Are Uncertainty Shocks Expansionary? Evidence from the Michigan Survey of Consumers

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Abstract

This paper introduces new direct measures of uncertainty derived from the Michigan Survey of Consumers. The series underlying these new measures are more strongly correlated with economic activity than many others that are the basis for uncertainty proxies. The survey also facilitates comparison of these measures with response dispersion or disagreement, other commonly used proxies for uncertainty. Dispersion measures have low correlation with the direct measures and often have causal effects of opposite sign, suggesting that they are poor proxies for uncertainty. For the measures based on series most closely correlated with economic activity, positive uncertainty shocks are mildly expansionary.

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1 Introduction

In recent years, much attention has been given to the role of uncertainty in macroeconomic fluctuations. Since macroeconomic uncertainty is not directly observed, a large portion of the literature has been focused on finding proxies for uncertainty. These have included measures based on stock market volatility, disagreement among survey respondents, and forecast errors from large macroeconomic and financial datasets.[1] In this paper, I construct new measures of uncertainty from the Michigan Survey of Consumers based on the share of respondents who say they are uncertain about various aspects of the economy. The responses to these survey questions are strongly correlated with future economic activity, leading strong credence to the use of the uncertainty measures derived from them.

The Michigan Survey is a monthly survey of approximately 500 individuals. It asks questions about respondents' views of business conditions over the next year(s) and the favorability of conditions for buying new houses or cars or large household durable items.[2] The exact responses coded in the survey differ depending on the question (I describe these in detail below), but in all cases respondents can answer that they are uncertain, they see both pros and cons to the situation, or they simply do not know. It is these responses, as well as the disagreement among respondents, that I use to construct measures of uncertainty. It is a particular strength of the Michigan Survey that both direct and dispersion measures of uncertainty can be constructed, allowing for an informal test of the external validity of Bachmann, Elstner and Sims's (2013) approach of using survey dispersion or disagreement as proxies for uncertainty.

[1] Bloom's (2009) seminal contribution, and many subsequent papers, use stock market volatility as a measure of uncertainty. Bachmann, Elstner and Sims (2013) construct their measure based on dispersion of responses about future economic activity from manufacturing businesses. Jurado, Ludvigson and Ng (2015) and Ludvigson, Ma and Ng (2020) construct macroeconomic and financial uncertainty measures using large datasets.

[2] Leduc and Liu (2016) also use a measure of uncertainty based on the Michigan Survey. As I describe below, the particular measure they choose appears to be incorrectly identified as "uncertainty" as a result of a classification error on the Michigan Survey's website.

I use these new measures to estimate the effects of uncertainty shocks using a number of structural vector autoregression (SVAR) models. Shocks to direct uncertainty measures and shocks to disagreement or response dispersion give estimates of the *opposite sign*. In particular, I find that increases in direct measures of uncertainty are expansionary, leading to modest declines in unemployment, while increases in disagreement are contractionary. The latter finding is consistent with results based on survey dispersion or disagreement, but the former suggests that these survey disagreement-based measures may not be good proxies for uncertainty.

The notion that uncertainty is contractionary is motivated primarily by the observation that most proxies for uncertainty tend to rise during recessions. The economic theory of uncertainty, however, is ambiguous regarding the sign of its effects.[3] As discussed in Ludvigson, Ma and Ng (2020), who also find shocks to macroeconomic uncertainty to be expansionary, estimating the *causal* effects of uncertainty depends crucially on both measurement and identification; that is, existing proxies are imperfect, and common identifying assumptions for uncertainty shocks (typically based on Cholesky decompositions in VAR models) are problematic. This paper attempts to makes progress on both fronts, introducing new measures of uncertainty and estimating causal effects using external instruments. In line with their results, I find that shocks that increase these new measures of uncertainty are expansionary. Results from recursively identified VARs and models using external instruments for identification are broadly consistent, at least for a subset of the new measures I construct.

In Section 2, I describe the data from the Michigan Survey and the new measures of uncertainty derived from it. In this section I also compare these new measures with existing

[3]Contractionary effects of uncertainty include "real options" or "wait-and-see" effects, as discussed in Bernanke (1983) and Bloom (2009). Expansionary effects include "growth options" in which downside effects of investment risk are limited, and exist in neoclassical growth models (see Gilchrist and Williams (2005) and Basu and Bundick (2017)). Bloom (2014) provides a broad overview of the theory.

uncertainty proxies. In Section 3, I estimate the effects of uncertainty shocks using SVARs. Section 4 concludes.

2 Survey-based measures of uncertainty

This section describes the Michigan Survey of Consumers and various measures of uncertainty derived from it and other surveys. In the first subsection below, I describe the Michigan Survey and the direct measures of uncertainty that I construct from it. I then discuss existing measures of uncertainty from survey data: Leduc and Liu's (2016) measure from the Michigan Survey and Bachmann, Elstner and Sims's (2013) method of measuring survey response dispersion or disagreement. The former measure is a particularly problematic measure of uncertainty, as I discuss below. The latter method can be applied in a straightforward way to construct dispersion (or disagreement) measures from the Michigan Survey.

2.1 Direct measures from the Michigan Survey of Consumers

The Michigan Survey of Consumers is a monthly survey of individuals in the United States[4] 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.[5] Data are available on a monthly basis since 1978 and quarterly since 1960.

Among the questions asked of survey respondents are questions about general business conditions and whether now is a good time to purchase a house, a car, or large durable goods. In this paper, I will focus on the following questions:

> (BUS): *"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*

[4] Excluding Alaska and Hawaii.

[5] 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.

times, or what?"

(VEHIC): *"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?"*

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

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

Responses are coded into six categories for the BUS question: Good times; good with qualifications; pros and cons or uncertain; bad with qualifications; bad times; or don't know. The other three questions do not have "with qualifications" responses coded separately, but are otherwise the same.

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 is considered to be a period of high uncertainty. To assess the reasonableness of these measures, as a first pass, Figure 1 displays the share of positive responses—that is that times are good, or that buying conditions are good—to these questions with real GDP growth. All series are procyclical, declining in recessions and increasing during expansions. Table 1 displays the correlations with GDP and industrial production growth and the unemployment rate at various leads and lags. It also includes the same correlations for other measures from which uncertainty proxies are constructed. All four series are correlated with future growth and lower unemployment, especially the response about general economic activity (BUS). This measure is more strongly correlated with output growth than the stock market or the

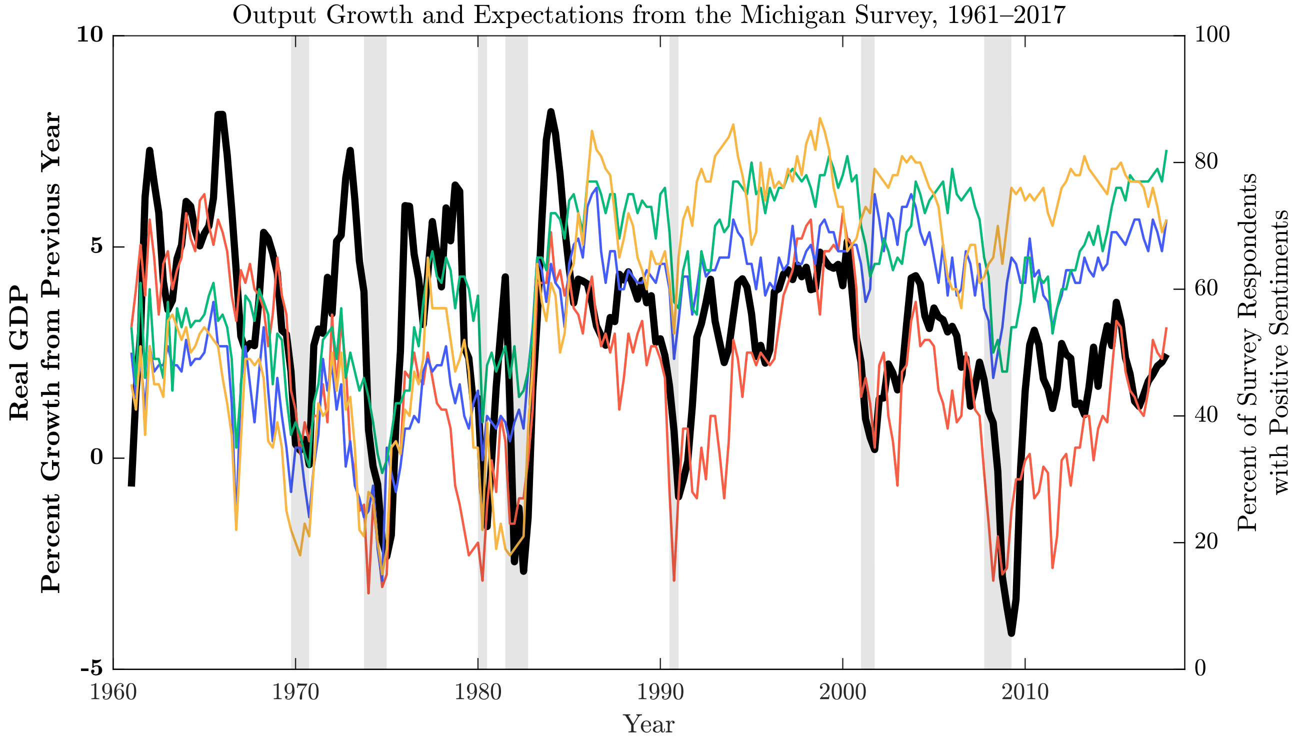

Figure 1: Left axis: **real GDP growth**. Right axis: positive answers to BUSS, VEHIC, DUR, and HOUSE. Shaded areas indicate NBER recessions, quarterly, 1961–2017.

survey responses used in Bachmann, Elstner and Sims (2013). Because they *predict* economic activity so well, the measures proposed above are well-suited as proxies for macroeconomic uncertainty.

2.2 Alternative uncertainty measures

After the questions VEHIC, DUR, and HOUSE, respondents are asked why they gave the answer they did. It is on this follow-up question to VEHIC that Leduc and Liu (2016) base their measure of uncertainty. Table 38 of the Michigan Survey's time series data[6] 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

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

	Leads & lags real GDP growth (quarters)								
Measure	-4	-3	-2	-1	0	+1	+2	+3	+4
BUS_GOOD	0.28	0.37	0.46	0.57	0.65	0.69	0.65	0.57	0.46
VEHIC_GOOD	-0.10	-0.06	-0.01	0.04	0.09	0.13	0.14	0.12	0.08
DUR_GOOD	0.10	0.14	0.19	0.24	0.25	0.25	0.19	0.11	0.01
HOUSE_GOOD	-0.10	-0.07	-0.03	0.01	0.06	0.12	0.14	0.12	0.07
BOS_INCR (1968–2017)	-0.53	-0.51	-0.43	-0.28	-0.07	0.14	0.31	0.42	0.44
Consumer Sentiment	0.31	0.39	0.48	0.57	0.63	0.65	0.60	0.51	0.39
S&P 500	-0.16	-0.15	-0.06	0.12	0.31	0.45	0.49	0.42	0.28
	Leads & lags of industrial production growth (quarters)								
	-4	-3	-2	-1	0	+1	+2	+3	+4
BUS_GOOD	0.20	0.26	0.33	0.42	0.52	0.57	0.56	0.50	0.39
VEHIC_GOOD	-0.17	-0.13	-0.09	-0.04	0.02	0.09	0.12	0.13	0.10
DUR_GOOD	0.00	0.05	0.10	0.16	0.21	0.23	0.19	0.13	0.01
HOUSE_GOOD	-0.12	-0.09	-0.06	-0.01	0.04	0.11	0.15	0.15	0.11
BOS_INCR (1968–2017)	-0.49	-0.47	-0.42	-0.33	-0.14	0.06	0.24	0.38	0.43
Consumer Sentiment	0.20	0.27	0.35	0.43	0.52	0.55	0.52	0.45	0.32
S&P 500	-0.16	-0.19	-0.12	0.03	0.24	0.45	0.54	0.51	0.38
	Leads & lags of the unemployment rate (quarters)								
	-4	-3	-2	-1	0	+1	+2	+3	+4
BUS_GOOD	-0.15	-0.21	-0.27	-0.35	-0.44	-0.53	-0.60	-0.65	-0.67
VEHIC_GOOD	0.17	0.14	0.10	0.05	-0.01	-0.07	-0.13	-0.18	-0.22
DUR_GOOD	0.11	0.04	-0.04	-0.12	-0.21	-0.28	-0.33	-0.36	-0.37
HOUSE_GOOD	0.20	0.17	0.13	0.08	0.02	-0.05	-0.11	-0.16	-0.21
BOS_INCR (1968–2017)	0.27	0.36	0.44	0.49	0.49	0.46	0.40	0.33	0.26
Consumer Sentiment	-0.21	-0.28	-0.35	-0.44	-0.55	-0.63	-0.70	-0.74	-0.76
S&P 500	0.24	0.26	0.25	0.19	0.09	-0.02	-0.12	-0.19	-0.22

Table 1: Correlations of the share of positive responses to Michigan Survey and Business Outlook Survey (BOS) questions, the Index of Consumer Sentiment, and the S&P 500 with leads and lags of output measures: year-over-year growth in real GDP and industrial production or the unemployment rate (in levels). Quarterly, 1961–2017, except where otherwise indicated.

responding that now is a bad time to buy a car because the future is uncertain. The response categories in this table, 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.[7] 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." While this response could indeed be capturing some measure of uncertainty, it is at least equally plausible that it is instead measuring mostly bad news about the future, rather than uncertainty *per se*. It is not perhaps not surprising, then, that shocks to this measure of "uncertainty" are strongly contractionary. The measures I construct are arguably more reasonable measures of uncertainty, and I compare them with Leduc and Liu's (2016) measure below.

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, Elstner and Sims (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). Bachmann, Elstner and Sims (2013) use the following measure of disagreement as a proxy for uncertainty:

$$Uncertainty_t = \sqrt{Incr_t + Decr_t - (Incr_t - Decr_t)^2} \tag{1}$$

where $Incr_t$ ($Decr_t$) 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 my direct measures

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

of uncertainty are based. This allows for a convenient comparison of direct uncertainty measures with disagreement-based proxies.

The dispersion measures constructed from the Michigan Survey have low (or negative) correlations with the direct measures. For BUS, VEHIC, DUR, and HOUSE the correlations are, respectively, -0.09, -0.24, -0.06, and 0.01. Although this is already suggestive that dispersion measures something different from uncertainty, I provide additional results in the next section on the estimated effects of shocks to these measures.

3 Estimating the effects of uncertainty shocks

In this section, I describe estimates of the effects of shocks to uncertainty, using these new measures, on the macroeconomy. I first describe identification based on a recursive ordering in a VAR, starting from Leduc and Liu's (2016) specification and assessing a number of extensions.[8] I then estimate the effects of uncertainty shocks using a "proxy SVAR," which uses external instruments, as in Stock and Watson (2012), Mertens and Ravn (2013), and Gertler and Karadi (2015). Identification in this setup is achieved by isolating the variation in survey-based estimates of uncertainty that is due to fluctuations in broader measures of uncertainty taken from the literature.

3.1 Recursive VARs

As mentioned above, the most common approach to identifying uncertainty shocks has been by imposing short-run timing restrictions in VAR systems using the Cholesky decomposition. Bloom (2009) achieved identification in a medium-size VAR by arguing that uncertainty—as measured by stock market volatility—responds to stock-market fluctuations within a period

[8] Most of the literature studying the effects of uncertainty shocks makes use of recursive ordering schemes. See, for example, Bloom (2009), Bachmann, Elstner and Sims (2013), Jurado, Ludvigson and Ng (2015), and Baker, Bloom and Davis (2016).

(a month), but uncertainty shocks do not affect the stock market within a period, while all macroeconomic variables are allowed to respond contemporaneously to the uncertainty shock. Bachmann, Elstner and Sims (2013) estimate the effects of uncertainty shocks using both a series bivariate VARs with uncertainty measures order first and Bloom's (2009) larger VAR. Leduc and Liu (2016), in a smaller VAR, order their Michigan Survey-based uncertainty measure first.

As a first step and a point of comparison, I re-estimate Leduc and Liu's (2016) VAR, with the time period extended through 2017.[9] The system includes their measure of uncertainty, ordered first, followed by the unemployment rate, CPI inflation, and the three-month treasury rate. The data are monthly from 1978–2017. Impulse responses to a one standard deviation uncertainty shock are displayed in Figure 2. The shock leads to an increase in unemployment of about 0.15 percentage points and declines in inflation and short-term interest rates of similar magnitudes. The results are essentially identical to Leduc and Liu's (2016) baseline estimates.

I next estimate a similar system using the measures of uncertainty from the Michigan Survey that were described above. Figure 3 displays impulse responses to the same system, using instead the share of "uncertain" responses to the questions described above, BUS, VEHIC, DUR, and HOUSE. An uncertainty shock using these measures is *expansionary* leading to a decline in unemployment and an increase in inflation and interest rates of similar magnitude to the *contractionary* effects estimated using Leduc and Liu's (2016) uncertainty measure.

Bachmann, Elstner and Sims (2013) provide an alternative survey-based measure of uncertainty. Using the Federal Reserve Bank of Philadelphia's Business Outlook Survey, they construct an uncertainty measure based on response dispersion. Their index of dispersion

[9] The sample period in their original VAR was 1978 through October 2013. The results are essentially unchanged by the inclusion of these additional years in the sample.

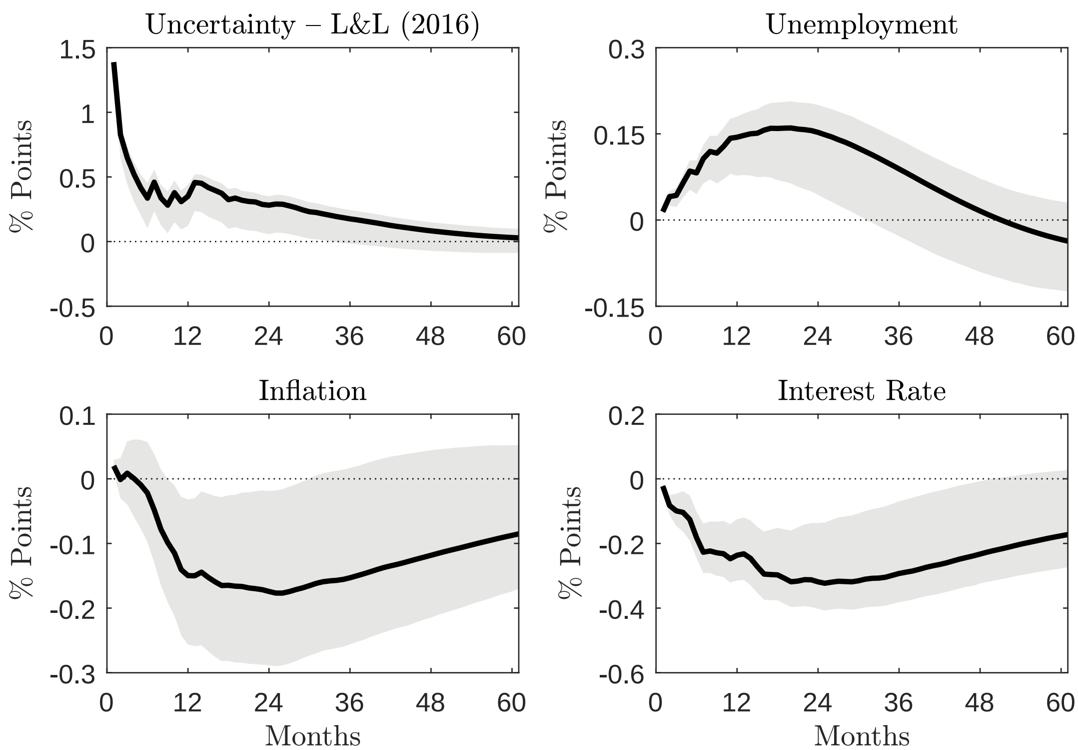

Figure 2: Impulse responses to a one-standard deviation shock to uncertainty, using Leduc and Liu's (2016) measure—the share of survey respondents answering that now is bad time to buy a car because "people should save more" or there are "bad times ahead." Error bands are 95% confidence intervals from a bootstrap.

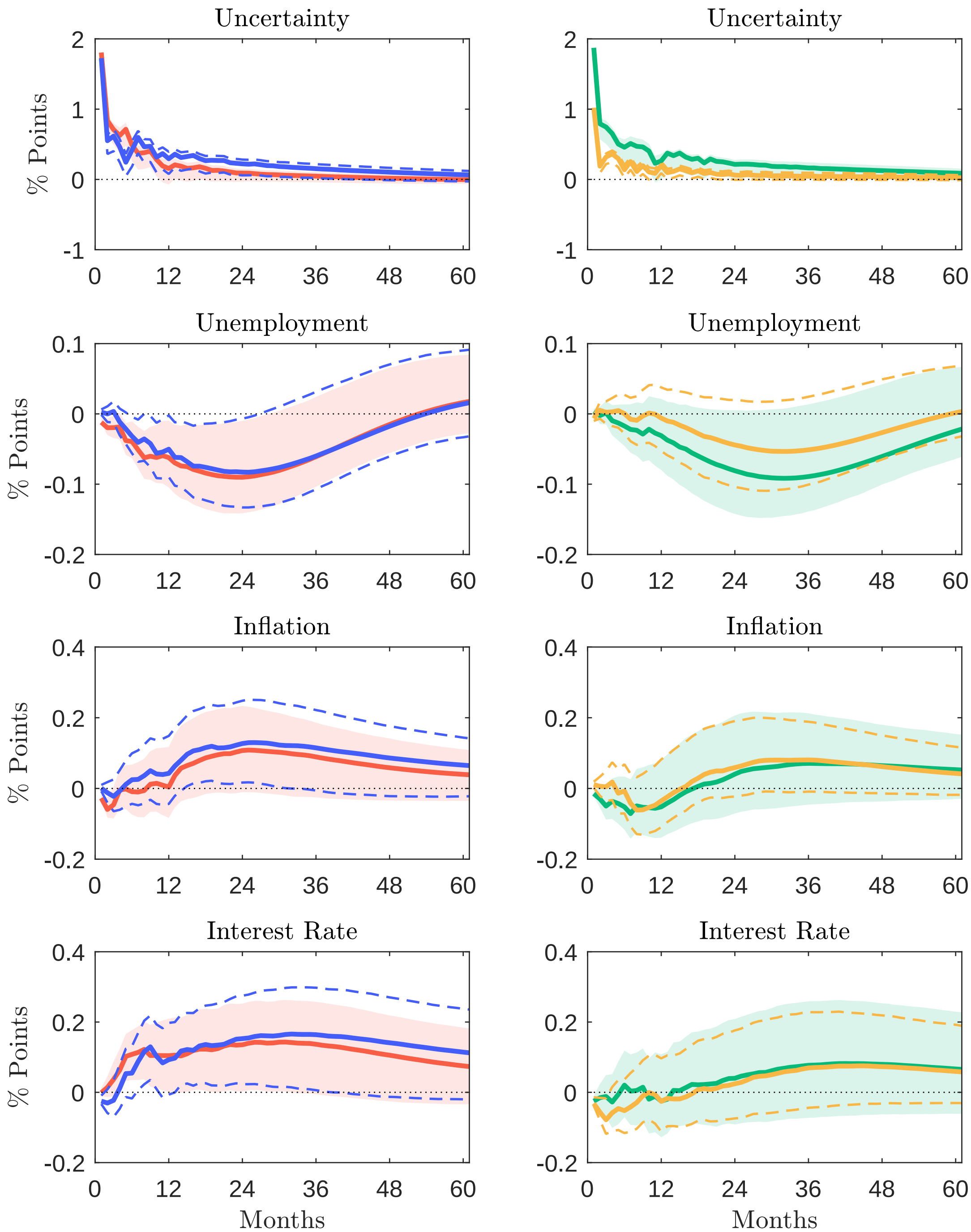

Figure 3: Impulse responses to a one-standard deviation shock to the share of BUSS and VEHIC (*left column*) and DUR and HOUSE (*right column*) respondents answering "uncertain," "don't know," or "pros and cons." Error bands are 95% confidence intervals from a bootstrap.

for a particular question is given by Equation 1. The Business Outlook Survey does not have a direct measure of uncertainty, however. The questions on the Michigan Survey allow for the construction of analogous dispersion indices, and comparison with the direct measures described above to assess the reliability of dispersion-based uncertainty proxies. This is of interest since dispersion of survey responses is not necessarily indicative of uncertainty. Survey response dispersion could also indicate differing—but precise—forecasts. Comparison with direct measures of uncertainty gives some indication of how good a proxy dispersion measures are for uncertainty.

Figure 4 displays impulse responses using Bachmann, Elstner and Sims's (2013) measure of dispersion from the Philadelphia Fed's Business Outlook Survey in the same VAR specification and time period as the estimates above.[10] A shock to uncertainty using their survey dispersion measure produces a small increase in the unemployment rate and small and insignificant changes in inflation and interest rates.

Figure 5 displays the impulse responses to analogous dispersion measures for the questions asked in the Michigan Survey. In three of the four cases, shocks to dispersion lead to increases in unemployment, as in Bachmann, Elstner and Sims (2013), while shocks to the direct measures of uncertainty are uniformly expansionary. This discrepancy suggests caution using dispersion measures as proxies for uncertainty.[11]

One potential issue with these small-scale VARs is that they do not account fully for "first-moment" information contained in uncertainty measures. To account for this, Bloom (2009) includes the S&P 500 index in his VAR, while Leduc and Liu (2016) and Baker, Bloom and Davis (2016) include the Michigan Consumer Sentiment Index, constructed from the Michigan Survey, in their VARs. Estimates of the real effects of uncertainty shocks

[10]Note that the sample period differs from Bachmann, Elstner and Sims (2013), whose sample period runs from 1968 to 2011.

[11]These results are in line with the finding of Rich and Tracy (2010), who document differences between uncertainty and disagreement among professional forecasters.

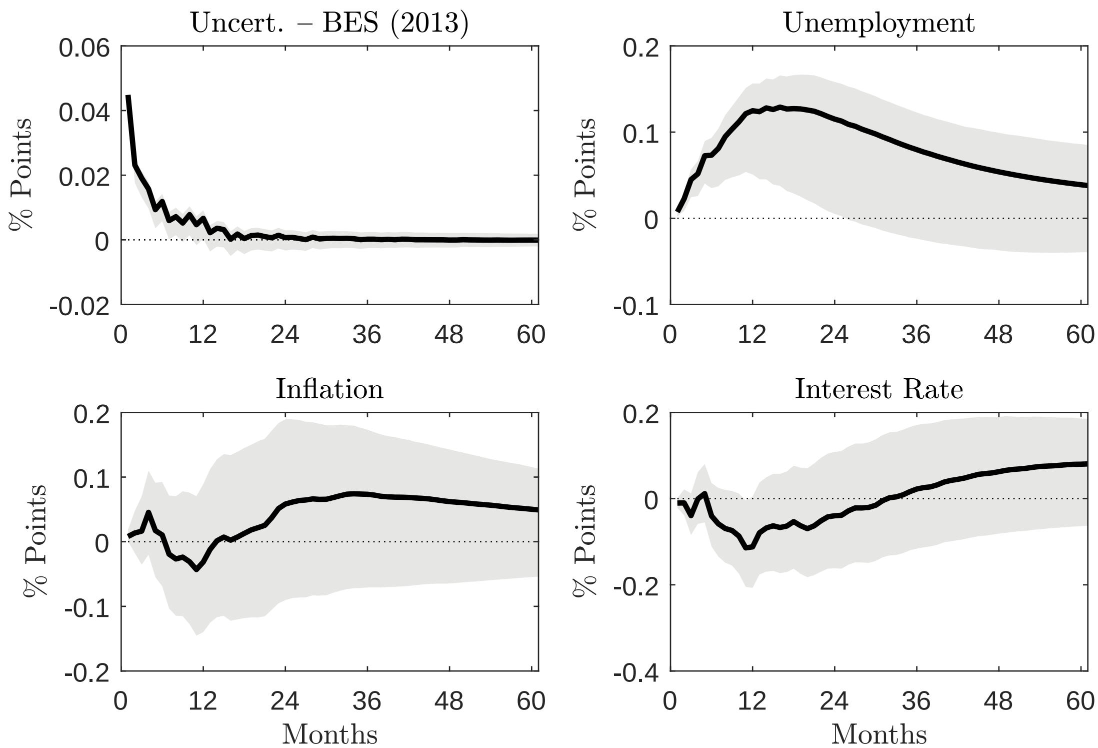

Figure 4: Impulse responses to a one-standard deviation shock to uncertainty, using Bachmann, Elstner and Sims's (2013) measure of survey dispersion from the Business Outlook Survey, 1978–2017. Error bands are 95% confidence intervals from a bootstrap.

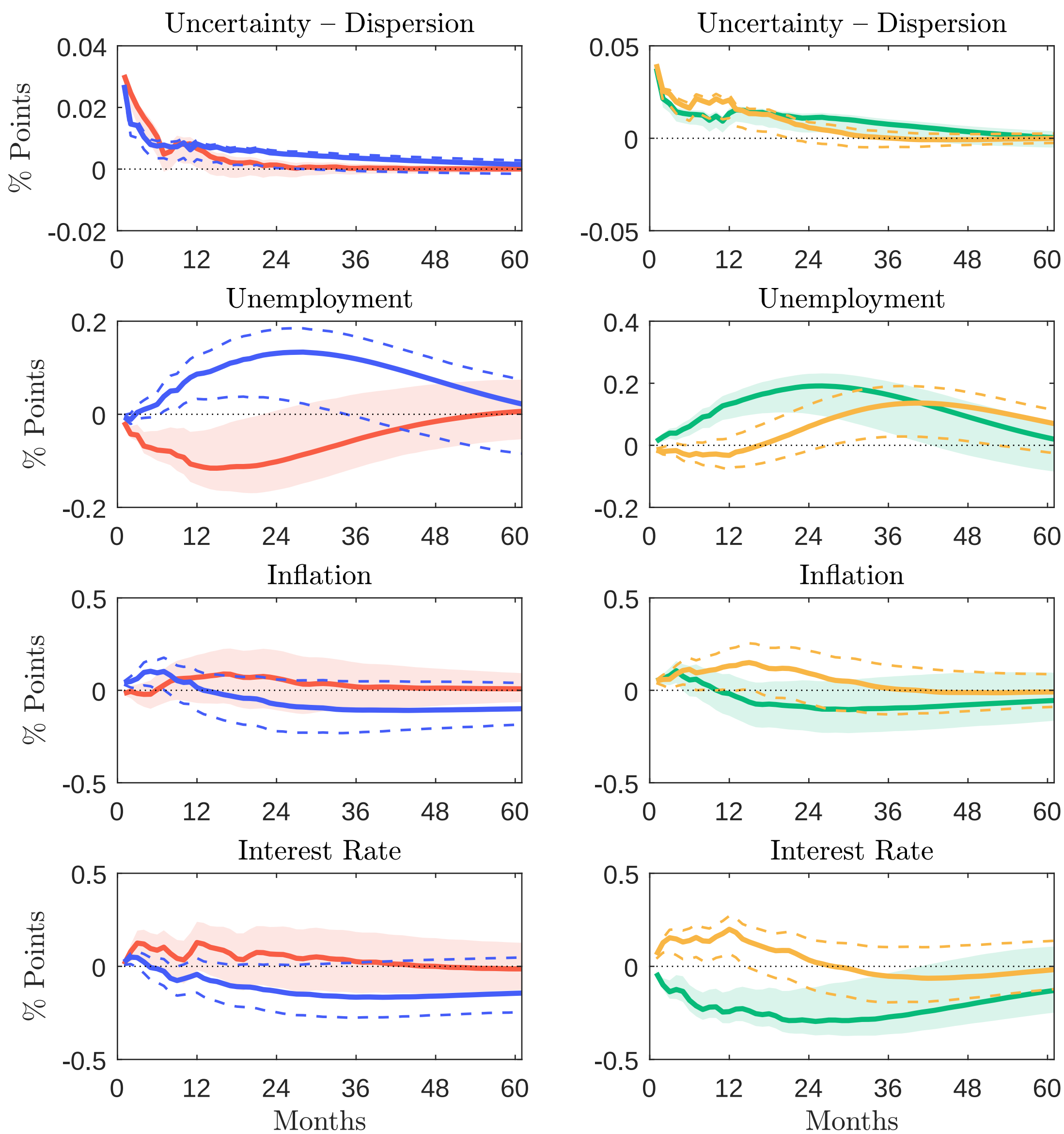

Figure 5: Impulse responses to a one-standard deviation shock to response dispersion of BUSS and VEHIC (*left column*) and DUR and HOUSE (*right column*), as computed from Equation 1. Error bands are 95% confidence intervals from a bootstrap.

decline when these first-moment variables are included, indicating that uncertainty measures contain some first-moment information.

This same phenomenon occurs using the new measures of uncertainty constructed above. Indeed the effect of uncertainty shocks on unemployment are more modest and largely insignificant (although point estimates are still of the same sign). Figure 6 displays the impulse responses to the unemployment rate when including either the S&P 500 or Consumer Sentiment Index in the baseline VAR above. Bloom (2009) orders the S&P 500 before his volatility-based measure of uncertainty, while Leduc and Liu (2016) order sentiment after their uncertainty measure. Following Baker, Bloom and Davis (2016), I display the results for either ordering.[12] In nearly all cases, for either ordering or first-moment measure, the estimated effects from above are diminished.

These results suggest the importance of including first-moment measures in estimating and identifying uncertainty shocks. The restrictions implicit in the recursive identification scheme involving these variables, however, are strong and arguably unreasonable. When uncertainty is ordered after the first-moment variable, uncertainty shocks are assumed not to affect that variable within the month, but the first-moment variable's level is controlled for in estimating the shock; when uncertainty is ordered before the first-moment variables, that variable's level is *not* accounted for in estimating the shock, but uncertainty shocks can affect it within the period. Neither of these conditions is entirely realistic. Financial variables such as the stock market or expectations-based variables like consumer sentiments are likely to respond quickly to any shock. Therefore, in the next section I make use of external instruments to estimate proxy SVARs in which these unsatisfactory restrictions can be relaxed.

[12] Neither condition—that the stock market or sentiment can affect uncertainty within a period but not *vice versa*, or the reverse restriction—is completely satisfactory. See Section 3.2, below.

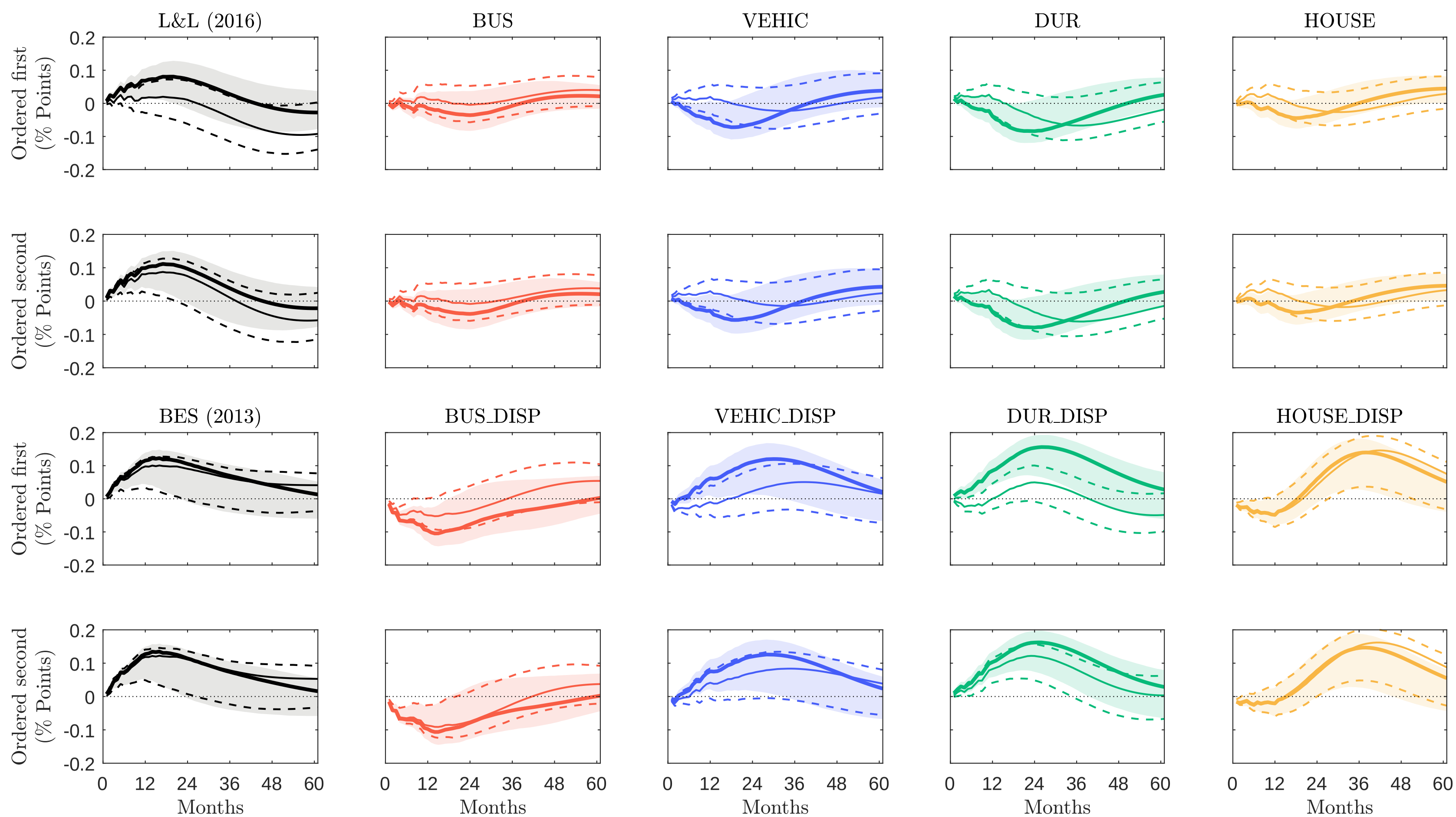

Figure 6: Impulse responses of the unemployment rate to uncertainty shocks with "first-moment" variables included. First and third rows have first-moment variables ordered first (before uncertainty). Second and fourth rows have first-moment variables ordered second (after uncertainty). Thick lines and shaded error bands: S&P 500. Thick lines and dashed error bands: Index of Consumer Sentiment. *Upper panel:* Leduc and Liu (2016) and direct measures introduced above. *Lower panel:* Bachmann, Elstner and Sims (2013) and dispersion measures described above. Error bands are 95% confidence intervals from a bootstrap.

3.2 Proxy VARs

The restrictions underlying recursive identification schemes in the previous section can be dispensed with if one uses the "external instruments" approach pioneered by Stock and Watson (2012) and Mertens and Ravn (2013).[13] This approach requires the use of an instrument for the structural shock obtained from outside the VAR system. External instruments obviate the need for arguably unrealistic timing restrictions in recursive identification schemes; in particular, in the setting described above, they allow for the incorporation of multiple fast-moving "first-moment" variables such as consumer sentiment, stock market levels, or measures of credit conditions.

The appealing features of this approach do not come without costs, however; external instruments must satisfy conditions analogous to those encountered in the usual setting of estimating causal effects by instrumental variables. In particular, they must satisfy instrument relevance and exclusion restriction conditions. Letting $\mathbf{Z}_t$ denote a vector of instrumental variables and $\boldsymbol{\varepsilon}_t = [\varepsilon_t^u \; \boldsymbol{\varepsilon}_t^o]'$ denote a partitioned vector of the structural shocks affecting the system, where ε_t^u is the structural shock of interest, these conditions can be written as

$$\mathbb{E}\left[\mathbf{Z}_t \varepsilon_t^{u\prime}\right] = \boldsymbol{\Sigma}$$

$$\mathbb{E}\left[\mathbf{Z}_t \boldsymbol{\varepsilon}_t^{o\prime}\right] = \mathbf{0}.$$

The first condition says that the instrument is correlated with the shock of interest, while the second says that it is orthogonal to all other structural shocks.

With a set of valid instruments in hand, estimation is straightforward. First, estimate the VAR system to obtain reduced-form residuals $\mathbf{u}_t$, then regress the residuals associated with

[13] Many authors have used external instruments in other contexts, including Gertler and Karadi (2015), who identify monetary policy shocks using a hybrid method of high-frequency identification and VAR estimation, and Stock and Watson (2018) who discuss the use of external instruments for identification in macroeconomics more generally.

the shock measures (i.e., uncertainty), u_t^u on the instrument set to obtain $\widehat{u}_t^u$. Intuitively, this isolates the portion of the residual that is due to the (unobserved) structural shock ε_t^u via the instruments $\mathbf{Z}_t$. Combining estimated coefficients from regressing $\mathbf{u}_t^o$ on $\widehat{u}_t^u$ with a variance normalization identical to that in recursively identified systems gives an estimated linear relationship between the reduced-form residuals and the structural shock: $\varepsilon_t^u = \widehat{\boldsymbol{\gamma}}'\mathbf{u}_t$. Construction of impulse response functions and other objects of interest follows the same process as in other SVARs.[14]

The difficulty, however, is find a valid set of instruments for the shock of interest. This is particularly true in the case of uncertainty, most measures of which are expected to move endogenously in response to other "first-moment" shocks, evidence of which was presented in Section 3.1. Gertler and Karadi (2015) are able to identify monetary policy shocks using price changes of Fed Funds futures contracts around a 30-minute window of Federal Reserve policy announcements, while Stock and Watson (2012) use a variety of externally-identified shock series, including uncertainty. Since there is no obvious high-frequency series to instrument for uncertainty, I follow the latter approach but do so making use of a new dataset that was unavailable to Stock and Watson (2012).

As instruments for uncertainty, they use innovations to stock market volatility and Baker, Bloom and Davis's (2016) index of policy uncertainty. In contrast, I use the macroeconomic uncertainty indices of Jurado, Ludvigson and Ng (2015) (JLN) as instruments for uncertainty shocks.[15] The JLN series is constructed from a large dataset of hundreds of macroeconomic times series. They motivate the construction of their series by the observation that economic decisions are not made based on volatility or dispersion, but rather whether the economy "has become more or less *predictable*; that is, less or more uncertain."(Jurado, Ludvigson and

[14] The method is described in detail by Mertens and Ravn (2013) and Gertler and Karadi (2015). Inference involves incorporating the first stage into a wild bootstrap.

[15] I have also used the VIX and the Economic Policy Uncertainty index as instruments, but they are very weak and give impulse responses that are insignificantly different from zero at all horizons.

Ng, 2015). Their measures of uncertainty are weighted aggregates of the expected squared forecast errors of many macroeconomic times series at various horizons. They argue that this measure isolates the purely unforecastable component of the macroeconomy.

To be sure, these are not perfect instruments. To the extent that uncertainty responds endogenously to other events in the economy, it is difficult to argue that they are perfectly orthogonal to other macroeconomic shocks. Therefore, I follow Stock and Watson (2012) and use the residuals from estimated AR(2) processes on the one-, three-, and twelve-month horizon JLN series as instruments for a shock to uncertainty. I estimate both the baseline four-variable VAR from Leduc and Liu (2016) and a larger VAR system that includes the S&P 500 or the Michigan Index of Consumer Sentiment and Gilchrist and Zakrajsek's (2012) excess bond premium—a measure of credit conditions—in addition to the variables in the baseline VARs estimated above.

Figure 7 displays the impulse responses from the baseline four-variable VARs with shocks identified using JLN's macroeconomic uncertainty indices as external instruments. For the two series most correlated with economic activity—DUR and BUS—unemployment falls and interest rates rise or remain unchanged. For BUS, inflation increases slightly, while it falls for DUR. For both VEHIC and HOUSE, unemployment increases, while inflation rises and interest rates remain largely unchanged. The expansionary effects of uncertainty shocks measured by BUS or DUR are consistent with Ludvigson, Ma and Ng (2020), who argue that recursively identified systems are invalid and who also find that shocks to macroeconomic uncertainty are mildly expansionary.[16] The impulse responses of unemployment in the larger proxy VAR are displayed in Figure 8, and are essentially the same as in the baseline proxy VAR. In all cases, first-stage F-statistics are indicative of weak instruments; this is especially true for the specification using HOUSE as the uncertainty measure, which has a first-stage

[16]They argue that the increases in macroeconomic uncertainty during recessions are mostly an endogenous response to other shocks, but they do find a large role for *financial* uncertainty shocks.

F-statistic less than one.[17]

Overall, the results from VARs are mixed. In recursively-identified systems, shocks to any of the new measures of uncertainty results in lower unemployment, although the magnitude of the decline is somewhat sensitive, and the identifying assumptions are dubious. In systems estimated by external instruments, shocks to BUS and DUR result in lower unemployment, but the reverse is true for VEHIC and HOUSE. However, in addition to the difficulty of finding valid instruments to begin with, these estimates suffer from weak instruments.

Taken altogether, the results from this section are suggestive of mildly expansionary effects of uncertainty shocks, at least with respect to the series most closely correlated with economic activity. These results are consistent with "growth options" theories of uncertainty. In such settings, if downside risk is bounded while upside risk is potentially unbounded, increases in uncertainty can be expansionary—intuitively, a widening distribution of outcomes leads to a heavier right tail, while the lower bound limits the widening of the left tail.

4 Conclusion

In this paper, I introduced new measures of uncertainty based on the Michigan Survey of Consumers. They are direct measures of uncertainty, in the sense that they represent the share of respondents who said they were uncertain about macroeconomic conditions. Responses to questions about business conditions or durable goods are strongly correlated with future economic activity; positive views of business conditions are more strongly correlated with current and future economic activity than the S&P 500 or positive responses to the Business Outlook Survey, two series from which other uncertainty measures have been constructed.

[17] In all cases, first-stage F-statistics are below the typical threshold of ten. However, as Gertler and Karadi (2015) observe, impulse responses are little changed when using similar, but weaker, instruments with F-statistics around 3 or 4.

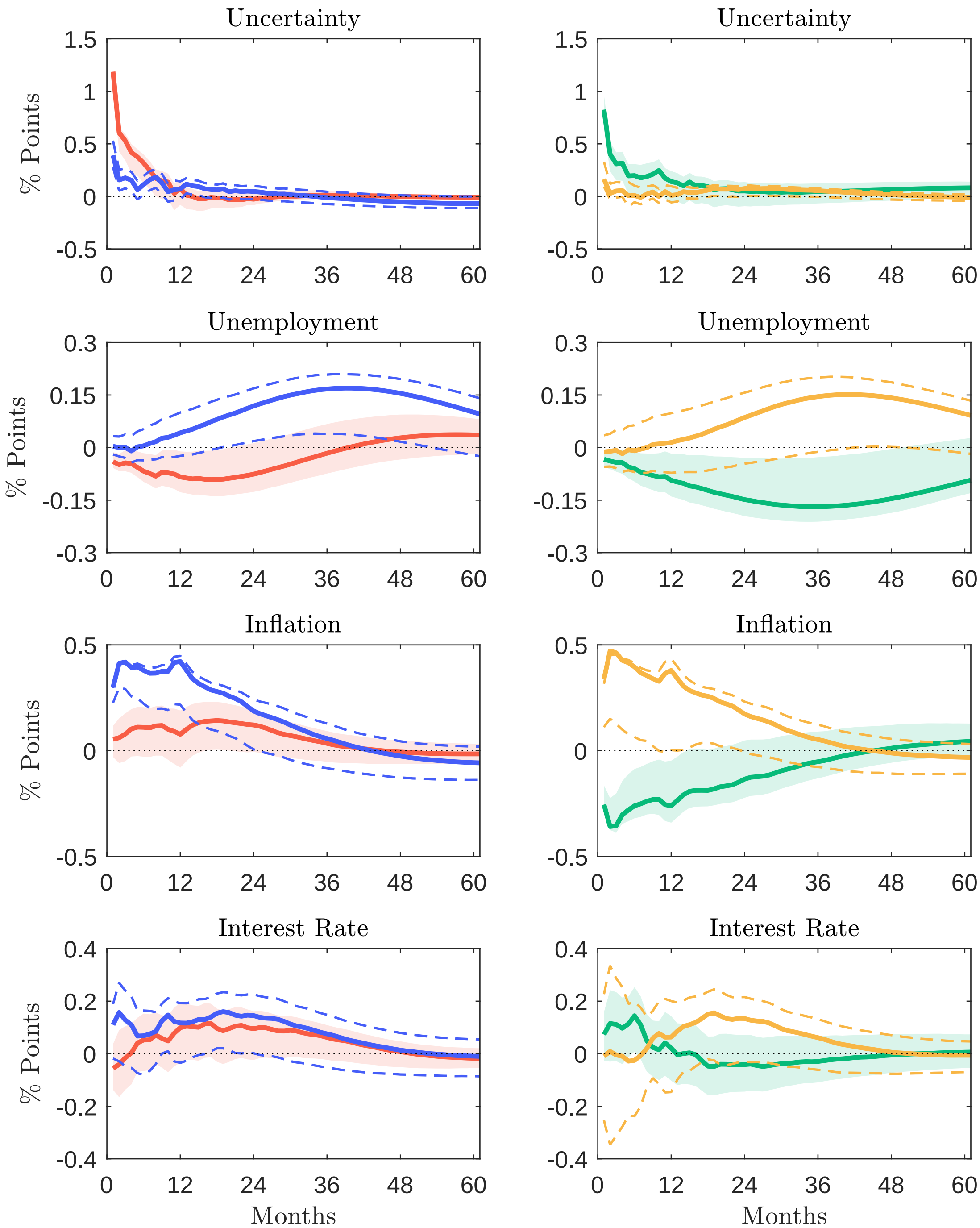

Figure 7: Responses of the unemployment rate to uncertainty shocks measured by BUS, VEHIC, DUR, HOUSE in a small proxy VAR. External instruments are JLN's macroeconomic uncertainty index at one-, three-, and twelve-month horizons, residuals from an estimated AR(2) process. First-stage F-statistics: 4.37, 1.12, 2.31, 0.23. Error bands are 95% confidence intervals from a bootstrap.

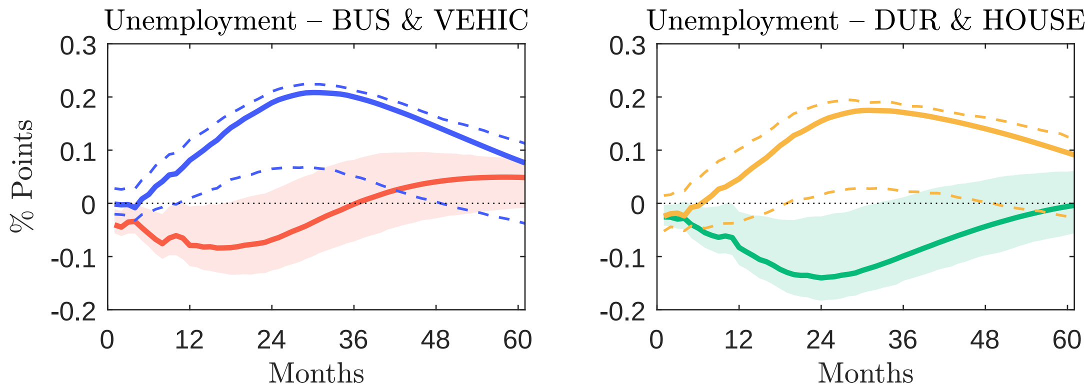

Figure 8: Responses of the unemployment rate to uncertainty shocks measured by BUS, VEHIC, DUR, HOUSE in a larger proxy VAR, including the S&P 500 and Gilchrist and Zakrajsek's (2012) excess bond premium. External instruments are JLN's macroeconomic uncertainty index at one-, three-, and twelve-month horizons, residuals from an estimated AR(2) process. First-stage F-statistics: 3.64, 1.43, 2.89, 0.68. Error bands are 95% confidence intervals from a bootstrap.

I also construct measures of survey response dispersion from the Michigan Survey. Comparison with the direct measures suggests that dispersion is a poor proxy for uncertainty. Dispersion measures have low (or negative) correlation with uncertainty when both are constructed from the same series. In addition, the effects of uncertainty shocks measured by dispersion or the direct measures are of opposite sign.

Evidence from SVARs points to uncertainty shocks having mildly expansionary effects. In recursively identified systems shocks that increase uncertainty lead consistently to small declines in unemployment and increases in inflation and interest rates. Proxy VAR systems using external instruments yield mixed results. I find expansionary effects of uncertainty shocks when using the measures most correlated with economic activity, but contractionary effects for other measures. These mixed results and their sensitivity to different identifying assumptions should motivate future research to focus on cleaner identification of uncertainty shocks.

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