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A Global Oil Market Model with Shipping Costs

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Abstract

This paper investigates the role of shipping costs in global crude oil and refined petroleum markets and their effects on regional and country-level inflation and real activity. For this purpose a Global VAR (GVAR) model is estimated jointly for the oil and refined petroleum markets; this includes the Baltic Dirty Tanker Index (BDTI) and the Baltic Clean Tanker Index (BCTI) as measures of the cost of shipping crude oil and refined petroleum commodities, respectively. The results suggest that shocks to the cost of shipping petroleum commodities have a particularly severe negative impact on real economic activity and on petroleum consumption in most regions, while shocks to the price of crude oil and petroleum have inflationary effects, especially in oil-importing countries. Further, it appears that the relationship between commodity prices and their respective shipping costs has broken down since the beginning of the Covid-19 pandemic. Specifically, a counterfactual analysis shows that the pandemic moved the prices of crude oil and petroleum and their costs of shipping in opposite directions.

Keywords: Oil markets; petroleum prices; shipping costs; Baltic Dirty Tanker Index (BDTI); Baltic Clean Tanker Index; Global VAR (GVAR); real economic activity; inflation; Covid-19 counterfactual

JEL Classification: C32; F47; O50; Q43

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1. Introduction

During the Covid-19 pandemic the cost of oceanic shipping surged to unprecedented levels and since then it has been closely monitored by economic agents and academics. Recent studies have investigated the effect of shipping cost shocks on inflation and real activity in individual economies, these being found to be large and persistent, especially in economies which rely heavily on imports (Michail et al., 2022; Carrière-Swallow et al., 2023; Anderl and Caporale, 2024). This literature focuses on the cost of shipping dry bulk or general freight rates; however, no studies currently exist which examine the effects of shocks to the cost of shipping oil commodities on macroeconomic aggregates through changes in oil prices. The latter are a well-documented source of fluctuations in real economic activity and inflation (Kilian, 2008; 2014); it is surprising therefore that oil market models do not normally incorporate the cost of shipping oil commodities, this potentially being a key driver of their dynamics. The present paper aims to fill this gap by including both the price and the cost of shipping crude oil and refined petroleum in a single dynamic global model.

Note that the relationship between commodity prices and shipping costs is bidirectional. First, oil is both the cargo that is being shipped and the fuel required to operate the shipping tankers, hence its price can influence the cost of shipping directly. Second, oil shipping markets play an important role in balancing demand and supply in the market for oil commodities, which makes them an important determinant of their prices (Pouliasis and Bentsos, 2023). For instance, higher costs of shipping crude oil increase production costs for refineries, which can lead to higher refined petroleum prices. In order to investigate this bidirectional causality and the effects on macroeconomic aggregates in individual countries a modelling framework is needed that allows to analyse the simultaneous interactions between crude oil and refined petroleum prices and their respective shipping costs. The Global Vector Autoregressive (GVAR) method is ideally suited for this purpose, since it allows to establish the direction of causality in the context of a complex systems including several endogenous relationships.

The present paper makes a fourfold contribution to the existing literature. First, it extends the existing GVAR models of the global oil market by Mohaddes and Pesaran (2016) and Considine et al. (2022) by differentiating between the price of crude oil and that of refined petroleum commodities and by including equations for both sets of prices. Crude oil and refined petroleum are two separate though integrated markets, where the former is a direct input in the production of the latter. Second, it adds to the crude oil and petroleum price equations their respective shipping costs, measured by the Baltic Dirty Tanker Index (BDTI) and the Baltic Clean Tanker Index (BCTI). Third, it includes these two variables in a global model with price equations for each of them. Fourth, it uses monthly rather than quarterly data for the analysis, which allows to capture more dynamic interactions between the variables. Specifically, it estimates a global VAR (GVAR) for a large set of 34 countries, which collectively account for over 90% of global GDP, over the period from January 2000 until May 2024. Finally, it conducts a counterfactual analysis to assess the impact of the Covid-19 pandemic on the global variables in the model.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature; Section 3 discusses the modified GVAR model for the oil markets that includes shipping costs; Section 4 presents the empirical results; Section 5 provides some concluding remarks.

2. Literature Review

Global oil shocks and their effects on individual economies have been investigated at length in the economic literature. For instance, Kilian (2009) estimates a structural VAR model of the global crude oil market and distinguishes between an aggregate demand, oil-specific demand and oil supply shocks which affect the real oil price. His findings indicate that oil price shocks have different macroeconomic effects depending on the underlying cause of the shock and suggest that for future investigations of oil price shocks a model which endogenises the price of oil should be used. Kilian (2014) notes that a structural model of the global economy and the global oil market is required to identify correctly the relationship between oil prices and individual economies.

While the evidence concerning crude oil shocks is vast, less is known about shocks stemming from refined petroleum commodities, despite their being frequently consumed by households and firms. Petroleum commodities are also demanded indirectly by consumers who purchase goods and services which are reliant on petroleum commodities, such as flights which require jet fuel or shipped goods which require gasoline or diesel for transportation. Therefore, the prices of these petroleum commodities are more representative of those faced by households and firms than the price of crude oil. In this context it is important to distinguish between the different refined product categories, such as gasoline, distillate fuels, fuel oil and kerosene, which are included in the aggregate price of petroleum commodities. Kilian (2008) finds that the consumption of individual components, especially gasoline, responds strongly to unanticipated increases in energy prices. Kilian (2010) estimates a joint VAR model of the crude oil market and the US gasoline market to assess the causes of gasoline price shocks. His results show the importance of the latter for assessing the responses of gasoline consumption. Melichar (2016) examines the effect of alternative energy price shocks stemming from gasoline, diesel, natural gas and heating oil on US economic activity and finds that models incorporating alternative energy prices outperform those including crude oil prices. Kilian and Zhou (2022) investigate the effects of gasoline price shocks on US inflation expectations and finds that they account for 42% of the variation in household inflation expectations. Kilian and Zhou (2023) differentiate between energy categories, such as gasoline, diesel and jet fuel, in a structural VAR model of inflation and conclude that focusing only on gasoline price shocks underestimates the inflationary effects of energy price shocks. At present, there is only a handful of studies analysing the effects of refined petroleum product price shocks on individual countries other than the US or the global economy as a whole (Olanipekun et al., 2019; Liddle and Huntington, 2020).

GVAR models have become very popular owing to their ability to model interdependencies between countries in a multi-country setting. Concerning oil shocks, the study by Cashin et al. (2014) estimates a Global Oil VAR distinguishing between demand- and supply-driven oil price shocks. The latter are found to reduce (increase) economic activity in oil importing (exporting) countries. Demand-driven oil price shocks, on the other hand, appear to increase inflationary pressures and real output in almost all countries. Mohaddes and Pesaran (2016) develop a multi-country GVAR approach to examine the impact of country-specific oil supply shocks, the global effects of which differ substantially depending on the country of origin. Mohaddes and Pesaran (2017) use the same model to investigate the effects of low oil prices, which seem to have had a positive effect on real output globally and on economic activity in the US. Considine et al. (2022) explicitly account for country-specific oil inventories. Their results suggest that the global implications of an oil price shock are determined by market conditions existing prior to the shock. Considine et al. (2023) include the prices of critical minerals (lithium, cobalt, nickel) in their GVAR oil model; these are found to respond to oil price shocks and affect inflation, although the latter effect is only significant for two of the countries included in the model.

There is only a very small number of studies to date which are concerned with the cost of shipping crude oil and petroleum commodities. The Baltic Dirty Tanker Index (BDTI) measures the freight rates for shipping unrefined crude oil, while the Baltic Clean Tanker Index (BCTI) does the same for carrying clean petroleum commodities such as gasoline, kerosene and diesel. Shi et al. (2013) use a structural VAR model to assess the effects of supply and non-supply driven crude oil price shocks on BDTI, which they find to be positive but not as sizeable as those of other types of shocks. Michail (2020) estimates a Vector Error Correction Model (VECM) to analyse the long-run relationship between the cost of shipping crude oil, petroleum and dry cargo and world GDP and the price of oil. Output growth in middle-income economies is found to have a particularly strong effect on the transportation cost of both oil and petroleum commodities, while oil prices appear to have a significant effect only on the latter. Michail and Melas (2020) use both GARCH and VAR specifications to assess the response of freight rates to the Covid-19 pandemic shock and find that BCTI, but not BDTI, is strongly affected by the demand side of the economy. Their results also point to strong second-round effects through oil prices which seem to drive a large part of the demand for shipping services. Finally Pouliasis and Bentsos (2023) investigate the co-movement in the returns of the price of oil and BDTI in the presence of oil market uncertainty. Their findings indicate a negative impact of oil price uncertainty on the correlation between oil and BDTI returns.

3. Empirical Framework

3.1 The general model setup

Global VAR models are constructed by combining many country-specific models together with common variables into a global model which can account for many transmission channels of shocks. The method is ideally suited to assess the country-specific or regional responses to shocks stemming from global markets, such as the market for oil or shipping. Two attractive features of the model are that it allows to establish the direction of causality in complex systems with endogenous relationships and that it can incorporate counterfactual scenarios.

Consider first the following aggregate crude oil and refined petroleum demand functions:

$$Qd_t^O = a_{d^O} + \epsilon_{y^O} a_{y^O}(L) y_t - \epsilon_{b^O} a_{b^O}(L) b_t^O - \epsilon_{p^O} a_{p^O}(L) p_t^O + \varepsilon_{d_t^O} \qquad (1)$$

$$Qd_t^P = a_{d^P} + \epsilon_{c^P} a_{c^P}(L) c_t - \epsilon_{b^P} a_{b^P}(L) b_t^P + \epsilon_{I^P} a_{I^P}(L) I_t^P - \epsilon_{p^P} a_{p^P}(L) p_t^P + \varepsilon_{d_t^P} \qquad (2)$$

where Qd_t^O is the world demand for crude oil and Qd_t^P the world demand for refined petroleum, y_t stands for world real activity, c_t for petroleum consumption, I_t^P for petroleum inventories, b_t^O and b_t^P denote the Baltic Dirty and Clean Tanker Indices respectively, and p_t^O and p_t^P stand for the real world prices of crude oil and petroleum respectively;[1] a_{d^O} and a_{d^P} are constants, and $a_{y^O}(L)$, $a_{y^P}(L)$, $a_{b^O}(L)$, $a_{b^P}(L)$, $a_{p^O}(L)$ and $a_{p^P}(L)$ are polynomials in the lag operator whose coefficients add up to unity. It follows that ϵ_{y^O} and ϵ_{p^O} are the long-run income and price elasticities of the demand for crude oil, ϵ_{c^P} and ϵ_{p^P} the long-run income and price elasticities of the demand for refined petroleum, ϵ_{b^O} the long-run cross-elasticity of the demand for crude oil and the cost of shipping crude oil, and ϵ_{p^P} the long-run cross-elasticity of the demand for petroleum and the cost of shipping petroleum. The crude oil and petroleum supply functions take the following general form:

$$Qs_t^O = a_{s^O} + \epsilon_{s^O} a_{s^O}(L) p_t^O + \varepsilon_{s_t^O} \tag{3}$$

$$Qs_t^P = a_{s^P} + \epsilon_{P^P} a_{P^P}(L) p_t^O + \epsilon_{s^P} a_{s^P}(L) p_t^P + \epsilon_{b^P} a_{b^P}(L) b_t^O + \varepsilon_{s_t^P} \tag{4}$$

where Qs_t^O is the world supply of crude oil and Qs_t^P is the world supply of petroleum. One can assume that the supply of crude oil depends solely on its price, whilst the supply of petroleum depends on the price of petroleum as well as the price of crude oil and the cost of shipping crude oil, since the latter two are direct costs of petroleum production. It is noteworthy that in our GVAR model crude oil production, but not petroleum production, is observed. In addition, the crude oil and petroleum shipping cost markets can be described by the following equations:

$$b_t^O = b_{b^O} + b_{y^O}(L) y_t + b_{\pi^O}(L) \pi_t + b_{p^O}(L) p_t^O + \varepsilon_{b_t^O} \tag{5}$$

$$b_t^P = b_{b^P} + b_{y^P}(L) c_t + b_{\pi^P}(L) \pi_t + b_{p^P}(L) p_t^P + \varepsilon_{d_t^P} \tag{6}$$

where π_t is world inflation and $b_{y^O}(L)$, $b_{y^P}(L)$, $b_{\pi^O}(L)$, $b_{\pi^P}(L)$, $b_{p^O}(L)$ and $b_{p^P}(L)$ are polynomials in the lag operator whose coefficients add up to unity.

We then assume that crude oil and petroleum prices adjust to remove any imbalances between the demand and the supply of crude oil and petroleum in their respective markets:

[1] It is important to note that there is no single global price for petroleum, which includes several products such as gasoline, diesel and other fuel oils, all of which are priced differently. For our purposes we create a global production-share weighted price index which is computed using the prices of the individual petroleum categories. We believe this measure to be a reasonable approximation for the aggregate global petroleum price.

$$\Delta p_t^O = a_{s^O} + \lambda_O (Qd_t^O - Qs_t^O) + \varepsilon_{p_t^O} \tag{7}$$

$$\Delta p_t^P = a_{s^P} + \lambda_P (Qd_t^P - Qs_t^P) + \varepsilon_{p_t^P} \tag{8}$$

where λ_O is the speed of adjustment between crude oil supply and demand, and λ_P is the speed of adjustment between petroleum supply and demand; a_{s^O} and a_{s^P} are constants which reflect scarcity of crude oil and petroleum, respectively, and $\varepsilon_{p_t^O}$ and $\varepsilon_{p_t^P}$ represent speculative changes in the price of crude oil and petroleum which are not related to fundamental factors.

Substitution of (1) and (2) into (5) and (6) gives:

$$\begin{gathered}\Delta p_t^O = a_{p^O} + \lambda_O (a_{d^O} + \epsilon_{y^O} a_{y^O}(L) y_t - \epsilon_{b^O} a_{b^O}(L) b_t^O - \epsilon_{p^O} a_{p^O}(L) p_t^O + \\ + \varepsilon_{d_t^O} - Qs_t^O) + \varepsilon_{p_t^O}\end{gathered} \tag{9}$$

$$\begin{gathered}\Delta p_t^P = a_{p^P} + \lambda_P (a_{d^P} + \epsilon_{y^P} a_{y^P}(L) c_t - \epsilon_{b^P} a_{b^P}(L) b_t^P + \epsilon_{I^P} a_{I^P}(L) I_t^P - \\ - \epsilon_{p^P} a_{p^P}(L) p_t^P + \varepsilon_{d_t^P} - Qs_t^P) + \varepsilon_{p_t^P}\end{gathered} \tag{10}$$

or

$$\begin{gathered}\Delta p_t^O = a_{f^O} + \lambda_O (\epsilon_{y^O} a_{y^O}(L) y_t - \epsilon_{b^O} a_{b^O}(L) b_t^O - \epsilon_{p^O} a_{p^O}(L) p_t^O - \\ - Qs_t^O) + \varepsilon_{f_t^O}\end{gathered} \tag{11}$$

$$\begin{gathered}\Delta p_t^P = a_{f^P} + \lambda_P (\epsilon_{y^P} a_{y^P}(L) c_t - \epsilon_{b^P} a_{b^P}(L) b_t^P + \epsilon_{I^P} a_{I^P}(L) I_t^P - \\ - \epsilon_{p^P} a_{p^P}(L) p_t^P - Qs_t^P) + \varepsilon_{f_t^P}\end{gathered} \tag{12}$$

where $a_{f^O} = a_{s^O} + \lambda_O a_{d^O}$, $a_{f^P} = a_{s^P} + \lambda_P a_{d^P}$, $\varepsilon_{f_t^O} = \varepsilon_{s_t^O} + \lambda_O \varepsilon_{d_t^O}$ and $\varepsilon_{f_t^P} = \varepsilon_{s_t^P} + \lambda_P \varepsilon_{d_t^P}$. One can then solve for p_t^O and p_t^P to obtain the following autoregressive distributed lag (ARDL) models:

$$p_t^O = c_O + \sum_{l=1}^{m_{p^O}} \alpha_l^O p_{t-l}^O + \sum_{l=1}^{m_{y^O}} \beta_l^O y_{t-l} + \sum_{l=1}^{m_{b^O}} \gamma_l^O b_{t-l}^O + \sum_{l=1}^{m_{q^O}} \delta_l^O Qs_{t-l}^O + v_t^O \tag{13}$$

$$p_t^P = c_O + \sum_{l=1}^{m_{p^P}} \alpha_l^P p_{t-l}^P + \sum_{l=1}^{m_{y^P}} \beta_l^P c_{t-l} + \sum_{l=1}^{m_{b^P}} \gamma_l^P b_{t-l}^P + \sum_{l=1}^{m_{b^P}} \theta_l^P I_{t-l}^P + \sum_{l=1}^{m_{q^P}} \delta_l^P Qs_{t-l}^P + v_t^P \tag{14}$$

where the maximum lag lengths m_{p^O}, m_{y^O}, m_{b^O}, m_{q^O}, m_{p^P}, m_{y^P}, m_{b^P} and m_{q^P} are selected using the Schwartz-Bayesian information criterion and are allowed to vary for the different variables.

3.2 The country-specific VARX* models

The GVAR model is estimated in two steps. First, Vector Autoregressive Models with foreign variables (VARX*) are estimated for each country individually; these include both domestic and foreign variables as well as a set of global variables which are common across all countries, namely the world crude oil and petroleum prices in addition to the corresponding shipping costs. In the second step, all individual models are combined into a GVAR one for the whole world. The country-specific equations take the following form:

$$X_{it} = \mu_{i0} + \mu_{i1}t + \Phi_i(L)X_{it} + \Theta_i(L)X_{it}^* + \Gamma_{\mathrm{i}}(L)Z_t + u_{it} \tag{15}$$

where X_{it} is a $(k_i \times 1)$ vector of country-specific endogenous variables for $i = 1,2, \dots, N$, X_{it}^* is a $(k_i \times 1)$ vector of country-specific *star* foreign variables which are weakly exogenous, and Z_t is a (4×1) vector of global variables, more specifically $Z_t = (p_t^O, p_t^P, b_t^O, b_t^P)$. The country-specific domestic variables are given by the vector $X_{it} = \left(Qs_{it}^O, y_{it}, c_{it}^P, \pi_{it}, I_{it}, ep_{it}, eq_{it}, r_{it}^S, r_{it}^L\right)$, where Qs_{it}^O stands for the production of crude oil at time t for country i, y_{it} for real GDP, c_{it}^P for the consumption of refined petroleum goods, π_{it} for the inflation rate, ep_{it} for the real exchange rate, eq_{it} for the equity price index, and r_{it}^S and r_{it}^L for the short- and long-term interest rates respectively. The foreign variables are trade-weighted using country-specific trade shares:

$$X_{it}^* = \sum_{j=1}^{N} w_{ij} X_{jt} \tag{16}$$

where w_{ij} are bilateral trade weights with $i, j = 1,2, \dots, N$, with $w_{ii} = 0$ and $\sum_{j=1}^{N} w_{ij} = 1$. The trade weights are computed as a three-year moving average.

3.3 Solving the GVAR model

In the second stage, we solve the GVAR where all variables are endogenous. For this purpose the country-specific equations are combined with the oil and petroleum price ones and the corresponding shipping cost ones. The combined model allows for bidirectional linkages between the global economy and the prices and shipping costs of both crude oil and petroleum. While the estimation is done country-by-country, the GVAR model is solved for the global variables and all country variables simultaneously, which are collected in the vector $Y_t = (Z_t, X_{it}')'$, where $X_{it}^* = W_i X_t$ and W_i is a $k_i^* \times (k+1)$ matrix of the trade weights w_{ij} with $k = \sum_{i=1}^{N} k_i$. One then obtains $A_i W_i X_t = \mu_{i0} + \mu_{i1} t + B_i W_i X_{t-1} + e_{it}$ such that the country-specific models can be stacked as follows:

$$GX_t = \mu_0 + \mu_1 t + \Phi(L) X_t + \Gamma(L) Z_t + u_t \tag{17}$$

where $\mu_0 = \begin{pmatrix} \mu_{10} \\ \mu_{20} \\ \vdots \\ \mu_{N0} \end{pmatrix}$, $\mu_1 = \begin{pmatrix} \mu_{11} \\ \mu_{21} \\ \vdots \\ \mu_{N1} \end{pmatrix}$, $G = \begin{pmatrix} \mathrm{A}_{10}\mathrm{W}_1 \\ \mathrm{A}_{20}\mathrm{W}_2 \\ \vdots \\ \mathrm{A}_{\mathrm{N}0}\mathrm{W}_\mathrm{N} \end{pmatrix}$, $\Phi_\mathrm{j} = \begin{pmatrix} \mathrm{B}_{1j} W_1 \\ \mathrm{B}_{2j} W_2 \\ \vdots \\ \mathrm{B}_{Nj} W_N \end{pmatrix}$, $\Gamma_\mathrm{j} = \begin{pmatrix} \Gamma_{1\mathrm{j}} \\ \Gamma_{2\mathrm{j}} \\ \vdots \\ \Gamma_{\mathrm{Nj}} \end{pmatrix}$, $u_t = \begin{pmatrix} u_{1t} \\ u_{2t} \\ \vdots \\ u_{Nt} \end{pmatrix}$, $j = 1, 2, \dots, p$ with maximum lag length p and $A_i W_i$ and $B_i W_i$ are both k-dimensional matrices of coefficients that differ across countries, and Γ is a matrix of coefficients on the global variables. The GVAR can then be expressed in terms of the endogenous variables Y_t as:

$$GY_t = \mu_0 + \mu_1 t + HY_{t-1} + \vartheta_t \tag{18}$$

which has the following reduced-form solution:

$$Y_t = d_0 + d_1 t + FY_{t-1} + \xi_t \tag{19}$$

where $d_i = G^{-1}\mu_i$, $i = 0,1$, $F = G^{-1}\mathrm{H}$ and $\xi_t = G^{-1}\vartheta_t$. The above model combines the country-specific models with the global oil and petroleum price equations as well as the oil and petroleum shipping cost equations.

One can allow for feedback from the domestic variables to the global variables through the price equations for oil (15) and petroleum (16), and through the shipping cost equations for crude oil (5) and petroleum (6), by attaching the following weights to the global macroeconomic variables:

$$y_t^* = \sum_{j=1}^{N} \omega_j^y y_{jt}\,; \quad Qs_t^{O*} = \sum_{j=1}^{N} \omega_j^{Q^O} Qs_{jt}^O$$

$$I_t^* = \sum_{j=1}^{N} \omega_j^I I_{jt}\,; \quad c_t^{P*} = \sum_{j=1}^{N} \omega_j^{Q^P} c_{jt}^P$$

where ω_j^y is the three-year average of the PPP-GDP weights of country j with $\sum_{j=1}^{N} \omega_j^y = 1$, and $\omega_j^{Q^O}$ and $\omega_j^{Q^P}$ are the three-year average of the weighted contribution of country j to global crude oil and petroleum production respectively with $\sum_{j=1}^{N} \omega_j^{Q^O} = 1$ and $\sum_{j=1}^{N} \omega_j^{Q^P} = 1$.

Next impulse response functions can be obtained. Specifically, generalised impulse response functions as in Pesaran and Shin (1998) are estimated here since they are invariant to the ordering of the variables - restrictions would otherwise have to be imposed to achieve identification, which would not feasible in a model with 34 countries and a large set of endogenous variables, since too many would be required. For the estimation the toolbox provided by Smith and Galesi (2014) is used. The lags lengths for the unit root tests, the VARX models and the weak exogeneity tests are determined using the Schwartz-Bayesian information criterion.

3.4 Counterfactual analysis

The Covid-19 pandemic had large effects on supply chains and oceanic shipping markets, which increased the cost of seaborn transportation. In order to assess them in the context of our GVAR model we estimate it for a subsample ending in December 2019, i.e. shortly before the Covid-19 pandemic outbreak, as well as for the full sample ending in May 2024, with January 2000 as the start date in both cases. A counterfactual analysis is then conducted to investigate the impact of the Covid-19 shock by using growth forecast revisions as in Chudik et al. (2021). Specifically, we compare the IMF GDP forecasts made in December 2019 (before the start of the pandemic) with those in April 2020 (shortly after the start of the pandemic). The difference between the two, i.e. the forecast revisions, can be attributed to the Covid-19 shock.

4. Data and Empirical Results

4.1 Data description

We use monthly data from January 2000 to May 2024. The Baltic Dirty Tanker Index (BDTI) and the Baltic Clean Tanker Index (BCTI) are obtained from Bloomberg. Brent spot prices are used for the global crude oil prices, but the analysis is also repeated using WTI (West Texas Intermediate) prices as a robustness check. Both are obtained from the US EIA (Energy Information Administration). The petroleum price is constructed as a global production-share weighted price index computed using the prices of the individual petroleum categories, namely gasoline, kerosene, diesel fuel, heating oil and propane; details are provided in Appendix A. The sample includes a total of 34 countries; these represent six regions and together account for over 90% of world GDP. They are the same countries as in Mohaddes and Pesaran (2016) and are listed in Table 1. Detailed data sources for all country-specific variables are provided in Appendix A.

Table 1. Countries and regions in the GVAR model

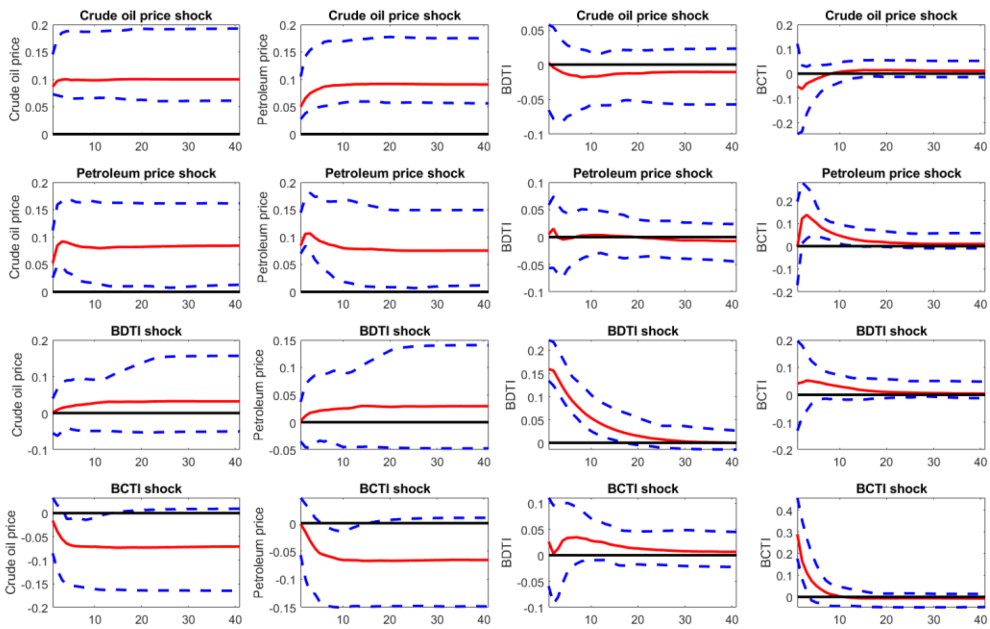
Net oil exporters	**Net oil importers**	**Europe**	**Asia Pacific**	**Latin America**	**Rest of the world**
Canada	Brazil	Austria	Australia	Chile	South Africa
Indonesia	China	Belgium	India	Peru	Turkey
Iran	UK	Finland	Japan		
Mexico	US	France	South Korea		
Norway		Germany	Malaysia		
Russia		Italy	New Zealand		
Saudi Arabia		Netherlands	Philippines		
		Spain	Singapore		
		Sweden	Thailand		
		Switzerland			

Notes: Countries and regions in the GVAR model.

4.2 Responses of the global variables

In this section we present the responses of the global variables to the global shocks. Figure 1 shows the responses to a positive one standard deviation shock to the crude oil and refined petroleum prices as well as to BDTI and BCTI. This corresponds to an increase by 8.67% and 8.4% in the price of crude oil and refined petroleum respectively, and by 15.90% and 28.89% in the case of BDTI and BCTI in turn. There appear to be strong linkages between crude oil and refined petroleum, but not between their prices and shipping costs. The results are robust to whether the Brent spot prices or the WTI ones are used (the latter results are not reported to save space). Despite the lack of a significant relationship between oil prices and shipping costs, the latter might still affect regional or country-level macroeconomic variables, which we investigate next.

Figure 1. Global variable responses to global shocks



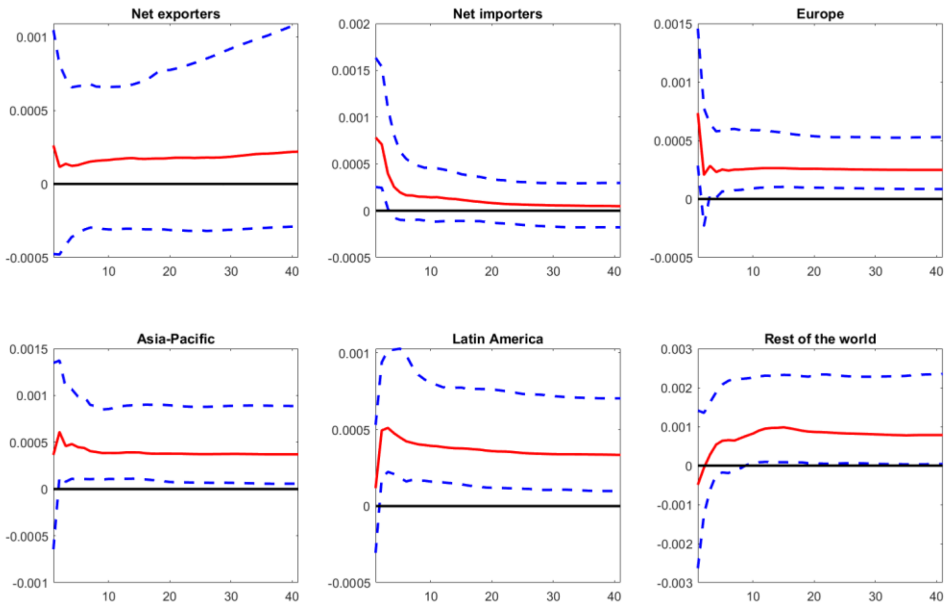
Notes: Impulse responses to a one-standard deviation positive shock to the global variables. Bootstrap median estimates with 90% bootstrap error bounds.

4.3 Regional and country-level responses to global shocks

Evidence on the responses of regional and country-level inflation and real economic activity to the global shocks is presented in the following figures, which only include significant results. Specifically, Figures 2 and 3 report regional inflation responses to a crude oil and a petroleum price shock respectively. It can be seen that net importers of crude oil and European countries are affected the most by an increase in the price of crude oil; in both cases inflation increases by around 0.08%. A shock to the price of petroleum instead increases inflation not only for net importers (0.1%) and in Europe (0.08%) but also in Latin America (0.03%) and the rest of the world, namely South Africa and Turkey (0.22%). Figures 4 and 5 report the responses of regional petroleum consumption and real economic activity to a BCTI shock. A positive shock to the cost of shipping petroleum lowers petroleum consumption by 0.12% in net exporting countries, by 0.76% in net importing countries, by 0.30% Latin America and by 0.22% in the rest of the world. Real economic activity decreases for net importers and in Europe by 0.83% and by 1.56% for the rest of the world in response to the same shock.

Next we report country-specific responses to the global shocks. Figure 6 displays the responses of inflation to a positive BCTI shock for selected countries. In India, the Philippines, South Africa, Saudi Arabia and Thailand the response is negative, while in Brazil, Norway and Sweden it is positive. This is not very surprising since the former set of countries have large refining industries while the latter are heavily reliant on refined petroleum imports. The size of the responses is largest in India (-0.16%), Thailand (-0.15%) and Sweden (0.10%). Figure 7 shows the responses of petroleum consumption to a positive BCTI shock. As expected, petroleum consumption falls in all countries and especially in Italy (-1.40), France (-0.90%), the UK (-0.80%) and the US (-0.76%). Finally, Figure 8 displays the effects of a positive BCTI shock on real economic activity in individual countries. The latter falls in all countries with the exception of Finland, Indonesia, Japan, Norway, Russia and Singapore. The strongest responses are recorded for Indonesia (9.13%), Singapore (8.05%), India (-3.89%), South Africa (-2.14%) and Russia (1.78%). The effect is also relatively large for Italy, Mexico, Turkey, Austria, Peru, China and Brazil, with values ranging between 1.10% and 1.39%.

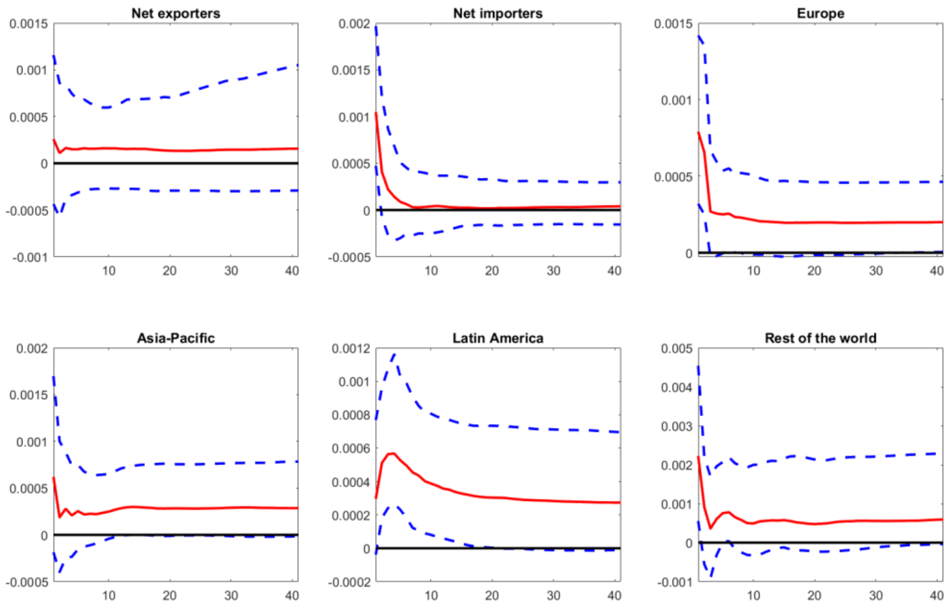
Figure 2. Regional inflation responses to crude oil price shock



Notes: Impulse responses to a one-standard deviation positive crude oil price shock. Bootstrap median estimates with 90% bootstrap error bounds.

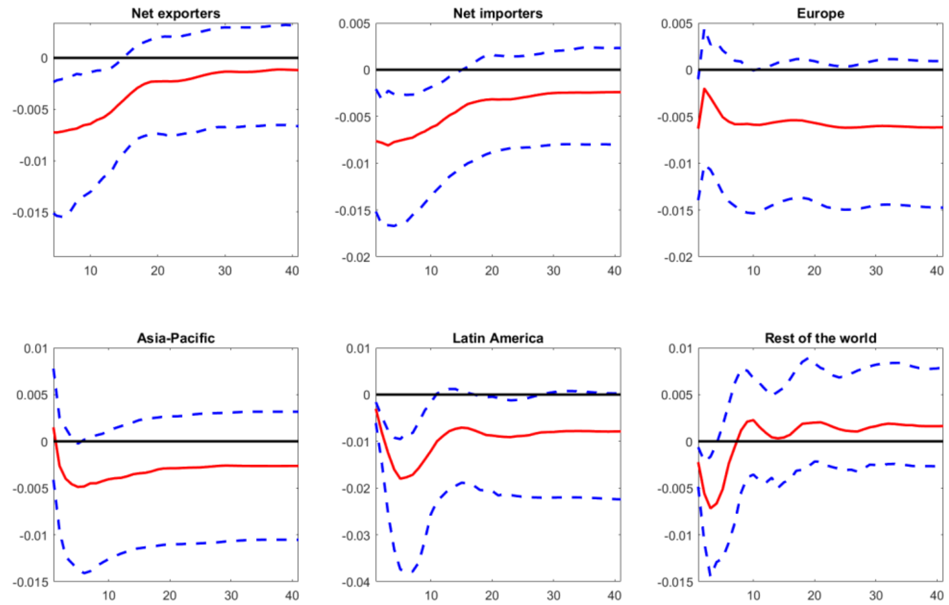
In summary, it seems that inflation is primarily affected by shocks to the price of crude oil and petroleum, while refined petroleum consumption and real economic activity respond mainly to shocks to the cost of shipping petroleum commodities. By contrast, the cost of shipping crude oil does not appear to have an impact on either inflation or real economic activity.

Figure 3. Regional inflation responses to petroleum price shock



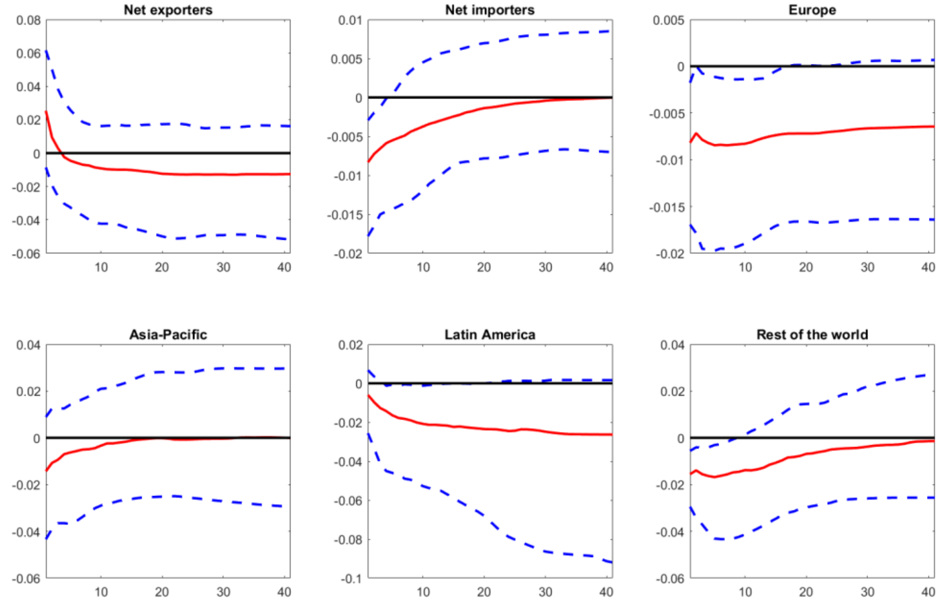
Notes: Impulse responses to a one-standard deviation positive refined petroleum oil price shock. Bootstrap median estimates with 90% bootstrap error bounds.

Figure 4. Regional petroleum consumption responses to BCTI shock



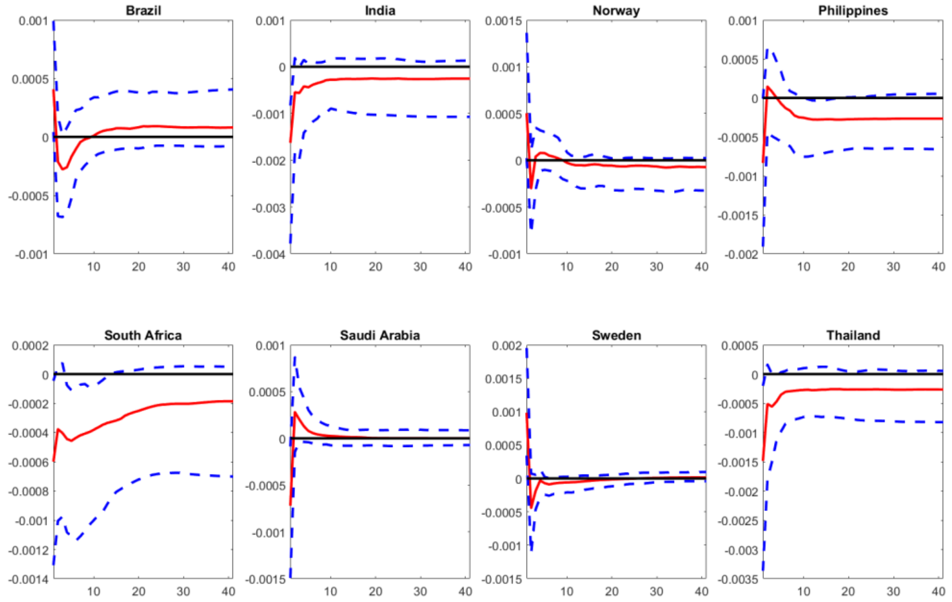
Notes: Impulse responses to a one-standard deviation positive BCTI shock. Bootstrap median estimates with 90% bootstrap error bounds.

Figure 5. Regional real activity responses to BCTI shock



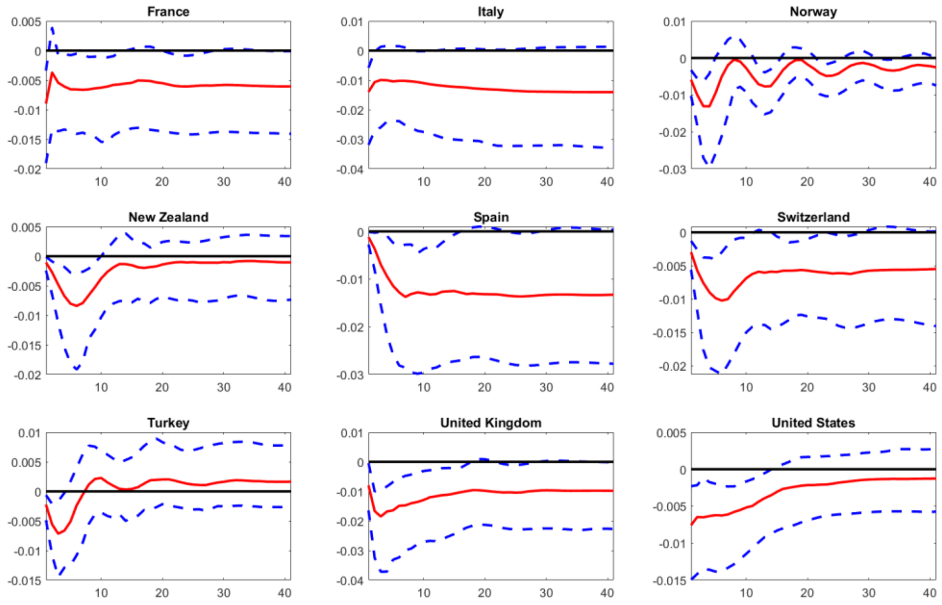
Notes: Impulse responses to a one-standard deviation positive BCTI shock. Bootstrap median estimates with 90% bootstrap error bounds.

Figure 6. Country-level inflation responses to BCTI shocks



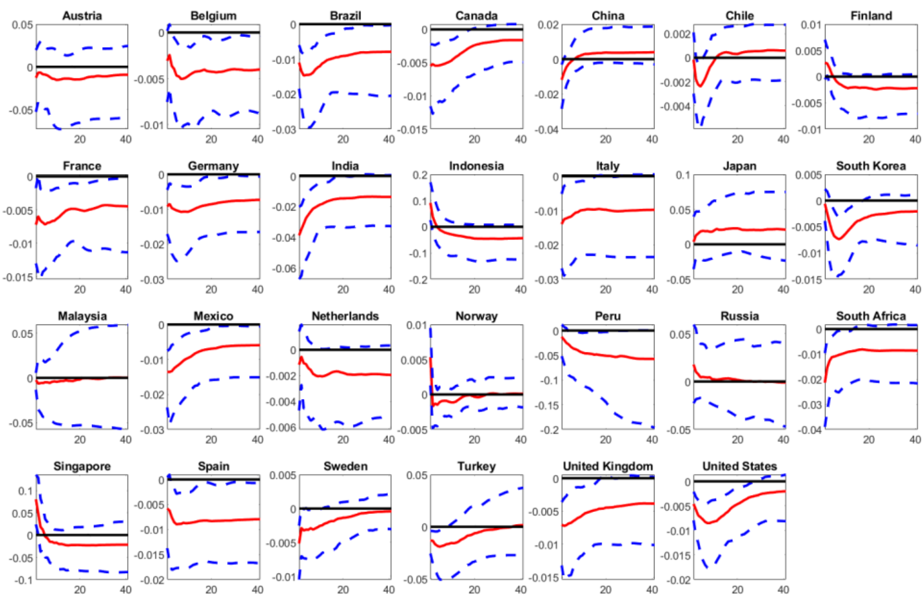
Notes: Impulse responses to a one-standard deviation positive BCTI shock for selected countries. Bootstrap median estimates with 90% bootstrap error bounds.

Figure 7. Country-level petroleum consumption responses to BCTI shocks



Notes: Impulse responses to a one-standard deviation positive BCTI shock for selected countries. Bootstrap median estimates with 90% bootstrap error bounds.

Figure 8. Country-level real activity responses to BCTI shock

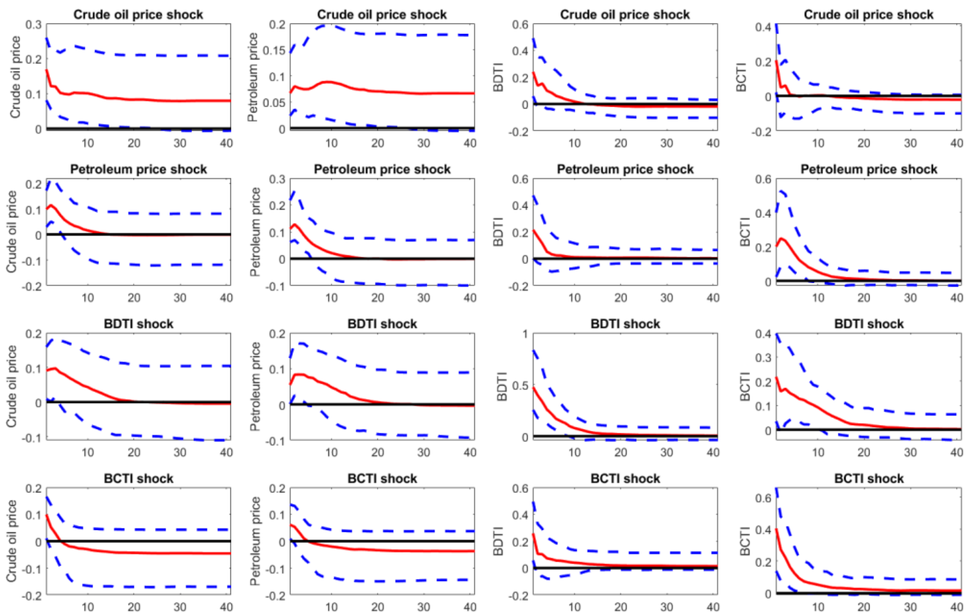


Notes: Impulse responses to a one-standard deviation positive BCTI shock. Bootstrap median estimates with 90% bootstrap error bounds.

4.4 The effect of the Covid-19 pandemic

Next we investigate the effect of the Covid-19 pandemic on the dynamic linkages between the variables in the model. For this purpose, first we estimate the GVAR model for a subsample ending in December 2019, which yields different results for the global variables compared to the full sample ones (see Figure 9). More precisely, we now find a significant response of BDTI and BCTI to crude oil and refined petroleum price shocks and vice versa, which suggests a stronger link between commodity prices and shipping costs before the pandemic. This suggests that since its beginning shipping costs might have been more strongly influenced by general supply chain pressures and bottlenecks rather than the price of the commodity that is being shipped. To analyse more rigorously the impact of the pandemic on the global variables in the model, we conduct a counterfactual analysis using the IMF growth projection revisions between December 2019 and April 2020. These results are reported in Table 10 and indicate that the Covid-19 shock caused a large increase of around 10% in BDTI and BCTI, although there is a significant amount of uncertainty around the counterfactual paths. Crude oil and refined petroleum prices decreased by around 5% in response to the Covid-19 shock. Overall, the results indicate that the pandemic introduced a large amount of noise, which led to shipping costs moving in the opposite direction to crude oil and petroleum prices.

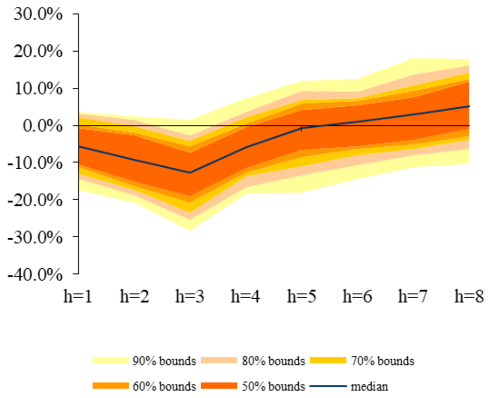
Figure 9. Global variable responses to global shocks before the Covid-19 pandemic



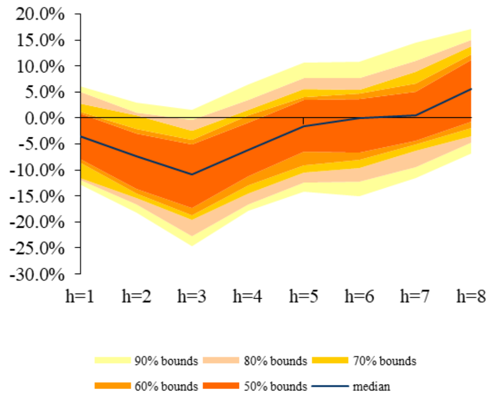
Notes: Impulse responses to a one-standard deviation positive to the global variables for the subsample ending in December 2019. Bootstrap median estimates with 90% bootstrap error bounds.

Figure 10. The impact of the Covid-19 pandemic on the global variables

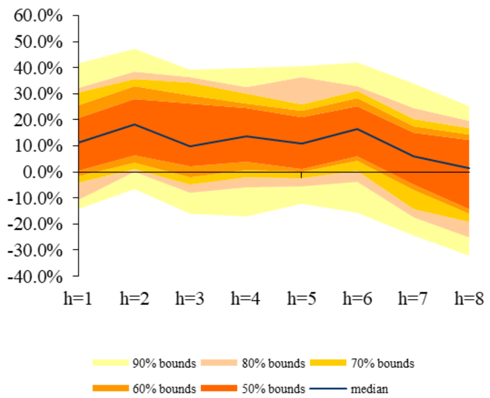
Panel A. Crude oil price



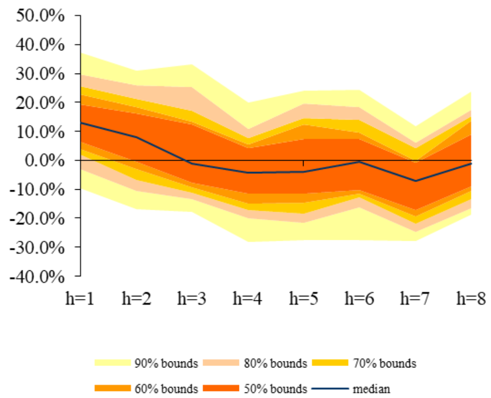
Panel B. Petroleum price



Panel C. BDTI



Panel D. BCTI



Notes: Impact of the Covid-19 shock in percent deviation from the baseline.

5. Conclusions

This paper examines the role of shipping costs for crude oil and refined petroleum commodities in the global oil markets and their impact on the world economy. For this purpose a GVAR model is estimated for 34 countries using monthly data from January 2000 until May 2024, with the Baltic Dirty and Clean Tanker Indices being included as measures of shipping costs in the crude oil and refined petroleum markets. A counterfactual analysis is then conducted to assess the effects of the Covid-19 shock on the global variables.

Our findings can be summarised as follows. First, there appears to be linkages between the price of crude oil or petroleum and their respective shipping costs only in the period before the start of the Covid-19 pandemic, during which crude oil price shocks had large positive effects on shipping costs and vice versa. Since the pandemic, this relationship has broken down, which suggests that shipping costs and oil prices have been driven by other factors. Second, inflation is primarily affected by shocks to the price of crude oil and refined petroleum, while refined petroleum consumption and real economic activity mainly respond to shocks to the cost of shipping petroleum commodities. Third, the Covid-19 counterfactual analysis shows that the shipping costs for crude oil and refined petroleum increased by around 10% as a result of the pandemic shock, while crude oil and refined petroleum prices fell by approximately 5%, namely they moved in the opposite direction.

These findings have important implications for policymakers. In particular, given the inflationary effects of oil price shocks and the recessionary effects of petroleum shipping cost shocks, a simultaneous shock to both can increase the risk of stagflation. This poses a difficult challenge to central banks with dual mandates and rules-based policies, since interest rate changes cannot solve both inflation and recession. In such cases policies to reduce dependency on oil and supply-side policies aimed at increasing productivity might be the only effective measures. Finally, given the evidence on the impact of the Covid-19 pandemic, future work should investigate in greater depth the time-varying nature of the relationship between crude oil and refined petroleum prices and shipping costs and the transmission to the domestic and global economy of shocks to these variables.

References

Anderl, C. and Caporale, G.M., 2024. Shipping cost uncertainty, endogenous regime switching and the global drivers of inflation. *International Economics*, *178*, p.100500.

Carrière-Swallow, Y., Deb, P., Furceri, D., Jiménez, D. and Ostry, J.D., 2023. Shipping costs and inflation. *Journal of International Money and Finance*, *130*, p.102771.

Cashin, P., Mohaddes, K., Raissi, M. and Raissi, M., 2014. The differential effects of oil demand and supply shocks on the global economy. *Energy Economics*, *44*, pp.113-134.

Chudik, A., Mohaddes, K., Pesaran, M.H., Raissi, M. and Rebucci, A., 2021. A counterfactual economic analysis of Covid-19 using a threshold augmented multi-country model. *Journal of International Money and Finance*, *119*, p.102477.

Considine, J., Galkin, P., Hatipoglu, E. and Aldayel, A., 2023. The effects of a shock to critical minerals prices on the world oil price and inflation. *Energy Economics*, *127*, p.106934.

Considine, J., Hatipoglu, E. and Aldayel, A., 2022. The sensitivity of oil price shocks to preexisting market conditions: A GVAR analysis. *Journal of Commodity Markets*, *27*, p.100225.

Kilian, L., 2008. The economic effects of energy price shocks. *Journal of Economic Literature*, *46*(4), pp.871-909.

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), pp.1053-1069.

Kilian, L., 2010. Explaining fluctuations in gasoline prices: a joint model of the global crude oil market and the US retail gasoline market. *The Energy Journal*, *31*(2), pp.87-112.

Kilian, L., 2014. Oil price shocks: Causes and consequences. *Annual Review of Resource Economics*, *6*(1), pp.133-154.

Kilian, L. and Zhou, X., 2022. Oil prices, gasoline prices, and inflation expectations. *Journal of Applied Econometrics*, *37*(5), pp.867-881.

Kilian, L. and Zhou, X., 2023. A broader perspective on the inflationary effects of energy price shocks. *Energy Economics*, *125*, p.106893.

Liddle, B. and Huntington, H., 2020. ‘On the Road Again’: A 118 country panel analysis of gasoline and diesel demand. *Transportation Research Part A: Policy and Practice*, *142*, pp.151-167.

Melichar, M., 2016. Energy price shocks and economic activity: Which energy price series should we be using?. *Energy Economics*, *54*, pp.431-443.

Michail, N.A., 2020. World economic growth and seaborne trade volume: quantifying the relationship. *Transportation Research Interdisciplinary Perspectives*, *4*, p.100108.

Michail, N.A. and Melas, K.D., 2020. Shipping markets in turmoil: An analysis of the Covid-19 outbreak and its implications. *Transportation Research Interdisciplinary Perspectives*, *7*, p.100178.

Michail, N.A., Melas, K.D. and Cleanthous, L., 2022. The relationship between shipping freight rates and inflation in the Euro Area. *International Economics*, *172*, pp.40-49.

Mohaddes, K. and Pesaran, M.H., 2016. Country-specific oil supply shocks and the global economy: A counterfactual analysis. *Energy Economics*, *59*, pp.382-399.

Mohaddes, K. and Pesaran, M.H., 2017. Oil prices and the global economy: Is it different this time around?. *Energy Economics*, *65*, pp.315-325.

Olanipekun, I., Olasehinde-Williams, G. and Akadiri, S.S., 2019. Gasoline prices and economic policy uncertainty: what causes what, and why does it matter? Evidence from 18 selected countries. *Environmental Science and Pollution Research*, *26*, pp.15187-15193.

Pesaran, M.H. and Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 1998, 58, 1, pp. 17-29.

Pouliasis, P.K. and Bentsos, C., 2024. Oil price uncertainty and the relation to tanker shipping. *International Journal of Finance & Economics*, *29*(2), pp.2472-2494.

Shi, W., Yang, Z. and Li, K.X., 2013. The impact of crude oil price on the tanker market. *Maritime Policy & Management*, *40*(4), pp.309-322.

Smith, L., Galesi, A., 2014. Gvar Toolbox 2.0. University of Cambridge: Judge Business School.

Appendix A. Data Sources

A.1. Global variables

The price of crude oil is the Brent spot price in dollar per barrel, which is obtained from the EIA (Energy Information Administration). The petroleum price is computed by weighting the prices of individual petroleum commodities listed in Table A.1 by their share of world total production. The resulting price is then multiplied by 42 to convert it from Dollars per gallon to Dollars per barrel. The Baltic Clean and Dirty Tanker indices are obtained from Bloomberg.

Table A.1. Petroleum product prices included in construction of the petroleum price

Variable	Description	Source
Gasoline	New York Harbor Conventional Gasoline Regular Spot Price FOB (Dollars per Gallon)	EIA
Diesel fuel	Los Angeles, CA Ultra-Low Sulfur CARB Diesel Spot Price (Dollars per Gallon)	EIA
Heating oil	New York Harbor No. 2 Heating Oil Spot Price FOB (Dollars per Gallon)	EIA
Kerosene	U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price FOB (Dollars per Gallon)	EIA
Propane	Mont Belvieu, TX Propane Spot Price FOB (Dollars per Gallon)	EIA

Notes: Individual fuel prices to compute the aggregate petroleum price.

A.2. Country-specific oil market variables

All country-specific oil market variables are obtained from the EIA. The crude oil production data is total crude oil production including lease condensate; petroleum inventories are the country-level inventories from the monthly OECD petroleum and other liquids stocks dataset; and petroleum consumption data are obtained from the monthly OECD refined petroleum products consumption dataset.

A.3. Real activity

The real activity measure is the total industry production volume obtained from the OECD Key Economic Indicators database for all countries except Australia, China, Chile, Finland, Indonesia, Iran, Malaysia, Mexico, New Zealand, Peru, Philippines, South Africa, Singapore, Switzerland and Thailand for which the series are obtained from Bloomberg. For Australia and New Zealand we interpolated the quarterly real activity series using the multiplicative cubic spline method. We construct the real activity series by deflating the nominal industrial production series by the CPI index.

A.4. Consumer price index

The headline consumer price indices are obtained from the OECD national Consumer Price Indices for Energy (COICOP 1999) dataset for most countries except Australia, Iran, Malaysia, New Zealand, Peru, Philippines, Singapore and Thailand for which they are obtained from Bloomberg. For Australia and New Zealand we interpolated the quarterly inflation series using the multiplicative cubic spline method (Considine et al., 2023).

A.5. Short-term interest rates

Short-term interest rates are rates on 3-month government securities obtained from the OECD Key Economic Indicators database for most countries, except for Brazil, China, Chile, India, Iran, Malaysia, Peru, Philippines, Russia, Saudi Arabia, Singapore, Thailand and Turkey for which they are obtained from Bloomberg.

A.6. Long-term interest rates

Long-term interest rates are rates on 10-year government bonds obtained from the OECD Key Economic Indicators database for all countries except China, Chile, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Singapore, Thailand and Turkey for which they are obtained from Bloomberg. We could not obtain long-term interest rates for Iran and Saudi Arabia.

A.7. Real equity price index

All nominal equity price indices are obtained from Bloomberg with the exception of Iran, for which we could not obtain any equity price index. We construct the real equity price series by deflating the nominal series by the CPI index.

A.8. Exchange rates

The nominal exchange rates for all country currencies against the US dollar are obtained from the Pacific exchange rate service (PERS) except for the case of Iran for which the series is obtained from Bloomberg. The real exchange rate of all currencies vis-à-vis the US dollar is constructed by deflating the nominal exchange rate by the CPI index.

A.9. Weighting data

The bilateral trade weights are taken from the IMF direction of trade statistics database and are in monthly frequency. Exports (free on board) and imports (cost, insurance and freight) were averaged to construct the bilateral trade weights. We also obtain annual PPP-GDP weights from the World Bank for the regional analysis to aggregate groups of countries to represent regions and subregions as outlined in Table 1.

A.10. Transformations and seasonality

All variables are entered in logs except for the inflation series which is a month-on-month growth rate and the short- and long-term interest rate series which are included without any transformation. Following the method in Considine et al. (2023) seasonality tests were performed on all series and seasonal adjustment was performed were required.