Online Appendix to:
"The Interplay between Oil and Food Commodity Prices: Has It Changed over Time?"

Gert Peersman[*,a], Sebastian K. Rüth[b,c], Wouter Van der Veken[a]

[a] *Ghent University, Department of Economics. Sint-Pietersplein 5, 9000 Gent (BE)*
[b] *University of Erfurt, Faculty of Economics, Law and Social Sciences. Nordhäuser Str. 63, 99105 Erfurt (DE)*
[c] *Heidelberg University, Alfred-Weber-Institute for Economics. Bergheimer Str. 58, 69115 Heidelberg (DE)*

Abstract

Section A of this online appendix contains details on the TVP-BVAR methodology and the data used in the paper. Section B presents results for several robustness checks involving model specifications/extensions of the TVP-BVAR. Section C provides evidence on price spillovers of oil and food supply shocks to disaggregate food commodity price data. Section D analyzes the role of financialization and the volatility of macroeconomic shocks for price spillovers via several extensions of the baseline local projections, while section E explores instabilities in the interplay of commodity prices by means of linear BVARs, estimated over sub-samples. In addition, the section documents a significant and time-varying pass-through of the commodity price spillovers to consumer prices

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[*] Corresponding author. Phone: +32 (0)9 264 35 14.

Email addresses: `gert.peersman@ugent.be` (Gert Peersman[*]), `sebastian.rueth@uni-erfurt.de` (Sebastian K. Rüth), `wouvdrve.vanderveken@ugent.be` (Wouter Van der Veken)

Appendix A: TVP-BVAR Model Details

The main empirical laboratory of our analysis is a TVP-BVAR model (equation 1 in the paper). To capture instabilities in the relationship between oil and food commodity prices, we need a framework capable of accounting for gradual changes in the interplay between both markets over time, rather than imposing arbitrary sample splits as previous studies have done. Specifically, the rise in the use of biofuels occurred over several years. The gradual globalization and financialization of commodity markets, as well as time-varying informational frictions, further reinforces the notion of a continuous evolution of the structure of commodity markets.[1] In addition, Monte Carlo simulations in Baumeister and Peersman (2013b) show that a BVAR model with drifting coefficients is also capable of capturing discrete shifts should they occur. Accordingly, the data can reveal when and how changes have occurred over the sample period.

The time-varying variance-covariance matrix of the innovations in equation 1 of the paper, $\boldsymbol{u}_t$, is denoted by $\boldsymbol{\Omega}_t$. Specifically, we consider a triangular reduction of $\boldsymbol{\Omega}_t$:

$$\boldsymbol{A}_t \boldsymbol{\Omega}_t \boldsymbol{A}_t' = \boldsymbol{\Sigma}_t \boldsymbol{\Sigma}_t' \tag{A.1}$$

where the diagonal matrix $\boldsymbol{\Sigma}_t$ contains stochastic volatility of additive innovations:

$$\boldsymbol{\Sigma}_t = \begin{pmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{pmatrix} \tag{A.2}$$

and $\boldsymbol{A}_t$ comprises coefficients capturing time-varying contemporaneous relations among the VAR variables as follows:

$$\boldsymbol{A}_t = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{2,1,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n,1,t} & \cdots & \alpha_{n,n-1,t} & 1 \end{pmatrix}. \tag{A.3}$$

[1] Slowly-evolving yet continuous adjustments are also consistent with adaptive expectations of market participants, which result from ongoing learning behavior. In particular, when agents do not update expectations simultaneously, the aggregation among them results in a gradual evolution of expectations (Primiceri 2005).

While Cogley and Sargent (2005) applied a comparable matrix reduction, yet modeled matrix $\boldsymbol{A}_t$ to be time-invariant (i.e. $\boldsymbol{A}_t = \boldsymbol{A}$), we follow the approach of Primiceri (2005) and Del Negro and Primiceri (2015). In particular, for our simultaneous equation model that incorporates financial variables such as oil and food prices—for which the majority of the shock absorption should take place on impact—modeling time variation in the simultaneous interactions is crucial. We thus allow the contemporaneous impact of series i on j; that is, the off-diagonal and non-zero elements in $\boldsymbol{A}_t$, to gradually evolve over time.

Finally, rewriting equation 1 of the paper by using the definitions from above yields:

$$\boldsymbol{y}_t = \boldsymbol{X_t}'\boldsymbol{\theta_t} + \boldsymbol{A}_t^{-1}\boldsymbol{\Sigma}_t\boldsymbol{\varepsilon}_t, \text{ with } \boldsymbol{X_t}' = \boldsymbol{I_n} \otimes [\boldsymbol{1}, \boldsymbol{y}'_{t-1}, ..., \boldsymbol{y}'_{t-p}], \tag{A.4}$$

where $\otimes$ is the Kronecker-product. Our estimation strategy consists of modeling the $t = 1, ..., T$ sequence of VAR parameters according to equation A.4. We stack the strictly lower-triangular coefficients of $\boldsymbol{A}_t$ into vector $\boldsymbol{\alpha}_t = [\alpha_{2,1,t}, ..., \alpha_{n,n-1,t}]'$, and we define $\boldsymbol{\sigma}_t$ as a vector containing the diagonal entries of $\boldsymbol{\Sigma}_t$. The processes driving the VAR's unobservable and time-varying states are specified as follows:

$$\boldsymbol{\theta_t} = \boldsymbol{\theta_{t-1}} + \boldsymbol{\nu_t}, \ \boldsymbol{\alpha_t} = \boldsymbol{\alpha_{t-1}} + \boldsymbol{\zeta_t}, \text{ and } \log(\boldsymbol{\sigma_t}) = \log(\boldsymbol{\sigma_{t-1}}) + \boldsymbol{\eta_t}. \tag{A.5}$$

The coefficients in $\boldsymbol{\theta_t}$ and the free entries in $\boldsymbol{A}_t$ follow random walks without drift, and we account for stochastic volatility via modeling $\boldsymbol{\sigma_t}$ as a geometric random walk. Following Primiceri (2005), we model all the disturbances in each state equation as jointly normally distributed. The covariances of $\boldsymbol{\nu_t}$ and $\boldsymbol{\eta_t}$ are left unrestricted; that is, we allow for multivariate stochastic volatility, while the innovations to the states of the structural relations are allowed to be correlated within each equation of the VAR.

The start of our estimation sample (1974Q1) is inspired by Kilian (2009), who stresses the fact that oil prices were strictly regulated before 1974. The end (and frequency) of the sample is determined by the availability of the food production index.[2] All variables in $\boldsymbol{y_t}$ enter the model as growth rates, which is the convention in TVP-BVAR models that study trending data; that is, we include stationary time series. The transformed series are plotted in Figure A1.

[2] De Winne and Peersman (2016) combine annual data from the FAO with crop calendars of the staples to allocate the harvest volumes to a specific quarter. This is feasible because most countries have only one harvest season, which lasts only for a few months. For some countries, it is not possible to assign the production to a specific quarter because there is more than one harvesting period. This production is not included in the index. The resulting quarterly index covers roughly two-thirds of global harvests.

We perform a Bayesian shrinkage approach to estimate the richly parameterized TVP-BVAR along the lines of Kim et al. (1998) and Kim and Nelson (1999). The sampler we use to simulate the posterior distribution and the priors employed are in line with Primiceri (2005) and Del Negro and Primiceri (2015). Specifically, we need to choose prior distributions for the initial conditions of the states $\boldsymbol{\theta_0}$, $\boldsymbol{A_0}$, and $\boldsymbol{\sigma_0}$, and prior scale matrices and degrees of freedom for the IW-distributions of the hyperparameters, $\boldsymbol{Q}$, $\boldsymbol{S}$, and $\boldsymbol{W}$, which represent the variance-covariance matrices of innovations to the respective states.[3] As in Primiceri (2005) and Del Negro and Primiceri (2015), we inform our prior by estimating a time-invariant VAR with OLS on a training sample spanning the 58 quarters that precede the period of interest.[4] In particular, we assume the following specification for the prior:

$$
\begin{aligned}
\boldsymbol{\theta_0} &\sim N\left(\hat{B}_{OLS}, 4 \cdot V(\hat{B}_{OLS})\right) \\
\boldsymbol{A_0} &\sim N\left(\hat{A}_{OLS}, 4 \cdot V(\hat{A}_{OLS})\right) \\
log\ \boldsymbol{\sigma_0} &\sim N\left(log(\hat{\sigma}_{OLS}), I_n\right) \\
\boldsymbol{Q} &\sim IW\left(k_B^2 \cdot n_{min}^{Q} \cdot V(\hat{B}_{OLS}), n_{min}^{Q}\right) \\
\boldsymbol{S_i} &\sim IW\left(k_A^2 \cdot n_{min}^{S_i} \cdot V(\hat{A}_{i,OLS}), n_{min}^{S_i}\right),\ i = 1, 2, 3 \\
\boldsymbol{W} &\sim IW\left(k_H^2 \cdot n_{min}^{W} \cdot I_n, n_{min}^{W}\right),
\end{aligned}
$$

where $V(\cdot)$ denotes a variance-covariance matrix, n_{min} denotes the minimum amount of degrees of freedom that is required to have an inverse-Wishart distribution with a proper mean and variance, and with $k_A = 0.5$, $k_B = 0.01$, and $k_H = 0.01$. Three exceptions notwithstanding, this parameterization of the prior is identical to the approach in Primiceri (2005) and Del Negro and Primiceri (2015).

We slightly deviate from Primiceri (2005) and take a value of $k_A = 0.5$, where the original value was 0.1. k_A is the parameter governing our prior belief about the amount of time variation in the off-diagonal elements of the variance-covariance matrix of the residuals. Our motivation for this choice is threefold. First, our main results do not crucially depend on the choice of k_A, and reducing this value to Primiceri's benchmark value of 0.1 does not qualitatively change the

[3] $\boldsymbol{Q} = E[\boldsymbol{\nu_t}\boldsymbol{\nu_t'}]$, $\boldsymbol{S} = E[\boldsymbol{\zeta_t}\boldsymbol{\zeta_t'}]$, and $\boldsymbol{W} = E[\boldsymbol{\eta_t}\boldsymbol{\eta_t'}]$. $\boldsymbol{S}$ is block-diagonal as in Primiceri (2005) and Del Negro and Primiceri (2015).

[4] To properly reflect the information in the training sample, the degrees of freedom of the prior of the variance-covariance matrix of the innovations should match the training sample size. A lower bound is imposed by the restriction that the degrees of freedom of an Inverse-Wishart distribution must exceed the dimensionality of the variance-covariance matrix. Accordingly, the training sample should not be smaller than 58 quarters.

results. Second, one should also note that k_A parameterizes neither the direction nor the timing of the time variation. Third, the relative responses of food and oil prices after both supply shocks as they emerge from the sample split in section E of this appendix are quantitatively very closely related to their relative responses derived by averaging the impact responses from the TVP-BVAR for the quarters ranging from 1988Q3 to 2003Q4 and from 2004Q1 to 2016Q4.

Finally, in line with, among others, Cogley and Sargent (2005), Canova and Gambetti (2006), Canova and Gambetti (2009), and Baumeister and Peersman (2013b), we impose a stability constraint on the lagged coefficients in every state. We do this by attaching zero prior probability to any draw of the lagged coefficients $\{\boldsymbol{\theta_1}, \boldsymbol{\theta_2}, \ldots, \boldsymbol{\theta_T}\}$ for which at *any* time t the stability constraint is violated.

We generate draws from the posterior by using the Gibbs sampler of Del Negro and Primiceri (2015). This sampler slightly diverges from the original sampler in Primiceri (2005), which has been shown not to produce draws from the correct posterior. We choose for 50,000 passes of the sampler and discard the first 10,000 iterations as burn-in. The results are insensitive to substantial changes in both the total number of iterations and the size of the burn-in period. To further assess the convergence of the chain, we calculate inefficiency factors for the states and the hyperparameters; they are shown in Figure A2. Following Primiceri (2005), we consider inefficiency factors lower than 20 to signal satisfactory mixing of the Markov chain, which we observe for all parameters.

Upon having simulated the posterior distributions of the lagged coefficients, the volatilities, and the covariances of the error terms, we turn to the structural analysis. As discussed in Section 2 of the paper, we build on the particular construction of the food production index to justify the identification of the food supply shock by placing the food production index first in a Cholesky-ordering. In order to identify the oil supply shock by means of sign restrictions, we build on existing literature, e.g., Canova and Gambetti (2006), Canova and Gambetti (2009), and Baumeister and Peersman (2013b).[5] We, however, depart from this literature for imposing sign restrictions in TVP-BVARs in two ways.

First, as shown in Koop and Potter (2011), the existing algorithms fail to correctly use the draws from the unrestricted posterior to simulate the posterior distribution of the structural

[5]Technically, we implement sign restrictions using the algorithm of Rubio-Ramírez et al. (2010). Kilian (2009) uses contemporaneous exclusion restrictions to identify oil supply shocks; that is, he assumes that oil supply shocks are the sole disturbances that have an immediate impact on oil production, but that assumption is not realistic in a quarterly model.

model. To see this, first note that one draw Φ from the unrestricted posterior consists of T states of the economy: $\{\phi_1, \phi_2, \ldots, \phi_T\}$. Next, let Ξ denote a set of T rotation matrices, $\{\xi_1, \xi_2, \ldots, \xi_T\}$ that are drawn from a uniform distribution over the set of orthogonal matrices (as in e.g. Rubio-Ramírez et al., 2010). Further note that a draw from the posterior of the structural model $\bar{\Phi}$ consists of T structural states of the economy, $\{\bar{\phi}_1, \bar{\phi}_2, \ldots, \bar{\phi}_T\}$, where each structural state $\bar{\phi}_t$ consists of a combination of a state ϕ_t from the reduced-form model and a rotation matrix ξ_t for which the implied impulse responses $f(\phi_t, \xi_t)$ satisfy the identifying sign restrictions for $t = 1, \ldots, T$.

Canova and Gambetti (2006), Canova and Gambetti (2009), and Baumeister and Peersman (2013b) claim to generate a draw $\bar{\Phi}$ from the posterior of the structural model by first selecting a state ϕ_t from a draw Φ of the unrestricted posterior, then drawing a rotation matrix ξ_t, and finally retaining the couple (ϕ_t, ξ_t) as one state $\bar{\phi}_t$ within one draw $\bar{\Phi}$ of the posterior of the structural model if the implied impulse responses $f(\phi_t, \xi_t)$ satisfy the sign restrictions. A complete draw $\bar{\Phi}$ from the posterior of the structural model is then generated by retaining, for each date in the sample, one couple of (ϕ_t, ξ_t) that satisfies the sign restrictions.

Koop and Potter (2011) show that this procedure may not be accurate. To correctly generate a draw $\bar{\Phi}$ from the posterior of the structural model, we adjust the existing algorithms by selecting, first, a draw Φ from the unrestricted posterior (rather than only one state ϕ_t), and second, a set Ξ of T rotation matrices (rather than just one ξ_t). This couple (Φ, Ξ) is retained as a draw from the structural posterior if the whole sequence of implied impulse responses $\{f(\phi_1, \xi_1), \ldots, f(\phi_T, \xi_T)\}$ satisfy the sign restrictions, otherwise the draw is discarded. Note that Koop and Potter (2011) show that this procedure is only an approximation of the true posterior of the structural model. The approximation error, however, is small since the probability that one individual impulse response $f(\phi_t, \xi_t)$ satisfies the sign restrictions is sufficiently large.

Second, we diverge from the algorithms used by Canova and Gambetti (2006), Canova and Gambetti (2009), and Baumeister and Peersman (2013b) by forcing the rotation matrix to be the same for all t within one draw of the posterior distribution of the structural model. More precisely, we draw only one rotation matrix ξ^* rather than a set Ξ of T different rotation matrices. We then retain the couple (Φ, ξ^*) as one draw $\bar{\Phi}$ from the posterior of the structural model if the whole sequence of impulse responses $\{f(\phi_1, \xi^*), \ldots, f(\phi_T, \xi^*)\}$ satisfies the sign restrictions.

This second modification to the existing algorithms avoids the introduction of an arbitrary amount of time variation within each draw of the Gibbs-sampler. Although the impact of such an additional arbitrary amount of time variation is negligible or even absent for the posterior distribution of the impulse responses, it is an important drawback when we construct the distribution for the amount of time variation present in the model by calculating the within-draw changes over time in the impulse responses.

Appendix B: Robustness of TVP-BVAR Estimations

In this section, we examine the sensitivity of the baseline TVP-BVAR results. Note that these results are based on two shocks that have been isolated with very different identification strategies, which is a robustness check in itself.

First, results are robust to several perturbations to the model specification. In particular, we have re-estimated the benchmark models for oil and food spillovers with a hierarchical prior (using a uniform distribution over the interval (0,1]) for the scaling parameters as in Amir-Ahmadi et al. (2020). Other robustness checks that we have conducted include reducing/increasing the number of lags ($p = 4$ and $p = 8$), using real commodity prices rather than their nominal values (using U.S. CPI as deflator), using SDR-denominated prices, calculating the growth rates of the time series entering the TVP-BVARs exactly rather than by log-differencing, imposing the sign restrictions for the oil supply shock over longer horizons, or adding a quantitative restriction (minus 0.8) on the maximum price elasticity of oil demand (Kilian and Murphy, 2012). These modifications do not materially affect the conclusions. Results for the normalized time variation of the oil and food price responses induced by oil and food commodity supply shocks are summarized in Figures A3 to A9.

Second, we also estimate five-variable TVP-BVARs with four lags, in which both supply shocks are identified simultaneously and spillovers between oil and food commodity prices are estimated along with spillovers to metals commodity prices and the prices of agricultural raw materials, respectively. The vectors of variables are then $\boldsymbol{y}_t = [\Delta q_t^{food}, \Delta q_t^{oil}, \Delta p_t^{oil}, \Delta p_t^{food}, \Delta p_t^{metal}]'$ and $\boldsymbol{y}_t = [\Delta q_t^{food}, \Delta q_t^{oil}, \Delta p_t^{oil}, \Delta p_t^{food}, \Delta p_t^{arm}]'$. In these larger VARs, the shocks are orthogonal by construction.[6] The time-varying spillover effects are very similar (see Figure A10).

[6] For these five-variable TVP-BVARs, we first recover food supply shocks by the block-recursive identification, which corresponds to a Cholesky decomposition of the residuals' variance-covariance matrix with food production ordered first. This determines the first row and column of the contemporaneous impact matrix. We then perform rotations to the remaining columns/rows of this matrix to identify oil supply shocks. Hereby, we again impose that there is a single shock that shifts oil prices and production in opposite directions.

Third, we test the sensitivity of our findings with respect to the inclusion of variables measuring economic activity and inflation at a global scale. We follow Baumeister and Peersman (2013a) by using the world industrial production index from the Netherlands Bureau for Economic Policy Analysis (quarterly average of monthly data). To measure inflationary pressure at a most comprehensive global level, we rely on the inflation rate for OECD economies. The latter time series starts in 1970, which—due to the required length of the TVP-BVAR's training sample—shortens the effective sample of the respective analysis. For these specifications, we keep the identifying restrictions unaltered. In a first step, we include the measures of global activity and inflation one at a time in 4-variables TVP-BVAR(4) models; in a second step, we include them simultaneously in 5-variables TVP-BVAR(4) models. Ultimately, we also run one 6-variables TVP-BVAR(2) model featuring (i) both commodity prices, (ii) both commodity production volumes, and (iii) both global variables, and we identify the two shocks of interest within this single model analogue to Figure A10. Overall, these modifications likewise do not affect our main results; in particular, we observe time-varying price spillovers between commodity markets that peak at the onset of the Great Recession, albeit magnitudes somewhat vary across specifications. These findings are summarized in Figures A11 to A14.

Figures A15, A16, and A17 further show the price responses, when we include three different real-time indicators reflecting expected economic activity (see also Figure 4 of the paper). These extra variables are added one by one to the TVP-BVARs.[7] Again, the time variation of the price spillovers remains remarkably stable across these model extensions.

Ultimately, in Section 2.1 of the paper, we briefly discuss that the correlation between the oil and food supply shocks that we obtain from the separately estimated benchmark oil and food market models turns out to be small (0.1) in absolute magnitude and statistically insignificant. This statement, however, is with respect to the full sample, on average. In Figure A18, panel A, we show time-varying versions of this correlation. The correlation between both shocks is virtually zero in the early part of the sample (dashed line), and slightly positive (around 0.2) in the second part of the sample. However, these sample-split correlations are insignificantly different from zero during both episodes.[8]

[7] Notice that the length of the time series available for MSCI emerging markets is too short to estimate a four-variable TVP-BVAR. Therefore, this index is left out of this robustness exercise. The starting dates of the remaining models vary due to the availability of the time series.

[8] We draw inference as follows: first, we calculate 500 correlation coefficients by randomly drawing oil and food supply shocks from their respective posterior distributions. Second, for each of these estimates, we simulate a distribution of 10.000 draws, using the estimated standard deviations of the correlation coefficients and Fishers

Inspecting measures of 5-year rolling-window correlations (dotted lines), there is in fact some time-varying correlation that is qualitatively akin to the one observed in the raw data (see Figure 1, panel B in the paper), but substantially smaller in size. Yet, these coefficients are insignificantly different from zero, too. More importantly, similar correlation patterns can be observed in panel B of Figure A18. This panel shows the corresponding correlations for the model presented in Figure A10 in which both shocks are simultaneously identified in a richer 5-variables model. Thus, time-varying correlations between the shocks are still present in the TVP-BVAR during some episodes (and correlation windows) even if shocks are restricted to be orthogonal by construction. Interestingly, qualitatively similar correlations further arise in the 6-variables model from Figure A14 that is simultaneously identified and further features global output and inflation. Since our impulse response analyses are very similar across these different types of models, we thus conjecture that the observed correlations of the shocks do not drive our results in the baseline models.

Appendix C: Commodity Supply Shocks and Disaggregate Food Commodity Prices

The robustness check in Figure A19 assesses whether—relative to the baseline VAR model results that we establish based on a composite food commodity price index—there is similar time variation in the spillovers of crude oil and food supply shocks to more disaggregate food commodity prices.[9] In this vein, we re-estimate the TVP-BVAR(6) models for the oil and the food commodity markets and replace the composite food price index by the prices of respectively corn, rice, soybeans and wheat in the vector of endogenous variables. Notice that these are also the four crops that have been used to construct the baseline food production index. The results for the four commodities are shown in Figure A19. As can be observed, the qualitative dynamics are consistent with the evidence on aggregate food prices. However, it appears that rice prices are less subject to time variation conditional on crude oil supply shocks, even though the uncertainty of these estimates is rather high.

z-transformation. Ultimately, we present the quantiles of interest for the resulting 5 million draws.

[9] These individual price series are strongly correlated among each other (see Figure A1). Notice that also the prices of other staples are typically strongly correlated with these four commodities. De Winne and Peersman (2016) employ a broader food price index, including prices for cereals, vegetable oils, meat, seafood, sugar, bananas, and oranges. We prefer the more narrow index as it corresponds exactly to the production index. Results are, however, robust to using the broad index.

Appendix D: Extensions of the Local Projections Evidence

In Section 5.4 of the paper, we analyze the contribution of financialization and the volatility of macroeconomic shocks to the commodity price spillovers that we have uncovered in the TVP-BVAR models. By means of local projections, we have quantified the importance of both phenomena for the spillovers of food supply shocks on oil prices and of oil supply shocks on food prices. Now we repeat this analysis and apply it to the price for metals and, alternatively, the price for raw agricultural materials. Specifically, we use these prices in turn as dependent variables in the local projections from equation 2 in the paper and trace their reactions to oil and food supply shocks; the latter are hereby further interacted with measures of financialization and/or the volatility of macroeconomic shocks.[10] For these specifications, we rely on TVP-BVAR shocks that we obtain from models that also include the prices of metals or agricultural raw materials; consistently, we also include lags of metals prices or raw agricultural materials prices in the vector of controls $\boldsymbol{y}_{t-l}^{i}$ in equation 2 of the paper.

Overall, the results for these two commodities are fully consistent with the evidence for oil and food commodity prices, where the influence of the interaction between volatility and/or financialization is particularly pronounced for the spillovers to metal prices (see Figure A20).

In a next step, we conduct some extensions to our baseline local projections model for the spillovers to oil and food commodity prices from Figure 5 in the paper. First, we acknowledge that the financialization index is the only time series in these local projections that is non-stationary. To address this issue, we add six lags—just like for the control variables in the model—of the financialization index to the local projections from equation 2 in the paper. That is, we now include several cointegrated time series (the financialization index is cointegrated with its own lags) on the right-hand side making the stationarity requirement obsolete, which is analogue to a VAR model.

Second, we test the hypothesis to what extent the size of the identified commodity supply shocks affects our results. In this vein, it is conceivable that informational frictions about the underlying shocks could be particularly pronounced for small shocks in real time, while large shocks may be easier to detect. To test such a proposition, we add another interaction term to

[10] The open interest data underlying the financialization index can be accessed via the "Commitment of Traders" tables provided by the Commodity Futures Trading Commission. The final index covers the following commodities: Chicago wheat, corn, soybeans, coffee, sugar #11, cocoa, cotton #2, live cattle, feeder cattle, crude oil, heating oil, gold and silver.

equation 2 in the paper, namely, the product of the commodity supply shocks and a dummy variable taking a value of 1 in quarters during which the absolute value of the commodity supply shocks is less than one standard deviation in size, and zero otherwise. Thus, we directly test whether there are stronger spillovers in periods of small commodity market disruptions.

Third, we augment the local projections by an additional interaction term aimed to speak more directly to the role of the biofuels revolution for our findings. A complication to do so concerns the measurement of global biofuels activity, since (i) we only have quarterly data on biofuels consumption for the U.S. economy and (ii) global biofuels consumption data are available from the FAO only annually from 2001 onward. Keeping this lack of appropriate global biofuels data as a caveat in mind, we generate a global biofuels consumption index as follows. For the episode up to 2001, we back cast the global consumption series via U.S. biofuels consumption. For the episode since 2001, we interpolate the annual global data via the Chow Lin procedure using the high-frequency fluctuations of U.S. biofuels consumption during that period as an indicator. The final series is plotted in Figure 1, panel D of the paper, along with the U.S. counterpart. In a next step, we add to equation 2 in the paper an additional interaction term representing the product of the commodity supply shocks and the standardized global biofuels index; that is, we capture additional price spillovers for the case in which global biofuels consumption is one unit above its mean.

Fourth, we replace our benchmark measure for the volatility of macroeconomic shocks. In the paper, we proxy the latter with the series provided by Mumtaz and Musso (2021). These authors rely on 22 OECD countries to generate their index. However, informational frictions about the stance of the global business cycle may be particularly relevant for emerging market economies for which timely and reliable information on aggregate activity is scarce. As an alternative to the series by Mumtaz and Musso (2021), we thus use the macroeconomic uncertainty index of Miescu (2019) that exclusively relies on data for emerging economies. Her series is constructed according to the methodology of Jurado et al. (2015) and is reproduced in panel E of Figure 1 in the paper.

Figures A21 to A25 summarize the respective results. The inclusion of additional lags of the financialization index in the estimations does not affect our inference, albeit magnitudes are somewhat smaller (Figure A21). The modeling of an additional interaction term capturing the size of the commodity market shocks leaves our main findings (the first four panels) virtually unchanged (Figure A22). Moreover, during the impact period, which is the key statistic for our question of interest, there is no amplification due to the size of the shocks (the last panels). The point estimates are either insignificant or even negative in the case of the oil supply shock, i.e., spillovers even become somewhat muted. In addition, our main results (first four panels) remain intact for the biofuels-augmented models (Figure A23). Magnitudes are even more pronounced for the food supply shock, while in the case of the oil supply shock, results become less significant. However, the point estimates for the impact period following oil supply shocks are still stable in this extension.[11] Turning to the interaction effects arising from developments in global biofuels markets (the last panels), we do not find support for the hypothesis of biofuels inducing price spillovers. In the case of food supply shocks, spillovers are even smaller in the era of highly established biofuels markets, while for the oil supply shock, there is virtually no amplification or mitigation of spillovers to observe. Taken as a whole, we view this evidence as a further quantitative demonstration showing that biofuels are unlikely to be the main source of the price spillovers observed in our paper. Ultimately, in Figure A25 we observe very similar results as in Figure 5 of the paper; that is, the specific choice of the macroeconomic volatility series is not crucial for our findings.

Appendix E: Linear VARs Estimated over Sub-Samples and Pass-Through to Consumer Prices

Finally, we assess the robustness of the spillovers documented in the TVP-BVARs by applying our identification scheme in linear VARs, where the time variation in the causal effects is recovered by splitting the sample into two sub-periods: the era before 2004 and the episode since.[12] Specifically, we estimate linear counterparts of the TVP-BVARs presented in Figures 2 to 4 of the paper.

Figure A26 presents the adjustment patterns of the core block of variables; in addition, we rotate into these BVARs—one at a time—the prices of metals and of agricultural raw materials and show the respective IRFs. While oil supply shocks (panel A) did not affect the prices of other commodities in the early sample, there are strong spillover effects in the late sample

[11] We have further produced the IRFs for the *isolated* volatility-financialization-interaction in Figure A24; i.e., not the sum of the interactions of (i) volatility, (ii) financialization, and (iii) their combined effect as depicted in Figure A23, but only the last component. These isolated interactions turn out positive and statistically significant; thus, corroborating our baseline findings and our favored explanation of the results.

[12] Given the gradual character of the time variation we have documented in the paper, these sample-splits should be viewed with the caveat of constituting a rather rough approximation of underlying non-linear time variation. At the same time, the sample-splits serve as an additional test whether an enhanced link between commodity prices in more recent data can also be detected in less parametrized models with non-drifting coefficients.

period. For food commodity supply shocks (panel B), we document negative spillover effects in the early sample period, while there is a positive pass-through in the late sample.

Second, Figures A27, A28, and A29 illustrate the robustness of the documented spillovers when three different proxies of expected economic activity are included as an extra variable in the BVARs. At the same time, these results confirm the general pattern of a more optimistic response of these indicators following adverse commodity supply shocks during the more recent sample, as also documented in Figure 4 of the paper.

Finally, we also cast the models augmented with the shadow rate from Figure 3 of the paper into linear VARs estimated over two sample periods. Figure A30 confirms the observation from the TVP-BVARs that potential time variation in the Fed's policy response is unlikely to contribute to the cross-commodity spillovers: the more recent sample is characterized by a less accommodating policy response to adverse commodity supply shocks, and thereby provides, if anything, a counteracting rather than supporting force for the documented commodity price spillovers.

A natural follow-up question for policymakers is to what extent the observed spillovers matter for consumer price dynamics; that is, whether they propagate along the supply chain to energy and food retail prices.[13] To examine this question, we re-estimate the linear sample-split VARs for the benchmark variables and augment them with data on the energy and food components of consumer prices for the U.K. and the U.S. economy.

Figure A31 shows the effects on the newly-added CPI components in the subsamples. Panel A shows that unfavorable crude oil production shocks tend to induce a negative impact on food retail prices in the early sample period. However, for the more recent period, we observe significant surges in food CPI in both countries. After a one percent shortfall in global crude oil production, retail prices for food items increase in the U.S. by roughly 0.3 percent, and by around 0.5 percent in the U.K. economy. Similar findings emerge for the repercussions of unfavorable food commodity production shocks on energy consumer prices (panel B). In both countries, energy prices substantially fall in the early era, but feature striking run-ups of up to 0.6 percent during the post-2004 episode. Taken together, we find that the price spillovers across commodity classes also pass on to the prices for consumer products.

Notice that these spillovers appear to be quite persistent. This is somewhat surprising in the

[13]Other studies have shown the relevance of commodity prices for business cycle fluctuations (e.g. Fernández et al., 2017).

context of informational frictions, since information about the state of the real economy should become available over time. A possible explanation is that informational frictions are amplified by speculative trading. In particular, Singleton (2013) emphasizes that informational frictions and the associated speculative activity may induce prices to drift away from their fundamental values and could result in price booms and busts. In other words, financial markets may amplify errors of investors and generate price changes that are unrelated to fundamentals. Overall, the sample splits confirm the results of the TVP-BVARs. Notice that this conclusion also applies to the stronger impact of both shocks on the own price.

References

Amir-Ahmadi, Pooyan, Christian Matthes, and Mu-Chun Wang (2020) "Choosing Prior Hyperparameters: With Applications to Time-Varying Parameter Models," *Journal of Business & Economic Statistics*, Vol. 38, pp. 124–136.

Baumeister, Christiane and Gert Peersman (2013a) "The Role Of Time-Varying Price Elasticities In Accounting For Volatility Changes In The Crude Oil Market," *Journal of Applied Econometrics*, Vol. 28, pp. 1087–1109.

——— (2013b) "Time-Varying Effects of Oil Supply Shocks on the US Economy," *American Economic Journal: Macroeconomics*, Vol. 5, pp. 1–28.

Canova, Fabio and Luca Gambetti (2006) "Structural Changes in the US Economy: Bad Luck or Bad Policy?" CEPR Discussion Papers 5457, C.E.P.R. Discussion Papers.

——— (2009) "Structural changes in the US economy: Is there a role for monetary policy?," *Journal of Economic Dynamics and Control*, Vol. 33, pp. 477–490.

Cogley, Timothy and Thomas J. Sargent (2005) "Drift and Volatilities: Monetary Policies and Outcomes in the Post WWII U.S," *Review of Economic Dynamics*, Vol. 8, pp. 262–302.

De Winne, Jasmien and Gert Peersman (2016) "Macroeconomic Effects of Disruptions in Global Food Commodity Markets: Evidence for the United States," *Brookings Papers on Economic Activity*, Vol. 47, pp. 183–286.

Del Negro, Marco and Giorgio E. Primiceri (2015) "Time Varying Structural Vector Autoregressions and Monetary Policy: A Corrigendum," *Review of Economic Studies*, Vol. 82, pp. 1342–1345.

Fernández, Andrés, Schmitt-Grohé Stephanie, and Martín Uribe (2017) "World shocks, world prices, and business cycles: An empirical investigation," *Journal of International Economics*, Vol. 108, pp. 2–14.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng (2015) "Measuring Uncertainty," *American Economic Review*, Vol. 105, pp. 1177–1216.

Kilian, Lutz (2009) "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review*, Vol. 99, pp. 1053–1069.

Kilian, Lutz and Daniel P Murphy (2012) "Why agnostic sign restrictions are not enough: Understanding the dynamics of oil market VAR models," *Journal of the European Economic Association*, Vol. 10, pp. 1166–1188.

Kim, Chang-Jin and Charles R. Nelson (1999) *State-space models with regime switching: Classical and Gibbs-sampling approaches with applications*: Cambridge, MA: MIT Press.

Kim, Sangjoon, Neil Shephard, and Siddhartha Chib (1998) "Stochastic volatility: Likelihood inference and comparison with ARCH models," *Review of Economic Studies*, Vol. 65, pp. 361–393.

Koop, Gary and Simon M. Potter (2011) "Time varying VARs with inequality restrictions," *Journal of Economic Dynamics and Control*, Vol. 35, pp. 1126–1138.

Miescu, Mirela S. (2019) "Uncertainty shocks in emerging economies: a global to local approach for identification," Economics Working Paper Series 2019/017, Lancaster University.

Mumtaz, Haroon and Alberto Musso (2021) "The Evolving Impact of Global, Region-Specific, and Country-Specific Uncertainty," *Journal of Business & Economic Statistics*, Vol. 39, pp. 466–481.

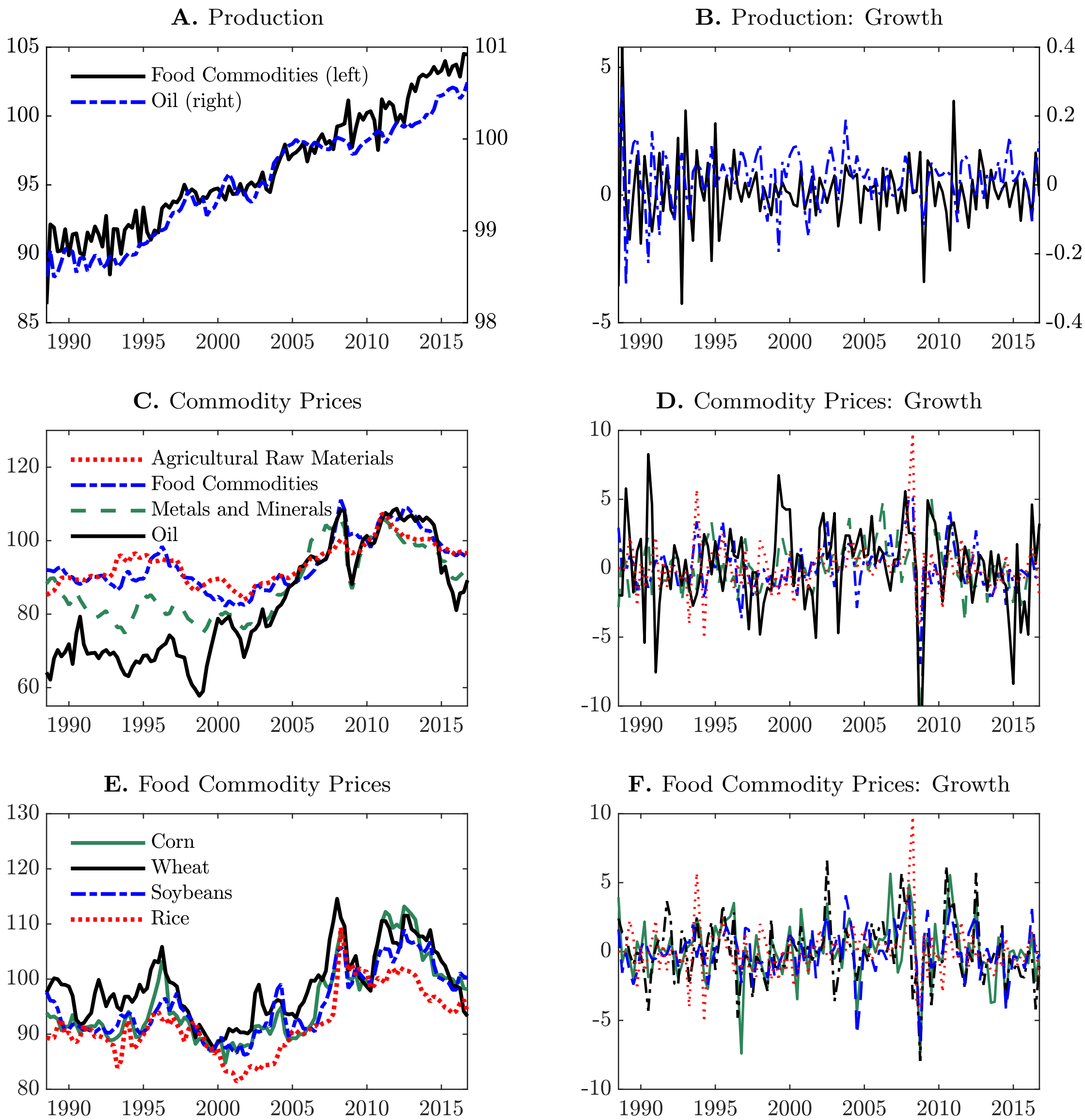
Primiceri, Giorgio E. (2005) "Time Varying Structural Vector Autoregressions and Monetary Policy," *Review of Economic Studies*, Vol. 72, pp. 821–852.

Rubio-Ramírez, Juan F., Daniel F. Waggoner, and Tao Zha (2010) "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference," *Review of Economic Studies*, Vol. 77, pp. 665–696.

Singleton, Kenneth J. (2013) "Investor flows and the 2008 boom/bust in oil prices," *Management Science*, Vol. 60, pp. 300–318.

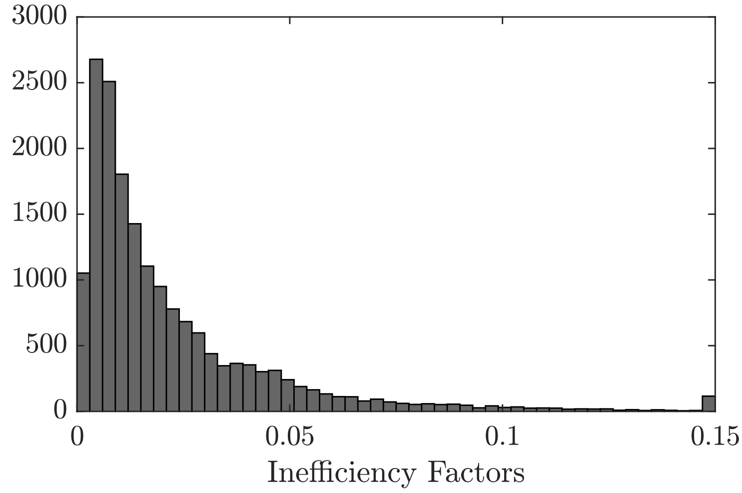
Appendix: Figures

Figure A1: Data



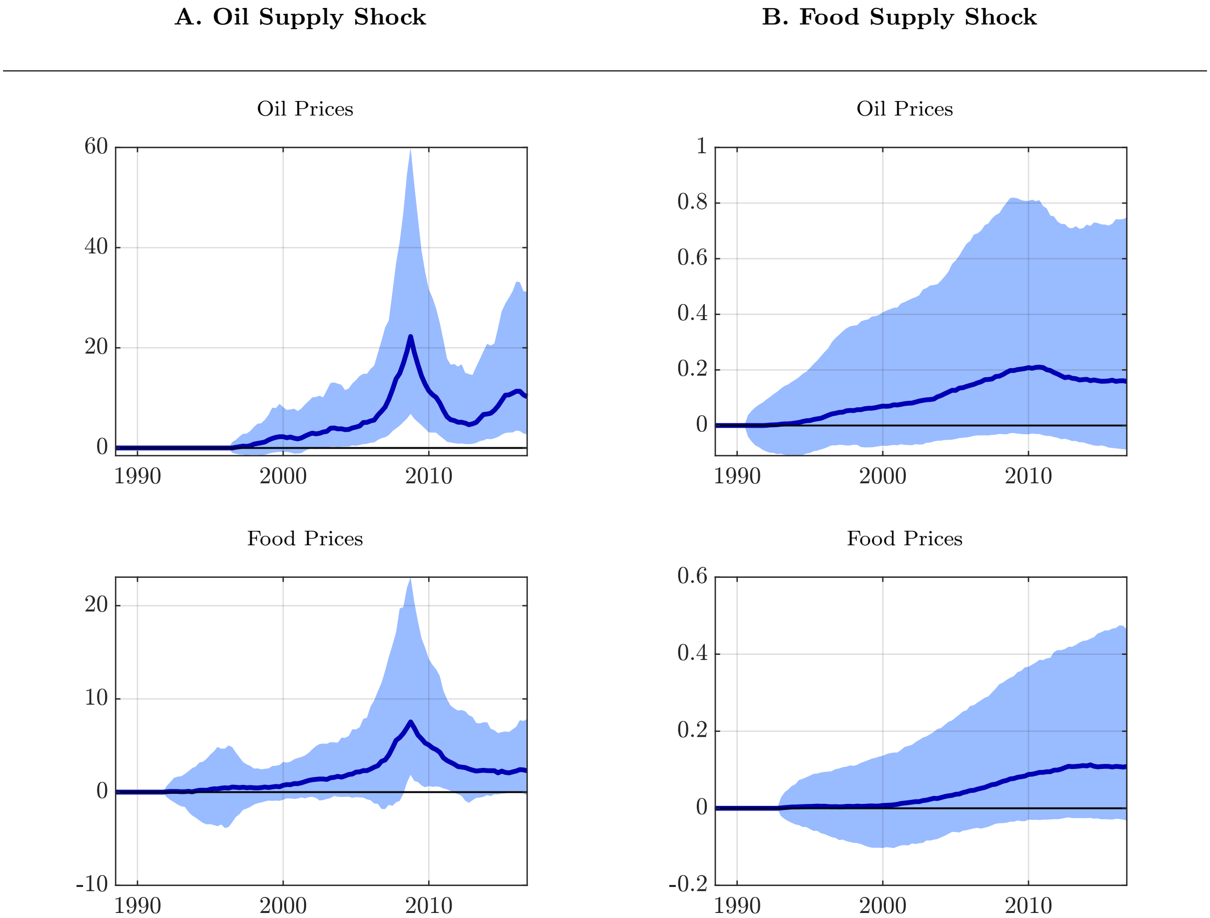
Notes: The left panels show (natural logarithms of) price and production indices normalized to 2010=100. The right panels show the variables in non-annualized quarterly growth rates.

Figure A2: Histogram of Inefficiency Factors for the Two Benchmark Models



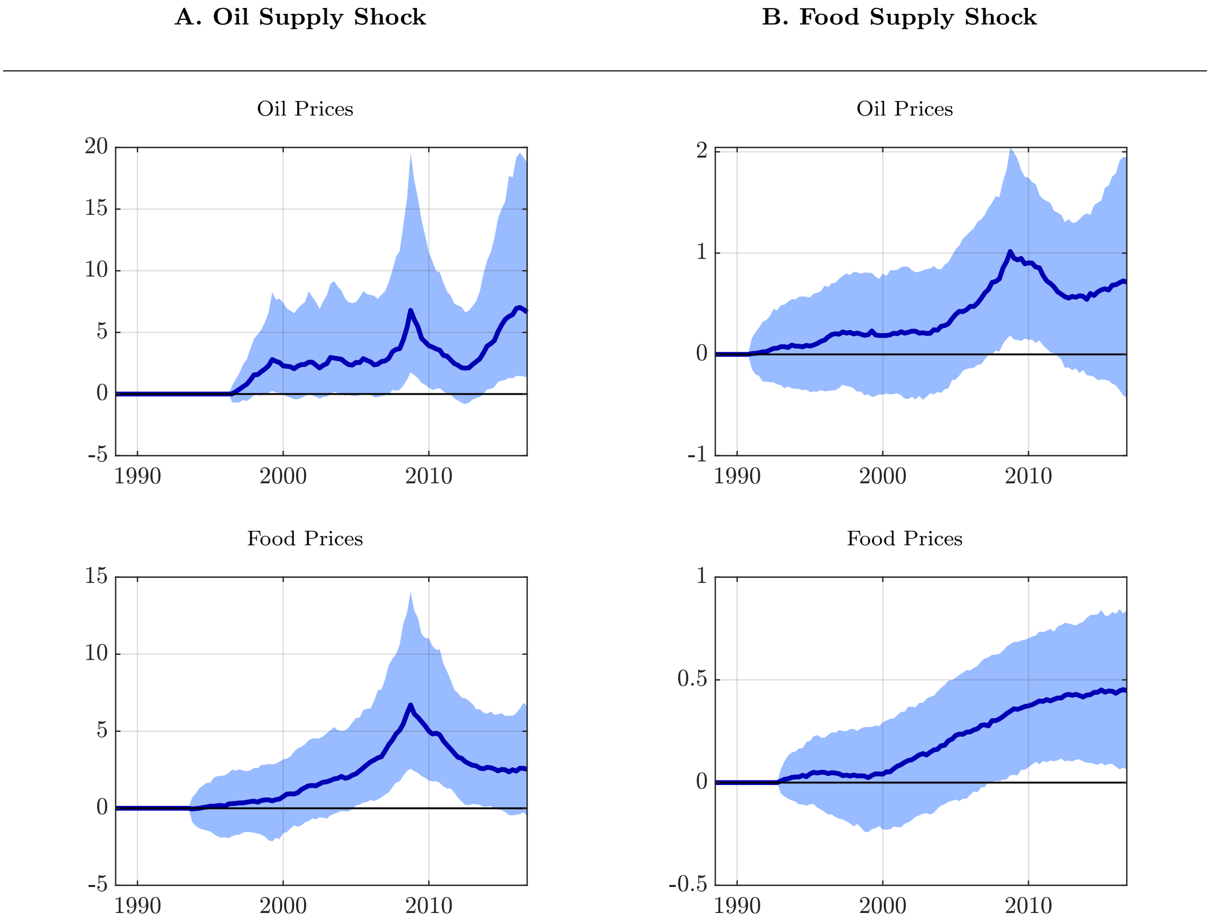
Notes: The histogram collects all inefficiency factors for the two benchmark TVP-BVAR models. For ease of exposition, inefficiency factors larger than 0.15 enter the last bin.

Figure A3: Hierarchical Prior for Scaling Parameters as in Amir-Ahmadi et al. (2020)



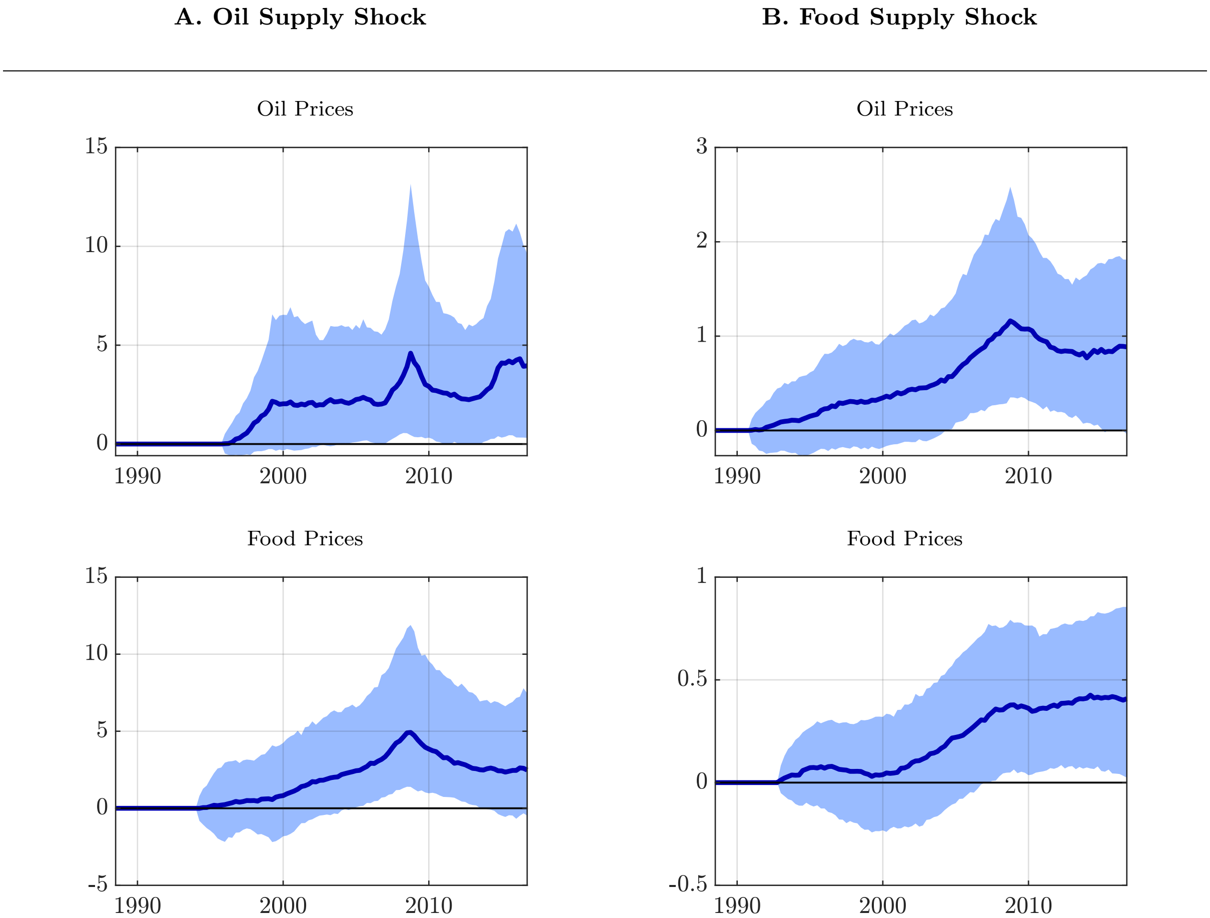
Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A4: Lag-Order of $p = 4$ in the TVP-BVAR Estimation



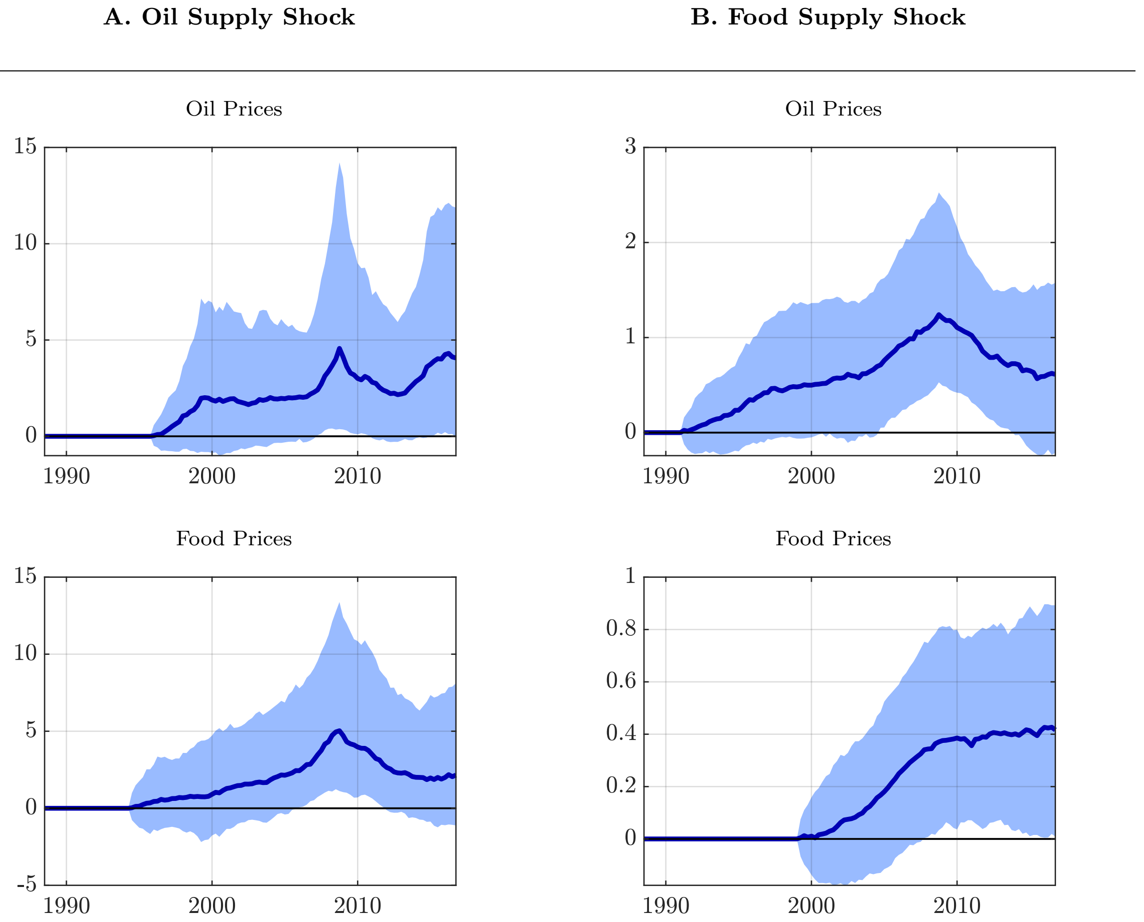
Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A5: Lag-Order of $p = 8$ in the TVP-BVAR Estimation



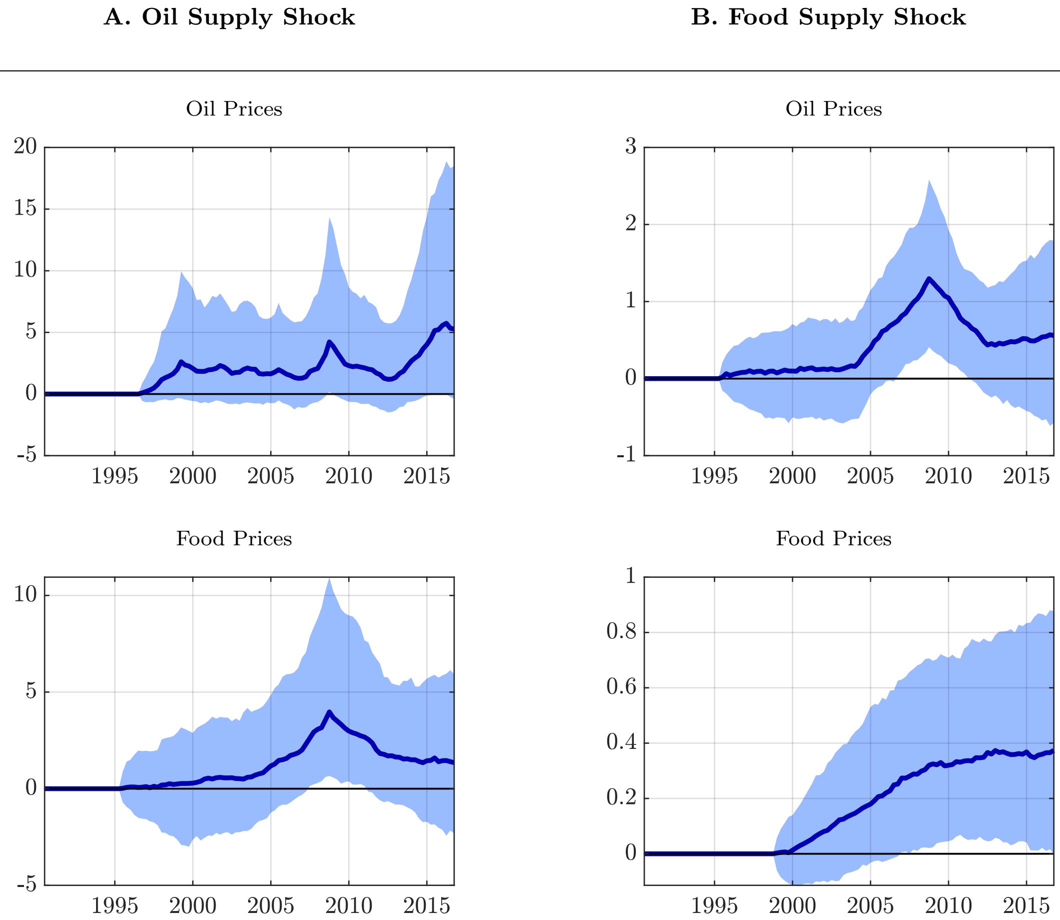
Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A6: Real Commodity Prices



Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

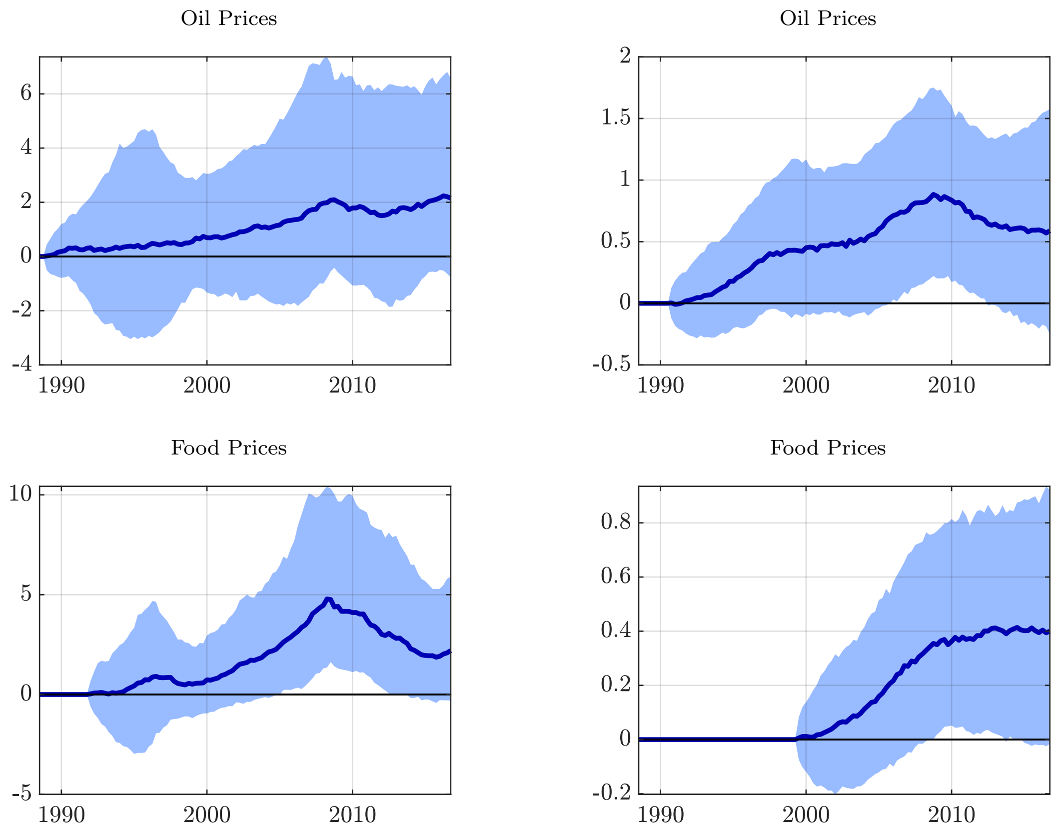
Figure A7: SDR-Denominated Commodity Prices



Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets. Data availability necessitates the use of four lags instead of six (to shorten the length of the training sample) and a shorter estimation sample.

Figure A8: Exact Growth Rate Calculation instead of Log-Differencing

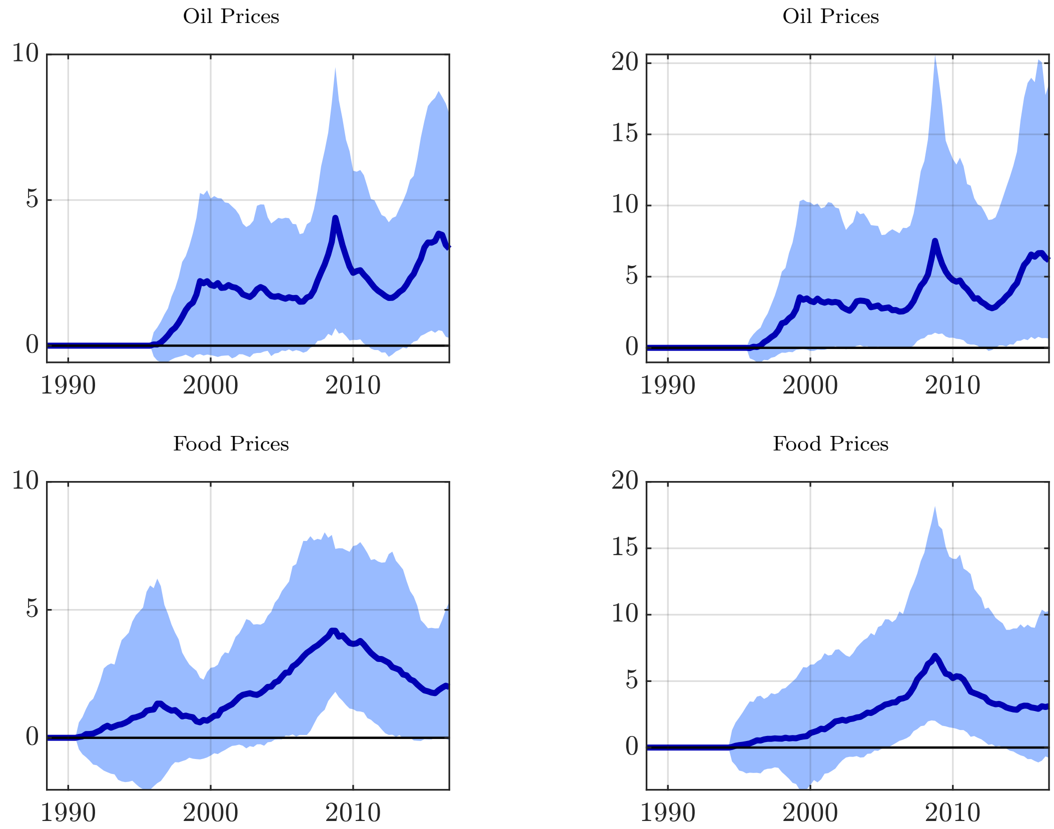
A. Oil Supply Shock **B. Food Supply Shock**



Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

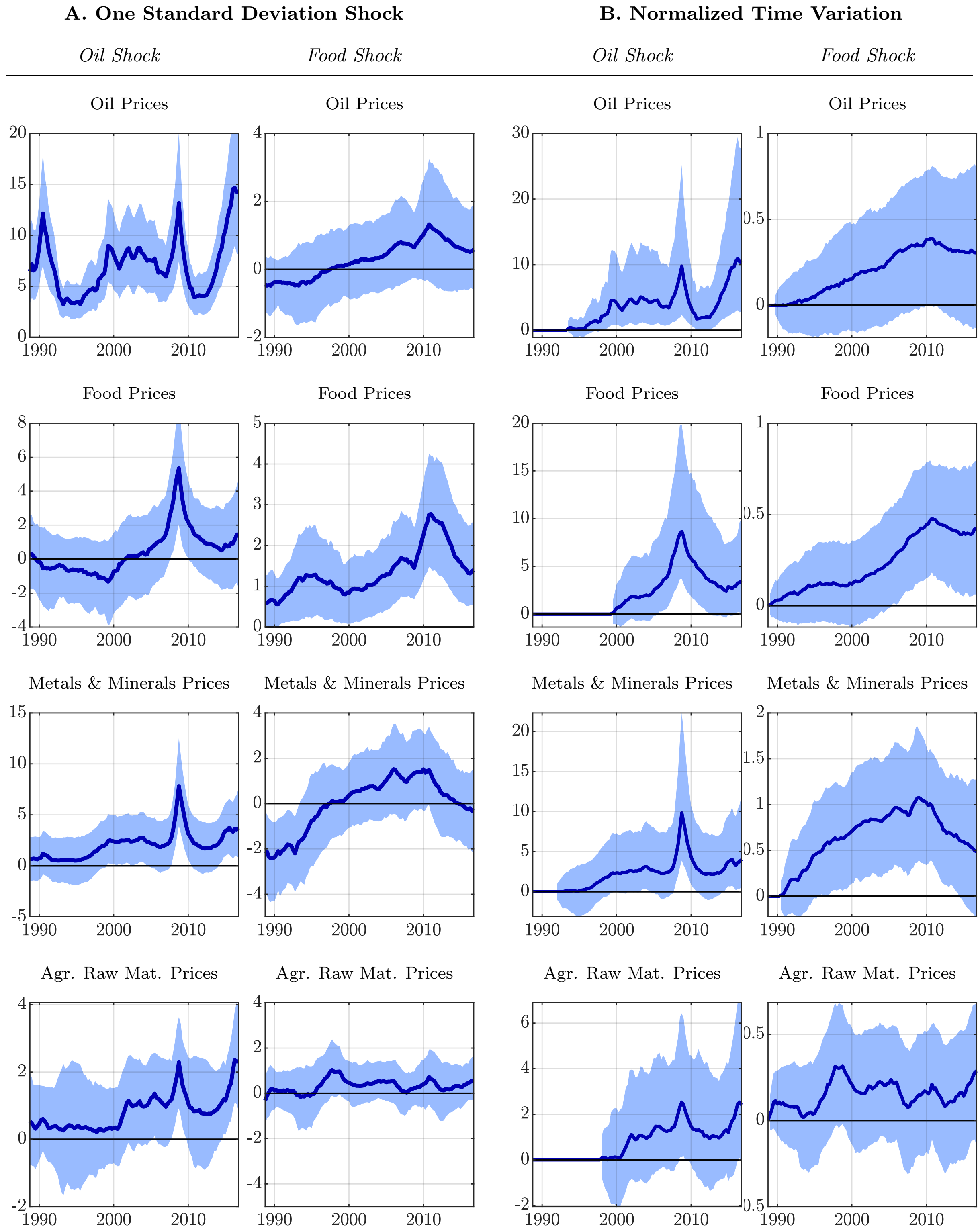
Figure A9: Adjustments to the Identification Scheme for Oil Supply Shocks

A. Restrictions Imposed for Four Quarters **B. Restriction on Oil Demand Elasticity**



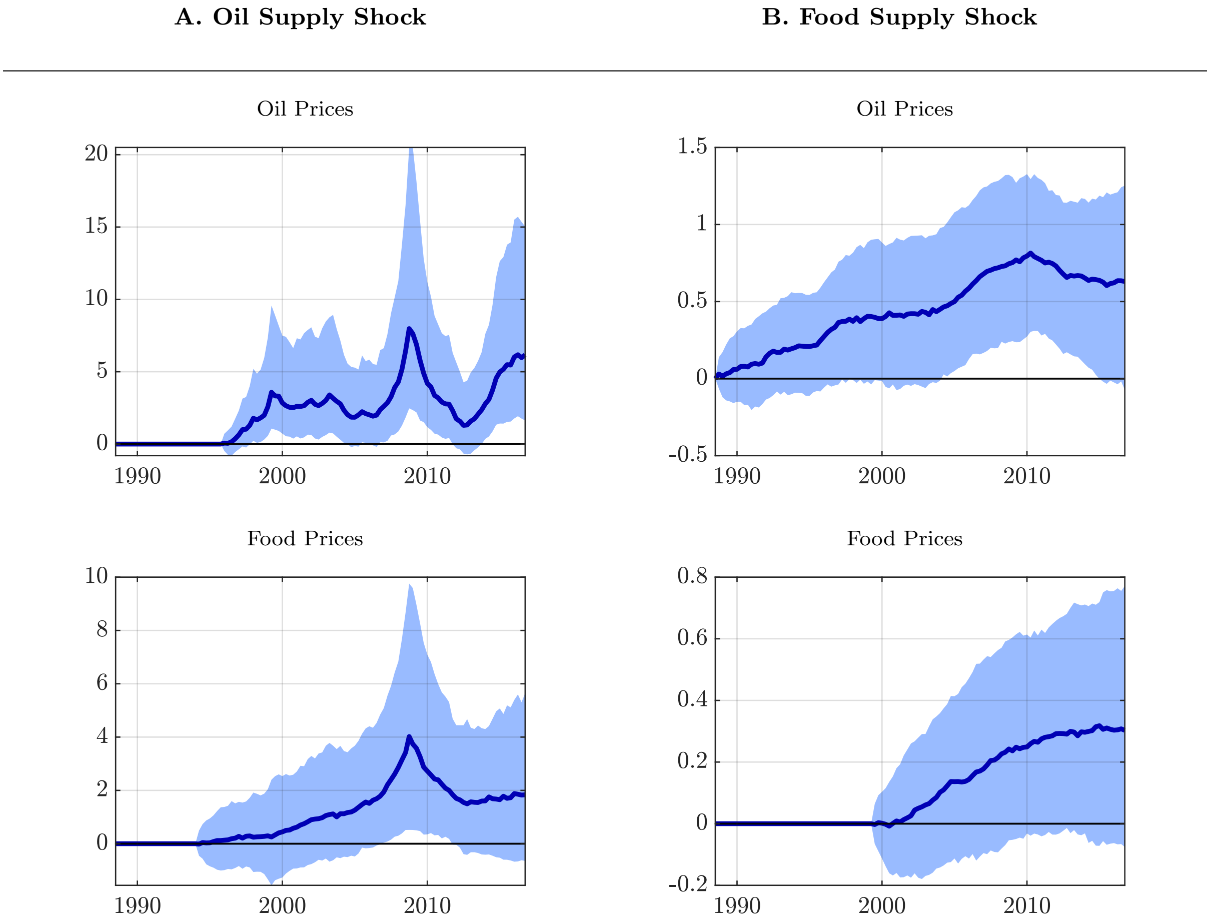
Notes: The figure shows the time-varying responses of oil and food prices to adverse oil supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. In panel A, sign restrictions are imposed to hold for four quarters, rather than only on impact. In panel B, we augment the sign restrictions identification by the quantitative restriction that the price elasticity of oil demand is not allowed to exceed -0.8 (Kilian and Murphy, 2012). The shaded areas are the 16th and 84th percentile credible sets.

Figure A10: Time-Varying Effects of Oil and Food Supply Shocks: 5-Variable TVP-BVAR(4)



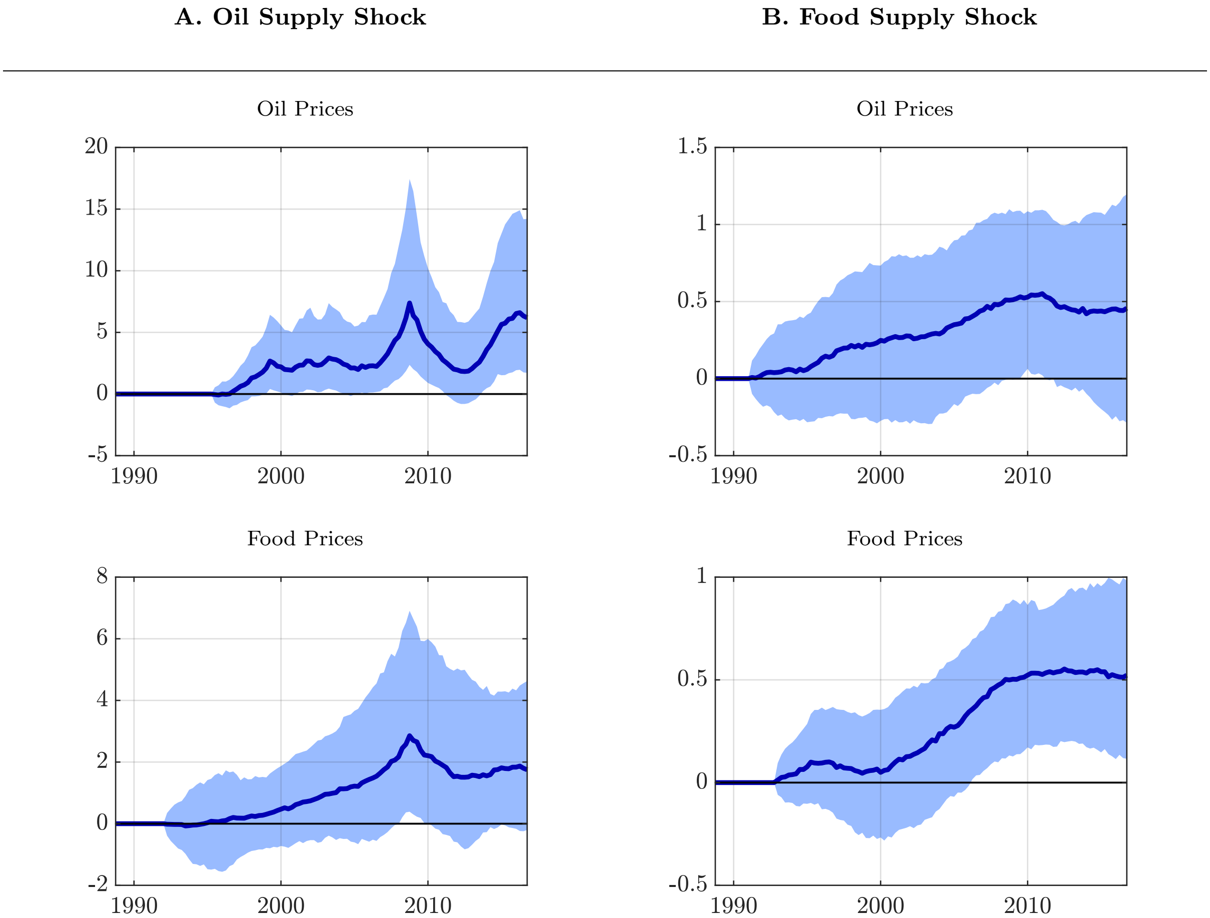
Notes: Panel A shows the contemporaneous impact of a one standard deviation shortfall in the production of oil (first column) and food (second column) based on 5-variable TVP-BVARs. Panel B shows the time variation in these responses, calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A11: Inclusion of World Industrial Production in the TVP-BVAR



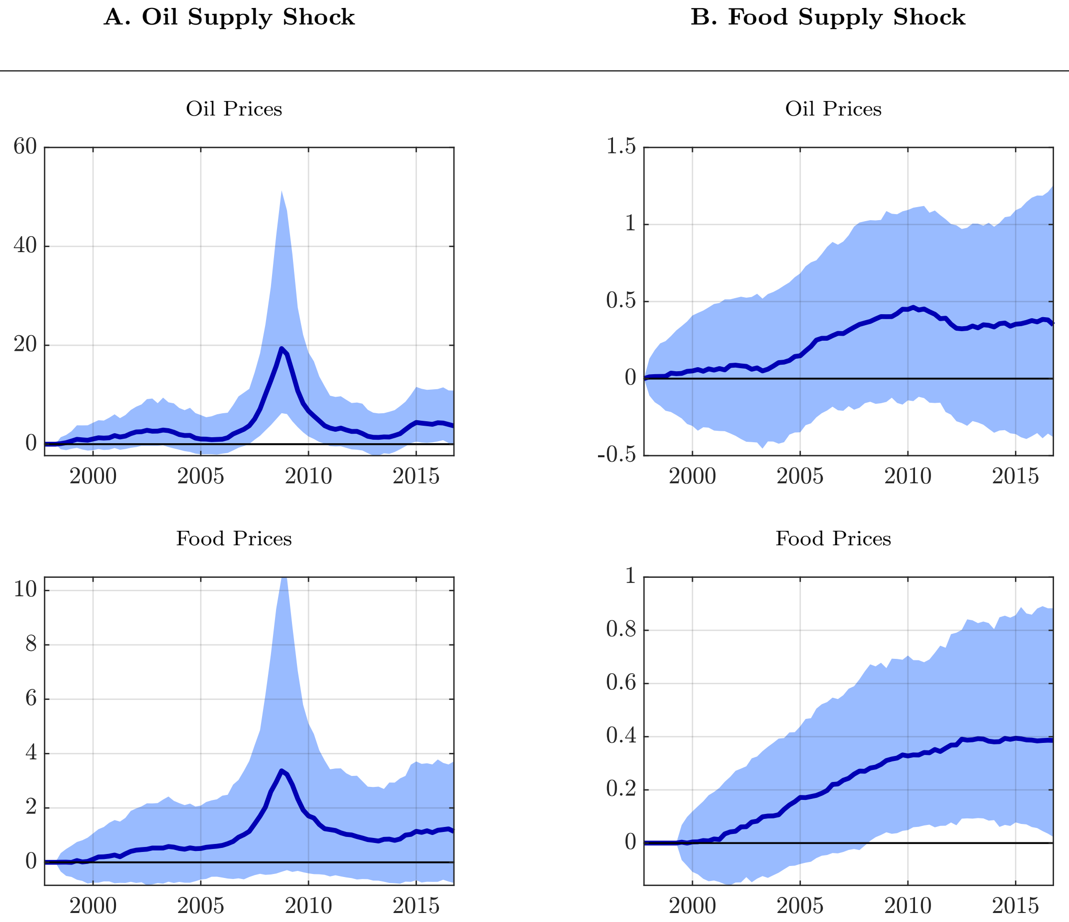
Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A12: Inclusion of the Inflation Rate for OECD Countries in the TVP-BVAR



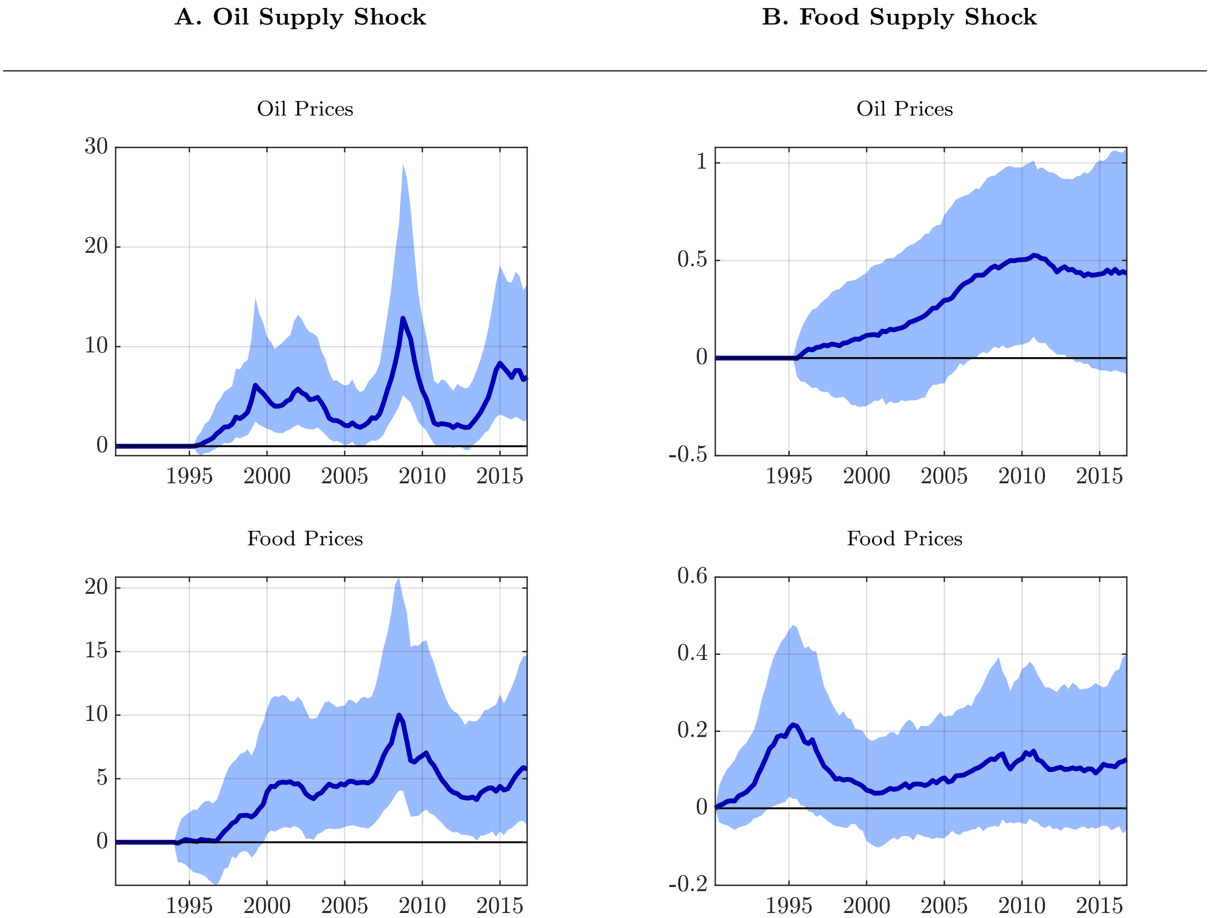
Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A13: 5-Variables Models Including World Industrial Production and the OECD Inflation Rate



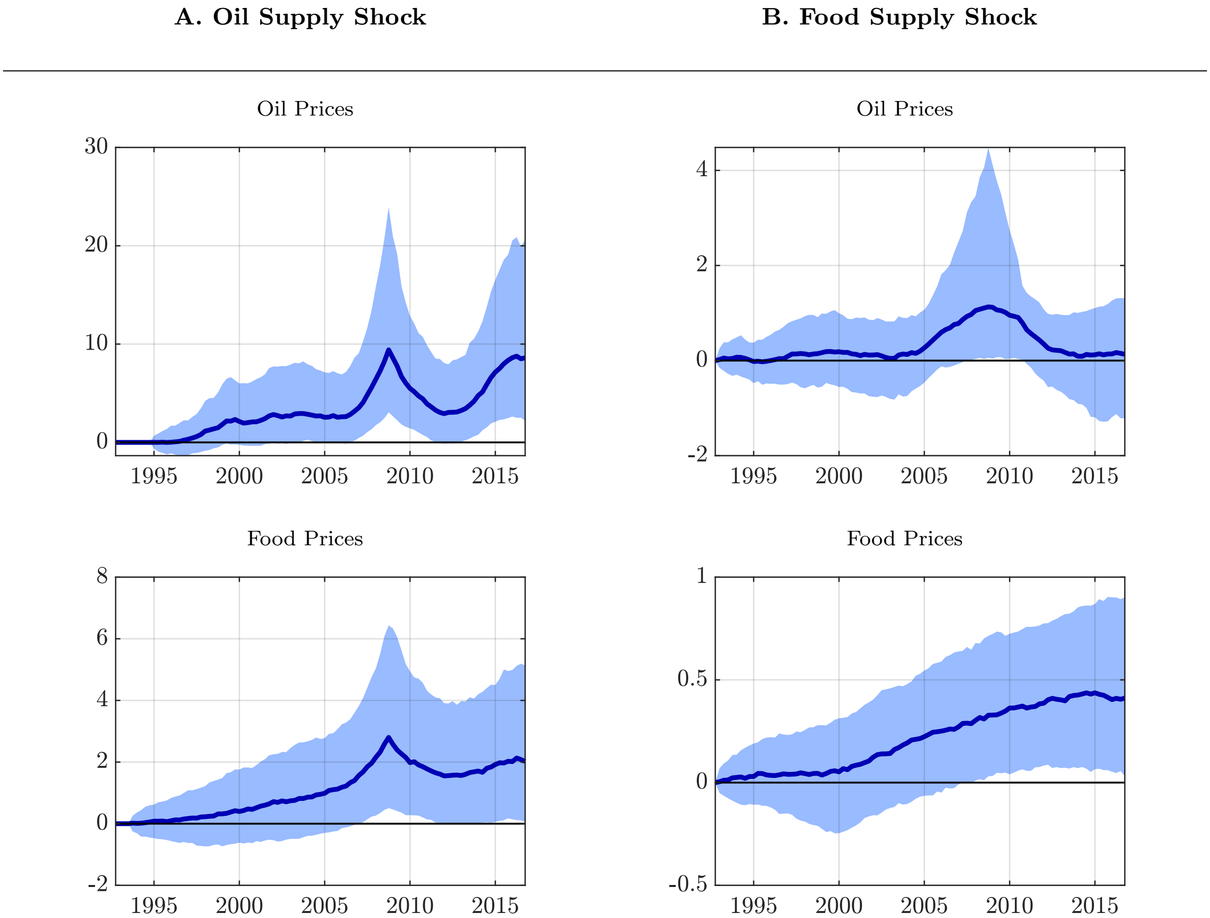
Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A14: 6-Variables Model Including World Industrial Production and the OECD Inflation Rate



Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

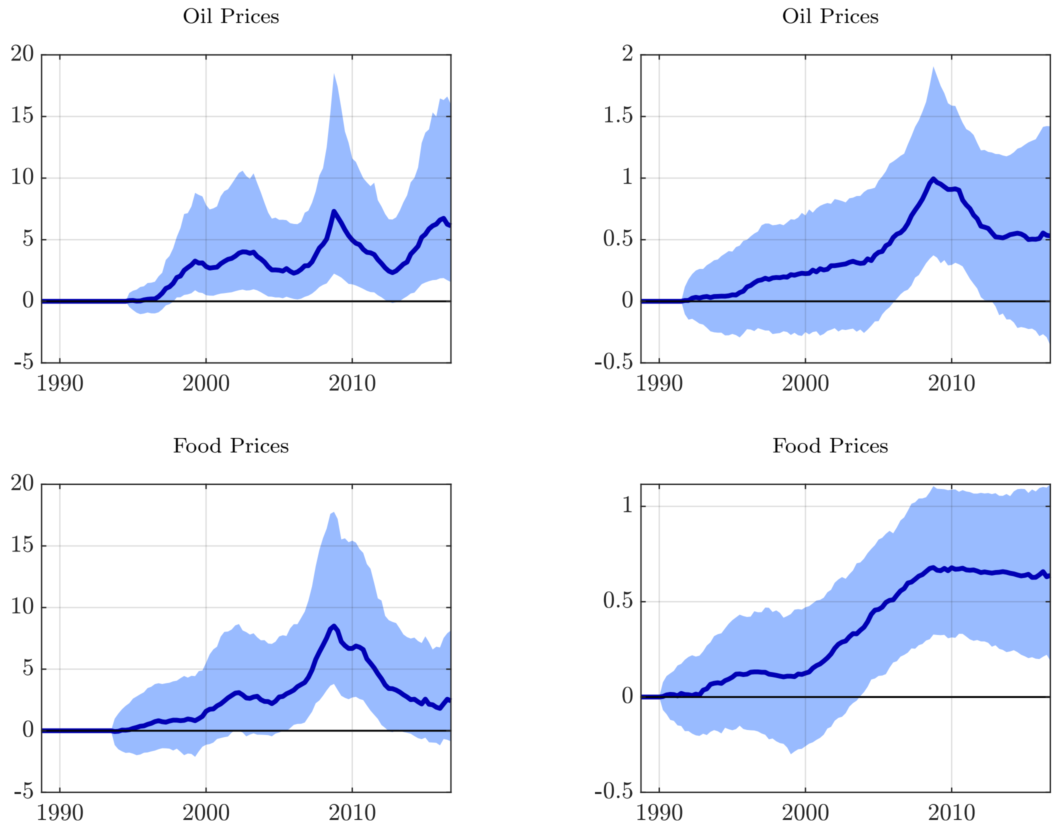
Figure A15: Inclusion of OECD Business Confidence Index in the TVP-BVAR



Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

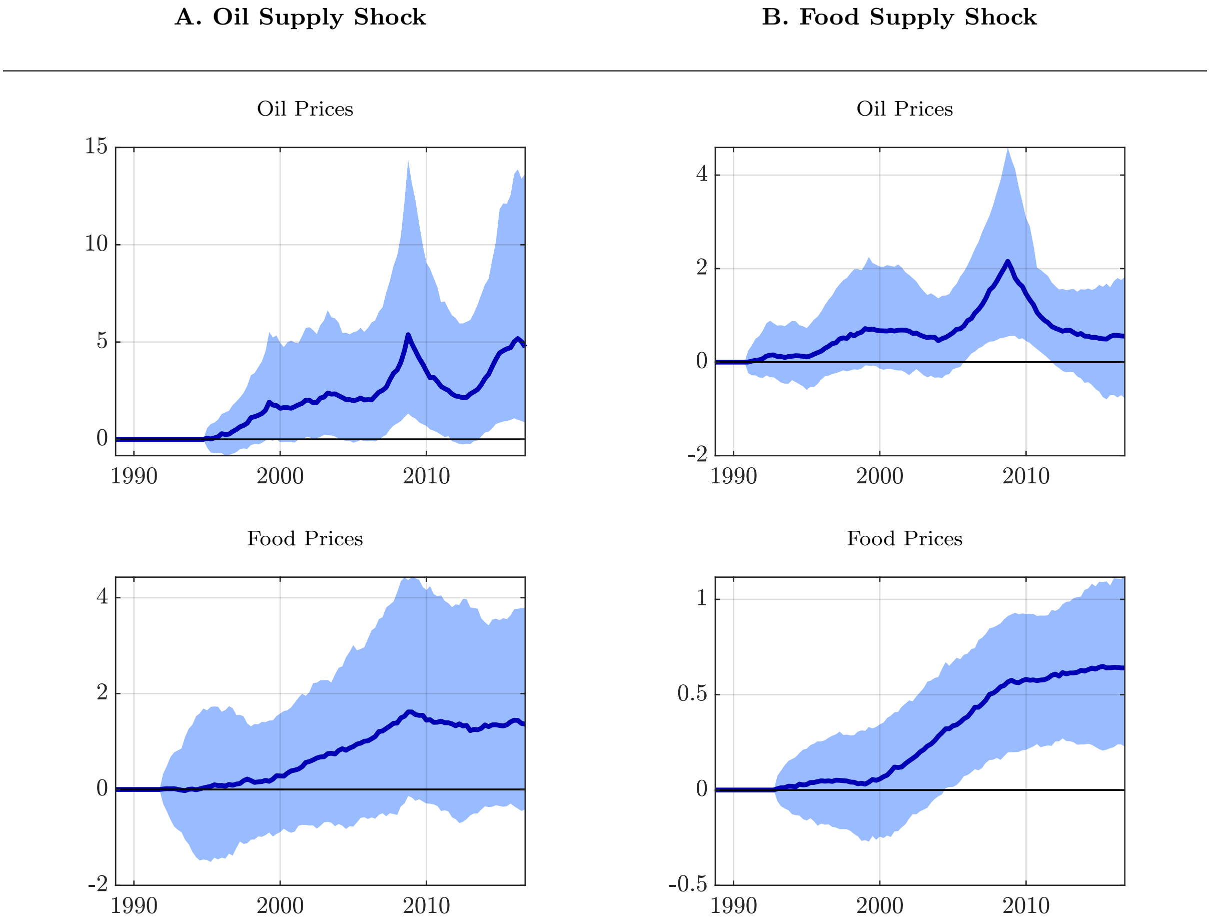
Figure A16: Inclusion of MSCI World in the TVP-BVAR

A. Oil Supply Shock **B. Food Supply Shock**



Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A17: Inclusion of OECD Composite Leading Indicator in the TVP-BVAR

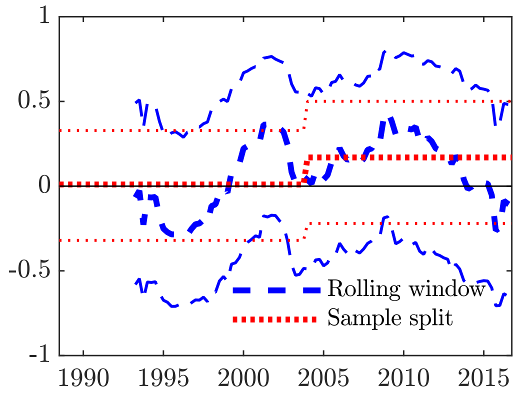


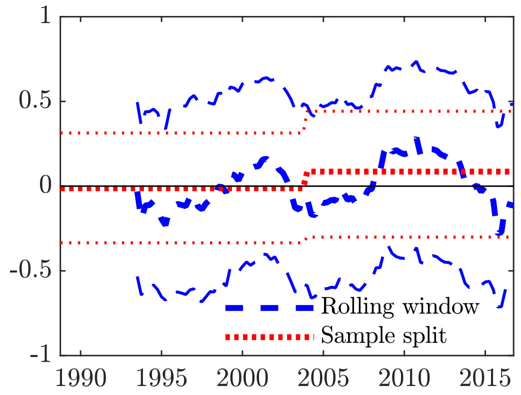
Notes: Panel A shows the time-varying responses of oil and food prices to adverse oil supply shocks. Panel B traces the respective adjustment patterns following from food supply shocks. The time variation in these price responses is calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A18: Time-Varying Correlations between Oil and Food Commodity Supply Shocks

A. Benchmark 3-Variables VARs

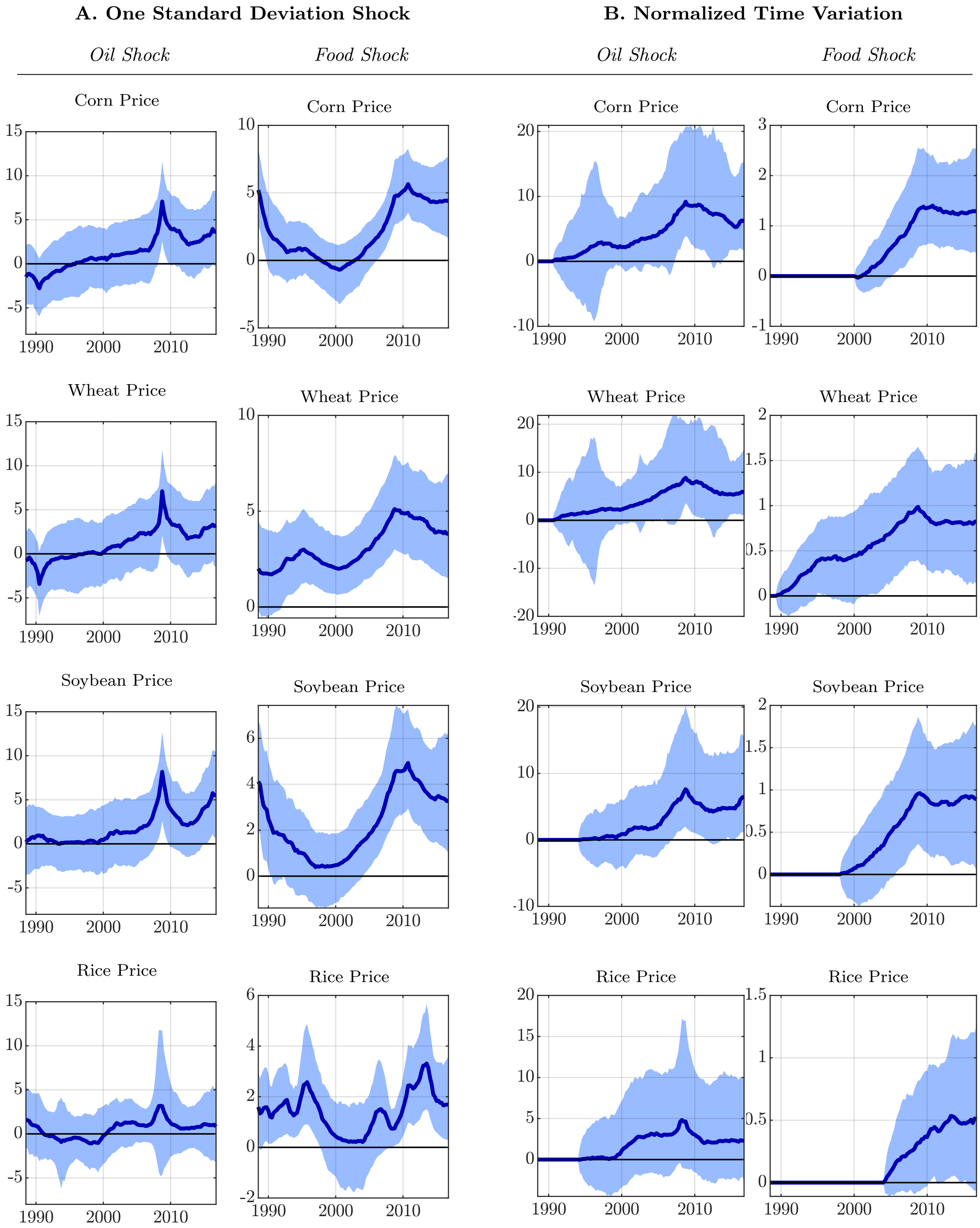
B. Joint Identification (5-Variables VAR)





Notes: The figure shows time-varying correlations between the identified crude oil and food commodity supply shocks. The dashed line shows correlation coefficients for a sample split in 2003Q4/2004Q1. The dotted line displays correlations derived from (lagged) 5-year rolling windows. Panel A is based on the shocks from the model of Figure 2 in the paper, while panel B uses the shocks obtained from the model used in Figure A10 of this appendix, in which shocks are identified simultaneously. Credible sets cover 95% of the posterior probability mass.

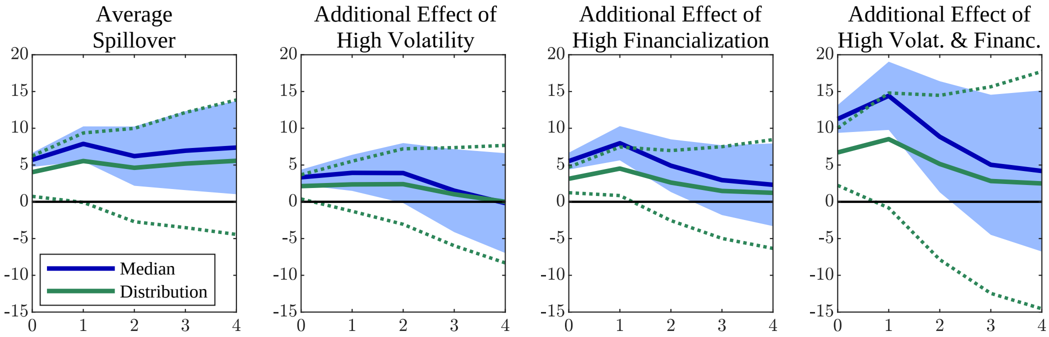
Figure A19: Time-Varying Effects of Oil and Food Supply Shocks: Disaggregated Analysis



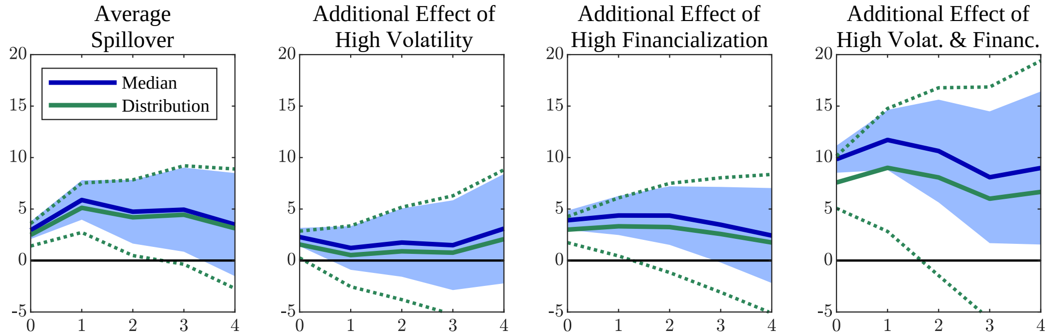
Notes: Panel A shows the contemporaneous impact of a one standard deviation shortfall in the production of oil (first column) and food (second column) based on TVP-BVARs. Panel B shows the time variation in these responses, calculated as the change in the contemporaneous response (normalized to represent a 1 percent production shortfall) over time relative to a benchmark quarter. The benchmark quarter is selected as the quarter with the lowest median (normalized) response. The shaded areas are the 16th and 84th percentile credible sets.

Figure A20: Financialization, Volatility, and Spillovers: Metals and Agricultural Materials

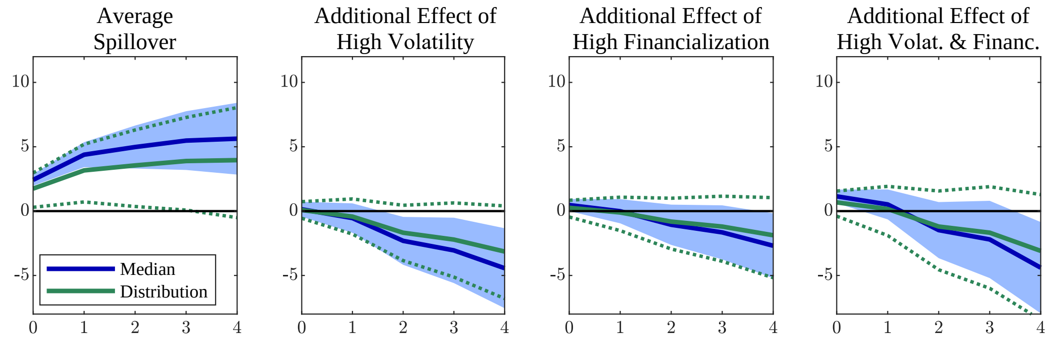
A. Spillovers of Oil Supply Shocks to Metals and Minerals Prices



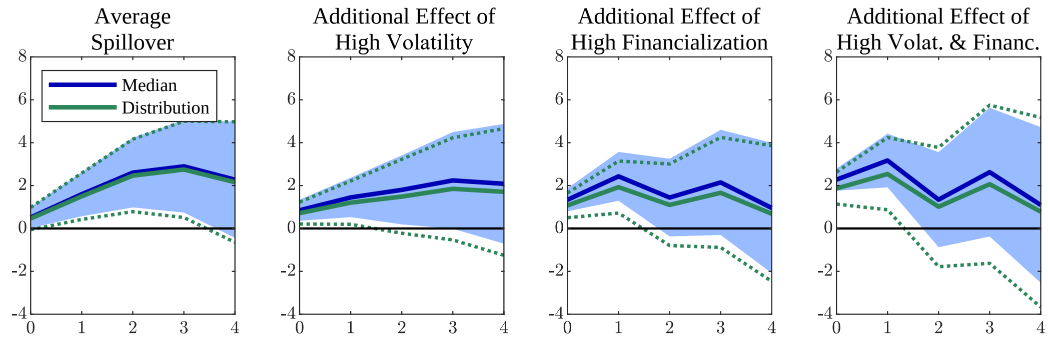
B. Spillovers of Food Supply Shocks to Metals and Minerals Prices



C. Spillovers of Oil Supply Shocks to Agricultural Raw Materials Prices



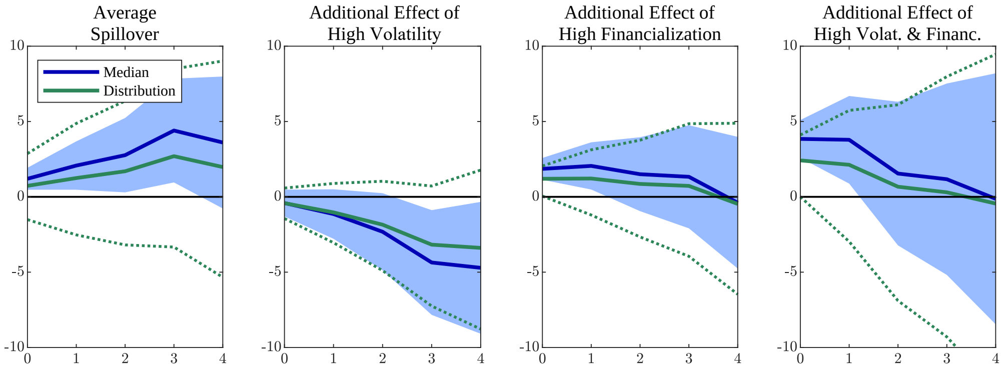
D. Spillovers of Food Supply Shocks to Agricultural Raw Materials Prices



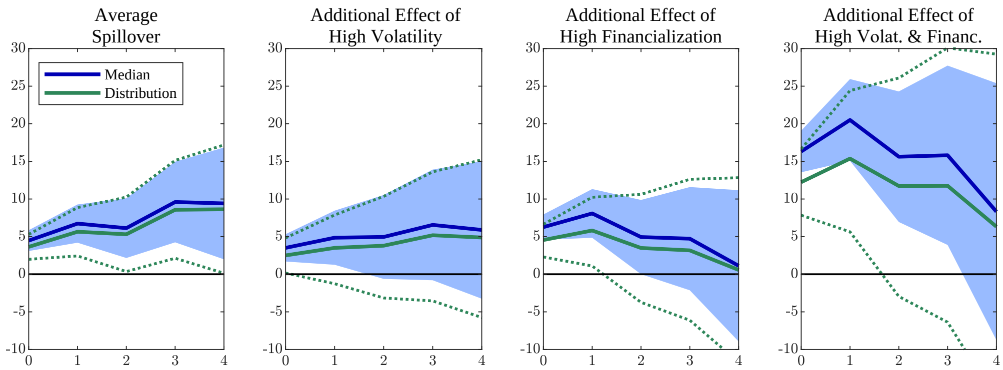
Notes: The figure plots impulse responses of metals and minerals and agricultural raw materials prices to a one standard deviation oil supply (panels A and C) and food supply (panels B and D) shock. The blue lines correspond to estimates that are based on the median from the TVP-BVARs' shock distributions, while the solid green lines refer to the median impulse response when we (i) use 1,000 shocks from the posterior distributions and estimate local projections for each of these shocks and (ii) generate 100 draws from a normal distribution for these estimates. Blue shaded areas and dotted green lines represent 68% confidence intervals/credible sets.

Figure A21: Adding Lags of the Financialization Index as Controls

A. Spillovers of Oil Supply Shocks to Food Commodity Prices



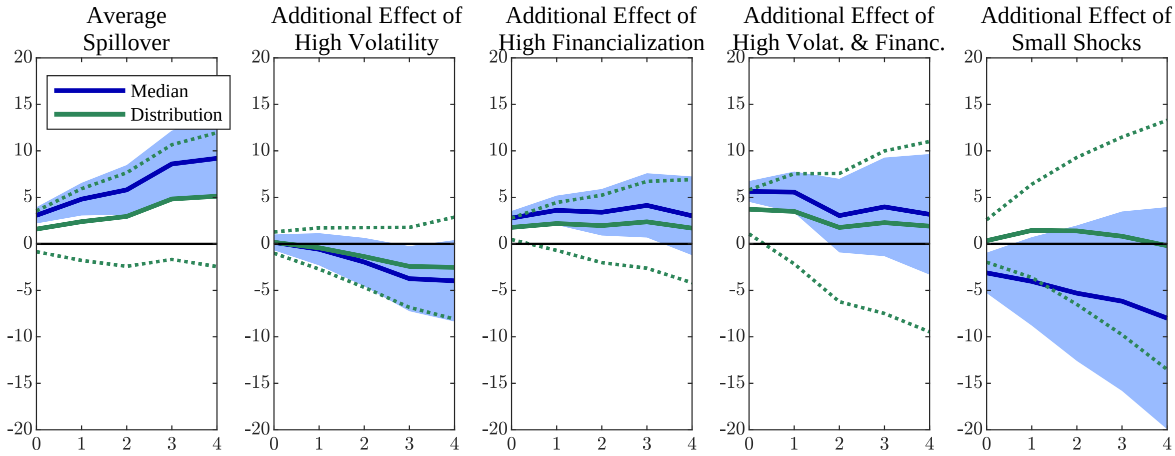
B. Spillovers of Food Supply Shocks to Crude Oil Prices



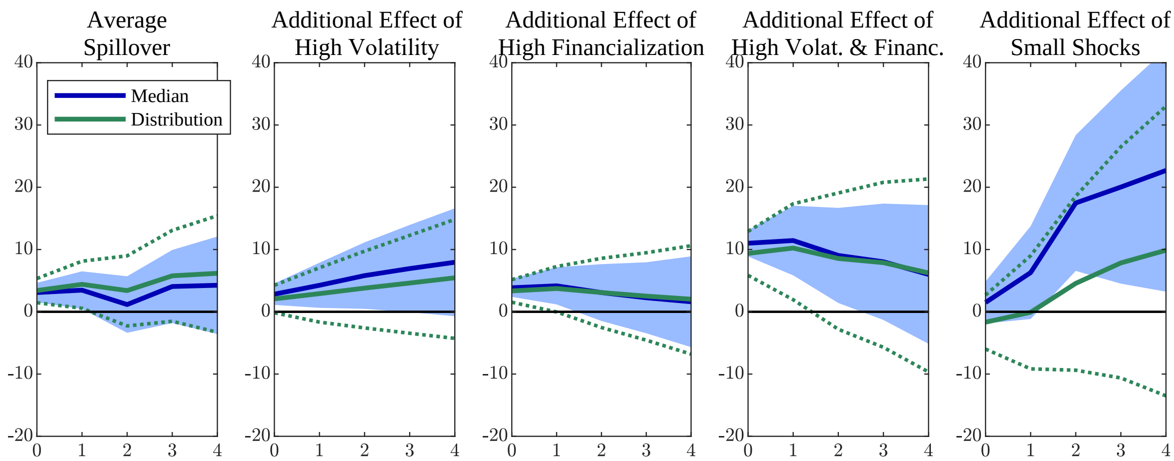
Notes: The figure plots impulse responses of food and oil prices to an adverse, one standard deviation oil supply (panel A) and food commodity supply (panel B) shock. The blue lines correspond to estimates that are based on the median from the TVP-BVARs' shock distributions, while the solid green lines refer to the median impulse response when we (i) use 1,000 shocks from the posterior distributions and estimate local projections for each of these shocks and (ii) generate 100 draws from a normal distribution for these estimates. Blue shaded areas and dotted green lines represent 68% confidence intervals/credible sets.

Figure A22: Additional Interaction Term for Small Shocks

A. Spillovers of Oil Supply Shocks to Food Commodity Prices



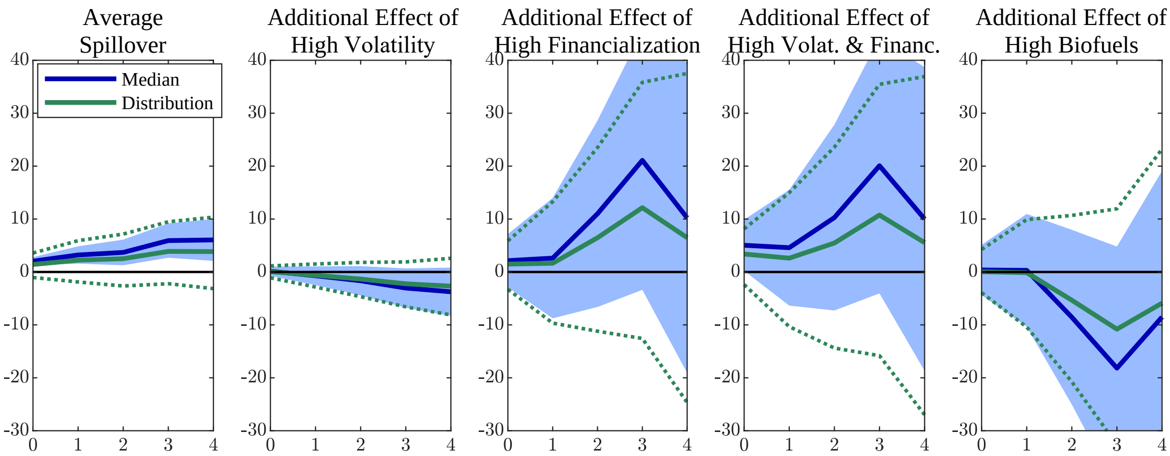
B. Spillovers of Food Supply Shocks to Crude Oil Prices



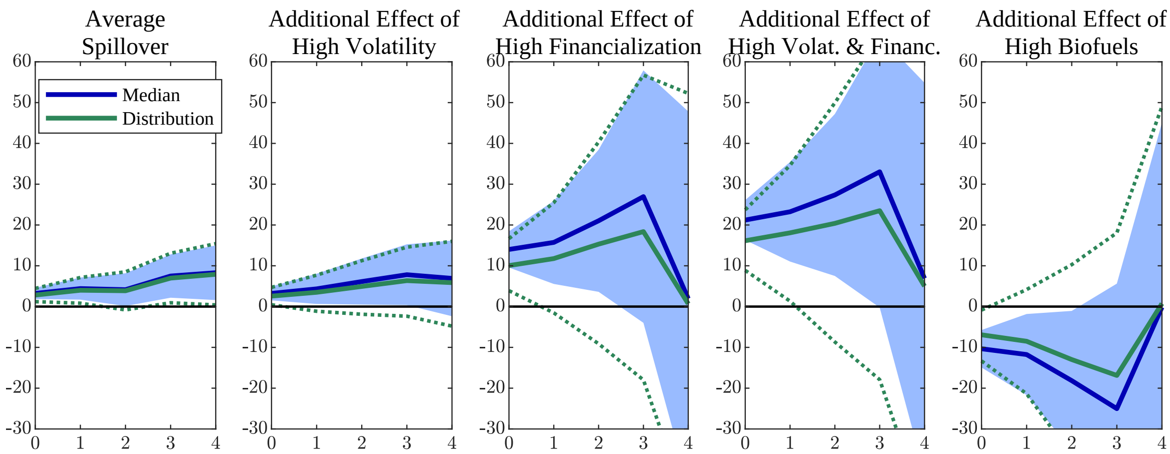
Notes: The figure plots impulse responses of food and oil prices to an adverse, one standard deviation oil supply (panel A) and food commodity supply (panel B) shock. The blue lines correspond to estimates that are based on the median from the TVP-BVARs' shock distributions, while the solid green lines refer to the median impulse response when we (i) use 1,000 shocks from the posterior distributions and estimate local projections for each of these shocks and (ii) generate 100 draws from a normal distribution for these estimates. Blue shaded areas and dotted green lines represent 68% confidence intervals/credible sets.

Figure A23: Additional Interaction Term for Global Biofuels Consumption

A. Spillovers of Oil Supply Shocks to Food Commodity Prices

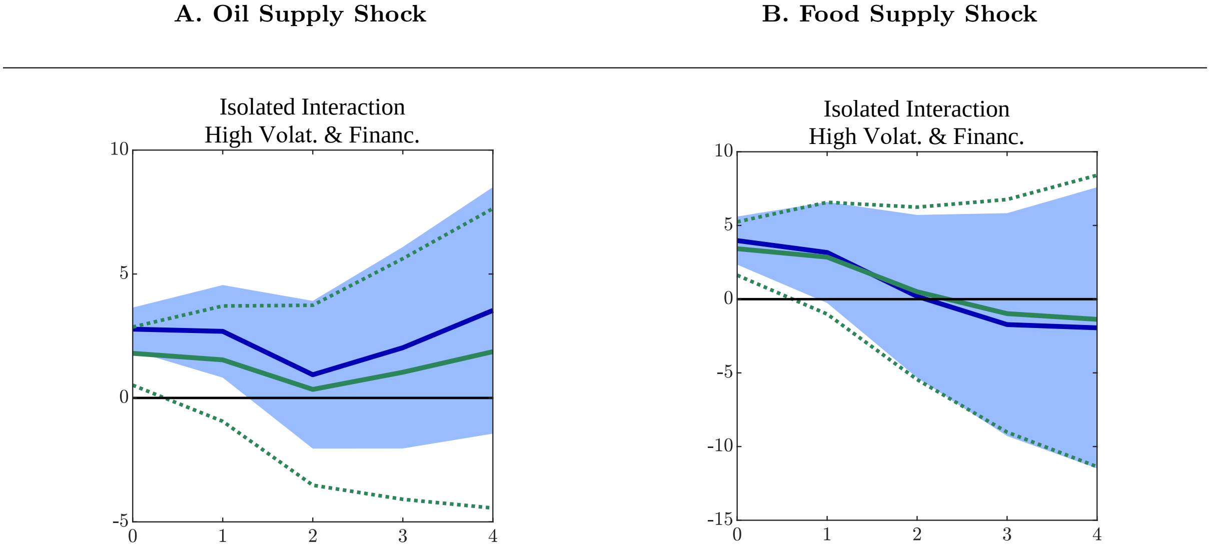


B. Spillovers of Food Supply Shocks to Crude Oil Prices



Notes: The figure plots impulse responses of food and oil prices to an adverse, one standard deviation oil supply (panel A) and food commodity supply (panel B) shock. The blue lines correspond to estimates that are based on the median from the TVP-BVARs' shock distributions, while the solid green lines refer to the median impulse response when we (i) use 1,000 shocks from the posterior distributions and estimate local projections for each of these shocks and (ii) generate 100 draws from a normal distribution for these estimates. Blue shaded areas and dotted green lines represent 68% confidence intervals/credible sets.

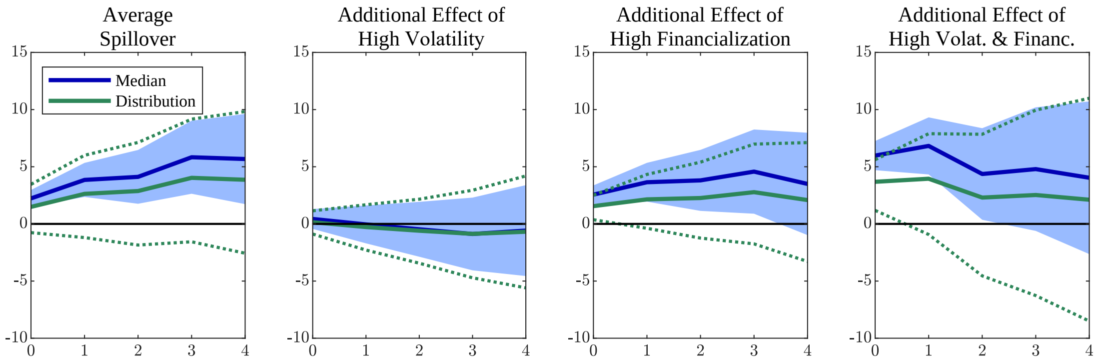
Figure A24: Interaction Term for Financialization and Volatility in the Biofuels Model



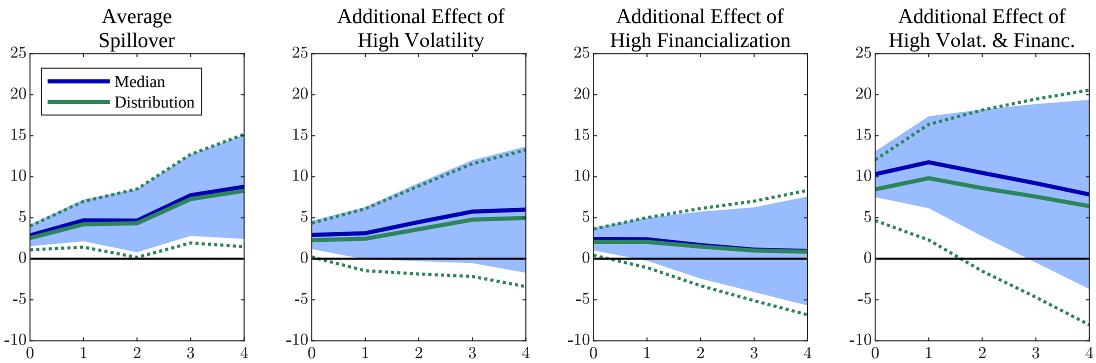
Notes: The figure plots impulse responses of food and oil prices to an adverse, one standard deviation oil supply (panel A) and food commodity supply (panel B) shock. The blue lines correspond to estimates that are based on the median from the TVP-BVARs' shock distributions, while the solid green lines refer to the median impulse response when we (i) use 1,000 shocks from the posterior distributions and estimate local projections for each of these shocks and (ii) generate 100 draws from a normal distribution for these estimates. Blue shaded areas and dotted green lines represent 68% confidence intervals/credible sets.

Figure A25: Using Emerging Markets Macroeconomic Volatility

A. Spillovers of Oil Supply Shocks to Food Commodity Prices



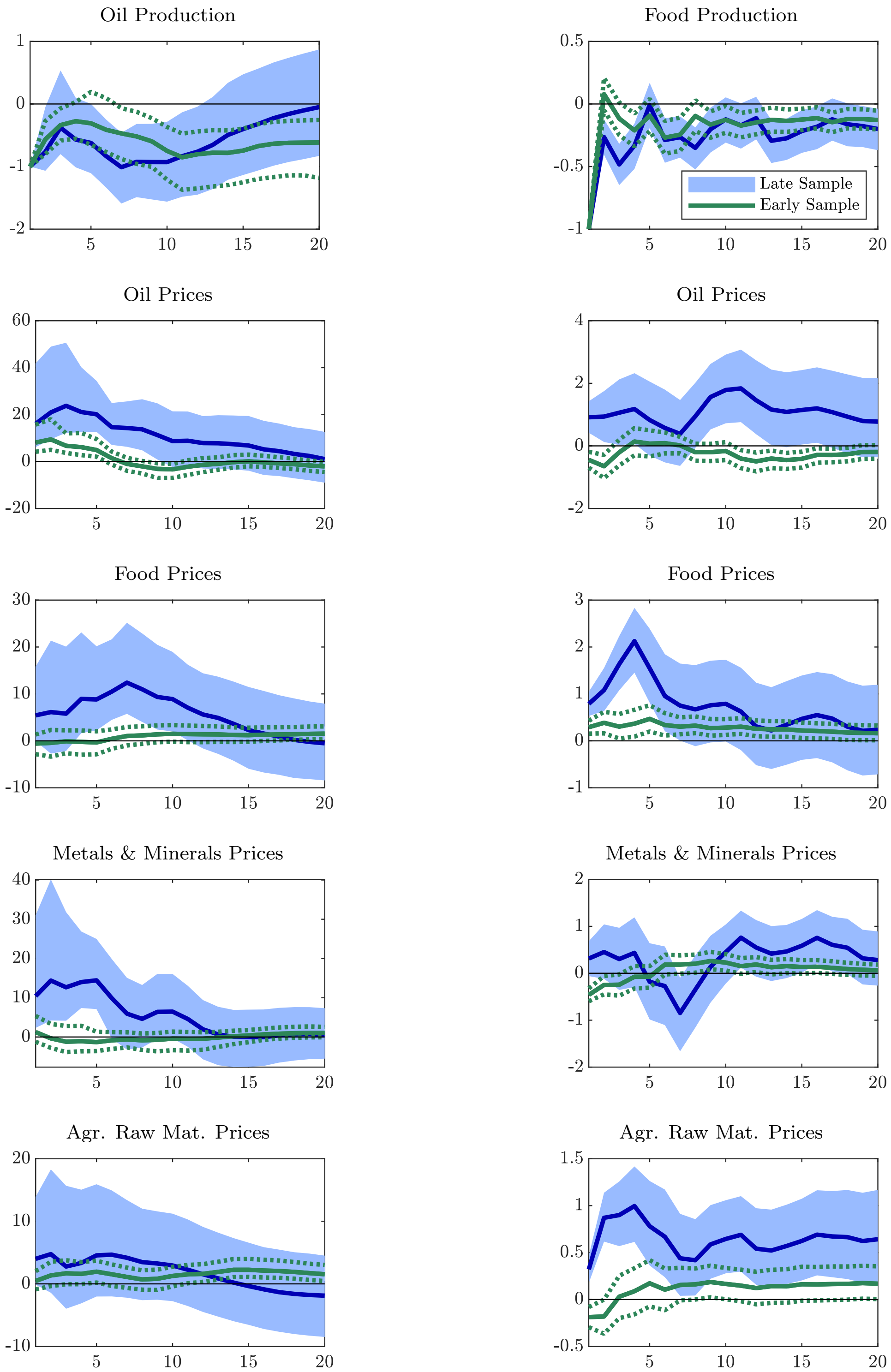
B. Spillovers of Food Supply Shocks to Crude Oil Prices



Notes: The figure plots impulse responses of food and oil prices to an adverse, one standard deviation oil supply (panel A) and food commodity supply (panel B) shock. The blue lines correspond to estimates that are based on the median from the TVP-BVARs' shock distributions, while the solid green lines refer to the median impulse response when we (i) use 1,000 shocks from the posterior distributions and estimate local projections for each of these shocks and (ii) generate 100 draws from a normal distribution for these estimates. Blue shaded areas and dotted green lines represent 68% confidence intervals/credible sets.

Figure A26: Linear BVARs Estimated over Sub-Samples

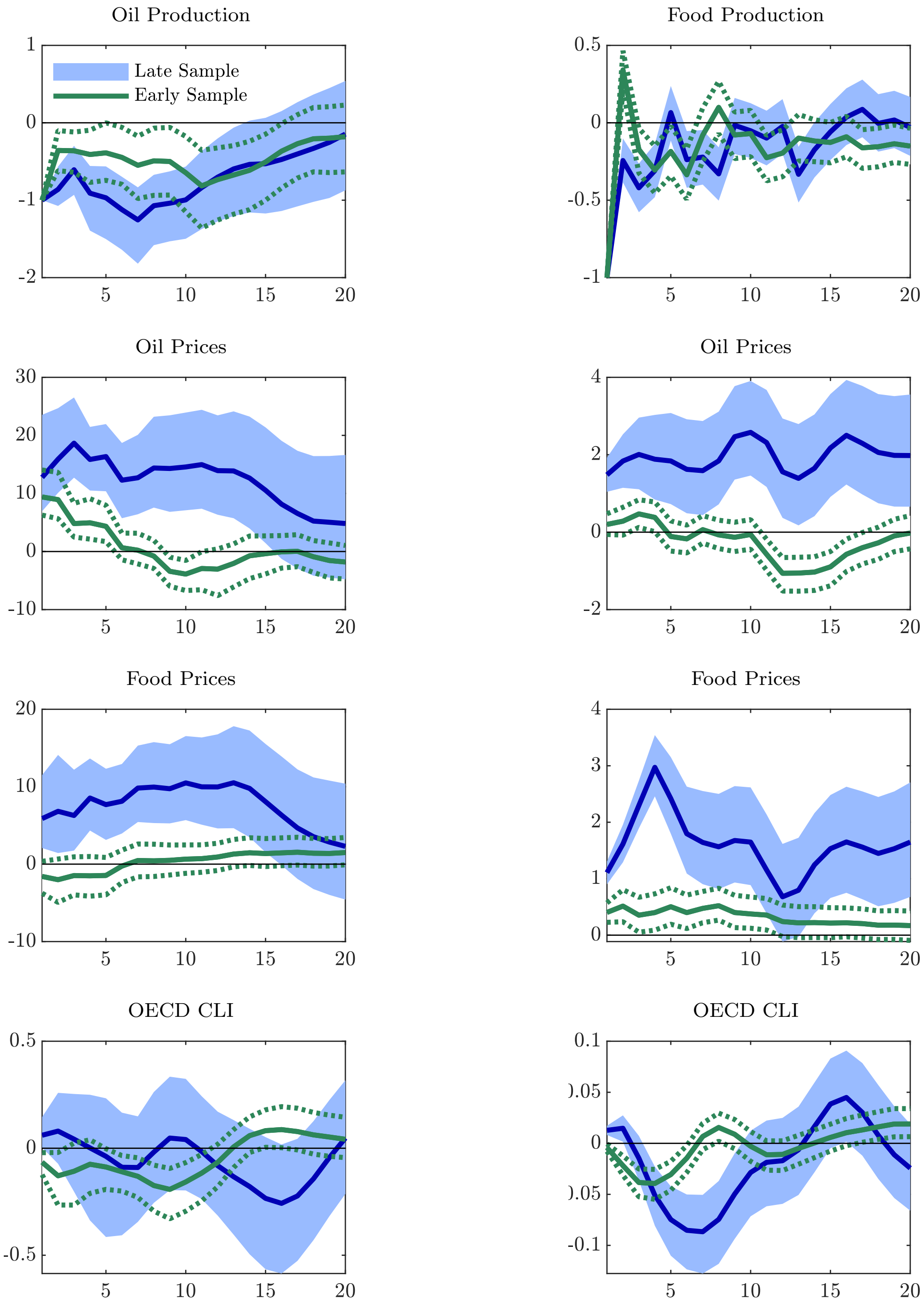
A. Oil Supply Shock **B. Food Supply Shock**



Notes: The early sample corresponds to the period from 1988Q3 to 2003Q4, while the late sample ranges from 2004Q1 to 2016Q4. The impulse responses are normalized to represent a 1 percent production shortfall in the oil or food market. The shaded areas and dotted lines are the 16th and 84th percentile credible sets.

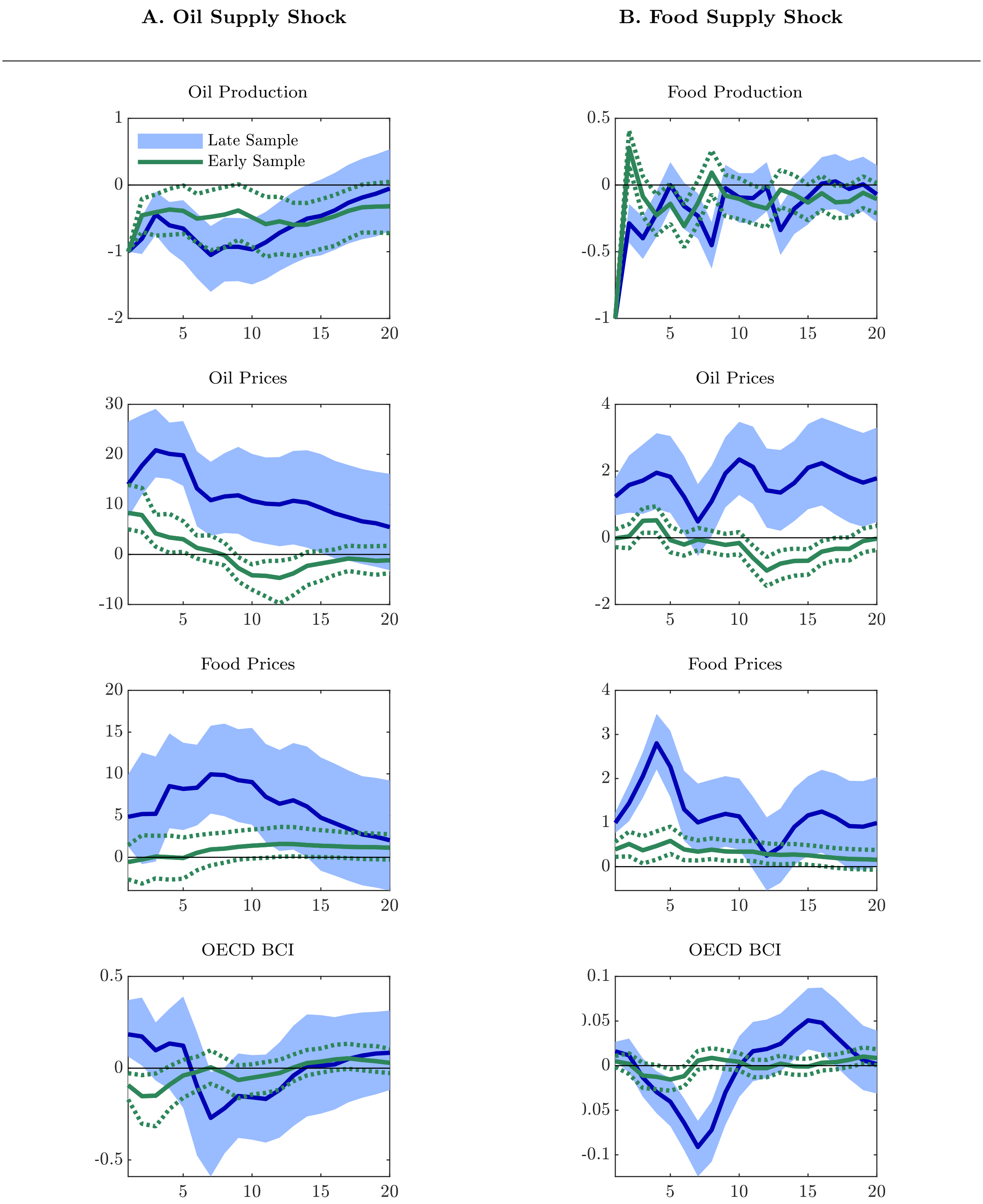
Figure A27: Inclusion of OECD Composite Leading Indicator in the Linear BVARs

A. Oil Supply Shock **B. Food Supply Shock**



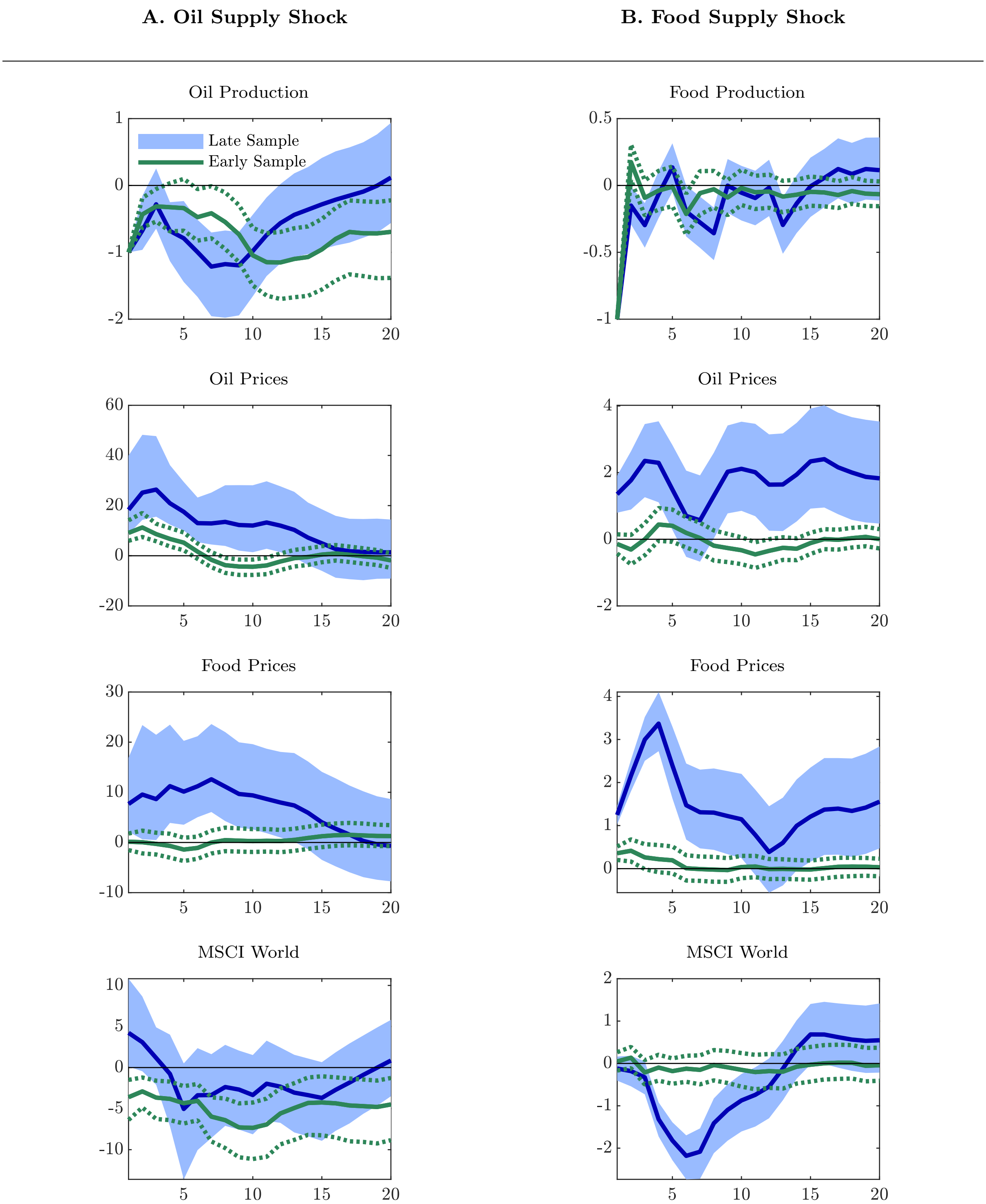
Notes: The early sample corresponds to the period from 1988Q3 to 2003Q4, while the late sample ranges from 2004Q1 to 2016Q4. The impulse responses are normalized to represent a 1 percent production shortfall in the oil or food market. The shaded areas and dotted lines are the 16th and 84th percentile credible sets.

Figure A28: Inclusion of OECD Business Confidence Index in the Linear BVARs



Notes: The early sample corresponds to the period from 1988Q3 to 2003Q4, while the late sample ranges from 2004Q1 to 2016Q4. The impulse responses are normalized to represent a 1 percent production shortfall in the oil or food market. The shaded areas and dotted lines are the 16th and 84th percentile credible sets.

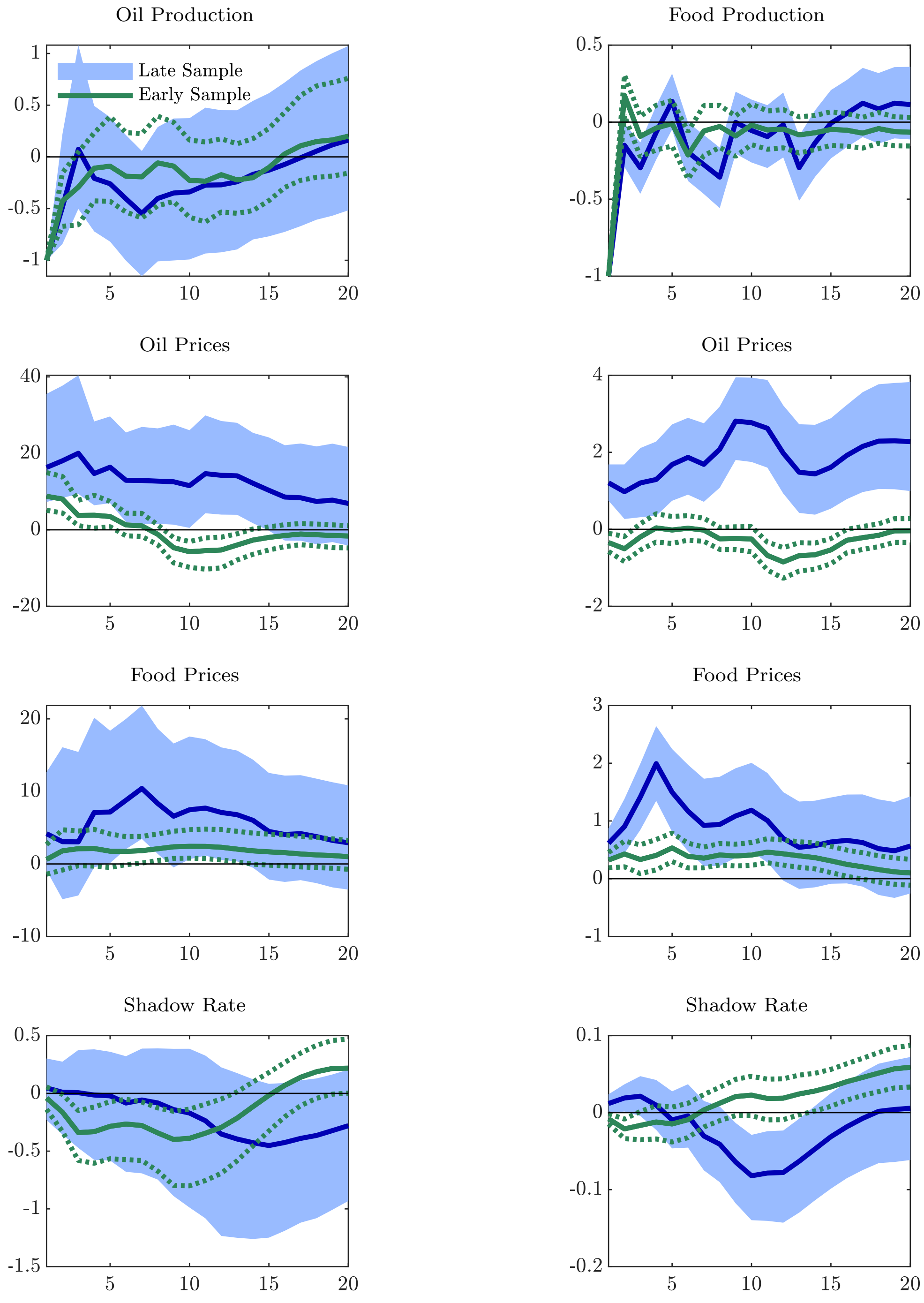
Figure A29: Inclusion of MSCI World in the Linear BVARs



Notes: The early sample corresponds to the period from 1988Q3 to 2003Q4, while the late sample ranges from 2004Q1 to 2016Q4. The impulse responses are normalized to represent a 1 percent production shortfall in the oil or food market. The shaded areas and dotted lines are the 16th and 84th percentile credible sets.

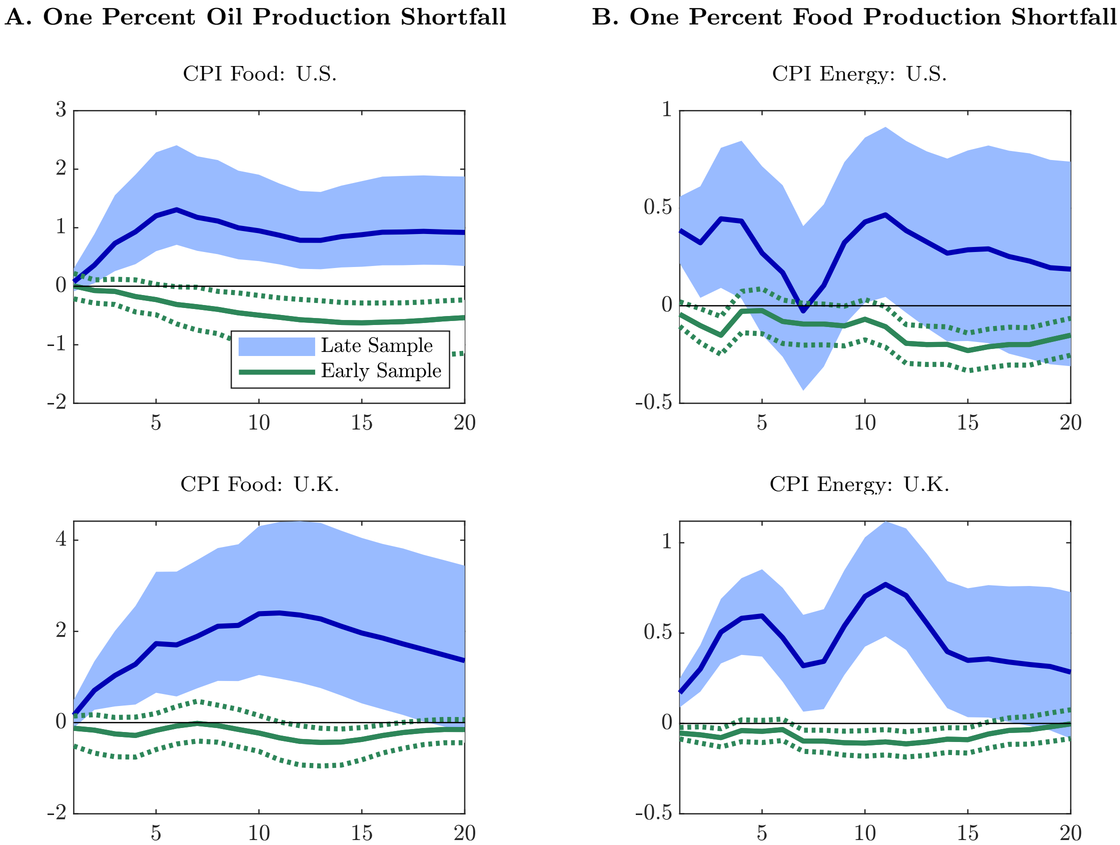
Figure A30: Inclusion of the Shadow Rate in the Linear BVARs

A. Oil Supply Shock | **B. Food Supply Shock**



Notes: The early sample corresponds to the period from 1988Q3 to 2003Q4, while the late sample ranges from 2004Q1 to 2016Q4. The impulse responses are normalized to represent a 1 percent production shortfall in the oil or food market. The shaded areas and dotted lines are the 16th and 84th percentile credible sets.

Figure A31: Effects of Oil and Food Commodity Supply Shocks on Consumer Prices



Notes: The early sample corresponds to the period from 1988Q3 to 2003Q4, while the late sample ranges from 2004Q1 to 2016Q4. The impulse responses are normalized to represent a 1 percent production shortfall in the oil or food market. The shaded areas and dotted lines are the 16th and 84th percentile credible sets.