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The effects of a shock to critical minerals prices on the world oil price and inflation

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ABSTRACT

Critical minerals (CMs) such as lithium, cobalt, nickel, and rare earth metals, are essential to the development of clean energy technologies, electronics, and defense and space industries, among others. Demand for these minerals is expected to grow quickly as energy transitions accelerate. As the post-pandemic economic recovery demonstrated, disturbances in CM supplies can also create serious bottlenecks in global supply-chains. In this study, we develop a GVAR model that can examine the consequences of market disturbances from CM price shocks on major global and country-specific macroeconomic indicators. Counterfactual simulations of a CM price shock suggest that that CMs, as a rising industry, are starting to have an impact on the macro level. The industry and its impacts are not fully developed yet but appear to have diverse implications across countries similar in some respects to the current major commodity – oil. A CM price shock has statistically significant implications for inflation in the UK and South Korea. At the same time, geopolitical shocks to crude oil prices have significant implications for CM prices. The cross-price elasticity of oil with respect to CM prices is positive in the United States, where CM's and oil are substitutes, and negative for Saudi Arabia where CMs and oil are compliments. These scenarios indicate the unsuitability of a one size fits all energy policy and a need for closer examination of the national and country specific relationships between the oil and CM sectors.

1. Introduction

1.1. The role of critical minerals

Critical metals and minerals (CMs) have been playing an increasingly important role in the global energy transition. These elements are critical to the whole value chain of solar and wind power. Elements such as gallium, indium, and tellurium are key in thin-film solar cells. Lithium, cobalt, cadmium, tellurium, and magnesium are central to battery storage, ranging from electric vehicle batteries to grid scale storage. The emerging uses of hydrogen as an energy vector have further increased demand for CMs, especially relating to fuel cells such as lithium and graphene. CMs are also used in conventional fossil fuel applications: minerals such as chromium, nickel, manganese, and molybdenum play a central role in the manufacture of tubular goods for operation in high pressure/highly corrosive environments. The industries where CMs play a key role extend beyond energy spanning the production of consumer electronics, medical imaging equipment, auto parts, and many other high-tech industrial goods. CMs are also critical for the defense and space industries, such as to produce sonar, night-vision goggles, laser range finders, sophisticated communications, and advanced aviation systems.

The definitions used to characterize this category of commodities, such as rare earths, critical earth minerals, critical minerals generally imply (1) strategic importance to national economy / national economy or technological development and (2) high risks associated with supply disruption (IEA, 2022a, 2022b, Australian Government, 2022, Burton, 2023). Thus, the set of "critical minerals" can vary over time and across

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countries. For example, in 2022, the bU.S. Geological Survey added nickel and zinc, while removing helium, potash, rhenium, and strontium to their list of critical minerals (Burton, 2022). For the purpose of this study, we represent the CMs in the model via the price index derived by the U.S. Bureau of Labor Statistics Inorganic Chemicals; Organic or Inorganic Compounds of Precious Metals, of Rare-Earth Metals, of Radioactive Elements or of Isotopes (U.S. Bureau of Labor Statistics, 2022).[1] For a comprehensive overview of CMs and their fields of application see Bazilian (2018).

The CMs tend to include the rare earth metals group, 17 metals that share electromagnetic chemical properties (ifpen, 2023). Although many minerals in this category are called critical and/or rare, they are actually widely available in the earth's crust (Eggert, 2011). However, the minable concentrations are generally lower than those of other minerals making the extraction process challenging and capital-intensive. Considerable investment is also needed to transform CMs into usable intermediate goods or end products. These challenges, coupled with the unequal distribution of resources, have led to heavy market concentration, especially evident in certain CM market sectors. As a result, China accounted for 60% of global rare earth production in 2021 (United States Geological Survey (USGS), 2021), while the Democratic Republic of Congo produced over 70% of global cobalt (KITCO, 2022), and South Africa with Russia captured over 75% of total palladium production (Statistics Canada, 2022). The disparities are exacerbated by strong demand projections. According to the U.S. Administration, the next several decades will see an overall CM demand increase of 400–600%. Specific segments, such as the minerals used in the electric vehicles' batteries, are projected to rise precipitously surging to levels as high as 40-fold (The White House, 2022; Foss, 2023).

Not surprisingly, the increasing demand for CMs, coupled with concentrated means of extraction and processing, has created vulnerabilities in the global commodities market and economic development. In 2010, a maritime clash led China to stop exporting CMs including rare earth oxides, rare earth salts, and pure rare earth metals to Japan for two months, which put the Japanese automotive industry under strain (Bradhser, 2010). Most recently, the post-pandemic economic recovery, followed by the 2022 Russia-Ukraine conflict, has illustrated how shocks to CM supplies and prices have the potential to influence the course of country specific, and perhaps even global economic development. To illustrate, the ensuing significant upward price shocks in such CMs as nickel and lithium have raised the risk of CM supply shortages for the European EV industry (Shaikhmahmud, 2022). The rising global demand for copper increases manufacturing costs for EVs and the levelized costs for new renewable energy generation plants and threatens to make replacing aging grids in many cities prohibitively expensive.

The increasingly central role CMs play in global manufacturing and service industries makes it imperative for us to understand how CMs relate to various global and country-level macroeconomic indicators. Among these indicators, inflation especially stands out as "[t]he pursuit of 'green' energy targets and mandates induces stress on already fragile raw materials supply chains," putting "extraordinary upward pressure on commodity prices" (Foss, 2022, p. 3). Our study is one of the first empirical attempts to see whether increases in CM price levels translate into country-level inflation in today's economic conditions.[2] In relation, CMs' growing salience in global supply chains motivates us to understand how CMs relate to other major commodities in the global economy, in particular, oil.

There is a growing body of literature addressing the potential implications of a supply shock to critical and rare earth minerals. Sophisticated econometric techniques such as Markov Switching models have been used to measure price spillovers between rare earth stocks, financial markets, and oil prices (Reboredo and Ugolini, 2020). Keilhacker and Minner (2017) use a system dynamics approach to study an individual companies' reaction to export restrictions from China. Vector error correction models have been used to disentangle the complex interactions between China's complex rare earth metal quotas, statecraft, and pricing policies (Vekasi, 2019).

From the policy perspective, the majority of the studies to date tend to focus on the micro level, in particular – on industry development (Dou et al., 2023), risk management (Keilhacker and Minner, 2017), and impacts on downstream segments (Liu et al., 2022). On the country level, the main policy research agenda concentrates on related geopolitical (Fan et al., 2022; Guliyev, 2022) and supply security aspects (Barteková and Kemp, 2016). For many economies, the issue of identifying and classifying CMs remains also relevant to this day (Galos et al., 2021). In the macroeconomic policy domain, the most explored area is the CM trade-security nexus both on the country (Hau et al., 2022; He, 2018) and global (Yu et al., 2022) levels. A few particular studies explore the macroeconomic characteristics of CMs (Proelss et al., 2020) and their links with other indicators (Černý et al., 2021), however, there is an evident research gap in applied macroeconomic analysis and policy support studies that focus on the role of CMs in the countries' and global economy, and on relevant potential scenarios.

The price performance of CMs in recent years has been characterized by significant spikes and increased volatility in commodity prices. According to IEA, the price of lithium increased by 738% over the period of January 2021–March 2022, followed by cobalt (156%) and nickel (94%) (IEA, 2022a, 2022b). Such price dynamics raise concerns among the policy makers about the potential harmful impacts for the energy transition (IMF, 2021; OECD, 2023). Recent studies confirm the possibility of such scenario, as CM prices are found to have had a significant impact on renewable energy consumption (Apergis and Apergis, 2017), green investments (Sohag et al., 2023), and the energy transition in general (Jiang and Jiang, 2023). CM price fluctuations are likely to continue and even intensify as countries scramble to ensure their supply security and global supply chains are rapidly overhauled amid geopolitical and macroeconomic uncertainties.

The other issue – that so far appears to have received less attention from researchers and policy makers – is the cross-sectoral and macroeconomic implications of CM price shocks, which can occur on national and global levels. A few individual studies have established and identified such relationships, specifically, the spillover effects across the fossil energy, clean energy, and metal markets (Chen et al., 2022), the implications of rare earth shocks on the performance of high-tech industry (Flaeschner and Netland, 2017), and how rare earth prices affect consumer prices (Apergis and Apergis, 2017). The primary focus of the publications in this area, however, tends to be on how the CM prices

[1] We choose the price index derived by the U.S. Bureau of Labor Statistics based on the import price index of imports under the Harmonized System (HS) Code 28: Inorganic Chemicals; Organic or Inorganic Compounds of Precious Metals, of Rare-Earth Metals, of Radioactive Elements or of Isotopes instead of a more global representation such as the Rare Earth MMI index due to a number of factors including the large U.S. share in the world critical minerals market, the existence of a long and comprehensive historical time series, and the ability to estimate the index quarterly starting from 1979:Q2 (see Appendix B).

[2] There is an argument to be made that the primary accelerator of greenflation is fiscal and monetary policy so that it can not solely be attributed to rising commodity prices. In the words of Cochrane (2023): "Unfortunately, many governments are responding to inflation by borrowing or printing even more money to subsidize energy, housing, childcare, and other costs, or to hand out more money to cushion the blow from inflation – for example, by forgiving student loans. These policies will lead to even more inflation."

affect the financial markets (Kamal and Bouri, 2023; Chen et al., 2022; Ul Haq et al., 2022).

The sparsity of research subjects in the domain of CMs becomes especially apparent when compared to another major commodity – oil. An extensive body of research has been produced over the years on the topic of oil price dynamics and the implications for various sectors of economy: from agriculture (Nazlioglu and Soytaz, 2012) to tourism (Katircioglu et al., 2018), and macroeconomic indicators: from inflation (Salisu et al., 2017) to the current account balance (Allegret et al., 2014). These studies utilize a comprehensive set of methodologies including General Equilibrium models, GVAR (Mohaddes and Pesaran, 2016a, 2016b; Vargas and Hess, 2019; Marçal et al., 2018).

Moreover, a number of papers explore the price dynamics and volatility spillovers in the oil and metal sectors. The consensus confirms the spillover effects from oil price fluctuations to the base metals market (Reboredo and Ugolini, 2020). Other metals can be even more susceptible to such spillover effects. For example, copper, which is often classified as a CM, tends to be more easily affected by oil price shocks (Zhang and Tu, 2016) and demonstrates a "leverage effect" (Behmiri and Manera, 2015). As for the reverse causality, the implication of oil price shocks on CMs, the results tend to be mixed. Mroz (2022) fails to find clear evidence that fossil fuel prices affect clean energy metal prices, while Shao and Zhang (2020) show a significant positive spillover effect of crude oil prices in on clean energy metals at different time scales. To the best of our knowledge, such relations have not yet been explored in the context of a global macroeconomic model. Neither do existing studies include rare earth metals – an essential component of CMs.

A similar set of knowledge and methodologies that already exists for the analysis of oil price impacts needs to be developed for the CM sector. The metals comprising the CM group need to be distinguished from the other base metals, as they may demonstrate different patterns driven by intensified energy transition and structural shifts in demand. Moreover, a shortage or a prohibitively high price of any particular CM component can become detrimental to timely energy transition.

It can be argued that CMs also need to be assessed within the context of their effects on macroeconomic variables such as GDP and inflation. This is true as the CM and clean energy sectors play an increasingly important role in countries' energy sectors and economies. In order to secure reliable supplies of CM's, many countries must make strategic decisions in the areas of domestic mining development, foreign direct investment, and trade alliances. The costs and risks associated with such decisions must consider the potential sectoral and macroeconomic implications of supply shocks and rapidly increasing prices. Without a clear understanding of the industry dynamics, specific policy tools such as CM import / export tariffs, sectoral subsidies, and resource taxes can lead to unintended, and unwanted, consequences.

The dynamics of the CM markets and the need for more representation of this sector in global macroeconomic models make understanding how CMs relate to global financial and economic markets a timely and relevant endeavor. We model the dynamic interactions between CMs and oil, which is arguably the most important globally traded commodity.

1.2. Modeling the effects of CM price shocks: A GVAR approach

Since its origin in 2004, the use of the GVAR to study the importance of trade and financial links among countries has become well recognized. The GVAR approach is especially useful for our research question at hand, i.e., whether and how CMs relate to oil markets and inflation. GVAR is designed to assess how a hypothesized structural change in one market-indicator (commodity, financial, or service-related) reverberates to other markets across space and time. More specifically, GVAR models allow us to hypothesize and test co-movements among variables of interest, in our case price of CMs and oil, in the short- and longer terms. Second, GVAR models allow us to evaluate how such variables interact with other macroeconomic variables such as inflation. In doing so, GVAR models can establish direction of causality in complex systems characterized by the presence of many endogenous relationships. One can also design various counterfactual scenarios using GVAR, hence allowing researchers to run policy-relevant simulations. To cite only a few examples: In the energy field Dees et al. (2007) examine the international linkages of the Euro Area, and for counterfactual analysis including the evaluation of UK entry into the Euro (Dees et al., 2007; Pesaran et al., 2007; Konstantakis et al., 2015a, 2015b). Mohaddes and Pesaran (2016a) develop a GVAR model for the world oil market and integrate this with a quarterly model of the global economy a GVAR-Oil model for 27 countries to investigate the effects of country specific supply shocks on the global economy. The system is expanded to the GVAR-Oil model, by adding a simple dynamic oil price equation combining it with the country-specific models (Mohaddes and Pesaran, 2016b). Other studies include the use of GVAR to explore trade linkages between the Caribbean and the United States and crude oil prices (Vargas and Hess, 2019), as well as the interdependence of exchange rate policies among major economies in the world (Marçal et al., 2018).

More recently, the GVAR has been used to investigate the international implications of a monetary policy shock in the Euro area using shadow interest rates as a proxy for monetary policy. The authors propose a new method of identifying a 'euro' specific shock by using a step procedure for individual and aggregate variables (Benecká et al., 2018). Bettendorf (2017) studies the potential implications of shocks to key U. S. macroeconomic variables and the oil price for international trade balances using a GVAR approach. The effects of the shock are quantified by means of a variance decomposition of the Generalized Forecast Errors.[3] McAdam et al. (2022) employ a structural Bayesian GVAR to investigate trade imbalances between the South euro Area (SEA) and the North euro area (NEA). Long- and short-run restrictions are used to disentangle the structural shocks to the system. In addition, the authors use counterfactual analysis to show that if fiscal austerity or policies improving competitiveness were employed prior to 2010, the EU debt crisis might have been averted.

The modeling framework of the GVAR enables the analysis of potential spillover effects from economic shocks and sanctions (Hoyn, 2021; Kwok, 2022). To cite only a few examples: Sznajderska (2019) employs a GVAR model to estimate the spillover effects of a negative demand shock in China on global GDP growth. Zahedi et al. (2022) examine how China's monetary policy shocks spill over to global trade patterns. Kempa and Khan (2017) analyze the spillover effects of public debt and economic growth in the Euro area. They find that debt shocks do not impede growth trajectories but tend to raise debt levels across the euro area. Salisu et al. (2022) investigate the spillover effects of financial uncertainty in the United States using a GVAR framework in which uncertainty shocks to developed and emerging economies are conditional on the state of the Global Financial Cycle.

From the commodities perspective, oil has traditionally been in the focus of the GVAR modeling studies, which assessed the impacts of oil supply or oil price shocks on the global economy (Mohaddes and Pesaran, 2016a), country-specific macroeconomic indicators (Considine et al., 2022), and global equity markets (Salisu et al., 2022) among other potential consequences. Beyond oil, GVAR has been used to estimate the impacts of non-fuel commodity (generally, base metals) price shocks on trade patterns (Wei and Lahiri, 2019) and economic activity (Gündüz, 2021), as well as to explore the nexus between various commodity types (Rehman and Vo, 2021). A separate field of study is represented by modeling the global agricultural market and how it is affected by various shocks and policy constraints (Gutierrez et al., 2022; Breman, 2014). However, to the best of the authors knowledge, CM or rare earth metals sectors have not been included in a GVAR system, presumably, due to a relatively recent "priority status", blurred definition of this minerals

[3] Intriguingly, the study shows that real GDP is a relatively unimportant variable when compared to exchange rates, interest rates and the oil price.

group, and more difficult to obtain production, trade, and price data.

1.3. Modifications to the traditional GVAR model

This paper contributes to understanding of energy markets in three novel ways. First, the model we present in this paper is the first of its kind (to the best of our knowledge) that incorporates CMs in a global economics and energy model. To this end, we expand the GVAR model developed by Mohaddes and Pesaran (2016a) and KAPSARC (Considine et al., 2020) to include a new global variable, the Critical Minerals price index. Secondly, the study features the updated version of KAPSARC's global oil vector autoregression (GOVAR) model including data for all variables to the first quarter of 2022. Finally, the updated model adds Russian long term interest rates, and extends the temporal coverage of the trade weights and linking matrices to 2022Q1 and 2021, respectively.

The original GOVAR model had extended Mohaddes and Pesaran (2016a, 2016b) by adding Russia, Venezuela, and Iran, and oil inventories as an additional variable (Considine et al., 2020). This KAPSARC GOVAR model has been employed to evaluate the time sensitivity of oil shocks under tight and loose market conditions (Considine et al., 2022), and to assess the extent of regional spillover effects of trade and/or financial sanctions on an oil producing country (Hatipoglu et al., 2022).[4] The result of these modifications is a revised or augmented version of the GVAR Oil and Inventory Model, (GOVAR) a theoretical framework to examine factor interdependencies and the international co-movements of variables affecting the global macroeconomy with an emphasis on the interplay between the crude oil industry and CMs (Considine et al., 2022).

Our model also constitutes the basis for a policy tool that can perform scenario and counterfactual analysis of market disturbances to the CM price and oil markets, and potential policy prescriptions. The GVAR econometric model is uniquely suited to this analysis. We designed a GVAR model that is able to capture the interdependencies between CM prices and the world oil market. In the KAPSARC specification of the GVAR, the CM price is affected by changes in variables such as the world oil price, GDP inflation and world oil inventories with a lag. The CM price, in turn, has the potential to affect the individual country-specific economies.

The structure of the paper is as follows: Section 2 provides a description of the augmented GOVAR, including a brief discussion of the new oil and CM model, and GVAR system. Section 3 presents the empirical results, including the specification of country-specific vector autoregression models and counterfactual analysis of CM and oil price shocks. Section 4 presents the conclusion and suggestions for future research. Appendix A and B describe the data sources and statistical properties of the country-specific models. Appendix C presents the results of the weak exogeneity tests for the country-specific foreign variables and shows the ability of the model to account for interdependencies and international co-movements via the calculation of pair-wise cross section correlations for the endogenous variables and residuals. The selection of lag orders, cointegrating relationships, and persistence profiles are provided in Appendix D.

[4] Once fully specified, the model will provide a stylized representation of the global oil market, and will have the potential to separate different types of innovative shocks such as political uncertainty, global recession, changes in interest rates and monetary policy, crude oil supply shocks, shocks to above ground crude oil inventories reflecting speculation concerning future levels of the supply and demand for crude oil, and shocks to CM prices, reflecting the rise of the renewable energy industry.

2. Modeling the dynamics of global oil and CM markets in GVAR framework

The framework for the world oil and critical minerals study builds on a model developed by Dees et al. (2007) and Mohaddes and Pesaran (2016a). We first develop a GVAR to examine the effects of oil and CM price shocks on global economies. The oil and CM prices are modeled separately and introduced to the GVAR by adding the prices and their lagged values in the individual vector autoregressive with exogenous foreign variable (VARX*) models (Smith and Galesi, 2014).[5] In a departure from the existing literature at the time, the authors model the oil price equation separately and introduce the oil price variable as weekly exogenous in all the countries including the United States (Mohaddes et al., 2020). The data series utilized in the model and corresponding data sources are described in detail in Appendix B.

2.1. The model for oil and critical minerals prices

The KAPSARC oil price and CM model expands on the GOVAR model presented in Considine et al. (2020). The dynamics of global oil and CM market can be described by the following equations for the dynamic aggregate demand for oil and CM price.

$$\mathrm{Qd}_t^0 = a_d + \varepsilon_y a_y(L) y_t + \varepsilon_R a_R(L) \mathrm{Rp}_t^0 - \varepsilon_p a_p(L) p_t^0 + \varepsilon_I a_I(L) I_t^0 + \varepsilon_{dt} \tag{1a}$$

$$\mathrm{Rp}_t^0 = b_d + b_y(L) y_t + b_R(L) \mathrm{Rp}_t^0 - b_p(L) p_t^0 + b_{Dp}(L) \mathrm{Dp}_t^0 + b_{Qs}(L) \mathrm{Qs}_t^0 + \varepsilon_{dt} \tag{1b}$$

where:

- $Qd_t^0 \equiv$ *Logged value of oil demand*
- $Qs_t^0 \equiv$ *Logged value of oil supply*
- $Rp_t^0 \equiv$ *Logged value of the rare earth metal price index*
- $Dp_t^0 \equiv$ *Inflation first difference of the loged value of CPI*
- $Y_t \equiv$ *Logged value of Real Seasonally Adjusted Gdp*
- $P_t \equiv$ *Logged Value of the Real Price of Oil*
- $I_t^0 \equiv$ *Logged value of oil inventories*
- $a_y(L),\quad a_p(L),\quad a_R(L),\quad a_I(L) \equiv$ *Polynomials in the lag operator*, L, *whose coefficients add to* 1
- $a_y(L) = a_{y0} + a_{y1}L + a_{y2}L^2 + \dots$
- $a_R(L) = a_{R0} + a_{R1}L + a_{R2}L^2 + \dots$

$$a_p(L) = a_{p0} + a_{p1}L + a_{p2}L^2 + \dots \tag{2}$$

$$a_I(L) = a_{I0} + a_{I1}L + a_{I2}L^2 + \dots$$

$$a_y(L) = a_R(L) = a_p(L) = a_I(L) = 1$$

- $b_y(L), b_p(L), b_R(L), b_{Dp}(L), b_{Qs}(L) \equiv$ Polynomials in the lag operator, L, whose coefficients add to 1.

It can be shown that ε_y, ε_p, ε_R and ε_I are the long run income, price, and inventory elasticities of the demand for oil, and ε_R is the long run cross elasticity of the demand for oil and the CM price.

Oil prices respond to supply and demand imbalances to create equilibrium or balance on global oil markets (Considine et al., 2020).

$$\Delta p_t^0 = a_s + \lambda\left(\mathrm{Qd}_t^0 - \mathrm{Qs}_t^0\right) + \varepsilon_{st} \tag{3}$$

[5] The country specific VAR* models include both domestic variables and foreign (*) varialbles, where the foreign variables are constructed as weighted averages of the domestic variables across the different countries (Smith and Galesi, 2014).

where:

- $\lambda \equiv$ *The speed of adjustment between oil supply and demand*
- $a_s \equiv$ *a fixed constant representing the scarcity of oil*
- $\varepsilon_{st} \equiv$ *Speculative oil price changes that are not related to fundamental factors*

Substituting Eq. (1a) into Eq. (3), and solving for Δp_t^0 yields:

$$\Delta p_t^0 = a_p + \lambda\left(\varepsilon_y a_y(L) y_t - \varepsilon_p a_p(L) p_t^0 + \varepsilon_R a_R(L)\mathrm{Rp}_t^0 + \varepsilon_I a_I(L) I_t^0 - \mathrm{Qs}_t^0\right) + \varepsilon_{pt} \tag{4}$$

where:

- $a_p \equiv a_s + \lambda a_d$
- $\varepsilon_{pt} \equiv \varepsilon_s + \lambda \varepsilon_{dt}$

Solving for p_t^0 yields a standard autoregressive distributed lag model (ARDL) in oil prices, CM prices, income, inventory, and world oil production.

$$p_t^0 = \left(\frac{1}{1+\lambda\varepsilon_{po}a_{po}}\right) a_p + \left(\frac{1-\lambda\varepsilon_{po}a_{po}}{1+\lambda\varepsilon_{po}a_{po}}\right) p_{t-1}^0 - \left(\frac{\lambda\varepsilon_{po}}{1+\lambda\varepsilon_{po}a_{po}}\right)\sum_{l=2}^{\infty} a_{pl}p_{t-l}^0 + \tag{5}$$

$$\left(\frac{\lambda\varepsilon_y}{1+\lambda\varepsilon_{po}a_{po}}\right) a_y(L) y_t + \left(\frac{\lambda\varepsilon_I}{1+\lambda\varepsilon_{po}a_{po}}\right) a_I(L) I_t^0 + \left(\frac{\lambda}{1+\lambda\varepsilon_{po}a_{po}}\right)\mathrm{Qs}_t^0 +$$

$$\left(\frac{\lambda\varepsilon_R}{1+\lambda\varepsilon_{po}a_{po}}\right) a_R(L)\mathrm{Rp}_t^0 + \left(\frac{1}{1+\lambda\varepsilon_{po}a_{po}}\right)\varepsilon_{pt}$$

Following Considine et al. (2020), we estimate the ARDL model described by Eq. (6). Endogeneity problems are avoided by using lagged values of y_t *and* Qs_t^0.

$$p_t^0 = c_p + \sum_{l=1}^{m_{p0}} a_l p_{t-l}^0 + \sum_{l=1}^{m_y}\beta_l y_{t-l} + \sum_{l=1}^{m_{qo}}\gamma_l Q_{t-l,s}^0 + \sum_{l=1}^{m_{Ro}}\vartheta_l Rp_{t-l}^0 + \sum_{l=1}^{m_I}\delta_l I_{t-l}^0 + \upsilon_t^0 \tag{6}$$

Where m_{p0}, m_y, m_{qo}, $m_{Ro}$and m_I are allowed to vary across the different variables and will be selected using the Akaike Information Criteria (AIC) (Akaike, 1981).

It can be shown that the long term- price, income and inventory elasticities and the long run cross elasticity of the demand for oil and the CM price are:

$$\begin{aligned}
\varepsilon_{po} &= -\left(\sum_{l=1}^{m_{qo}}\gamma_l\right)^{-1}\left(1-\sum_{l=1}^{m_{p0}}a_l\right) \\
\varepsilon_y &= -\left(\sum_{l=1}^{m_{qo}}\gamma_l\right)^{-1}\left(\sum_{l=1}^{m_y}\beta_l\right) \\
\varepsilon_R &= -\left(\sum_{l=1}^{m_{qo}}\gamma_l\right)^{-1}\left(\sum_{l=1}^{m_{Ro}}\vartheta_l\right) \\
\varepsilon_I &= -\left(\sum_{l=1}^{m_{qo}}\gamma_l\right)^{-1}\left(\sum_{l=1}^{m_I}\delta_l\right)
\end{aligned} \tag{7}$$

2.2. Expanding the system: An international perspective in the GVAR model

The GVAR methodology is a two-step modeling procedure. In the first stage, the countries are estimated individually by means of country-specific vector error correction models which include domestic and foreign variables, and two global variables that are common across all countries, specifically the oil and CM prices. All countries, except the United States, are treated as small open economies. In the second stage, the individual models are combined and the GVAR is solved for the world as a whole, considering the fact that all the variables are endogenous to the system as a whole.

2.2.1. Stage 1: Estimating the country-specific vector error correction models

We begin by estimating a single equation for each country specific model:

$$\boldsymbol{x}_{it} = \boldsymbol{a}_{io} + \boldsymbol{a}_{i1}\boldsymbol{t} + \boldsymbol{\phi}_{i1}\boldsymbol{x}_{i,t-1} + \ldots\boldsymbol{\phi}_{ip_i}\boldsymbol{x}_{i,t-p_i} + \boldsymbol{A}_{i1}\boldsymbol{x}^*_{i,t-1} + \ldots\boldsymbol{A}_{iq}\boldsymbol{x}^*_{i,t-q_i} + \boldsymbol{u}_{it} \tag{8}$$

Or equivalently:

$$\boldsymbol{\Phi}_i(\boldsymbol{L},\boldsymbol{p}_i)\boldsymbol{x}_{it} = \boldsymbol{a}_{io} + \boldsymbol{a}_{i1}\boldsymbol{t} + \Lambda_i(L,q_i)\boldsymbol{x}^*_{i,t} + \boldsymbol{u}_{it} \tag{8a}$$

where:

- a_{io}, a_{i1} $=$ $K\times$ 1 *vectors of fixed intercepts and coefficients on the deterministic time trends.*
- x_{it} $= k_i \times 1$ *vector of country specific domestic variables*
- x^*_{it} $=$ $k_i\times$ 1 *vector of country specific weekly exogeonous star (foreign) variables*
- ϕ_i, $\ldots\phi_{ip}$, A_{io}, $\ldots$, $A_{iq} \equiv k_i x1$ *vectors or matrices of fixed coefficients that vary across countriesi*
- u_{it} $= k_i \times 1$ *vector of country* $-$ *specific supply shocks*
- $u_{it} \sim i.i.d.(0,\Sigma_{ii})$ *the shocks are serially uncorrelated with zero mean and non singual covariance matrix.*
- $\Phi_i(L,p_i)$ $= I-$ $\sum_{i=1}^{pi}\Phi_i L^i \equiv$ *the matrix lag polynomial of the domestic variable coefficients*
- $\Lambda_i(L,q_i)$ $=$ $\sum_{i=1}^{qi}\Lambda_i L^i \equiv$ *the matrix lag polynomial of the foreign variable coefficients*

The variables $x_{it} = \left(\mathrm{Qs}_{it}^0, Y_{it}, P_t, I_{it}^0, r_{it}, rl_{it}, Dp_{it}, ep_{it}, eq_{it}\right)$ are the country specific domestic variables

- $Qs_{it}^0 \equiv$ *Logged value of oil supply*
- $Y_{it} \equiv$ *Logged value of Real Seasonally Adjusted Gdp*
- $P_t \equiv$ *Logged Value of the Real Price of Oil*
- $I_{it}^0 \equiv$ *Logged value of oil inventories*
- r_{it} $= 0.25{*}ln(1+R_{it}/100)$
- $R_{it} \equiv$ *Nominal Short Term Interest Rates*
- rl_{it} $= 0.25{*}ln(1+Rl_{it}/100)$
- $Rl_{it} \equiv$ *Nominal Long Term Interest Rates*
- $Dp_{it} \equiv$ *Inflation first difference of the loged value of CPI*
- $ep_{it} \equiv$ *Equity Prices, Logged Value of Nominal Equity Prices divided by CPI*
- $eq_{it} \equiv$ *Exchange Rates, Logged Value of Nominal Exchange Rates divided by CPI*

The variables x^*_{it} $= \left(Y_{it}^*, I_{it}^{0*}, r^*_{it}, rl^*_{it}, Dp^*_{it}, ep^*_{it}, eq^*_{it}\right)$ are country specific

Table 1
Fixed trade weight matrix (2019–2021).

	Argentina	Australia	Brazil	Canada	China	Chile	Euro	India	Indonesia	Iran	Japan	Korea	Malaysia
Argentina	0.0000	0.0018	0.0520	0.0011	0.0050	0.0286	0.0042	0.0072	0.0056	0.0183	0.0012	0.0017	0.0029
Australia	0.0083	0.0000	0.0038	0.0039	0.0534	0.0053	0.0125	0.0273	0.0258	0.0014	0.0461	0.0309	0.0289
Brazil	0.2243	0.0031	0.0000	0.0075	0.0347	0.0649	0.0185	0.0158	0.0102	0.0475	0.0082	0.0101	0.0100
Canada	0.0100	0.0077	0.0177	0.0000	0.0255	0.0156	0.0200	0.0129	0.0089	0.0081	0.0190	0.0131	0.0066
China	0.1659	0.4022	0.3357	0.0817	0.0000	0.3604	0.1774	0.1847	0.2785	0.4399	0.2853	0.3417	0.2895
Chile	0.0495	0.0013	0.0240	0.0023	0.0150	0.0000	0.0050	0.0037	0.0010	0.0001	0.0073	0.0064	0.0009
Euro	0.1487	0.0783	0.1472	0.0639	0.1683	0.1144	0.0000	0.1352	0.0674	0.1149	0.0969	0.0888	0.0728
India	0.0407	0.0329	0.0214	0.0072	0.0277	0.0143	0.0251	0.0000	0.0604	0.0958	0.0148	0.0225	0.0328
Indonesia	0.0218	0.0189	0.0088	0.0031	0.0251	0.0023	0.0073	0.0304	0.0000	0.0114	0.0247	0.0170	0.0349
Iran	0.0091	0.0033	0.0124	0.0045	0.0217	0.0011	0.0147	0.0552	0.0152	0.0000	0.0250	0.0254	0.0079
Japan	0.0149	0.1244	0.0304	0.0232	0.0969	0.0615	0.0384	0.0296	0.0873	0.0119	0.0000	0.0845	0.0633
Korea	0.0167	0.0684	0.0242	0.0133	0.0796	0.0385	0.0259	0.0369	0.0490	0.0226	0.0657	0.0000	0.0380
Malaysia	0.0159	0.0262	0.0079	0.0022	0.0260	0.0027	0.0105	0.0271	0.0549	0.0124	0.0273	0.0211	0.0000
Mexico	0.0175	0.0029	0.0283	0.0270	0.0301	0.0248	0.0190	0.0165	0.0057	0.0001	0.0181	0.0262	0.0252
Norway	0.0009	0.0010	0.0051	0.0036	0.0052	0.0023	0.0244	0.0025	0.0011	0.0004	0.0023	0.0032	0.0011
New Zealand	0.0021	0.0217	0.0005	0.0011	0.0063	0.0013	0.0023	0.0016	0.0045	0.0005	0.0041	0.0033	0.0038
Peru	0.0230	0.0005	0.0082	0.0042	0.0064	0.0188	0.0030	0.0036	0.0013	0.0001	0.0026	0.0037	0.0005
Philippines	0.0047	0.0038	0.0030	0.0013	0.0107	0.0006	0.0043	0.0046	0.0240	0.0012	0.0179	0.0123	0.0134
Russia	0.0123	0.0019	0.0137	0.0018	0.0359	0.0068	0.0563	0.0206	0.0080	0.0656	0.0161	0.0270	0.0059
South Africa	0.0072	0.0039	0.0042	0.0008	0.0087	0.0015	0.0118	0.0154	0.0042	0.0002	0.0069	0.0029	0.0028
Saudi Arabia	0.0091	0.0033	0.0124	0.0045	0.0217	0.0011	0.0147	0.0552	0.0152	0.0000	0.0250	0.0254	0.0079
Singapore	0.0022	0.0340	0.0101	0.0029	0.0308	0.0017	0.0183	0.0306	0.1141	0.0005	0.0302	0.0346	0.1630
Sweden	0.0021	0.0044	0.0041	0.0019	0.0056	0.0036	0.0466	0.0037	0.0018	0.0012	0.0033	0.0031	0.0016
Switzerland	0.0203	0.0089	0.0097	0.0075	0.0125	0.0087	0.0821	0.0397	0.0067	0.0059	0.0109	0.0052	0.0043
Thailand	0.0177	0.0316	0.0106	0.0029	0.0266	0.0069	0.0101	0.0222	0.0459	0.0075	0.0478	0.0150	0.0441
Turkey	0.0079	0.0035	0.0100	0.0029	0.0085	0.0052	0.0366	0.0137	0.0051	0.1284	0.0038	0.0081	0.0054
UK	0.0152	0.0291	0.0139	0.0241	0.0311	0.0108	0.1297	0.0269	0.0080	0.0028	0.0157	0.0122	0.0101
USA	0.1297	0.0810	0.1783	0.6996	0.1799	0.1959	0.1807	0.1714	0.0901	0.0013	0.1736	0.1543	0.1215
Venezuela	0.0021	0.0000	0.0023	0.0001	0.0011	0.0006	0.0005	0.0057	0.0001	0.0002	0.0001	0.0000	0.0006

Sources: Internal KAPSARC calculations, International Monetary Fund, Direction of Trade Statistics, 2022.

star foreign variables constructed using country-specific trade shares, and defined by Eq. (8b). Note: $\boldsymbol{a}_{i1}$=0 as there is no time trend in this specification of the model. The variable Qs_{it}^{0}, and Rp_{t}^{0} are excluded because they have already been included in the models for oil and CM prices. These variables are common factors present in all of the country specific models. They can be modeled as global or dominant variables and have implications for the world as well as individual countries (Pesaran, 2015). Following Mohaddes and Raissi (2020), the real exchange rate is defined as the logarithm of the real exchange rate (the nominal exchange rate divided by the CPI), and the U.S. dollar is the' reference currency' for the model.

$$\boldsymbol{x}_{it}^{*} = \sum_{j=1}^{N} \boldsymbol{w}_{ij}\boldsymbol{x}_{jt} \tag{8b}$$

where $\boldsymbol{w}_{ij}$, I,j = 1,2…N, are bilateral trade weights with $\boldsymbol{w}_{ii} = 0$, *and* $\sum_{j=1}^{N}\boldsymbol{w}_{ij} = \mathbf{1}$. The trade weights, $\boldsymbol{w}_{ij}$, are computed as a three-year moving average to reduce the impact of extreme annual movements on the trade weights.

Specifically:

$$w_{ij} = \frac{\boldsymbol{T}_{ij,2019} + \boldsymbol{T}_{ij,2020} + \boldsymbol{T}_{ij,2021}}{\boldsymbol{T}_{i,2019} + \boldsymbol{T}_{i,2020} + \boldsymbol{T}_{i,2021}} \tag{8c}$$

where $\boldsymbol{T}_{ijt}$, I, is the bilateral trade of country I with country j during a given year t, and is equal to the average of exports and imports of country I with country j, and $\boldsymbol{T}_{it} = \sum_{j=1}^{N}\boldsymbol{T}_{ijt}$ (the total trade of country i) for t = 2019,2020,2021, and j = 1,2, …N. The weights used for the world oil and CM study are presented in Table 1.

To accommodate regional analysis of geopolitical shocks to the system, we define the following regions—the Euro Area, net oil exporters and importers, Latin America, Asia Pacific, and the rest of the world (ROW). The weights are calculated based on the PPP valuation of the individual countries' real GDP, for both regional aggregation and the derivation of aggregate impulse response functions. According to Dees et.al, the PPP method has been shown to be more reliable than weights based solely on U.S. dollar valuations (Dees et al., 2007).

2.2.2. Including the dominant and global variables: The oil price and critical minerals

The global variables: the oil and CM prices are added to the system—the conditional country models—as global or dominant variables. The addition entails the following augmentation to Eq. (8a):

$$\boldsymbol{\Phi}_i(\boldsymbol{L},\boldsymbol{p}_i)\boldsymbol{x}_{it} = \boldsymbol{a}_{io} + \boldsymbol{a}_{i1}\boldsymbol{t} + \Lambda_i(L,q_i)\boldsymbol{x}_{i,t}^{*} + \boldsymbol{\Psi}(\boldsymbol{L},s_i)\boldsymbol{\varpi}_{it} + \boldsymbol{u}_{it} \tag{9}$$

where, $\boldsymbol{\varpi}_{\mathbf{t}}$ is a vector of global or dominant variables and its lagged values. The model can be augmented to allow for feedback effects from the domestic variables as follows:

$$\boldsymbol{\varpi}_{\mathbf{t}} = \sum_{l=1}^{p_w} \boldsymbol{\Phi}_{wl}\boldsymbol{\varpi}_{\mathbf{i,t-1}} + \sum_{l=1}^{p_w} \boldsymbol{\Lambda}_{wl}\boldsymbol{x}_{i,t-1}^{*} + \boldsymbol{\eta}_{wt} \tag{10}$$

where $\boldsymbol{\Phi}_i(\boldsymbol{L},\boldsymbol{p}_i) = \boldsymbol{I} - \sum_{i=1}^{pi}\boldsymbol{\Phi}_i\boldsymbol{L}^i$ is the matrix lag polynomial of the global and dominant variable coefficients. In the new specification, $\mathbf{p}_{\boldsymbol{\omega}}$ is allowed to vary and can be selected by the Akaike information criterion (AIC), or Schwarz information criterion (SBC) methodologies (Mohaddes et al., 2020).

The oil and CM prices are treated as dominant or global variables, and Eq. (10) is specified by the oil and CM price models specified in Eqs. (1b) and (6). While the common variables $\boldsymbol{\varpi}_{\mathbf{t}}$ can be treated as a foreign variable for the purposes of modeling and share the same lag order (q), this specification allows for different lag orders for the dominant and foreign variables. $\left(Y_{it}^{\ *}, I_{it}^{0*}, Dp_{it}^{*}, Qs_{t}^{0*}\right)$

The oil and CM price Eqs. (1b) and (6) are standard autoregressive distributed lag (ARDL) models in oil and CM prices. The fixed weights

Mexico	Norway	New Zealand	Peru	Philippines	Russia	South Africa	Saudi Arabia	Singapore	Sweden	Switzerland	Thailand	Turkey	UK	USA	Venezuela
0.0021	0.0004	0.0024	0.0218	0.0020	0.0022	0.0037	0.0039	0.0005	0.0011	0.0032	0.0042	0.0028	0.0014	0.0027	0.0101
0.0030	0.0026	0.1773	0.0027	0.0139	0.0017	0.0110	0.0051	0.0395	0.0073	0.0080	0.0363	0.0051	0.0153	0.0110	0.0004
0.0105	0.0100	0.0021	0.0431	0.0063	0.0127	0.0115	0.0154	0.0111	0.0070	0.0076	0.0095	0.0130	0.0061	0.0174	0.0629
0.0382	0.0178	0.0133	0.0454	0.0097	0.0042	0.0090	0.0128	0.0043	0.0087	0.0116	0.0092	0.0102	0.0238	0.1630	0.0065
0.0815	0.0630	0.2782	0.3380	0.3503	0.2634	0.2627	0.2720	0.2019	0.0748	0.0630	0.2632	0.0962	0.1105	0.1802	0.2773
0.0039	0.0012	0.0026	0.0361	0.0014	0.0018	0.0012	0.0005	0.0003	0.0023	0.0020	0.0027	0.0026	0.0015	0.0071	0.0044
0.0669	0.3972	0.0942	0.1114	0.0710	0.3661	0.2419	0.1504	0.0946	0.5739	0.5089	0.0755	0.4356	0.4509	0.1529	0.1263
0.0090	0.0083	0.0122	0.0328	0.0117	0.0215	0.0752	0.1085	0.0555	0.0079	0.0400	0.0283	0.0270	0.0172	0.0265	0.2274
0.0016	0.0025	0.0184	0.0036	0.0409	0.0048	0.0103	0.0164	0.0582	0.0027	0.0042	0.0349	0.0058	0.0028	0.0086	0.0019
0.0011	0.0014	0.0103	0.0011	0.0064	0.0020	0.0251	0.0000	0.0187	0.0052	0.0045	0.0160	0.0178	0.0056	0.0078	0.0001
0.0184	0.0155	0.0683	0.0376	0.1050	0.0434	0.0544	0.1020	0.0613	0.0171	0.0239	0.1342	0.0129	0.0213	0.0601	0.0048
0.0199	0.0191	0.0401	0.0427	0.0614	0.0487	0.0179	0.0846	0.0462	0.0120	0.0072	0.0333	0.0263	0.0115	0.0418	0.0029
0.0033	0.0021	0.0246	0.0031	0.0355	0.0040	0.0079	0.0169	0.1260	0.0034	0.0042	0.0549	0.0103	0.0046	0.0129	0.0270
0.0000	0.0017	0.0066	0.0247	0.0177	0.0044	0.0049	0.0009	0.0061	0.0046	0.0056	0.0164	0.0054	0.0057	0.1658	0.0220
0.0007	0.0000	0.0013	0.0032	0.0005	0.0051	0.0025	0.0005	0.0021	0.0781	0.0025	0.0022	0.0086	0.0352	0.0029	0.0001
0.0006	0.0006	0.0000	0.0011	0.0030	0.0009	0.0012	0.0025	0.0040	0.0012	0.0007	0.0059	0.0007	0.0023	0.0023	0.0000
0.0027	0.0004	0.0019	0.0000	0.0012	0.0009	0.0010	0.0002	0.0002	0.0013	0.0039	0.0013	0.0012	0.0009	0.0045	0.0043
0.0010	0.0004	0.0077	0.0008	0.0000	0.0021	0.0010	0.0049	0.0233	0.0010	0.0016	0.0235	0.0006	0.0013	0.0054	0.0001
0.0037	0.0147	0.0057	0.0063	0.0053	0.0000	0.0064	0.0065	0.0050	0.0147	0.0120	0.0052	0.0972	0.0267	0.0082	0.0078
0.0009	0.0017	0.0031	0.0007	0.0012	0.0021	0.0000	0.0143	0.0022	0.0043	0.0035	0.0079	0.0042	0.0091	0.0041	0.0001
0.0011	0.0014	0.0103	0.0011	0.0064	0.0020	0.0251	0.0000	0.0187	0.0052	0.0045	0.0160	0.0178	0.0056	0.0078	0.0001
0.0043	0.0077	0.0351	0.0009	0.0756	0.0076	0.0058	0.0236	0.0000	0.0053	0.0185	0.0534	0.0051	0.0125	0.0212	0.0096
0.0010	0.1934	0.0032	0.0035	0.0012	0.0108	0.0059	0.0040	0.0026	0.0000	0.0055	0.0026	0.0108	0.0177	0.0054	0.0090
0.0031	0.0068	0.0088	0.0276	0.0050	0.0097	0.0222	0.0093	0.0239	0.0160	0.0000	0.0196	0.0214	0.0479	0.0228	0.0022
0.0041	0.0040	0.0315	0.0058	0.0497	0.0061	0.0190	0.0239	0.0367	0.0043	0.0164	0.0000	0.0054	0.0063	0.0146	0.0017
0.0018	0.0091	0.0021	0.0066	0.0013	0.0611	0.0096	0.0155	0.0022	0.0130	0.0113	0.0038	0.0000	0.0201	0.0067	0.0312
0.0054	0.1636	0.0288	0.0106	0.0070	0.0484	0.0637	0.0205	0.0207	0.0559	0.0696	0.0126	0.0703	0.0000	0.0359	0.0047
0.7099	0.0534	0.1101	0.1868	0.1092	0.0622	0.0997	0.0849	0.1336	0.0714	0.1559	0.1273	0.0845	0.1364	0.0000	0.1552
0.0004	0.0000	0.0000	0.0008	0.0000	0.0001	0.0000	0.0000	0.0004	0.0005	0.0000	0.0000	0.0010	0.0001	0.0005	0.0000

used to construct the feedback variables are: (i) the PPP for the financial economic variables, real GDP, inflation, real equity prices, real exchange rates, and short- and long-term interest rates; (ii) contributions to OECD inventories for the inventory variable; and (iii) contribution to total oil production for the crude oil production variable (see Eq. (10a)):

$$Y_t^{*} = \sum_{j=1}^{N} \boldsymbol{\omega}_j^{Y} \boldsymbol{Y}_{jt} \tag{10a}$$

$$Qs_t^{0*} = \sum_{j=1}^{N} \boldsymbol{\omega}_j^{Q} \boldsymbol{Qs}_{jt}$$

$$Dp_t^{*} = \sum_{j=1}^{N} \boldsymbol{\omega}_j^{Y} \boldsymbol{Dp}_{jt}$$

$$I_t^{0*} = \sum_{j=1}^{N} \boldsymbol{\omega}_j^{I} I_{jt}^{0}$$

where:

$\boldsymbol{\omega}_j^{Y}$ is calculated as a three-year average 2019, 2020 and 2021 of the PPP GDP weights of country j, and $\sum_{j=1}^{N} \boldsymbol{\omega}_j^{Y} = \mathbf{1}$.

$\boldsymbol{\omega}_j^{I}$ is calculated as a three-year average from 2019Q1 to 2021Q1 of quarterly weights of country j in terms of its contribution to OECD inventories, and $\sum_{j=1}^{N} \boldsymbol{\omega}_j^{I} = \mathbf{1}$

$\boldsymbol{\omega}_j^{Q}$ is calculated as a three-year average from 2019Q1 to 2021Q1 of quarterly weights of country j in terms of its contribution to total oil production from the producing countries listed in the GVAR model, and $\sum_{j=1}^{N} \boldsymbol{\omega}_j^{Q} = \mathbf{1}$.

The weights used in the feedback equations for the oil and CM price model are given in Table 2.

The combined GVAR model permits a two-way link between real GDP, oil supplies, oil inventories, CM price, and the world oil price. Changes in GDP, inventories, CM prices and oil supplies affect the world oil price with a lag. World oil prices, in turn, can affect variables in the country-specific economies. The CM price is affected by changes in the world oil price, GDP inflation and world oil inventories with a lag, and the CM price, in turn, has the potential to affect the country-specific economies. The fact that aggregate global GDP, oil inventory, inflation, and oil production variables are excluded from the global price equations allows us to identify and evaluate country-specific shocks to inventories, income, and oil supplies (Mohaddes and Pesaran, 2016a).

2.2.3. *Stage 2: Solving for the system as a whole*

In the second stage of estimation process, we combine the oil and CM equations and individual country specific models to complete the GVAR model. The GVAR is solved for the world as a whole, and all variables are treated as endogenous to the system. The GVAR model and solution are described in detail in Appendix A.

3. Empirical results: Estimation of base case country-specific models

3.1. *The scope of the model*

The world oil and CM GVAR represents 36 countries, 4 regions and sub-regions, and 8 country-specific variables (see Table 3). The dataset includes quarterly data from 1979:Q1 to 2022:Q1 and was taken from a variety of industry sources including the EIA, World Bank, IMF, and Bloomberg. The data sources for the study are described in detail in Appendix B.

The oil producing countries include Net Oil Exporters: Canada, Indonesia, Venezuela, Russia, Iran, Mexico, Norway, and Saudi Arabia. Net Oil Importers include Brazil, China, the UK, and the USA. These 12 countries accounted for 67% of world crude oil production and hold approximately 67% of the world's proved oil reserves, see Table 4 (BP, 2021, 2022).

The Euro block of countries includes Austria, Belgium, Finland, France, Germany, Italy, The Netherlands, and Spain, and the time series for the euro area are calculated using weight averages of the eight Euro area countries using Purchasing Power Parity GDP (PPP) weights averaged over the 2019–2021 period.

3.2. Specification of country-specific vector autoregression models

Given quarterly estimates of the data for the domestic variables from 1979Q2 to 2022Q1, we estimate the 36 individual country specific models. The modeling exercise assumes that the country–specific foreign variables are weakly exogenous variables, and that the parameters are stable over time. Unit root tests performed on the variables utilized by the GVAR show that the variables utilized in the model are integrated of order one. The unit root tests, weak exogeneity, and structural stability test results are reported in Appendix C. The weights matrix that is used to calculate the foreign specific star variables, and the solution to the GVAR model, including the W or link matrices (see eqs. 8a and b), and bootstrapping is shown in Table 1.

The variables specified by the country specific VARX models are illustrated in Table 5. The model for the United States differs from the specification of all other countries in one respect: U.S. dollar exchange rates are included as endogenous variables in all other countries, except the US. This reflects the importance of the U.S. financial system in the world economy and is supported by empirical evidence that the global financial cycle in capital flows, asset prices, and credit growth is driven primarily by the monetary policy settings of the United States (Chudik and Smith, 2013) (Mohaddes and Pesaran, 2016b). Foreign, country-specific interest rates have been omitted from the country-specific models.

The stability of the GVAR system can be verified by eigenvalues. The model has 165 endogenous variables with 59 cointegrating relationships, so that at least $165–59 = 106$ must lie on the unit circle for the system to be stable. In fact, the system has 108 eigenvalues on the unit circle, and all of the remaining values are less than one. This suggests that the system as a whole is stable, and that some shocks can be expected to have permanent effects on the endogenous variables. The price shock scenarios are run without restrictions on the equations or parameters. The price shock scenarios are run without restrictions on the equations or parameters. The selection of lag orders, cointegrating relationships, and persistence profiles is described in detail in Appendix D.

3.3. Counterfactual analysis of price shocks

The GVAR model has been fully specified and can be utilized to study the time profile of the effects of shocks to the global system. To illustrate the dynamic properties of the model we investigate the implications of positive and negative shocks to the CM price and the world oil price. The shocks are analyzed by means of Generalized Impulse Response Functions (GIRFs), which consider shocks to individual errors and integrate the effects of all 'other' shocks 'out', using the observed distribution of all of the shocks (Koop et al., 1996). The impulse response function is calculated from the moving average representation of the GVAR and is the difference between the conditional and unconditional forecasts where the conditioning information set is the shock to the variable under consideration (see Appendix A).

For our counterfactual analysis, we consider four scenarios, First, we apply a one standard deviation positive shock to CM prices and oil prices in turn. For the other two scenarios, we apply a one standard deviation negative shock to CM prices and oil prices instead.

3.3.1. The impact of a positive shock to CM and world oil prices

Given the period under consideration, 1979Q1 to 2022Q2, the positive price shock to CM prices is roughly equivalent to a 5% increase. The implications for world oil prices and output are negligible and not statistically significant. This result is expected. CMs account for a fraction of non-fuel extraction of metals and minerals. Further, the portion of CM relating to the energy mix is even smaller; for instance, about 7% of total consumption of lithium, nickel, manganese, and cobalt is used for batteries and large format battery uses (e.g., EVs, grid-based energy storage) (Foss, 2021; IEA, 2022a, 2022b, p. 144).[6] Still, this increase in CM prices creates small but notable inflationary pressures for most countries in our sample (see Figs. 1, 2.a and 3.a).

As illustrated in Fig. 2.a, the increase in CM prices results in a significant increase in inflation in most of the countries captured in the GVAR analysis. The impacts are stronger in the first and second quarters, dying out after three or four quarters. This general observation holds for all countries except the United Kingdom and India, where the effects are stronger than for the rest of the countries, and permanent throughout the forecast period. The effects of the shock are strongest in the United Kingdom, where inflation increases by 0.3%–0.4% in the first two years of the forecast period. Prices remain steady in the United States and fall slightly in South Korea and China during the second year of the forecast period. In the case of China, the declines are delayed to the second year following the forecast period, tend to be less pronounced, and are not statistically significant (See Table 6). Our results on China are not surprising as Chinese fiscal policy and other market intervention policies (e.g., export restrictions) play an important role in determining domestic CM prices (Nikkei Asia, 2021, Mancheri, 2016).

It is interesting to compare these results to a one standard deviation increase in the price of crude, roughly equivalent to a 14% increase. The two shocks are asymmetric. The shock to the world oil price has an immediate effect on CM prices, which rise steadily to 5% throughout the forecast period. The results are statistically significant and permanent, lasting throughout the 44-quarter forecast period. As anticipated, the increase is inflationary, and has a strong positive effect on world oil production (see Figs. 1, 2.b, and 3). This finding falls in line with the current literature, which points to spillover effects from oil price fluctuations to the base metals market (Reboredo and Ugolini, 2020), copper (Zhang and Tu, 2016), and other "clean energy metals" Shao and Zhang (2020). Our findings also operationally make sense as prospecting, mining, transport, and processing of ores are energy-intensive processes mostly reliant on oil and gas.

Similarly, our findings reflect the consensus in the literature on the relationship between oil prices and inflation (see, inter alia, Aharon et al., 2023; Wen et al., 2021; Raheem et al., 2020). As illustrated in Fig. 2.b, the positive shock to oil prices results in a significant increase in inflation in most of the countries captured in the GVAR analysis. The impacts are stronger in the first and second quarters for all the countries and die out after the first two years in the United States, Saudi Arabia, and the United Kingdom. The United States and UK experience inflation hikes of 0.52% and 0.24%, respectively, in the first year following the price shock. These inflationary hikes are slightly lower in China, South Korea, and India, where the effects are permanent throughout the forecast period. The results are statistically significant for all the countries under observation except Saudi Arabia, which features the least liberalized domestic fuel market in our sample (see Table 6).

The results for an increase in oil prices on oil production are as expected, as exhibited in Fig. 3. Oil production rises in response to an increase in oil prices in both Russia and Saudi Arabia. The greatest increase is seen in Saudi Arabia, where production increases by 3–4% for

[6] We would like to thank the reviewers for bringing this point to our attention. Whether increasing use of CMs for energy (both in absolute and relative terms) will make CM prices a significant determinant of oil prices constitutes an interesting question for future scholarly inquiry. One must also note the way the global governance of CM will evolve (e.g., the extent to which spot markets play a role, aggressive onshoring, etc.) will be an intervening factor in how CM production will interact with other major energy commodities. Likewise, the way CMs evolve in specific industries may diverge. For example, the market to CMs committed for transport may interact differently with oil prices than the market for CMs committed to solar and wind energy.

Table 2
Fixed feedback weight matrix (2019–2021).

Country weights for real GDP, production, and inventories			
Countries	GDP-PPP	Production	Inventories
Argentina	0.008967	0.000000	0.000000
Australia	0.012086	0.000000	0.000000
Brazil	0.028838	0.000000	0.000000
Canada	0.016471	0.096625	0.054790
China	0.219809	0.094564	0.000000
Chile	0.004449	0.000000	0.000000
Euro	0.131847	0.000000	0.160484
India	0.084293	0.000000	0.000000
Indonesia	0.029923	0.074818	0.000000
Iran	0.011486	0.091314	0.000000
Japan	0.047190	0.000000	0.152316
Korea	0.020537	0.000000	0.056688
Malaysia	0.008279	0.000000	0.000000
Mexico	0.022158	0.085766	0.000000
Norway	0.003284	0.084776	0.000000
New Zealand	0.002031	0.000000	0.000000
Peru	0.003786	0.000000	0.000000
Philippines	0.008618	0.000000	0.000000
Russia	0.039830	0.106897	0.000000
South Africa	0.007320	0.000000	0.000000
Saudi Arabia	0.014843	0.105093	0.000000
Singapore	0.005237	0.000000	0.000000
Sweden	0.005130	0.000000	0.000000
Switzerland	0.005602	0.000000	0.000000
Thailand	0.011602	0.000000	0.000000
Turkey	0.020894	0.000000	0.000000
UK	0.028597	0.078214	0.022598
USA	0.191410	0.107672	0.553123
Venezuela	0.005482	0.074260	0.000000

Sources: EIA, 2022, World Bank Development Indicator database 2022, KAPSARC internal calculations.

Table 3
Countries and regions in the GVAR model.

Countries utilized in the world oil and CM model		
Argentina	Indonesia	Russia
Australia	Iran	South Africa
Austria	Italy	Saudi Arabia
Belgium	Japan	Singapore
Brazil	Korea	Spain
Canada	Malaysia	Sweden
China	Mexico	Switzerland
Chile	Netherlands	Thailand
Finland	Norway	Turkey
France	New Zealand	United Kingdom
Germany	Peru	USA
India	Philippines	Venezuela
Regions and subregions accounted for in the world oil and CM model		
Net oil exporters	Europe	Latin America
Euro area	Net oil importers	Asia Pacific
Rest of world		
Global variables in the world oil and CM model		
World oil price	CM price	
Country-specific variables in the world oil and CM model		
Real GDP	Oil inventories	Real exchange rates
Inflation	Crude oil production	Short term interest rates
Real equity prices		Long term interest rates

Source: Considine et al., 2020.

at least two years after the oil price shock. Production in the U.S. falls slightly immediately following the shock and begin to rise later in the forecasts period. The minor reduction is likely due to a lack of investment in the oil industry during Covid, and high shale oil decline rates. However, it should be noted that the impacts on the U.S. oil output are merely indicative as they are not significant at a 90% confidence level.

An increase in CM prices has negligible implications for oil production. This is an expected outcome; while certain CMs are critical in producing tubular goods for oil drilling in corrosive environments (e.g., molybdenum) (Bazilian, 2018), this demand is minimal compared both to overall oil capital expenditures and global CM production. Such an increase in CM prices leads to a slight increase in output in the United States of less than 0.5% in the first years after the forecast period. There is a larger effect in Saudi Arabia, where oil production falls by almost 1% per annum in the first two years following the CM price shock. The results for both the U.S. and Saudi Arabia should be interpreted with caution due to the wide range the confidence intervals exhibit. Nevertheless, these results suggest that the cross-price elasticity of oil with respect to CM prices may be positive in the United States, where CM's and oil are substitutes, and negative for Saudi Arabia, where CMs and oil are compliments. In other words, rising prices for CMs may increase the joint cost of CMs and oil as inputs to renewable energy in some regions, which will induce consumers to consume slightly less crude oil relative to the base case. This relationship between CMs and conventional energy sources should be more closely monitored with the advent of new technologies that utilize both, such as blue hydrogen and advanced plastics recycling.

Table 4
Crude oil production and reserves.

2021		
Country	Oil production	Oil reserves
	Thousand barrels daily	Billion barrels
Net exporters		
Canada	5429	169.1
Indonesia	692	2.4
Iran	3620	157.8
Mexico	1928	6.1
Norway	2025	7.9
Russia	10,944	107.8
Saudi Arabia	10,954	297.5
Venezuela	2110	303.2
Net importers		
Brazil	654	11.9
China	3994	26.0
United Kingdom	874	2.5
United States	16,585	68.8
Total	59,809	1161.0
Rest of world	30,068	571.4
World total	89,877	1732.4
Model producers as a percent of the world total	67%	67%

Sources: Total proved reserves at end of 2020, thousand million barrels. BP, 2021, 2022.

3.3.2. The impact of a negative shock to CM and world oil prices

We now consider another scenario with a one standard deviation negative shock to CM and Brent prices. Given the period under consideration, 1979Q1 to 2022Q2, the shocks are roughly equivalent to a 5% reduction in CM prices per quarter and a 14% reduction in the price of crude. In a nutshell, the implications of a negative shock to CM prices for world oil prices (Fig. 4) and output (Fig. 6) are negligible. Such a shock tends to be deflationary for most countries in the short term, although statistically significant inflationary results emerge for the U.S. and South Korea in the longer term (Fig. 5.a). Table 7 presents the results of the significance tests that we run for each analysis in this subsection.

The negative shock to price of Brent, on the other hand, has significant implications for the CM price index and deflation. Fig. 4 demonstrates that the negative shock to price of Brent has an immediate negative effect on CM prices of about 5%. This effect is amplified in the second year after the price shock and lasts throughout the forecast period. This finding mirrors our previous discussion on how CM industry is dependent on oil.

Once again, the implications of the negative price shocks on inflation are asymmetric and vary according to the nature of the shock and the country under observation. The negative shock to the CM price index

Table 5
List of variables included in the country specific VARX models.

Models	Domestic variables								Foreign variables						Global variables	
	Y_{it}	Dp_{it}	eq_{it}	ep_{it}	r_{it}	rl_{it}	I_{it}^{0}	Qs_{it}^{0}	Y_{it}	Dp_{it}	eq_{it}	ep_{it}	rl_{it}	I_{it}^{0}	p_t^0	Rp_t^0
Argentina	1	1	1	1	1				1	1	1		1	1	1	1
Australia	1	1	1	1	1	1			1	1	1		1	1	1	1
Brazil	1	1		1	1				1		1		1		1	1
Canada	1	1	1	1	1	1	1	1	1		1		1		1	1
China	1	1		1	1			1	1	1	1		1	1	1	1
Chile	1	1	1	1	1				1	1	1		1	1	1	1
Euro	1	1	1	1	1	1	1		1	1	1		1	1	1	1
India	1	1	1	1	1	1			1	1			1	1	1	1
Indonesia	1	1		1	1			1	1	1	1		1		1	1
Iran	1	1		1	1	1		1	1	1	1		1	1		
Japan	1	1	1	1	1	1	1			1	1		1	1	1	1
Korea	1	1	1	1	1	1	1		1	1	1		1	1	1	1
Malaysia	1	1	1	1	1						1		1	1	1	1
Mexico	1	1		1	1			1	1	1	1		1		1	1
Norway	1	1	1	1	1	1		1	1	1	1		1	1	1	1
New Zealand	1	1	1	1	1	1				1	1		1	1	1	1
Peru	1	1		1	1					1	1		1	1	1	1
Philippines	1	1	1	1	1				1	1	1		1		1	1
Russia	1	1		1	1	1		1	1	1	1		1	1		1
South Africa	1	1	1	1	1	1			1		1		1	1	1	1
Saudi Arabia	1	1		1				1	1				1			
Singapore	1	1	1	1	1				1	1	1		1	1	1	1
Sweden	1	1	1	1	1	1			1	1	1		1	1	1	1
Switzerland	1	1	1	1	1	1			1	1	1		1	1	1	1
Thailand	1	1	1	1	1				1		1		1		1	1
Turkey	1	1		1	1				1	1	1		1	1	1	1
UK	1	1	1	1	1	1	1	1	1	1	1		1	1	1	1
USA	1	1	1		1	1	1	1	1			1		1	1	
Venezuela	1	1		1	1			1	1	1	1			1		

Note: A value of 1 is given if the variable is included in the analysis.
Source: Considine et al., 2020.

Table 6
Significance tests: Selected results by country and region; positive shock to CM index and Brent.

Variable	CM price shock			Oil price shock		
	Median cumulative changes %		Significance	Median cumulative changes %		Significance
	1 year	2 years		1 year	2 years	
CM price				4.81%	9.64%	F
Oil price	−1.31%	−2.88%				
Inflation-US	0.01%	0.00%		0.52%	0.11%	D
Inflation-Saudi Arabia	0.04%	0.02%		0.06%	0.09%	
Inflation-UK	0.33%	0.40%	G	0.24%	−0.06%	C
Inflation-China	0.08%	−0.18%		0.24%	0.25%	A
Inflation-South Korea	−0.27%	−0.32%	E	0.27%	0.28%	B
Inflation-India	0.06%	0.19%		0.24%	0.41%	G
Oil production-Saudi Arabia	−0.91%	−0.82%		2.88%	4.17%	A
Oil production-USA	0.29%	0.48%		−1.29%	−0.20%	
Oil production-Russia	0.51%	0.31%		0.76%	1.72%	F

Notes: Median cumulative changes after one year in %, * refers to 90% confidence intervals. A - statistically significant in one quarter. B - statistically significant in two quarters. C - statistically significant in three quarters. D - statistically significant in four quarters. E – statistically significant in five quarters. F Statistically significant in six quarters. G -statistically significant for at least two years.

results in deflation or falling prices in most of the countries captured in our analysis. The impacts are amplified in the second year following the shock. Deflation is most pronounced in Saudi Arabia, the United Kingdom, and India. In the U.S., China and South Korea, the shock results in an increase in the inflation level in the second year following the shock. The effects of the shock are strongest in the United Kingdom, where the CPI falls by 0.3%–0.4% in the first two years of the forecast period (see Fig. 5.a). This is not surprising as the UK is heavily dependent on CM imports and has the highest share of renewables among the sample countries. The effects of the CM price shock are significant for the United States, Saudi Arabia, the UK, South Korea, and India, but not China. Not surprisingly, the extent of government controls over the domestic CM industry allows China, the only major CM producer and processor in our model, to alleviate the market fluctuations via export and price regulations (Mancheri, 2016).

Interestingly, the impact of negative CM price shocks on inflation tends to be larger than positive CM price shocks. In the second year, this situation reverses itself in the UK, and China, and the effects of a negative shock to the CM price index are larger. Notably, China – the biggest player in the CM market – has a relatively small, compared to other countries, and statistically insignificant implications for its CPI.

In the oil market, the effects of a negative shock to oil prices are less pronounced than the effects of a negative oil price shock for all of the countries under observation during the first year following the shock. It is interesting to notice that this effect holds for all of the countries except the United States, where the implications of a positive shock to oil prices

Table 7
Significance tests: Selected results by country and region; negative shock to CM index and crude.

Variable	(−) CM price shock			(−) Oil price shock		
	Median cumulative changes %		Significance	Median cumulative changes %		Significance
	1 year	2 years		1 year	2 years	
CM price				−4.76%	−9.42%	G
Oil price	1.67%	3.11%				
Inflation-U.S.	−0.03%	0.18%	F	−0.57%	−0.19%	G
Inflation-Saudi Arabia	−0.19%	−0.19%	C	0.01%	0.10%	F
Inflation-UK	−0.35%	−0.38%	G	−0.21%	0.10%	G
Inflation-China	−0.11%	0.15%		−0.24%	−0.25%	
Inflation-South Korea	0.32%	0.48%	F	−0.27%	−0.32%	F
Inflation-India	−0.15%	−0.35%	F	−0.20%	−0.33%	F
Oil production-Saudi Arabia	3.57%	5.84%	C	−5.15%	−9.78%	A
Oil production-U.S.	−1.05%	−1.79%	B	1.50%	1.06%	B
Oil production-Russia	−0.47%	−0.30%		−0.50%	−1.27%	

Notes: Median cumulative changes after one year in %, * refers to 90% confidence intervals. A - statistically significant in one quarter. B - statistically significant in two quarters. C - statistically significant in three quarters. D - statistically significant in four quarters. E – statistically significant in five quarters. F Statistically significant in six quarters. G -statistically significant for at least two years.

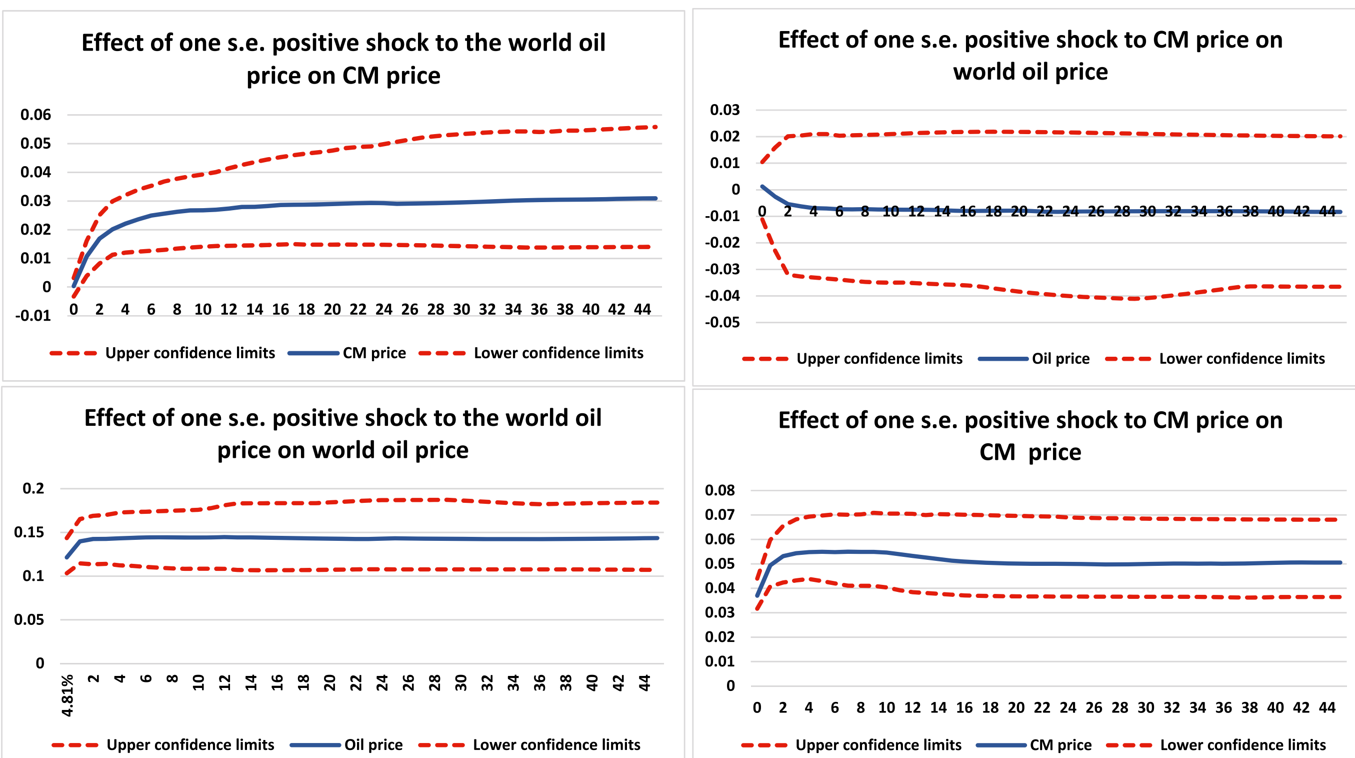

Fig. 1. The effects of a positive shock to CM and world oil prices.
Note: Bootstrap median estimates with 90% bootstrap error bounds.

on inflation are slightly lower than the deflationary implications of a negative shock to oil prices. This might be attributed to a number of factors including strong response from domestic producers (as seen in Fig. 6), releases from the U.S. SPR during the time period under observation, shifts in foreign trade due to the ban on Russian imports of oil from Russia announced on March 8, 2022, macroeconomic forces such as the U.S. Federal Reserve's policy to increase the frequency of interest rate hikes starting at the beginning of 2022, hedging and the large contribution of supply constrained (subsidized) Canadian imports to U. S. refining industry.

For most of the countries under observation, the deflationary effects of the negative shock to crude give a symmetric picture to that of a positive oil price shock, and in line with general consensus. Fig. 5.b shows that the deflationary effects of the shock are greatest in the United States (−0.57%), followed by South Korea (−0.27%), China (−0.24%), the UK (−0.21%), and India (−0.20%) in the first year following the Brent price shock. The effects of inflation in the U.S. and UK die out rapidly in the second year of the forecast period. The results are significant at a 90% confidence level for all the countries mentioned here except China, where the effects of the shock are minimal.

Note: Dp = inflation. Bootstrap median estimates with 90% bootstrap error bounds.

In contrast with a positive shock, a negative price shock to CM prices appears to have significant implications for oil production in our model. Our findings indicate oil production increases by 3.5% in the first year, and almost 6% in the second year for Saudi Arabia following a negative price shock in CMs. In the U.S., crude oil production fall by 1–2% in the first year following the CM price shock with a subsequent return to

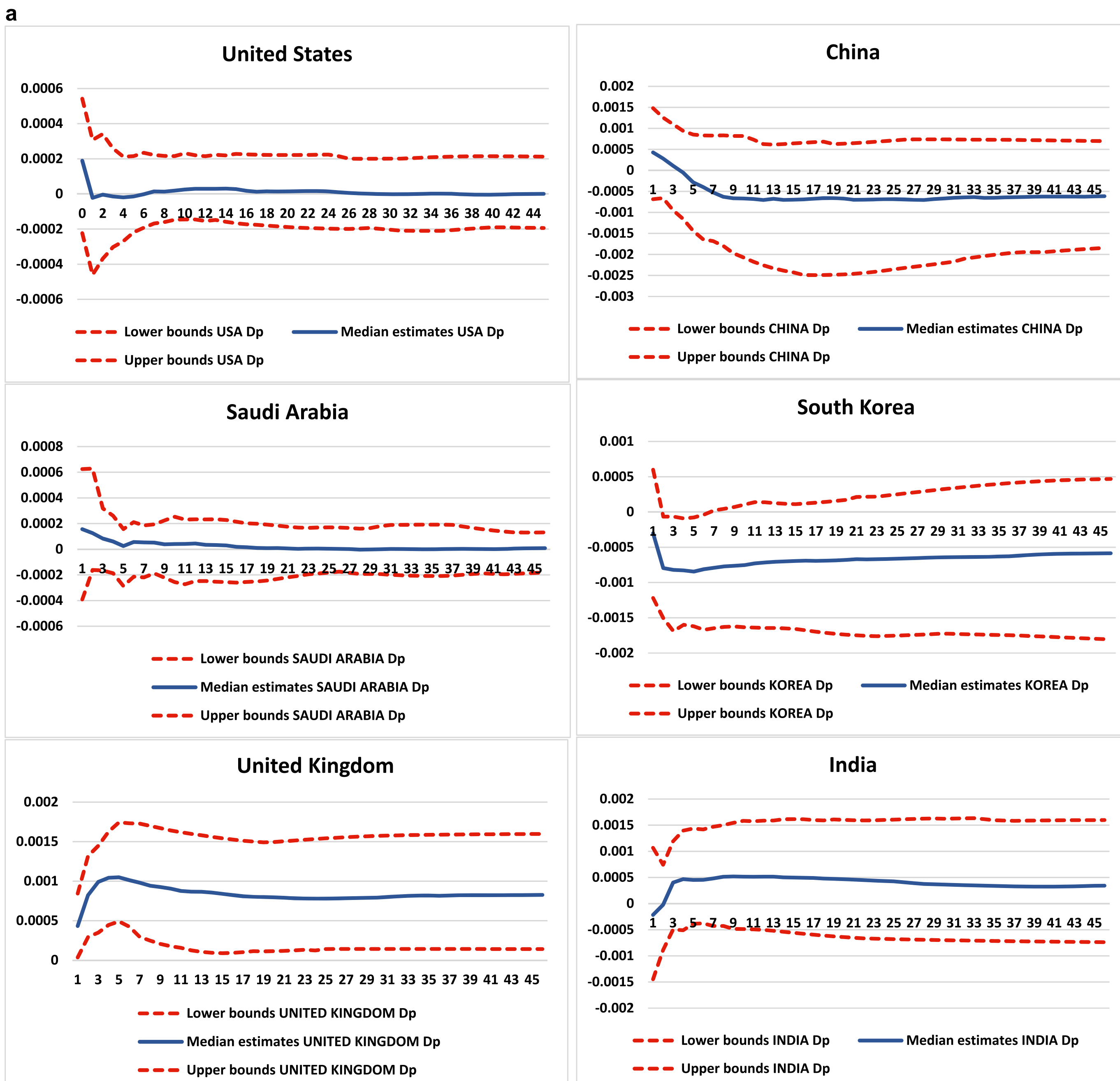

Fig. 2.a. The effects of a positive shock to CM prices on inflation in selected countries.
Note: Bootstrap median estimates with 90% bootstrap error bounds.

status quo. There are negligible implications for Russia, where production falls by almost 0.5% in the first two years after the forecast period with a subsequent further decline around a 1% level (See Fig. 6). Interestingly, the impacts of the negative shock to oil price are also not statistically significant in the case of Russia. Other major oil producers demonstrate the opposite reactions: The U.S. tends to increase its production, especially in the short run, while Saudi Arabia responds with a substantial reduction in output – below 5% in the first year and up to 10% in the second – in alignment with the usual policy deployed by OPEC members in such market conditions. The results for both of these producers are statistically significant (see Table 7).

Once again, these results suggest that the cross-price elasticity of oil with respect to CM prices is positive in the United States, where CM's and oil are substitutes, and negative for Saudi Arabia where CMs and oil are compliments. The results suggest that the falling CM price index reduces the joint cost of CMs and oil as inputs to renewable energy in some of the regions that are customers of Saudi Arabian oil production, encouraging consumers to use more oil. These findings also introduce CMs to the debate on whether the dynamics governing value chains in the Global South are diverging from those in the Global North (Horner and Nadvi, 2018).

4. Conclusion

The results of the empirical analysis show that implications of CM and oil price shocks are asymmetric in several ways:

b

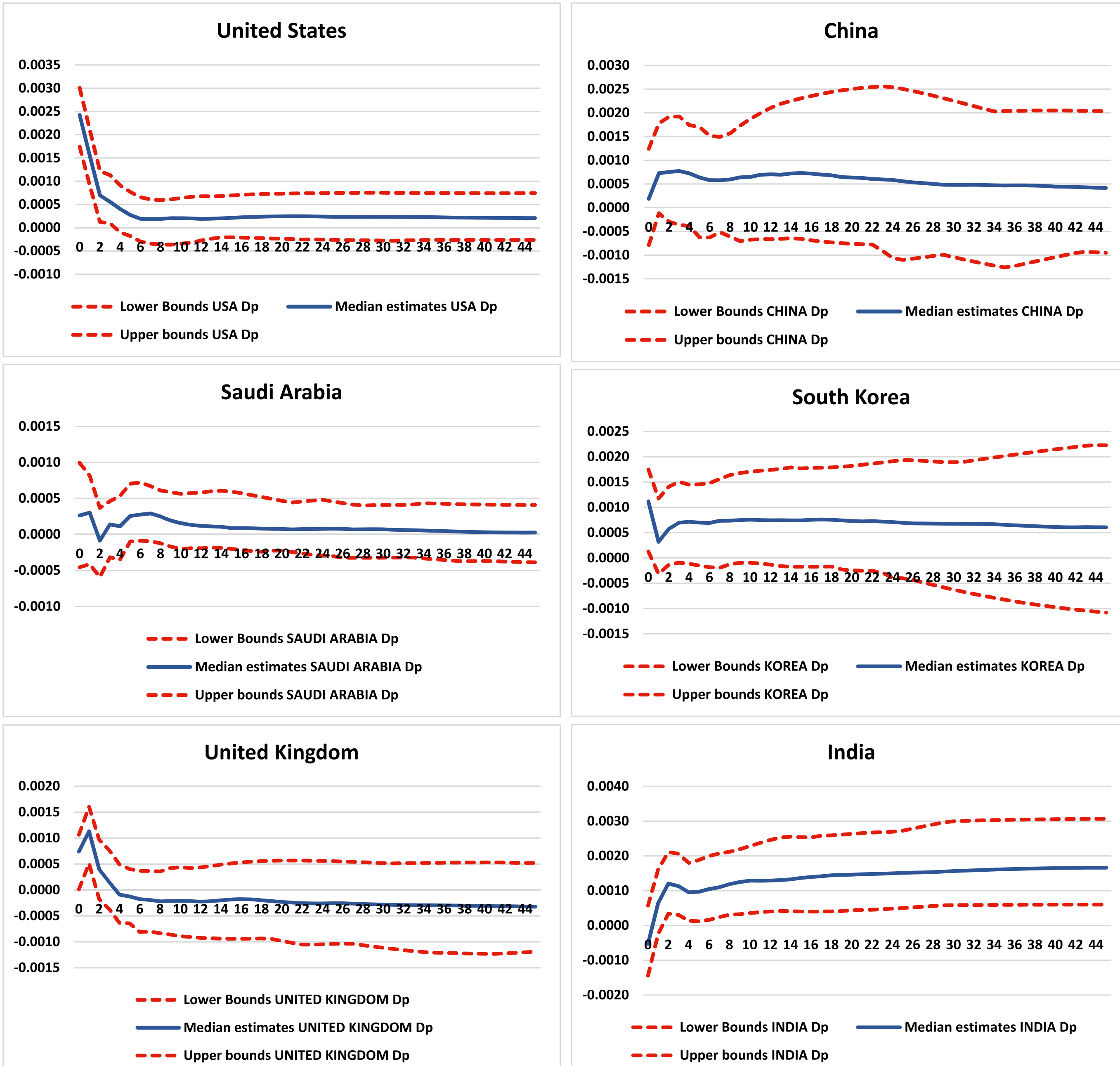

Fig. 2.b. The effects of a positive shock to oil prices on inflation– selected countries.
Note: Dp = inflation. Bootstrap median estimates with 90% bootstrap error bounds.

1. Shocks to world oil prices tend to have more of an effect on CM prices than CM prices do on world oil prices. The output of the model simulations confirms the spillover effect between the oil and CM (or their individual components) prices, which has been established in previous works (Shao and Zhang, 2020; Chen et al., 2022). However, we find that this relationship tends to be unidirectional at this time. This is an expected result as the CM market still constitutes a very small portion of the global economy.
2. For most of the countries under observation, the deflationary effects of a negative price shock to crude are less pronounced than the inflationary effects of a positive price shock. This is true in the first year following the shock for all countries under observation except the U. S., where the deflationary implications of a negative shock to oil prices are higher than the inflationary implications of a positive shock to oil.
3. The cross-price elasticity of oil with respect to CM prices is positive in the United States, where CMs and oil are substitutes, and negative for Saudi Arabia where CMs and oil are compliments.
4. The macroeconomic impacts of oil price shocks tend to be stronger, more uniform, and statistically significant than those of CM price shocks. While our findings align with the existing consensus on the effects of oil price shocks on inflation (Salisu et al., 2017; Siok, 2017), the impacts of CM prices tend to be less pronounced and more varied across the countries.

The results suggest that CMs are starting to have an impact on the world's economy at the macro level – due in part to their crucial role in

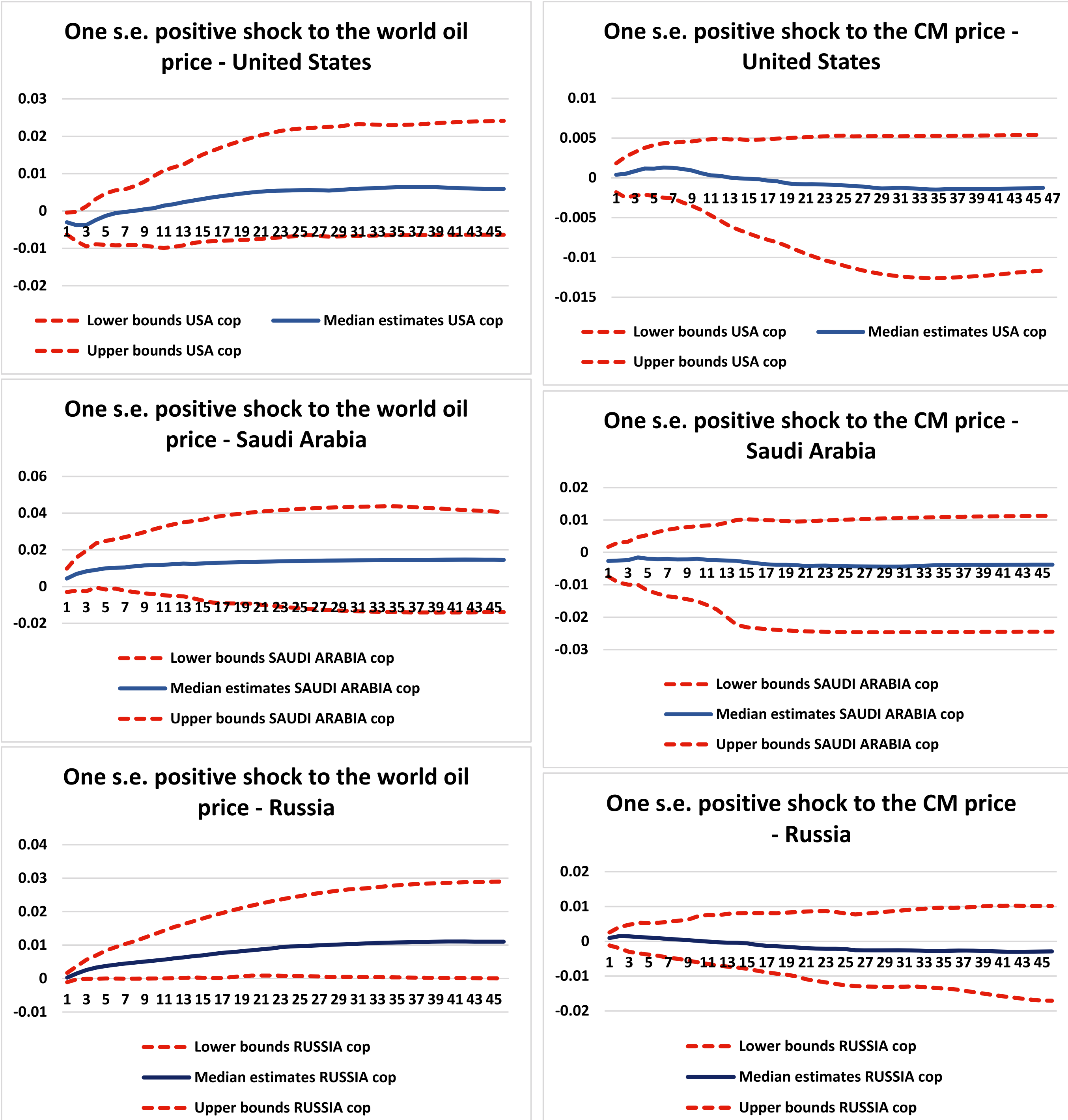

Fig. 3. The effects of a positive shock to CM and crude prices on oil production in selected countries.
Note: cop = oil production. Bootstrap median estimates with 90% bootstrap error bounds.

energy transition and other industrial value chains. This impact is likely to intensify in the future, as the relevant industries increase their share in the countries' economies. Moreover, the volatility of CM price index can be expected to accelerate due to increasing geopolitical tensions and rising protectionism trends affecting the global supply chains. Nevertheless, compared to that of oil, the impact of CMs on macroeconomic indicators remains quite small at the time of writing, July 2023.

Interestingly, the way CMs impact national economies varies is similar in some respects to that of the world's current major commodity – oil. The demonstrated variability of the effects of CM price shocks across the countries highlights the necessity for future studies concerning the complex dynamics of CM markets – and energy transition in general – in the context of country specific macroeconomic implications. Such an approach will account for the unequal distribution of CM reserves, varying stages of sophistication of nations in the transition to low hydrocarbon or green energy, as well as the differences in economic structure and trade patterns of individual countries and regions. The potential value of this line of inquiry is reflected in our findings on cross-price elasticities.

Out of the countries taken into consideration in this analysis, China

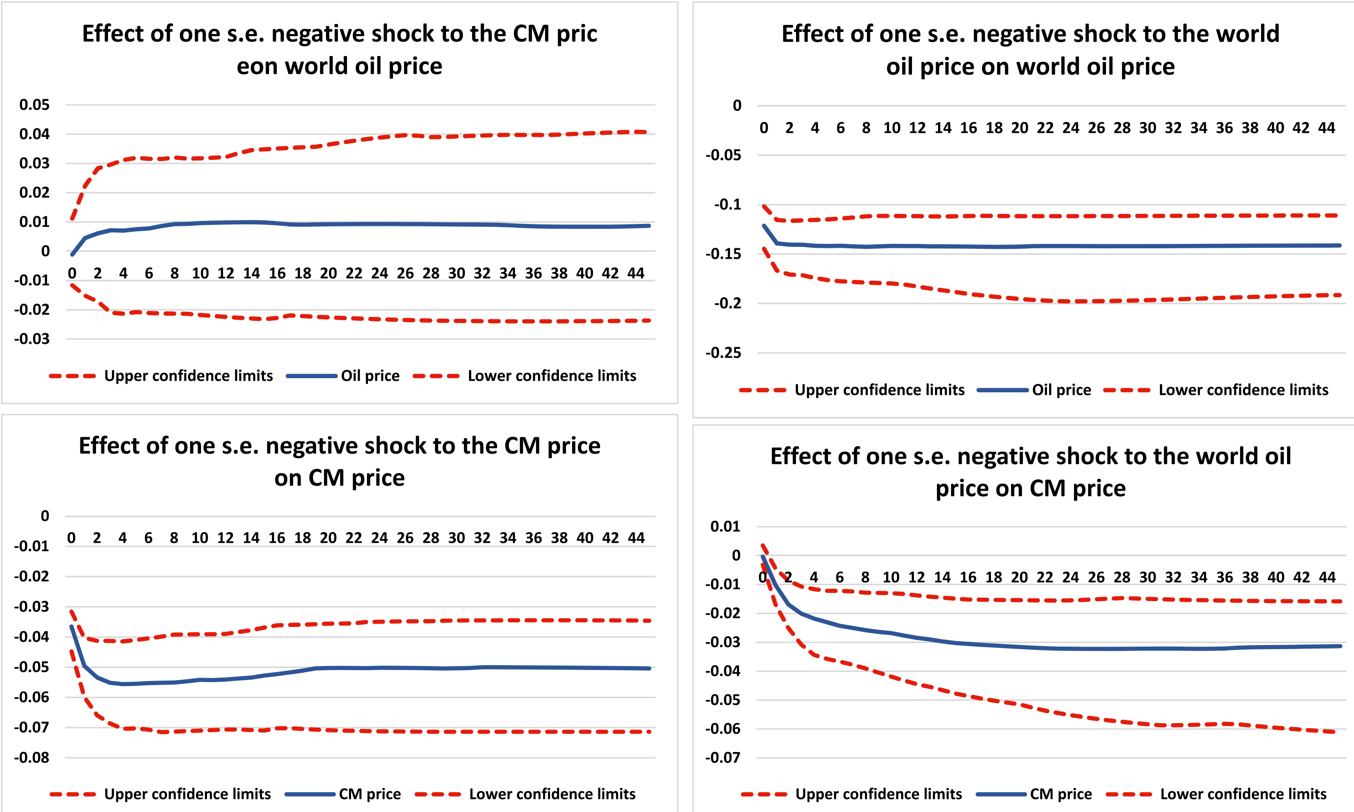

Fig. 4. The effects of a negative shock to CM and world oil prices.
Note: Bootstrap median estimates with 90% bootstrap error bounds.

appears to be the only one unaffected by the CM price shocks in the model simulations. Uncoincidentally, China is the only major CM producer represented in the model. The extent of government controls over the domestic CM industry also allows it to alleviate the market fluctuations via export and price regulations (Global Times, 2022; Mancheri, 2016). On the other hand, the UK, where inflation increases the most in response to a CM price shock, is heavily dependent on CM imports and has the highest share of renewables among the sample countries.

The results suggest that for some economies accounted for in the GVAR analysis, the specific commodities included in our CM price index may not be deemed "critical" according to prevailing definitions of CM. Future research and extensions of this study can be tailored to look at specific CMs such as copper, nickel, or aluminum to derive detailed industry- or country-specific findings. Changing the focus to individual commodities will allow for (i) the incorporation of production figures (in addition to price) as necessary, (ii) the modeling of cross-border flows of these commodities, and (iii) the utilization of more granular (e.g., monthly) data, subject to its availability for all of the macroeconomic variables of interest on a global scale.

A significant, technology-related caveat remains for our study. Our time coverage arguably covers major technological breakthroughs that has reshaped the market for CMs until the time of writing. We are, however, unable to predict how fundamental technological breakthroughs may reshape the global CM market. The prevailing supply-chain bottlenecks and vulnerabilities pressure the CM industry to innovate. For example, increasing CM prices can lead to new and cheaper "battery chemistries…as manufacturers seek to encourage customer adoption for larger scale energy storage and mobility" (Foss, 2022, p.9).[7] The net effect could be a migration away from CMs and/or an increase in energy price volatility.

From the policy perspective, our study also makes a case of divorcing geopolitics from CM supply chains. To illustrate, India's inflation rate has been shown to be affected by the positive shock in CM price, demonstrating the problem that many developing nations may face on their energy transition paths. A nation, which does not have a developed CM industry, and is not endowed with relevant mineral reserves, might have a difficult time competing with global powerhouses like the US, EU, or G7 countries and various partnerships they have been building on their existing alliance foundations (e.g., the Mineral Security Partnership). The use of CM supplies for geopolitical leverage increases CM prices. Our findings suggest this price hike tends to increase inflation globally and for some individual countries. Developing countries suffer disproportionately more from higher levels of global inflation (UN, 2022), suggesting an unintended adverse consequence of using access to CMs as a tool of economic statecraft.

In the current phase there is no universal policy solution to alleviate potential CM price shocks, which would be applicable to all countries (unlike, for example, strategic petroleum reserves, and OPEC, in the case of oil). However, it is essential to develop a comprehensive CM strategy that covers the whole value chain and is tailored to the country's existing and target industrial, economic, and trade parameters. Understanding the cross-sectoral and macroeconomic impacts associated with the CM dynamics allows a more comprehensive assessment of the costs, benefits, and risks associated with the development of the CM industry. It is critical to the evaluation of country-specific energy transition pathways.

One promising line of future research concerns the incorporation of (country-specific) production levels of CMs as another set of equation(s) to the GVAR system. Such an extension of the model could reveal policy-relevant insights into the interaction of the production of CMs and global and country-level macroeconomic variables. Granular, country-level analysis can help to answer a number of important issues such as

[7] We thank the reviewers for bringing this point to our attention.

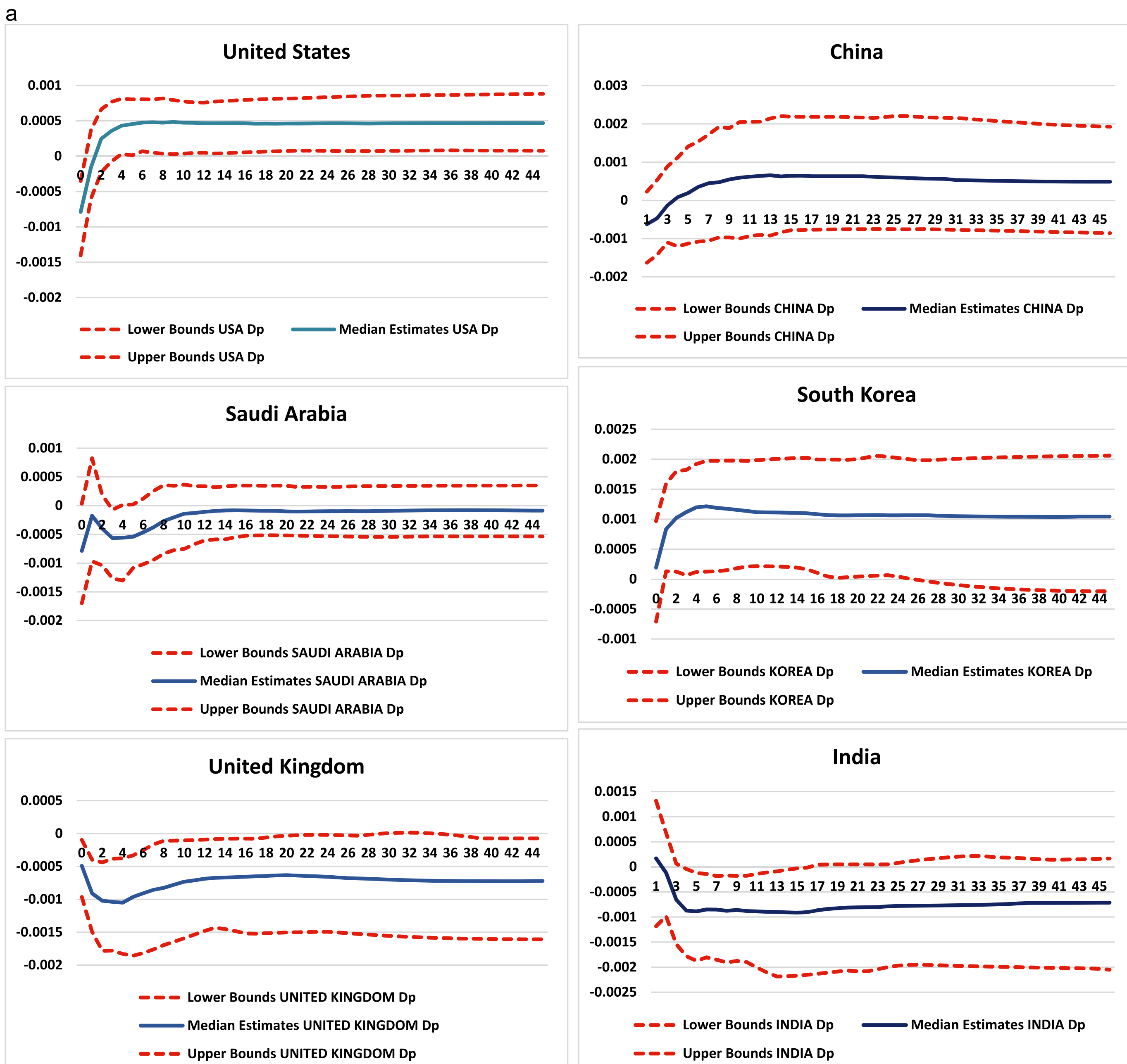

Fig. 5.a. The effects of a negative shock to CM prices on inflation– selected countries.
Note: Dp = inflation. Bootstrap median estimates with 90% bootstrap error bounds.

whether or not, (and how) varying levels of the quality of corporate governance can affect levels of supply for CMs.[8] Indeed, good corporate governance under the SDG framework is fast becoming a requisite towards securing a sustainable supply of CMs in the longer term (Hine et al., 2023; Nieri et al., 2023).

As well as developing domestic CM mining and processing sectors, best practices and capacity management policies can also be instrumental in enhancing CM supply security at the individual country level. The maintenance of spare capacity can help to keep commodity prices in check (Kesicki, 2010; Boussena and Locatelli, 2017). The development of spare production capacity for CMs, and strategic CM reserves emerges as a policy option to ameliorate the inflationary pressure that rising CM prices can put on consuming economies. While the maintenance of spare CM mines and processing plants, similar to the way OPEC maintains spare oil capacity, might prove to be excessively costly, the development of recycling capacity could emerge as a viable option. If successful, many of the CMs would be readily available in processed form, and geographically dispersed in consuming countries.

At the global level, the observed asymmetric impact of oil prices on CM prices indicates the essential role of oil in the smooth transition to green energy in the short and medium term. Regardless of how much a country divorces its energy supply from oil, oil prices will continue to play an important role in that country's energy policy. The study results suggest another aspect of "dependence on oil," namely its effect on CM price levels and, consequently, on the country's macroeconomic indicators. Hence, oil is essential to a smooth energy transition in the short term, and medium term.

[8] We thank the reviewers for bringing this point to our attention.

b

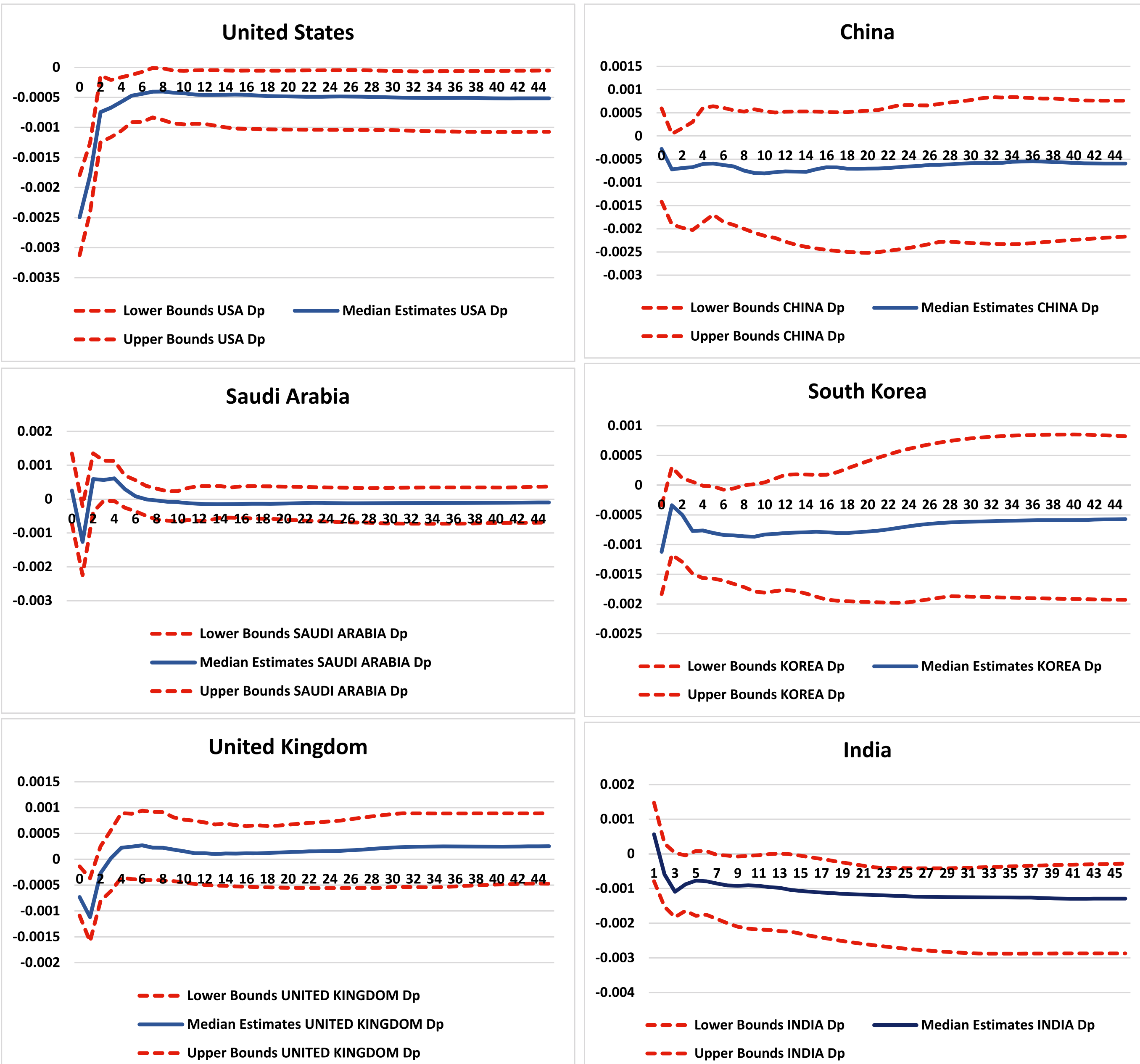

Fig. 5.b. The effects of a negative shock to oil prices on inflation– selected countries.

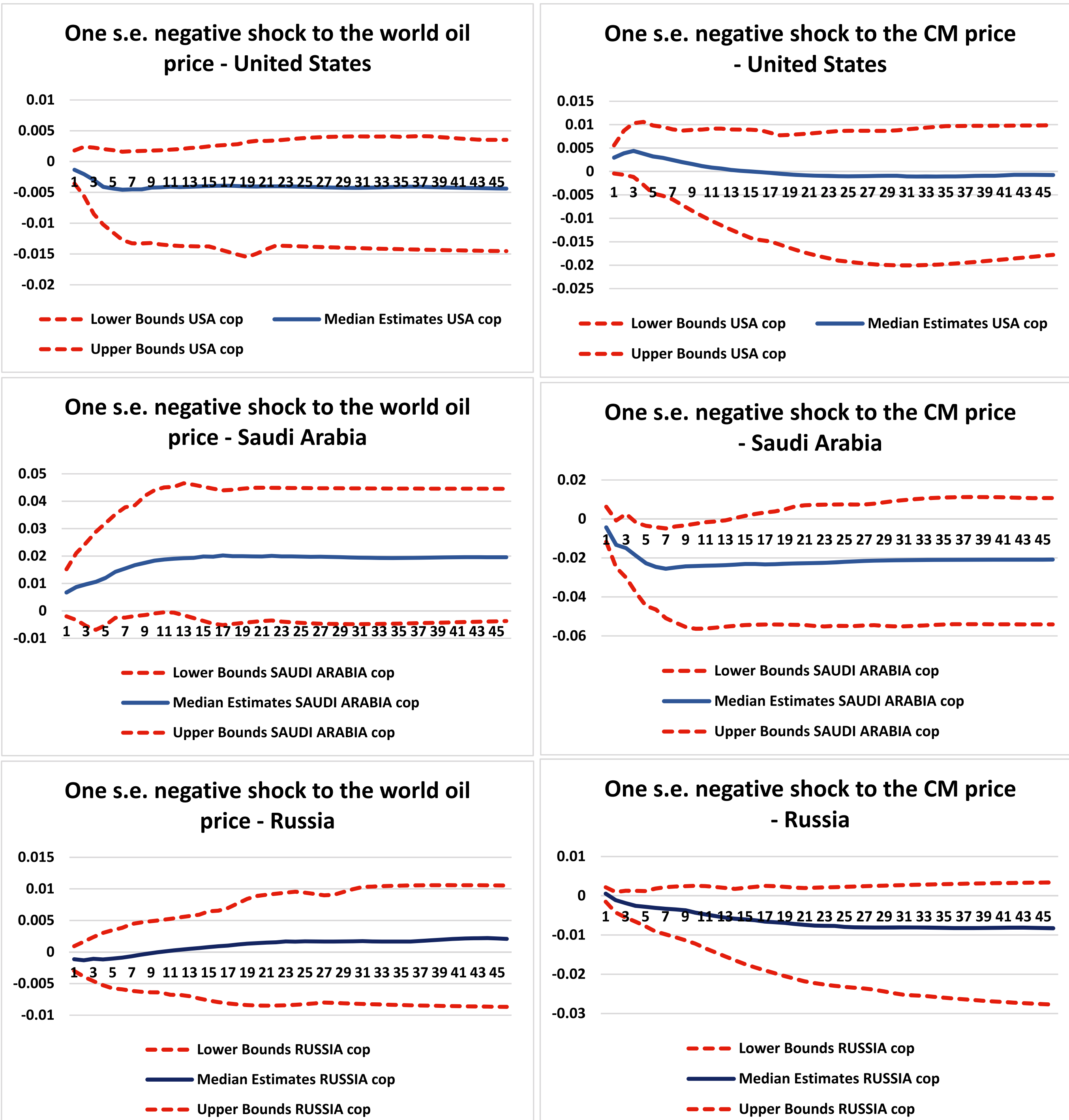

Fig. 6. The effects of a negative shock to CM and Brent prices on oil production in selected countries.
Note: cop = oil production. Bootstrap median estimates with 90% bootstrap error bounds.

CRediT authorship contribution statement

Jennifer Considine: Conceptualization, Writing – review & editing, Methodology, Software. **Philipp Galkin:** Visualization, Investigation, Writing – review & editing. **Emre Hatipoglu:** Conceptualization, Writing – review & editing. **Abdullah Aldayel:** Data curation, Writing – original draft.

Appendix A

Given the country-specific models estimated individually and the world oil and CM price models, the combined GVAR model described above can be estimated as follows:

Let:

$$z_{it} = \begin{pmatrix} x_{it} \\ x_{it}^{*} \end{pmatrix} \tag{A.1}$$

Eq. (8) can be written for each region as:

$$A_{io} z_{it} = a_{io} + a_{i1} t + A_{i1} z_{it-1} + \ldots + A_{ip_i} z_{it-p_i} + u_{it} \tag{A.2}$$

Where:

$$A_{io} = (I_{k_i} - \Lambda_{io}), A_{ij} = (\theta \Phi_{ij}, \Lambda_{ij}) \; for \; j = 1, \ldots p_i \tag{A.3}$$

Then the trading weights, or aggregation weights can be defined so that:

$$z_{ioit} = W_i x_t \tag{A.4}$$

where $x_t = (x_{ot}^{'}, x_{1t}^{'} \ldots, x_{Nt}^{'})$ is the k x 1 vector which includes all of the endogenous variables of the system, and W_i is a $(k_i \times k_i^{*}) \times k$ matrix.

$$A_{io} W_i x_t = a_{io} + a_{i1} t + A_{i1} W_i x_{t-1} + \ldots + A_{ip_i} W_i x_{t-p_i} + u_{it} \text{ for } \mathbf{I} = 0, 1, 2 \ldots, N \tag{A.5}$$

The individual models can be stacked to give the model for x_t

$$\mathbf{G_o x_t} = \mathbf{a_{io}} + \mathbf{a_{i1} t} + \mathbf{G_{i1} x_{t-1}} + \ldots + \mathbf{G_p x_{t-p}} + \mathbf{u_{it}} \tag{A.6}$$

where:

$$G_0 = \begin{bmatrix} A_{00} W_0 \\ A_{10} W_1 \\ \cdot \\ \cdot \\ \cdot \\ A_{N0} W_N \end{bmatrix}, G_j = \begin{bmatrix} A_{00} W_0 \\ A_{10} W_1 \\ \cdot \\ \cdot \\ \cdot \\ A_{N0} W_N \end{bmatrix} \text{ for } \mathbf{j} = 1, 2 \ldots, \mathbf{p} \tag{A.7}$$

$$a_o = \begin{bmatrix} a_{00} \\ a_{10} \\ \cdot \\ \cdot \\ \cdot \\ a_{N0} \end{bmatrix}, a_i = \begin{bmatrix} a_{01} \\ a_{11} \\ \cdot \\ \cdot \\ \cdot \\ a_{N1} \end{bmatrix}, u_t = \begin{bmatrix} u_{0t} \\ u_{1t} \\ \cdot \\ \cdot \\ \cdot \\ u_{Nt} \end{bmatrix}$$

where G_0 is a known non-singular matrix that depends on trade weights and parameter estimates.

The GVAR(p) model is obtained by pre-multiplying Eq. (A.6) by G_0^{-1}.

$$x_t = b_0 + b_1 t + F_1 x_{t-1} + \ldots + F_p x_{t-p} + \varepsilon_t \tag{A.8}$$

where:

$$b_0 = G_0^{-1} a_0, b_{10} = G_1^{-1} a_1, F_j = G_j^{-1} G_j, j = 1, 2, 3, \ldots., p, \varepsilon_t = G_{j0}^{-1} u_t \tag{A.9}$$

Eq. (A.9) can be solved recursively, and if desired sign restrictions may be imposed on the impulse response functions of the model ε_t.

A.1. Properties of the GVAR model structure

A.1.1. Persistence profiles

The properties of the GVAR are determined by Eq. (A.7), these include the persistence profiles, impulse response functions, and variance decompositions. All bootstrapping of the GVAR is preformed according to u_t innovations.

The persistence profiles are determined as follows:

Let an infinite moving average of the GVAR be given by:

$$x_t = d_t + \sum_{s=0}^{\infty} B_s \varepsilon_{t-s} \tag{A.10}$$

where d_t represents the deterministic component of x_t, $\varepsilon_t = G_{j0}^{-1} u_t$ and

$$B_s = F_1 B_{s-1} + F_2 B_{s-2} + \dots F_p B_{s-p} \tag{A.11}$$

The cointegrating relationships of the country-specific models are given by the matrix of cointegrating vectors $z_{it} \bullet \beta_i$, where:

$$z_{it} = \left(x_{it}^{'}, x_{it}^{*'}, w_t^{'}\right) \text{ and } \beta_i = \left(\beta_{im}^{'}, \beta_{im}^{*'}, \beta_{iw}^{'}\right) \tag{A.12}$$

The relationship, or mapping between the GVAR variables x, and z is given by $z_{it} = W_{i1} y_t$ where:

$$W_i = \begin{bmatrix} W_i & 0 \\ 0 & I_m \end{bmatrix} \tag{A.13}$$

$$z_{it} = W_i d_t + W_i B_0 \varepsilon_t + \sum_{s=1}^{\infty} W_i B_0 \varepsilon_{t-s} \tag{A.14}$$

The persistence profiles for a system wide shock are given by:

$$PP\left(\beta_{ji}^{'} w_t \bullet \varepsilon_t, n\right) = \frac{\beta_{ji}^{'} W B_n \sum_e B_n^{'} W^{'} B_{ji}}{\beta_{ji}^{'} W B_{n0} \sum_e B_{n0}^{'} W^{'} B_{ji}}, n = 0, 1, 2, \dots \tag{A.15}$$

Where $\beta_{ji}^{'} z_{it}$ is the jth cointegrating relation in the ith country, n is the horizon, and $\sum_e$ is the (kxm) x (kxm) covariance matrix of ε_t (Smith and Galesi, 2014).

A.1.2. Generalized impulse response functions for country-specific models

Given a one standard deviation shock to the system v_t, the generalized impulse response function is:

$$GIRF(h, x_i, v_t) = E\left(yx_{t+h} | v_t = \sqrt{b^{'} \theta_\gamma b}\, I_{t-1}\right) - E\{x_{t+h} | I_{t-1}\} \tag{A.16}$$

where b is a (k + m) x 1 vector of PPP-GDP weights with zero values everywhere except for the variables to be shocked for the countries involved, scaled to sum to 1, and I_{t-1} is the information set at time t-1. The vector b can consider country specific shocks, regional shocks, and shocks to global variables (Smith and Galesi, 2014).

Appendix B: Data sources

The World Oil Inventory Model includes data from 36 countries and one region. The data set follows the standard GVAR set up used by Smith and Galesi (2014) in their original GVAR toolbox. The countries and regions utilized by the model are listed in Table B1.

Table B1
Countries utilized in the GVAR model.

Countries utilized in the GVAR Model		
Argentina	Indonesia	Russia
Australia	Iran	South Africa
Austria	Italy	Saudi Arabia
Belgium	Japan	Singapore
Brazil	Korea	Spain
Canada	Malaysia	Sweden
China	Mexico	Switzerland
Chile	Netherlands	Thailand
Finland	Norway	Turkey
France	New Zealand	United Kingdom
Germany	Peru	U.S.
India	Philippines	Venezuela
Regions and subregions accounted for in the World Oil Inventory Model		
Euro area	Net oil exporters	Asia Pacific
Europe	Net oil importers	Latin America
Rest of world		
Global variables in the World Oil Inventory Model		
World oil price		
Country specific variables in the world oil inventory model		
Real GDP	Oil inventories	Real exchange rates
Inflation	Crude oil production	Short term interest rates
Real equity prices		Long term interest rates

Source: KAPSARC 2022.

The primary data sources for the variables may be listed as follows:

A.2. Global variables and sources

- Crude Oil Production: U.S. Energy Information Administration,
- Oil Price Index: Brent crude price from Bloomberg Ticker 01 Comdty. The quarterly series was constructed using the simple mathematical average of daily closing prices for all trading days in the quarter.
- CM price Index: Import Price Index (Harmonized System): Inorganic Chemicals; Organic or Inorganic Compounds of Precious Metals, of Rare-Earth Metals, of Radioactive Elements or of Isotopes (IP28)

A.3. Country-specific variables and sources

- Petroleum Stocks: Petroleum Stocks in OECD Countries, November 2016 Monthly Energy Review
- Crude Oil Production: U.S. EIA

Real GDP, the Consumer Price Index, Equity Price Index, Exchange Rates, Short Term Interest Rates, Long Term Interest Rates from 1979Q1 to 2013Q1 were obtained from Smith and Galesi (2014). The observations from 2013Q2 to 2016Q4 were obtained by revising and updating the existing GVAR dataset in the following manner:

A.4. Real GDP

The real GDP variables include quarterly values for seasonally adjusted real GDP for all countries, indexed to the year 2005 = 100. The original 2013 vintage, which includes data from 1979Q1 to 2013Q1, divides the country-specific real GDP estimates into three groups:

Group I. International Financial Statistics (IFS) data for GDP, real index, quarterly, 2005 = 100) data was used for Australia, Canada, France, Germany, Italy, Japan, Netherlands, New Zealand, South Africa, Spain, Switzerland, United Kingdom, and United States (IMF, 2022a, 2022b) (Smith and Galesi, 2014).

Group II. IFS data for GDP, real index, quarterly, 2005 = 100) data was used for Austria, Belgium, Finland, India, Indonesia, Korea, Malaysia, Singapore, Sweden, Thailand, and Turkey. When IFS data was not available, in India and Singapore, the data was taken from Bloomberg. The series were seasonally adjusted using Eviews, applying the National Bureau's X12 program (see the Note on Seasonality below). For Saudi Arabia, annual IFS data for GDP were interpolated to obtain quarterly values to the year 2012 (Smith and Galesi, 2014).

Group III. Inter-American Development Bank (IABD) data for GDP, real index, quarterly, 2005 = 100) were used for the Latin American Countries: Argentina, Brazil, Chile, Mexico, Venezuela, and Peru (Inter-American Development Bank, 2017). For the Philippines, the quarterly rate of change of the seasonal adjusted real GDP index (Bloomberg) was used to extrapolate forward from the year 2011 to 2013. In Norway, continued seasonality—post X-12—was corrected by using OECD data (Ticker: GPSA). The real seasonally adjusted data for China was constructed using data from the National Bureau of Statistics (NBS) of China (Smith and Galesi, 2014).

The GDP time series includes quarterly values for seasonally adjusted GDP for all countries, indexed to the year 2010 = 100. 1979Q2 to 2016Q4 are taken from Mohaddes and Raissi (2018). The numbers from 2016Q4 to 2018Q2 are from International Financial Statistics, (IMF, 2021).

The 1979–2016 data set was extended to 2018 vintage using the quarterly growth rates of the adjusted (and non-adjusted) series from 2016Q4 to 2018Q2. In the case of Venezuela and Argentina, data from the Inter-American Development Bank (IABD) data for GDP, real index, quarterly, were used, (Inter-American Development Bank, 2017, IMF 2022).

For Venezuela, the time series was completed using an interpolated annual value from the World Bank Financial Statistics. (IMF, 2021) Data for 2018 was taken from Focus Economics projections (FocusEconomics, 2018) and (Laya and Rosati, 2018). For Iran, yearly data were obtained from World Bank for the years 1979–1987, 2008 and 2009. For Russia, yearly real GDP data were obtained from the following: 1979–1989, CIA Reference Book on Soviet Economy; 1988–1990, Hokkaido University Slavic-Eurasian Research Center Soviet Economical Statistical Series (Slavic Research Center, 2022); 1990–1994, FRED (2022). 1994Q1-2017Q4 quarterly data from IMF (2022a). 2018 Q1 and Q2 figures calculated from real growth data from CEIC (2022a, 2022b, 2022c). The time series were spliced together in 1988, 1990, 1994, and normalized.

When only yearly data present, quarterly data were interpolated from yearly values using the multiplicative cubic spline method and seasonally adjusted. Canadian values were obtained from Statistics Canada (2022).

The 1979–2018 data set was extended to 2022 vintage using the quarterly growth rates of the adjusted (and non-adjusted) series from 2018 Q1 to 2022 Q1. Iranian GDP growth was obtained from Bloomberg (2022) (ticker IAGDP Index), the Central Bank of Iran, and CEIC (2022a, 2022b, 2022c). Malaysian GDP was obtained from the Department of Statistics Malaysia (DoSM, 2022). In case of missing or unreported values, the data was obtained from Trading Economics (2022a).

A.5. Consumer price index (CPI)

The CPI time series includes quarterly values for seasonally adjusted CPI for all countries, indexed to the year 2010 = 100. 1979Q2 to 2016Q4 are taken from Mohaddes and Raissi (2018).The numbers from 2016Q4 to 2018Q3 are from International Financial Statistics, (IMF, 2021).

The 1979–2016 data set was extended to 2022 vintage using the quarterly growth rates of the adjusted (and non-adjusted) series from 2016Q4 to 2022Q1. In the case of Argentina, data from the Inter-American Development Bank (IABD) data for GDP, real index, quarterly, 2005 = 100) were used, (Inter-American Development Bank 2017, IMF, 2022a, 2022b). For Canada, the Euro Area, the Philippines, and the Netherlands, data from FRED were used to update the series by extrapolating forward using quarterly growth rates.

Venezuelan yearly CPI data (1979–1989) was taken from FRED (St Louis FED, quarterly data), thereafter (1990–2016) from IFS. Note that IFS stopped reporting CPI for Venezuela from 2017Q1. 2017–2018 data were extrapolated. For Iran, quarterly data for 2008 onwards was obtained from IFS; annual data for 1979–2007 from FRED and the Central Bank of Iran. For Russia, 1979–1980 yearly from "U.S. Congress Report (1991) USSR: Measures of Economic Growth and Development:1950-80;" 1980–1991 yearly from Shleifer and Vishny (1991); 1991–1992 from Filatochev and Bradshaw (1992); quarterly data from 1993Q1 onwards from IFS. When only annual data was available quarterly values were interpolated from annual values using the multiplicative cubic spline method.

A.6. Short term interest rates

The short-term interest rate time series includes quarterly values for the deposit rate percent per annum. The data from 1979Q2 to 2016Q4 are taken from Mohaddes and Raissi (2018).The numbers from 2016Q4 to 2018Q2 are from International Financial Statistics (IMF, 2021). For the 2016 vintage, IFS data for interest rates selected indicators, deposit rate, percent per annum were collected for Austria, Argentina, Chile, China, Malaysia, and Turkey for the years 1979 to 2016 inclusive. For Peru, IFS data for interest rates, discount rate percent per annum was used for the years 1979 to 2016. The IFS Treasure Bill Rate was used for Canada, Belgium, France, Germany, Italy, Mexico, Norway, Philippines, South Africa, Sweden, the UK, and the U.S.. For Australia, Brazil, Finland, India, Indonesia, Japan, Korea, Saudi Arabia, Singapore, Spain, Switzerland, and Thailand, the IFS Money Market rate percent per annum was used for all years 1979 to 2016 (CEIC, 2022a, 2022b, 2022c).

For Germany, the 3-month T-Bill rate was used from 2010Q1 onward, and for Singapore the overnight rate average was used from 2005Q3 onward. In Australia, Belgium, France, Italy, Japan, Norway, short term interest rates for 2016Q1 onwards were extrapolated forward using quarterly growth rates taken from the OECD short term interest rate series based on 3 month Money Market Rates (OECD, 2022). The T-Bill rate for Canada from 2017Q3 on was taken from the Bank of Canada (Bank of Canada, 2018). For Indonesia, the Money Market rate which was used in earlier vintages was no longer available, the series was extrapolated forward using quarterly growth rates for the Deposit Rate (IMF, 2022a). For Malaysia, the series was unavailable from 2017Q1, and extrapolated forward using the quarterly rate of change of the Money Market rate. For the United Kingdom, the data was extrapolated forward using T-Bill rates from FRED.(Bank of England 2018)

For Venezuela, the time series includes quarterly values for the discount rate from International Financial Statistics. (IMF, 2021, 2022a, 2022b). For Iran, yearly figures for 1979–2003 were obtained from Iran Central Bank; quarterly data between 2003Q4-2016Q4 from IFS; 2017–2022 from trading.com (Trading.com, 2022). For Russia, quarterly data between 1995Q1-1996Q3 was obtained from Russian Central Bank, 1997Q1-2003Q2 was obtained from OECD. 1996Q4 was interpolated. Short Term Interest Rate: monthly average actual rates on Moscow bank's credits–MIACR: 1 to 3 Months were obtained from the Bank of Russia (CEIC, 2022a, 2022b, 2022c).

For all other variables, the 1979–2016 data set was extended to 2018 vintage using the quarterly growth rates from 2016Q4 to 2018Q2.

The 1979–2018 data set was extended to 2022 vintage using the quarterly growth rates of the adjusted (and non-adjusted) series from 2018Q1 to 2022Q1. In Australia, Belgium, France, Italy, Japan, Norway, the UK, and the Euro Area, short term interest rates for 2018Q1 onwards were extrapolated forward using quarterly growth rates taken from the OECD short term interest rate series and forecast series based on 3 month Money Market Rates (OECD 2022).

For Brazil, data for 2022Q1 was taken from Countryeconomy.com (2022). For Indonesia, the Money Market rate, which was used in earlier vintages, was no longer available, the series was extrapolated forward using quarterly growth rates for the Deposit Rate (IMF, 2022a) . CEIC data was used for Singapore short term interest rates in 2021Q4 and 2022Q1 (CEIC, 2022a, 2022b, 2022c). For Sweden, the deposit rate was no longer available, OECD data was used to extrapolate the series forward. For Turkey and Thailand, OECD data was used to extrapolate the series forward. For Venezuela, 2018Q1 onwards was extrapolated forward using quarterly growth rates of short-term interest rates from Countryeconomy.com (2022).

A.7. Equity price index

The equity price series 1979Q2 to 2016Q4 are taken from Mohaddes and Raissi (2018). The numbers from 2016Q4 to 2018Q3 are from Bloomberg, MSCI Country Index, quarterly averages from 2017Q1 to 2018Q2 (Bloomberg, 2022). For Argentina, the data was taken from Bloomberg ticker M1AR Index from 2009 onwards. For Chile, Finland, France, India, Korea, Malaysia, Netherlands, Norway, New Zealand, Philippines, South Africa, Sweden, and Thailand, the values were extrapolated forward from the 2016 vintage using the rate of change of the Bloomberg MCSI Country Index (Bloomberg, 2022).

The 1979–2018 data set was extended to 2022 vintage using Bloomberg data when appropriate. Bloomberg codes used for the equity indices are: MVLEAR Index, MSDLAS Index, MSDLAT Index, MSDLBE Index, MXBR000V Index, MSDLCA Index,MXCL000V Index, MSELTCF Index, MSDLFI Index, MSDLFR Index, MSDLGR Index, MXIN Index, MXID Index, MSDLIT Index,MSDLJN Index,MXKR Index, MSDLMAF Index, MSELTMXF Index, MSDLNE Index,MSDLNZ Index, MSDLNO Index, MSELTPR Index, MXPH Index,MISAD Index, MSDLSG Index, MXZA Index, MSDLSP Index, MSDLSW Index, MSDLSZ Index, MSELTTHF Index,MXTR Index, MSDLUK Index, GDDLUS Index (Bloomberg, 2022).

A.8. Exchange rates

The exchange rate series 1979Q2 to 2016Q4 are taken from Mohaddes and Raissi (2018). The numbers from 2016Q4 to 2018Q2 are from International Financial Statistics (IMF, 2021). Bloomberg, Foreign Exchange quarterly values from 1979Q1 to 2016Q4 (Bloomberg, 2022). The rest of the data series was completed to 2016 by extrapolating forward using the rate of change of the Bloomberg data series (Smith and Galesi, 2014).

The list of Bloomberg Tickers is as follows: Australian AUD BGN, Argentina ARS BGN, Austria ATS BGN, Belgium BEF BGN, Brazil BRL BGN, Canada CAD BGN, China CNY BGN, Chile CLP BGN, Colombia COP BGN, Finland FIM BGN, France FRF BGN, Germany DEM BGN, India INR BGN, Indonesia IDR BGN, Italy ITL BGN, Japan JPY BGN, Korean KRW BGN, Malaysia MYR BGN, Mexico MXN BGN, Netherlands NLG BGN, Norway NOK BGN, New Zealand NZD BGN, Peru PEN BGN, Philippines PHP BGN, South Africa ZAR BGN, Saudi Arabia SAR BGN, Singapore SGD BGN, Spain ESP BGN, Sweden SEK BGN, Switzerland CHF BGN, Thailand THB BGN, Turkey TRY BGN, and the United Kingdom GBP BGN (Bloomberg, 2022).

For the Euro Area—Austria, Belgium, Finland, France, Germany, Italy, Netherlands, and Spain—the exchange rates refer to the pre-euro exchange rates (national currency per USD). The quarterly average was completed using the last price, as described by the Bloomberg ticker description. The quarterly average of the euro exchange rate per USD was used to define the exchange rates in terms of the Euro (Bloomberg Ticker Eur Curncy). This value was extrapolated backwards from 1999Q1 using the rate of change of the national currency foreign exchange rates series. From the years

1990Q1 to 2016, the series is equal to the quarterly average of the Euro Currency expressed in U.S. dollars (Smith and Galesi, 2014).

For Russia the exchange rates from 1929Q2 to 1991 are taken from black market estimates (Alexashenko 1992).

The 1979–2018 data set was extended to 2022 vintage using the quarterly growth rates of the adjusted (and non-adjusted) series from 2018Q1 to 2022Q1.

A.9. Long-term interest rates

The long term interest rate time series includes quarterly values for government bonds for all countries from the IFS database (concept: Interest Rates selected Indicators, Government Bonds, Percent per Annum) (Smith and Galesi, 2014). The data from 1979Q2 to 2016Q4 are taken from Mohaddes and Raissi (2018). The numbers from 2016Q4 to 2018Q3 are from International Financial Statistics. (IMF, 2021) For the 2016 vintage, IFS data for Interest Rates, Government Securities, Government Bonds are used to extend the series for all countries except for India, for which Long Term interest rate data are available, namely Australia, Austria, Belgium, Canada, France, Germany, Italy, Japan, Korea, Netherlands, New Zealand, Norway, South Africa, Spain, Sweden, Switzerland, United Kingdom, and the United States. The 2016 Vintage Long Term Interest rates are extended with these series from 2013Q2 to 2016Q4.

For India, the 10-year government bond yield from the Reserve Bank of India over the period 1996Q2 to 2022Q1 was used. For the period 1979–1996, annual data from RBI was available and used for interpolation (DBIE-RBI, 2022).

For the Eurozone, the 1979–2018 data set was extended to 2022 vintage using the quarterly growth rates for the EU Convergence Criteria –Maastricht criterion bond yields (mcby) are long-term interest rates, used as a convergence criterion for the European Monetary Union, based on the Maastricht Treaty (Eurostat, 2022). For Australia, Canada, Japan, Norway, New Zealand, and the United States, the data set was extended to the 2018 vintage using quarterly growth rates from the 10 year government bond yield from the Federal Reserve Bank of St Louis (FRED, 2019).

For Iran, yearly "long-term interest rates" between 1979 and 2013 were obtained from Iran Central Bank; 2017–2018 from trading.com. 2014–2016 data were interpolated. For Russia, quarterly T-bill rates between 1995Q2-2000Q3 were obtained from IFS; quarterly rates for "180-360-day T-bill interest rates" between 2000Q4-2003Q1 were obtained from Russian Central Bank. From lending rates for the Russian Federation were obtained from IMF, (2022a).

The 1979–2018 data set was extended to 2022 vintage using the quarterly growth rates of the adjusted (and non-adjusted) series from 2018 Q1 to 2022 Q1. For Australia, Canada, Japan, Norway, New Zealand, the United Kingdom, and the United States, the data set was extended to the 2018 vintage using quarterly growth rates from the 10 year government bond yield from the Federal Reserve Bank of St Louis (FRED, 2022).

A.10. Oil price index

The oil price index is a Brent Crude Oil Price taken from Bloomberg (Series: Current Pipeline Export Quality Brent Blend. Ticker: CO1 Comdty). To construct a quarterly series, the average of daily closing prices was obtained for all trading days in the quarter. The quarterly rate of change was used to extrapolate forward the 2011 vintage to 2018 (Smith and Galesi, 2014).

A.11. Agricultural raw material, world shipping and metals price indices

The agriculture and metals indices were taken from the IMF's primary Commodity Prices monthly data (IMF, 2022a, 2022b). As the IMF series starts in the year 1980, data from the World Bank was used for the years 1979 to 1980 to extrapolate the series back to 1979. Quarterly data represents a simple arithmetic average of monthly data (Smith and Galesi, 2014). The IMF series was discontinued in June 2017. From this date, the metals' price series is taken from the U.S. Bureau of Labor Statistics, Import Price Index: Primary metal manufacturing for Industrialized Countries (COINDUSZ331) (FRED, 2022). The agriculture raw material price is taken from the U.S. Bureau of Labor Statistics, Import Price Index: Agricultural products used for industrial supplies and materials (IR120) (FRED, 2019). As before, the quarterly rate of change was used to extrapolate forward the 2016 vintage to 2018.

The world shipping index is the Index of Global Real Economic Activity developed by Kilian (2009) (Dallas Fed, 2022)

A.12. Critical minerals price index

The CM price index is taken from the U.S. Bureau of Labor Statistics, U.S. Import and Export Indexes. The Fred Economic Data portal of the St. Louis Fed (FRED, 2022) Import Price Index (Harmonized System): Inorganic Chemicals; Organic or Inorganic Compounds of Precious Metals, of Rare-Earth Metals, of Radioactive Elements or of Isotopes (IP28). The time series goes from 1993Q1 to 2022Q1.

The time series from 1979Q2 to 19929Q4 is not available, so a combination of titanium and potassium prices were used to extrapolate the index back using a linear regression estimated using historical data on titanium and potassium prices from 1979Q2 to 2009Q1. For titanium we use the Producer Price Index by Commodity: Metals and Metal Products: Titanium and Titanium-Base Alloy Mill Shapes, Index 1982 = 100, Monthly, Not Seasonally Adjusted. For potassium prices we use the Producer Price Index by Industry: Other Basic Inorganic Chemical Manufacturing: Potassium and Sodium Compounds, Excluding Bleaches, Alkalies, and Alum, Index Dec 1982 = 100, Monthly, Not Seasonally Adjusted (FRED, 2022). Estimated coefficients of the analysis are available on request.

An argument can be made that the choice of an US-based data for the CM index is less than ideal. However, this index's availability, and ability to reflect the import prices paid for commodities that have no transparent reported prices makes it ideal for our analysis. To further address this concern, the US is chosen to be the dominant unit economy in our model. In addition, the CM index is highly correlated with similar indices. The substitution of alternative indices such as REE Titanium Potassium and Copper, into the index model did not substantively change our results. Finally, one could argue that a U.S.-based index gives us a conservative bias, making finding significant relationships at the global level, or for other individual countries more difficult. Still, we are able to present a series of significant results at the global level, or for some individual countries (e.g., United Kingdom).

A.13. Crude oil inventories and crude oil production

The oil inventories data series was taken from the EIA's Table 11.3 Petroleum Stocks in OECD Countries (EIA, 2022) . The crude oil production was taken from the EIA's Table 11.1a World Crude Oil Production: OPEC Members, and Table 11.1b World Crude Oil Production: Persian Gulf Nations, Non-OPEC, and World (EIA, 2022). Crude Oil Production for Indonesia for the months August –December 2016 was taken from the U.S. EIA from a secondary source, Trading Economics (Trading Economics, 2022b). Quarterly figures are a simple arithmetic average of monthly values. The data are for crude oil and lease condensate. (EIA, 2022)

A.14. PPP-GDP data

The purchasing power parity – gross domestic product (PPP-GDP) weights were constructed using data from the World Bank Development Indicator database. The GDP in purchasing power parity terms in current international dollars (Ticker: NY:GDP:MKTP:PP:CD) was downloaded for all countries from 2009 to 2021 (Ticker: "GDP, PPP (Current International $ 2022) (World Bank, 2022).

A.15. Trade matrix

IMF Direction of Trade statistics were used to construct the trade matrices. The Matrix of Exports Free on board (FOB) and Imports Cost, Insurance, Freight (CIF) was downloaded and averaged at an annual frequency from 1972 to 2021 (IMF, 2022). EViews was used to interpolate missing values in the middle of the dataset. Values for the Russian Federation were extrapolated backwards using the time series for the USSR in the years 1981 to 1990. For Belgium and South Africa, the time series were unavailable for the years 1981 to 1997, data from the 2016 vintage was used for the years 1979 to 1980 to extrapolate the series back to 1981.

A.16. Note on seasonality

Following Smith and Galesi, the time series were tested for the joint significance of seasonal effects as follows:

Given seasonal dummy variables, S_1, S_2, S_3, S_4, where S_i is equal to 1 in the ith quarter, and zero in the remaining quarters.

Let:

$$S_{14} = S_1 - S_4$$

$$S_{24} = S_2 - S_4$$

$$S_{34} = S_3 - S_4$$

A simple linear regression is run on $\Delta log(Y_t)$,where Y is the variable to be tested for seasonal effects, and S_{14}, S_{12}, $S3_4$. The OLS estimates of S_{14}, S_{12}, $S3_4$ are labeled a_1, a_2, a_3. The joint significance of the seasonal components is tested under the null hypothesis that $a_1 = a_2 = a_3 = 0$ by means of the F-statistic. In cases where the null hypothesis was rejected at a 10% level of significance, the X-12 procedure was performed on the log-difference of the original time series Y (Smith and Galesi, 2014).

The series $\Delta log(Y_t)$ was adjusted using the X-12 quarterly seasonal adjustment method in Eviews under the additive option. The resulting series $\Delta log(Y_t)_{SA}$ was then used to obtain the estimated seasonally adjusted series $log(Y_t)_{SA}$ by taking the first value of the raw series $\log(Y_{t=1})$ and adding the first differences cumulatively. Finally, the seasonally adjusted series Y_{tSA} is obtained by taking the exponential of $log(Y_t)_{SA}$.

Appendix C: Unit root, weak exogeneity, and structural stability tests

The GVAR modeling exercise assumes that the country-specific foreign variables are weakly exogenous variables, and that the parameters are stable over time. Unit root tests were performed on all the variables utilized by the GVAR, domestic, foreign, and global, using the Alternative Dickey-Fuller tests and WS statistic suggested by Park and Fuller (Park and Fuller, 1995). Following Dees, the lag length selected for the WS test statistic is selected by the Akaike Information Criteria (AIC) and based on standard ADF techniques (Dees et al., 2007). The results of the standard Dickey-Fuller, ADR, and WS test statistics are presented in Tables C.1. C.2. and C.3. for zero, first and second differences, with and without trends. The results show that the variables utilized in the model are integrated of order one.

Table C.1
Unit root tests for the domestic variables at a 5% significance level.

Dp (with trend)	Dp (with trend)	DDy	DDy	Dy	Dy	y (no trend)	y (no trend)	y (with trend)	y (with trend)	Domestic Variables
WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	Statistic
-3.24	-3.45	-2.55	-2.89	-2.55	-2.89	-2.55	-2.89	-3.24	-3.45	Critical Value
-3.8536**	-3.6861**	-9.4414**	-9.3363**	-6.7577**	-6.5837**	-0.1533	-0.0785	-1.6333	-2.5875	ARGENTINA
-3.9136**	-3.9936**	-11.2954**	-11.1124**	-8.0265**	-8.0628**	2.3824	-0.8394	-2.3152	-2.0759	AUSTRALIA
-3.1273	-3.1166	-9.1957**	-10.1928**	-6.7762**	-7.1937**	1.0613	-0.5966	-1.8491	-1.4891	BRAZIL
-4.1682**	-4.2171**	-11.3739**	-11.2338**	-7.1243**	-6.9929**	1.7708	-1.4807	-1.2249	-0.9080	CANADA
-3.8136**	-3.8458**	-13.6793**	-13.6055**	-2.9266**	-2.7155	-0.0087	-1.6367	-0.8052	-0.1234	CHINA
-4.2745**	-4.8282**	-11.6709**	-11.5997**	-5.3637**	-5.4924**	1.2994	-1.1222	-1.6188	-1.3419	CHILE
-1.1357	-1.9172	-12.3380**	-12.2440**	-5.8496**	-5.7921**	2.0500	-1.9216	-0.9212	-0.7406	EURO
-5.7767**	-5.6758**	-11.6393**	-11.6658**	-9.0178**	-9.1766**	1.8946	-0.0583	-2.7003	-2.6845	INDIA
-6.8905**	-6.8252**	-9.6240**	-9.4374**	-6.0952**	-6.0513**	1.5987	-0.3675	-2.7757	-2.6029	INDONESIA
-4.8132**	-4.6366**	-10.0336**	-9.8344**	-8.3049**	-8.4553**	-0.3993	-0.5239	-2.0169	-3.2151	IRAN
-3.1608	-4.4505**	-10.0438**	-9.8497**	-5.9573**	-5.8354**	1.7327	-3.2622	0.0189	-1.8031	JAPAN
-2.9868	-5.1522**	-9.0666**	-9.9299**	-5.5587**	-5.6350**	1.0259	-3.8499**	-0.1455	-0.5152	KOREA
-7.4391**	-7.3355**	-9.1401**	-8.9627**	-6.6087**	-6.5002**	2.3380	-1.1809**	-2.1228	-2.0193	MALAYSIA
-4.1160**	-4.1102**	-11.3163**	-11.1118**	-7.4010**	-7.4879**	1.1688	-0.9406	-2.8893	-2.6959	MEXICO
-3.0783	-2.8676	-10.2606**	-12.3535**	-6.3988**	-7.6663**	1.9946	-2.3023	-0.0483	-0.1139	NORWAY
-3.8913**	-4.4024**	-10.4036**	-9.9317**	-5.6673**	-5.6119**	1.4681	-0.0425	-2.0191	-2.0212	NEW ZEALAND
-3.8853**	-3.7961**	-11.3182**	-11.2319**	-8.0074**	-7.8935**	-0.0196	-0.3166	-1.8233	-2.0136	PERU
-6.1439**	-6.1070**	-11.3041**	-11.0930**	-4.2443**	-4.0923**	0.6299	0.7226	-1.7405	-2.6157	PHILIPPINES
-2.3475	-2.2867	-11.8869**	-11.6641**	-3.7811**	-3.5902**	-1.0832	-0.6061	-1.4053	-1.0970	RUSSIA
-4.8971**	-4.7376**	-9.4983**	-9.5728**	-8.0708**	-8.0149**	1.6948	-0.2566	-1.7278	-1.5342	SOUTH AFRICA
-5.7265**	-5.6452**	-17.2704**	-17.0675**	-3.7830**	-3.8033**	0.8276	1.2984	-0.1650	-2.6566	SAUDI ARABIA
-5.0669**	-5.3574**	-9.6898**	-9.4220**	-7.5706**	-7.5225**	2.2874	-2.9226**	0.1277	-0.2051	SINGAPORE
-3.0337	-3.4521**	-9.8081**	-9.6280**	-5.4350**	-5.3211**	1.0920	-0.0460	-3.3163**	-3.5695**	SWEDEN
-5.5842**	-5.4838**	-10.5699**	-10.5918**	-5.1664**	-5.5399**	1.4467	-0.4942	-3.2328	-3.0408	SWITZERLAND
-3.6302**	-5.3711**	-10.9114**	-10.7028**	-7.2840**	-7.1516**	1.5852	-2.6938	-0.4940	-0.8503	THAILAND
-1.8867	-1.9585	-10.2446**	-10.1094**	-8.1346**	-8.1675**	1.6851	-0.6036	-3.6761**	-3.4856**	TURKEY
-2.1336	-5.4531**	-12.4808**	-12.2977**	-4.7239**	-5.2133**	0.3022	-1.3460	-1.7579	-1.4110	UNITED KINGDOM
-1.1082	-3.8792**	-8.8429**	-9.1422**	-5.2622**	-5.4055**	1.2859	-1.7010	-1.1274	-0.8443	USA
-3.1669	-2.7846	-9.5195**	-9.3211**	-7.7634**	-7.5841**	0.5412	1.0559	-0.3866	0.0909	VENEZUELA

Deq	eq (no trend)	eq (no trend)	eq (with trend)	eq (with trend)	DDDp	DDDp	DDp	DDp	Dp (no trend)	Dp (no trend)
ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF
-2.89	-2.55	-2.89	-3.24	-3.45	-2.55	-2.89	-2.55	-2.89	-2.55	-2.89
-8.0129**	-3.1970**	-3.1477**	-3.1931	-3.1413	-12.0787**	-11.8558**	-14.5865**	-14.4267**	-3.5543**	-3.3655**
-7.7177**	-0.5805	-1.6283	-3.1643	-2.9598	-12.9926**	-12.7985**	-11.8941**	-11.7161**	-2.3314	-2.9965**
					-10.5510**	-10.3443**	-7.4742**	-7.2942**	-2.6707**	-2.4315
-7.4074**	-0.4727	-0.8117	-3.0584	-3.0429	-12.2081**	-12.1530**	-9.0727**	-8.9853**	-2.1386	-2.9584**
					-10.4203**	-10.2109**	-10.5370**	-10.3960**	-3.7189**	-3.6068**
-7.2455**	-0.4030	-1.4134	-1.3094	-0.9166	-10.4969**	-10.3342**	-8.1716**	-8.2628**	-2.1609	-3.8258**
-8.2118**	-0.7628	-1.9058	-2.1408	-2.1186	-12.1652**	-12.2016**	-6.6148**	-6.5907**	-1.0222	-3.1937**
-7.9226**	-0.5026	-1.5565	-3.7797**	-3.7268**	-12.2982**	-12.1121**	-10.0771**	-9.8562**	-5.2333**	-5.2667**
					-10.7289**	-10.5224**	-8.4892**	-8.3625**	-6.4994**	-6.5396**
					-10.8509**	-10.7219**	-8.5365**	-8.4901**	-4.7702**	-4.6142**
-8.2183**	-1.6923	-2.6734	-2.0200	-2.5920	-12.5427**	-12.4429**	-8.4178**	-8.4278**	-2.4117	-4.4761**
-6.8158**	-1.4033	-1.6756	-3.1704	-2.9647	-10.7211**	-10.2611**	-8.5479**	-9.0896**	-2.1477	-5.2869**
-7.0567**	-1.9002	-2.3918	-3.0548	-2.9449	-13.1609**	-12.8990**	-10.1213**	-9.9584**	-3.7492**	-3.9688**
					-17.6739**	-17.4577**	-6.7900**	-6.6242**	-3.0532**	-2.8358
-6.5675**	-0.8479	-1.2915	-3.1247	-2.9198	-12.0520**	-12.0055**	-9.5902**	-10.0826**	-2.3868	-2.5815
-5.0373**	-3.2981**	-3.8623**	-3.9212**	-4.0800**	-11.6605**	-11.3796**	-8.9242**	-8.8341**	-2.8543**	-4.0063**
					-12.0666**	-11.8466**	-9.4812**	-9.2877**	-3.5311**	-3.3558**
-7.2359**	-1.3433	-1.3855	-1.9695	-1.7098	-10.5886**	-10.4289**	-8.1002**	-7.9960**	-4.7295**	-4.9441**
					-13.3528**	-13.1130**	-5.8623**	-5.6882**	-2.3621	-2.1717
-9.6066**	-0.3413	-1.5411	-3.7004**	-3.6330**	-11.3508**	-12.1366**	-10.0521**	-9.8955**	-3.0396**	-3.0710**
					-11.8633**	-11.7286**	-10.8914**	-10.7887**	-5.4541**	-5.3076**
-7.2267**	-1.9169	-3.5898**	-3.5396**	-4.3452**	-12.8111**	-11.8644**	-9.4424**	-9.2615**	-4.9439**	-5.4550**
-8.0747**	0.0488	-1.9064	-2.6929	-3.0129	-11.1449**	-11.6346**	-8.4114**	-8.3227**	-2.1673	-3.5504**
-7.7671**	-0.1347	-1.0056	-2.1664	-1.9014	-12.1472**	-11.7856**	-11.3973**	-11.2955**	-2.7077**	-2.9081**
-8.4131**	-1.7199	-1.7873	-2.4025	-2.1489	-11.8789**	-13.0523**	-9.3099**	-11.1693**	-2.8057**	-5.2924**
					-11.5938**	-11.7477**	-7.7679**	-7.9870**	-1.6557	-2.5686
-8.8725**	-0.6200	-2.3360	-1.6049	-1.8494	-9.9554**	-11.4728**	-8.8170**	-9.4135**	-1.1486	-5.4887**
-7.6424**	0.3916	-0.8177	-2.4669	-2.2534	-13.5534**	-13.6727**	-11.0235**	-10.8277**	-0.6560	-4.5441**
					-23.3866**	-23.8864**	-4.9918**	-4.7682**	-2.9921**	-2.7819

r (with trend)	DDep	DDep	Dep	Dep	ep (no trend)	ep (no trend)	ep (with trend)	ep (with trend)	DDeq	DDeq	Deq
ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS
-3.45	-2.55	-2.89	-2.55	-2.89	-2.55	-2.89	-3.24	-3.45	-2.55	-2.89	-2.55
-2.6986	-11.0409**	-10.8288**	-8.5211**	-8.4569**	-1.7437	-1.5815	-2.4133	-2.1885	-9.7203**	-9.9474**	-7.6168**
-4.4378**	-10.7080**	-10.4805**	-9.0314**	-8.9100**	-0.2446	-1.1027	-2.8458	-2.6445	-10.9195**	-10.7093**	-7.3951**
-3.4573**	-12.5599**	-12.3819**	-9.8841**	-9.6989**	-0.8352	-1.2484	-2.4294	-2.1718			
-3.8427**	-10.7501**	-10.5625**	-8.5618**	-8.4348**	0.7095	-1.8719	-1.7030	-2.1323	-9.4237**	-9.1205**	-7.5850**
-2.1401	-9.0958**	-8.8730**	-8.3677**	-8.2664**	-0.7185	-0.3106	-0.9744	-2.4155			
-4.3185**	-9.5285**	-9.4051**	-8.0992**	-8.0783**	-1.2509	-1.5050	-2.6328	-2.4088	-10.0224**	-10.3711**	-6.9010**
-3.4148	-10.2051**	-9.9664**	-8.3238**	-8.3272**	-0.8646	-1.6044	-1.9796	-1.7611	-10.1667**	-9.9742**	-8.3298**
-3.8719**	-9.0539**	-8.8000**	-8.3150**	-8.2817**	0.1014	0.0834	-1.6370	-1.3984	-10.3838**	-10.1935**	-8.0666**
-4.5865**	-10.9150**	-10.7056**	-9.4944**	-9.3633**	-2.1074	-1.8430	-2.6562	-2.4918			
-3.0974	-17.3141**	-17.0853**	-4.5382**	-4.4144**	-2.9264**	-2.7278	-2.8371	-2.6184			
-2.8236	-8.7326**	-8.8625**	-5.9626**	-5.8407**	-0.5676	-2.5777	-1.5577	-2.0039	-9.4450**	-9.2509**	-8.3461**
-3.2159	-10.1415**	-9.8596**	-6.8024**	-6.6304**	-0.7056	-1.8181	-2.8713	-2.7798	-8.9446**	-8.7808**	-6.8295**
-3.0345	-9.2823**	-8.9949**	-8.3958**	-8.3185**	-1.3613	-2.1013	-2.5370	-2.4899	-11.8608**	-11.7250**	-7.0791**
-3.1677	-12.6377**	-12.4537**	-8.3378**	-8.2472**	-0.8367	-1.8170	-2.2805	-2.1816			
-4.2895**	-11.2055**	-10.9365**	-8.4417**	-8.3649**	-0.5220	-1.8382	-1.9295	-1.9002	-9.3779**	-9.2695**	-6.6556**
-3.6637**	-10.3637**	-10.1435**	-7.7783**	-7.6453**	0.0102	-1.0162	-3.0846	-2.9063	-17.0970**	-16.9214**	-5.1947**
-3.8825**	-10.2522**	-10.0476**	-9.9723**	-9.8966**	0.6644	-2.1986	-1.0377	-1.4756			
-4.1093**	-8.9929**	-8.8254**	-7.0831**	-7.0905**	0.0674	-0.6568	-2.7433	-2.5172	-11.8629**	-11.6790**	-7.2688**
-3.2119	-8.9518**	-8.7880**	-3.8148**	-3.6670**	-0.3559	-1.4766	-0.9199	-0.4398			
-4.2808**	-13.0205**	-12.8303**	-8.9581**	-8.8967**	-1.8857	-2.3141	-2.9131	-2.8337	-10.4241**	-10.5342**	-9.6214**
	-10.9965**	-10.7861**	-3.8620**	-3.9361**	-0.1044	0.4222	-1.5389	-1.9500			
-3.1613	-10.2670**	-9.9880**	-7.3931**	-7.4615**	1.2021	-1.5730	-1.4376	-1.6318	-12.0337**	-11.9018**	-7.3364**
-4.6910**	-10.8656**	-10.5348**	-7.9713**	-7.9412**	-1.3454	-1.8832	-2.2879	-2.1187	-15.0686**	-14.9116**	-8.1791**
-2.9696	-9.4653**	-9.1995**	-8.9567**	-8.8762**	-0.2474	-1.2509	-2.3600	-2.1282	-8.9754**	-8.7804**	-7.8744**
-4.2564**	-10.6794**	-10.5001**	-6.2595**	-6.5744**	-0.2774	-1.3415	-2.4586	-2.3405	-10.8002**	-10.5938**	-8.4009**
-2.9658	-11.9928**	-11.7449**	-4.9009**	-5.0284**	-0.9065	-0.7395	-2.9892	-3.4941**			
-3.8057**	-11.0823**	-10.2179**	-6.6526**	-7.2127**	-0.1981	-1.4682	-1.8617	-1.7540	-9.9075**	-9.9694**	-8.6779**
-3.9038**									-10.8041**	-10.6532**	-7.7308**
-1.6689	-11.9925**	-11.7734**	-17.0022**	-16.8227**	-1.9263	-1.7083	-2.5733	-2.4096			

Dlr	lr (no trend)	lr (no trend)	lr (with trend)	lr (with trend)	DDr	DDr	Dr	Dr	r (no trend)	r (no trend)	r (with trend)
ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS
-2.89	-2.55	-2.89	-3.24	-3.45	-2.55	-2.89	-2.55	-2.89	-2.55	-2.89	-3.24
					-15.3086**	-15.0442**	-18.7335**	-18.5396**	-2.5872**	-2.3963	-2.8738
-6.8129**	-0.9479	-0.6614	-2.3019	-3.6225**	-13.0273**	-12.8553**	-5.6578**	-5.6555**	-1.7501	-1.4771	-3.8790**
					-10.4968**	-10.2907**	-10.8915**	-10.7158**	-2.5007	-2.2882	-3.2545**
-6.5636**	-1.2047	-1.4747	-3.6969**	-3.7442**	-10.9616**	-11.3615**	-6.8862**	-6.7628**	-1.2089	-1.7700	-4.0377**
					-9.4765**	-9.2790**	-8.3862**	-8.2525**	-1.6061	-1.2574	-1.9701
					-10.0567**	-9.9218**	-7.9297**	-7.7805**	-1.0359	-2.5858	-3.9467**
-6.2832**	-0.7774	-1.1170	-3.4953**	-3.5264**	-9.5294**	-9.9139**	-4.7222**	-5.8769**	-1.3282	-1.5522	-3.4151**
-9.6387**	-1.3633	-1.3529	-1.1405	-2.2453	-14.0685**	-13.8632**	-8.5900**	-8.4558**	-3.3540**	-3.1647**	-3.9390**
					-14.2798**	-14.1210**	-7.6106**	-7.4002**	-4.0615**	-3.8985**	-4.7025**
-9.1870**	-0.5700	-1.5213	-1.5054	-1.1911	-9.5992**	-9.4006**	-8.7844**	-8.6230**	-1.5285	-1.4131	-2.9600
-6.8864**	-0.5518	-2.2517	-2.4147	-2.4634	-6.3007**	-7.3033**	-5.8214**	-10.7549**	-1.8806	-2.5640	-3.0201
-7.4394**	-0.0114	-3.3182**	-2.4851	-4.1351**	-11.1251**	-10.6706**	-9.1733**	-9.4722**	-0.6366	-2.2667	-2.9357
					-10.0546**	-9.8560**	-6.9314**	-6.8290**	-2.1942	-1.9687	-2.7040
					-12.9512**	-12.7168**	-7.3797**	-7.2595**	-1.9078	-1.6016	-2.3655
-9.0046**	-1.0110	-0.7049	-1.5546	-2.9694	-10.1554**	-10.0687**	-7.3016**	-7.2910**	-1.4162	-1.2242	-3.3924**
-8.3315**	-0.6513	-0.9958	-2.4836	-2.3744	-11.1555**	-10.9499**	-7.5298**	-7.3477**	-1.7287	-1.6641	-3.6449**
					-10.6397**	-10.4310**	-5.2540**	-5.0802**	-3.5724**	-3.3722**	-3.9564**
					-11.5386**	-11.3198**	-7.5085**	-7.3283**	-2.2460	-2.0374	-3.8509**
-6.2962**	-1.3982	-2.0724	-2.3087	-2.0178	-11.7705**	-11.5665**	-11.6400**	-11.5218**	-2.6611**	-2.4396	-3.0124
-8.8647**	-1.5646	-1.4277	-0.7896	-3.1584	-9.6906**	-9.5243**	-7.0278**	-6.9658**	-2.6277**	-2.7049	-3.1772
					-9.9003**	-10.5365**	-7.0991**	-7.4478**	-1.4092	-2.3577	-3.2496**
-7.5245**	-0.5200	-0.4538	-2.5472	-3.9372**	-12.5027**	-12.2888**	-5.4486**	-6.0986**	-1.2337	-0.9084	-2.6713
-7.5126**	-1.2743	-0.9426	-2.3775	-3.8017**	-10.2397**	-9.9831**	-5.9091**	-6.1242**	-1.8944	-1.6057	-2.4410
					-9.3169**	-9.0077**	-7.4381**	-7.2110**	-2.0729	-2.2064	-4.4304**
					-10.6347**	-10.4292**	-10.5677**	-10.4272**	-1.7186	-1.9696	-1.6235
-9.8628**	-0.1974	-1.6290	-3.4487**	-3.2840	-10.4398**	-10.8285**	-7.8136**	-8.3197**	-1.1453	-1.8331	-3.9576**
-4.9700**	-1.8217	-2.1530	-3.0720	-2.7597	-8.6887**	-7.2856**	-4.5018**	-4.3994**	-1.4534	-2.4412	-3.9062**
					-9.7675**	-9.5300**	-10.5750**	-10.4398**	-0.9575	-1.2522	-1.7900

cop (with trend)	DDcoi	DDcoi	Dcoi	Dcoi	coi (no trend)	coi (no trend)	coi (with trend)	coi (with trend)	DDlr	DDlr	Dlr
ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS
-3.45	-2.55	-2.89	-2.55	-2.89	-2.55	-2.89	-3.24	-3.45	-2.55	-2.89	-2.55
									-9.3745**	-9.2289**	-6.6888**
-3.3367	-16.4643**	-16.3382**	-12.4957**	-12.7439**	0.0269	-0.9240	-4.4646**	-4.3540**	-9.8817**	-9.7718**	-6.4256**
-2.0012											
	-12.3728**	-12.3625**	-5.0282**	-7.0405**	-0.7461	-2.4274	-0.7641	-2.4481	-9.0765**	-8.9816**	-5.7403**
									-10.0808**	-9.8781**	-9.7765**
-1.5970											
-3.0050									-11.2383**	-11.0237**	-9.3216**
	-14.8580**	-14.8638**	-3.5181**	-6.1682**	1.6416	-2.2373	1.2525	-0.9269	-9.5702**	-9.4753**	-6.4604**
	-10.9234**	-10.7045**	-7.5655**	-7.4314**	-0.0089	-1.5922	-1.2387	-0.9166	-10.8960**	-11.1483**	-6.9069**
-2.6255											
-1.2711									-9.6024**	-9.5924**	-8.8998**
									-10.6230**	-10.4087**	-8.4978**
-1.4440									-9.1933**	-9.0246**	-6.1164**
									-10.1089**	-9.9669**	-9.0281**
-3.4993**											
									-9.6329**	-9.3061**	-7.6002**
									-9.1247**	-8.9730**	-7.0064**
-2.2462	-11.5372**	-11.3989**	-5.3764**	-6.0192**	-0.7150	-0.2819	-1.2799	-3.4979**	-10.1927**	-9.9389**	-9.1898**
-0.3923	-18.7161**	-18.6349**	-4.5561**	-5.4875**	-0.7485	-2.0029	-3.1739	-3.4861**	-7.8256**	-7.3219**	-5.0953**
-0.7374											

DDcop	DDcop	Dcop	Dcop	cop (no trend)	cop (no trend)	cop (with trend)
WS	ADF	WS	ADF	WS	ADF	WS
-2.55	-2.89	-2.55	-2.89	-2.55	-2.89	-3.24
-11.6328**	-12.0490**	-6.6817**	-6.5684**	0.6827	1.0496	-0.8914
-9.3836**	-10.1647**	-5.2194**	-5.2344**	0.3225	-1.6841	-2.0611
-9.0037**	-8.8494**	-7.4201**	-7.2402**	0.3583	0.2764	-1.7071
-14.9868**	-14.8359**	-3.6095**	-5.7058**	-2.6513**	-2.4160	-2.9136
-12.6081**	-12.9968**	-2.9923**	-4.9183**	-0.0905	-1.9047	0.1790
-16.4803**	-18.0133**	-3.6498**	-4.6928**	0.9129	-2.3592	0.0597
-11.4658**	-11.2515**	-2.9941**	-2.8381	-1.5646	-1.3514	-1.5914
-9.5814**	-9.5513**	-7.0837**	-6.9919**	-2.1513	-1.9587	-2.6913
-14.8809**	-14.6486**	-4.5237**	-4.4021**	-0.7879	-0.2944	-1.2664
-11.9381**	-11.7321**	-4.6098**	-4.4310**	-0.7016	-0.4285	-0.7817
-10.5237**	-10.3319**	-5.6138**	-5.4782**	-0.9293	-0.5616	-1.2842

Table C.2
Unit root tests for the foreign variables at a 5% significance level.

Dps (with trend)	DDys	DDys	Dys	Dys	ys (no trend)	ys (no trend)	ys (with trend)	ys (with trend)	Foreign Variables
ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	Statistic
-3.45	-2.55	-2.89	-2.55	-2.89	-2.55	-2.89	-3.24	-3.45	Critical Value
-2.9611	-8.8351**	-9.1721**	-5.0843**	-4.9714**	1.7644	-1.7877	-0.0901	0.4902	ARGENTINA
-3.7458**	-12.3882**	-12.3290**	-3.6994**	-3.5242**	0.2459	-2.3106	-0.0042	1.0954	AUSTRALIA
-2.8600	-12.1237**	-12.1885**	-3.8331**	-3.6610**	0.8488	-1.8647	0.1812	1.0207	BRAZIL
-2.4652	-8.7069**	-8.7274**	-5.0482**	-5.0810**	1.9059	-2.2125	-0.1821	0.2562	CANADA
-2.9295	-8.8471**	-8.4804**	-6.0375**	-5.8939**	1.9923	-2.1976	-0.4891	-0.2857	CHINA
-2.9097	-12.3787**	-12.5533**	-3.6509**	-3.4611**	0.3217	-1.8109	-0.3040	0.6707	CHILE
-2.0682	-8.9177**	-8.7000**	-4.9348**	-4.8382**	1.0524	-1.7253	-0.3867	0.1846	EURO
-2.3317	-9.2077**	-9.0210**	-4.9377**	-4.7954**	1.6054	-2.1394	0.5338	1.2860	INDIA
-3.1096	-9.0516**	-8.8148**	-5.6375**	-5.5384**	0.9488	-2.3103	0.3156	1.1755	INDONESIA
-2.3859	-9.4629**	-9.2829**	-5.7026**	-5.5651**	0.8434	-1.6711	-0.3267	0.2406	IRAN
-2.3179	-9.0133**	-8.7759**	-4.1289**	-3.9799**	0.6524	-2.2829	0.2838	1.3906	JAPAN
-2.7787	-8.9819**	-8.8844**	-3.9443**	-3.7651**	0.9159	-2.0178	0.3110	1.2309	KOREA
-3.2891	-9.1350**	-8.8854**	-5.6832**	-5.6225**	1.0032	-2.4419	0.4887	1.3469	MALAYSIA
-2.7155	-8.6467**	-8.6597**	-4.9482**	-4.9928**	1.8674	-2.2414	-0.1953	0.2254	MEXICO
-2.3808	-11.3804**	-11.4280**	-5.3087**	-5.2250**	1.4269	-1.6039	-1.0219	-0.6245	NORWAY
-3.7311**	-11.8645**	-11.8901**	-4.1532**	-3.9815**	0.9790	-2.2814	0.4511	1.4514	NEW ZEALAND
-2.8189	-12.4912**	-12.6218**	-3.6939**	-3.5093**	0.3003	-1.8677	-0.2501	0.7550	PERU
-3.5204**	-8.9945**	-8.8260**	-5.3631**	-5.3053**	0.9187	-2.4565	0.4971	1.4098	PHILIPPINES
-1.9556	-9.3312**	-9.1611**	-6.3404**	-6.2198**	1.1118	-2.3233	0.8172	1.5972	RUSSIA
-2.1503	-12.1000**	-12.0651**	-4.2196**	-4.1076**	0.9902	-2.0731	0.8757	1.7452	SOUTH AFRICA
-2.3186	-12.2815**	-12.1773**	-5.9852**	-5.8559**	0.9660	-2.4132	0.3440	1.1275	SAUDI ARABIA
-3.9386**	-8.9136**	-8.7015**	-6.0715**	-5.9674**	1.1029	-1.9754	-0.2373	0.3880	SINGAPORE
-1.8866	-8.8473**	-8.8719**	-7.3021**	-7.2414**	2.3561	-2.4092	-0.1107	0.2482	SWEDEN
-2.1387	-11.7966**	-11.7464**	-7.3215**	-7.1938**	2.2746	-2.2430	-0.2875	0.1061	SWITZERLAND
-3.2460	-9.0625**	-8.8729**	-5.8851**	-5.8237**	1.0452	-2.2379	0.3367	1.1895	THAILAND
-2.4170	-8.8093**	-8.6603**	-6.8619**	-6.7431**	1.9958	-1.6497	-1.0857	-0.6759	TURKEY
-1.9376	-8.8794**	-8.8451**	-6.9179**	-6.8365**	2.1784	-2.3112	-0.0106	0.4182	UNITED KINGDOM
-2.2281	-9.0381**	-8.8281**	-6.5596**	-6.5345**	1.2968	-2.1349	0.6598	1.2873	USA
-3.1682	-12.8616**	-12.7708**	-4.2874**	-4.1896**	1.0262	-1.7342	-0.1984	0.3965	VENEZUELA

eqs (no trend)	eqs (with trend)	eqs (with trend)	DDDps	DDDps	DDps	DDps	Dps (no trend)	Dps (no trend)	Dps (with trend)
ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS
-2.89	-3.24	-3.45	-2.55	-2.89	-2.55	-2.89	-2.55	-2.89	-3.24
-1.5370	-2.1523	-2.0442	-10.2961**	-10.1341**	-7.1706**	-6.9957**	-2.5103	-2.2719	-3.0206
-1.8208	-2.6359	-2.6828	-11.3827**	-11.2292**	-8.3833**	-8.2390**	-2.6158**	-2.8041	-3.9123**
-1.4280	-2.5409	-2.3674	-10.5607**	-10.4846**	-15.0986**	-14.9347**	-2.5086	-2.3947	-3.0636
-1.0082	-2.3032	-2.0871	-13.4390**	-13.5514**	-10.3347**	-10.1693**	-1.0155	-2.9773**	-1.8000
-1.5731	-2.5458	-2.4808	-10.4733**	-10.6019**	-9.3430**	-9.2624**	-1.8831	-2.0115	-3.1126
-1.3827	-2.6115	-2.4650	-10.9047**	-10.7744**	-9.0396**	-8.9063**	-2.4973	-2.2760	-2.9618
-1.4655	-2.3640	-2.2741	-10.8825**	-11.4290**	-8.2643**	-8.3221**	-2.0786	-2.0304	-2.3275
-1.4671	-2.4746	-2.3516	-11.4803**	-11.6213**	-12.8070**	-12.6551**	-1.9317	-2.0126	-2.5825
-1.8019	-2.8032	-2.8163	-11.9674**	-11.8481**	-8.2021**	-8.0639**	-2.1132	-2.2586	-3.2990**
-1.6187	-3.0140	-2.9208	-10.6289**	-10.6493**	-10.4023**	-10.2617**	-2.3265	-2.1099	-2.4891
-1.3292	-2.5448	-2.3510	-11.8711**	-11.8374**	-8.3609**	-8.2314**	-1.9658	-2.1883	-2.5688
-1.6522	-2.4651	-2.5069	-11.2854**	-11.1489**	-11.7655**	-11.6207**	-2.4889	-2.3136	-2.8903
-1.8604	-2.7959	-2.8806	-12.1554**	-11.9089**	-8.3380**	-8.1992**	-2.5923**	-2.6919	-3.4751**
-0.9613	-2.3766	-2.1524	-13.1820**	-13.2950**	-10.0165**	-9.8331**	-1.2348	-3.1190**	-1.9882
-1.8914	-2.1484	-2.2486	-11.7195**	-12.1182**	-7.2434**	-7.1269**	-1.5955	-2.9711**	-2.2096
-1.6164	-2.6485	-2.6169	-11.8979**	-11.7657**	-8.6040**	-8.4628**	-2.1327	-2.5762**	-3.8853**
-1.3372	-2.4902	-2.3199	-11.3457**	-11.2091**	-11.1038**	-10.9626**	-2.3988	-2.2450	-2.9413
-1.7989	-2.7894	-2.8063	-11.6671**	-11.5104**	-8.3678**	-8.2297**	-2.8514**	-2.8956**	-3.6963**
-1.7780	-2.2696	-2.2462	-11.4044**	-11.8015**	-7.8768**	-7.7782**	-1.6968	-2.3944	-2.1513
-1.6806	-2.3682	-2.3636	-11.6842**	-11.6188**	-8.3514**	-8.2287**	-1.9476	-2.1306	-2.4310
-1.6373	-2.7627	-2.7457	-11.7059**	-11.6714**	-8.4173**	-8.2655**	-1.8974	-2.2114	-2.5526
-1.5294	-2.6415	-2.5379	-12.2157**	-12.0962**	-9.2641**	-9.0853**	-1.8441	-2.3957	-4.0674**
-1.7449	-2.2009	-2.1357	-11.6760**	-11.8281**	-8.5840**	-8.9362**	-1.4721	-2.6241	-1.9145
-1.7311	-2.2151	-2.1891	-12.2825**	-12.3874**	-6.9994**	-7.2834**	-1.5109	-2.7458	-2.0548
-1.7967	-2.6639	-2.7523	-12.0761**	-11.8501**	-12.5406**	-12.3899**	-2.1586	-2.2299	-3.4312**
-1.7338	-2.2086	-2.1626	-10.7310**	-10.6397**	-7.8991**	-7.8485**	-2.4333	-2.2417	-2.6255
-1.6071	-2.3007	-2.2142	-11.5287**	-11.6307**	-8.0827**	-8.1873**	-1.7909	-2.3808	-2.1414
-1.5512	-2.7889	-2.6722	-10.4635**	-10.3386**	-7.3107**	-7.2231**	-1.7113	-1.5702	-2.2739
-1.4382	-3.0870	-3.0558	-11.3128**	-11.1783**	-9.7915**	-9.6429**	-2.6544**	-2.4727	-3.2359

Deps	eps (no trend)	eps (no trend)	eps (with trend)	eps (with trend)	DDeqs	DDeqs	Deqs	Deqs	eqs (no trend)
ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS
-2.89	-2.55	-2.89	-3.24	-3.45	-2.55	-2.89	-2.55	-2.89	-2.55
-5.8776**	0.1447	-0.6806	-2.1685	-1.9447	-10.7768**	-10.5872**	-8.3648**	-8.2392**	0.0271
-8.4926**	-0.2077	-0.3413	-2.4198	-2.6772	-10.3123**	-10.1286**	-8.3675**	-8.2700**	-0.4837
-8.2999**	0.2422	-0.1193	-2.0533	-2.4028	-10.5739**	-10.3692**	-8.6373**	-8.5050**	-0.4061
-8.3068**	0.1815	-0.7229	-2.1518	-1.9460	-10.8058**	-10.6472**	-7.9202**	-7.8313**	0.2966
-7.3425**	0.7491	-1.6041	-1.0004	-0.5935	-10.5763**	-10.3842**	-8.4371**	-8.3186**	-0.2440
-5.9279**	-0.0030	-0.1631	-2.3453	-2.6995	-10.5401**	-10.3367**	-8.4525**	-8.3344**	-0.2903
-6.4263**	0.3457	-1.0527	-1.1836	-0.8152	-10.6392**	-10.4699**	-8.4218**	-8.3331**	0.0615
-5.7532**	0.4620	-0.5118	-2.2425	-2.1021	-10.6641**	-10.4766**	-8.5168**	-8.3988**	-0.1886
-7.8471**	0.3917	-0.3925	-2.3786	-2.3205	-10.1992**	-10.0188**	-8.5133**	-8.4016**	-0.5305
-6.5235**	0.1835	-0.4808	-1.2924	-1.5064	-9.1196**	-8.9475**	-8.8932**	-8.7795**	-0.5564
-7.4904**	0.3883	-0.2668	-2.3327	-2.4970	-10.6694**	-10.4805**	-8.5659**	-8.4578**	-0.1965
-7.2953**	0.3128	-0.4276	-1.8983	-2.0080	-10.5164**	-10.3319**	-8.4400**	-8.3215**	-0.1292
-7.8187**	0.2949	-0.3409	-2.3102	-2.2980	-10.2886**	-10.1291**	-8.6236**	-8.5168**	-0.4614
-7.7563**	0.3739	-0.6913	-2.0196	-1.8246	-10.7976**	-10.6320**	-7.9718**	-7.8756**	0.2895
-8.2089**	-0.1060	-1.3594	-1.6603	-1.3855	-10.1572**	-9.9795**	-8.4162**	-8.3329**	-0.2423
-8.0217**	0.0953	-0.4951	-2.4612	-2.3962	-10.6857**	-10.4910**	-8.5515**	-8.4180**	-0.2895
-5.9019**	0.0718	-0.1139	-2.3261	-2.7566	-10.6675**	-10.4632**	-8.3328**	-8.2057**	-0.0942
-8.1227**	-0.0336	-0.3971	-2.3847	-2.4919	-10.3142**	-10.1340**	-8.4992**	-8.3898**	-0.5472
-8.5959**	-0.4130	-0.7349	-2.4509	-2.4103	-10.4359**	-10.2476**	-8.4231**	-8.3212**	-0.4666
-8.4228**	0.0567	-0.4953	-2.4834	-2.4546	-10.4605**	-10.2806**	-8.5211**	-8.4328**	-0.2281
-8.1702**	0.1304	-0.4817	-2.4617	-2.4637	-10.3124**	-10.1251**	-8.5213**	-8.4250**	-0.3118
-7.6913**	0.0220	-0.5841	-2.5174	-2.3801	-10.3535**	-10.1627**	-8.6162**	-8.4987**	-0.2877
-8.2781**	-0.1026	-1.3155	-1.6851	-1.3919	-10.4538**	-10.2555**	-8.4848**	-8.3598**	-0.5202
-8.2619**	-0.0233	-1.2788	-1.7577	-1.4754	-10.5048**	-10.3239**	-8.4560**	-8.3552**	-0.3605
-8.2151**	0.1785	-0.5405	-2.4659	-2.3610	-10.2443**	-10.0556**	-8.3402**	-8.2158**	-0.3607
-5.9768**	0.1795	-1.3140	-0.9598	-0.5039	-10.4766**	-10.2914**	-8.4470**	-8.3423**	-0.4071
-7.8875**	0.2485	-1.1957	-1.3705	-1.0107	-10.3741**	-10.1791**	-8.4033**	-8.2801**	-0.3292
-8.2933**	0.5584	-1.0878	-1.8229	-1.5293	-10.5904**	-10.3924**	-8.5990**	-8.4769**	-0.4139
-8.2251**	0.3628	0.3039	-1.7943	-2.4657	-9.2462**	-9.0645**	-8.6748**	-8.5769**	-0.0338

DDrs	DDrs	Drs	Drs	rs (no trend)	rs (no trend)	rs (with trend)	rs (with trend)	DDeps	DDeps	Deps
WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS
-2.55	-2.89	-2.55	-2.89	-2.55	-2.89	-3.24	-3.45	-2.55	-2.89	-2.55
-13.4472**	-13.2056**	-10.6075**	-10.4356**	-2.6453**	-2.4301	-3.0986	-3.3336	-11.8414**	-11.5938**	-5.9835**
-7.7449**	-7.7346**	-6.1660**	-6.4431**	-1.4416	-1.4356	-2.7833	-2.8083	-10.0775**	-9.7237**	-8.5558**
-14.3355**	-14.0993**	-16.8496**	-16.6762**	-1.7183	-1.5276	-3.0492	-3.0021	-11.0295**	-10.8185**	-8.2738**
-11.3912**	-11.7024**	-5.7991**	-5.7513**	-1.3057	-1.5515	-3.1977	-3.0824	-10.5803**	-10.1987**	-8.2819**
-13.1914**	-12.9656**	-12.6764**	-12.5439**	-1.6626	-1.3561	-2.5301	-2.9995	-10.3185**	-10.0523**	-7.4756**
-12.3541**	-12.1277**	-12.3556**	-12.2081**	-2.0611	-1.7717	-2.8944	-3.1333	-10.1707**	-9.8852**	-5.9686**
-12.4424**	-12.2483**	-12.3708**	-12.2623**	-1.3912	-0.9973	-1.9458	-2.8390	-9.7998**	-9.5231**	-6.5003**
-11.9392**	-11.7615**	-7.5981**	-7.5541**	-1.6205	-1.3300	-2.5432	-2.9890	-11.4023**	-11.1872**	-5.7476**
-11.0224**	-10.8666**	-6.6892**	-6.7490**	-1.5116	-1.3197	-2.6236	-2.8439	-10.1616**	-9.8072**	-7.8760**
-12.6629**	-12.4316**	-12.7719**	-12.6204**	-1.9076	-1.6496	-2.1843	-2.9886	-11.3809**	-11.1688**	-6.6776**
-10.5433**	-10.4681**	-6.8833**	-7.0255**	-1.2377	-1.0734	-2.4048	-2.7261	-9.8771**	-9.6183**	-7.4820**
-11.4329**	-11.2801**	-7.5815**	-7.6279**	-1.3107	-0.9803	-1.9800	-2.5837	-9.4541**	-9.1580**	-7.3759**
-11.2418**	-11.1319**	-7.3409**	-7.4908**	-1.2575	-1.0476	-2.3052	-2.7335	-10.0137**	-9.6822**	-7.8244**
-11.7605**	-11.9342**	-6.2823**	-6.1791**	-1.4013	-1.7006	-3.4346**	-3.2586	-10.5141**	-10.2053**	-7.7843**
-12.1810**	-12.0730**	-8.0688**	-8.4811**	-1.0396	-0.8806	-1.9023	-2.7250	-10.9077**	-10.4679**	-8.1796**
-19.6080**	-19.4254**	-5.6245**	-5.8162**	-1.2828	-1.1979	-2.9350	-3.2036	-10.3959**	-10.0385**	-8.0697**
-12.2570**	-12.0390**	-13.1472**	-12.9984**	-2.0344	-1.7637	-2.8675	-3.0965	-10.2148**	-9.9406**	-5.9051**
-12.7138**	-12.5420**	-6.1249**	-6.4277**	-1.3308	-1.2307	-2.5340	-2.7165	-9.9359**	-9.6103**	-8.1759**
-12.0293**	-11.8438**	-11.8086**	-11.7286**	-1.1623	-0.7008	-1.5348	-2.8292	-10.2722**	-10.0867**	-8.5538**
-11.7872**	-11.6242**	-7.8043**	-7.8420**	-1.3165	-1.0573	-2.2530	-2.6738	-10.3748**	-9.9724**	-8.4024**
-12.1811**	-11.9780**	-12.2664**	-12.1521**	-1.2789	-0.9394	-2.0542	-2.6220	-10.3549**	-10.0317**	-8.1933**
-11.7120**	-11.5429**	-11.7428**	-11.6518**	-1.1512	-0.8314	-2.1342	-2.7975	-10.1159**	-9.7733**	-7.7458**
-11.2901**	-11.2789**	-7.2424**	-7.6712**	-1.0380	-0.9014	-2.1020	-2.6885	-10.5248**	-10.2241**	-8.2734**
-11.2609**	-11.2875**	-6.3471**	-6.8026**	-1.2626	-1.2033	-2.6752	-2.9621	-10.5778**	-10.2339**	-8.2352**
-11.1838**	-11.0315**	-7.0275**	-7.1311**	-1.3399	-1.0944	-2.3168	-2.7557	-10.0606**	-9.7100**	-8.2839**
-12.3979**	-12.2361**	-11.7359**	-11.6942**	-1.2422	-0.9695	-2.1383	-2.6772	-9.4331**	-9.1909**	-6.0764**
-11.1547**	-11.1484**	-6.7771**	-7.2116**	-1.1221	-0.9044	-2.0972	-2.8328	-10.2137**	-9.9780**	-7.9101**
-12.5417**	-12.3417**	-8.5068**	-8.5020**	-1.1949	-0.7159	-1.0417	-2.7949	-10.5406**	-10.2339**	-8.3041**
-13.1252**	-12.8882**	-12.7605**	-12.6100**	-2.1531	-1.8862	-2.6764	-3.1177	-10.3765**	-10.1135**	-8.3130**

cois (no trend)	cois (with trend)	cois (with trend)	DDlrs	DDlrs	Dlrs	Dlrs	lrs (no trend)	lrs (no trend)	lrs (with trend)	lrs (with trend)
ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF
-2.89	-3.24	-3.45	-2.55	-2.89	-2.55	-2.89	-2.55	-2.89	-3.24	-3.45
-2.0610	-0.8379	-1.9966	-8.5690**	-8.2661**	-5.5306**	-5.5929**	-1.1421	-1.5520	-3.4696**	-3.3512
-2.2230	0.5765	-0.3905	-9.3545**	-9.2557**	-5.9151**	-6.2903**	-0.5154	-2.1266	-2.6539	-2.4186
-1.9689	-0.7813	-1.8262	-8.4833**	-8.1691**	-5.5556**	-5.5647**	-1.1376	-1.7381	-2.8171	-2.5691
-2.0333	-3.0562	-3.6364**	-7.9682**	-7.4903**	-5.1287**	-5.0401**	-1.7015	-2.1145	-3.1625	-2.8426
-2.0627	-0.1268	-0.7044	-8.8229**	-8.6338**	-6.0052**	-6.2292**	-0.8040	-1.8064	-2.5373	-2.2065
-1.9696	-0.3606	-1.1992	-8.4243**	-8.1554**	-5.5580**	-5.5726**	-1.0455	-1.9211	-2.5722	-2.2317
-2.5057	-0.9621	-2.4160	-8.7495**	-8.3920**	-5.7776**	-5.8479**	-1.0001	-1.6442	-2.6966	-2.4302
-1.9677	-0.5295	-1.3872	-8.6158**	-8.3420**	-5.8603**	-5.9278**	-1.1274	-1.6912	-3.1118	-2.8965
-2.1600	0.0230	-0.4698	-8.9835**	-8.8584**	-5.6798**	-6.0064**	-0.8577	-1.7642	-3.2110	-2.9123
-1.9538	-0.2888	-0.6754	-8.8697**	-8.8122**	-5.4804**	-6.2855**	-1.1482	-1.5292	-2.5183	-2.4310
-1.9770	-0.7130	-1.0735	-8.6028**	-8.4015**	-6.0127**	-6.0899**	-0.9519	-1.8025	-2.8155	-2.4917
-2.4115	-0.3763	-2.2247	-8.8620**	-8.5183**	-5.4237**	-5.4893**	-1.2334	-1.6720	-3.1914	-2.9983
-2.0692	-0.0659	-0.7459	-8.7241**	-8.5132**	-5.7055**	-5.8664**	-0.9334	-1.7928	-2.6528	-2.3310
-1.8338	-3.1382	-3.6959**	-7.9923**	-7.5407**	-5.1568**	-5.0787**	-1.7068	-2.1272	-3.1755	-2.8512
-2.1508	-0.2243	-2.1857	-9.5214**	-9.0976**	-6.4884**	-6.6655**	-0.5396	-1.0995	-3.0277	-3.0732
-2.1153	0.0835	-0.7241	-9.2455**	-9.0450**	-6.2516**	-6.5617**	-0.7850	-1.3163	-2.6886	-2.6695
-1.8910	-0.7094	-1.3951	-8.5112**	-8.2923**	-5.5498**	-5.5704**	-1.0789	-1.8300	-2.8451	-2.5240
-2.1506	-0.0351	-0.4663	-8.9020**	-8.8047**	-5.8038**	-6.0984**	-0.7090	-2.2139	-2.4920	-2.2447
-2.0544	0.0637	-0.9015	-9.3678**	-9.1412**	-6.0695**	-6.4061**	-0.6137	-1.4648	-2.9652	-2.7487
-2.3046	0.1044	-1.5727	-9.0547**	-8.7764**	-5.6442**	-5.8663**	-0.9596	-1.3817	-3.4926**	-3.4567**
-2.3237	0.0340	-0.4109	-9.2676**	-9.1988**	-5.7737**	-6.2043**	-0.6936	-1.7072	-3.0122	-2.7251
-2.0597	-0.1053	-0.7675	-8.8226**	-8.6207**	-5.7196**	-5.9136**	-0.9561	-1.6509	-2.9206	-2.6762
-2.5854	-0.4149	-2.2059	-9.1357**	-8.8488**	-6.0023**	-6.2621**	-0.7735	-1.2005	-3.4618**	-3.4843**
-3.0078**	-0.7166	-2.6838	-8.9955**	-8.6790**	-5.7598**	-5.9192**	-0.9411	-1.3866	-3.5079**	-3.4422
-2.2467	0.5165	-0.5406	-9.0231**	-8.7946**	-5.6829**	-5.9095**	-0.9223	-1.7607	-2.7177	-2.4137
-2.3377	-0.2617	-1.7400	-8.9116**	-8.6441**	-6.0481**	-6.3146**	-0.8383	-1.4764	-2.6728	-2.5023
-2.4757	-0.7596	-2.2886	-8.8676**	-8.5949**	-5.9031**	-6.0600**	-0.9511	-1.3198	-2.8724	-2.9442
-2.0453	-0.6001	-1.1740	-9.6831**	-9.6746**	-5.9681**	-6.3277**	-0.6494	-1.4519	-3.5742**	-3.3544
-2.3714	-2.3101	-3.5475**	-12.2389**	-12.1188**	-5.8995**	-6.2476**	-1.4041	-1.1860	-1.7439	-3.4527**

Dcops	cops (no trend)	cops (no trend)	cops (with trend)	cops (with trend)	DDcois	DDcois	Dcois	Dcois	cois (no trend)
ADF	WS	ADF	WS	ADF	WS	ADF	WS	ADF	WS
-2.89	-2.55	-2.89	-3.24	-3.45	-2.55	-2.89	-2.55	-2.89	-2.55
-4.8891**	0.0348	-0.1432	-1.8501	-1.5641	-17.4010**	-17.4188**	-3.6187**	-5.8108**	0.4415
-4.7272**	0.2533	-1.3343	-3.2405**	-3.2440	-13.1095**	-13.0153**	-5.2961**	-6.1592**	0.8395
-4.9450**	0.5561	-0.1673	-2.3433	-2.0833	-17.3709**	-17.3809**	-3.7123**	-5.7602**	0.5364
-4.3912**	-0.7419	-0.3800	-0.9075	-0.4922	-9.4502**	-9.5206**	-4.4882**	-5.5700**	-0.4546
-5.3959**	-0.7818	-0.4321	-0.9622	-0.6583	-12.5539**	-12.5070**	-4.8598**	-6.0350**	0.7719
-4.7742**	0.5436	-0.1323	-2.1260	-1.8420	-7.8132**	-8.0348**	-4.1166**	-5.7891**	0.7156
-4.9119**	-1.4251	-1.9679	-2.2675	-2.2681	-17.2717**	-17.2814**	-3.8405**	-5.4033**	0.0871
-5.1799**	-0.3920	-0.0773	-1.7841	-2.2383	-7.7927**	-7.9972**	-4.0633**	-5.7444**	0.5965
-5.0789**	0.4217	-0.3701	-3.1569	-3.0054	-12.9935**	-12.9168**	-5.1432**	-6.1139**	0.8454
-5.0974**	0.2602	-1.2860	-2.5706	-2.4102	-13.0485**	-12.9733**	-3.9110**	-5.5251**	0.5516
-5.2659**	0.3049	0.0774	-1.9975	-1.8637	-12.2098**	-12.1105**	-6.9451**	-7.5089**	0.6863
-5.3203**	0.4890	-0.1482	-2.5859	-2.4085	-18.8444**	-18.8534**	-3.3032**	-5.9421**	0.6016
-4.9595**	0.3912	-0.7063	-2.8508	-2.6671	-12.3409**	-12.3179**	-4.5928**	-5.9155**	0.8135
-4.4391**	-0.5592	-0.1623	-0.8160	-0.4701	-18.4151**	-18.3608**	-4.4068**	-5.5923**	-0.2062
-5.3077**	-1.6285	-1.3532	-1.8647	-2.5719	-18.0083**	-18.0231**	-3.9622**	-6.3107**	-0.1901
-4.7278**	0.1387	-0.7290	-3.0918	-2.8771	-12.3077**	-12.3026**	-4.4988**	-5.9933**	0.8499
-4.8867**	0.6513	0.0176	-2.0768	-1.7955	-7.9882**	-8.1591**	-4.5543**	-5.9834**	0.6766
-4.9294**	0.3732	-0.8600	-3.1682	-3.0110	-13.0269**	-12.9363**	-5.2549**	-6.1159**	0.8186
-4.6859**	0.0983	-1.8847	-2.5671	-2.9341	-12.2870**	-12.3056**	-4.3632**	-6.2725**	0.6977
-5.3070**	-0.3399	-1.2478	-2.9942	-2.7747	-17.7280**	-17.7671**	-3.6374**	-6.1779**	0.6680
-4.6410**	0.2443	-0.8760	-3.2572**	-3.1006	-13.0319**	-12.9256**	-4.1691**	-5.3016**	0.8973
-5.1854**	-0.5559	-0.6448	-2.2335	-2.0099	-12.2650**	-12.2345**	-4.6107**	-5.8847**	0.7631
-4.3859**	0.7876	-2.3582	-0.3345	-1.6494	-11.7454**	-11.7975**	-4.2900**	-6.6473**	-0.0659
-4.2802**	-1.7809	-1.4956	-1.8187	-1.4859	-17.4382**	-17.4554**	-3.9213**	-6.3808**	-0.2128
-5.1113**	0.2230	-0.4321	-2.6205	-2.3873	-8.1561**	-8.4060**	-4.1964**	-6.0853**	1.1050
-5.2271**	-1.5155	-1.3496	-2.2890	-1.9998	-11.5332**	-11.5985**	-4.0167**	-6.3503**	0.3349
-4.2250**	0.9461	0.5520	-1.4935	-1.1126	-11.5199**	-11.6030**	-4.0665**	-6.4761**	0.2575
-13.9147**	2.1966	-3.1074**	-0.0433	-1.7591	-12.4639**	-12.4280**	-5.5298**	-6.7903**	0.8109
-4.8135**	0.5363	-0.0738	-1.9963	-1.6982	-17.7923**	-17.7929**	-4.1092**	-5.9259**	-0.2007

DDcops	DDcops	Dcops
WS	ADF	WS
-2.55	-2.89	-2.55
-12.0736**	-11.8602**	-5.0430**
-18.1664**	-18.0182**	-4.8493**
-11.6605**	-11.4553**	-5.1060**
-11.9664**	-11.7602**	-4.5686**
-13.1968**	-13.0641**	-5.5547**
-16.1178**	-15.9212**	-4.9546**
-13.7315**	-13.6023**	-5.0861**
-10.5062**	-10.8800**	-4.7271**
-8.6944**	-9.8735**	-5.0447**
-9.3542**	-10.1853**	-5.0990**
-12.2983**	-12.1119**	-5.2819**
-11.9253**	-11.7404**	-5.3745**
-11.4528**	-11.2482**	-5.1289**
-11.9885**	-11.7811**	-4.6178**
-14.7336**	-14.5041**	-5.4804**
-19.0804**	-18.9157**	-4.8011**
-11.5576**	-11.3463**	-5.0651**
-15.5332**	-15.4069**	-5.0830**
-22.8432**	-22.6131**	-4.8433**
-13.4431**	-13.2478**	-5.1624**
-18.1423**	-17.9489**	-4.7902**
-12.3451**	-12.1554**	-5.1625**
-16.4211**	-17.3319**	-3.8928**
-25.0110**	-24.7188**	-4.4580**
-11.9409**	-11.7445**	-5.1813**
-13.2553**	-13.1323**	-5.3513**
-13.2681**	-13.3579**	-4.4089**
-11.4153**	-12.4414**	-13.8051**
-15.6925**	-15.4969**	-4.9933**

Note: ** indicates that the null hypothesis of a unit root can be rejected at a 5% level of significance.

Table C.3
Unit root tests for the global variables at a 5% significance level.

Global Variables	Test	Critical Value	Statistic
poil (with trend)	ADF	−3.45	−2.3863
poil (with trend)	WS	−3.24	−2.0323
poil (no trend)	ADF	−2.89	−1.0903
poil (no trend)	WS	−2.55	−1.4473
Dpoil	ADF	−2.89	−10.145 **
Dpoil	WS	−2.55	−10.188 **
DDpoil	ADF	−2.89	−10.150 **
Dpoil	WS	−2.55	−10.278 **
rem (with trend)	ADF	−3.45	−1.6909
rem (with trend)	WS	−3.24	−1.9517
rem (no trend)	ADF	−2.89	0.0967
rem (no trend)	WS	−2.55	1.0241
Drem	ADF	−2.89	−6.775 **
Drem	WS	−2.55	−6.860 **
DDrem	ADF	−2.89	−12.584 **
Drem	WS	−2.55	−12.766 **

Note: ** indicates that the null hypothesis of a unit root can be rejected at a 5% level of significance.

Table C.4
Lag order of weak exogeneity regression equations.

(p*: lag order of domestic variables, q*: lag order of foreign variables)

	p*	q*
ARGENTINA	2	1
AUSTRALIA	1	1
BRAZIL	1	1
CANADA	1	1
CHINA	1	1
CHILE	1	1
EURO	1	1
INDIA	1	1
INDONESIA	1	1
IRAN	1	1
JAPAN	1	1
KOREA	1	1
MALAYSIA	1	1
MEXICO	1	1
NORWAY	1	1
NEW ZEALAND	1	1
PERU	1	1
PHILIPPINES	1	1
RUSSIA	1	1
SOUTH AFRICA	1	1
SAUDI ARABIA	1	1
SINGAPORE	1	1
SWEDEN	1	1
SWITZERLAND	1	1
THAILAND	1	1
TURKEY	1	1
UNITED KINGDOM	1	1
USA	1	1
VENEZUELA	1	1

The assumption of weak exogeneity is tested using a procedure adopted by Johansen and Harbo (Harbo et al., 1998, Johansen, 1988). Each country specific VAR model is estimated separately under the assumption of weak exogeneity of all foreign and global variables. The next step is to run regressions on the lth element of x^*_{it}

$$\Delta x^*_{it,l} = \mu_{il} + \sum_{j=1}^{r_i} \gamma_{ij,l} \widehat{ECM}_{ij,t-1} + \sum_{n=1}^{p_i^*} \varphi^{"}_{ik,l} \Delta x_{i,t-k} + \sum_{m=1}^{q_i^*} \vartheta_{im,l} \Delta \widetilde{x^*_{i,t-m}} + \varepsilon_{it,l}$$

where $\widehat{ECM}_{ij,t-1}$ $j = 1,2,\ldots r_i$ are the estimated error correction terms corresponding to the r_i cointegrating relations found in the ith country model, p_i^* *and* q_i^* are the orders of the lag changes for the domestic and foreign variables, see Table C.4 and:

$$\Delta \widetilde{x^*_{it}} = \left(\Delta Y_{it}^*, \Delta I_{it}^{0*}, \Delta r_{it}^*, \Delta rl_{it}^*, \Delta Dp_{it}^*, \Delta ep_{it}^*, \Delta eq_{it}^*\right)'$$

The test for weak exogeneity is an F –test of the joint hypothesis that $\gamma_{ij,l} = 0, j = 1, 2, \ldots r_i$.(Dees et al., 2007). The test results are summarized in Table C.5. At a 5% level of significance, only 17 out of the 173 exogeneity tests are statistically significant. Considering the fact that if the weak exogeneity assumption was always valid one could expect up to 5% of the tests to be rejected, approximately 8.65, this is not an unreasonable number.

Over all the results tend to support the treatment of the foreign country-specific, and world oil price in the GVAR.

Table C.5
F-Statistics for weak exogeneity of the country-specific foreign and global variables.

Country	F test	Fcrit_0.05	Y_{it}	Dp_{it}	eq_{it}	ep_{it}	rl_{it}	I_{it}^0	p_t^0	Rp_t^0
ARGENTINA	F(1,147)	3.9055	0.3158	16.8603**	0.0871		2.0344	0.8414	3.5527**	0.0468
AUSTRALIA	F(3,150)	2.6649	1.1112	2.3968	0.5783		2.1372	0.8520	0.6441	0.8354
BRAZIL	F(1,156)	3.9018	2.0996		0.1850		0.4289		2.7294**	0.2892
CANADA	F(3,150)	2.6649	4.1044**		0.3656		0.6618		1.8260	2.7972**
CHINA	F(2,152)	3.0556	1.2241	2.5851**	0.1591		0.1802	0.8213	0.1085	0.9366
CHILE	F(3,151)	2.6645	6.6750**	0.0805	0.9366		1.9850	1.7799	0.4168	5.2272**
EURO	F(2,150)	3.0564	0.1181	0.1414	1.1474		1.3574	2.5829**	1.1323	1.1632
INDIA	F(1,153)	3.9030	1.9655	1.8325			0.2399	5.4939	1.5602	3.4715
INDONESIA	F(2,153)	3.0552	0.1697	0.6417	0.6404		0.4688		0.0588	0.9546
IRAN	F(1,154)	3.9026	0.3780	6.4706**	0.2458		0.0168	0.1291		
JAPAN	F(3,150)	2.6649		0.6729	0.0922		2.1937	1.4251	0.3351	0.5631
KOREA	F(3,149)	2.6653	0.7831	0.1696	2.5661**		1.4681	0.5621	0.9061	0.7768
MALAYSIA	F(1,155)	3.9022			7.0367**		0.1446	0.2693	5.6842**	9.9626**
MEXICO	F(2,153)	3.0552	0.7888	0.0147	0.9153		0.9965		0.1854	0.9317
NORWAY	F(3,149)	2.6653	4.5954**	0.2976	0.2801		0.5483	0.0635	0.7483	0.4047
NEW ZEALAND	F(2,152)	3.0556		0.5049	0.2238		0.0795	0.9056	2.3998	3.7594**
PERU	F(2,154)	3.0548		2.6489**	0.7902		0.1485	0.7386	0.6376	0.4373
PHILIPPINES	F(3,152)	2.6641	1.7906	0.3974	0.8786		1.4757		2.7644**	0.3286
RUSSIA	F(1,153)	3.9030	6.5791**	0.0802	1.9276		0.9034	0.5412		1.9877
SOUTH AFRICA	F(2,152)	3.0556	1.6133		0.6934		3.3616**	0.7269	1.2016	0.4587
SAUDI ARABIA	F(2,158)	3.0533	0.6113				1.6593			
SINGAPORE	F(2,152)	3.0556	0.4150	0.3938	1.4289		0.8003	0.6124	0.6078	0.1923
SWEDEN	F(3,150)	2.6649	1.5196	0.2018	1.4692		0.8289	0.9421	0.4339	0.8438
SWITZERLAND	F(1,152)	3.9034	1.3494	0.0762	3.5760**		0.1311	0.0907	1.2292	0.2662
THAILAND	F(3,153)	2.6637	0.6274		1.1603		0.8302		0.2177	2.6005**
TURKEY	F(1,154)	3.9026	1.7463	5.0462**	0.7290		2.9319**	1.0196	0.2629	2.6050**
UNITED KINGDOM	F(1,150)	3.9042	4.0734**	1.2195	0.0685		1.7030	3.1173**	0.0253	4.4064**
USA	F(3,152)	2.6641	1.4469			0.8525		1.6314	0.9014	
VENEZUELA	F(2,155)	3.0544	1.0587	0.3493	2.0600			0.1413		

Note: ** indicates that the null hypothesis of a unit root can be rejected at a 5% level of significance.

The structural stability of the estimated parameters is one of the most critical issues facing econometric modeling. Fortunately, the GVAR model structure is uniquely adept at dealing with structural problems that occur at roughly the same time in different countries and economies. Structural breaks due to global events, such as a major stock market collapse that arises in the United States and spills over into smaller economies around the word. As the country-specific equations specify equity returns that are conditional on U.S. equity returns, they are not likely to have the same structural breaks, so that the problem will be confined to one major economy. (Dees et al., 2007) Following Dees, the tests for structural stability in the model are primarily concerned with the structural stability of short run coefficients and are based on the residuals of the country specific-error correction models. These, in turn, depend on the rank of the cointegrating vectors, and not the means by which the cointegrating relationships have been identified (Dees et al., 2007). A list of the test statistics considered in this analysis includes:

- Ploberger and Kramer's OLS cumulative sum statistic (PK sup), and the mean square variant (PK msq) (Ploberger and Krämer, 1992)
- Nyblom tests for parameter constancy against non-stationary alternatives (Nyblom) and (Robust Nyblom) (Nyblom, 1989)
- Wald Tests Quandt's Likelihood ratio statistic (QLR) and (Robust QLR) (Stock and Watson, 2006)
- Mean Wald Test statistic (MW) and (Robust MW) (Hansen, 1992)
- The Andrews and Ploberger Wald Statistic based on the exponential average (APW) and (Robust APW) (Andrews and Ploberger, 1994)

The test results are summarized in Table B.6. The tests are conducted at a 1% level of significance, under the null hypothesis that the estimated parameters are stable, or constant across the country–specific models. As illustrated by Table C.6, the test results vary significantly across test statistics but are fairly consistent across variables. For the PK msq statistic the null hypothesis of parameter stability was rejected in only 11 out of a possible 165 cases, 7% of the tests at a confidence level of 1%. For Quandt's likelihood ratio statistic, and the APW test statistic this value is increased to 93–94 rejections or 57% of the tests. When the robust versions of both tests are used, the results are considerably different, with the number of rejections falling back to 16–18% null parameter rejections. This suggests a change in volatility, or structural breaks in the error variances, and not the estimated parameters. See Tables C.6 and C.7.

In summary, while there is evidence of structural breaks, it would appear to indicate structural breaks in the error variances and is solved using a robust standard errors procedure when calculating the impacts of foreign variables and using bootstrap measures with confidence intervals to estimate the impulse response functions. Table B.7 illustrates the structural break dates computed with the QLR test statistic at a 5% confidence level.

Table C.6
Number of rejections of the null hypothesis of parameter constancy per variable across the country- specific models at 1% confidence level.

All Countries										
Variables	Y_{it}	Dp_{it}	eq_{it}	ep_{it}	r_{it}	rl_{it}	I_{it}^0	Qs_{it}^0	Total	Percentage rejection rates
PK sup	3	3	0	2	2	1	0	4	15	9%
	10%	10%	0%	7%	7%	7%	0%	36%	9%	
PK msq	4	1	0	1	1	1	0	3	11	7%

(continued on next page)

Table C.6 (*continued*)

All Countries										
Variables	Y_{it}	Dp_{it}	eq_{it}	ep_{it}	r_{it}	rl_{it}	I^0_{it}	Qs^0_{it}	Total	Percentage rejection rates
	14%	3%	0%	4%	4%	7%	0%	27%	7%	
Nyblom	10	10	7	7	8	5	1	3	51	31%
	34%	34%	37%	25%	29%	33%	17%	27%	31%	
Robust Nyblom	2	4	3	2	7	5	1	3	27	16%
	7%	14%	16%	7%	25%	33%	17%	27%	16%	
QLR	14	21	11	10	19	9	3	6	93	56%
	48%	72%	58%	36%	68%	60%	50%	55%	56%	
Robust QLR	2	4	2	6	4	5	2	2	27	16%
	7%	14%	11%	21%	14%	33%	33%	18%	16%	
MW	14	14	10	11	12	8	1	3	73	44%
	48%	48%	53%	39%	43%	53%	17%	27%	44%	
Robust MW	5	4	5	8	4	5	1	3	35	21%
	17%	14%	26%	29%	14%	33%	17%	27%	21%	
APW	14	21	10	10	21	9	3	6	94	57%
	48%	72%	53%	36%	75%	60%	50%	55%	57%	
Robust APW	3	3	3	6	5	5	2	3	30	18%
	10%	10%	16%	21%	18%	33%	33%	27%	18%	

Table C.7
Structural break dates computed with the QLR statistic at 5% confidence level.

Variables	Y_{it}	Dp_{it}	eq_{it}	ep_{it}	r_{it}	rl_{it}	I^0_{it}	Qs^0_{it}
ARGENTINA	2015Q4	1990Q2	1986Q4	1989Q3	1989Q3			
AUSTRALIA	1988Q2	2008Q4	1989Q4	1986Q3	1986Q3	1989Q2		
BRAZIL	1986Q2	1990Q2		2015Q4	1990Q2			
CANADA	2011Q2	2015Q4	1986Q4	2004Q2	1996Q1	1997Q4	2009Q1	2013Q2
CHINA	2015Q4	1990Q4		1994Q4	2015Q4			2014Q4
CHILE	1987Q1	1987Q1	2015Q3	2001Q1	1986Q2			
EURO	2015Q4	2015Q4	1999Q3	1999Q3	1986Q2	1988Q1	1987Q3	
INDIA	2015Q4	1997Q3	1993Q2	1991Q3	1998Q1	1995Q1		
INDONESIA	2015Q4	1998Q3		1998Q1	1998Q3			1986Q2
IRAN	2015Q4	1987Q4		2012Q2	2011Q4	1990Q1		1986Q3
JAPAN	1990Q2	1986Q2	1998Q3	1988Q3	1986Q2	1993Q4	1991Q2	
KOREA	1996Q4	1986Q4	1995Q3	1996Q1	1998Q3	1990Q4	1991Q2	
MALAYSIA	1999Q1	2008Q3	1997Q4	1997Q4	1996Q1			
MEXICO	1994Q3	1988Q1		1989Q3	1988Q1			1986Q2
NORWAY	1987Q2	2002Q3	1992Q3	2008Q1	1993Q2	1991Q1		1986Q2
NEW ZEALAND	2015Q4	1986Q4	2015Q4	2000Q4	1986Q4	1986Q2		
PERU	1990Q4	1990Q4		1990Q1	1990Q2			
PHILIPPINES	1989Q1	1986Q3	1986Q4	1986Q2	1986Q2			
RUSSIA	2015Q4	1992Q4		2015Q4	2006Q1	2002Q4		1992Q1
SOUTH AFRICA	2015Q4	1994Q3	2015Q4	1986Q2	1986Q4	1993Q2		
SAUDI ARABIA	1987Q4	2010Q3		2010Q3				1987Q4
SINGAPORE	2010Q2	1986Q3	1987Q4	1997Q3	1986Q3			
SWEDEN	1986Q2	1987Q3	1987Q1	1999Q4	1987Q4	1987Q4		
SWITZERLAND	2009Q3	1986Q2	1987Q4	2002Q2	1989Q2	1993Q3		
THAILAND	2011Q3	1986Q2	1990Q3	1998Q2	1998Q1			
TURKEY	1992Q4	1994Q2		2015Q4	1994Q2			
UNITED KINGDOM	2015Q4	1991Q2	2015Q4	1994Q1	1986Q2	1987Q2	1992Q1	2014Q2
USA	1986Q2	2015Q1	1998Q3		1986Q2	2015Q1	2002Q3	2011Q3 2015Q4
VENEZUELA	2015Q4	2015Q4		2015Q4	1990Q4			

Appendix D: The selection of lag orders, cointegrating relationships, and persistence profiles

The lag orders for the domestic and foreign variables are selected by the Akaike Information Criteria (AIC) test statistic, which is applied to the underlying VARX models, with maximum lag orders set to 2. The results of the selection process are presented in Table 6 (Akaike, 1981). The cointegrating relationships, also shown in Table 6, were chosen using the MacKinnon trace test statistics and 95% critical values (MacKinnon, 1990).

Table D.1
The lag orders for the domestic and foreign variables.

	Lag orders for domestic variables	Lag orders for foreign variables	Cointegrating Relationships
Argentina	2	1	1
Australia	1	1	3
Brazil	2	1	1
Canada	1	2	3
China	1	1	2

(*continued on next page*)

Table D.1 (*continued*)

	Lag orders for domestic variables	Lag orders for foreign variables	Cointegrating Relationships
Chile	2	1	3
Euro	2	1	2
India	2	1	1
Indonesia	2	1	2
Iran	1	1	1
Japan	2	2	3
Korea	2	1	3
Malaysia	2	1	1
Mexico	2	2	2
Norway	2	1	3
New Zealand	2	2	2
Peru	2	2	2
Philippines	2	1	3
Russia	2	1	1
South Africa	2	1	2
Saudi Arabia	2	2	2
Singapore	2	1	2
Sweden	2	1	3
Switzerland	2	1	1
Thailand	2	1	3
Turkey	2	1	1
UK	2	2	1
USA	2	1	3
Venezuela	2	1	2

Source: KAPSARC 2022.

The dynamic properties of the model in response to a system wide shock are described by the persistence profiles (PP) and based on an infinite moving average of the GVAR (see Appendix A) As shown in Fig. 1, the PPs are normalized to a starting value of 1 on the impact of the system wide shock. The rate at which they tend to zero provides information to the analyst on the speed with which the system tends to return to equilibrium after the shock. If the relationship underlying the model is cointegrated, the PP's have the potential to overshoot, but will converge to zero in a finite time period (Esfahani, Mohaddes, and Pesaran, 2012).

All the variables return to their long-run equilibrium values after the initial systemwide shock. In most countries, the speed of convergence was very fast taking one to two years. In 50 out of 59 cointegrating relationships the value of PP was less than 20% after two years. By the fourth year all of the countries had returned to their equilibrium values. The countries reaching full convergence to equilibrium levels faster than two years include Argentina, Australia, Brazil, Canada, Chile, the Euro area, India, Indonesia, Iran, Korea, Malaysia, Mexico, Norway, New Zealand, South Africa, Singapore, Sweden Switzerland, Thailand, Turkey the UK, USA, and Venezuela. China, Japan, Peru, Russia, Saudi Arabia, and Singapore all took longer than 3 years to converge.

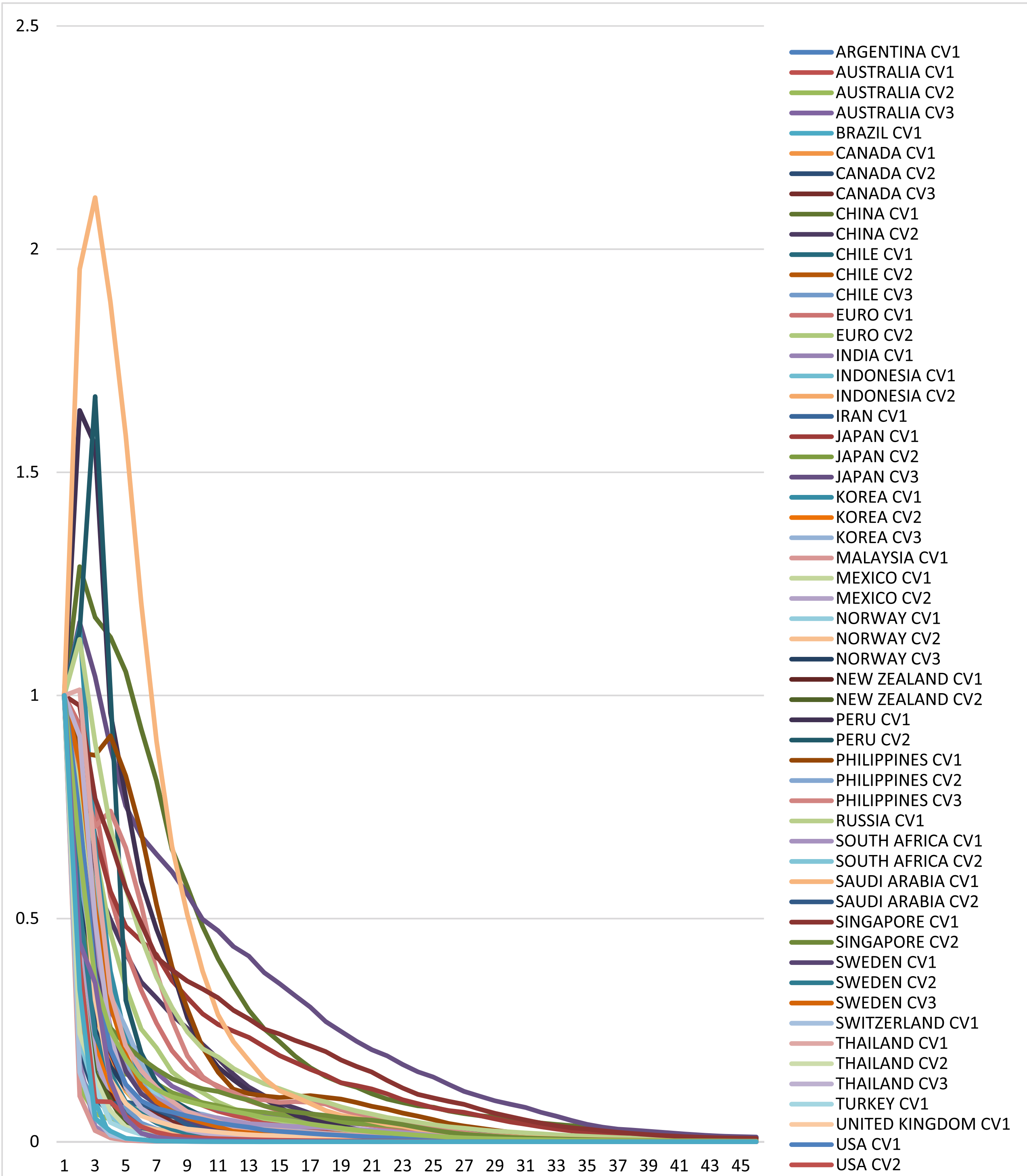

Fig. D.1. Persistence profiles of the effect of a system wide shock to the cointegrating relationships, bootstrap medians.
Source: KAPSARC 2022.

The persistence profiles for the net oil exporting countries and their 95% bootstrapped error bands are shown in Fig. 2. For all of the net oil exporters, the speed of convergence is very fast, and convergence is achieved in 3–4 years. Of these, Saudi Arabia and Russia are the slowest, at approximately 2 and ¾ years. In the cases of Saudi Arabia, this might be attributed due to the Sovereign Wealth Fund that can absorb shocks and lead to a more sluggish response to system wide shocks (Esfahani, Mohaddes, and Pesaran, 2012).

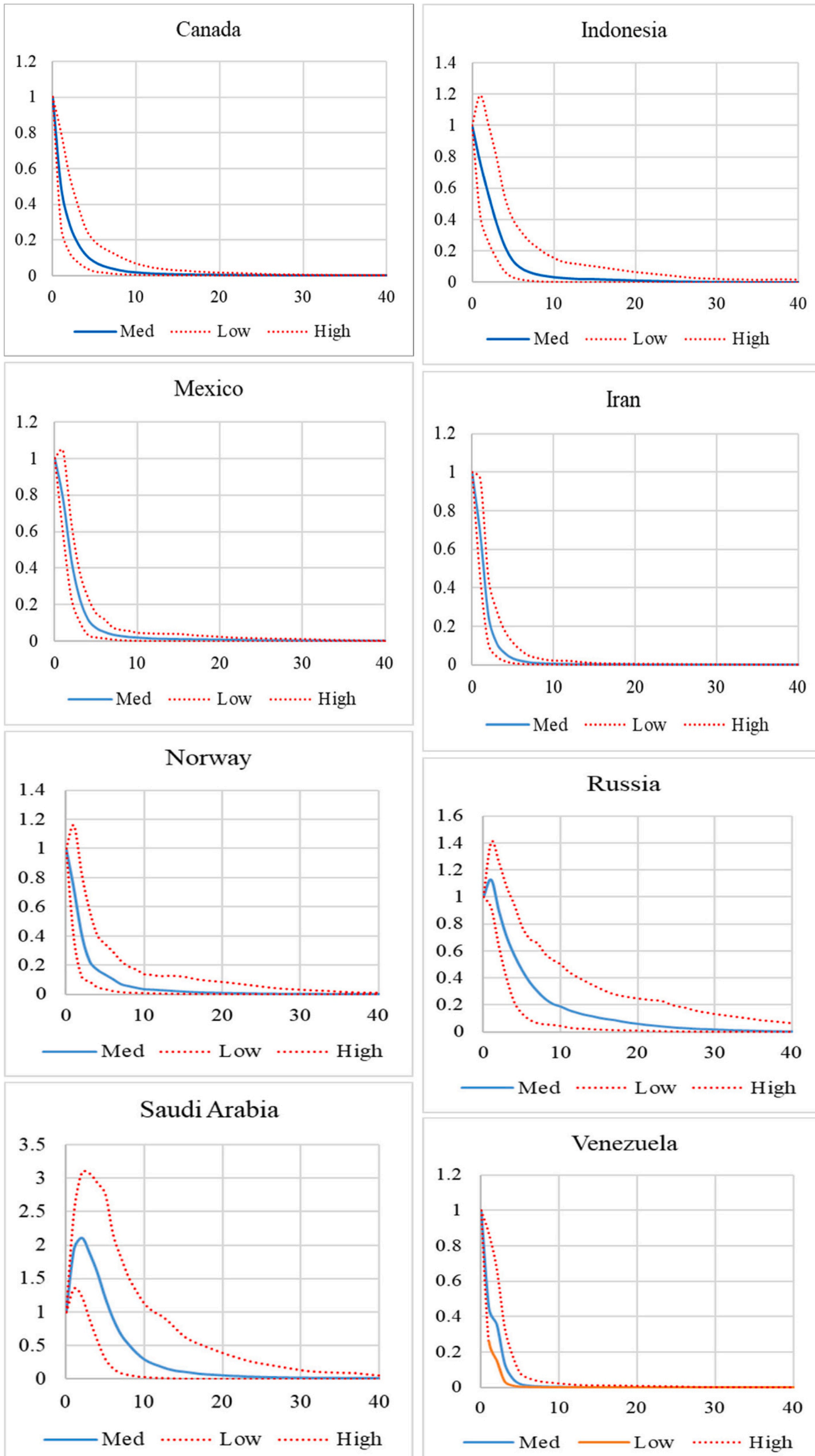

Fig. D.2. Persistence profiles for the net oil exporting countries.

The persistence profiles for the net oil importing countries, and their 95% bootstrapped error bands are shown in Fig. 3. It is interesting to notice the fact, that the speed of convergence for the net oil importers is considerably more diverse, ranging from less than one year for Brazil to over 3 years for China. The faster convergence speeds in some of the underdeveloped major oil exporting countries might be attributed to the relative underdeveloped capital markets (Mohaddes and Pesaran, 2016a)

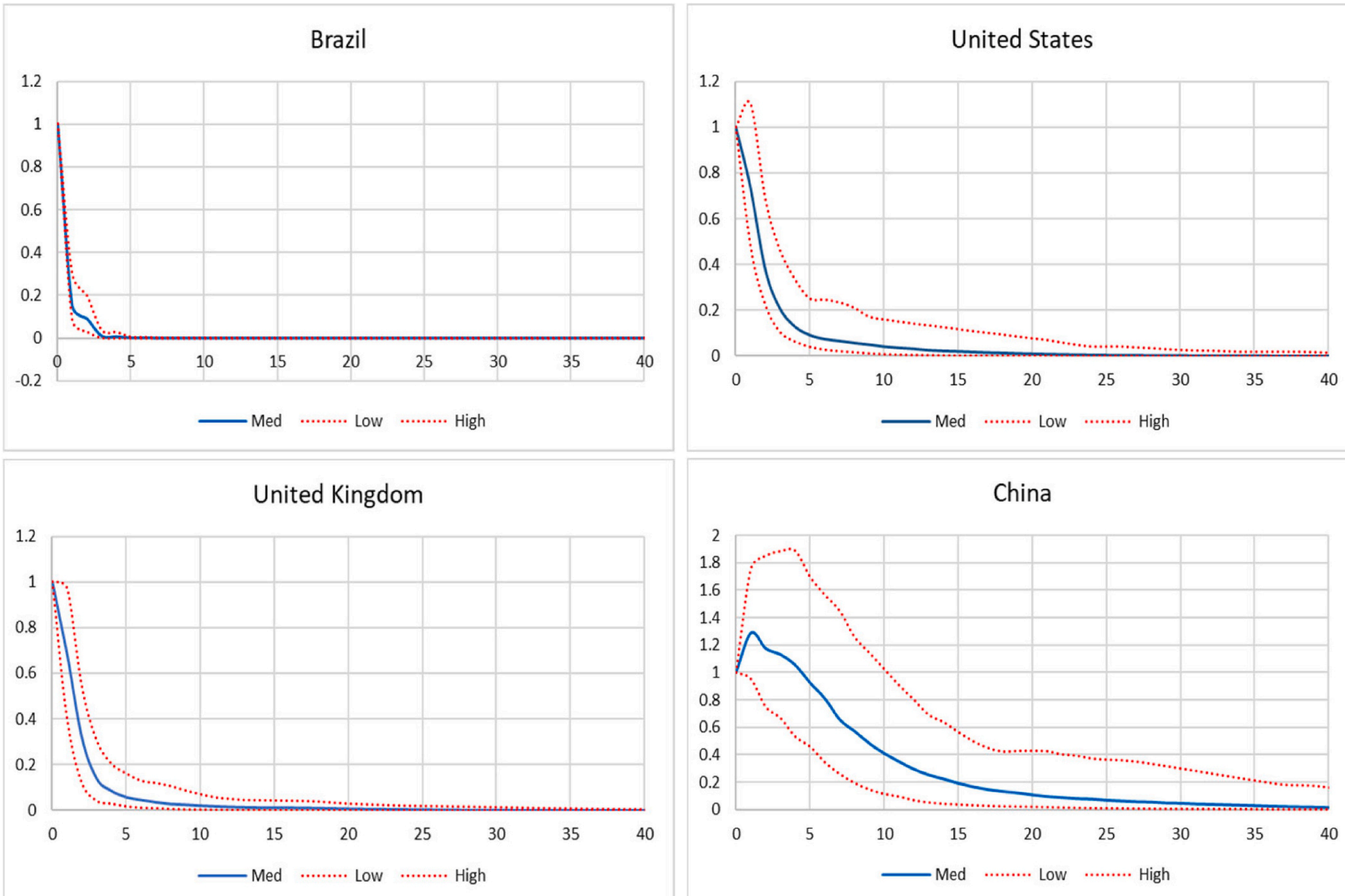

Fig. D.3. Persistence profiles for the net oil importing countries.

Appendix E. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106934.

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