Supplement to “Uncertainty shocks and inflation dynamics in the U.S.”

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A.1 Data

A.1.1 Data sources

Uncertainty proxies

- **VXO**: It is the Chicago Board of Options Exchange (CBOE) S&P100 Volatility Index, which captures an estimate of the expected 30-day volatility of the S&P 100 stock index. The data is obtained from FRED from 1986 onwards [https://fred.stlouisfed.org/series/VXOCLS](https://fred.stlouisfed.org/series/VXOCLS). Pre 1986, it is obtained from the monthly standard deviation of the daily S&P500 and normalized following Bloom (2009).

- **Michigan Consumer Uncertainty**: Since 1978, the Michigan Survey has conducted monthly interviews of households in the United States. One survey question asks: “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?” A follow-up questions asks: “Why do you say so?” The survey tallies the fraction of respondents who report that “uncertain future” is a reason why it will be a bad time to buy car or other durable goods over the next 12 months. Source: [https://data.sca.isr.umich.edu/data-archive/mine.php](https://data.sca.isr.umich.edu/data-archive/mine.php): “Table 38: Reasons for Opinions for Buying Conditions for Vehicles”.

Real activity indicators We use real GDP growth as the measure of economic activity in the baseline analysis. Additionally, we also estimate the model using consumption and investment growth as alternative measures of economic activity. All the variables are measured in billions of chained 2012 dollars and are seasonally adjusted. Their source is the U.S. Bureau of Economic Analysis and retrieved from FRED.

- **Real Gross Domestic Product** [https://fred.stlouisfed.org/series/GDPC1](https://fred.stlouisfed.org/series/GDPC1)

- **Personal Consumption Expenditures: Nondurable Goods** [https://fred.stlouisfed.org/series/PCND](https://fred.stlouisfed.org/series/PCND)

- **Fixed Private Investment** [https://fred.stlouisfed.org/series/FPI](https://fred.stlouisfed.org/series/FPI)
• **Industrial Production: Total Index** [https://fred.stlouisfed.org/series/INDPRO#0](https://fred.stlouisfed.org/series/INDPRO#0)

**Prices and interest rates** The implicit price deflators are from the U.S. Bureau of Economic Analysis, while the consumer price index and the average hourly earnings are provided by the U.S. Bureau of Labor Statistics. The different interest rates and yields are measured in percentage and are provided by the Board of Governors of the Federal Reserve System. Moody’s Seasoned Baa Corporate Bond Yield is also measured in percentage and provided by Moody’s. All the above-mentioned data are retrieved from FRED. The Wu-Xia Shadow Federal Funds Rate comes from Wu and Xia (2016) and retrieved from Federal Reserve Bank of Atlanta.

1 When the shadow fed funds rate is at least 25 basis points, it equals the federal funds rate. At the zero lower bound, the shadow rate uses information from the entire yield curve to summarize the stance of monetary policy.

• **Personal Consumption Expenditures: Implicit Price Deflator** [https://fred.stlouisfed.org/series/DPCERD3Q086SBEA](https://fred.stlouisfed.org/series/DPCERD3Q086SBEA).

• **Gross Domestic Product: Implicit Price Deflator** [https://fred.stlouisfed.org/series/GDPDEF](https://fred.stlouisfed.org/series/GDPDEF).

• **Consumer Price Index for All Urban Consumers: All Items in U.S. City Average** [https://fred.stlouisfed.org/series/CPIAUCSL](https://fred.stlouisfed.org/series/CPIAUCSL).

• **Gross Private Domestic Investment: Fixed Investment: Implicit Price Deflator** [https://fred.stlouisfed.org/series/A007RD3Q086SBEA#0](https://fred.stlouisfed.org/series/A007RD3Q086SBEA#0).

• **Personal Consumption Expenditures: Nondurable goods: Implicit Price Deflator** [https://fred.stlouisfed.org/series/DNDGRD3Q086SBEA](https://fred.stlouisfed.org/series/DNDGRD3Q086SBEA).

• **Average Hourly Earnings of Production and Nonsupervisory Employees, Total Private** [https://fred.stlouisfed.org/series/AHETPI](https://fred.stlouisfed.org/series/AHETPI).

• **Effective Federal Funds Rate** [https://fred.stlouisfed.org/series/FEDFUNDS](https://fred.stlouisfed.org/series/FEDFUNDS).
• 1-Year Treasury Constant Maturity Rate https://fred.stlouisfed.org/series/DGS1#0.

• 20-Year Treasury Constant Maturity Rate https://fred.stlouisfed.org/series/GS20#0.

• 30-Year Treasury Constant Maturity Rate https://fred.stlouisfed.org/series/DGS30#0.

• Moody’s Seasoned Baa Corporate Bond Yield https://fred.stlouisfed.org/series/BAA#0.


Other variables The Real S&P100 Composite Price index is obtained from Prof. Robert Shiller’s personal website while the Consumer Sentiment index is the one computed by the University of Michigan.\(^2\)


• Consumer Sentiment https://data.sca.isr.umich.edu/data-archive/mine.php.

A.1.2 Data transformation

In this subsection, we outline the way in which the data were transformed for the analyses in the manuscript.

1. **Uncertainty**: Quarterly average of the monthly series, demeaned and standardized.

The spikes in VXO correspond to at least 1.65 standard deviations above its HP-

\(^2\) The Consumer Sentiment index is calculated as an average of expectations about business conditions over the next year, expectations about aggregate business conditions over the next five years and expectations about personal financial conditions over the next year.
The quarterly dummy assumes 1 if there is one spike in any of the three months within the quarter, and zero otherwise.

2. **Inflation**: Log difference of the price index, multiplied by 400 to convert it into annualized rate.

3. **Real GDP, Consumption, and Investment**: The series are first divided by the civilian non-institutional population (16 years or over) to convert into per capita terms and the resulting per capita series is then deflated into 2012 Dollars using their respective price deflator. Annualized growth rates are computed by taking the log difference of the resulting series and multiplying by 400.

4. **Credit Spread**: Difference between the Baa 30-year yield and the 30-year Treasury bond yield. In periods when the 30-year bond is missing we use the 20-year treasury bond yield as in Bachmann et al. (2013).

5. **S&P100**: Detrended by applying the Hodrick-Prescott filter to the log of the S&P100 index with a smoothing parameter of 1600 following Caggiano et al. (2014).

6. **Consumer Sentiment**: Demeaned and standardized the quarterly series.

### A.2 Estimation and prior distributions

We estimate the TVP-VAR model with stochastic volatility using Bayesian MCMC methods. In particular, we use the MCMC routine developed by Nakajima (2011) and refer the readers to his paper for a detailed description of the sampling algorithms. The following priors are used for the \(i\)-th diagonals of the covariance matrices:

\[
\begin{align*}
(\Sigma_{\alpha})^{-2}_i & \sim \text{Gamma}(40, 0.0005), \\
(\Sigma_{\gamma})^{-2}_i & \sim \text{Gamma}(6, 0.005), \\
(\Sigma_{\delta})^{-2}_i & \sim \text{Gamma}(6, 0.005).
\end{align*}
\]

For the initial states of the time-varying parameters, we place flat priors as in Nakajima (2011):

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3 We use the MATLAB program written by Jouchi Nakajima for producing all the results in the paper, which is available on his personal website, https://sites.google.com/site/jnakajimaweb/program.
\[ \mu_{\alpha_0} = \mu_{\gamma_0} = \mu_{\delta_0} = 0 \text{ and } \Sigma_{\alpha_0} = \Sigma_{\gamma_0} = \Sigma_{\delta_0} = 10 \cdot I. \] To compute the posterior estimates, we draw 10,000 samples after discarding the initial 2000 draws as burn-in. Following Cogley and Sargent (2005) our posterior draws are comprised of only those that produce stable VAR dynamics at each point in time.\(^4\)

### A.3 Robustness checks

We conduct several robustness checks with respect to additional variables and alternative measures of inflation. First, our baseline model might capture variations in the level of the stock market as variations in uncertainty, since the level of the stock market is (negatively) correlated with the VXO. Therefore, to control for the level of the stock market, we estimate the VAR 
\[ y_t = (\text{S&P100}_t, u_t, \pi_t, \Delta y_t, R_t)' \], where S&P100 captures the level of the stock market.\(^5\) Likewise, consumer sentiment might be another important driver of the economy as it contains information concerning agents’ expectations over the future state of the economy, and, therefore, it might also incorporate anticipated effects of uncertainty shocks. Hence, we also estimate the VAR 
\[ y_t = (\text{sent}_t, u_t, \pi_t, \Delta y_t, R_t)' \], where “sent” stands for consumer sentiment and is the index of consumer expectations based on information collected via the Michigan Survey of Consumers. Additionally, Gilchrist et al. (2014) suggest that uncertainty shocks propagate primarily through changes in the credit spreads, and so we also estimate the five-variate VAR 
\[ y_t = (u_t, \text{spread}_t, \pi_t, \Delta y_t, R_t)' \], where “spread” is the corporate bond spread computed as the difference between the Baa 30-year yield and the 30-year Treasury bond yield following Bachmann et al. (2013).\(^6\) We also re-estimate the baseline four-variate VAR, but using CPI and GDP deflator as alternative measures of inflation. Finally, Born and Pfeifer (2017) show that it is the countercyclical wage markup that matters for understanding the transmission of uncertainty shocks more than the countercyclical price markup. Consequently, we replace price inflation with nominal wage inflation and re-estimate the VAR, where wage

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\(^4\) See Appendix B of Cogley and Sargent (2005) for more details on this step.

\(^5\) Since S&P100 exhibit a clear upward trend, we estimate the VAR using detrended data obtained by applying Hodrick-Prescott filter to the log of the S&P100 index with a smoothing parameter of 1600 following Caggiano et al. (2014).

\(^6\) In periods when the 30-year bond is missing we use the 20-year treasury bond yield as in Bachmann et al. (2013).
inflation is measured using Average Hourly Earnings of Production and Nonsupervisory Employees (AHE). Figure A.1, which plots the cumulated impulse responses at the 2-year ahead horizon, shows that our main results remain robust.

**Figure A.1: Robustness checks**

![Graphs showing responses](image)

*Note: Accumulated response at the 2-year ahead horizon. Gray shaded area corresponds to 68% credible interval from the baseline model.*

In addition, we conduct the following additional checks: i) using alternative indicators of economic activity, ii) using alternative measure of nominal interest rates, iii) prior sensitivity, and iv) different lag length. With regards to i), we replace real per capita GDP growth in the baseline VAR in turn with consumption growth (measured as the growth rate of real Personal Consumption Expenditure on Nondurable Goods per capita) and investment growth (measured as the growth rate of real Fixed Private Investment per capita) as alternative measures of economic activity. Regarding ii), we replace the nominal (shadow) interest rate of Wu and Xia (2016) with the 1-year constant maturity Treasury (CMT) rate. Regarding iii), we use an alternative prior for the hyper-parameter governing the rate at which the VAR
coefficients $\alpha_t$ drift over time. We now assume that $(\Sigma_\alpha)^{-2}_i \sim \text{Gamma}(20, 0.002)$. Finally, we re-estimate the baseline four-variate VAR with three and four lags instead of two.\(^7\)

Figure A.2 depicts the cumulated impulse responses to a normalized uncertainty shock at the 2-year ahead horizon for these various additional robustness checks along with the baseline results. The figure confirms that all our main results remain robust. The figure also shows that the negative response of investment growth is stronger in magnitude than consumption or output growth, which is in line with the findings of Caggiano et al. (2017).

**Figure A.2:** Additional robustness checks

Note: Accumulated response at the 2-year ahead horizon. Gray shaded area corresponds to 68\% credible interval from the baseline model. Ordering $y_t = [u_t, \pi_t, \text{activity}_t, R_t]'$.

The identification approach used in this paper - recursive with VXO ordered first - assumes that financial uncertainty is exogenous to the business cycle, implying that no macroeconomic shock can contemporaneously affect the level of uncertainty in the economic system. To check the extent to which this assumption affects our results, we order uncertainty last in

\(^7\) Figure A.2 depicts the results using three lags, which are essentially the same when using four lags.
our vector, that is, \( y_t = (\pi_t, \Delta y_t, R_t, u_t)' \). With uncertainty ordered last in the VAR, the effects of uncertainty shocks on the other variables in the system are measured after we have removed all the variation in uncertainty that is attributable to shocks to the other endogenous variables in the system. In line with Jurado et al. (2015), we find that when uncertainty is ordered last the effects of VXO shocks are muted, being statistically significantly different from zero only shortly after the shock and insignificant at other horizons (see Figure A.3). Nonetheless, uncertainty shocks continue to look like aggregate demand shocks over the entire sample.

**Figure A.3:** Impulse responses to a normalized uncertainty shock with uncertainty ordered last

![Impulse responses](image)

*Note:* Instantaneous, 1-quarter and 1-year ahead impulse responses. Gray shaded area represents 68% posterior credible intervals around the posterior median.

### A.3.1 Fixed-coefficient VAR

Estimating a time-varying parameter VAR in our analysis allows us to explore changes in the transmission mechanism of uncertainty shocks with a particular focus on inflation, in order
to understand whether such shocks look like aggregate supply or demand shocks in nature. Nonetheless, we also estimate a fixed-coefficient VAR with stochastic volatility to ascertain the implications of estimating a constant-coefficient framework. For the fixed-coefficient VAR with stochastic volatility equation (2.1) from the paper can be expressed as

\[ y_t = A_0 + A_1 y_{t-1} + \ldots + A_s y_{t-s} + \epsilon_t, \quad \epsilon_t \sim N(0, \Omega_t), \]

where \( \Omega_t = \Gamma^{-1} \Sigma_{\epsilon t} (\Gamma^{-1})' \), \( \Sigma_{\epsilon t} \) is a time-varying diagonal matrix comprising of variances of the structural shocks. Note that \( \Sigma_{\epsilon t} \) is the only time-varying component capturing stochastic volatility specified as

\[ \delta_{t+1} = \delta_t + \epsilon_{\delta t}, \]

for \( t = s + 1, \ldots, n \), where \( \delta_t = [\log \sigma^2_{1,t}, \ldots, \log \sigma^2_{k,t}]' \). As before, we assume \( \epsilon_{\delta t} \sim N(0, \Sigma_\delta) \), where \( \Sigma_\delta \) is a diagonal matrix and \( \delta_{s+1} \sim N(\mu_0, \Sigma_0) \). We estimate this fixed-coefficient VAR with stochastic volatility using the same number of lags, data set, sample period, and prior for the initial state as in the baseline analysis.

Figure A.4 shows the median and 68% credible intervals of the impulse response functions (IRFs) of uncertainty, inflation, real GDP growth and the nominal interest rate to a normalized uncertainty shock on impact and at the 1-year and 2-year ahead horizons.\(^8\) The figure shows that following an uncertainty shock inflation, output and nominal interest rate all go down. Therefore, a fixed-coefficient VAR would suggest that uncertainty shocks are aggregate demand shocks, as in Leduc and Liu (2016).

A.3.2 Michigan Survey Consumer Uncertainty

We estimate the baseline four-variate VAR using the consumer uncertainty measure of Leduc and Liu (2016), which is based on the monthly Michigan survey. The sample covers the period from February 1978 to December 2019. As Leduc and Liu (2016) point out, one advantage of this measure is that it allows us to exploit the timing of the survey interviews relative to the timing of the macroeconomic data releases. In the Michigan survey, when answering questions,

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\(^8\) To allow comparability over time as before, for each quarter, the IRFs have been normalized by setting the impact of uncertainty shocks on the uncertainty index equal to the sample mean of the estimated standard deviation of uncertainty shocks. That is, the IRFs depict the responses to an average-sized shock as before.
survey participants have information about the previous month’s macroeconomic data, but they do not have complete information about the current month’s macroeconomic conditions because those data are not yet publicly available. Hence, the use of monthly Michigan survey’s consumer uncertainty data makes the recursive identification with uncertainty ordered first more plausible. Nonetheless, we also estimate the model with consumer uncertainty ordered last. For this exercise, we use Industrial Production as a proxy for economic activity which is available on a monthly basis. Four lags are used for the estimation. The model contains the following four time-series: Michigan survey consumer uncertainty, the inflation rate measured as the year-over-year changes in the PCE deflator, economic activity measured as the year-over-year changes in the Industrial Production, and the Effective Fed Funds rate
appended with the shadow rate of Wu and Xia (2016) during the ZLB period. Figures A.5 and A.6 plot the IRFs to an average-sized uncertainty shock. The figures show that, despite some differences in the nature of the time variations, uncertainty shocks look like aggregate demand shocks in the post-WWII period.

**Figure A.5:** Impulse responses to a normalized uncertainty shock with consumer uncertainty ordered first

![Impulse response figures](image)

*Note:* Instantaneous, 1-year and 2-year ahead impulse responses. Gray shaded area represents 68% posterior credible intervals around the posterior median.

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9 In order to render the TVP-VARs stable when using monthly data, priors were adjusted such that we allow for relatively less movements in the VAR coefficients relative to the baseline prior.
Figure A.6: Impulse responses to a normalized uncertainty shock with consumer uncertainty ordered last

Note: Instantaneous, 1-year and 2-year ahead impulse responses. Gray shaded area represents 68% posterior credible intervals around the posterior median.
References


