University of Heidelberg

Department of Economics

Discussion Paper Series | No. 665

The Interplay between Oil and Food Commodity Prices: Has It Changed over Time?

Gert Peersman, Sebastian K. Rüth, and Wouter Van der Veken

September 2019

The Interplay between Oil and Food Commodity Prices: Has It Changed over Time?*

Gert Peersman
Ghent University

Sebastian K. Rüth
Heidelberg University

Wouter Van der Veken
Ghent University

August 2019

Abstract

Using time-varying BVARs, we find that oil price increases caused by oil supply shocks did not affect food commodity prices before the start of the millennium, but had positive spillover effects in more recent periods. Likewise, shortfalls in global food commodity supply—resulting from bad harvests—have positive effects on crude oil prices since the early 2000s, in contrast to the preceding era. Remarkably, we also document greater spillover effects of both supply shocks on metals and minerals commodity prices in recent periods, as well as a stronger impact on the own price compared to earlier decades. This (simultaneous) time variation of commodity price dynamics cannot be explained by the biofuels revolution and is more likely the consequence of heightened informational frictions and information discovery in more globalized and financialized commodity markets.

JEL classification: E31, F30, G15, Q11, Q41.

Keywords: Commodity markets, food prices, oil prices, spillovers.

---

*Gert Peersman: Ghent University, Department of Economics (gert.peersman@ugent.be); Wouter Van der Veken: Ghent University, Department of Economics (wouvdrve.vanderveken@ugent.be); Sebastian Rüth: Heidelberg University, Alfred-Weber-Institute for Economics (sebastian.rueth@awi.uni-heidelberg.be).

We thank Christiane Baumeister, Marco Bernardini, Hilde Bjørnland, Fabio Canova, Christian Conrad, Selien De Schryder, Jonas Dovern, Juan Rubio-Ramirez, James Stock, Carsten Trenkler, and conference/seminar participants at the 5th HeiKaMEtrics workshop in Heidelberg, the 6th Belgian Macroeconomics Workshop in Antwerp, the 5th Ghent University Workshop on Empirical Macroeconomics, the 24th Spring Meeting of Young Economists, the IAAE 2019 Annual Conference and Queen Mary's second Workshop in Structural VAR models for useful comments and suggestions. We are also grateful to Giorgio Primiceri and Deepa Datta for providing their codes. We acknowledge financial support from the Mecenaat portfolio of the National Bank of Belgium and the Ghent University Special Research Fund (BOF).

1 Introduction

As can be observed in Figure 1 (panel A), the global prices of crude oil and food commodities have experienced dramatic rollercoaster rides in recent decades. Another striking observation is that the comovement of both prices has varied considerably over time. In particular, panel B of the figure shows that several measures of time-varying unconditional correlations of the changes in both commodity prices were negative in the 1990s, in order to become positive from the early 2000s onward.

The reasons for the increased synchronization of the prices of crude oil and food commodities since the 2000s have received a lot of attention by academics, practitioners and policymakers. A first possible explanation is an increasing importance of common demand factors relative to idiosyncratic or supply shocks that have driven both commodity prices. There are two popular hypotheses that could rationalize this interpretation. On one hand, the stronger comovement may be induced by macroeconomic fundamentals; that is, global business cycle fluctuations that jointly induce shifts in oil and food commodity demand, which moves both prices in the same direction.[1] On the other hand, the enlarged synchronization may be caused by strong demand due to the worldwide financialization of commodity markets and the associated large capital inflows from the early 2000s onward, which is illustrated in panel C of Figure 1.[2] To the extent that the contribution of common demand factors to commodity price variation has increased relative to the contribution of supply and idiosyncratic commodity price shocks, a rise in the comovement of these prices is conceivable.

An alternative explanation for an enhanced positive link between crude oil and food commodity prices—beyond any common demand narrative—is the existence of direct price spillover effects of idiosyncratic and/or supply shocks that, at the same time, became stronger since the 2000s. In this vein, the soaring biofuels revolution represents a candidate to trigger (stronger) spillover effects of autonomous oil and food commodity shocks in recent periods. In particular, besides crude oil, agricultural sector output has increasingly been used as an

[1] Hamilton (2009) and Kilian and Murphy (2014) document that the run-up of oil prices in 2007-08 was mainly caused by global economic activity growth, while Abbott et al. (2011) ascribe the considerable rise of food commodity prices since the 2000s to high income growth in emerging economies. Fernández et al. (2018) highlight the importance of common factors in business cycles of emerging economies more generally.

[2] Tang and Xiong (2012) find that the prices of non-energy commodities became increasingly correlated with oil prices since 2004, and attribute this comovement to the rapidly growing index investment in commodity markets. Other studies that have found that the flows of financial investors have impacted commodity prices are Lombardi and Van Robays (2011), Singleton (2013), Henderson et al. (2015) and Cheng et al. (2015). On the other hand, Hamilton and Wu (2015) find no evidence that the positions of index traders affected agricultural commodity prices. See Cheng and Xiong (2014) for an overview of the consequences of the financialization of commodity markets.

input factor for the energy producing industry since the early 2000s. For example, as shown in Figure 1 (panel D), the share of biofuels in U.S. petroleum consumption rose from roughly 0.5 percent in 2000 to more than 5 percent in 2010. With a higher degree of substitutability, any shock affecting the price of one commodity will more likely shift the price of the substitute in the same direction, increasing their correlation. Numerous empirical studies conclude that this has indeed been the case; that is, biofuels appear to have played an important role for an increased synchronization between oil and agricultural commodity prices.[3]

Notwithstanding the overwhelming empirical support for price spillovers, several caveats apply to the methods that have been used so far in the literature. First, most existing empirical studies are based on reduced-form time series models that only explore unconditional comovement in the data.[4] Accordingly, it is not possible to establish causal links that have an economic interpretation. For example, these methods cannot disentangle a rise in the comovement between oil and food commodity prices that is caused by the common demand factors discussed above and stronger spillover effects as a consequence of biofuels. To uncover causal relationships between oil and food commodity prices, it is crucial to isolate price shifts that are strictly exogenous, which requires a structural econometric framework.

Second, the existing studies that evaluate changes over time are based on simple sample splits, such as the periods before and after the introduction of the U.S. Energy Policy Act of 2005 to promote the use of biofuels. However, the influence of biofuels on the relationship between oil and food commodities does not necessarily represent a one-time structural break in the data. In particular, as illustrated in panel D of Figure 1, the increase in the use of biofuels occurred over several years, which suggests a gradual transition process. Moreover, since food commodities are a substitute for oil to produce energy goods, but crude oil cannot be used as food, the influence of the biofuels revolution should also depend on the relative level of both commodity prices. Specifically, the unidirectional substitutability implies that substitution could only take place when the price of oil is equal or higher than the price

[3]For example, Tyner (2010), Mallory et al. (2012) and Avalos (2014) document a link between crude oil and corn prices since 2006 that did not exist historically and attribute this link to developments in biofuels markets, while Du et al. (2011) and Hertel and Beckman (2012) find that increases in biofuels production have resulted in volatility spillovers from energy markets to food markets. For a review of the biofuels-related price transmission literature, see Serra and Zilberman (2013). For a theoretical exposition, see Hassler and Sinn (2016).

[4]Examples are reduced-form Granger causality tests (e.g. Avalos 2014) and reduced-form or semi-structural VARs (e.g. Baumeister and Kilian 2014). Notice there also exists a literature that uses partial or general equilibrium models to calibrate the impact of biofuels on price spillovers between energy and food commodities (e.g. Hassler and Sinn 2016). Since these models are usually calibrated using annual data, they are not suitable to examine short-run price dynamics (Serra and Zilberman 2013). Moreover, these models are often criticized for being insufficiently validated and for performing poorly to reproduce historical outcomes (Beckman et al. 2011).

level of food commodities (measured per unit of energy), while the substitutability becomes non-operational when oil prices are below food commodity prices (Hassler and Sinn 2016). In addition, the existence of a blend wall; that is, refineries are unable to blend more than 10 percent ethanol into gasoline, could weaken the relationship between oil and food commodity prices when the wall becomes binding (Tyner 2010; Abbott 2014). These features suggest that the best modeling approach is one that allows for slow-moving but continuous changes, as well as for possible jumps and nonlinearities.

Finally, there has been another transformation in commodity markets that could have led to a larger direct contagion between both commodity prices in recent periods. In particular, a mechanism that has been ignored so far is that, in the presence of informational frictions, the globalization and financialization of commodity markets since the 2000s could also have resulted in enhanced spillover effects of idiosyncratic or supply shocks. Sockin and Xiong (2015) develop a model in which commodity prices serve as signals of the strength of the economy for goods producers that do not perfectly observe fundamentals. In their model, commodity price shifts that are not the consequence of changes in economic activity can be misinterpreted as signals about the strength of the economy, causing goods producers to change their commodity demand, which influences prices. Since goods producers cannot differentiate a price increase caused by an unfavorable supply shock from an increase triggered by an expansion in the global economy, they partly attribute the supply shock to the demand shock. As a result, they raise their commodity demand despite the price increase, which amplifies the impact of the supply shock on commodity prices.

Even though the model of Sockin and Xiong (2015) assumes that there is only one commodity, it can also be applied to many commodities; that is, price signals in one commodity class may be used to determine the demand for other commodities. For example, an unfavorable oil supply shock that raises oil prices may be interpreted as a signal of global economic strength, increasing the demand for food commodities and their prices. Clearly, the extent of informational frictions and such spillover effects likely vary over time. For example, macroeconomic uncertainty and the usefulness of commodity price signals to assess the state of the economy were probably higher in the era surrounding the Great Recession. In addition, the increased globalization (e.g. the participation of several emerging countries) should have increased informational frictions of market participants, while the financialization of commodity markets since the 2000s should have facilitated and encouraged information discovery in commodity markets. In sum, studies that attribute the increased synchronization of oil and food commodity prices to the biofuels revolution may be spuriously picking up the consequences of informational frictions and price discovery in commodity markets.

In this paper, we use time-varying parameter structural BVAR models with stochastic volatility in the spirit of Cogley and Sargent (2005) and Primiceri (2005) to investigate whether price spillovers of crude oil and food commodity supply shocks have changed over time. Our analysis incorporates several innovations relative to the previous literature to address the above caveats. First, rather than imposing an arbitrary sample split, all model coefficients can evolve continuously over the sample period. The modeling approach also accommodates discrete shifts and several possible nonlinearities. Second, within the BVAR models, we isolate price changes that are caused by exogenous oil and food commodity supply shocks, which allows us to estimate causal links between both commodity prices that can be interpreted as spillover effects. For the identification of the shocks, we build on existing strategies that have been used in the literature for alternative research questions. Specifically, Baumeister and Peersman (2013b) use sign restrictions on the covariance of innovations in oil prices and production to isolate oil price shifts that are triggered by oil supply disruptions, while De Winne and Peersman (2016) use unanticipated harvest shocks to identify food commodity price changes caused by exogenous supply innovations. Notice that, since we identify oil *and* food supply shocks, we can examine price spillovers in both directions, which contrasts with studies that only allow for a unidirectional pass-through of oil to food prices. Finally, we also estimate the time-varying spillovers of both shocks on metals and minerals commodity prices. Since the pass-through to metals and minerals prices should not be affected by the biofuels revolution, we can learn more about the source of the time variation. This cross-examination can be compared with a difference-in-difference approach, where the spillovers between food and oil prices are the treated variables, while the spillovers of both shocks on metals and minerals prices are control variables.

The main findings are as follows. First, oil price increases caused by shortfalls in oil supply did not affect food commodity prices before the early 2000s, but had positive spillover effects in the more recent era, particularly in the years around the Great Recession. Second, we find that disruptions in food commodity supply did not have spillover effects on oil prices prior to the start of the millennium, but do so since. Price spillovers thus exist in both directions. Third, we document that price spillovers have continuously built up over the sample period, but again gradually decreased since 2010, which is a pattern that cannot be captured by sample splits. Fourth, we find little support for the conjecture that the expansion of biofuels is the key source of the time variation. Specifically, we find similar time-varying spillovers of both supply shocks on metals and minerals commodity prices. This concurrent evolution is more likely the consequence of heightened informational frictions in financialized commodity markets. Finally, this hypothesis is further reassured by the time variation of the own price response to both supply shocks. In particular, we find that a (one percent) negative food commodity supply shock leads to a much stronger rise in food commodity prices since the 2000s. Similarly, the impact of a (one percent) oil supply disruption on oil prices was much higher in periods where we also find a stronger pass-through to food, and metals and minerals commodity prices. This is exactly what the model of Sockin and Xiong (2015) predicts: informational frictions also enhance the impact of a supply shock on the own price. We establish these empirical regularities in a variety of perturbations to the model specification and for individual crop price data. In addition, we observe consistent time variation using a fixed-coefficient VAR model estimated over two subperiods, which drastically reduces the dimension of the model.

Overall, our results provide a number of relevant considerations for practitioners, policymakers and future research. First, even though informational frictions are a plausible explanation for the time variation and spillover effects, and we are not aware of other possible interpretations, the mechanism requires further confirmation. Second, since crude oil and food commodity markets are often subject to major supply disruptions, the increased spillovers are important for hedging strategies of commodity producers and speculators' investment strategies. Moreover, since informational frictions appear to be the source of the time variation, the extent of spillovers will likely continuously change over time. Third, our results suggest that this also applies to the own price elasticity of both commodities. More generally, as also argued by Cheng and Xiong (2014), incorporating informational frictions into existing theoretical and empirical models could significantly improve our understanding of commodity market dynamics. Fourth, the presence of spillover effects between oil and food commodity prices should be taken into account for many countries' energy and food policies. Notably, our results suggest that the expansion of biofuels was not the source of the documented spillovers. Finally, our findings are important for monetary policy. The presence of spillovers between both commodities implies that food supply shocks do not only propagate via food retail prices to consumer prices, but also via energy prices, while oil supply shocks affect inflation via the prices of processed food, which was not the case in earlier periods.

Section 2 describes the methodology, data and identification strategy to isolate supply shocks. Section 3 presents the results and several robustness checks, while section 4 concludes.

2 Methodology

Since the global markets for crude oil and food commodities underwent plenty of institutional, technological and financial upheavals over past decades, changes in the propagation of oil and food commodity supply shocks and potential spillover effects are conceivable. In order to adequately allow for instabilities in the relationship between oil and food commodity prices, we rely on an empirical 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. As argued in the introduction and illustrated in Figure 1 (panel D), the rise in the use of biofuels for energy production occurred over several years. The gradual globalization and financialization of commodity markets over time (see e.g. panel C of Figure 1), as well as time-varying informational frictions, further reinforces the notion of a continuous evolution of the structure of commodity markets.[5]

The model we propose to accommodate these features of the underlying data-generating process is a Bayesian VAR that allows for time-varying parameters and a time-varying variance-covariance matrix of the reduced-form innovations. The drift in the parameters accommodates possible nonlinearities or changes in the lag structure of the VAR, while the multivariate stochastic volatility captures heteroscedasticity of innovations and nonlinearities in the simultaneous relations between the variables in the system. Although the existence of abrupt breaks in the dynamics cannot be excluded a priori, Monte Carlo simulations in Baumeister and Peersman (2013b) show that a BVAR model with drifting coefficients is capable of capturing discrete shifts should they occur (see also Benati and Mumtaz 2007). Accordingly, the data can reveal when and how changes may have occurred over the sample period.[6] Another advantage of our VAR methodology is that it allows to identify exogenous oil and food commodity supply shocks, which is crucial to properly examine spillover effects. Notably, by identifying disruptions in both oil and food supply, we explicitly test for the existence of bi-directional price spillovers between both markets.

[5]The idea of slowly-evolving yet continuous adjustments is also consistent with adaptive expectations of commodity 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).

[6]A popular alternative specification would be a Markov-switching VAR model, but that is not feasible for the interplay between oil and food commodity markets. In particular, given the multiple sources of nonlinearities and time variation, the number of states required for approximating this process is too large to be tractable with a Markov-switching framework. Moreover, unlike VARs with time-varying parameters, Markov-switching VARs require a degree of regularity that is not present in oil and food commodity markets (Baumeister and Peersman 2013a).

2.1 TVP-BVAR Framework for Crude Oil and Food Commodity Markets

As the benchmark, we model the behavior of crude oil and food commodity markets in the following VAR(p) framework, which incorporates time-varying coefficients and stochastic volatility along the lines of Cogley and Sargent (2005) and Primiceri (2005):

$$\boldsymbol{y}_t = \boldsymbol{C}_t + \sum_{l=1}^{p} \boldsymbol{B}_{l,t}\boldsymbol{y}_{t-l} + \boldsymbol{u}_t \equiv \boldsymbol{X_t}'\boldsymbol{\theta_t} + \boldsymbol{u}_t \tag{1}$$

where $\boldsymbol{y}_t$ is a 3x1 vector of observed endogenous variables, $\boldsymbol{C}_t$ captures time-varying regression intercepts and the 3x3 matrices $\boldsymbol{B}_{l,t}$ comprise the lag coefficients of the VAR for lag $l = 1, ..., p$. We stack the time-varying lag parameters and intercepts into $\boldsymbol{\theta_t}$, while $\boldsymbol{X_t}$ includes lagged realizations of $\boldsymbol{y}_t$ and a vector of constants. The vector $\boldsymbol{u}_t$ in the observation equation contains unconditionally heteroscedastic, unobservable innovations with variance-covariance matrix $\boldsymbol{\Omega}_t$.

To study the dynamics and spillover effects of oil supply shocks, the vector of endogenous variables $\boldsymbol{y}_t$ contains i) global crude oil production q_t^{oil}, ii) the price of crude oil p_t^{oil} and iii) the price of another commodity p_t^j. The latter variable is, in turn, an index of food commodity prices p_t^{food}, and metals and minerals prices p_t^{metal}, respectively. Similarly, to estimate the pass-through of food commodity supply shocks, the vector of endogenous variables includes i) an index of global food production q_t^{food}, ii) food commodity prices p_t^{food} and iii) respectively p_t^{oil} and p_t^{metal}. In the robustness section, we will also estimate a specification that includes all five variables simultaneously in the TVP-BVAR model (i.e. with less lags).

All variables are transformed to quarter-on-quarter growth rates by taking the first difference Δ of the natural logarithm. By transforming the data to growth rates, we obtain stationary time series, which is required for the estimation of TVP-BVARs. Notice that we also provide evidence for linear VARs based on the level variables in the sub-sample analysis in section 3.2, which allows for implicit co-integration relations. For more details about the data series, we refer to section 2.2. The overall sample spans the period 1974Q1-2016Q4. The start of the sample is motivated by the fact that oil prices were strictly regulated before 1974, which undermines the validity of time series models of the oil market before 1974 (see e.g. Kilian 2009). The end of the sample period (and the frequency of the data) is determined by the availability of the global food production index. The first 58 quarters are used as a training sample to initialize the priors for the actual sample period, which starts in 1988Q3.[7] To allow for transmission lags in the propagation of structural innovations, we

[7] In order to properly reflect the information in the training sample, the degrees of freedom of the prior of the variance-covariance matrix of the innovations discussed below (i.e. $\boldsymbol{\theta}_0$), should match the training sample

set $p = 6$ quarters. In sum, as the benchmark, we estimate four parsimonious TVP-BVAR(6) models: $\boldsymbol{y}_t = [\Delta q_t^{oil}, \Delta p_t^{oil}, \Delta p_t^{food}]'$ and $\boldsymbol{y}_t = [\Delta q_t^{oil}, \Delta p_t^{oil}, \Delta p_t^{metal}]'$ for oil supply shocks and, $\boldsymbol{y}_t = [\Delta q_t^{food}, \Delta p_t^{food}, \Delta p_t^{oil}]'$ and $\boldsymbol{y}_t = [\Delta q_t^{food}, \Delta p_t^{food}, \Delta p_t^{metal}]'$ for food commodity supply shocks.[8]

Furthermore, we consider a triangular reduction of $\boldsymbol{\Omega}_t$:

$$\boldsymbol{A}_t \boldsymbol{\Omega}_t \boldsymbol{A}_t' = \boldsymbol{\Sigma}_t \boldsymbol{\Sigma}_t' \tag{2}$$

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

$$\boldsymbol{\Sigma}_t = \begin{pmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{pmatrix} \tag{3}$$

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

$$\boldsymbol{A}_t = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{2,1,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n,1,t} & \cdots & \alpha_{n,n-1,t} & 1 \end{pmatrix}. \tag{4}$$

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

size. A lower bound for the degrees of freedom—and hence for the size of the training sample—is imposed by the restriction that the degrees of freedom of an Inverse-Wishart distribution must exceed the dimensionality of the variance-covariance matrix. Otherwise, the prior would be improper. Following this reasoning, the size of the training sample cannot be smaller than 58 quarters.

[8]Since TVP-BVARs are highly parameterized, we limit the number of endogenous variables for the benchmark estimations to three. The reason is that the underlying data generating process also requires several lags. In particular, lag length criteria in a constant parameter set-up suggest at least 5 (quarterly) lags for VARs that include the food production index that we use (De Winne and Peersman 2016). Hamilton and Herrera (2004) demonstrate the importance of allowing for at least one year of lags in an oil-market VAR model, while Kilian (2009) even includes 24 (monthly) lags in his VAR model for the global oil market. Having said this, our results turn out to be robust when we reduce (e.g. $p = 4$) or increase the number of lags (up to $p = 8$). These results are available upon request. Furthermore, when we assess the sensitivity of the results in section 3.2, we show that the results are also robust when we estimate a five-variable TVP-BVAR(4) in which we include all five variables and identify both supply shocks simultaneously.

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) by using the definitions from above yields:

$$\boldsymbol{y}_t = \boldsymbol{X_t}'\boldsymbol{\theta_t} + \boldsymbol{A}_t^{-1}\boldsymbol{\Sigma}_t\boldsymbol{\varepsilon}_t, \text{ with } \boldsymbol{X_t}' = \boldsymbol{I_n} \otimes [\boldsymbol{1}, \boldsymbol{y}'_{t-1}, ..., \boldsymbol{y}'_{t-k}], \tag{5}$$

where $\otimes$ is the Kronecker-product. Our estimation strategy consists of modeling the $t = 1, ..., T$ sequence of VAR parameters according to Equation (5). 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:

$$\boldsymbol{\theta_t} = \boldsymbol{\theta_{t-1}} + \boldsymbol{\nu_t}, \; \boldsymbol{\alpha_t} = \boldsymbol{\alpha_{t-1}} + \boldsymbol{\zeta_t}, \text{ and } \log(\boldsymbol{\sigma_t}) = \log(\boldsymbol{\sigma_{t-1}}) + \boldsymbol{\eta_t}. \tag{6}$$

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.[9] 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). In the appendix, we provide details on the sampler to simulate the posterior distribution and the priors we use, both in line with Primiceri (2005) and Del Negro and Primiceri (2015).

2.2 Data

The variables that are used in the estimations are shown in Figure 2. For the oil market, p_t^{oil} is the nominal U.S. refiners' acquisition cost of imported crude oil, while q_t^{oil} is global crude oil production (thousands of barrels). Both time series are a standard choice in the oil market literature (e.g. Kilian 2009; Baumeister and Peersman 2013b) and are obtained from the U.S. Energy Information Administration. p_t^{metal} is an index of metals and minerals commodity

[9]Results are robust to modeling stochastic volatility in a univariate and thus more restrictive fashion as in, for example, Benati and Mumtaz (2007).

prices made available by the World Bank. For the sake of brevity, we henceforth refer to it as a metals price index. We use nominal price variables in the benchmark estimations, which is standard in the finance literature and most appropriate to study the pass-through to other prices. Note, however, that the results are quasi identical for real prices (see section 3.2).

For food commodity markets, we follow the approach of Roberts and Schlenker (2013) and De Winne and Peersman (2016). Specifically, q_t^{food} is a composite quarterly global food production index. The index is a caloric weighted aggregate of the harvests of the four most important staple food items: corn, wheat, rice and soybeans. These four commodities are storable and traded in integrated global markets. Together, they account for roughly 75 percent of the caloric content of food production worldwide. The index is based on FAO harvest data of 192 countries. Roberts and Schlenker (2013) use the harvest volumes to construct an annual global food commodity production index, which they use to estimate global supply and demand elasticities of agricultural commodities. De Winne and Peersman (2016) create a similar index at the quarterly frequency to estimate the consequences of global food supply shocks on the U.S. economy.[10] We have updated the quarterly index with three additional years of data (i.e. until 2016Q4). p_t^{food} is the corresponding price index measured in U.S. dollars. The price index is a weighted average (based on trend production volumes) of the four commodities, which are made available by the IMF. These benchmark prices are representative for the global market and determined by the largest exporter of each commodity. As shown in Figure 2, the prices of the four commodities fluctuate closely together. By aggregating the four staples, the implicit assumption is that the calories of the four commodities are perfect substitutes. This facilitates the analysis. Given the high substitutability of the staples and strong correlation of harvest shocks across crops, it would be very difficult to disentangle cross-price elasticities from own-price elasticities in the estimations, which would complicate the analysis and interpretation of the results.[11] The strong comovement between the prices of the staples suggests that substitution possibilities are indeed large so that the aggregate outcome characterizes the disaggregated markets reasonably well (Roberts and Schlenker 2013).

[10] De Winne and Peersman (2016) combine the annual data from the FAO with crop calendars of the staples for each of the 192 countries 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, however, 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 composite index covers roughly two-thirds of world food production (harvests).

[11] Notice that also the production and prices of other staples are typically strongly correlated with these four commodities (Roberts and Schlenker 2013). De Winne and Peersman (2016) also employ a broader food price index from the International Monetary Fund (IMF) including prices for cereals, vegetable oils, meat, seafood, sugar, bananas, and oranges. We prefer the more narrow index as it corresponds exactly to the food production index. Results are, however, robust to using the broad index of the IMF.

In fact, this is not surprising. Since corn, wheat and soybeans are used as feed for livestock, profit-maximizing farmers will switch to cheaper alternatives if prices per calorie deviate. Furthermore, these crops have to compete for the same planting acreage, which also synchronizes their prices. Nevertheless, since the four staples may not be perfect substitutes, we will also present results for a disaggregate analysis in the robustness section.

2.3 Identification of Oil and Food Supply Shocks

To properly estimate spillover effects between commodity prices, it is crucial to disentangle idiosyncratic supply shocks from common demand shocks. For example, popular interpretations of the strong correlation since the early 2000s is that shifts in oil and food commodity prices were driven by a common component that is associated with fluctuations in global activity and incomes (e.g. Baumeister and Kilian 2014) and the large capital inflows from index investors in commodity markets (e.g. Tang and Xiong 2012). A rise in the correlation between oil and food prices that results from common causation does obviously not imply that there are spillover effects, which is comovement that is the consequence of a direct causal link between price shifts. In fact, the bulk of the studies that examine a possible link between oil and food commodity prices do not address this problem. Specifically, most time-series studies typically use reduced-form approaches that cannot address causality, such as reduced-form causality tests (e.g. Avalos 2014; Mallory et al. 2012) or reduced-form or semi-structural VARs (e.g. Baumeister and Kilian 2014).[12] Another remarkable observation is that several studies analyzing linkages between crude oil and food commodity prices test for spillovers only from oil to food markets, but not the other way around (e.g. Hertel and Beckman, 2012). To study whether there exist spillovers between crude oil and food commodity prices, we therefore isolate price fluctuations that are exogenous and entirely supply driven. Moreover, we identify both oil and food commodity supply shocks, which allows us to analyze the pass-through in both directions. To do this, we rely on existing studies and approaches.

[12] Baumeister and Kilian (2014), who estimate bivariate semi-structural VARs under the identifying assumption that the price of oil is predetermined with respect to food commodity prices, acknowledge this problem. To evaluate the role of global shifts in economic activity for the stronger pass-through of oil price shocks after 2006, they turn to a different source of identifying information. On one hand, they also document a significant positive response of the price of nitrogen fertilizer to oil price shocks after 2006, whereas the production of this fertilizer relies on natural gas rather than crude oil. On the other hand, when they orthogonalize the price variables to a series of aggregate (flow) demand shocks, they find heterogeneous evolution across crop prices that are difficult to attribute to biofuels mandates. Based on these findings, they conclude that the link between oil and food commodity prices should be largely driven by common macroeconomic determinants.

2.3.1 Oil Supply Shocks

In an influential contribution, Kilian (2009) disentangles oil supply from demand shocks in a monthly fixed-coefficient VAR framework using contemporaneous exclusion restrictions. He identifies oil supply shocks as the sole disturbance that has an immediate impact on global oil production. In contrast, oil demand shocks do not have an instantaneous influence on global oil production (i.e. within one month), which implies that the short-run oil supply curve is vertical. Whereas this assumption may be justifiable in a monthly VAR, it is not realistic in a quarterly model. We therefore follow the approach proposed by Baumeister and Peersman (2013b) and subsequently used by many others in the oil literature, which is based on so-called sign restrictions that are imposed on the contemporaneous impact matrix of the shocks.[13] Specifically, oil supply shocks are identified as the innovations in global oil production that move oil prices on impact (within the same quarter) in the opposite direction. Conversely, all shifts in oil production that move oil prices instantaneously in the same direction are considered as demand shocks. This sign restriction corresponds to a shift of an upward-sloping oil supply curve along a downward-sloping oil demand curve and is sufficient to isolate oil supply shocks in the TVP-BVAR. Notice that no constraints are imposed on the responses of food and metals prices after the shock, which is determined by the data. To implement the sign restrictions, we apply the algorithm of Rubio-Ramírez et al. (2010).[14]

A couple of points are worth mentioning. First, Kilian and Murphy (2014) impose boundary restrictions on the magnitudes of the implied price elasticities of oil supply and demand as additional identification criteria to eliminate posterior draws with implausibly high elasticities. Whereas Kilian and Murphy (2014) identify several types of oil market shocks simultaneously, it appears that these boundaries are not important for the identification of oil supply shocks. In particular, nearly all draws from the posterior have an implied short-run price elasticity of oil demand that is consistent with their upper bound of -0.8, while the results are the same when we explicitly impose a restriction on the price elasticity of demand. Second, Sockin and Xiong (2015) argue that, in the presence of informational frictions, agents cannot disentangle supply and demand shocks in real time. Hence, through its informational role, an increase

[13] E.g. Peersman and Van Robays (2009), Lippi and Nobili (2012), Kilian and Murphy (2014), Juvenal and Petrella (2015) and Van Robays (2016). This approach, in turn, builds on applications that use sign restrictions to identify macroeconomic shocks, e.g. Canova and de Nicolo (2002), Uhlig (2005) and Peersman (2005).

[14] Baumeister and Hamilton (2015) have shown that this procedure implicitly imposes a uniform prior over the non-zero supply elasticities in a VAR model like ours. The derivation and simulation of a time-varying counterpart to the posterior distribution proposed in Baumeister and Hamilton (2015), which directly draws in the model's structural parameterization, is however beyond the scope of this paper.

of commodity prices caused by a supply shock can also be interpreted as a signal of stronger economic growth, which raises the demand for the commodity. Notice that this is not a critical problem for our identification approach. On one hand, if this rise in demand is smaller than the standard negative cost effect of a price rise on demand, the supply shock is still characterized by a negative comovement between production and prices, which is consistent with the restriction that we impose to isolate oil supply shocks. On the other hand, if this informational effect dominates the standard negative cost effect to acquire the commodity; that is, the oil supply shock shifts oil production and prices in the same direction, such shocks are (wrongly) identified as oil demand shocks in the estimations, but in this paper we are not interested in the dynamics of oil demand shocks. In essence, this would imply that we only consider a subset of all oil supply shocks in the analysis.[15] Finally, notice that the TVP-BVAR approach allows elasticities to vary over time. Put differently, in contrast to fixed-coefficient VARs, changes of informational frictions during the sample are captured by the model.

2.3.2 Food Commodity Supply Shocks

For the identification of food commodity supply shocks, following De Winne and Peersman (2016), we explore the fact that there is a time lag of at least one quarter (i.e. 3 to 10 months) between the planting and harvesting of cereal commodities, while harvest volumes are subject to shocks that are unrelated to the economy, such as weather variation or crop diseases. More specifically, the time lag of at least one quarter between the decision to produce (planting) and the actual production (harvest) of cereal commodities implies that food producers are able to immediately respond to changes in demand by adjusting their planting volumes. Yet, for the actual production volume, this is not the case due to the time lag. Put differently, actual food production can only respond to changes in demand after (at least) one quarter. The reduced-form innovations to food production (global harvests volume) in the TVP-BVAR can thus be considered as unanticipated food supply shocks that are orthogonal to economic developments.[16] Hence, ordering the quarterly food production

[15] Sockin and Xiong (2015) show that the price elasticity of commodity demand is only positive under certain conditions. This would clearly be a problem to analyze the effects of oil demand shocks in a VAR model. The presence of oil supply shocks that move prices and production in the same direction would, for example, also be a problem if we want to assess the relative importance of supply shocks to explain oil price fluctuations; that is, for variance decompositions.

[16] Remark that this approach assumes that farmers cannot influence harvest volumes anymore during the harvesting quarter, for example, by raising fertilization activity. Several studies have shown that in-season fertilization is indeed inefficient and even counterproductive for the food commodities that we consider (De Winne and Peersman 2016). The best times to apply fertilizer for these crops is before or shortly after planting. Note that farmers can in principle always reduce food production by destroying crops, but that is not likely to happen at a large (global) scale. Overall, the influence of farmers on the volumes during the harvesting quarter

index first in a recursive identification scheme—which is equivalent to applying a Cholesky-factorization to $\mathbf{\Omega}_t$—recovers structural food supply innovations. Notice that the responses of all the variables in the model are left unrestricted to the food commodity supply shocks. Thus, the data could determine whether the standard cost effect is dominated by the above informational effect (sign of the own-price response), and whether there are spillover effects to crude oil and metals commodity prices.

3 Time-Varying Spillover Effects

3.1 Benchmark Results

Figure 3 shows the benchmark results for crude oil and food commodity supply shocks, respectively. Panel A displays the impact over time of a one standard deviation adverse supply shock on all the variables that are included in the TVP-BVARs; that is, the median and the 16th and 84th percentiles of the posterior distributions as confidence intervals. This is the conventional way in the literature to show the results of TVP-BVARs. As can be observed in the figure, the size of both (one standard deviation) shocks has varied considerably over the sample period. This supports the choice of a model that features stochastic volatility, but it also complicates comparisons over time of the magnitudes of spillovers. Therefore, in panel B, we show for each variable the changes over time of the impact of a normalized supply shock. Specifically, for each period t we show the *difference* between the impact of a one percent decline in oil (food) production and a one percent decline in oil (food) production in a benchmark period. As the benchmark period, we systematically select the quarter in the sample with the lowest normalized (median) impact or pass-through. Put differently, the figures show the estimated time variation in the own and cross-price responses to both supply shocks, together with confidence intervals. Notice that we only show the contemporaneous effects (within the quarter). Conclusions at longer horizons (by constructing impulse response functions) are the same and available on request. For the TVP-BVARs with metals prices, we only report the effects on metals prices since the effects on the other variables are nearly identical to those shown in the figures.

---

is plausibly meager relative to variation induced by, for example, weather conditions. De Winne and Peersman (2016) conduct several ex post tests and sensitivity checks and conclude that shocks to the food production index are exogenous with respect to the economy and are not picking up other shocks.

3.1.1 The Interplay Between Oil and Food Commodity Prices

Consider first the spillover effects of crude oil supply shocks on food commodity prices. As can be observed in Figure 3, unfavorable oil supply shocks did not affect food commodity prices before the start of the millennium. If anything, the comovement of oil and food commodity prices in response to the shock was negative. This can be explained by a global slowdown of economic activity due to the unfavorable shock, which, in turn, leads to a decline in the demand for food commodities. However, since the 2000s, we observe positive spillover effects of oil supply shocks on food commodity prices. Moreover, these spillovers gradually increased over the years, reaching a peak around 2008. In particular, in 2008, a typical oil supply shock triggered a rise in crude oil prices of 14 percent and, at the same time, resulted in a rise of food commodity prices by roughly 5 percent. This is also reflected in the time variation shown in the second column; that is, the price response compared to the benchmark quarter in the mid 1990s is for many years significantly larger. At its peak, there is a positive spillover effect and time variation for more than 90 percent of the posterior draws. Finally, the spillover effects became again more subdued in the years after the Great Recession.

A similar pattern can be observed for the consequences of food commodity supply shocks on oil prices. Specifically, bad harvests that resulted in food commodity price increases had a negative impact on the price of crude oil in the 1990s, which is consistent with a reduction in the demand for oil in periods of lower economic activity.[17] However, since the second half of the 1990s, the spillover effects switched sign to become positive. Again, there was a gradual increase of the spillovers during the 2000s, which reached a peak in 2008. Even though the uncertainty is high, the magnitudes are strong. A supply shock that augmented food commodity prices by 3.5 percent in 2008, also resulted in a rise of crude oil prices by 2.4 percent. Overall, compared to the early 1990s, the impact of a one percent decline in global food production on crude oil prices was approximately 1.2 percentage points larger in 2008, while more than 90 percent of the posterior draws suggest a larger effect over time.

The positive spillover effects between oil and food commodity prices in recent periods is consistent with numerous studies that have documented increased synchronization between oil and agricultural commodity prices (e.g. Tyner 2010; Mallory et al. 2012; Avalos 2014). In contrast to these studies, which typically examine unconditional comovement in the data, we show that the stronger correlation also exists conditional on idiosyncratic supply shocks. We also find that the synchronization has been a gradual process over time, rather than a

[17] De Winne and Peersman (2016, 2018) document a decline in global economic activity in response to adverse harvest shocks.

structural break. Moreover, we document spillovers in both directions. The latter observation is important because it suggests that the increased comovement is not the consequence of a stronger unidirectional pass-through of oil to food prices, for example, due to the mechanization of agriculture in developing countries over the past two decades and the rising relevance of energy intensive inputs in the production of agricultural products (e.g. fertilizers).[18]

Is the time variation consistent with developments in biofuels markets? At first sight, this is the case. The production of corn-based ethanol and policies to promote the use of ethanol already exist since the 1970s and became more popular over time (Avalos 2014). For example, the Clean Air Act of 1990 required gasoline to contain a minimum percentage of oxygen, while ethanol was a possible additive to increase its oxygen content. Notwithstanding these developments and policies, the use of biofuels was limited because MTBE was a more popular and cheaper additive than ethanol. However, this changed dramatically with the New Renewable Fuels Standard of the U.S. Energy Policy Act of 2005, which required motor fuels to contain a minimum amount of fuel coming from renewable sources. This was the moment when MTBE was banned and ethanol took over the entire market for oxygenator enhancers in gasoline, which resulted in a boost of ethanol production. For example, in 2000 only about 5 percent of U.S. corn production was used for ethanol production, which increased to almost 40 percent in 2010. Roughly 70 percent of the increase in global corn production between 2004 and 2010 was absorbed by ethanol production (Headey and Fan 2010). Clearly, this also affected the production and prices of other food commodities via substitution effects. Around the same time, the expansion of European biodiesel production resulted in crowding out of the wheat area by oilseeds. Hence, the gradual rise over time of spillover effects between the prices of crude oil and food commodities, with an acceleration in the period 2005-2008, is consistent with the biofuels narrative.

Also the decline of spillover effects after 2008 can potentially be explained by biofuels. On one hand, the price of crude oil collapsed much more than food commodity prices between 2008 and 2010 (see Figure 1). Since food can be used to produce energy, but oil cannot be used as food, substitution between both commodities is not possible when oil prices are below food commodity prices (both measured per unit of energy). The unidirectional substitutability could thus have contributed to a weakening of the relationship between the prices of both commodities after 2008.[19] This also applies to the so-called blend wall in the U.S. market.

[18] For example, for the period 1996-2000, the average share of energy inputs (fertilizer, fuel, lube and electricity) in total corn producer costs was 19.6 percent. This share increased to 31.5 percent for the period 2007-2008 (Hertel and Beckman 2012).

[19] Similarly, the substantial rise of crude oil prices between 2005 and 2008 could have contributed to the

Since refineries were unable to blend more than 10 percent ethanol into gasoline at that time, substitution between both commodities became much more difficult, resulting in a possible weakening of the link between food and oil prices (Hertel and Beckman 2012). Overall, developments in biofuels markets are in principle consistent with the time-varying spillover effects that we have found, which is a hypothesis that we further explore in the next subsections.

3.1.2 Effects on Metals and Mineral Commodity Prices

The concurrent evolution of the time variation and developments in biofuels markets does not imply that these developments are, in fact, the source of the time variation. For example, given the very limited use of biofuels in earlier decades, it is surprising that the rise of spillover effects already started in the 1990s. Moreover, there could have been other transformations in commodity markets that give rise to a larger contagion between crude oil and food commodity prices. To address this issue, we examine the pass-through of both supply shocks to metals commodity prices. More specifically, if a higher degree of substitutability of both commodities for the energy producing industry is indeed the source of the increased spillover effects, we should not observe such time variation for metals commodity prices, since metals commodities are not used to produce energy. In essence, such an analysis can be compared with a difference-in-difference approach, where the spillovers between food and oil prices are the treated variables, while the spillovers of both shocks to metals commodity prices are the control variables.

The impact of oil and food commodity supply shocks on metals commodity prices is shown in the bottom row of Figure 3. As can be observed in the figure, the time-varying spillover effects are remarkably similar to those between oil and food commodity prices. Once more, we find a gradual increase over time of the normalized spillover effects of oil supply shocks on metals commodity prices, which reached a peak at the end of 2008, and a decline afterward. Additionally, while unfavorable food supply shocks had a negative effect on metals prices in the early 1990s, the spillovers have been positive since the 2000s. Notice that also the magnitudes of the changes in the normalized spillover effects are very similar for metals commodity prices compared to the alternative commodity for both supply shocks.

The analogous time-varying effects on metals commodity prices suggest that developments in biofuels markets are not the key reason of the increased synchronization of oil and food commodity prices in response to supply shocks. Indeed, if the substitutability between oil and food commodities was the source of spillover effects between their prices, as the biofuels

stronger spillover effects in this period.

narrative suggests, then why would metals and minerals, which show no degree of substitutability with either food or oil, exhibit the same spillover? In sum, the strong similarity of the impact on metals commodity prices raises questions about the existing evidence that attributes the strengthened relationship between food and energy commodity markets to the increased relevance of biofuels production.

3.1.3 Informational Frictions in Commodity Markets

Another mechanism that can lead to spillover effects is the presence of informational frictions in commodity markets. Specifically, it is widely recognized that centralized trading in asset markets serves as a platform to aggregate dispersed information possessed by individual market participants (e.g. Grosmann and Stiglitz 1980). Building on this principle, Sockin and Xiong (2015) have developed a useful theoretical framework to analyze informational frictions in commodity markets and its influence on commodity demand. According to their model, changes in commodity prices could serve as signals of the strength of the economy when market participants (goods producers) cannot observe fundamentals. In particular, by trading the commodity, they aggregate dispersed information about unobserved global economic activity. For example, a rise in commodity prices signals a stronger economy, which encourages goods producers to raise their commodity demand. However, since the fundamentals cannot be observed directly, commodity price shifts that are not the consequence of changes in economic activity can be misinterpreted as signals about the strength of the economy, causing some participants to change their commodity demands. For example, an adverse oil supply shock that raises oil prices may be interpreted as a signal of global economic strength, increasing the demand for commodities. Accordingly, also the prices of non-oil commodities could increase as a result of the oil supply shock. In contrast to a biofuels induced correlation, the existence of informational frictions could thus be an explanation for also having spillover effects on metals commodity prices.

A natural question is whether informational frictions in commodity markets can also explain the time variation of the spillover effects. This is indeed possible. First, the financialization of commodity markets since the start of the millennium documented in Figure 1 has facilitated and encouraged information discovery in commodity markets. In particular, since trading physical commodities in spot markets is subject to several distortions such as heterogeneity in quality, storage and transportation costs, the lower trading costs and highly standardized futures contracts facilitate the aggregation of dispersed information among market participants and encourages participation in commodity markets for information discovery

(Sockin and Xiong 2015). For example, it is well known that the centralized futures prices of key commodities have been widely used as barometers of the global economy in recent years (Cheng and Xiong 2014). Second, informational frictions have likely increased since the 1990s, and particularly during the 2000s. Specifically, there is a broadly held perception that the increased globalization of commodity markets and increasing importance of commodity demands from rapidly growing emerging economies in this period has made it more difficult to assess the strength of the global economy (e.g. Cheng and Xiong 2014). Reliable statistics about economic activity in emerging countries are, for example, rather scarce. As a result of the enhanced informational frictions, it is more likely that agents have misinterpreted shifts in commodity prices caused by exogenous supply shocks as changes in macroeconomic conditions in recent periods.

Furthermore, information discovery is particularly relevant in times of great economic uncertainty such as the period around the Great Recession. For example, as a result of lack of reliable data for emerging countries, it was difficult to measure the strength of these economies in real time in the period 2005-2008. Prices of commodities were regarded as important signals, which should have strengthened the consequences of information discovery.[20] Hence, to the extent that commodity price shifts emerged from supply shocks in commodity markets rather than from changes in macroeconomic demand, the inferred signal was a misinterpretation. The result is that market participants adjusted their commodity demand and affected commodity prices across the board. The same applies to the Great Recession. It is conceivable that, during periods of large fluctuations in economic activity, market participants believe that changes in commodity prices are more likely triggered by real economy shocks, which enhances spillover effects of commodity supply shocks. Conversely, in the period after 2010, oil supply shocks gained importance as a consequence of aggressive supply increases by Saudi Arabia, which could have mitigated misinterpretation of price signals. Similarly, serious droughts around the world in the summers of 2010 and 2012 increased the probability that food price changes were caused by supply shocks. Hence, in this period, it was less likely that price fluctuations were revealing information about economic activity, diminishing spillover effects.

Additional support for this interpretation of time-varying spillover effects follows from the time variation in the own-price elasticities of the demand for food and oil, which are also shown in Figure 3. More specifically, the commodity markets model of Sockin and Xiong (2015) predicts that informational frictions should also increase the impact of supply

[20] Sockin and Xiong 2015 describe the decision of the ECB to increase interest rates on the eve of the Great Recession (March 2008), as an example of information discovery in commodity markets by policy institutions. Specifically, ECB policy reports refer to high prices of oil and other commodities as a key factor for their decision. Ex post, this turned out to be a serious misinterpretation.

shocks on the own price of a commodity. Consider an adverse supply shock in the global oil market that raises oil prices. Because this price increase is partly interpreted as a signal of a stronger global economy, there is an increase in oil demand and thus also in the price of oil through a feedback effect. Accordingly, if informational frictions are the source of the time-varying spillover effects, we should see similar time variation in the impact of a decline in food and oil production on the own price. This is exactly what we observe in Figure 3; that is, both shocks appear to have a stronger impact on the own price in recent periods compared to earlier decades. Moreover, the pass-through was particularly strong in the era around the Great Recession. In sum, we have found evidence against the biofuels channel of spillover effects between oil and food commodity prices. However, informational frictions and information discovery in financialized commodity markets are a plausible explanation for spillover effects and the time variation of such effects that we observe in the data.

3.2 Robustness Analysis and Extensions

In this subsection, we provide some additional analysis and examine the sensitivity of the baseline results. Note that the benchmark results are based on two shocks that have been isolated with very different identification strategies, which is a robustness check in itself.

First, the results are robust to several perturbations to the model specification. In particular, we have re-estimated the four three-variable benchmark models using a more restrictive univariate stochastic process for the volatility states as in Benati and Mumtaz (2007), as well as using a hierarchical prior (using a uniform distribution over the interval (0,1]) for the scaling parameters as in Amir-Ahmadi et al. (2018). These modifications do not materially affect the conclusions. Other robustness checks that we have done included increasing/reducing 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 price series, imposing the sign restrictions for the oil supply shock over longer horizons and adding a quantitative restriction (minus 0.8) on the maximum price elasticity of oil demand. The results (available on request) are always very similar.

Since TVP-BVARs are highly parameterized, we have limited the number of endogenous variables for the benchmark estimations to three; that is, we have estimated four three-variable TVP-BVAR(6) models. As another robustness check, we now estimate a five-variable TVP-BVAR(4) model that nests the four benchmark models into a single model. To limit the number of parameters, we include only four lags of the endogenous variables. More precisely, the vector of endogenous variables becomes $\boldsymbol{y}_t = [\Delta q_t^{food}, \Delta q_t^{oil}, \Delta p_t^{oil}, \Delta p_t^{food}, \Delta p_t^{metal}]'$, while we identify the oil and food supply shocks simultaneously. By construction, the shocks are orthogonal in such a set-up. The results are reported in Figure 4. As can be observed in the figure, the results are very similar to the benchmark results.

In our analysis, we have postulated a drifting coefficient model. From a methodological perspective, this implies a high-dimensional and richly parameterized framework. To test whether an enhanced link between food commodity prices, energy prices and metals prices in recent data can also be detected in a linear and less parameterized model, we have also estimated fixed-coefficient VARs over two subperiods by imposing a simple sample split in 2004 (results are similar for alternative split dates). The linear framework further allows to explore the level properties of the data by including the variables in log-levels and allowing for co-integration in the system, as shown in Sims et al. (1990). Accordingly, we can also assess the dynamics of the spillovers at longer horizons. Given the gradual character of the time variation that we obtained in the TVP-BVAR model, the sample split should be viewed with the caveat of constituting a rather rough linear approximation of underlying non-linear time variation. The identifying assumptions to achieve causal inference are identical to the TVP-BVAR.

The dynamic effects of a one percent decline in oil (food) production caused by a supply disturbance for the sample split are shown in Figure 5. While oil supply shocks did not affect the prices of food and metals commodities in the early sample, there are strong spillover effects in the late sample period. For food market supply shocks, we document negative spillover effects in the early sample period, while there is a positive pass-through in the late sample. Notice that the spillovers appear to be quite persistent. This is somewhat surprising in the 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 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 also applies to the stronger impact of both shocks on the own price.

Finally, we assess whether there is similar time variation for different types of food commodities. In this vein, we re-estimate the TVP-BVAR(6) models and include the prices of respectively corn, rice, soybeans and wheat as the third variable in the vector of endogenous variables. Notice that these are also the four crops that have been used to construct the food production index. The results for the four commodities are shown in Figure 6. 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, even though the uncertainty of these estimates is rather high.

4 Conclusions

In this paper, we have modeled crude oil and food commodity markets in a time-varying Bayesian VAR framework with stochastic volatility to study potential changes in spillovers between both markets over time. We identify structural supply shocks in crude oil and food commodity markets and find that exogenous declines in oil supply that increased the price of oil had no impact on food commodity prices prior to the start of the millennium, but had positive spillover effects more recently. Similarly, unfavorable disruptions in the supply of food commodities have positive spillover effects on crude oil prices since the early 2000s, in contrast to the preceding era. Notably, the time variation of the spillover effects has been gradual over time, reached a peak around 2008, and declined again somewhat afterwards.

A popular explanation for an increased synchronization between oil and food commodity prices conditional on supply shocks in both markets is the biofuels revolution. Specifically, since both commodities have become substitutes over time to produce energy goods, their prices should have become more correlated. However, our results cast doubt about this conjecture. In particular, we find very similar time variation in the spillover effects of both shocks on metals and minerals commodity prices, while metals are not a substitute to produce energy. We also find a stronger impact of both supply shocks on their own price.

A plausible mechanism that can explain the time variation of the spillover effects and stronger impact on the own price is a heightening of informational frictions and information discovery in financialized commodity markets as postulated in Sockin and Xiong (2015). In particular, the financialization of commodity markets since the early 2000s serves as a platform to aggregate dispersed information about the strength of the global economy. Accordingly, a rise in commodity prices signals a stronger economy, leading to a rise of commodity demand by market participants and hence further price increases of commodities. However, since the fundamentals cannot be observed directly, increases in commodity prices that are caused by an adverse supply shock in one of the commodities can be misinterpreted as a signal of economic strength. As a consequence, the demand for all commodities increases in response to the supply shock, raising also other commodity prices. In fact, a lot of the time variation that we observe in the data is consistent with this hypothesis.

Overall, the presence of time-varying spillover effects between commodities are important for hedging and investment strategies. The interplay between oil and food commodity prices should also be taken into account for countries' energy and food policies. Furthermore, it matters for monetary policy, since the presence of spillovers implies that oil (food) price fluctuations affect inflation via food (energy) prices. Our results also suggest that the incorporation of informational frictions into theoretical and empirical models of commodity markets could improve our understanding of its dynamics. Finally, even though informational frictions are a plausible explanation of the (time-varying) spillover effects between commodity markets, the mechanism requires further confirmation in future research.

References

Abbott, Philip (2014) "Biofuel, Binding Constraints, and Agricultural Commodity Price Volatility," in J. Chavas, D. Hummels, and B. Wright eds. *The Economics of Food Price Volatility*: NBER, Chap. 3, pp. 91–134.

Abbott, Philip, Christopher Hurt, and Wallace E. Tyner (2011) "What's driving food prices in 2011?"Technical report, Farm Foundation.

Amir-Ahmadi, Pooyan, Christian Matthes, and Mu-Chun Wang (2018) "Choosing Prior Hyperparameters: With Applications to Time-Varying Parameter Models," *Journal of Business & Economic Statistics*, Vol. 0, pp. 1–13.

Avalos, Fernando (2014) "Do oil prices drive food prices? The tale of a structural break," *Journal of International Money and Finance*, Vol. 42, pp. 253–271.

Baumeister, Christiane and James D. Hamilton (2015) "Sign Restrictions, Structural Vector Autoregressions, and Useful Prior Information," *Econometrica*, Vol. 83, pp. 1963–1999.

Baumeister, Christiane and Lutz Kilian (2014) "Do oil price increases cause higher food prices?" *Economic Policy*, Vol. 29, pp. 691–747.

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.

Beckman, Jayson, Thomas Hertel, and Wallace Tyner (2011) "Validating energy-oriented CGE models," *Energy Economics*, Vol. 33, pp. 799–806.

Benati, Luca and Haroon Mumtaz (2007) "U.S. evolving macroeconomic dynamics: a structural investigation," Working Paper Series 746, European Central Bank.

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.

Canova, Fabio and Gianni de Nicolo (2002) "Monetary disturbances matter for business fluctuations in the G-7," *Journal of Monetary Economics*, Vol. 49, pp. 1131–1159.

Cheng, Ing-Haw, Andrei Kirilenko, and Wei Xiong (2015) "Convective Risk Flows in Commodity Futures Markets," *Review of Finance*, Vol. 19, pp. 1733–1781.

Cheng, Ing-Haw and Wei Xiong (2014) "Financialization of Commodity Markets," *The Annual Review of Financial Economics*, pp. 6:419–41.

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.

——— (2018) "Agricultural Price Shocks and Business Cycles - A Global Warning for Advanced Economies," *CESifo Working Paper No. 7037*.

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.

Du, Xiaodong, Cindy L. Yu, and Dermot Hayes (2011) "Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis," *Energy Economics*, Vol. 33, pp. 497–503.

Fernández, Andrés, Andrés González, and Diego Rodríguez (2018) "Sharing a ride on the commodities roller coaster: Common factors in business cycles of emerging economies," *Journal of International Economics*, Vol. 111, pp. 99–121.

Grosmann, S. and J. Stiglitz (1980) "On the impossibility of informationally efficient markets," *American Economic Review*, Vol. 70, pp. 393–408.

Hamilton, James D. (2009) "Causes and Consequences of the Oil Shock of 2007-08," *Brookings Papers on Economic Activity*, Vol. 40, pp. 215–283.

Hamilton, James D. and Ana Maria Herrera (2004) "Oil Shocks and Aggregate Macroeconomic Behavior: The Role of Monetary Policy: Comment," *Journal of Money, Credit and Banking*, Vol. 36, pp. 265–86.

Hamilton, James D. and Jing C. Wu (2015) "Effects of Index-Fund Investing on Commodity Futures Prices," *International Economic Review*, Vol. 56, pp. 187–205.

Hassler, John and Hans-Werner Sinn (2016) "The fossil episode," *Journal of Monetary Economics*, Vol. 83, pp. 14 – 26.

Headey, Derek and Shenggen Fan (2010) "Reflections on the global food crisis: How did it happen? How has it hurt? And how can we prevent the next one?,"Technical report, International Food Policy Research Institute, Washington.

Henderson, Brian J., Neil D. Pearson, and Li Wang (2015) "New Evidence on the Financialization of Commodity Markets," *The Review of Financial Studies*, Vol. 28, pp. 1285–1311.

Hertel, Thomas W. and Jayson Beckman (2012) *Commodity Price Volatility in the Biofuel Era: An Examination of the Linkage between Energy and Agricultural Markets*, Vol. The Intended and Unintended Effects of U.S. Agricultural and Biotechnology Policies: Editors: Joshua S. Graff Zivin and Jeffrey M. Perloff, University of Chicago Press.

Juvenal, Luciana and Ivan Petrella (2015) "Speculation in the Oil Market," *Journal of Applied Econometrics*, Vol. 30, pp. 621–649.

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 (2014) "The Role of Inventories and Speculative Trading in the Global Market for Crude Oil," *Journal of Applied Econometrics*, Vol. 29, pp. 454–478.

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.

Lippi, Francesco and Andrea Nobili (2012) "Oil and the Macroeconomy: A Quantitative Structural Analysis," *Journal of the European Economic Association*, Vol. 10, pp. 1059–1083.

Lombardi, Marco J. and Ine Van Robays (2011) "Do Financial Investors Destabilize the Oil Price?" *ECB Working Paper Series*, Vol. 1346.

Mallory, Mindy L., Scott H. Irwin, and Dermot J. Hayes (2012) "How market efficiency and the theory of storage link corn and ethanol markets," *Energy Economics*, Vol. 34, pp. 2157–2166.

Peersman, Gert (2005) "What caused the early millennium slowdown? Evidence based on vector autoregressions," *Journal of Applied Econometrics*, Vol. 20, pp. 185–207.

Peersman, Gert and Ine Van Robays (2009) "Oil and the Euro area economy," *Economic Policy*, Vol. 24, pp. 603–651.

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

Roberts, Michael J. and Wolfram Schlenker (2013) "Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate," *American Economic Review*, Vol. 103, pp. 2265–2295.

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.

Serra, Teresa and David Zilberman (2013) "Biofuel-related price transmission literature: A review," *Energy Economics*, Vol. 37, pp. 141–151.

Sims, Christopher A., James H. Stock, and Mark W. Watson (1990) "Inference in Linear Time Series Models with Some Unit Roots," *Econometrica*, Vol. 58, pp. 113–44.

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

Sockin, Michael and Wei Xiong (2015) "Informational Frictions and Commodity Markets," *Journal of Finance*, Vol. LXX, pp. 2063–98.

Tang, Ke and Wei Xiong (2012) "Index Investment and the Financialization of Commodities," *Financial Analyst Journal*, Vol. 68, pp. 54–74.

Tyner, Wallace E. (2010) "The integration of energy and agricultural markets," *Agricultural Economics*, Vol. 41, pp. 193–201.

Uhlig, Harald (2005) "What Are the Effects of Monetary Policy on Output? Results From an Agnostic Identification Procedure," *Journal of Monetary Economics*, Vol. 52, pp. 381–419.

Van Robays, Ine (2016) "Macroeconomic Uncertainty and Oil Price Volatility," *Oxford Bulletin of Economics and Statistics*, Vol. 78, pp. 671–693.

Appendix

The Bayesian estimation of the TVP-VAR discussed in Section 2 requires the choice of 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.[21] 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. In particular, we assume the following specification for the prior:

$$
\begin{aligned}
\boldsymbol{\theta_0} &\sim N\left(\hat{B}_{OLS}, 4 \cdot V(\hat{B}_{OLS})\right) \\
\boldsymbol{A_0} &\sim N\left(\hat{A}_{OLS}, 4 \cdot V(\hat{A}_{OLS})\right) \\
log\ \boldsymbol{\sigma_0} &\sim N\left(log(\hat{\sigma}_{OLS}), I_n\right) \\
\boldsymbol{Q} &\sim IW\left(k_B^2 \cdot n_{min}^{Q} \cdot V(\hat{B}_{OLS}), n_{min}^{Q}\right) \\
\boldsymbol{S_i} &\sim IW\left(k_A^2 \cdot n_{min}^{S_i} \cdot V(\hat{A}_{i,OLS}), n_{min}^{S_i}\right),\ i = 1,2,3 \\
\boldsymbol{W} &\sim IW\left(k_H^2 \cdot n_{min}^{W} \cdot I_n, n_{min}^{W}\right),
\end{aligned}
\tag{7}
$$

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 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 the robustness section are quantitatively very closely related to their relative responses derived by averaging the impact responses from the TVP-VAR for the quarters ranging from 1988Q3 to 2003Q4 and from 2004Q1 to 2016Q4.

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

Second, we cannot follow Primiceri's choice to put the prior degrees of freedom for $\boldsymbol{Q}$ equal to the number of observations in the training sample. This follows from the fact that the size of our training sample is smaller than the dimensionality of $\boldsymbol{Q}$. As an alternative, and in line with the priors for $\boldsymbol{S}$ and $\boldsymbol{W}$, we opt for a prior that is as loose as possible by choosing the prior degrees of freedom as small as possible given the dimensionality of $\boldsymbol{Q}$.

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 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 A1. 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, 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 algorithms, used by, e.g., Canova and Gambetti (2006), Canova and Gambetti (2009), and Baumeister and Peersman (2013b). We, however, depart from these algorithms for imposing sign restrictions in TVP-VARs 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 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, $\left\{\bar{\phi}_1, \bar{\phi}_2, \ldots, \bar{\phi}_T\right\}$, 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 $t = 1, \ldots, T$.

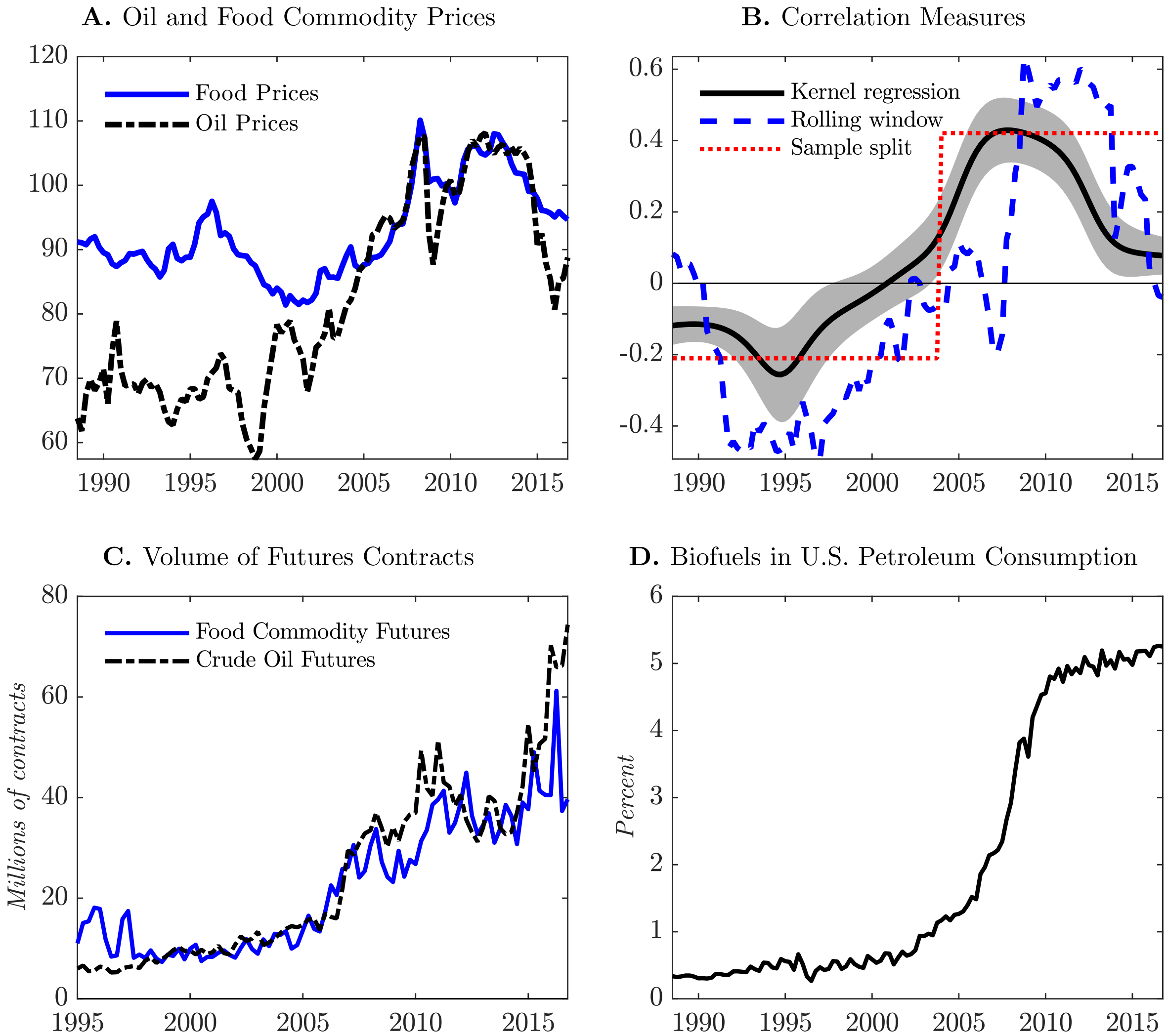
Canova and Gambetti (2006), Canova and Gambetti (2009), and Baumeister and Peersman (2013b) claim to generate a draw $\bar{\Phi}$ from the posterior of the structural model by first selecting a state ϕ_t from a draw Φ of the unrestricted posterior, then drawing a rotation matrix ξ_t, and finally retaining 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.

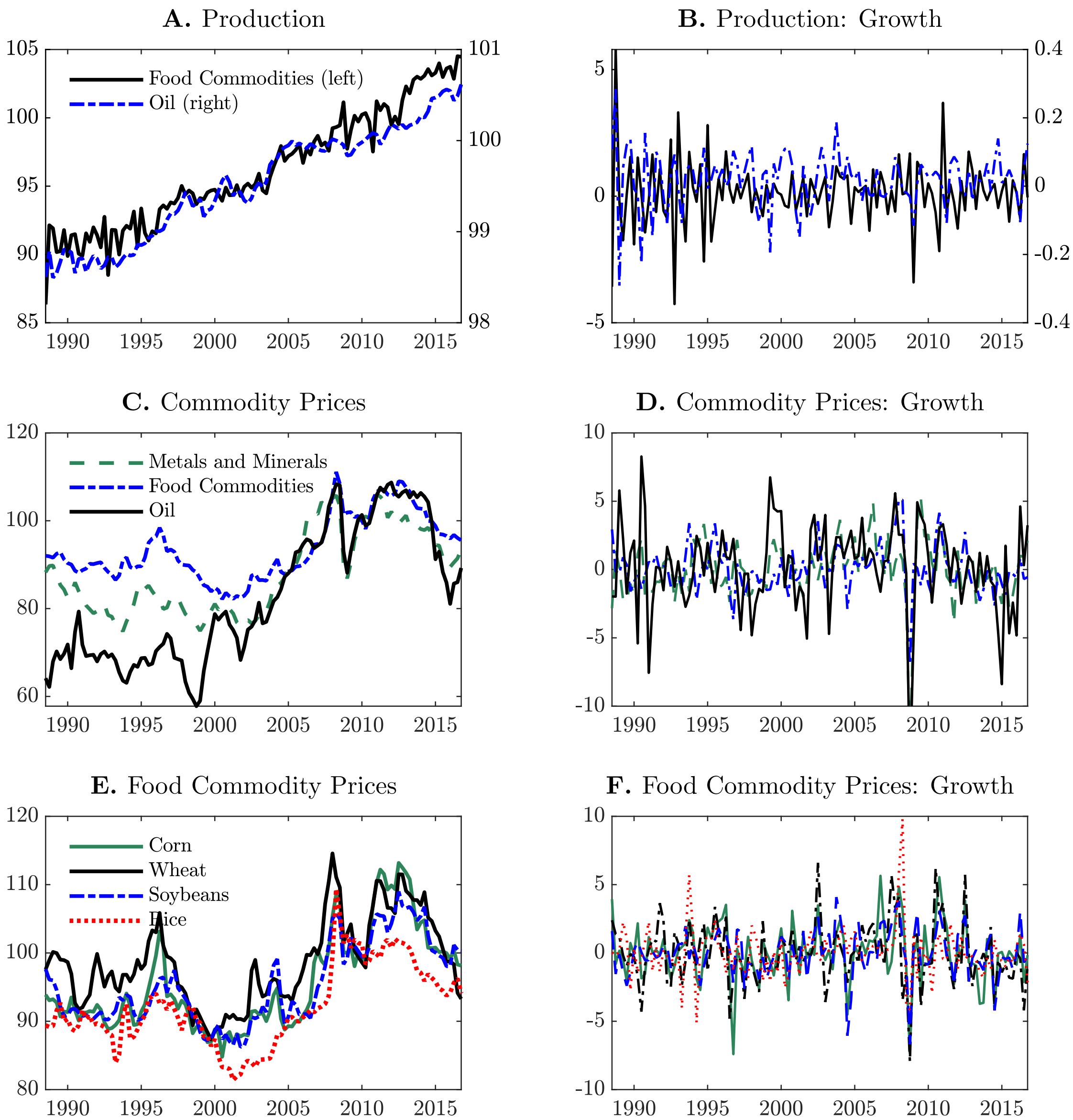
This second modification to the existing algorithms avoids the introduction of an arbitrary amount of time variation within each draw of the Gibbs-sampler. Although the impact of such an additional arbitrary amount of time variation is negligible or even absent for the posterior distribution of the impulse 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.

Figure 1: Comovement between Oil and Food Commodity Prices



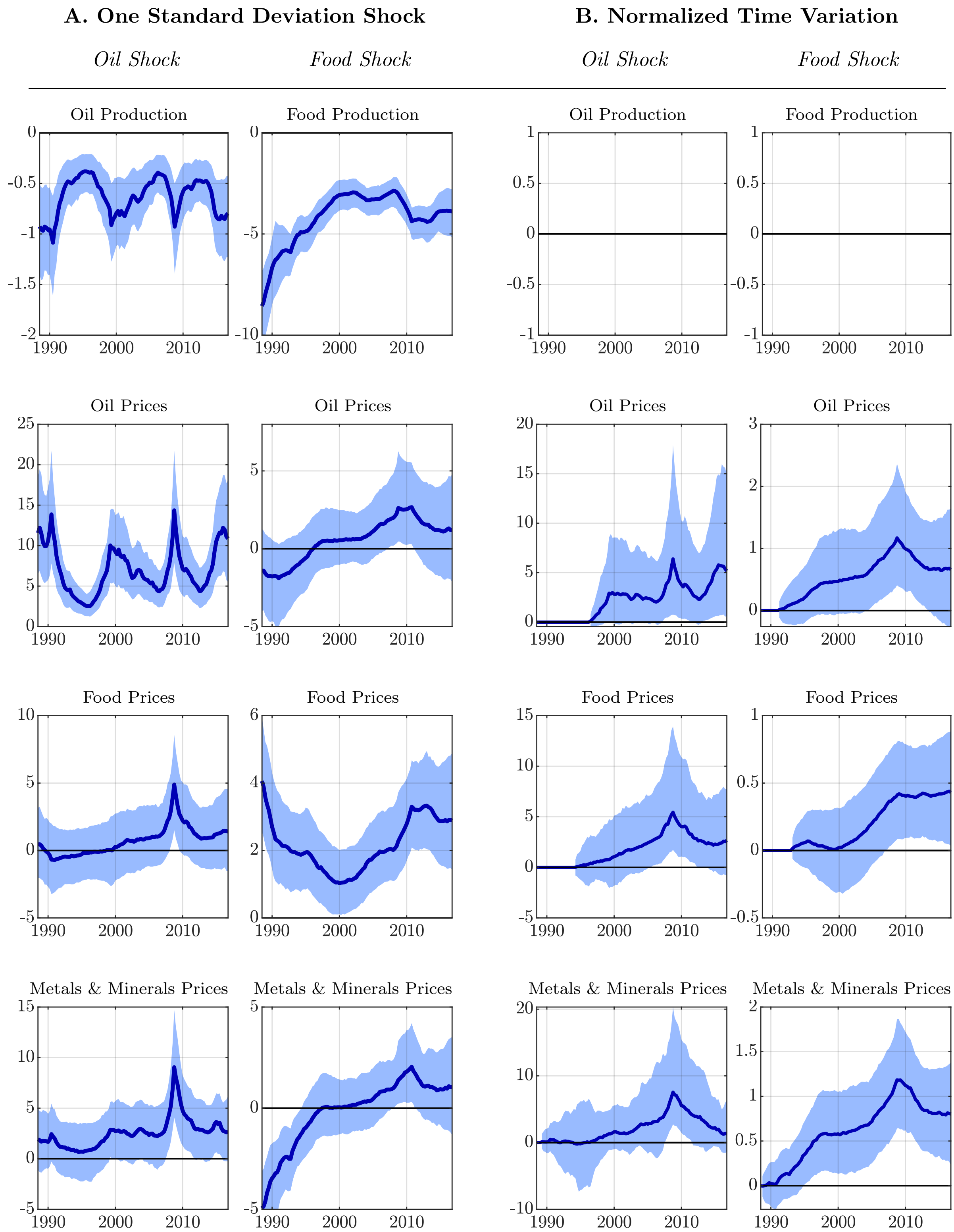
Notes: Panel A shows (the natural logarithm of) crude oil and food commodity prices, indexed to 2000=100. Food commodity prices are a weighted average of the prices of corn, soybeans, wheat and rice. The solid line and the shaded area in panel B denote kernel regression coefficients and the associated 68 percent confidence bands. The dotted line shows correlation coefficients for a sample split in 2003Q4/2004Q1. The dashed line displays correlations derived from 5-year rolling windows. These computations are based on the growth rates of the variables in panel A. The solid line in panel C plots NYMEX trading volumes of crude oil WTI futures contracts (dashed line) and corresponding CBOT aggregates for accumulated total corn, soybeans, wheat and rice futures, in millions of contracts (solid line). Panel D represents the share of biofuels in total U.S. petroleum consumption, measured in percent, and is computed using data made available by the U.S. Energy Information Administration.

Figure 2: Data



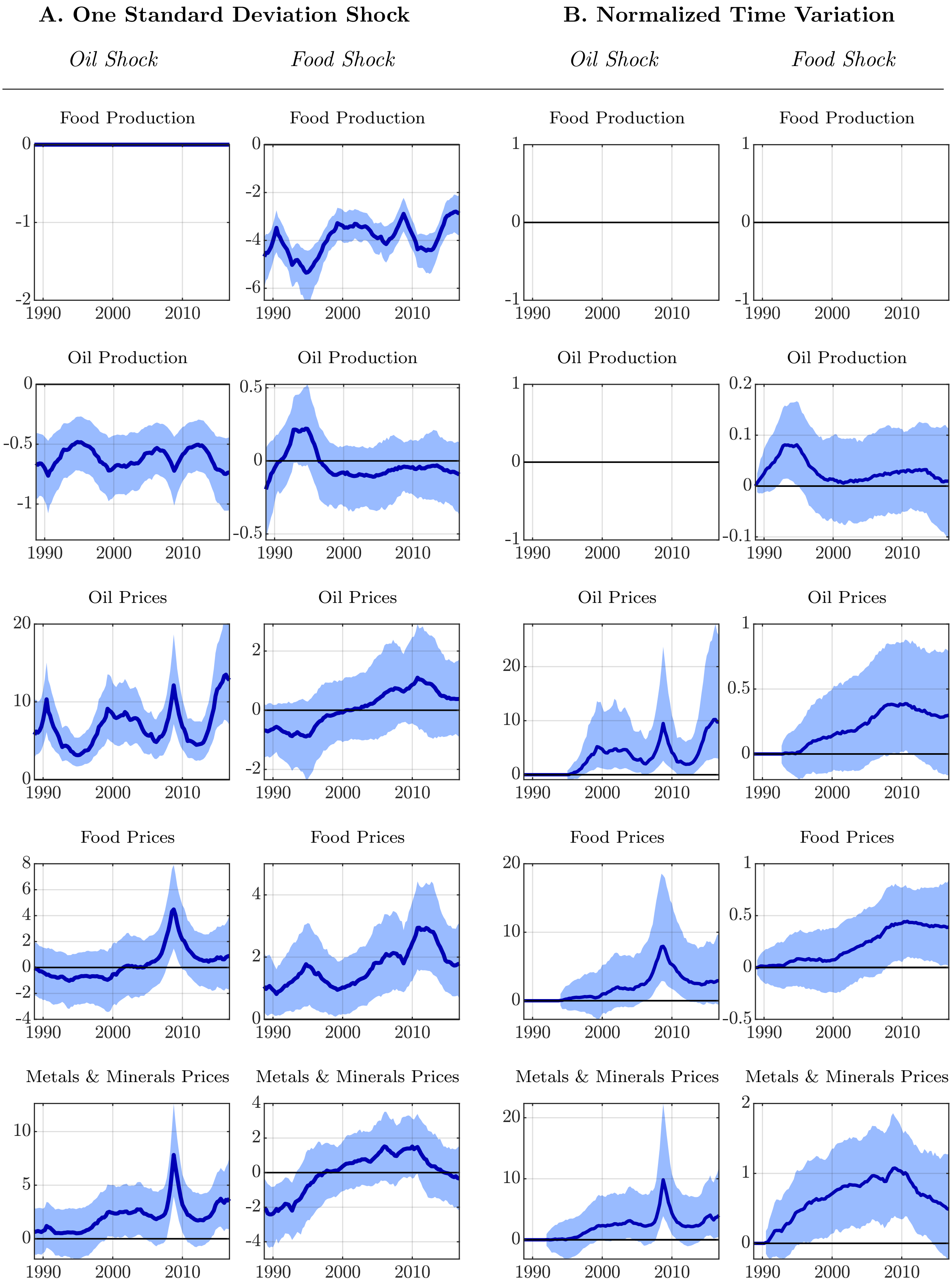
Notes: The left panels show (natural logarithms of) price and production indices normalized to 2010=100. The right panels show the variables in non-annualized quarterly growth rates.

Figure 3: Time-Varying Effects of Oil and Food Supply Shocks: Benchmark Results



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 the TVP-BVAR. 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 confidence bands.

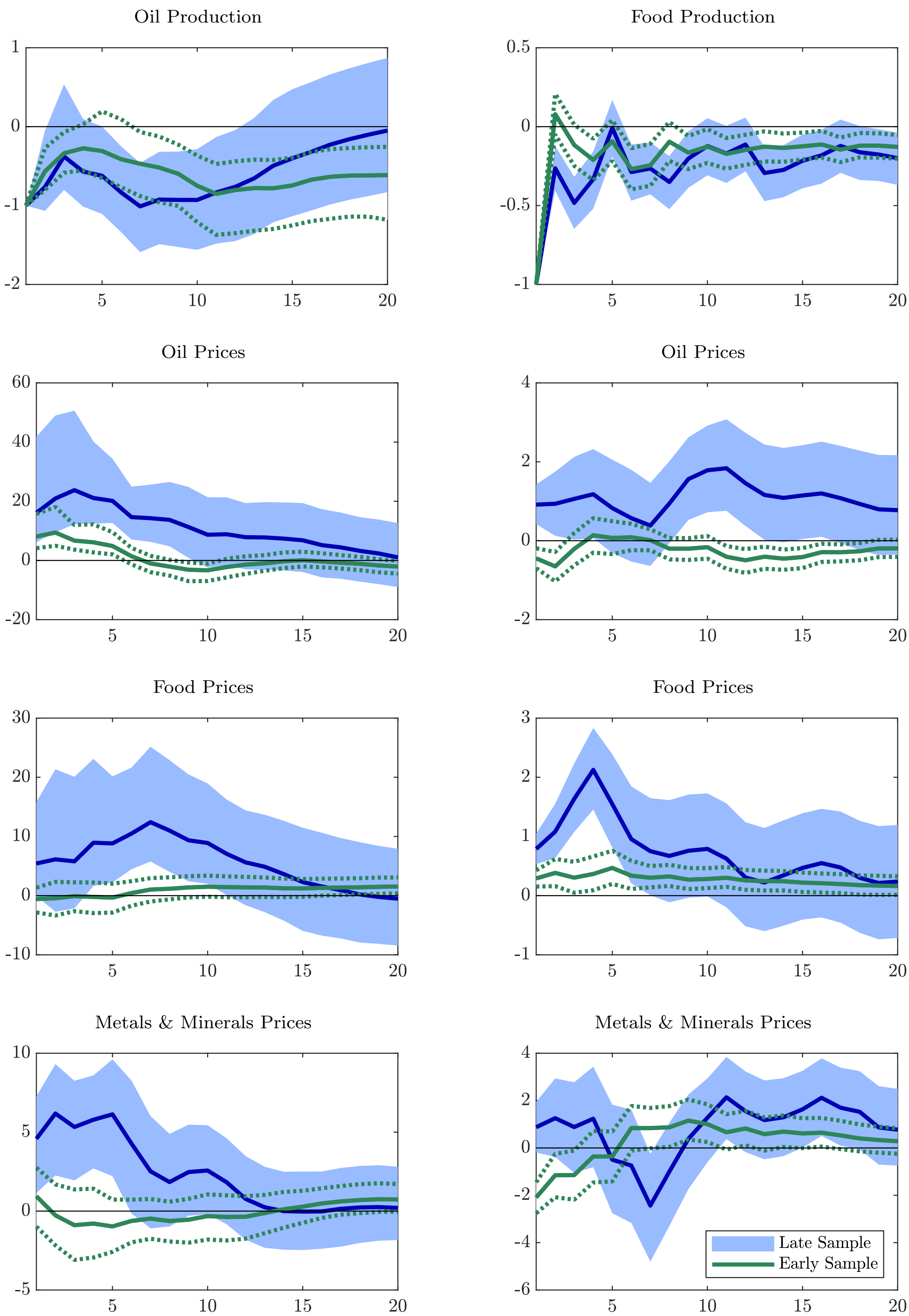
Figure 4: Time-Varying Effects of Oil and Food Supply Shocks: 5-Variable TVP-BVAR(4)



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 a 5-variable TVP-BVAR. 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 with 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 confidence bands.

Figure 5: Dynamic Effects of Oil and Food Supply Shocks Using a Sample Split in 2004Q1

A. 1 percent Oil Production Shortfall **B. 1 percent Food Production Shortfall**

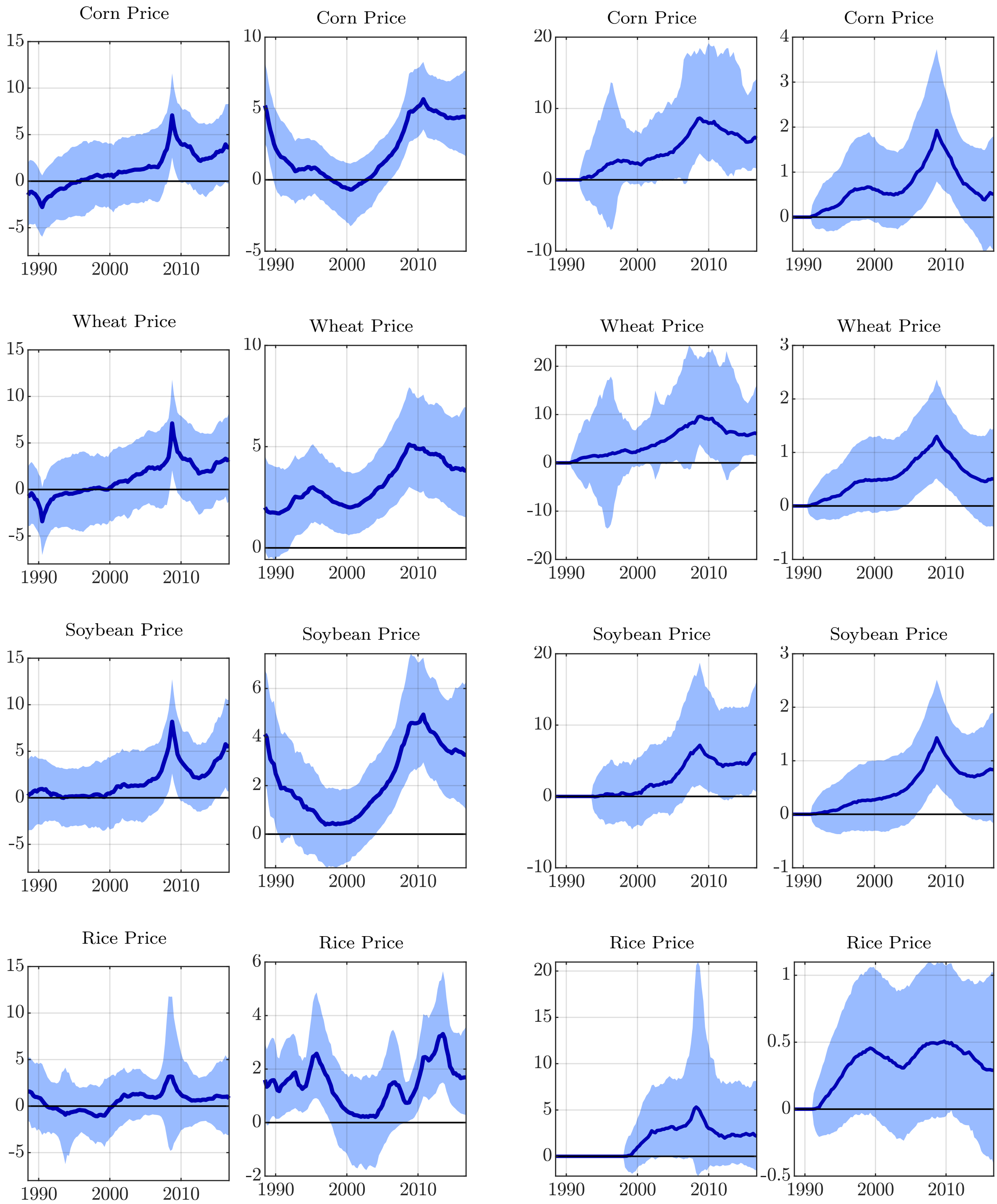


Notes: The early sample corresponds to the period from 1988Q3 to 2003Q4, while the late sample ranges from 2004Q1 to 2016Q4. The impulse responses are normalized to represent a 1 percent production shortfall in the oil or food market. The shaded areas and dotted lines are the 16th and 84th percentile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

Figure 6: Time-Varying Effects of Oil and Food Supply Shocks: Disaggregated Analysis

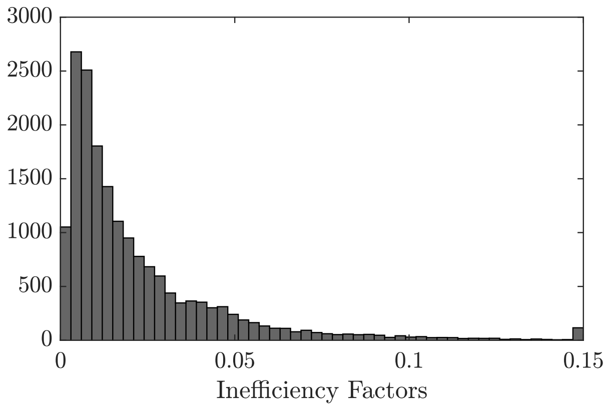
A. One Standard Deviation Shock | **B. Normalized Time Variation**

Oil Shock | *Food Shock* | *Oil Shock* | *Food Shock*



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 the TVP-BVAR. 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 confidence bands.

Figure A1: 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.