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Uncertainty shocks and inflation dynamics in the US

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JEL Classification

C32, E31, E32, E44

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Uncertainty shocks and inflation dynamics in the U.S.*

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1 Introduction

The macroeconomic effects of uncertainty shocks is a key topic of research, see Castelnuovo (2019) for an extensive literature review. The consensus is that uncertainty shocks result in adverse real effects on the economy (Bloom, 2009; Caggiano et al., 2014). However, the response of inflation to an uncertainty shock remains ambiguous. We estimate a TVP-VAR with stochastic volatility to investigate the role played by uncertainty shocks in driving inflation dynamics.

Our investigation is motivated by the observation that the price reaction to an uncertainty shock is itself uncertain. Leduc and Liu (2016) conduct a VAR analysis and find that uncertainty shocks are aggregate demand-type shocks, that is, they increase unemployment and decrease inflation. This result is in line with their New Keynesian model with search and matching frictions. Nevertheless, Fasani and Rossi (2018) demonstrate that empirically plausible interest rate smoothing in Leduc and Liu's model lead to an increase in inflation, that is uncertainty shocks look like aggregate supply shocks instead.

In models featuring price rigidities, the sign of the inflation response to an uncertainty shock is theoretically unclear. On the one hand, the aggregate demand channel implies a deflationary response to an uncertainty shock given its negative real effects due to, for instance, precautionary savings motive, see Basu and Bundick (2017). On the other hand, firms might find optimal to raise prices in response to contractionary uncertainty shocks in order to avoid the risk of being stuck with lower prices (Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015).

On the empirical side, the findings are also mixed. While Leduc and Liu (2016) find uncertainty shocks to be deflationary, Mumtaz and Theodoridis (2018) find inflationary effects for the entire post-WWII period. Alessandri and Mumtaz (2019) find uncertainty shocks to be inflationary only in normal times and deflationary during the financial crisis. Caggiano et al. (2020) note that uncertainty shocks trigger a temporary fall in prices, which is statistically significant in recessions only, while being insignificant in normal times. Meinen and Roehe (2018) estimate SVAR models with sign restrictions and find the response of inflation to be ambiguous.

We investigate time-varying effects of uncertainty shocks on inflation to understand whether such shocks correspond to supply or demand shocks in nature.[1] We find the response of inflation to an uncertainty shock to be statistically insignificant until mid-to-late 1990s and negative thereafter. We also find that the negative real effects of uncertainty shocks have declined over time, but became more pronounced during the zero lower bound (ZLB) and subsequent periods. Our findings suggest that uncertainty shocks do not propagate like aggregate supply shocks, and look like aggregate demand shocks since late 1990s.

2 Econometric framework

We estimate a TVP-VAR with stochastic volatility, based on the framework of Cogley and Sargent (2005) and Primiceri (2005) which has the following structural form representation

$$\Gamma_t \mathsf{y}_t = \Lambda_{0,t} + \Lambda_{1,t}\mathsf{y}_{t-1} + \ldots + \Lambda_{s,t}\mathsf{y}_{t-s} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_{\varepsilon t}),$$

for $t = s+1, \ldots, n$, where y_t is an $k \times 1$ vector of observables, $\Lambda_{0,t}$ is an $k \times 1$ vector of intercepts, $\Lambda_{1,t}$,..., $\Lambda_{s,t}$ are $k \times k$ matrices of time-varying coefficients, Γ_t is a lower triangular matrix with ones in the main diagonal (recursive identification), $\Sigma_{\varepsilon t} = \text{diag}\left(\sigma^2_{1,t}, \ldots, \sigma^2_{k,t}\right)$ is a diagonal matrix of variances. The reduced form representation is

$$\mathsf{y}_t = A_{0,t} + A_{1,t}\mathsf{y}_{t-1} + \ldots + A_{s,t}\mathsf{y}_{t-s} + \epsilon_t, \quad \epsilon_t \sim N(0, \Omega_t), \tag{2.1}$$

where $\Omega_t = \Gamma_t^{-1}\Sigma_{\varepsilon t}\left(\Gamma_t^{-1}\right)'$. Define α_t as the stacked row vector of $[A_{0,t}, A_{1,t}, \ldots, A_{s,t}]$, γ_t as the stacked row vector of the free lower triangular elements of Γ_t, and $\delta_t = \left[\log \sigma^2_{1,t}, \ldots, \log \sigma^2_{k,t}\right]'$.

[1] In a closely related paper, we study the dynamics of consumption and investment and their comovement following an uncertainty shock using a TVP-VAR estimated with post-WWII U.S. data, see Haque et al. (2019).

The model's parameters evolve as

$$\alpha_{t+1} = \alpha_t + e_{\alpha t}, \quad \gamma_{t+1} = \gamma_t + e_{\gamma t}, \quad \delta_{t+1} = \delta_t + e_{\delta t},$$

for $t = s+1, \ldots, n$. Following Nakajima (2011), we assume $(e_{\alpha t}, e_{\gamma t}, e_{\delta t})' \sim N\left[0, \text{diag}(\Sigma_\alpha, \Sigma_\gamma, \Sigma_\delta)\right]$, where Σ_α, Σ_γ and Σ_δ are diagonal matrices, $\alpha_{s+1} \sim N\left(\mu_{\alpha_0}, \Sigma_{\alpha_0}\right)$, $\gamma_{s+1} \sim N\left(\mu_{\gamma_0}, \Sigma_{\gamma_0}\right)$ and $\delta_{s+1} \sim N\left(\mu_{\delta_0}, \Sigma_{\delta_0}\right)$. We estimate the model with two lags using Bayesian methods (Primiceri, 2005; Nakajima, 2011).

The vector $\mathsf{y}_t = (u_t,\ \pi_t,\ \Delta y_t,\ R_t)'$ contains the uncertainty proxy measured using the S&P 100 Volatility Index (VXO) (u_t), the inflation rate measured using the PCE deflator (π_t), the growth rate of real GDP (Δy_t), and the nominal policy rate (R_t) measured by Wu and Xia (2016). Since the proxy for uncertainty is based on stock market volatility, our focus is on financial uncertainty. We use quarterly time series data over the period 1962Q3 to 2019Q4.[2] The online appendix contains details on the data and estimation. We adopt short-run restrictions implied by the Cholesky decomposition with the ordering as shown in y_t. These restrictions, which follow the literature (Bloom, 2009; Caggiano et al., 2014, 2017; Leduc and Liu, 2016; Basu and Bundick, 2017), are justified by the results of Angelini et al. (2019) and Ludvigson et al. (2020), who show that financial uncertainty shocks are exogenous drivers of the business cycle.

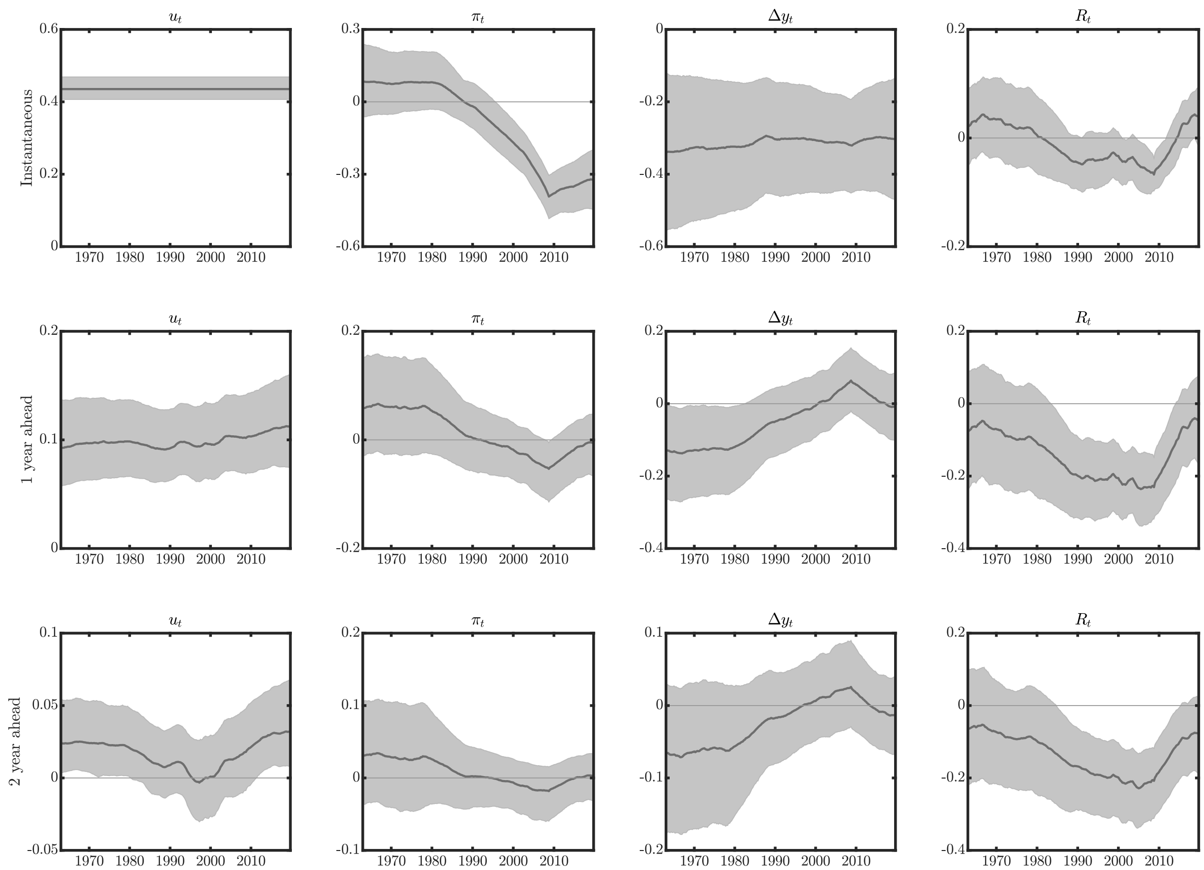
3 Results

Figure 1 shows the median and 68% credible intervals of the IRFs of uncertainty, inflation, real GDP growth and the nominal interest rate to a normalized uncertainty shock.[3]

[2] The TVP-VAR is not flexible enough to model observations during the Covid-19 pandemic period, see Lenza and Primiceri (2020).

[3] The impact of uncertainty shocks on the uncertainty index is normalized by the sample mean of the estimated standard deviation of uncertainty shocks.

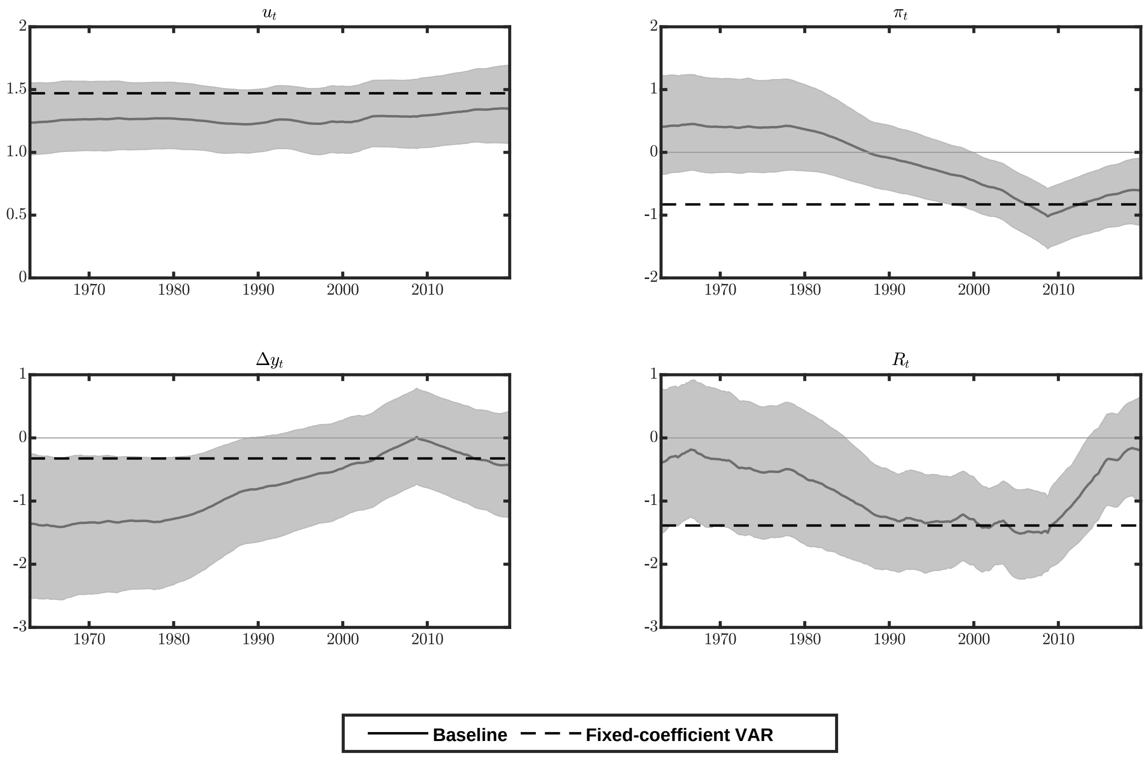
Figure 1: Impulse responses to a normalized uncertainty shock



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

First, consistent with previous studies, we confirm that uncertainty shocks are contractionary shocks that aggravate economic conditions with output growth declining significantly. However, we find no 'overshooting' of economic activity as documented in Bloom (2009), which is in line with the findings of Jurado et al. (2015). Second, the response of inflation to an uncertainty shock is statistically insignificant until mid-to-late 1990s and negative afterwards, suggesting that uncertainty shocks look more like aggregate demand shocks as found by Leduc and Liu (2016) and Basu and Bundick (2017), but only since late 1990s. This result differs from the predictions of Born and Pfeifer (2014) and Fasani and Rossi (2018), who suggest that uncertainty shocks act like aggregate supply shocks, resulting in decline of economic activity and a rise in inflation.

Figure 2: Accumulated impulse responses to a normalized uncertainty shock



Note: Accumulated response at the 2-year horizon; sample period 1962Q3-2019Q4.

Figure 2 plots the median and 68% credible interval of the cumulated impulse responses at the 2-year ahead horizon (labelled Baseline) and documents the time-varying effects more clearly.[4] Like Mumtaz and Theodoridis (2018), the figure shows that the response of real GDP growth to an uncertainty shock has waned over time. We find, however, a systematic decline in the response of inflation and the nominal interest rate over time until late 2000s.[5] The positive response of inflation, albeit statistically insignificant, eventually turns negative in the 1990s. The effect on nominal interest rate turns more negative as well over time. One explanation is the Federal Reserve's anti-inflationary stance.[6] The increased responsiveness of interest rates to inflation makes price-setting firms less forward looking, which, in turn, allows

[4] Our results are robust to alternative horizons.
[5] Mumtaz and Theodoridis (2018) study 'macroeconomic' uncertainty while we consider financial uncertainty.
[6] Several studies offer evidence regarding changes in the policy reaction function, see Clarida et al. (2000), Lubik and Schorfheide (2004), Castelnuovo and Fanelli (2015).

the central bank to cut back interest rates more quickly and aggressively, thereby dampening the adverse effects of uncertainty shocks on real activity (Mumtaz and Theodoridis, 2018). The resulting decrease in firms' pricing bias implies a diminished role for this channel vis-à-vis the standard aggregate demand channel, explaining why the response of inflation declines and finally switches to a negative response after an uncertainty shock. Yet, other factors, such as an increased degree of interest rate smoothing (Fasani and Rossi, 2018) or a flattening of the Phillips curve due to increased price stickiness (Mumtaz and Theodoridis, 2018), have an upward effect on the pricing bias channel. Therefore, our results point toward a strengthening of the standard aggregate demand channel over time relative to the pricing bias channel.

Figure 2 also highlights a change in the impact of uncertainty shocks during the ZLB period: the response of output growth becomes more negative while that of both inflation and nominal interest rate become less negative. Several studies demonstrate that the real effects of uncertainty shocks are more pronounced when the ZLB binds (Basu and Bundick, 2017; Caggiano et al., 2017). For instance, Caggiano et al. (2017) argue that more negative real effects are due to the "missing fall in the short-term nominal and real interest rates in the presence of the ZLB". Our findings also suggest that the price effects are less negative despite more pronounced real effects following an uncertainty shock, resembling the "missing deflation" during the Great Recession.

Finally, we estimate a fixed-coefficient VAR with stochastic volatility to ascertain how much one misses when sticking to the constant-coefficient framework.[7] Figure 2, which plots the posterior median of the cumulated responses at the 2-year ahead horizon for a normalized uncertainty shock (dotted line), shows that inflation, output and nominal interest rate all go down.[8] Therefore, the fixed-coefficient VAR suggests that uncertainty shocks are aggregate demand shocks as in Leduc and Liu (2016).

We conduct several robustness checks with respect to priors, lag lengths, additional variables, alternative measures of inflation, real activity and interest rates. Our results remain

[7] See Section S3.1 in the Appendix for more details.
[8] As in the baseline model, the IRFs depict responses to an average-sized shock.

robust as shown in the online Appendix. Overall, the implication is that uncertainty shocks do not act like aggregate supply shocks. Instead, they look like aggregate demand shocks but only since late 1990s.

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

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Contents

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S1 Data

We use quarterly time series data for the U.S. over the period 1962Q3 to 2019Q4, 1962Q3 being the first available quarter for the uncertainty index.

S1.1 Data sources

Uncertainty proxy - 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`. Pre 1986, it is obtained from the monthly standard deviation of the daily S&P500 and normalized following Bloom (2009).

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`
- **Personal Consumption Expenditures: Nondurable Goods** `https://fred.stlouisfed.org/series/PCND`
- **Fixed Private Investment** `https://fred.stlouisfed.org/series/FPI`

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]

- **Personal Consumption Expenditures: Implicit Price Deflator** `https://fred.stlouisfed.org/series/DPCERD3Q086SBEA`.
- **Gross Domestic Product: Implicit Price Deflator** `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`.
- **Gross Private Domestic Investment: Fixed Investment: Implicit Price Deflator** `https://fred.stlouisfed.org/series/A007RD3Q086SBEA#0`.
- **Personal Consumption Expenditures: Nondurable goods: Implicit Price Deflator** `https://fred.stlouisfed.org/series/DNDGRD3Q086SBEA`.
- **Average Hourly Earnings of Production and Nonsupervisory Employees, Total Private** `https://fred.stlouisfed.org/series/AHETPI`.
- **Effective Federal Funds Rate** `https://fred.stlouisfed.org/series/FEDFUNDS`.
- **1-Year Treasury Constant Maturity Rate** `https://fred.stlouisfed.org/series/DGS1#0`.
- **30-Year Treasury Constant Maturity Rate** `https://fred.stlouisfed.org/series/DGS30#0`.
- **20-Year Treasury Constant Maturity Rate** `https://fred.stlouisfed.org/series/GS20#0`.
- **Moody's Seasoned Baa Corporate Bond Yield** `https://fred.stlouisfed.org/series/BAA#0`.

[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.

- **Wu-Xia Shadow Federal Funds Rate** `https://www.frbatlanta.org/cqer/research/shadow_rate.aspx?panel=1`.

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]

- **Real S&P100 Composite Price** `http://www.econ.yale.edu/~shiller/data.htm`.

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

S1.2 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.

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

3. **Real GDP:** Real GDP series is 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 the GDP deflator. Annualized growth rate is computed by taking the log difference of the resulting series and multiplying by 400.

4. **Consumption:** Personal Consumption Expenditure: Nondurable Goods (PCND) is 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 the Personal Consumption Expenditures: Nondurable goods: Implicit

[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.

Price Deflator. Annualized growth rate is computed by taking the log difference of the resulting series and multiplying by 400.

5. **Investment:** Fixed Private Investment (FPI) is 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 Gross Private Domestic Investment: Fixed Investment: Implicit Price Deflator. Annualized growth rate is computed by taking the log difference of the resulting series and multiplying by 400.

6. **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).

7. **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).

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

S2 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.[3] The following priors are used for the $i-$th diagonals of the covariance matrices:

$(\Sigma_\alpha)_i^{-2} \sim Gamma(40, 0.0005)$,

$(\Sigma_\gamma)_i^{-2} \sim Gamma(6, 0.005)$,

$(\Sigma_\delta)_i^{-2} \sim Gamma(6, 0.005)$.

For the initial states of the time-varying parameters, we place flat priors as in Nakajima (2011): $\mu_{\alpha_0} = \mu_{\gamma_0} = \mu_{\delta_0} = 0$ 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

[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`.

Sargent (2005) our posterior draws are comprised of only those that produce stable VAR dynamics at each point in time.[4]

S3 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 $\mathsf{y}_t = (\text{S\&P100}_t,\ u_t,\ \pi_t,\ \Delta y_t,\ R_t\ )'$, 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 $\mathsf{y}_t = (\text{sent}_t,\ u_t,\ \pi_t,\ \Delta y_t,\ R_t)'$, 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 $\mathsf{y}_t = (u_t,\ \text{spread}_t,\ \pi_t,\ \Delta y_t,\ R_t)'$, 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 inflation is measured using Average Hourly Earnings of Production and Nonsupervisory

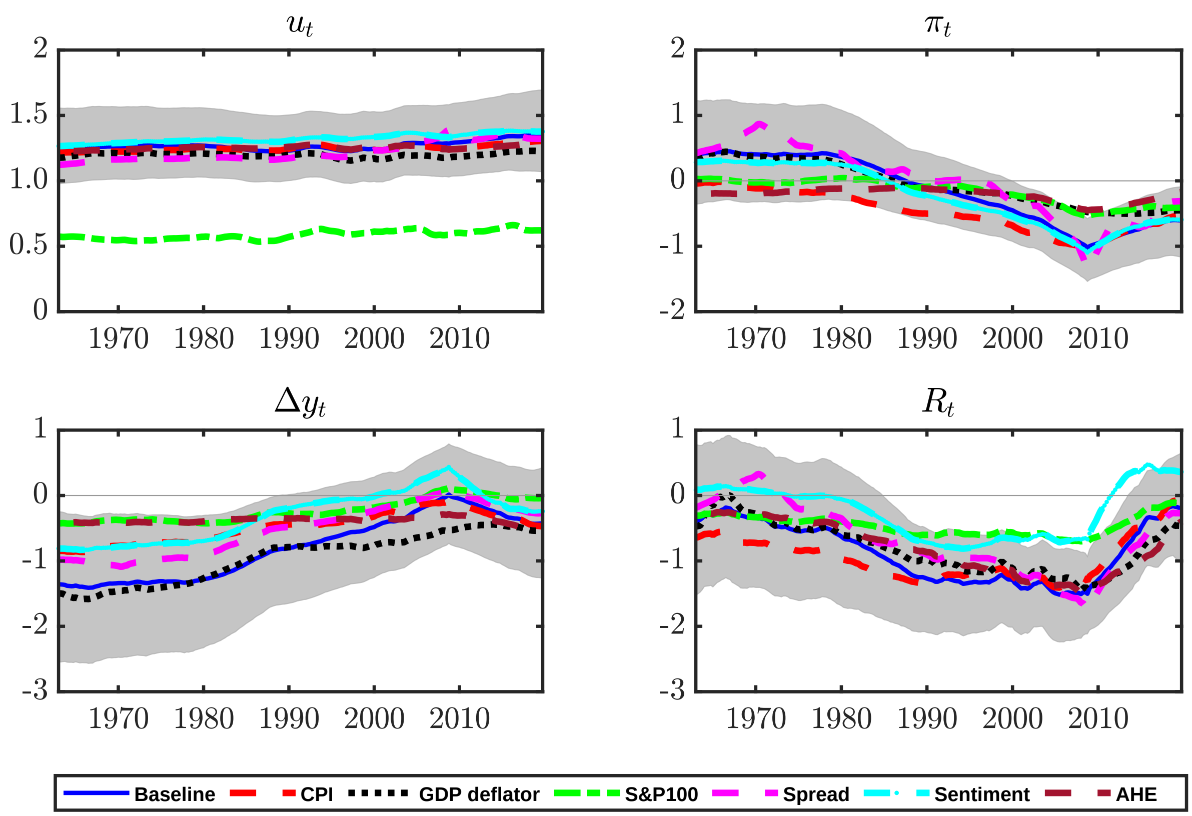
[4] See Appendix B of Cogley and Sargent (2005) for more details on this step.

[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).

Employees (AHE). Figure S.1, which plots the cumulated impulse responses at the 2-year ahead horizon, shows that our main results remain robust.

Figure S.1: Robustness checks

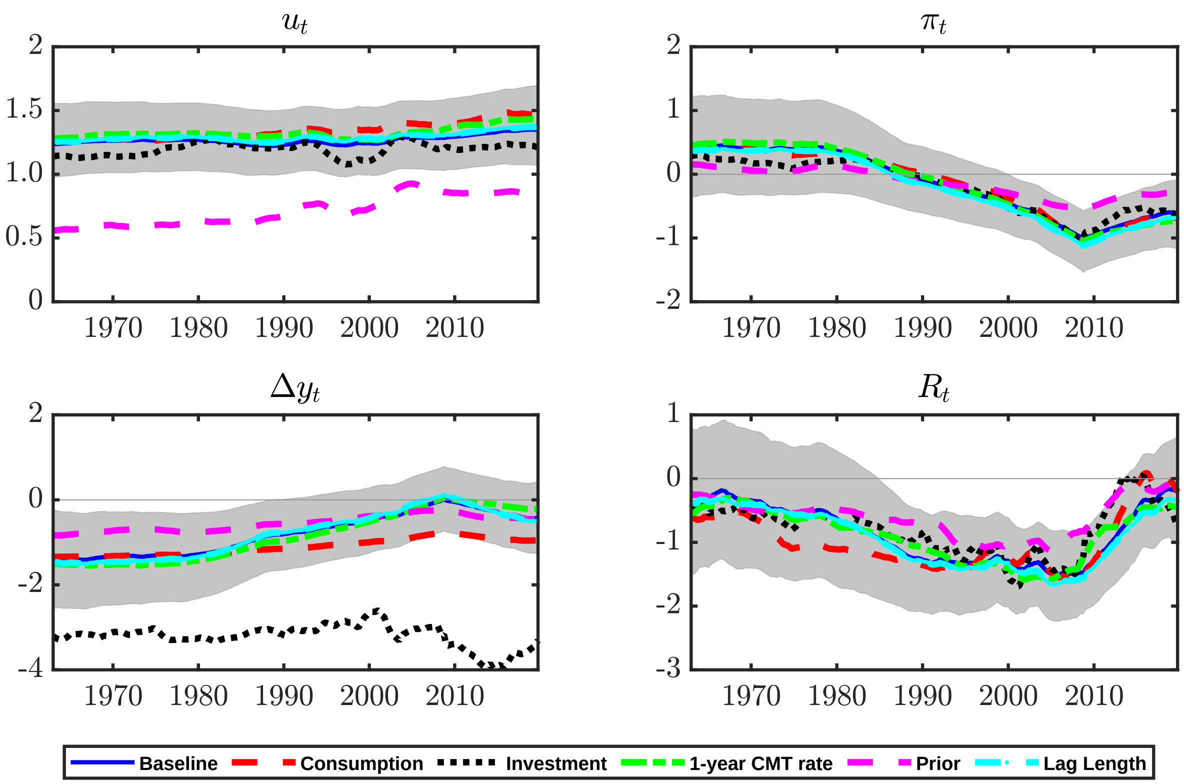


Note: Accumulated response at the 2-year ahead horizon. Gray shaded area corresponds to 68% credible interval from the baseline model.

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 α_t drift over time. We now assume that $(\Sigma_\alpha)_i^{-2} \sim Gamma(20, 0.002)$. Finally, we re-estimate the baseline four-variate VAR with three lags instead of two.

Figure S.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 S.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 $\mathsf{y}_t = [\ u_t,\ \pi_t,\ activity_t,\ R_t\ ]'$.

S3.1 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

$$\mathsf{y}_t = A_0 + A_1\mathsf{y}_{t-1} + \ldots + A_s\mathsf{y}_{t-s} + \epsilon_t, \quad \epsilon_t \sim N(0, \Omega_t),$$

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

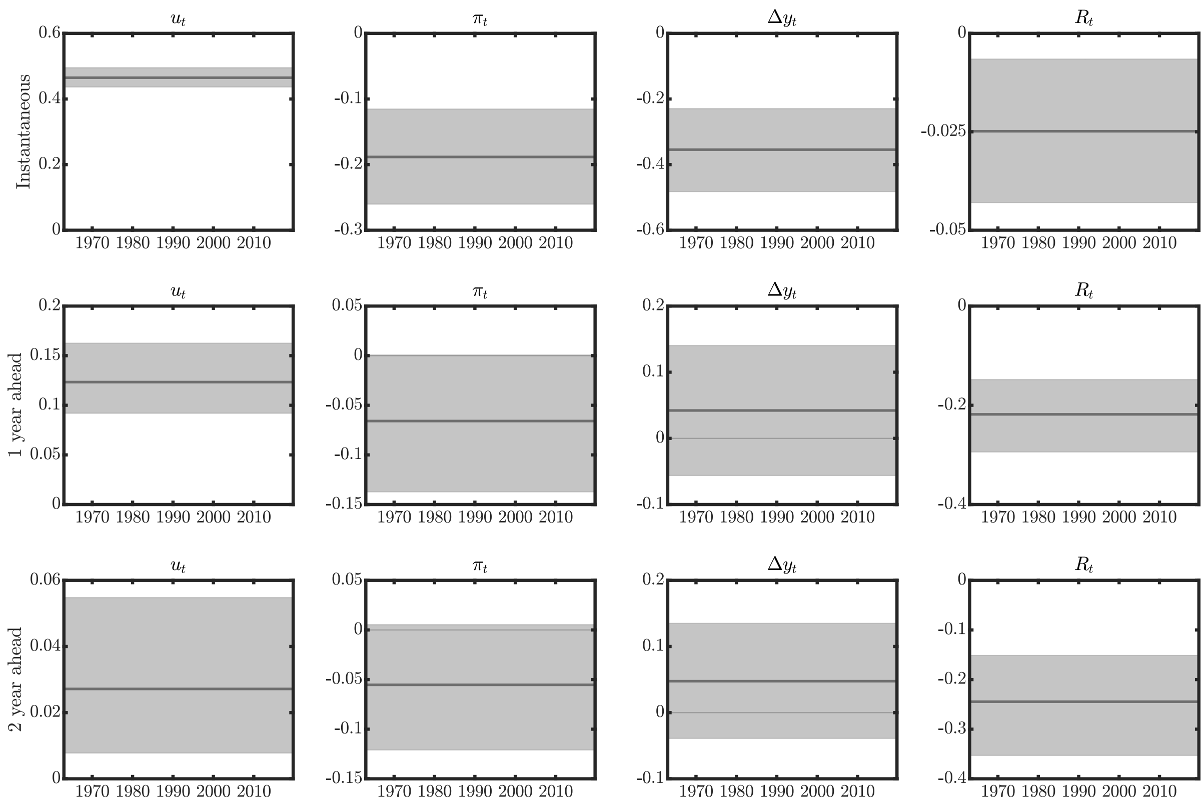
$$\delta_{t+1} = \delta_t + e_{\delta t},$$

for $t = s+1, \ldots, n$, where $\delta_t = \left[\log\sigma^2_{1,t}, \ldots, \log\sigma^2_{k,t}\right]'$. As before, we assume $e_{\delta,t} \sim N\left(0, \Sigma_\delta\right)$, where Σ_δ is a diagonal matrix and $\delta_{s+1} \sim N\left(\mu_{\delta_0}, \Sigma_{\delta_0}\right)$. 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 S.3 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.[7] 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). Hence, this exercise points to the importance of time-varying coefficients in driving our results in the baseline framework.

[7] 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.

Figure S.3: Impulse responses to a normalized uncertainty shock from a fixed-coefficient VAR



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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