simultaneously identify first- and second-moment shocks. This fact in part motivates the new approach to joint identification of uncertainty and confidence shocks below.

Before doing that, it should be noted that the indices based on disagreement proxies discussed in Section 2.2 can be extended back to 1960 on a quarterly basis.[24] While this allows for estimation based on a longer sample period, quarterly data availability means the overall number of observations 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.

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

The results, however, are mostly in line with the monthly estimates that begin in 1978. Figure 7 displays impulse responses and forecast error variance decompositions for unemployment, real GDP, consumption, and durable goods consumption to uncertainty (disagreement) and confidence 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. (2024). Uncertainty shocks nevertheless still account for less than 5 percent 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

[24]Direct uncertainty indices cannot be extended to this prior period because a separate breakdown does not exist in this earlier period that differentiates respondents who directly say they are uncertain or don't know from those who refused to answer or whose response is missing.

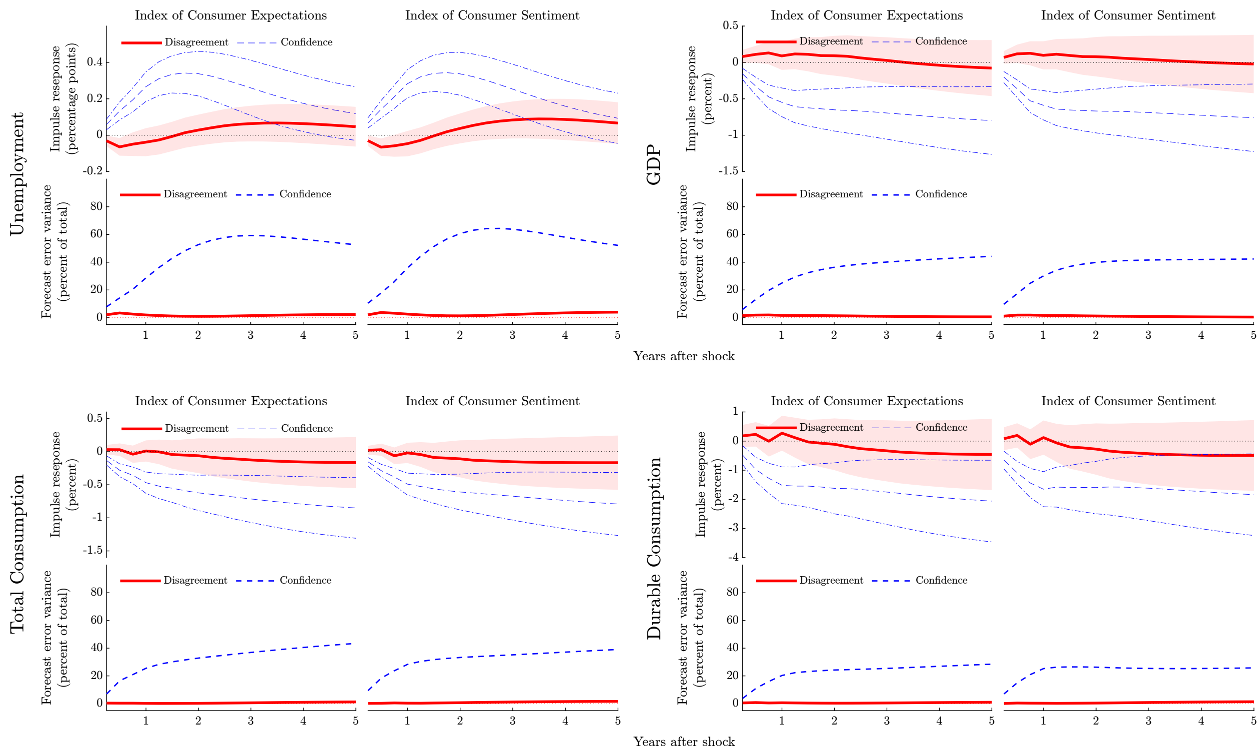

FIGURE 7: HOUSEHOLD SENTIMENT SHOCKS, CHOLESKY VARS: QUARTERLY, 1960–2019

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.

of the variance of real activity.

It is instructive to compare these results to similar ones for *firm* uncertainty. Figure 8 displays the impulse responses and forecast variance decompositions for the same variables as Figures 6 and 7 when the measures of household sentiment are replaced with firm confidence and uncertainty (proxied using disagreement) from the Federal Reserve Bank of Philadelphia's Manufacturing Business Outlook Survey, as in Bachmann et al. (2013).

The differences are stark. Firm uncertainty shocks significantly increase unemployment and decrease industrial production in the monthly specification and decrease real GDP, consumption, durable goods consumption, and investment in the quarterly specification.[25]

[25]Since the BOS data begin in July 1968, the sample period is the same in both the monthly and quarterly specifications; for that reason, I substitute investment in place of unemployment in the quarterly specification since the responses are essentially the same regardless of the frequency of the data.

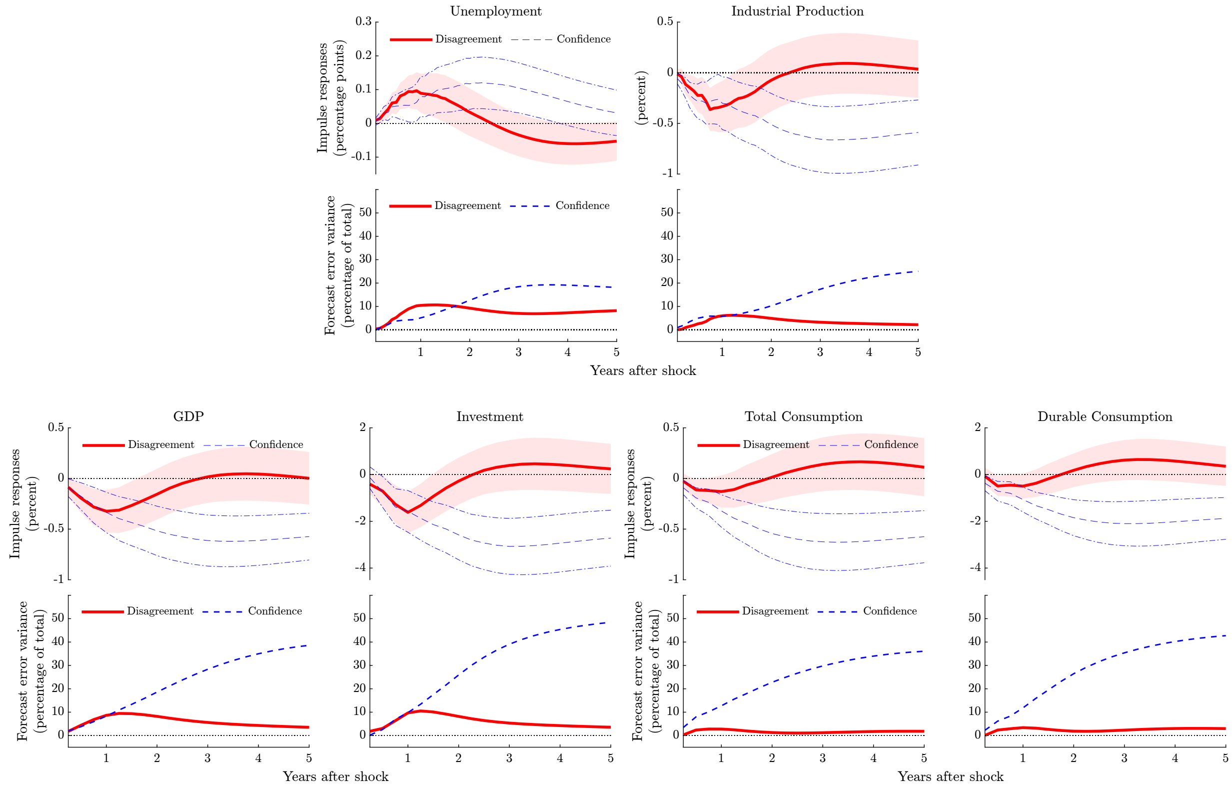

FIGURE 8: FIRM SENTIMENT SHOCKS, CHOLESKY VARS: 1968:Q3–2019

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

Investment in particular falls by about two percent in the year following a one standard deviation shock to firm uncertainty. Firm uncertainty shocks still explain a relatively small fraction of real activity (about 10 percent for investment), but a larger fraction than household uncertainty does. On the other hand, shocks to firm confidence have somewhat smaller effects than household confidence, although the effects are still large.

Thus, the simplest and most common method of identifying uncertainty shocks 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 easily defensible, especially when trying to jointly identify uncertainty and confidence shocks. To see this last point, note that the argument in Section 3.1 applies to both confidence and uncertainty: identification of first-moment shocks require properly controlling for second-moments. One cannot hold both the iso-quants curves in Figure 5 fixed: at least one curve has to shift if responses change. In a recursively identified system, contemporaneous values of one of these can appear in the equation for the other, but not both.[26]

Another potential issue regards the definition of disagreement. Suppose total responses to a survey question are modeled as a multinomial random variable in which favorable responses are coded with a $+1$, unfavorable responses are coded as a -1, neutral or missing responses are coded as a 0, and those outcomes obtain with probabilities g, b, and $1-g-b$, respectively. Then the expected value (first moment) of the fraction of total responses made up by favorable responses is $g-b$, which is the typical measure of confidence; moreover its variance (a second moment) is $g+b-(g-b)^2$. These are exactly the measures of confidence and disagreement used above for both the Michigan Survey and the Business Outlook Survey; the expressions are therefore defensibly interpreted as measuring first- and second-moment measures of sentiment.

Although this particular numerical coding of qualitative responses is natural, it is also somewhat arbitrary. By the logic above, other numerical codings of these qualitative responses would imply different confidence and disagreement measures. For example, the Institute for Supply Management's indices of manufacturing activity code neutral responses as equal to $+\frac{1}{2}$ instead of zero; the resulting mean and variance of the random variable based on that definition are different from the ones above. In this convention, the mean is $c = g - b + \frac{1}{2}s$ and the variance is $d^2 = g + b + \frac{1}{4}s - (g - b + \frac{1}{2}s)^2$, where $s = 1 - g - b$ denotes a neutral response ("same"). Thus differences in the somewhat arbitrarily chosen numerical coding of qualitative responses lead to different measures of disagreement, different shapes of the iso-quant curves, and different estimates of the effects of uncertainty shocks. These differences are illustrated in the left two columns of Figure 9.

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

These shortcomings motivate the next section, in which I propose a new method of jointly identifying confidence and uncertainty shocks in a way that does *not* depend on the arbitrary numerical assignment described above.[27] I use sign restrictions to separately identify first-

[26] Using very different methods both Ludvigson et al. (2021) and Bernstein et al. (forthcoming) also strongly reject contemporaneous zero restrictions to identify uncertainty shocks.

[27] Indeed, it is consistent even with using other concepts like the Shannon entropy or Fisher information

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 Joint identification by sign restrictions

Uhlig (2005) proposed identifying monetary policy shocks by somewhat more "agnostic" restrictions on the signs of impulse responses: a contractionary monetary policy shock increases the federal funds rate and lowers inflation, for example. In this section I extend this approach of sign restrictions to simultaneously identify confidence and uncertainty shocks (using disagreement proxies) without imposing the unpalatable zero restrictions in the Cholesky-identified systems considered above. But these less restrictive assumptions come at a cost: there are many orthogonalizations of the reduced-form VAR residuals that will satisfy the sign restrictions.

Figure 4 makes it clear that commonly used uncertainty measures are conditionally correlated with confidence. But Figures 5 and 9 make equally clear that less restrictive measures of changes in confidence and uncertainty can be constructed in a fairly straightforward way. Regardless of how confidence and disagreement are measured—or how qualitative responses to survey questions are coded numerically—a shock that increases confidence is associated with an increase in favorable responses and a decrease in unfavorable responses, while a shock increase in uncertainty (disagreement) sees an increase in both favorable and unfavorable responses. This is evident in the left two columns of Figure 9.

So, to jointly identify confidence and uncertainty shocks, I simply assume that a positive shock to confidence causes an increase in g and a decrease in b, while a positive shock to uncertainty causes an increase in both g and b. The right column of Figure 9 illustrates how this approach correctly identifies both confidence and uncertainty shocks regardless of the details of how one chooses to numerically code qualitative survey responses.

With any of the survey measures above, suppose for simplicity that $x_t = [g_t, b_t]'$ follows a structural VAR(1) process

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

With estimates for the reduced-form VAR coefficients and residuals from

$$x_t = A x_{t-1} + u_t,$$

of a random variable to measure uncertainty, at least over the regions of observed (g, b) pairs.

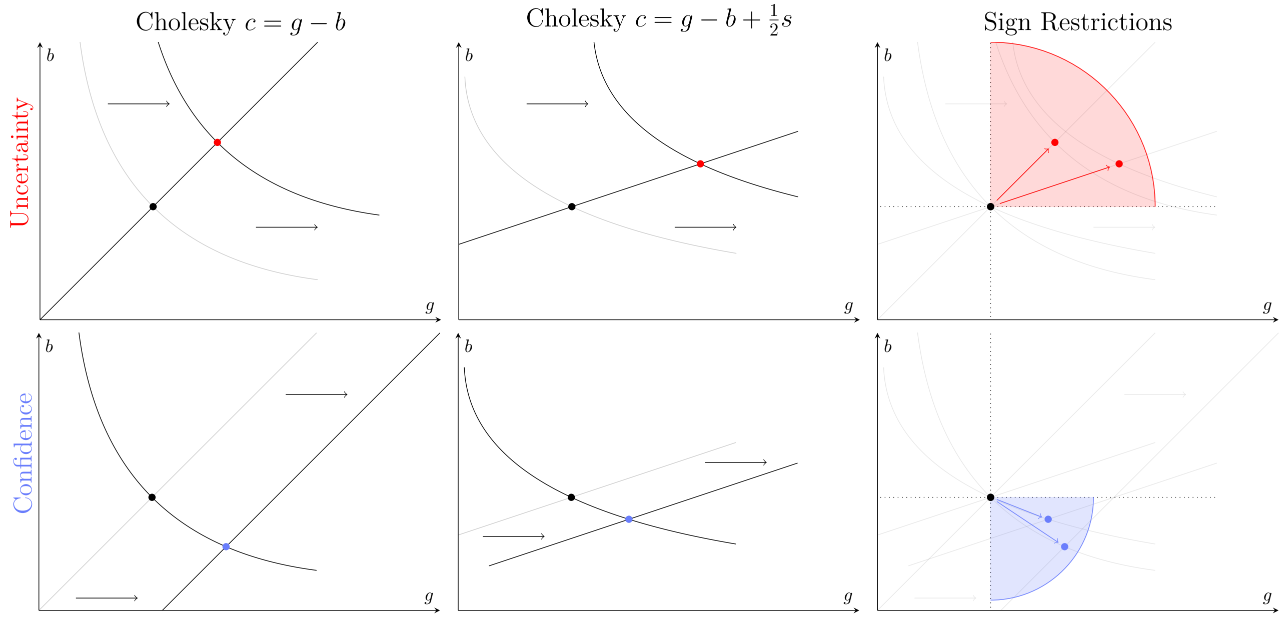

FIGURE 9: CHOLESKY VS. SIGN RESTRICTIONS FOR IDENTIFICATION

Notes: The upper panel illustrates an uncertainty 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 by the Insitute for Supply Management's, in which neutral responses are coded as $+\frac{1}{2}$, which changes both iso-confidence and iso-uncertainty curves. The right column illustrates how sign restrictions correctly classify the shocks as either uncertainty or confidence regardless of the particular assumptions made on how to code the qualitative responses numerically.

the goal is to find the set of B_0 matrices consistent with the less restrictive identification assumptions above, namely that the impulse responses satisfy the following sign restrictions:

$$\mathbf{IR}_0 = \begin{bmatrix} g_0 \\ b_0 \end{bmatrix} = \begin{array}{c} \\ g \\ b \end{array} \!\!\begin{array}{c} \text{Conf.} \quad \text{Uncert.} \\ \begin{bmatrix} + & \quad + \\ - & \quad + \end{bmatrix} \end{array},$$

where $\mathbf{IR}_0$ denotes the matrix of the impulse response on impact. Uncertainty shocks cause favorable and unfavorable responses to move in the same direction, while confidence shocks cause them to move in opposite directions. I impose these restrictions only on the impact effect of the shocks. 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.

One way to obtain this set of $\widehat{B}_0^*$ matrices in the two-dimensional case is to begin with any matrix B that satisfies the orthogonality condition—from a Cholesky decomposition, for example. Any rotation of the coordinate system given by the columns of B will maintain its orthogonality, and any counterclockwise rotation of it by angle θ can be found by multiplying B by

$$\mathcal{R}(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}.$$

For each value of θ on a fine grid on the interval from zero to 2π—or alternatively for each of many draws of random values of θ from the uniform distribution on that same interval—obtain the candidate matrix $\widehat{B}_0 = \mathcal{R}(\theta)B$ and compute impulse responses from it. The identified set $\left\{\widehat{B}_0^*\right\}$ is all such matrices whose impulse responses satisfy the required restrictions.

Extension of this simple process to dimensions higher than two, however, is not straightforward. So, to find this set of matrices below, I use the algorithm described in Rubio-Ramírez, Waggoner and Zha (2010). As above, begin with a matrix B that satisfies the orthogonality condition. Let X be a matrix with each element independently drawn from the standard normal distribution, and let $X = QR$ be the QR decomposition of X, which decomposes any square matrix into an orthogonal matrix Q and an upper-triangular matrix R, 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 $\widehat{B}_0 = QB$ satisfy the sign restrictions, it is in the identified set; if they do not, discard the draw; regardless of the outcome, return to the first step and draw a random matrix X until the desired number of draws is reached. Just as uniformly distributed two-dimensional rotation matrices can be obtained by drawing random values of θ from the continuous uniform distribution on $[0, 2\pi]$, the random orthogonal matrices Q are drawn from a "uniform" distribution in that any K-dimensional orthogonal matrix is equally likely to be selected by this algorithm, in the appropriate measure-theoretic sense.

For each admissible draw, full-horizon impulse responses and forecast error variance decompositions can be computed; this leads to an identified set of impulse responses and forecast error variance decompositions in contrast to point estimates from the Cholesky VARs above. This set of responses reflects *identification uncertainty* from a single estimate of reduced-form coefficients that itself is subject to *estimation uncertainty.* To accurately reflect this additional source of econometric uncertainty, I repeat the sign-identification algorithm for each bootstrap draw of reduced form coefficients from the same bootstrap algorithm

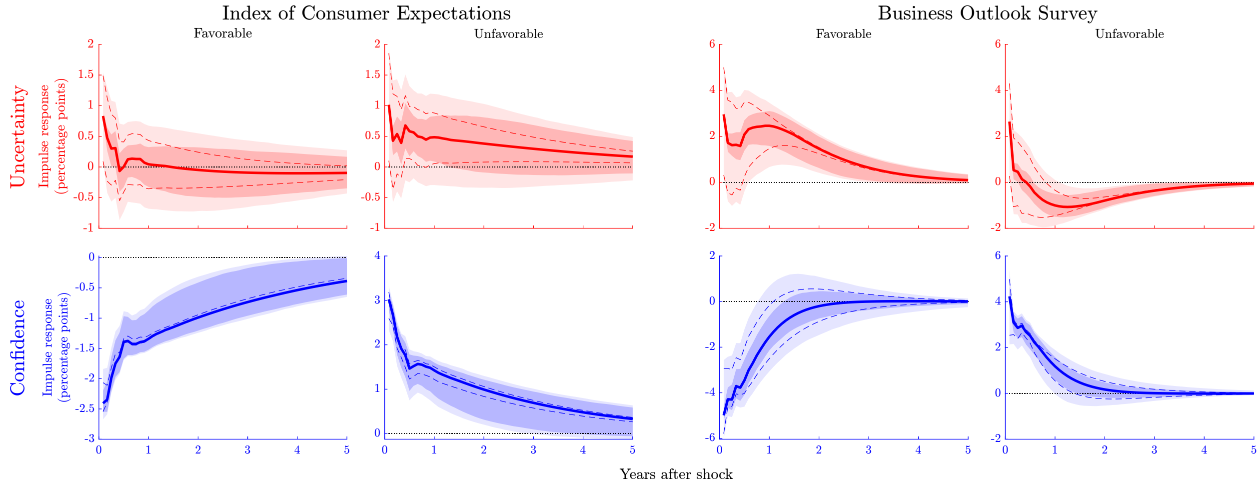

FIGURE 10: SENTIMENT SHOCKS: SIGN RESTRICTIONS, TWO-VARIABLE SYSTEM

Notes: Impulse responses of favorable and unfavorable responses to one standard deviation shocks. Uncertainty shocks (upper panel, red) and confidence shocks (lower panel, blue), identified by sign restrictions described in Section 3.3. Solid lines are medians from point estimates. Dashed lines reflect identification uncertainty while shaded areas measure estimation uncertainty, both 90% confidence intervals, as described in Section 3.3.

as in Section 3.2. To reduce computation times, in all estimates that follow I include six lags of each variable, which does not alter the results in any meaningful way.

Impulse responses to uncertainty and confidence shocks for the simple two-variable system of favorable and unfavorable responses for both the ICE and the Business Outlook Survey are displayed in Figure 10 (ICS responses are virtually identical to those of the ICE). The solid lines are the median responses from the point estimates of reduced-form coefficients. Dashed lines are the 90th percentile of all admissible rotations that satisfy the sign restrictions: they reflect identification uncertainty. Dark shaded bands indicate the 90th percentile of median responses from the bootstrap estimates, while the lightest and widest bands are the 90th percentile of the all admissible rotations of the bootstrap samples associated with the 90th percentile of the medians displayed. The shaded areas reflect estimation uncertainty.

Household confidence shocks have large and persistent effects on responses, while household uncertainty shocks have small, short-lived, and mostly insignificant effects. Firm confidence shocks have less persistent effects, but firm uncertainty shocks have larger and more signficant effects on favorable and unfavorable responses. Uncertainty shocks also explain a much larger share of the variance (not displayed) of firm-level survey responses (roughly 40 percent), while about 90 percent of the variance of household survey responses is due to confidence shocks.

This small two-variable system is illustrative of the key innovation of simultaneously identifying confidence and uncertainty shocks, but to associate these estimated effects of favorable and unfavorable responses with actual macroeconomic *shocks* requires expanding the system to include macroeconomic variables and additional identifying assumptions. I do so 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 uncertainty shocks. But it excludes macroeconomic variables, estimating the effects on which is the primary reason for identifying these shocks in the first place. In this section, I incorporate the method of identifying confidence and uncertainty shocks described above into a larger VAR system that includes the same macroeconomic variables in the monthly specifications above: unemployment, inflation, and the three-month 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.[28] Combined with the identifying assumptions from the previous section, the larger five-variable system is summarized by

[28]The additional restriction that the nominal interest rate moves in the same direction as inflation assumes the Fed increases rates in response to higher inflation. It does not change the results for confidence and uncertainty shocks.

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

where $\times$ indicates that no restriction is placed on the sign of the impact response.

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 plausible outcome since unemployment, inflation, and interst rates all 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 that end, I follow much of the literature on shocks to economic sentiment[29] 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 the interest rate than monetary policy shocks. These additional size restrictions, in conjunction with the sign restrictions described above, are sufficient to separately identify all five shocks.

I estimate two different models below. In the first, I do not impose any additional restrictions on the signs of the responses to unemployment, inflation, and the interest rate to uncertainty or confidence shocks. In the second, I impose the additional restriction that uncertainty and negative confidence shocks increase unemployment, but not until 6 months out. I impose this additional sign restriction half a year after the shock because of the forward-looking nature of the underlying survey questions. This second specification effectively "stacks the deck" in favor of finding larger effects of uncertainty shocks relative to the first.

Nevertheless, shocks to household uncertainty have essentially no effect on unemployment even when negative effects are *imposed* in identification. Impulse responses and forecast error decompositions of the unemployment rate for uncertainty and confidence shocks are displayed in Figure 11. I include both household ICE measures and firm measures from the Business Outlook Survey.[30] Neither household nor firm uncertainty shocks have large

[29]For example, Beaudry and Portier (2006), Bachmann and Sims (2012), Beaudry and Lucke (2010)

[30]As in Section 3.2, results from the ICS are virtually identical to those from the ICE.

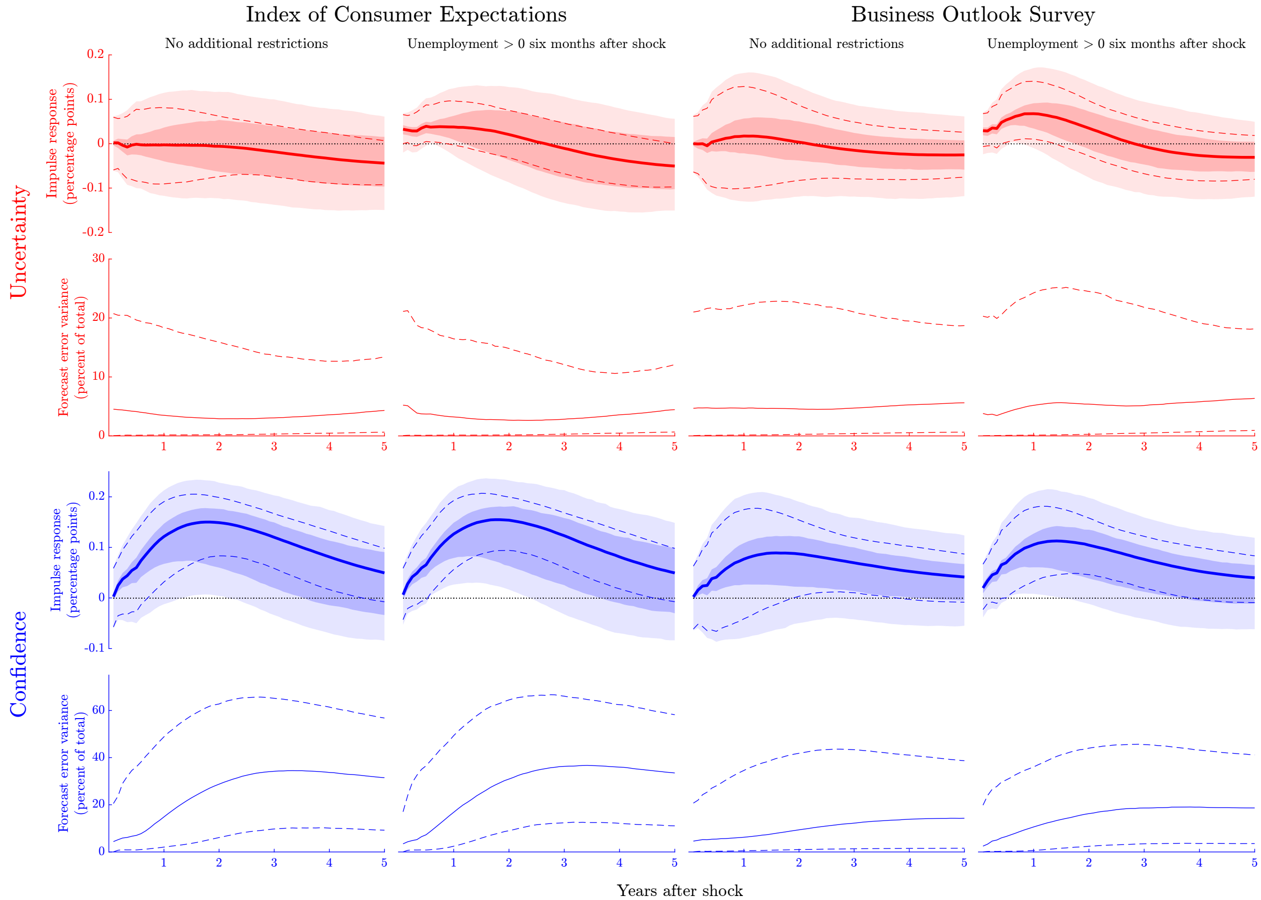

FIGURE 11: SENTIMENT SHOCKS, SIGN AND SIZE RESTRICTIONS

Notes: Impulse responses and forecast error variance decompositions of the unemployment rate. Uncertainty shocks (upper panel, red) and confidence shocks (lower panel, blue), identified by sign restrictions described in Section 3.4. Solid lines are medians from point estimates. Dashed lines reflect identification uncertainty while shaded areas measure estimation uncertainty, both 90% confidence intervals, as described in Section 3.3.

effects on unemployment, although at least in some estimates firm uncertainty seems to have slightly larger effects. At the median point estimates, household uncertainty shocks explain less than 5 percent of the variance at all horizons, while firm uncertainty shocks explain around 10 percent of its variance and with more upside identification uncertainty at longer horizons.

Conversely, household confidence shocks have large and significant effects even after accounting for the large degree of estimation uncertainty present in sign-identified systems. They explain between 30 and 40 percent of the the variance of the unemployment rate. Firm confidence shocks, by contrast, have smaller and less statistically significant effects and explain 10 to 20 percent of the variance of the unemployment rate.

This novel joint identification of first- and second-moment sentiment shocks by sign and size restrictions, despite being arguably more credible than the other strategies described in Section 3.2, nonetheless gives a result consistent with what was found above: household uncertainty shocks are not a source of economic fluctuations in the U.S.

3.5 Is uncertainty a transmission mechanism?

The previous sentence 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 response of household uncertainty to other macroeconomic shocks amplifies those shocks' effects.

To assess this possibility, I use the method 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. 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 that shock. To do this exercise 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 simply replaces those actual values with zeros.[31]

Although it is impossible to comprehensively assess this against all 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).

[31] Another slightly different approach would be to shut down only the direct response of uncertainty to the shock, and allow it to fluctuate as usual in response to the ensuing endogenous changes in output and other variables, similar to Kilian and Lewis (2011). Thus, in a sense, the results from my counterfactual experiment will put an upper bound on the importance of the endogenous response of uncertainty as a transmission mechanism.

- 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, associated with the Federal funds rate and identified from a Cholesky decomposition.

A more detailed description of each of these shocks is contained in the appendix.

The VAR is recursive, with all externally identified shocks 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. The data are from Ramey (2016), and, for comparability with that paper, I detrend the macroeconomic data using a quadratic polynomial.

The time period is 1960–2005, which starts later than Ramey (2016)'s estimates because of the unavailability of Michigan Survey data prior to 1960.[32] Similar to Ramey's (2016) results, this set of shocks accounts for between 63 and 73 percent of the variance of output and between 49 and 67 percent of hours at business cycle frequencies.

The actual and counterfactual forecast error variance decompositions are displayed in Figure 12. For each shock, the counterfactual considered is the following: "What would the response of GDP or hours be if uncertainty did *not* respond to the shock?" 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 five-year horizon. Counterfactual impulse responses (not displayed) similarly lie almost exactly on top of the actual values. By contrast, firm uncertainty, as measured by the Business Outlook Survey, seems to be a more important transmission mechanism, with sizable changes in the effects of MEI and monetary policy shocks and, to a lesser extent, TFP and IST news shocks when it is counterfactually held constant. 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.

[32]For the Business Outlook Survey, the sample period begins in the third quarter of 1968.

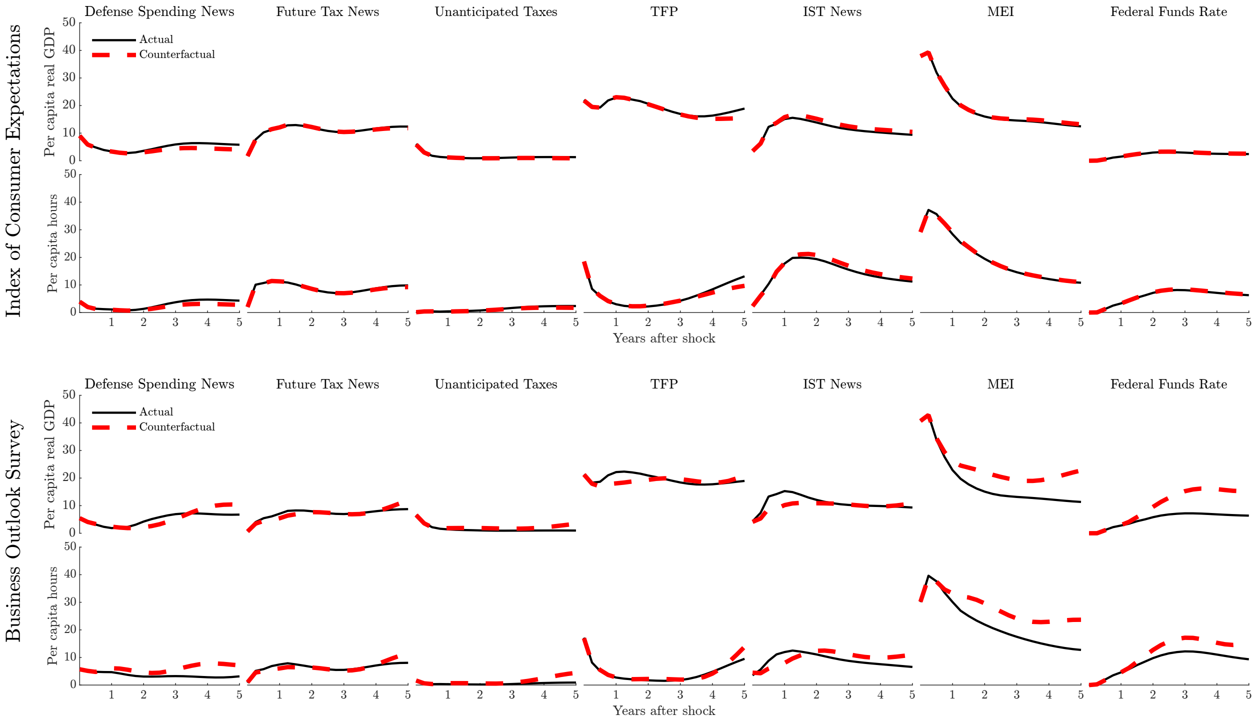

FIGURE 12: ACTUAL AND COUNTERFACTUAL FEVDS FROM RAMEY'S (2016) LARGE VAR

Notes: Fraction of forecast error variance of real per capita GDP and per capita hours due to each shock in Ramey's (2016) representative VAR. Upper panel: ICE disagreement index, quarterly 1960–2005. Lower panel: Business Outlook Survey disagreement measure, quarterly 1968Q3–2005, lower panel. Black lines are actual values, dashed red lines are what obtains when uncertainty is counterfactually held constant. See Section 3.5.

3.6 Discussion

A consistent pattern emerges from these exercises. Household uncertainty shocks lead to insignificant responses of and explain very little of the fluctuations in real activity in the U.S. Firm uncertainty shocks have more significant contractionary effects, especially on investment in Cholesky-identified systems, for which a one standard deviation shock leads to a 2 percent decline in the year after the shock. A two standard deviation shock to firm uncertainty could cause a decline in investment on par with declines seen in some small U.S. recessions. These results suggest that careful attention should be paid to whose uncertainty matters for the business cycle, and how uncertainty should be incorporated in macroeconomic models.[33]

[33] Fernández-Villaverde and Guerrón-Quintana (2020) show a number of examples of how different types of uncertainty shocks can have different effects in DSGE models.

Coibion et al. (2024) find large consumption responses of European households to uncertainty, a result seemingly at odds with the modest and insignificant declines found in this paper; however, an important takeaway from the results above is that the exact type of uncertainty being considered matters. In their survey, households are treated with information about disagreement among professional forecasters, which might not reflect the exact same type of uncertainty captured in the Michigan Survey, which elicits households' own beliefs.[34] Although the effects of household uncertainty shocks as measured by the ICE and ICS are similar, the comparison of these results with those from Coibion et al. (2024) suggest that significant differences may exist when households are exposed to others' uncertainty than when they report their own sentiments. On the other hand, also in the European context, Mikosch, Roth, Sarferaz and Wohlfart (2024) find that Swiss households with more uncertainty about exchange rates do not demand more information about exchange rates, while high-uncertainty firms do, a result that again highlights that firms and households might take qualitatively different actions in response to changes in uncertainty.

Another striking result from above is the large estimated effects of confidence shocks, especially for households. It raises the natural question of whether these shocks are primarily driven by news about future fundamentals as in Beaudry and Portier (2006) and Beaudry and Lucke (2010) or whether they reflect pure sentiment or "animal spirit" shocks, a possibility raised in Bachmann and Sims (2012) and Barsky and Sims (2012).

Although a full treatment of this distinction is outside the scope of this paper, in the appendix, I show how a combination of short- and long-run restrictions in a VAR similar to that of Beaudry and Lucke (2010) can be used to jointly identify uncertainty shocks and shocks to *news* about future productivity along with other fundamental shocks. The results again imply small and mostly insignificant effects of household uncertainty shocks, while news shocks explain more than half of the variation in per-capita hours; fluctuations in uncertainty itself are mostly endogenous responses to TFP, IST, and news shocks.

Thus, as in Barsky and Sims (2012), preliminary evidence suggests that the confidence shocks identified above primarily reflect news about future productivity rather than pure animal spirits. More is needed to fully account for the types of sentiment that are captured by the confidence shocks identified above, but since the focus of this paper is primarily on uncertainty, I leave this exploration for future work.

[34] A more prosaic explanation is that European households are systematically different from American ones when it comes to uncertainty.

4 Conclusion

Survey-based measures of household uncertainty fluctuate significantly both independently of other macroeconomic variables and in response to other macroeconomic shocks. The evidence presented above indicates that shocks to household uncertainty are not a driver of macroeconomic fluctuations in the U.S., nor is the endogenous response of household uncertainty to other shocks an important propagation mechanism.

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 business outlook surveys. These results hold both in traditional Choleksy-identified VARs and when using a novel method of joint identification of confidence and uncertainty shocks by sign and size restrictions, although there is substantial estimation uncertainty involved in the latter technique. Preliminary evidence suggests that household confidence shocks identified in this way primarily reflect news about future productivity growth, consistent with Barsky and Sims (2012).

This new method jointly identifying first- and second-moment sentiment shocks can be applied in and extended to different contexts. For example, the Michigan Survey also includes questions about future monetary policy actions and other government policies. It would be fairly straightforward to apply the same techniques to these questions to obtain household-based measures of monetary policy uncertainty and economic policy uncertainty—as well as confidence—to complement those of Husted, Rogers and Sun (2020) and Baker, Bloom and Davis (2016) and to study the role of these types of household uncertainty in U.S. business cycles. I leave this work for future research.

Appendix

Identification of uncertainty and news shocks

In this brief appendix, I illustrate how a different approach can be taken to simultaneously identify uncertainty and shocks to news about future productivity, as opposed to the confidence shocks identified in the main paper that do not distinguish between news shocks and pure sentiment or “animal spirit” shocks. By combining short- and long-run restrictions on impulse responses, I am nevertheless able to identify these shocks while allowing for contemporaneous feedback between uncertainty and news shocks, consistent with the evidence in

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.

Ludvigson et al. (2021) and Bernstein et al. (forthcoming).

The VAR systems I consider below are 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, and news shocks in a baseline structural 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 additional assumptions must be made. To minimizes the changes from Beaudry and Lucke's (2010) identification of news shocks, I include additional long-run restrictions from Fisher (2006) to identify 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

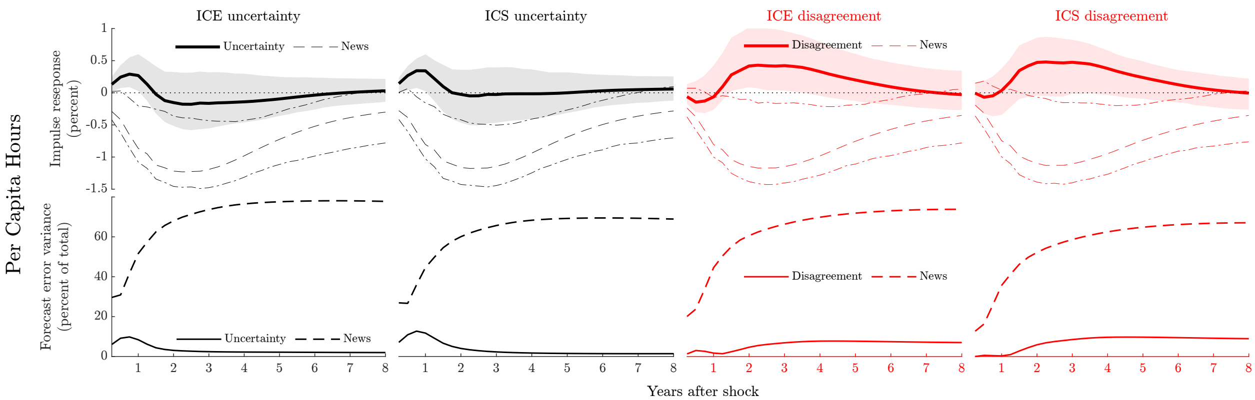

FIGURE 13: UNCERTAINTY AND NEWS SHOCKS: IRFS AND FEVDS

Notes: Impulse response functions with 90% confidence 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.

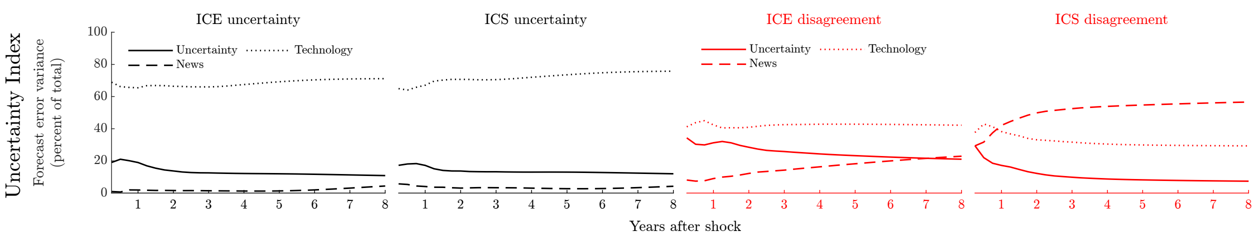

FIGURE 14: FORECAST ERROR VARIANCE DECOMPOSITION OF UNCERTAINTY MEASURES.

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.

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.[35]

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. Impulse responses and forecast error decompositions are displayed in Figures 13 and 14.

Uncertainty shocks account for a slightly more meaningful share of the variance of per-capita hours, but not for unemployment or GDP growth. Moreover, the majority of the variance of uncertainty is accounted for by technology and, for some measures, news shocks.

[35]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.

These results give some support to the confidence shocks identified in the main text as reflecting news about future productivity, and show that uncertainty responds endogenously to both news and fundamental shocks.

Description of shocks in Ramey's (2016) VAR

Francis et al. (2014) identify TFP shocks by specifying that they maximize the forecast-error variance of labor productivity over a finite horizon. Romer and Romer (2010) identify tax shocks using a narrative approach and Mertens and Ravn (2012) further decompose their shocks into anticipated and unanticapated shocks by separating out tax changes that were to be enacted in the future (anticipated) and within the current quarter (unanticipated). Justiniano et al. (2011) estimate marginal efficiency of investment (MEI) shocks from a DSGE; in their model investment-specific technology (IST) shocks affect the productivity of the sector that produces investment goods, while MEI shocks affect the rate at which gross investment-sector output is transformed into productive capital. Ben Zeev and Pappa (2017) use a similar method to that of Barsky and Sims (2011) to identify a news shock to governement spending that is orthogonal to current spending and maximizes the forecast-error variance of spending over the subsequent five years. Ben Zeev and Khan (2015) identify shocks news about future IST also using the method of Barsky and Sims (2011) and the effect of IST shocks on the relative price of investment goods (similar to the long-run restriction imposed in the first appendix section, above, from Fisher (2006)). Finally, Leeper et al. (2012) expected tax changes based on interest rate spreads. Monetary policy shocks are identified as the innovation to the Federal Funds Rate orthogonal to all these shocks as well as to the innovations in the other included variables.

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