Appendix of the paper "Economic Policy Uncertainty Spillovers in Booms and Busts" by Giovanni Caggiano, Efrem Castelnuovo, and Juan Manuel Figueres

This Appendix reports further details about: the linearity test used to discriminate between a linear vs. a Smooth Transition VAR model; the computation algorithm of the GIRFs; the computation of the Generalized FEVD; a detailed discussion of our dating of the Canadian business cycle; extra robustness checks involving two different transition indicators alternative to the one used in the exercises documented in the main text; a robustness check involving a longer sample for Canada; a robustness check allowing for heteroskedasticity in the estimated residuals as in Caggiano, Castelnuovo, and Groshenny (2014) and one allowing for state-dependent constants; the Generalized FEVD for all robustness checks; the autocorrelation functions of the estimated residuals of our baseline framework; a robustness check of the US-UK investigation involving a longer sample than our baseline one; and checks related to the US-UK investigations where we show that our results are robust to employing a dummy variable for the US EPU shocks.

**Linearity test.** We test the null hypothesis of a linear VAR vs. the alternative of a Smooth Transition VAR model with a single transition variable using the LM testing procedure proposed by Teräsvirta and Yang (2014). Consider the following \( p \)-dimensional \( n \)-th order Taylor approximation of the baseline logistic STVAR model:

\[
X_t = \Theta'_0 Y_t + \sum_{i=1}^{n} \Theta'_i Y_t z_i^t + \varepsilon_t \tag{A1}
\]

where \( X_t \) is the \((p \times 1)\) vector of endogenous variables included in the baseline specification, \( Y_t = [X_{t-1} \ldots X_{t-k} | \alpha] \) is the \(((k \times p + q) \times 1)\) vector of exogenous variables (including endogenous variables lagged \( k \) times and a column vector of constants \( \alpha \)), \( z_t \) is the transition variable, and \( \Theta_0 \) and \( \Theta_i \) are matrices of parameters. In our case, the number of endogenous variables is \( p = 7 \), the number of exogenous variables is \( q = 1 \), and the number of lags is fixed to \( k = 1 \) to overcome the "curse of dimensionality", as indicated in Teräsvirta and Yang (2014). Under the null hypothesis of linearity, \( \Theta_i = 0 \) \( \forall i \).

The Teräsvirta-Yang test for linearity versus the STVAR model is performed as follows:

1. Estimate the restricted model \( (\Theta_i = 0, \forall i) \) by regressing \( X_t \) on \( Y_t \). Collect the
residuals $\tilde{E}$ and the matrix residual sum of squares $RSS_0 = \tilde{E}'\tilde{E}$.

2. Run an auxiliary regression of $\tilde{E}$ on $(Y_t, Z_n)$ where $Z_n \equiv [Z_1|Z_2| \ldots |Z_n] = [Y_t'z_t|Y_t'z_t^2| \ldots |Y_t'z_t^n]$. Collect the residuals $\tilde{E}$ and compute the matrix residual sum of squares $RSS_1 = \tilde{E}'\tilde{E}$.

3. Compute the test-statistic

$$LM = T tr \{RSS_0^{-1}(RSS_0 - RSS_1)\} = T(p - tr\{RSS_0^{-1}RSS_1\})$$

Under the null hypothesis, the test statistic is distributed as a $\chi^2$ with $np(kp + q)$ degrees of freedom.\(^1\) For our model, we set $n = 3$, as suggested by Luukkonen, Saikkonen, and Teräsvirta (1988), and get a value of $LM = 241.12$ with a corresponding p-value equal to 0.00. Hence, we reject the null hypothesis of a linear specification versus the alternative of a STVAR. Results are robust to fixing the order of the Taylor approximation to $n < 3$.

**Generalized Impulse Response Functions and confidence bands.** We compute the Generalized Impulse Response Functions from our STVAR model by following the approach proposed by Koop, Pesaran, and Potter (1996). The algorithm features the following steps:

1. Given all available observations, with sample size $t = 1985 : M1, \ldots, 2014 : M10$, construct the set of all possible histories $\{\lambda_{t-1,i} \in \Lambda\}$ of length $l$, where $l$ is the number of lags of the STVAR and $\lambda_{t-1,i} = \{X_{t-1}, \ldots, X_{t-i}; z_{t-1}\}$. Then, $\Lambda$ will contain $T - l$ histories $\lambda_{t-1,i}$, with $T = 358$ and $l = 2$.\(^2\)

2. Separate the set of all recessionary (busts) histories from that of all expansionary (booms) histories. Given the estimated threshold, $\hat{c}$, for each $\lambda_{t-1,i} \in \Lambda$, if $z_{\lambda_{t-1,i}} \leq \hat{c}$, then $\lambda_{t-1,i} \in \Lambda^R$, where $\Lambda^R$ is the set of all recessionary histories; if $z_{\lambda_{t-1,i}} > \hat{c}$, then $\lambda_{t-1,i} \in \Lambda^E$, where $\Lambda^E$ is the set of all expansionary histories.\(^3\)

\(^1\)Notice that, since the transitional indicator is endogenous in our case, we do not include in $Z_n$ the vector of constant terms $\alpha$ to avoid perfect collinearity problems. As a consequence, the number of degrees of freedom is equal to $np$ times the column dimension of $Z_n$, and is equal to 147.

\(^2\)The number of lags of the STVAR has been selected according to the AIC.

\(^3\)The estimated threshold is $\hat{c} = -0.78$. The estimated value of the slope parameter is $\hat{\gamma} = 6.36$.  

3. Select at random one history $\lambda_{t-1,i}$ from the set $\Lambda^R$. Then, draw randomly with replacement from the empirical distribution of the residuals $\hat{\varepsilon}_t$, and get $\hat{\varepsilon}^{(j)*} = \{\hat{\varepsilon}_t^{*}, \hat{\varepsilon}_{t+1}^{*}, \ldots, \hat{\varepsilon}_{t+h}^{*}\}$, where $h$ is the maximum horizon of interest for the GIRFs and $\hat{\varepsilon}_{t+i}^{*}$ is a column vector of residuals of size $p$, where $p = 7$ is the dimension of the vector of endogenous variables of the baseline STVAR model.

4. Orthogonalize the bootstrapped residuals to recover the structural shocks:

$$e^{(j)*} = \hat{C}^{-1}\hat{\varepsilon}^{(j)*}.$$  \hspace{1cm} (A2)

where $\hat{C}$ is the Cholesky factor of the residuals’ variance-covariance matrix $\hat{\Omega}$.

5. Form another set of bootstrapped shocks, $e^{(j)}$, which will be equal to $e^{(j)*}$ except for the first element of the first column, corresponding to the US EPU uncertainty shock at time $t$, which will be equal to the corresponding element in $e^{(j)*}$ plus $\delta$, where $\delta$ is set to one-standard deviation of the orthogonalized residuals: $e^{(j)} = e^{(j)*}_{(1,1)} + \delta$.

6. Transform back $e^{(j)*}$ and $e^{(j)}$, and get the bootstrapped residuals:

$$\hat{\varepsilon}^{(j)*} = \hat{C}e^{(j)*} \hspace{1cm} (A3)$$

and

$$\hat{\varepsilon}^{(j)} = \hat{C}e^{(j)} \hspace{1cm} (A4).$$

7. Conditional on the initial history $\lambda_{t-1,i}$, use $(A3)$ and $(A4)$ to simulate the evolution of all the variables incorporated in the vectors $X^{(j)*}_{\lambda_{t-1,i}}$ and $X^{(j)}_{\lambda_{t-1,i}}$ - endogenous transition indicator included - and compute the GIRF as:

$$\text{GIRF} (h, \delta, \lambda_{t-1,i})^{(j)} = X^{(j)}_{\lambda_{t-1,i}} - X^{(j)*}_{\lambda_{t-1,i}}.$$ 

8. Conditional on history $\lambda_{t-1,i}$, repeat for $j = 1, \ldots, B$ vectors of bootstrapped residuals and get $\text{GIRF}^{(j)} (h, \delta, \lambda_{t-1,i})$. Set $B = 500$.

9. Calculate the GIRF for $\lambda_{t-1,i}$ as

$$\overline{\text{GIRF}}^{(i)} (h, \delta, \lambda_{t-1,i}) = B^{-1} \sum_{j=1}^{B} \text{GIRF}^{(j)} (h, \delta, \lambda_{t-1,i}). \hspace{1cm} (A5)$$
10. Repeat steps 3 to 9 for \( i = 1, \ldots, N = 500 \) histories belonging to the set of recessionary histories, \( \lambda_{t-1,i} \in \Lambda^R \), and get \( \text{GIRF}^{(i,R)} (h, \delta, \lambda_{t-1,i}) \), where \( R \) denotes explicitly that we are conditioning upon recessionary (busts) histories.

11. Compute the recessionary GIRF as:
\[
\hat{\text{GIRF}}^{(R)} (h, \delta, \Lambda^R) = N^{-1} \sum_{i=1}^N \text{GIRF}^{(i,R)} (h, \delta, \lambda_{t-1,i}).
\]

12. Repeat all previous steps - 3 to 11 - for 500 histories belonging to the set of all expansions (booms) and get \( \hat{\text{GIRF}}^{(E)} (h, \delta, \Lambda^E) \).

13. Estimate the confidence bands as follows. Generate a set of artificial data \( Y_t^* \) via the bootstrap procedure proposed by Kilian (1998). Use \( Y_t^* \) to estimate a STVAR model. Repeat steps 3 – 8 for recessions (busts) and expansions (booms) and store the average realization \( \hat{\text{GIRF}}^{(Y_t^*,R)} (h, \delta, \lambda_{t-1,i}) \) and \( \hat{\text{GIRF}}^{(Y_t^*,E)} (h, \delta, \lambda_{t-1,i}) \), respectively. Repeat this step for 500 sets of artificial data \( Y_t^* \). Compute the confidence bands by taking the 14th and the 86th percentiles of the empirical densities for each regime.

**Generalized Forecast Error Variance Decomposition.** We calculate the FEVD for our STVAR model following the procedure proposed by Lanne and Nyberg (2016).

1. Draw a sequence of reduced form residuals \( \varepsilon^{(j)} \). Select an initial history \( \lambda_{t-1,i} \) from the set of recessionary (busts) histories \( \Lambda^R \).

2. Conditional on \( \varepsilon^{(j)} \) and \( \lambda_{t-1,i} \), compute \( GIRQ_k (h, \delta_{kt}, \lambda_{t-1,i})^{(j)} \), where \( h = 1, \ldots, H \) is the horizon of interest, \( \delta_{kt} \) denotes the shock to variable \( k = 1, \ldots, K \), and \( K \) is the number of endogenous variables. Set \( \delta_{kt} = 1 \).

3. The contribution of shock \( k_1 \) to the forecast error variance of variable \( k_2 \) at horizon \( H \), i.e. the GFEVD, conditional on \( \varepsilon^{(j)} \) and \( \lambda_{t-1,i} \) is given by:
\[
\omega_{k_1k_2} (H, \lambda_{t-1,i})^{(j)} = \frac{\sum_{h=1}^H \left[ GIRQ_k (h, \delta_{kt}, \lambda_{t-1,i})^{(j)} \right]^2}{\sum_{k=1}^K \sum_{h=1}^H \left[ GIRQ_k (h, \delta_{kt}, \lambda_{t-1,i})^{(j)} \right]^2}
\]

4. Repeat steps 2 – 3 for \( j = 1, \ldots, J \) vectors of bootstrapped residuals \( \varepsilon^{(j)} \), thus generating \( J \) different \( \omega_{k_1k_2} (H, \lambda_{t-1,i})^{(j)} \). Set \( J = 500 \).
5. Obtain the GFEVD for shock $k_1$ and variable $k_2$ conditional on $\lambda_{t-1,i}$ as:

$$GFEVD_{k_1,k_2}(H, \lambda_{t-1,i}) = J^{-1} \sum_{j=1}^{J} \omega_{k_1,k_2}(H, \lambda_{t-1,i})^{(j)}.$$ 

6. Repeat steps 1–5 for $i = 1, \ldots, I$ initial histories $\lambda_{t-1,i} \in \Lambda^R$, and get $I$ values for $GFEVD_{k_1,k_2}(H, \lambda_{t-1,i})$.

7. The GFEVD for shock $k_1$ and variable $k_2$ in recessions (busts) is then given by:

$$GFEVD_{k_1,k_2}(H, \Lambda^R) = I^{-1} \sum_{i=1}^{I} GFEVD_{k_1,k_2}(H, \lambda_{t-1,i}).$$

8. Obtain the GFEVD for shock $k_1$ and variable $k_2$ in expansions (booms), $GFEVD_{k_1,k_2}(H, \Lambda^E)$, by repeating steps 1–7 conditioning on histories belonging to the set of expansions (booms).

**FEVD: Robustness checks.** Table A1 reports the contribution of US EPU shocks for the Canadian indicators considered in our analysis across a number of different models. The main message is that our qualitative results are robust to a number of controls added to our baseline vector.

**Discussion on the dating of the Canadian Business cycle.** As documented in Section 4 of the paper, our estimated logistic function point to a high probability of being in a recession for Canada in the early 2000s. However, according to the ECRI, such period is not a recession. The reason why our estimated logistic function indicates a high probability of slack in the early 2000s is the evolution of our transition indicator, i.e., the (standardized) 18-month growth rate of industrial production. The growth rate of industrial production experienced a dramatic fall between January 2000 and December 2001. In non-standardized terms, the 18-month growth rate fell from 13.6% to -8.3%. The magnitude of this fall is similar to the one recorded in correspondence of the two official recessions in our sample. This indicator of real activity fell from 12.5% to -7.1% in the May 1988-March 1991 period, and from 0.3% to -15.6% during the July 2008-May 2009 Great Recession phase. As shown in Figure A1, the evolution of the growth rate of industrial production in this sample mimics the one of the growth rate of the real GDP. Then, why were the early 2000s not officially classified as "recession"? The answer is that not all indicators of the business cycle pointed to a recession. A look at the Canadian unemployment rate (whose sign is switched in Figure A1 to ease
the comparison with the evolution of industrial production and real GDP) helps us make this point. The unemployment rate went up from 6.8% to 8.1% from January 2000 to the end of 2001. The variation (difference between these two rates) reads 1.3%. Differently, the unemployment rate jumped from 7.8% to 10.5% in the 1988-1991 period (difference: 2.7%) and from 6.1% to 8.6% during the Global Financial Crisis (difference: 2.5%). The evolution of the employment rate confirms that the early 2000s slowdown affected the Canadian labor market less than in the two occasions classified as recessions. Hence, while the early 1990s and the 2008-09 periods clearly featured strong and converging signals in favor of a recession, the early 2000s looked more like a severe downturn. In light of this evidence, our analysis should be interpreted as focusing on phases of growth of industrial production above vs. below the sample average, more than on official "expansions" and "recessions".

Alternative transition indicators. Our results are driven by our modeling choices, the one of the transition indicator included. While being a plausible indicator of the business cycle, the moving average of industrial production is clearly not the only indicator one may consider. In particular, a measure of real GDP at a monthly frequency is actually available for Canada. We then estimate two models which use - alternatively - two different transition indicators. The first model employs a moving average of the real GDP growth rate to replace industrial production in our VAR. The second model employs the common factor computed via a principal component analysis which considers four different business cycle indicators, i.e., the growth rates of industrial production and real GDP and the rates of unemployment and employment. Figure A2 shows that our results are robust to the employment of these alternative transition indicators.

Initial conditions to identify booms and busts. A somewhat different robustness check regards the role that initial conditions may play in computing our impulse responses. Our baseline results are obtained by separating initial conditions (historical realizations of the lags of the variables we model with our nonlinear VAR) in two different groups, i.e., those indicating that the economy is in a boom and those that indicate that it is in a bust. These initial conditions are technically associated to the transition indicator $z_{t-1}$, which per each given $t$ is compared with the estimated threshold $\hat{c}$. In particular, values of $z_{t-1} > \hat{c}$ ($z_{t-1} \leq \hat{c}$) indicate that the economy is in a boom (bust).

\footnote{Such measure is available at the following website: https://www.cdhowe.org/sites/default/files/attachments/other-research/pdf/Main-Economic-Indicators-used-to-Establish-the-Historical-Chronology-of-Canadian-Business-Cycles1%20%281%20%29.xls. We use the 12-month growth rate of the "Real GDP (2002 constant prices)" series.}
As in all nonlinear analysis of this kind, the risk to incorrectly classify booms and busts is present, above all when initial conditions are associated to values of $z_{t-1}$ close to the threshold. We then check the robustness of our results by dropping initial conditions associated to values of $z_{t-1}$ which are "too close" to the threshold. Given that the transition indicator $z_{t-1}$ is a standardized variable with unitary variance, we conduct two robustness checks so that initial conditions are considered only if $|z_{t-1} - \bar{z}| > 1/\delta$, where $\delta$, with $\delta \in \{1, 2\}$. These robustness checks are basically based on the selection of "extreme" realizations of the business cycle (say, deep downturns or solid booms). When $\delta = 2$, about 9% (65%) of the observations in the sample are classified as recessions (expansions) according to our model, while when $\delta = 1$, our model classifies on about 5% (42%) of observations as recessionary. Given that the relevant effects of uncertainty shocks are found in busts, we focus on realizations of $z_{t-1}$ which are below the threshold. Figure A3 shows the outcome of this exercise. Evidently, our responses are robust to different selections of initial conditions.

**Longer sample for Canada.** As written in the text, the measure of EPU we use for Canada is based on information contained in newspapers only. An equivalent measure - the historical EPU series - is available for the US up to 2014, which justifies the end date of our sample. A highly correlated, updated series for the US is available starting from 1985. Figures A4 reports the outcome of an exercise related to a robustness check conducted with this updated series (sample: 1985:M1-2018:M7). Our results are virtually unchanged with respect to those documented in this paper.

**State-dependent constants.** Figure A5 shows that allowing for state-dependent constants (something which, for parsimony, we do not do in the baseline exercise) does not change our results.

**AutoCorrelation Functions of the residuals of the baseline model.** Figure A6 shows the AutoCorrelation Functions of the estimated residuals of the baseline framework. In general, such ACFs point to well-behaved residuals.

**US-UK spillover with longer sample.** The paper documents spillover effects related to US EPU shocks also for the US-UK pair. It does so by sticking to the 1985-2014 sample, which is the one employed for Canada. However, a longer sample is available to perform this analysis. Using a longer sample enables us to handle more recessions and, possibly, obtain more precise estimates. Figures A7 and A8 show that this is indeed the case, in that our results (that are robust to using the longer sample) are also assigned higher precision, which is reflected by - for instance - the statistically significant different between the response of unemployment in recessions and that in...
expansions. For this exercise, we use as transition indicator the MA(6) build on the growth rate of industrial production because it does ensure stability of the vectors conditional on recessions/expansions, a condition which is sufficient to guarantee the stability of the nonlinear VAR framework at play.

**US-UK spillover with EPU shocks identified with a dummy approach.** The results documented in the paper are obtained by appealing to the US EPU index. As discussed in the paper for the US-Canada case, such index is likely to be contaminated by global events. Figure A9 confirms that our results are robust to employing the same dummy approach used for the robustness check for Canada. We then perform the same exercise conditional on the longer 1959:M1-2014:M10 sample. Again, we first isolate the estimated US EPU shocks which are larger than two standard deviations. Second, we judge spike-by-spike which ones represent pure US-related shocks (as opposed to global ones). Table A2 lists those we judge as US-related ones, which are those that take non-zero values in our dummy variable. We then use the dummy to compute our GIRFs. To ease comparison with the case documented in the paper, we calibrate the logistic function with the estimates obtained from the baseline exercise. Figure A10 shows that our results are robust also to employing the dummy approach in this longer sample.

**Heteroskedasticity.** The STVAR we employ allows for state dependence of the coefficient matrices but not of the covariance matrix. One may wonder to what extent this constraint is relevant for our results. We investigate this issue by following the approach proposed by Auerbach and Gorodnichenko (2012) and employed in the context of uncertainty shocks by Caggiano, Castelnuovo, and Groshenny (2014), which allows the covariance matrix to be state dependent. Following Caggiano, Castelnuovo, Colombo, and Nodari (2015), we endogenize the transition indicator \( z \) and compute GIRFs (instead of conditionally linear IRFs). To facilitate the convergence toward the global maximum of the likelihood function, we fix the slope parameter of the logistic function \( \gamma \) and the threshold parameter \( c \) to their baseline values, which are \( \hat{c} = 0.78 \) and \( \hat{\gamma} = 6.36 \). Formally, our STVAR model reads as follows:

\[
X_t = [1 - F(z_{t-1})]\Pi_R(L)X_t + F(z_{t-1})\Pi_E(L)X_t + \varepsilon_t \tag{A6}
\]

\[
\varepsilon_t \sim N(0, \Omega_t) \tag{A7}
\]

\[
\Omega_t = (1 - F(z_{t-1}))\Omega_R + F(z_{t-1})\Omega_E \tag{A8}
\]

\[
F(z_t) = \begin{cases} 
1 + \exp[-\gamma(z_t - c)]^{-1}, & \gamma > 0, z_t \sim d(0, 1)
\end{cases} \tag{A9}
\]
where $X_t$ 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 is $\gamma$, $z_t$ is a transition indicator, $c$ is the threshold parameter identifying the two regimes under scrutiny, $\Pi_R$ and $\Pi_E$ are the VAR coefficients capturing the dynamics of the system during recessions and expansions, $\varepsilon_t$ is the vector of reduced-form residuals having zero-mean and whose time-varying, state-contingent variance-covariance matrix is $\Omega_t$, and $\Omega_R$ and $\Omega_E$ are covariance matrices of the reduced-form residuals computed during recessions and expansions, respectively. Conditional on the calibration of the nuisance parameters $\gamma$ and $c$, the model is estimated by Monte-Carlo Markov-Chain simulations via the algorithm proposed by Chernozhukov and Hong (2003).

The paper shows that the impulse responses obtained by this model are similar to those obtained under the assumption of homoskedasticity. For the sake of brevity, the paper omits to show that the state-specific GIRFs are indeed statistically different, an evidence that the reader can find in this Appendix (see Figure A11). The bands of our GIRFs are bootstrapped. Three ingredients are needed to compute such bands: i) a set of bootstrapped coefficients; ii) a sequence of bootstrapped shocks; iii) a set of bootstrapped initial histories (loading VAR lags, the transition indicator $z$, and the logistic function $F(z)$). Our algorithm for bootstrapping the GIRFs bands is the following:

1. Draw $T$ random observations from a normal distribution $N(0,1)$, where $T$ is the length of the sample.

2. Employ the draws from step 1 and the mean of $\Omega_R$ and $\Omega_E$ conditional on the MCMC draws to obtain two sequences of draws distributed as $N(0, \Omega_R)$ and $N(0, \Omega_E)$, respectively.

3. Employ the draws from step 2 and the MCMC mean of $\Pi_R$ and $\Pi_E$ to bootstrap the coefficients of the model via the standard bootstrap procedure as in Caggiano, Castelnovo, and Groshenny (2014). This step bootstraps two linear VARs independently. Notice that the bootstrap procedure provides us with a draw for the coefficients only, i.e., it does not simulate data. This procedure also generates two sets of constant (one for each regime). Since our model features a state-independent constant, the bootstrapped counterpart is obtained by taking the average value of the constant coefficients across regimes, i.e., $(c_R + c_E)/2$. 

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4. Employ the bootstrapped coefficients from step 3 to compute GIRFs conditional on the observed data (to load the initial conditions, \( z \) and \( F(z) \)).

5. Repeat steps 1-4 500 times to construct the bootstrapped distributions of the GIRFs, and compute the moments of interest.

References


Figure A1: Canada: Real Activity Indicators. Sample: 1985:M1-2014:M10. Moving averages of the monthly growth rates of industrial production and real GDP consider eighteen and twelve terms, respectively. The sign of the unemployment rate was switched to highlight the correlation with the other real activity indicators. Grey vertical bars indicate recessions as dated by the Economic Cycle Research Institute. All indicators have been standardized so to have mean zero and unit variance.
Figure A2: State-contingent unemployment response: Robustness to alternative transition indicators. Sample: 1985:M1-2014:M10. Moving averages of the monthly growth rates of real GDP and the principal component constructed by considering eighteen and twelve terms, respectively. Principal component (PC) constructed by considering four different business cycle indicators, i.e., the growth rates of industrial production and real GDP and the rates of unemployment and employment.
Figure A3: Effects of a Shock to the US EPU Index on the Canadian economy: Role of Initial Conditions. Sample: 1985:M1-2014:M10. Generalized median impulse responses to a one-standard deviation shock to the US EPU shock computed by considering three different sets of initial conditions identified with upward/downward deviations of sizes 0, 0.5, 1 with respect to the estimated threshold. Transition indicator for Canada: 18-term moving average of the monthly growth rate of the Canadian industrial production.
Figure A4: Effects of a shock to the US EPU Index on the Canadian economy: Longer sample. Sample: 1985:M1-2018:M7. Median generalized impulse responses to a one-standard deviation shock to the US EPU index hitting the Canadian economy in busts (red solid line) and booms (blue dashed-dotted line). 68% confidence intervals identified via shaded areas (busts) and dashed blue lines (booms). Transition indicator for Canada: 18-term moving average of the monthly growth rate of the Canadian industrial production.
Figure A5: Effects of a shock to the US EPU Index on the Canadian economy: State-specific constants. Sample: 1985:M1-2014:M10. Median generalized impulse responses to a one-standard deviation shock to the US EPU index hitting the Canadian economy in busts (red solid line) and booms (blue dashed-dotted line). 68% confidence intervals identified via shaded areas (busts) and dashed blue lines (booms). Transition indicator for Canada: 18-term moving average of the monthly growth rate of the Canadian industrial production.
Figure A6: **Autocorrelation functions of the estimated residuals of our baseline framework.** Sample: 1985:M1-2014:M10. Variables modeled as explained in the text. Solid blue lines: ACFs. Dotted black lines: 95% confidence bands.
Figure A7: Effects of a shock to the US EPU index on the UK economy: Longer sample. Sample: 1959:M1-2014:M10. Median generalized impulse responses to a one-standard deviation shock to the US EPU index hitting the UK economy in busts (red solid line) and booms (blue dashed-dotted line). 68% confidence intervals denoted by shaded areas (busts) and dashed blue lines (booms). Transition indicator for the UK: 6-term moving average of the monthly growth rate of the UK industrial production index.
Figure A8: Effects of a shock to the US EPU index on the UK economy, longer sample: Difference between states. Sample: 1959:M1-2014:M10. Differences between median generalized impulse responses in booms and busts to a one-standard deviation shock to the US EPU index. Median realizations denoted with black lines, 68% confidence intervals denoted with shaded areas. Transition indicator for the UK: 6-term moving average of the monthly growth rate of the UK industrial production index.
Figure A9: Effects of a shock to the US EPU index on the UK economy: US EPU dummy. Sample: 1985:M1-2014:M10. Median generalized impulse responses to a one-standard deviation shock to the US EPU index hitting the UK economy in busts (red solid line) and booms (blue dashed-dotted line). 68% confidence intervals denoted by shaded areas (busts) and dashed blue lines (booms). Transition indicator for the UK: 12-term moving average of the monthly growth rate of the UK industrial production index.
Figure A10: Effects of a shock to the US EPU index on the UK economy, longer sample: US EPU dummy. Sample: 1959:M1-2014:M10. Median generalized impulse responses to a one-standard deviation shock to the US EPU index hitting the UK economy in busts (red solid line) and booms (blue dashed-dotted line). 68% confidence intervals denoted by shaded areas (busts) and dashed blue lines (booms). Transition indicator for the UK: 6-term moving average of the monthly growth rate of the UK industrial production index.
Figure A11: Effects of a Shock to the US EPU Index on the Canadian economy: Difference between States - Role of Heteroskedasticity. Sample: 1985:M1-2014:M10. Statistical model as in Caggiano, Castelnuovo, and Groshenny (2014). Differences between median generalized impulse responses in busts and booms to a one-standard deviation shock to the US EPU Index. Median realizations identified via black lines, 68% confidence intervals identified via shaded areas. Transition indicator for Canada: 18-term moving average of the monthly growth rate of the Canadian industrial production.
### Table A1: Forecast Error Variance Decomposition: US EPU Shocks, Different Scenarios.

2 year-ahead forecast error variance decomposition. The figures reported in the table refer to the point estimates of the contribution of US EPU shocks to the forecast error variance decomposition of the variables included in the baseline STVAR.

#### Busts

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<th>$\pi_t$</th>
<th>$R_t$</th>
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Table A2: **Major US and Global Economic Policy Uncertainty Shocks: Sample 1959:M1-2014:M10.** Baseline: Dates corresponding to positive realizations of the estimated shocks exceeding 2 standard deviations according to our baseline model. Dummy: Dates selected by focusing on domestic (US) events only.