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ECONOMIC POLICY UNCERTAINTY AND UNEMPLOYMENT IN THE UNITED STATES: A NONLINEAR APPROACH

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Economic Policy Uncertainty and Unemployment in the United States: A Nonlinear Approach*

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Abstract

We model U.S. post-WWII monthly data with a Smooth Transition VAR model and study the effects of an unanticipated increase in economic policy uncertainty on unemployment in recessions and expansions. We find the response of unemployment to be statistically and economically larger in recessions. A state-contingent forecast error variance decomposition analysis confirms that the contribution of EPU shocks to the volatility of unemployment at business cycle frequencies is markedly larger in recessions.

Keywords: Economic Policy Uncertainty Shocks, Unemployment Dynamics, Smooth Transition Vector AutoRegressions, Recessions, Expansions.

JEL codes: C32, E32, E52.

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1 Introduction

Baker, Bloom, and Davis (2016) construct an index of economic policy uncertainty (EPU) and find that an unexpected increase in such index is associated to a significant and persistent drop in real activity in the U.S. and a number of other countries. This paper shows that the response of the U.S. unemployment rate to an EPU shock is asymmetric along the business cycle. We do so by fitting monthly post-WWII U.S. data with a Smooth Transition VAR (STVAR) model in which EPU shocks are allowed (but not required) to exert a different effect on the unemployment rate in recessions and expansions. Results show that EPU shocks trigger a peak response of unemployment six times larger in recessions than in expansions. The contribution of EPU shocks to the volatility of the unemployment rate at business cycle frequencies is found to be markedly larger in bad times than in good ones.

Evidence in favor of the asymmetric evolution of the U.S. unemployment rate along the business cycle is provided by Morley and Piger (2012) and the literature cited therein. Our paper shows that EPU shocks may be among the contributors to this asymmetric behavior. Our results complement those in Caggiano, Castelnuovo, and Groshenny (2014) and Nodari (2014). Caggiano, Castelnuovo, and Groshenny (2014) find the real effects of financial uncertainty shocks on U.S. unemployment to be larger in recessions than what a linear model would suggest. Nodari (2014) shows that financial economic policy uncertainty shocks have state-dependent effects on unemployment. With respect to them, we i) focus on EPU shocks; ii) identify events associated with large realizations of the economic policy uncertainty index, which are likely to isolate exogenous shocks that are informative to estimate the real effects of economic policy uncertainty; iii) directly estimate the key parameters of the STVAR model, i.e. the slope of the logistic function dictating the probability of being in a given state, and the threshold that identifies the two regimes; iv) compute generalized impulse responses (GIRFs) à la Koop, Pesaran, and Potter (1996), therefore enabling the economic system to switch from a state to another (e.g., from expansions to recessions) after a shock.

This paper is structured as follows. Section 2 offers a brief presentation of the EPU index and of our empirical model. Section 3 documents our empirical findings. Section 4 concludes.

2 EPU index and empirical framework

U.S. EPU index. Baker et al. (2016) construct indices of economic policy uncertainty based on newspaper coverage frequency for the U.S. and a number of other countries. Per each country, they consider a set of newspapers and count the number of articles that contain terms referring to three categories, i.e., the economy (E), policy (P), and uncertainty (U). They scale the raw count by the total number of articles in the same newspaper/month. Finally, they standardize the monthly series of scaled counts and average them across the newspapers they consider to obtain the monthly EPU index. Further details on the construction of this index can be found in Baker, Bloom, and Davis (2016) and our Appendix.

STVAR model. We identify the macroeconomic effects of uncertainty shocks during post-WWII U.S. recessions by modeling some selected U.S. macroeconomic series with a Smooth-Transition VAR framework. Formally, our STVAR model reads as follows:

$$\boldsymbol{X}_t = [1 - F(z_{t-1})]\boldsymbol{\Pi}_R(L)\boldsymbol{X}_t + F(z_{t-1})\boldsymbol{\Pi}_E(L)\boldsymbol{X}_t + \boldsymbol{\varepsilon}_t \tag{1}$$

$$\boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\Omega}) \tag{2}$$

$$F(z_t) = \{1 + \exp[-\gamma(z_t - c)]\}^{-1}, \gamma > 0, z_t \sim D(0,1) \tag{3}$$

where $\boldsymbol{X}_t$ is a set of endogenous variables which we aim to model, $F(z_{t-1})$ is a logistic transition function which captures the probability of being in an expansion and whose smoothness parameter γ regulates the rapidity of the switch from a regime to another (the higher γ, the faster the switch), z_t is a transition indicator, c is the threshold parameter identifying the two regimes, $\boldsymbol{\Pi}_R$ and $\boldsymbol{\Pi}_E$ are the VAR coefficients capturing the dynamics of the system during recessions and expansions (respectively), and $\boldsymbol{\varepsilon}_t$ is the vector of reduced-form residuals having zero-mean and variance-covariance matrix $\boldsymbol{\Omega}$. As regards the transition indicator z_t, we employ a standardized moving average of the growth rate of industrial production.[1]

Given z_t, we jointly estimate the parameters $\{\boldsymbol{\Pi}_R, \boldsymbol{\Pi}_E, \boldsymbol{\Omega}, \gamma, c\}$ of model (1)-(3) with conditional maximum likelihood as suggested by Teräsvirta, Tjøstheim, and Granger (2010). We model the vector of data $\boldsymbol{X}_t = [EPUD_t, \overline{\Delta IP}_t, u_t, \pi_t, R_t]'$. $EPUD_t$ refers

[1] We focus on a moving average of the month-over-month growth rate of industrial production involving six terms. Conditional on our sample, this moving average returns a higher correlation (in absolute value) with the NBER recession dummy (-0.60) than alternatives such as the simple monthly growth rate of industrial production (-0.48) and a moving average involving twelve terms (-0.51).

to a 0/1 dummy identifying spikes in economic policy uncertainty (discussed below), $\overline{\Delta IP}_t$ stands for the six-term moving average of the monthly growth rate of industrial production (percentualized and annualized), u_t is the unemployment rate, π_t is CPI inflation (year-over-year percentualized growth rate of the monthly index), and R_t is the federal funds rate. All data were downloaded from the Federal Reserve Bank of St. Louis' website, except the EPU index, which was downloaded from the website http://www.policyuncertainty.com/ . We focus on the sample 1954M7-2014M10. The beginning of the sample refers to the month in which the effective federal funds rate became available, while the end of the sample is due to the availability of the newspaper-based EPU historical index for the United States. Testing the null hypothesis of linearity versus the alternative of a STVAR specification as in Teräsvirta and Yang (2014) returns a value of the LM-test statistic of 58.14, with associated p-value equal to 0.0002.[2]

Construction of the EPU dummy. To construct the $EPUD_t$ 0/1 dummy, we first compute the cyclical component of the U.S. EPU index via the Hodrick-Prescott filter. This is done to control for changes in the low-frequency component of this index over the post-WWII period which are possibly due to the increasing role played by fiscal components and political polarization in the U.S. economic system (see Baker, Bloom, Canes-Wrone, Davis, and Rodden (2014)). Second, we follow Bloom (2009) and isolate spikes in uncertainty by selecting realizations of the cyclical component of the EPU index larger that 1.65 times its standard deviation. This strategy helps us isolate realizations of uncertainty with a strong exogenous component and, therefore, identify the causal response of unemployment to movements in the EPU index.

Table 1 reports the dating of the non-zero realizations of the so-constructed EPU-dummy. Examples are historical events like wars, the dissolution of the Soviet Union, and 9/11, which can be seen as huge external shocks which cast doubts in agents' minds on the type of reaction policymakers would implement, as well as fiscal- or monetary-policy related events like discussions on the budget, the fiscal cliff, and large monetary policy adjustments, which are clearly specific to U.S. economic policy decisions.

[2] The STVAR features the number of lags selected for the linear version of the VAR(p) model, with $1 \leq p \leq 12$. The BIC and HQ information criteria point to the use of two lags. The estimated model is found to closely track the U.S. recessions and expansions as dated by the NBER (evidence confined in our Appendix).

3 Empirical evidence

Orthogonalization of the EPU shock and computation of the GIRFs. To make sure that the EPU shock is orthogonal to the other stochastic elements in our VAR, we model the impulse vector responsible of the on-impact response of the variables in the vector $\boldsymbol{X}_t$ by employing a Cholesky-decomposition of the reduced-form variance covariance matrix $\boldsymbol{\Omega}$. This implies that, on impact, EPU shocks can affect the rest of the system, while the EPU dummy is assumed to be contemporaneously exogenous to the rest of the system. In light of the construction of this dummy discussed above, we believe this assumption to be reasonable. We then compute GIRFs à la Koop, Pesaran, and Potter (1996) and report the median response in recessions and expansions. Our Appendix provides details on the computation of the GIRFs.

GIRFs. Figure 1 depicts the dynamic responses of our variables to a one-standard deviation increase in the dummy. The evidence of nonlinear effects on EPU shocks on unemployment is clear. The peak response of unemployment in recessions reads 0.14%, seven times larger than the response in expansions (0.02%). The difference between the responses in recessions and expansions - plotted in Figure A3 in our Appendix - confirms that the response of unemployment in recessions is significantly stronger from a statistical viewpoint. This result is in line with the theoretical predictions by Cacciatore and Ravenna (2015). They develop a model of the labor market with matching frictions and an occasionally binding constraint on downward wage adjustment, and show that the negative effects of uncertainty shocks on labor market outcomes are magnified during recessions. We find that the larger response of unemployment to EPU shocks is robust to: i) the employment of the EPU index (in lieu of our EPU dummy); ii) controlling for financial uncertainty, as in Baker et al. (2016); iii) the inclusion of the Baa-Aaa corporate bond spread to control for first moment financial shocks; iv) the inclusion of a factor extracted from the large panel of U.S. variables documented by McCracken and Ng (2015) to control for first moment macroeconomic shocks. Our Appendix documents these robustness checks (Figure A4).

It is important to notice that also industrial production and inflation react asymmetrically to an EPU shock. The peak response of industrial production in recessions (-1.10%) is four times larger than in expansions (-0.22%), while the peak deflationary impact in recessions reads -0.27%, compared to a peak response of -0.05% in expansions. Finally, the response of the federal funds rate in recessions is also larger, with a maximum decrease in the policy rate of about 23 basis points vs. 10 basis points in expansions. The asymmetric response of industrial production, inflation and the policy rate is statistically significant and is robust to the same controls discussed above – results are reported in Figures A3 and A4 in the Appendix.

FEVD. Table 2 documents the outcome of the state-dependent two-year ahead forecast error variance decomposition analysis à la Lanne and Nyberg (2016). To control for first moment shocks, we perform this analysis with the previously discussed Factor-Augmented STVAR (FASTVAR) model. In recessions, EPU shocks explain 8% of the volatility of unemployment. This contribution is larger than that of monetary policy shocks, which explain 7%. Not surprisingly, the bulk of the unemployment dynamics is explained by first moment shocks (overall, about 80%), while shocks to inflation contribute for 6%. Turning to expansions, most of the volatility of unemployment is still explained by first moment shocks. Interestingly, the contribution to inflation shocks raises to 20%. Most importantly for this study, EPU shocks are found to play no role in expansions. This result confirms that EPU shocks exert a much larger effect on unemployment during recessions.

4 Conclusions

This paper estimates the response of the U.S. unemployment rate to an unexpected increase in the level of economic policy uncertainty with a nonlinear model and post-WWII data. We find the response of unemployment to be significantly larger in recessions. Policy uncertainty shocks are shown to explain a non-negligible fraction of the volatility of unemployment at business cycle frequencies in recession. In contrast, they play no role in expansions.

5 Funding

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References

Baker, S., N. Bloom, and S. J. Davis (2016): "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, forthcoming.

Baker, S. R., N. Bloom, B. Canes-Wrone, S. J. Davis, and J. Rodden (2014):

"Why Has US Policy Uncertainty Risen Since 1960?," *American Economic Review Papers and Proceedings*, 104(5), 56–60.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77(3), 623–685.

Cacciatore, M., and F. Ravenna (2015): "Uncertainty, Wages, and the Business Cycle," HEC Montreal, mimeo.

Caggiano, G., E. Castelnuovo, and N. Groshenny (2014): "Uncertainty Shocks and Unemployment Dynamics: An Analysis of Post-WWII U.S. Recessions," *Journal of Monetary Economics*, 67, 78–92.

Koop, G., M. Pesaran, and S. Potter (1996): "Impulse response analysis in nonlinear multivariate models," *Journal of Econometrics*, 74(1), 119–147.

Lanne, M., and H. Nyberg (2016): "Generalised Forecast Error Variance Decomposition for Linear and Nonlinear Multivariate Models," *Oxford Bulletin of Economics and Statistics*, forthcoming.

McCracken, M. W., and S. Ng (2015): "FRED-MD: A Monthly Database for Macroeconomic Research," Federal Reserve Bank of St. Louis Working Paper 2015 -012B.

Morley, J., and J. Piger (2012): "The Asymmetric Business Cycle," *Review of Economics and Statistics*, 94(1), 208–221.

Nodari, G. (2014): "Financial Regulation Policy Uncertainty and Credit Spreads in the U.S.," *Journal of Macroeconomics*, 41, 122–132.

Teräsvirta, T., D. Tjøstheim, and C. W. Granger (2010): "Modeling Nonlinear Economic Time Series," Oxford University Press, Oxford.

Teräsvirta, T., and Y. Yang (2014): "Linearity and Misspecification Tests for Vector Smooth Transition Regression Models," CREATES Research Papers 2014-04, School of Economics and Management, University of Aarhus.

Date	Event
January 1968	Tet offensive (Vietnam War)
March 1968	Congress repeals the requir. for a gold reserve to back the dollar
November 1971	Wage and price controls
January 1974	OPEC I
December 1974	Drop in the fed. funds rate, forecasters' revisions
July 1979	OPEC II
January 1986	Balance budget act
October 1987	Black Monday
September 1990	Pres. Bush's speech on the possible military intervention in Kuwait
January 1991	Gulf War I
December 1991	Dissolution of the Soviet Union
February 1992	Pres. Bush meets with Russian Pres. Yeltsin at Camp David
December 1992	Clinton election
September 1998	Russian, LTCM default
November 2000	Bush election
September 2001	9/11
January 2003	Gulf War II
March 2003	Iraq invasion
January 2008	Large interest rate cuts
September 2008	Lehman Brothers' bankruptcy
January 2009	Banking crisis
July 2010	Mid-term elections
September 2010	Mid-term elections
July 2011	Debt Ceiling
December 2011	Debt Ceiling
November 2012	Fiscal cliff
October 2013	Government shutdown

Table 1: **Major Economic Policy Uncertainty Realizations.** Spikes identified as realizations exceeding the value 1.65 times the standard deviation of the Hodrick-Prescott filtered version of the U.S. Economic Policy Uncertainty index developed by Baker, Bloom, and Davis (2016). Smoothing weight of the Hodrick-Prescott filter set to 129,600.

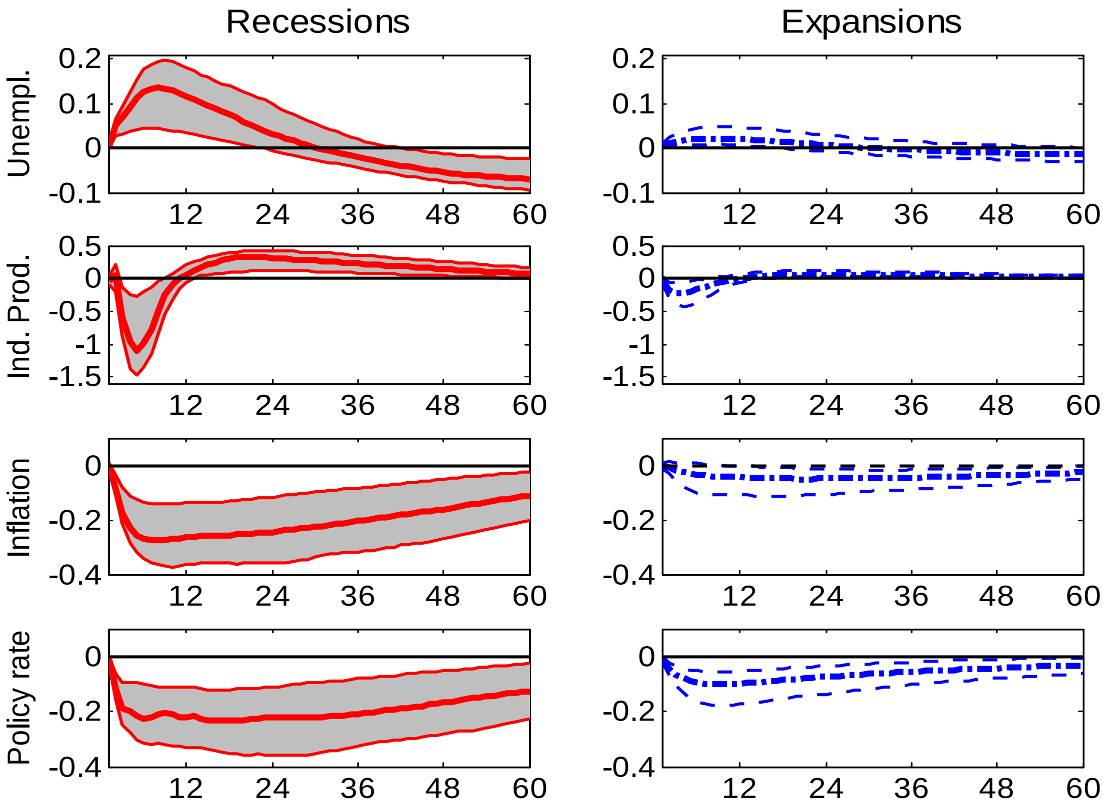

Figure 1: **Nonlinear Macroeconomic Effects of an EPU Dummy Shock.** Sample: 1954M7-2014M10. Generalized median impulse responses to a one-standard deviation shock to the U.S. EPU dummy hitting the U.S. economy in recessions (red solid line) and expansions (blue dash-dotted line). 68% confidence intervals identified via shaded areas (recessions) and dashed blue lines (expansions).

	Recessions					
Shock/Variable	f_t^1	EPU_t	ΔIP_t	u_t	π_t	R_t
$\widetilde{\varepsilon}^{f_t^1} + \widetilde{\varepsilon}^{\Delta IP_t} + \widetilde{\varepsilon}^{u_t}$	0.82	0.15	0.84	0.79	0.39	0.71
$\widetilde{\varepsilon}^{EPU_t}$	0.11	0.82	0.09	**0.08**	0.24	0.12
$\widetilde{\varepsilon}^{\pi_t}$	0.03	0.02	0.05	0.06	0.36	0.02
$\widetilde{\varepsilon}^{R_t}$	0.04	0.01	0.02	0.07	0.01	0.15

	Expansions					
Shock/Variable	f_t^1	EPU_t	ΔIP_t	u_t	π_t	R_t
$\widetilde{\varepsilon}^{f_t^1} + \widetilde{\varepsilon}^{\Delta IP_t} + \widetilde{\varepsilon}^{u_t}$	0.84	0.08	0.82	0.73	0.30	0.68
$\widetilde{\varepsilon}^{EPU_t}$	0.01	0.90	0.01	**0.00**	0.01	0.01
$\widetilde{\varepsilon}^{\pi_t}$	0.10	0.01	0.13	0.20	0.68	0.04
$\widetilde{\varepsilon}^{R_t}$	0.05	0.01	0.04	0.07	0.01	0.27

Table 2: **State-dependent Forecast Error Variance Decomposition.** 2 year-ahead forecast error variance decomposition. The figures reported in the table refer to the point estimates of the FASTVAR model.

Appendix

This Appendix reports additional results and information with respect to those documented in the paper.

U.S. EPU index. construct an index of economic policy uncertainty for the U.S. and a number of other industrialized countries. This index is based on newspaper coverage frequency. Baker, Bloom, and Davis (2016) use two overlapping sets of newspapers. The first spans the 1900-1985 period and comprises the Wall Street Journal, the New York Times, the Washington Post, the Chicago Tribune, the Los Angeles Times, and the Boston Globe. From 1985 until 2012, USA Today, the Miami Herald, the Dallas Morning Tribune, and the San Francisco Chronicle are added to the set.

Conditional on the newspapers they employ, Baker, Bloom, and Davis (2016) the authors perform month-by-month searches of each of the newspapers they consider, starting in January of 1900, for terms related to economic and policy uncertainty (the list of newspapers in detailed in our Appendix). In particular, they search for articles containing the term "uncertainty" or "uncertain", the terms "economic", "economy", "business", "commerce", "industry", and "industrial", and the terms: "congress", "legislation", "white house", "regulation", "federal reserve", "deficit", "tariff", or "war". The article is included in the count if it includes terms in all three categories pertaining to uncertainty, the economy and policy. To deal with changing volumes of news articles for a given paper over time, Baker, Bloom, and Davis (2016) divide the raw counts of policy uncertainty articles by the total number of news articles containing terms regarding the economy or business in the paper. They then normalize each paper's series to unit standard deviation prior to December 2009 and sum each paper's series. Further details on the construction of the index are reported in Baker, Bloom, and Davis (2016).

Extra Figures. Figure A1 plots the evolution of the EPU index, identifies spikes in uncertainty with vertical lines, and depicts NBER recessions with gray bars. Evidently, spikes are present both in recession and in expansions, something important for us to identify EPU shocks in both regimes.

Figure A2 plots the estimated probability of being in a recession, which is computed by considering the logistic function (3) in the paper, and the point estimates for the slope parameter $\widehat{\gamma} = 4.81$ and the threshold value $\widehat{c} = -0.90$. Noticeably, most realizations of $(1-\widehat{F})$ take a value larger than 0.5 hinting to a recession in correspondence to the official NBER recessions. The only two clear exceptions are due to two extremely negative realizations of our indicator z_t at the beginning of the sample. Overall, however, our estimated model appears to be able to clearly discriminate between booms and busts of the U.S. business cycle. A technical note is in order. Teräsvirta, Tjøstheim, and Granger (2010) point out that γ is not a scale-free parameter. To make it scale free, we follow their suggestion (p. 381 of their book) and standardize the transition indicator so that z_t features a mean equal to zero and a standard deviation equal to one. This operation makes our estimates more easily comparable with those present in the extant literature.

Figure A3 plots the density of the differences per each modeled variable between recessions and expansions. This figure confirms that our impulse responses are not only economically, but also statistically different between the two regimes.

Figure A4 plots the differences between the responses in recessions and the responses in expansions related to a number of different models we played with to assess the robustness of our findings. In particular, we plot the difference of the generalized impulse responses related to: i) the employment of the EPU index (in lieu of our EPU dummy); ii) controlling for the Baa-Aaa credit spread; iii) controlling for a measure of financial volatility such as the VXO;[1] iv) running a FASTVAR (Factor Augmented Smooth Transition VAR) featuring a factor computed with the large number of U.S. series documented by McCracken and Ng (2015). All the above mentioned omitted variables are modeled first in the vector, with the exception of the VXO which - following Baker, Bloom, and Davis (2016) - is ordered after the EPU index. The differences related to the baseline case are also plotted for facilitating comparisons. Our results turn out to be robust.

Computation of the GIRFs. Following Koop, Pesaran, and Potter (1996), we compute impulse responses as follows:

$$
\begin{aligned}
GIRF(h,\delta,\boldsymbol{\omega}_{t-1}) &= E\left\{\boldsymbol{X}_{t+h}\left|\widetilde{\varepsilon}_t^{EPU}=\delta,\boldsymbol{\varepsilon}_{t+h}=\widetilde{\boldsymbol{\varepsilon}}_{t+h},h>0,\boldsymbol{\omega}_{t-1}\right.\right\} \\
&\quad -E\left\{\boldsymbol{X}_{t+h}\left|\boldsymbol{\varepsilon}_{t+h}=\widetilde{\boldsymbol{\varepsilon}}_{t+h},h>0,\boldsymbol{\omega}_{t-1}\right.\right\}
\end{aligned}
$$

where h is the horizon of the impulse responses, δ is the size of the shock, $\boldsymbol{\omega}_{t-1}$ is the history (realizations of lagged values of the STVAR) identifying a particular recession or expansion in the sample, and $\widetilde{\boldsymbol{\varepsilon}}_{t+h}$ is a set of draws of residuals from the

[1] The VXO index is a function of the values of a range of call and put options on the Standard & Poor's 100 index. It represents the market's expectation of volatility over the next 30 days. Pre-1986 the VXO index is unavailable. Following Bloom (2009), we extend backwards the series by calculating monthly returns volatilities as the standard deviation of the daily S&P100 normalized to the same mean and variance as the VXO index for the overlapping sample (1986 onwards).

empirical distribution $\boldsymbol{\Omega}$. In practice, the GIRFs are computed as the difference between a stochastic simulation in which our orthogonal EPU shock $\widetilde{\varepsilon}_t^{EPU}$ takes the value δ and a stochastic simulation in which such shock takes a nil value. The shock is calibrated to induce a one-standard deviation impulse to the U.S. EPU indicator in our vector. Importantly, a given history $\boldsymbol{\omega}_{t-1}$ is associated to a given realization of the transition indicator z_{t-1}. Hence, conditional on our estimated threshold parameter $\widehat{c}$ in eq. (3) in the paper, it is possible to classify each given history as "recession" or "expansion".

For each identified regime, we draw with replacement 500 histories among the set of all possible histories belonging to that regime. Per each history, we draw 500 different realizations of the residuals, which deliver 500 different point estimates for our GIRFs. Then, per each history we compute the median across the different realizations of residuals. Finally, we compute median values across the 500 selected histories. Our figures plots the regime-specific horizon-wise median. In order to compute confidence bands, we repeat the previous steps for 500 bootstrap replications of the STVAR model (1)-(3). This provides us with 500 median realization for our GIRFs per each regime. The 16th and 84th percentiles are computed over the distribution of the medians. Notice that, to account for the correlation between the state-dependent GIRFs, we compute differences in recessions versus expansions conditional on the same set of draws of the stochastic elements of our model, as well as the same realizations of the coefficients of the vector.

References

Baker, S., N. Bloom, and S. J. Davis (2016): “Measuring Economic Policy Uncertainty,” *Quarterly Journal of Economics*, forthcoming.

Koop, G., M. Pesaran, and S. Potter (1996): “Impulse response analysis in nonlinear multivariate models,” *Journal of Econometrics*, 74(1), 119–147.

McCracken, M. W., and S. Ng (2015): “FRED-MD: A Monthly Database for Macroeconomic Research,” Federal Reserve Bank of St. Louis Working Paper 2015 -012B.

Teräsvirta, T., D. Tjøstheim, and C. W. Granger (2010): “Modeling Nonlinear Economic Time Series,” Oxford University Press, Oxford.

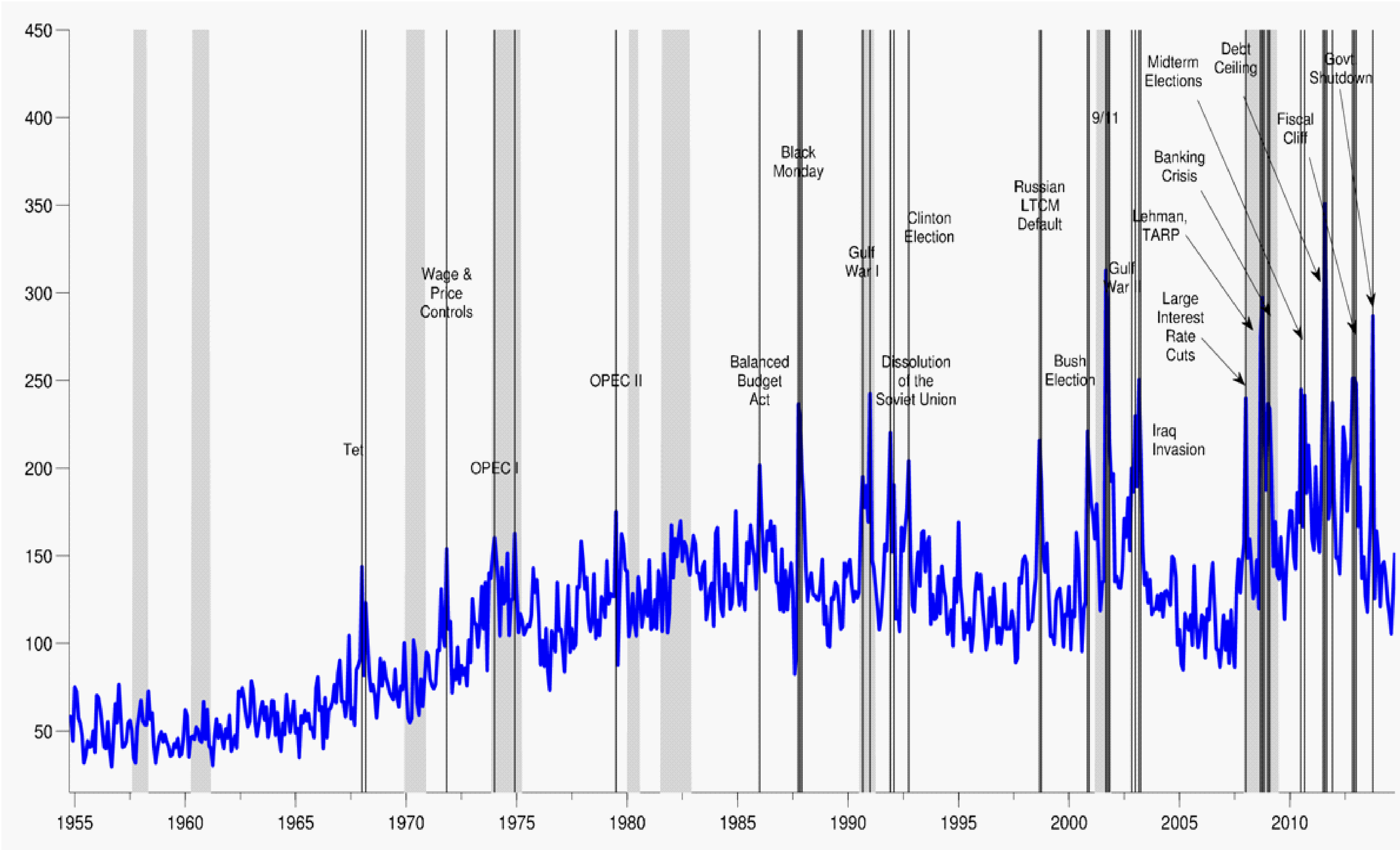

Figure A1: **U.S. EPU Index and Dummy.** Sample: 1954M7-2014M10. Black line: Historical EPU index for the United States as in Baker, Bloom, and Davis (2015). Blue vertical lines: Realizations of the cyclical component of the EPU index (computed via the Hodrick-Prescott filter, smoothing weight: 129,600) whose value is larger than 1.65 times the standard deviation of the EPU index cyclical component. In case of historical events associated to more than one spike, the dating reported in Table 1 in the paper refers to the first spike per each of such events. Grey vertical bars: NBER recessions.

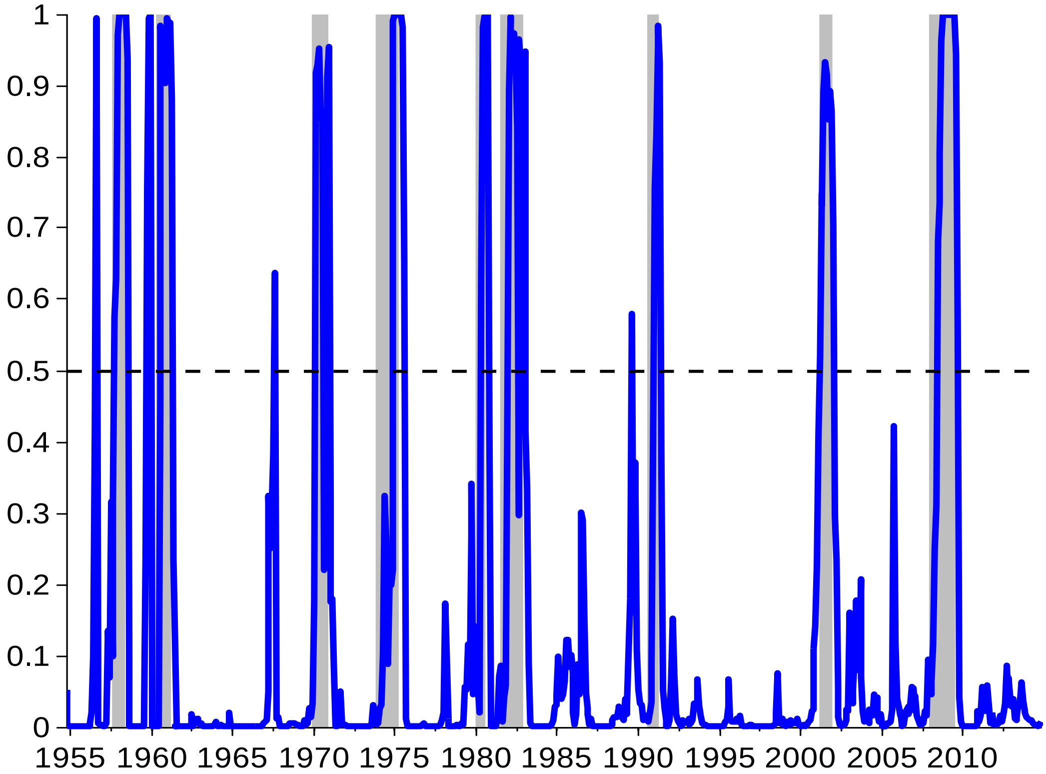

Figure A2: **Recession Probabilities for the U.S. as Estimated by the STVAR model.** Sample: 1954M7-2014M10**.** Function [1-F(z)] estimated jointly with the STVAR, baseline version with the U.S. EPU dummy.

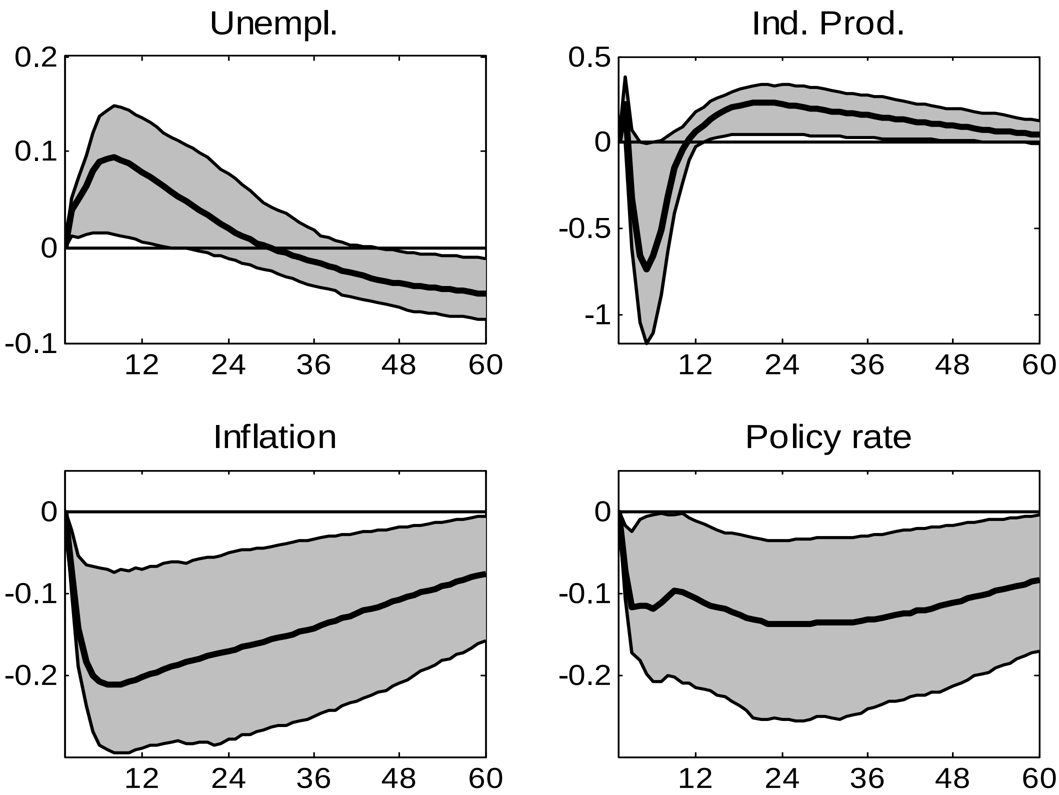

Figure A3: **Nonlinear Macroeconomic Effects of an EPU shock: Differences between GIRFs.** Sample: 1954M7-2014M10. Median differences between generalized impulse responses in recessions and expansions to a one-standard deviation shock to the U.S. EPU dummy. Median realizations identified via black lines, 68% confidence intervals identified via shaded areas.

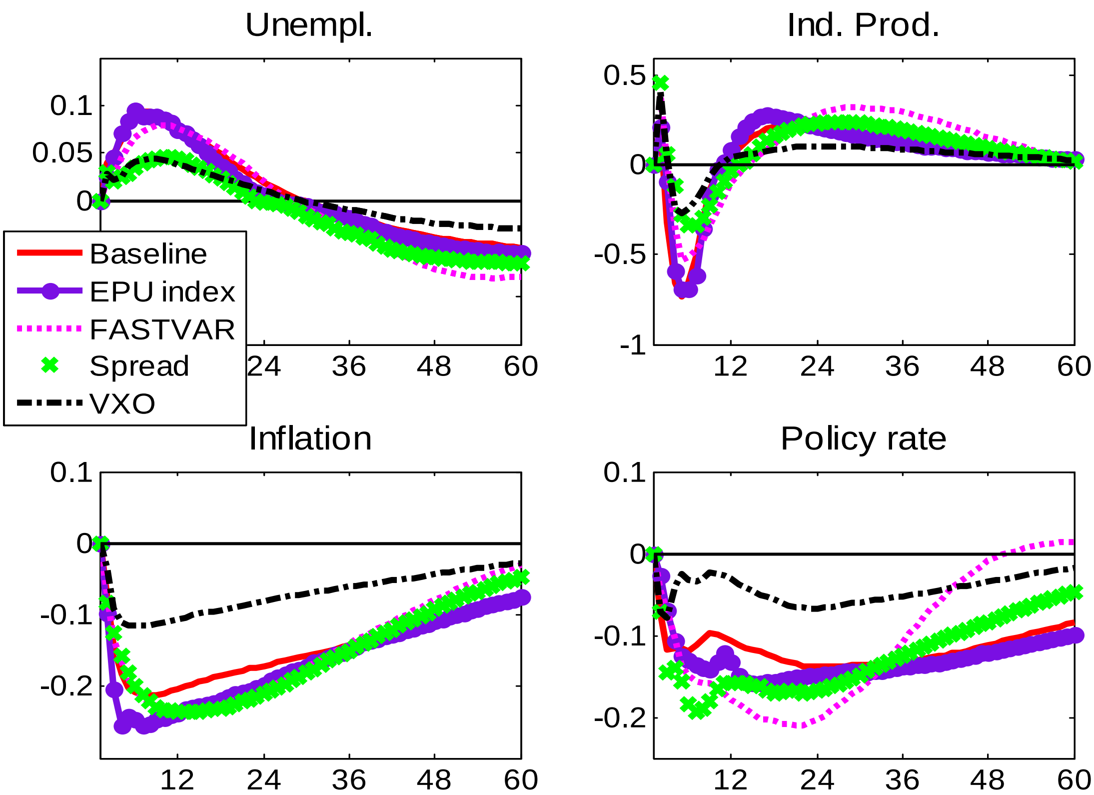

Figure A4: **Nonlinear Macroeconomic Effects of an EPU shock: Differences between GIRFs, Robustness Checks.** Median realizations of the differences between generalized impulse responses in recessions and expansions to a one-standard deviation shock to the U.S. EPU dummy where not otherwise specified. Sample: 1954M7-2014M10 with the exception of the exercise with the FASTVAR model, in which we use the sample 1960M1-2014M10 because of data availability, and the model with the VXO, for which following Bloom (2009) we use the sample 1962M7-2014M10.