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Title: Commodity markets and the global macroeconomy : evidence from machine learning and GVAR

Year: 2024

Version: Published version

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Please cite the original version:

Boakye, E. O., Heimonen, K., & Junttila, J. (2024). Commodity markets and the global macroeconomy : evidence from machine learning and GVAR. Empirical Economics, Early online. https://doi.org/10.1007/s00181-024-02612-0

Empirical Economics
https://doi.org/10.1007/s00181-024-02612-0

Commodity markets and the global macroeconomy: evidence from machine learning and GVAR

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Received: 8 December 2023 / Accepted: 5 May 2024
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Abstract

Based on a strongly data-intensive machine learning approach, this study first identifies the most essential globally traded commodities in view of their role for the global macroeconomic performance. At the second stage we estimate a global vector autoregressive model to assess in more detail these global reactions. Our results from the first stage indicate that of the 55 analyzed commodity markets, only four are revealed as the most important. At the second step, our GVAR analysis indicates that the commodity market effects on macroeconomic activity are neither unanimous across the commodities nor across macrovariables. As an overall result, the commodity market exposure is clearly stronger among the advanced countries such as the euro area, other developed economies, and China, compared to the emerging economies of Africa, Asia, and Latin America, at both the country and regional levels. This puts a lot of pressure on economic policies aimed at reducing, e.g., the depriving effects of commodity market price development on aggregate economic performance of these countries.

Keywords Commodity prices · Macroeconomy · Machine learning · Global VAR

JEL Classification C32 · E32 · F42 · Q43

1 Introduction

Commodity market prices are in strong connection to the global macroeconomic cycles and crises, as demonstrated, e.g., by the 2008–2009 global financial crisis and the COVID-19 pandemic, not to mention the most recent crisis due to the Russian attack

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Published online: 23 May 2024

to Ukraine. During these crises, for example at the beginning of pandemic the commodity prices initially declined but eventually rose as the global economic activity recovered after the recovery. As another possibility for the causal relationship between macroconditions and commodity price development, the war in Ukraine highlights the significant impact of changes in macroeconomic conditions (destroying of productive capacity) on commodity markets. Furthermore, it is widely acknowledged that certain commodities play a more crucial role in economic development, at both a national and global level. Recent evidence indicates that crises have significant effects on supply chains especially in food and energy-related commodity markets. On the other hand, for instance, Stuermer (2018) suggests that the relationship between commodity markets and macroeconomic performance is strongly influenced by demand shocks resulting from the changes in global economic activity.

While some researchers have investigated the impact of global economic activity on commodity price changes in general terms, others have focused on specific commodities and their relevance to the global economic performance (Duarte et al. 2021; Liu et al. 2020; Fasanya and Awodimila 2020; Abbas and Lan 2020; Chen et al. 2010; Kilian 2009; etc.). However, these studies have yet to reach a consensus on which commodities have the most significant price effects on the global economy. Consequently, it is still unclear which commodities, among the many traded globally, are the most important ones for driving global economic activities and promoting economic development in different regions. The present study aims to address this research gap by not only identifying the most significant commodities for the global economy but also examining their roles within different countries and groups.

We propose a novel, completely empirically oriented approach to address these questions. First, we employ machine learning techniques, specifically the Least Absolute Shrinkage and Selection Operator (LASSO) estimation procedure, to determine the time-varying significance of the most important commodity markets' price developments in relation to various macroeconomic indicators. Unlike previous studies that have *pre-selected specific commodities* based on their perceived relevance to macroeconomic indicators, we avoid this bias by *letting the data-driven LASSO technique identify the key commodities* for the global economy. Second, we utilize a global vector autoregressive (GVAR) analysis to examine the dynamic interactions and the speed at which economies adjust to the most relevant commodity market exposures identified through the LASSO estimation procedure. This analysis provides a deeper insight into the interdependence between the commodity market developments and macroeconomic performance across different countries and groups.

By combining these two techniques, we aim to provide a comprehensive understanding of the significance of various commodities for the global economy, without any a priori assumptions or pre-selection biases. This approach allows for a more robust and objective assessment of the relationship between commodity prices and macroeconomic indicators.

Empirical relationships between specific commodity prices and global economic activities have received considerable scholarly attention. For example, numerous studies have revealed the significance of oil price changes in affecting the real output changes at both country and global levels (Ge and Tang 2020; Cunado et al. 2015; Boschi and Girardi 2011). Additionally, previous research has focused on examining whether the commodity prices act as leading indicators for exchange rate movements in commodity-dependent economies, commonly known as commodity currencies. This set of countries includes, e.g., Australia, Canada, New Zealand, Norway, and South Africa (Beckmann et al. 2020; Liu et al. 2020; Baghestani et al. 2019; Chen et al. 2010; Ferraro et al. 2015). Furthermore, extensive analysis has been conducted on the relationship between commodity market exposure and aggregate inflation rates (Fasanya and Awodimila 2020; Abbas and Lan 2020; Gelos and Ustyugova 2017; Chen et al. 2014). These studies generally agree that the global commodity price changes can serve as leading indicators for inflation, especially in countries heavily dependent on commodity exports.

The GVAR framework has also been used to explore the impact of commodity prices on the global macroeconomy. Within this framework, the previous research has highlighted the significant role of food prices, including wheat, in the global cycles (Gutierrez and Piras 2013; Galesi and Lombardi 2009). Furthermore, extensive amount of research has been conducted on the global effects of commodity prices with particular emphasis on energy prices, especially oil, within the GVAR framework. Studies such as Bettendorf (2017), Chudik and Fidora (2012), Boschi and Girardi (2011), Pesaran, Schuermann, and Weiner (2004), Dées et al. (2007), and Cashin et al. (2014) have focused on oil prices. For instance, Boschi and Girardi (2011) identified oil prices as a global indicator in explaining output variability in the euro area, Latin America, and several major individual economies. Chudik and Fidora (2012) used oil prices to analyze the effects of a strong oil supply shock in a GVAR model comparing the real output developments of various emerging economies to those of advanced economies. They observed a negative impact on real GDP growth in oil-exporting economies, as well as changes on the real exchange rates for oil exporters and importers.

These studies provide valuable insights into the role of commodity prices, particularly oil prices, in the global macroeconomy within the GVAR framework. However, a closer scrutiny of the existing empirical studies reveals that only a limited number of individual commodities have been examined, based on subjective judgments of their importance. These studies often generalize their findings to global practical analyses or forecasting purposes. While we do not dispute the significance of the commodities that have been investigated, it is crucial to acknowledge the numerous traded commodities worldwide, many of which might have been overlooked in the previous studies despite their potential importance. Assuming that only a few of these commodities are globally significant, as suggested by Duarte et al. (2021) and Baghestani et al. (2019), without employing an appropriate model to determine their actual roles, seems unrealistic. Therefore, we consider already as a starting point for our analysis a comprehensive range of commodities as potentially influential and aim to *empirically identify* the most significant ones in relation to global macrovariables, such as real GDP, real exchange rates, and inflation.

We fully acknowledge that many previous studies have examined the connections between commodity market returns and, e.g., GDP growth using data based on a much more limited number of prominent commodities, such as 27 in Ge and Tang (2020), 17 in Liu et al. (2020), or 12 in Jacks and Stuermer (2020), who analyzed the agricultural goods, metals, and soft commodities from 1870 to 2013. However, in addition to analyzing the spot market price (indices) of 55 commodities, compared to these papers, our study employs different data and methodologies. By scrutinizing a large number of individual commodities and utilizing specific methodological choices, we aim to present novel findings on the roles that different commodities play in relation to the global economic indicators.

This paper makes several significant contributions to the existing literature, especially empirically. First, unlike previous studies that made ad hoc selections or assumptions regarding the importance of specific commodities, we consider all 55 individual commodities traded on a daily basis to be potentially equally important from the start. This approach ensures that no prior judgments are made, allowing for a more comprehensive analysis. Second, we utilize machine learning techniques to identify the most important commodities among the starting large set of globally traded individual commodities. This is in contrast to all existing studies that have often hand-picked only a limited number of commodities based on subjective reasoning. Hence, by employing machine learning, we enhance the objectivity and accuracy of our analysis. Finally, we employ the global vector autoregression (GVAR) model, which combines country-level time series panel data and factor analytic techniques. This model enables us to assess the impact of unit shocks on the identified globally important commodity markets and examine how these shocks are transmitted among different countries and groups of countries. By analyzing the reactions of various regions such as Africa, Asia, the euro area, Latin America, the Middle East, as well as individual large countries like the UK, China, and the USA, we gain valuable insights into the transmission mechanisms and dynamics of these shocks.

Based on global data from 1990Q1 to 2019Q4, our analysis reveals that among the 55 commodity markets considered, the price change, i.e., returns from c*opper, crude oil, gold, and lead markets are the most important for the development of global macroeconomic variables in general*. More specifically, we find that the changes in copper and crude oil prices have a significant impact on especially the global output changes. Furthermore, changes in gold and lead prices exhibit a strong correlation with the real exchange rate changes. Our results also support the traditional view that the global oil market plays a crucial role in transmitting the inflationary pressures across the global economy. This is in line with many previous studies (e.g., Ha, Kose, and Ohnsorge, 2022; Herwartz and Plödt 2016). Also the importance of copper and oil price changes on the aggregate output development is consistent with findings from other studies (e.g., Wen et al. 2019; Boschi and Girardi, 2011), suggesting that a shock to these commodity prices leads to a significant increase in the real GDP for both the advanced and emerging economies. Furthermore, we observe that a positive shock to the gold and lead price changes results in a significant depreciation of the real exchange rates. Considering the current global economic conditions, particularly influenced by the war in Ukraine, our analysis suggests that the oil price shocks will likely continue to transmit the inflationary pressures worldwide for an extended period of time.

However, in general terms it is important to note that the effects we have revealed here are not unanimous across different commodities, countries, or macrovariables. In addition, we provide evidence that the commodity market price exposure is significantly stronger among the advanced countries, such as those in the euro area, other developed economies, and China. We also observe less sizable effects for the emerging economies, including those in Africa, Asia, and Latin America, at both the national and regional levels. Our findings generally support the significance of several traditional commodities in the global economy, such as crude oil, copper, and gold. However, we also identify an additional commodity, *lead metal*, that emerges as a significant factor affecting the economic performance of the euro area and several advanced countries. This finding highlights the dynamic nature of commodity markets and the need to consider a range of commodities when analyzing their impact on the global economy.

Overall, our results indicate that commodity market exposure is a significant and prevalent phenomenon in the markets and overall economies. Therefore, given this significance, implementing policies that mitigate price volatility in these specific commodities can help in smoothing global economic performance. We strongly recommend the adoption of such policies.

The paper is organized as follows. Section 2 introduces the empirical models used in this study and provides a description of the data employed. In Sect. 3, a comprehensive discussion of the empirical results is presented. Finally, Sect. 4 concludes the study with a summary of the findings and potential implications for future research.

2 Methodology and data

2.1 Empirical background

The empirical framework employed in this paper consists of two key stages. In the first stage, the objective is to identify the essential commodity market price/return data that significantly influence the global output (real GDP), inflation, and real exchange rate changes. To achieve this, a LASSO machine learning approach is implemented. In the second stage, the focus is on exploring how the global macroeconomic variables react to the unexpected price fluctuations in the essential commodities identified from the first stage. This is accomplished by utilizing the GVAR (global vector autoregression) framework.

2.2 The machine learning model

We employed a dataset comprising of N observations for a set of variables denoted as $\left\{\left(x_t^m, y_{it}^j\right)|t = 1, 2, \ldots.., n\right\}$. In this context, x_t^m represents an input vector consisting of 55 global commodity indices, while y_{it}^j represents a vector of associated response variables ($j =$ real GDP, inflation, and real exchange rate) for each country i. The dimensionality, m, of the input vector is relatively high for standard econometric methods like OLS, which can lead to overfitting issues (Hastie, Tibshirani, and Wainwright, 2015). To address this concern and considering our lack of precise knowledge or prior judgment regarding the set features X for each y^j, it becomes necessary to regularize or constrain the estimation process. To this end, we have utilized a shrinkage estimation procedure known as the Least Absolute Shrinkage and Selection Operator (LASSO), introduced by Tibshirani in 1996. The choice of this model was driven by its capability to handle estimation problems involving high-dimensional input vectors, allowing for prediction and variable selection (Bühlmann and van de Geer, 2011).

The LASSO is a regularization technique that is commonly used in statistical modeling and machine learning. It aims to produce a parsimonious model by shrinking the coefficients of less relevant variables to zero, effectively selecting a subset of variables that have the most significant effects on the response variables. To fit a LASSO-regularized model, a least-squares optimization is performed. The model minimizes a loss function, which is typically a combination of a sum of squared errors term (to match the observed response variable) and a penalization term (to control for the size of the coefficients) as

$$\underset{\beta\in\mathbb{R}^m}{\text{mini mize}}, \left\{ \frac{1}{2N} \sum_{t=1}^{N} \left(y_{it}^{j} - \sum_{j=1}^{m} x_t^m \beta^j \right)^2 \right\} \text{subject to} \sum_{j=1}^{m} \left| \beta^j \right| \leq R, \tag{1}$$

where R can be considered the bound that restricts the sum of the absolute values of β^j.

The optimization problem can be rewritten succinctly in a matrix and Lagrangian form as

$$\underset{\beta\in\mathbb{R}^m}{\text{mini mize}}, \left\{ \frac{1}{2N} \|Y - \boldsymbol{X}\beta\|_2^2 + \lambda\|\beta\|_1 \right\} \tag{2}$$

where $\|y - X\beta\|_2^2 = \sum_{i=1}^{N} (Y - (\boldsymbol{X}\beta))^2$, and $\|\beta\|_1 = \sum_{j=1}^{m} \left|\beta_j\right|$.

This setting utilizes a one-to-one relationship between the variables R and λ, where $\lambda \geq 0$ represents a penalty or shrinkage parameter. The term $\lambda\|\beta\|_1$ controls the complexity of the model and enables the LASSO algorithm to perform model selection by excluding statistically insignificant covariates.[1] During the variable selection phase, the LASSO algorithm selects λ through cross-validation, evaluating a range of λ values and their corresponding predictors to minimize the cross-validation (CV) or prediction error (mean squared error (MSE)).

In cross-validation, the LASSO procedure divides the dataset randomly into $K = 10$ folds, utilizing one-fold as the test dataset and the remaining K-1 folds as the training dataset. The LASSO optimization problem is then applied to the K-1 dataset using different λ values to predict the test set and record the MSE. This process is repeated K times until the average λ yielding the minimum CV is found, along with the corresponding coefficients β. In LASSO, the shrinkage parameter (also known as lambda) is used to control the amount of regularization applied which helps in finding

[1] To address multicollinearity in the LASSO estimation, certain variables were excluded from the model, namely the natural gas prices for the USA and EU, as well as the prices of Brent and Dubai crude oil. The decision was made due to the high level of static correlation observed among these energy market time series. When variables are collinear, meaning they have a strong correlation, the LASSO regression may arbitrarily select one of these highly correlated commodities while dropping the others in its search for the optimal model (Tibshirani 1996). Therefore, to ensure appropriate control of multicollinearity, we conducted an examination of both the static and dynamic (conditional) correlations among the energy market price change series mentioned above. This examination was carried out in Sect. 2.2 before proceeding further.

the right balance between model complexity and predictive performance. For more in-depth discussions on LASSO, please refer to the works of Tibshirani and Wainwright (2015), Bühlmann and van de Geer (2011), and Tibshirani (1996).

We employed the adaptive LASSO selection method, which involves multiple steps. The adaptive approach uses 10 folds of cross-validation (CV) to select an optimal lambda [λ^*] through a two-step LASSO process. In the first step, a λ^* value is chosen, and the penalty weights are derived from the parameter estimates. These weights are then utilized in the second step to select another λ^* value that minimizes prediction error. The adaptive method is ideally suited for situations where LASSO is used for model selection, as in our case. Moreover, it is more robust compared to the ordinary (one-step) LASSO procedure.

In our application, we employ a two-stage estimation process. In the first stage, we focus on model selection by utilizing adaptive LASSO algorithms. These algorithms are employed to identify the model that best aligns with the data generation processes (DGP) of the commodity market and macrovariables under consideration. During this stage, the LASSO procedure helps us select the most suitable commodities from a set of potentially m-dimensional global commodities returns (X) for each macroresponse variable, denoted as y^j for each country, denoted as i. By utilizing the adaptive LASSO approach discussed earlier, we estimate the model based on this selection process.

$$\mathbf{E}\left[\Delta y_i^j | \Delta X\right] = \beta^j \Delta x^m, \tag{3}$$

where Δy_i^j denotes changes in the response variable j for each country i, and $\Delta x^m =$ (log) changes in the 59 global commodity price indices. From this initial estimation stage (Stage 1), we identify the most significant commodities, selected through adaptive LASSO, for each macroeconomic response variable (j). However, it's important to note that the selected coefficients (β) for these crucial commodities are presented without standard errors or test statistics. Therefore, no statistical inference can be drawn solely based on these coefficients.

To address this limitation and obtain statistical inference, we proceed to the second stage (Stage 2) of our analysis. In this stage, we employ the parsimonious model obtained from the adaptive LASSO estimation in Stage 1. Here, we regress each commodity selected by adaptive LASSO (refer to them as "A" in Stage 1) on the corresponding response variable y^j f for each country i. This approach allows us to estimate the relationship between the selected commodities and the specific response variables, while also providing statistical inference as

$$\mathbf{E}\left[\Delta y_i^j | \Delta \mathrm{A}\right] = \alpha^j \Delta A, \tag{4}$$

where A consists of variables that have been selected based on their association with the response variables, represented by the estimated coefficient matrix α^j for each response variable j. To ensure the reliability of our results, we employ a robust standard error estimation technique. This technique provides us with consistent coefficient estimates and robust standard errors, which account for potential heteroscedasticity and non-normality in the data. Once we have identified the variables using the adaptive LASSO method, we incorporate them into our subsequent estimation stage, known as the GVAR model. This stage aims to examine the structural dynamic impacts of the selected commodities on the macrovariables of interest. By employing these methodologies, we aim to provide robust and reliable insights into the relationship between the selected commodities and the macrovariables under investigation.

2.3 The GVAR model

GVAR methodology, which stands for global vector autoregressive modeling, is an innovative approach in macroeconometrics. It integrates time series and panel data features with factor analytic techniques to effectively analyze various economic and financial topics. This methodology is versatile and can be applied to diverse areas such as policy analysis and risk management.

By employing GVAR models, we can examine the interactions between different markets and economies and identify global spillover effects between them. This approach provides a comprehensive framework to understand how shocks in one market, country or region affect others, allowing for example the policymakers to assess better the potential impact of their decisions on the global economy.

In the empirical procedure described below, the first step involves estimating a multi-country augmented vector autoregressive (VARX*) model. This model takes into account the role of domestic variables, country-specific foreign variables (X*) weighted by international trade patterns, and global factors such as commodity price changes chosen using the LASSO method in our case. The GVAR model, initially introduced by Pesaran, Schuermann, and Weiner in 2004, has been further developed by Dées, di Mauro, Pesaran, and Smith in 2007. In this study, the model was estimated for a total of 33 countries, including both the developed and emerging economies (see Table 1 for more details). In the representation used, the global economy consists of $N + 1$ countries, indexed by $i = 0, 1, 2, \ldots, N$. For each country i, the VARX*(p, q) model was estimated, where the country-specific macrovariables (j) are related to their corresponding foreign variables (j^*) and the changes in global commodity prices are treated as weakly exogenous from the beginning.

Following the methods employed by Gutierrez and Piras (2013), Dées et al. (2007), and Pesaran et al. (2004), the dynamic VARX*(p, q) model allowing for the inclusion of global variables is given as

$$\boldsymbol{\Phi}_i(L, p)y_{it}^j = a_{io}^j + a_{i1}^j t + \boldsymbol{\Lambda}_i(L, q)y_{it}^{j*} + \boldsymbol{\Psi}_i(L, q)x_t + \epsilon_{it}^j, \tag{5}$$

In our specific case, we have the vector y_{it}^j= (real GDP, inflation, real exchange rate)' which represents the country-specific variables. Here, i refers to the country in question, j represents the macrovariable observed at time t. Additionally, the vector y_{it}^{j*} = (real GDP*, inflation*, real exchange rate*)' represents the foreign counterparts of these variables, reflecting the macro-level influences exerted by the rest of the world on a given economy i. Furthermore, x_t represents the vector of global variables, specifically the relevant commodity market returns extracted from the LASSO

Table 1 Countries and regions in the GVAR model

	Other developed countries	Emerging economies excl. China	
USA	Australia	Africa	Asia
UK	Canada	South Africa	Korea
China	Japan		India
	Norway	Middle East	Indonesia
Euro area	New Zealand	Saudi Arabia	Malaysia
Austria	Singapore		Philippines
Belgium	Sweden	Latin America	Thailand
Finland	Switzerland	Argentina	
France		Brazil	
Germany	Other European countries	Chile	
Italy	Turkey	Mexico	
Netherlands		Peru	
Spain			

stage of our analysis. Moreover, $y_{it}^{j*} = \sum_i^N w_{a,b} y_{\mathrm{it}}^j$ denotes the weighted average of country-specific variables, where $w_{a,b}$ is based on the trade weight of bilateral trade flows between country a and b. In the equations $\mathbf{\Phi}_i(L, p) = \mathrm{I} - \sum_{t=1}^{p} \mathbf{\Phi}_i L^t$, $\mathbf{\Lambda}_i(L, q) = \sum_{t=0}^{q} \mathbf{\Lambda}_i L^t$ and $\mathbf{\Psi}_i(L, q) = \sum_{t=0}^{q} \mathbf{\Psi}_i L^t$, we have the corresponding matrix lag polynomials of the unknown coefficients for the macrovariable j specific to each country i. L represents the lag operator, and p and q are the lag orders, which may vary across the country i equations and are selected based on the Akaike information criteria (AIC) value for each country.[2]

Additionally, a_{io} represents a vector of constants, while a_{i1} represents a vector of coefficients on the deterministic trend (t) for each variable j. The ϵ_{it}^j series represents the error term specific to country i for each macroeconomic variable j, assumed to be independent and identically distributed with a mean of 0 and covariance matrix Σ_{ii} These error terms are allowed to have weak correlations, consistent with the framework proposed by Chudik and Pesaran (2016). Subsequently, the estimated country VARX* (p, q) models, as depicted in Eq. 5, are stacked and solved simultaneously as a single GVAR model. This modeling approach incorporates trade flows and explicitly considers interdependencies across economies.

Following Chudik and Fidora (2012), we can succinctly write the reduced form as

$$\mathbf{G}y_t = a_o + a_1 t + \mathbf{H}_1 x_{t-1} + \mathbf{H}_1 x_{t-2} + \mathrm{u}_t. \tag{6}$$

In this context, G and H refer to global vector autoregressive (VAR) matrices that are constructed using country trade weights (W). These matrices are used in Eq. 6, which is further explained in the works of Chudik and Pesaran (2016), Pesaran et al. (2004), and

[2] Appendix 12 reports the VARX* orders in the country-specific models selected by the AIC.

Dées et al. (2007). The purpose of using these matrices is to analyze contemporaneous impacts, feedback effects, and conduct forecasting analyses. The impulse response functions, known as GIRFs (global impulse response functions), derived from these matrices are particularly attractive in this framework. They offer advantages over Sims's orthogonalized impulse response functions (OIRFs) from 1980, as GIRFs are invariant to the ordering of both variables and countries, as emphasized by Chudik and Pesaran (2016).

3 Description and sources of data

We utilized quarterly data on primary commodity market indices and three global macroeconomic variables: output (real GDP), inflation, and real exchange rate. The commodity market dataset contains time series observations on 55 global commodity indices obtained from the IMF primary commodities database (refer to Table 2). The macrodata were sourced from the global VAR modeling database (Smith and Galesi 2014),[3] originally compiled by Dées et al. (2007) and extended by Mohaddes and Raissi (2020).[4] This dataset encompasses 33 countries (as shown in Table 1), which collectively account for over 90% of the global GDP. Due to data limitations,[5] our analysis was conducted for the period ranging from 1990Q1 to 2019Q4. To focus on regional effects and shocks, we grouped the countries in the GVAR model into specific regions (refer to Table 1). In the VARX* model, the euro area is treated as a single region and aggregated using GDP-weighted averages of the country-specific variables, including real GDP, inflation, and real exchange rate. Table 2 provides an overview of the primary commodities based on the IMF primary commodity groupings. For consistency, all observations in the original dataset were transformed into logarithmic values. For a more detailed summary of these transformed series, please refer to Appendixes 9, 10, 11.

To address the issue of multicollinearity in LASSO estimation and to avoid erroneous identification of relevant commodities in the regression, we initiated our empirical analysis by examining the price correlations among different commodity sectors.[6] Given the strong correlation typically observed in global energy prices, especially in the oil and gas sectors, we anticipated finding high price correlations in these markets. Analysis of our data confirms that energy price series, including EU and US

[3] Available from https://sites.google.com/site/gvarmodelling/data, original version from 1979Q1 to 2013Q1.

[4] Available from https://www.mohaddes.org/gvar, the updated version from 2013Q2 to 2019Q4. See Mohaddes and Raissi (2020) for a detailed description and construction of the macrovariable data, sources, and related transformations.

[5] Since there was incomplete data for certain countries, such as in the case of the euro area, only 8 out of the original 11 European countries that joined the eurozone were included in the analysis. These 8 countries are treated as a single economic region in the model (for further reference, see Dees, di Mauro, Pesaran, and Smith, 2007). As for Africa and the Middle East, data were only available for South Africa and Saudi Arabia.

[6] The static price correlations in the other primary commodity sectors/categories (i.e., agricultural products, precious and base metals) range from 0.08 to 0.69, which is sufficiently low for all of them to be considered individually in further analyses. We do not report the results here, but they are available upon request.

Table 2 Primary commodities in groups

Vegetable oils	Cereals	Meats and sea food	Beverages	Raw materials	Others
Rapeseed oil	Wheat	Beef	Coffee	Soft Sawnwood	Groundnuts
Olive oil	Rice	Pork meat	Tea, Kenyan	Hard Sawnwood	Corn
Palm oil	Barley	Poultry	Cocoa	Soft Logs	Fertilizer
Sunflower oil	Sorghum	Lamb		Hard Logs	Orange
Soybeans oil	Oats	Shrimp		Cotton	Sugar
Soybeans		Fish		Rubber	Timber
Soybean meal				Softwood	Wool
				Hardwood	Bananas
Precious metals	Base metals	Energy			Potassium Fertilizer
Gold	Lead	EU natural gas			D. phosphate
Silver	Copper	US natural gas			Tomato
Palladium	Iron Ore	Brent crude oil			
Platinum	Nickel	Dubai crude oil			
	Aluminum	WTI crude oil			
	Zinc	Coal			
	Tin				
	Uranium				
	Cobalt				

natural gas prices, as well as various oil price series such as Brent, Dubai, and WTI, exhibit significant correlation. For instance, static correlations between the US and EU natural gas prices and WTI crude oil prices are 0.91 and 0.90, respectively (shown in Table 3). Multicollinearity in the energy market sectors is visualized in Fig. 1. The upper panels A and B of Fig. 1 illustrate collinearity in price and return movements within the crude oil market (Brent, Dubai, WTI). Similar patterns can be observed in the lower panels C and D for the natural gas market (USA and EU).

In order to gain a better understanding of the energy market price dependencies, the analysis was expanded to include the second moments for returns in the oil and natural gas markets. This analysis showed that the volatilities in these two markets are quite similar, with the US natural gas shocks appearing to dominate over time (refer to Fig. 2 panel A). Similar to Batten et al. (2017), the dynamic correlations between returns are

Table 3 Static price correlations in energy markets

	US natural gas	EU natural gas	Brent crude oil	Dubai crude oil	WTI crude oil
US natural gas	1				
EU natural gas	0.8212	1			
Brent crude oil	0.9423	0.9228	1		
Dubai crude oil	0.9222	0.9319	0.9982	1	
WTI crude oil	0.9144	0.9015	0.9969	0.9944	1

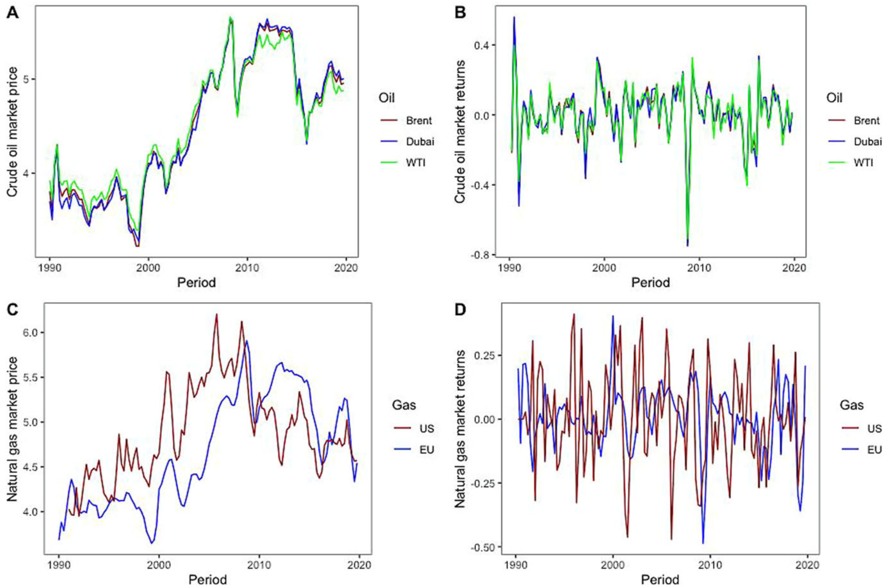

Fig. 1 The energy markets' price development: crude oil market price and returns (upper panels **A** and **B**), natural gas market price and returns (lower panels **C** and **D**)

not stable but rather vary over time[7] (refer to Fig. 2 panel B). It is also worth noting that the dynamic co-movement between the US natural gas and WTI crude oil markets is time-varying, but the correlation trend has remained relatively stable since the year 2000. Due to the high price co-movement and the similar variance development, it is reasonable to use WTI crude market data to understand the effects of natural gas and other crude oil markets in further estimations. This choice helps to also mitigate

[7] We employed a multivariate DCC-MGARCH (1,1) model to estimate the dynamic co-movement of the first and second moments in the oil and natural gas markets. The estimation method and equations used in this analysis are not provided in this paper but the interested readers can refer to Engle (2002) for a detailed explanation of the estimation process and derivation of the DCC-MGARCH model. For additional information on the estimation results based on our specific data, please feel free to request further details from the authors.

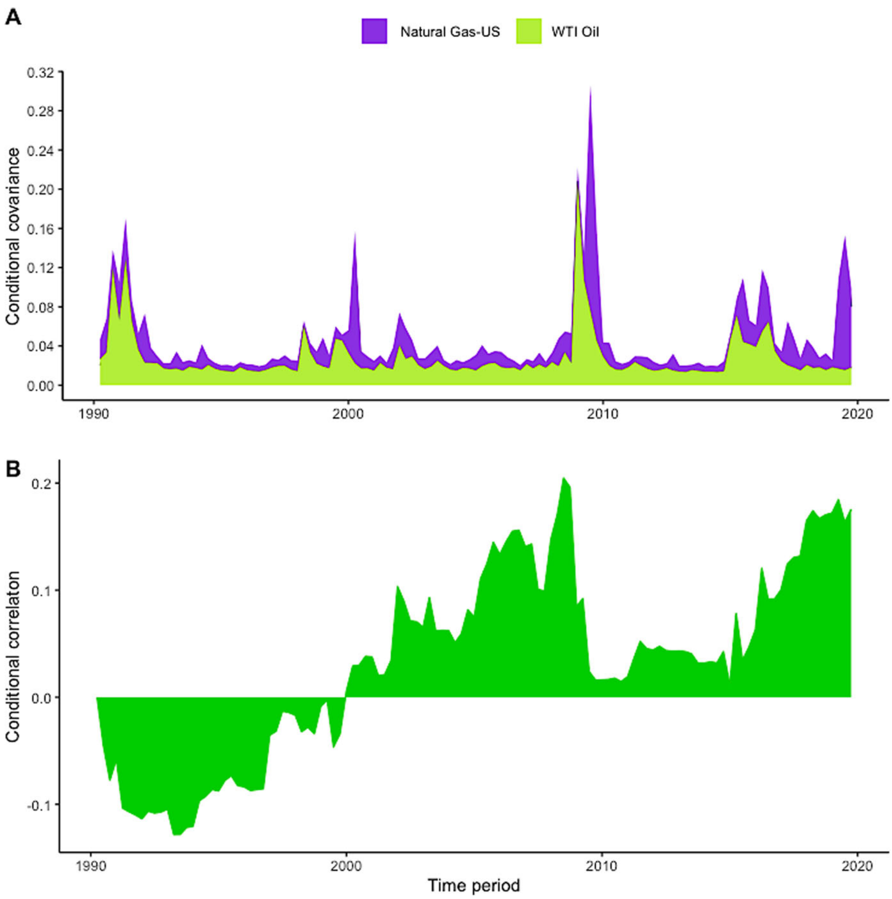

Fig. 2 The conditional covariance (**A**) and correlations (**B**) between the US natural gas and WTI crude oil price changes. *Note*: Authors' estimation based on a DCC-GARCH (1,1)- model for log changes in prices

the issue of multicollinearity in the LASSO regressions. Therefore, at this stage, we employed the LASSO model using a set of 55 individual commodity return series, instead of the originally extracted 59 time series.

4 Discussion of empirical results

4.1 Unit root tests

Our empirical analyses proceeded next based on unit root tests for all our data to determine the level of integration exhibited by the individual data series. This is crucial for both of the main estimation stages, especially in the context of GVAR modeling. The results obtained from the augmented Dickey–Fuller (ADF) unit root test, which utilizes the Akaike information criterion (AIC) lag selection criterion to determine the optimal lag length for the test equation, are presented in Table 4.

Panel A presents the test results for both the domestic and foreign macrovariables, analyzed both in levels and first differences. Furthermore, even though the results from our LASSO estimation stage are given actually in Table 5, already here in Panel B of Table 4 we report the unit root test results for the four most globally significant commodity market variables, for both the levels of prices and (log) changes in them, based on the identified series from the LASSO selection stage of our analyses. In general, the estimates provided in Table 4 clearly indicate that, except for domestic inflation, the majority of variables can be considered to possess an I (1) nature, meaning they follow unit root processes in levels. In most instances, the null hypothesis of a unit root process (indicating non-stationarity) cannot be rejected for the level observations, but it is rejected for the first differences. This rejection provides statistical support for the estimation of an error correction version of the GVAR model given by Eq. 5.

5 LASSO estimation results

In many cases, machine learning algorithms are employed in empirical analysis to utilize all available information and predict the response variable, without assuming causality for any particular predictor. Therefore, at the initial stage of our analysis, our focus was solely on identifying the set of most relevant commodities associated with macroeconomic changes. The structural impact analysis will commence from Sect. 3.3, where we will examine the macroeconomic responses to the structural shocks originating from a set of the most significant commodity markets, employing a purely empirical perspective.

Without making any prior assumptions in our machine learning estimation, the LASSO regression revealed that out of the 55 commodity price changes analyzed, only four—*crude oil, copper, gold, and lead prices*—emerged as relevant predictors for the global macroeconomic performance. These findings hold true even after accounting for the multicollinearity issues and conducting robustness checks. To validate these results, we conducted principal component analysis (PCA)[8] and factor analyses as the robustness checks. The results from PCA and factor analysis support the notion that these commodities (crude oil, copper, gold, and lead) are of utmost importance when it comes to the global macroeconomic performance. These findings are consistent with various previous studies that have also identified at least the crude oil, copper, and gold market price developments as indicators of global economic performance (Bildirici and Gokmenoglu 2020; Stuermer 2018; Arora and Cai 2014; Jaunky 2013; Boschi and Girardi, 2011).

The results reported in Table 5 indicate that changes in copper and crude oil prices are the most significant indicators for assessing the global output (real GDP) changes. Furthermore, our empirical estimates from this stage suggest that when the prices in these markets increase, there is a general improvement in the macroeconomic performance. These estimates further support the notion that the positive developments in the

[8] We do not report the results from the PCA and factor analyses here, but they are available upon request.

Table 4 Augmented Dickey–Fuller (ADF) unit root test statistics

Panel A	Domestic variables					Foreign variables				
	y	Δy	xr	Δxr	nfa	y^*	Δy^*	xr^*	Δxr^*	nfa^*
Argentina	− 1.80	− 3.98	− 2.31	− 5.23	− 8.01	− 0.86	− 5.52	− 1.72	− 7.05	− 7.11
Australia	− 0.80	− 3.89	− 2.07	− 7.47	− 8.62	− 1.12	− 5.28	− 1.68	− 7.58	− 7.18
Brazil	− 1.65	− 5.63	− 2.02	− 6.74	− 6.88	− 1.21	− 4.70	− 1.48	− 5.29	− 7.51
Canada	− 1.39	− 5.20	− 1.62	− 7.20	− 10.22	− 1.58	− 5.20	− 1.47	− 8.21	− 7.51
China	− 0.77	− 3.06	− 2.75	− 7.58	− 5.93	− 2.36	− 5.70	− 1.93	− 7.26	− 8.03
Chile	− 2.43	− 5.96	− 1.88	− 7.35	− 7.38	− 0.76	− 5.28	− 1.71	− 7.46	− 5.79
Euro area	− 1.93	− 4.97	− 1.86	− 7.77	− 7.28	− 1.60	− 5.11	− 1.50	− 8.29	− 7.40
India	− 2.91	− 5.01	− 3.46	− 6.96	− 9.58	− 1.30	− 5.19	− 1.76	− 7.31	− 9.77
Indonesia	− 1.72	− 5.87	− 2.49	− 8.00	− 7.06	− 1.65	− 5.22	− 1.85	− 7.22	− 10.50
Japan	− 3.84	− 6.78	− 2.80	− 5.17	− 9.90	− 0.80	− 5.22	− 1.91	− 6.97	− 8.72
Korea	− 2.29	− 5.15	− 3.18	− 8.06	− 7.99	− 0.69	− 5.16	− 1.69	− 7.35	− 8.87
Malaysia	− 3.30	− 5.74	− 2.33	− 6.76	− 8.82	− 1.62	− 5.23	− 1.84	− 6.97	− 7.04
Mexico	− 3.07	− 6.48	− 2.69	− 5.59	− 13.04	− 1.53	− 4.84	− 1.76	− 7.33	− 7.45
Norway	− 1.96	− 6.10	− 1.89	− 7.58	− 7.93	− 1.92	− 4.48	− 1.80	− 8.22	− 7.40
New Zealand	− 2.03	− 4.04	− 2.37	− 6.85	− 7.93	− 0.62	− 5.70	− 1.88	− 7.16	− 7.64
Peru	− 1.38	− 4.17	− 2.11	− 7.03	− 14.93	− 0.81	− 4.72	− 1.69	− 7.36	− 7.27
Philippines	− 2.38	− 3.81	− 1.91	− 5.79	− 8.80	− 1.97	− 5.28	− 1.93	− 7.24	− 7.49
South Africa	− 1.22	− 4.45	− 2.33	− 7.32	− 8.47	− 1.17	− 5.20	− 1.63	− 7.91	− 10.75
Saudi Arabia	− 1.43	− 3.74	− 1.27	− 5.46	− 7.88	− 1.51	− 5.49	− 1.68	− 7.55	− 10.73
Singapore	− 1.36	− 5.71	− 1.63	− 6.14	− 7.06	− 2.72	− 5.57	− 2.08	− 6.56	− 7.44

Table 4 (continued)

	Domestic variables					Foreign variables				
Panel A	y	Δy	xr	Δxr	nfa	y^*	Δy^*	xr^*	Δxr^*	nfa^*
Sweden	− 4.02	− 5.84	− 2.52	− 7.56	− 7.60	− 1.42	− 5.02	− 1.74	− 7.91	− 11.65
Switzerland	− 3.60	− 4.86	− 2.16	− 8.54	− 8.24	− 1.81	− 4.88	− 1.76	− 7.88	− 11.87
Thailand	− 2.86	− 7.05	− 2.18	− 6.98	− 8.02	− 1.85	− 5.54	− 1.86	− 7.27	− 9.84
Turkey	− 2.85	− 7.05	− 0.48	− 6.59	− 7.84	− 1.57	− 5.15	− 1.76	− 7.83	− 10.42
UK	− 1.56	− 4.69	− 1.85	− 9.27	− 8.52	− 1.68	− 5.12	− 1.71	− 7.65	− 11.71
USA	− 1.90	− 4.62			− 10.30	− 1.13	− 5.49	− 1.66	− 7.76	− 6.35
Panel B	copper	Δcopper	oil		Δoil	gold	Δgold	lead	Δlead	
Global variables	− 2.14	− 7.73	− 1.52		− 6.96	− 1.54	− 6.44	− 2.99	− 6.23	

The ADF test statistics presented are based on univariate AR(p) models in the levels with the lags p chosen according to the modified AIC, and a maximum lag order of 8. The regressions for all variables in the levels include an intercept and a linear trend. The critical value for a rejection in a test procedure including a trend series to the test equation is − 3.46 at a 5% significance level. For the notations, y denotes real output, xr is real exchange rate, and nfa refers to inflation (i.e., log change in the CPI index)

Table 5 Estimates for the effects on macroeconomy from the LASSO-selected commodity market returns – 1990Q1-2019Q4

	Output (real GDP)		Inflation	Real exchange rate	
Country	Copper	Oil	Oil	Gold	Lead
Argentina		0.03 (0.01) ***			
Australia			0.01 (0.00) ***	– 0.24 (0.04) ***	0.18 (0.04) ***
Austria	0.01 (0.00) **	0.02 (0.01) *	0.01 (0.00) ***	– 0.17 (0.05) ***	
Belgium	0.01 (0.00) **	0.01 (0.00) *	0.01 (0.00) ***	– 0.15 (0.05) ***	– 0.05 (0.02) **
Brazil	0.01 (0.01)	0.04 (0.01) ***		– 0.25 (0.08) ***	– 0.23 (0.06) ***
Canada			0.01 (0.00) **	– 0.15 (0.05) ***	– 0.10 (0.03) ***
China	0.00 (0.01)				
Chile	0.02 (0.01) **			– 0.20 (0.07) ***	– 0.11 (0.04) ***
Finland	0.02 (0.01) **	0.02 (0.01) **	0.02 (0.01) **	– 0.16 (0.05) ***	– 0.09 (0.04) ***
France	0.01 (0.00) **	0.01 (0.00) **	0.01 (0.0) ***	– 0.16 (0.04) ***	
Germany	0.01 (0.00) *		0.02 (0.00) ***	– 0.13 (0.05) **	– 0.06 (0.03) **
India	0.02 (0.01) *			– 0.13 (0.06) **	– 0.09 (0.02) ***
Indonesia	0.01 (0.00) *	0.01 (0.02)		– 0.41 (0.26) ***	
Italy	0.02 (0.00) **	0.02 (0.01) *	0.01 (0.00) **	– 0.15 (0.05) ***	– 0.08 (0.03) ***
Japan	0.02 (0.00) ***			– 0.38 (0.06) ***	0.09 (0.04) **
Korea	0.02 (0.01) *	0.02 (0.01) *		– 0.20 (0.07) **	– 0.14 (0.04) ***
Malaysia		0.02 (0.00) **	0.02 (0.00) **	– 0.20 (0.06) ***	
Mexico	0.02 (0.01) *		– 0.01 (0.01)		
Netherlands				– 0.14 (0.05) **	– 0.06 (0.03) **
Norway	0.02 (0.01) **	0.02 (0.01) **	0.01 (0.00) **	– 0.19 (0.06) ***	

Table 5 (continued)

	Output (real GDP)		Inflation	Real exchange rate	
Country	Copper	Oil	Oil	Gold	Lead
New Zealand		0.01 (0.00) ***		– 0.23 (0.07) ***	– 0.17 (0.04) ***
Peru	0.02 (0.01) *				
Philippines	0.02 (0.01) *	0.01 (0.00) *		– 0.10 (0.05) *	– 0.07 (0.03) **
South Africa	0.01 (0.01)	0.01 (0.00) **	0.00 (0.01)	0.41 (0.15) ***	– 0.20 (0.10) **
Saudi Arabia	– 0.00 (0.01)	0.01 (0.00) *		– 0.04 (0.01) ***	
Singapore	0.04 (0.01) ***		0.01 (0.00) *	– 0.17 (0.04) ***	– 0.015 (0.02)
Spain			0.01 (0.00) ***	– 0.11 (0.05) **	
Sweden	0.02 (0.01) *	0.01 (0.00) *		– 0.14 (0.04) ***	– 0.09 (0.03) ***
Switzerland	0.02 (0.01) **	0.01 (0.00) *	0.01 (0.00) **	– 0.14 (0.05) ***	
Thailand	0.02 (0.00) ***		0.02 (0.00) ***	– 0.35 (0.06) ***	– 0.06 (0.02) ***
Turkey	0.01 (0.00) **	0.02 (0.01) *			
UK			0.01 (0.01)		0.02 (0.07)
USA			0.02 (0.00) ***		0.04 (0.05)
Mean	0.02	0.02	0.01	– 0.16	– 0.06
Maximum	0.04	0.04	0.02	0.41	0.18
Minimum	– 0.00	0.01	– 0.01	– 0.41	– 0.23
Standard deviation	0.01	0.01	0.01	0.14	0.10
# of significant effects/total # of countries	20/33	17/33	15/33	26/33	17/33

This table presents the commodities selected by the LASSO method (4 out of the 55 commodity indices in row 2) that have a significant impact (in at least 50% of all analyzed cases) on global macroeconomic variables such as real GDP, inflation, and real exchange rate. The model is estimated using ordinary least squares (OLS) with robust standard errors in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. The reported estimates are rounded to two decimal points. For example, in the case of Argentina, the estimate for crude oil is 0.0313, rounded to 0.03. In Belgium, the estimates for copper and crude oil are 0.0131 and 0.0093, rounded to 0.01 and 0.01 respectively. In Finland, the estimates for copper and crude oil are 0.022 and 0.024, rounded to 0.02 and 0.02 respectively. Empty cells indicate that LASSO omitted statistically insignificant estimates copper market prices, often referred to as 'Dr Copper,' serve as significant indicators of global economic health, corroborating previous findings such as those of Stuermer (2018).

In addition, our estimation results consistently demonstrate that the crude oil market has the utmost significant role among the primary commodity markets when it comes to the global transmission of inflationary pressures. This finding aligns with several recent studies that have come to the same conclusion (Fasanya and Awodimila 2020; Bettendorf 2017; Chudik and Fidora 2012; Kilian 2009). When examining the economic impact, Table 5 illustrates that the changes in copper and oil market prices have similar effects on the real economic activity across different countries. In most cases, the coefficient ranges between 0.1 and 0.2, rounded to one decimal point. However, it is worth noting that the primary driver of aggregate inflation appears to be the changes in crude oil market prices, and this effect seems to be consistent across all countries. Furthermore, a comparison at the country level indicates that macroeconomic indicators in the European countries are particularly vulnerable to the commodity market price risks.

The results presented in Table 5 emphasize the significant impact of gold and lead market price changes on the development of the real exchange rate. Notably, an increase in gold prices is strongly associated with a depreciation of the real exchange rate. This outcome is not surprising, considering the gold market's sensitivity to global economic fluctuations, making its price a reliable indicator of global economic well-being.[9] Our findings align with previous studies (e.g., Capie et al. 2005), which have consistently shown a negative relationship between gold price movements and dominant currencies like the US dollar. Moreover, the research of Giannellis and Koukouritakis (2019) and Wang and Lee (2016), among others, provides support for the idea that the gold market offers protection against currency risks. Table 5 also reveals the diverse effects of various commodity markets on the real exchange rates of different countries. In the majority of cases, an increase in commodity market prices correlates with a depreciation in the domestic real exchange rate, implying a decline in the currency's value.

Based on our LASSO analysis, one of the four most important global commodities was detected to be the lead metal. Hence, our research revealed completely novel findings regarding the role of lead market prices, which bear similarity to the impact observed in the gold market. From our GVAR results it is now also evident that the lead market price changes significantly influence the real exchange rates of nearly every individual country. Digging deeper into the economic significance of the lead market, we found that lead, like the other base metals such as zinc, silver, and copper, is extracted from galena and sourced from ore. At the global level, over 86% of refined lead and lead-related products are utilized in various industries including automobile manufacturing, batteries, pigments, and ammunition (U.S. Geological Survey, 2019). China, Australia, and the USA are the primary producers of lead, followed by Peru, Canada, Mexico, Sweden, and South Africa (U.S. Geological Survey, 2019).

[9] Gold is widely acknowledged as a safe haven asset, making it an attractive component of asset portfolio diversification (Sui, Rengifo, and Court 2021; Behmiri et al. 2021). During periods of economic turbulence, investors often seek alternative assets to protect their holdings, particularly in foreign currencies. The reason behind this phenomenon is that gold is recognized for its ability to provide a hedge against the inherent risks present in stock and currency markets (recent evidence can be found in Wang and Lee 2021).

It is important to note that all these countries were included in our study to ensure comprehensive analysis.

Our newly revealed prominent role of lead in international trade may explain why the development of lead market prices is considered crucial for analyzing exchange rate movements using the LASSO method. Furthermore, according to the results reported in Table 5, the impact of lead market price development on economies varies across countries. For instance, when the global lead market prices increase, countries like Australia and Japan experience a significant appreciation of their real exchange rates, while others witness a depreciation. Recently, lead prices have surged to their highest level since 2018 amid the post-Covid-19 global economic recovery and the energy crisis. This increase is mainly attributed to the anticipation of supply disruptions in Europe and the growing global demand for the traditional lead-acid car batteries from China, the USA, and Europe (World Bank Group 2021). The World Bank's commodity market outlook for 2021 projected that lead prices would remain stable at pre-pandemic levels in both the medium and long terms (World Bank Group 2021). Nonetheless, this outlook might have changed due to the onset of the war in Ukraine in early 2022.

In order to conduct further robustness checks, we excluded the data from the global economic and financial crises of 2008–2009. These data spanned from 2007Q1 to 2009Q4. Subsequently, we performed the LASSO estimation on two sub-samples referred to as 'pre-crisis' (covering the period from 1990Q1 to 2006Q4) and 'post-crisis' (covering the period from 2010Q1 to 2019Q4). The results of these estimations are presented in Tables 9 and 10 in the Appendix. Overall, the set of four significant commodities identified in the full sample estimation remains consistent. Notably, we observed a significant increase in the overall importance of these commodities to the respective macrovariables during the post-crisis period (see Table 10 in the Appendix).

6 Testing for the weak exogeneity of foreign-specific and global variables in the GVAR model

Based on the results obtained from the unit root tests for our data, the second stage of our estimation process began by examining the weak exogeneity of the foreign and global variables in our estimated GVAR systems. The weak exogeneity assumption is critical in the estimation process of the global VAR approach. To test the joint significance of the foreign and global variables in each country-level regression equation, we estimated an error correction model. Following the approach used in studies by Pesaran et al. (2004), Boschi and Girardi (2011), and Gutierrez and Piras (2013), we first grouped the foreign and global variables together in the vector Δy^*_{it}. Subsequently, we constructed the regression model based on Eq. 7, i.e.,

$$\Delta y^*_{\mathrm{it},l} = \mu_{\mathrm{il}} + \sum_{j=1}^{r_i} \gamma_{ij,l} \mathrm{ECM}^j_{i,t-1} + \sum_{k=1}^{p_i} \varphi_{ik,l} \Delta \mathbf{y}^j_{i,t-k} + \sum_{m=1}^{q_i} \theta_{\mathrm{im},l} \Delta \widetilde{\mathbf{y}}^*_{i,t-m} + \varepsilon_{\mathrm{it},l}. \tag{7}$$

In the given equation, the ECM term, denoted as $\mathrm{ECM}^{j}_{i,t-1}$, $j = 1, 2, .., r_i$ corresponds to the estimated error correction term for each macrovariable (j) of each country. The value of r_i represents the number of cointegration relations found for that particular macrovariable. The notation Δ represents the first difference operator, so $\Delta \mathbf{y}^{j}_{i,t-k}$ implies the domestic macrovariables expressed as differences over the lag period of k. Similarly, $\Delta \tilde{\mathbf{y}}^{*}_{i,t-m}$ represents the foreign and global variables expressed as differences over the lag period of m. Furthermore, $k = 1, \ldots, p_i$ and$m = 1, \ldots, q_i$, where p_i and q_i are the maximum lag orders of the domestic, foreign and global variables for each of the i^{th} country models,[10] respectively. The test for weak exogeneity is an F test for the joint significance of the hypothesis $\gamma_{ij} = 0$, $j = 1, 2, .., r_i$ at a 5% risk level of the ith country model using the above regression representation. In particular, the test assumes that both the foreign-specific and global variables enter the model as weakly exogenous. We thus verify the null hypothesis of weak exogeneity for both the foreign-specific and global variables against the alternative hypothesis of no weak exogeneity for both the foreign-specific and global variables.

The results presented in Table 6 indicate that out of the 130 cases analyzed, only 10 cases show a rejection of the null hypothesis regarding the weak exogeneity assumption. This favorable outcome strengthens the support for the weak exogeneity hypothesis within our sample. However, it is important to note that the assumption of weak exogeneity for global variables is challenged in several countries. This implies that, from a purely statistical perspective, the changes in prices observed in these markets cannot be considered weakly exogenous in relation to the macroeconomic developments of those countries.

For instance, our analysis from this stage reveals that the changes in copper prices cannot be considered weakly exogenous for countries such as Indonesia, Norway, the Philippines, and Sweden. Similarly, the exogeneity of crude oil price changes is rejected for Malaysia. On the other hand, the exogeneity of gold price changes is only rejected for Saudi Arabia, while the exogeneity of lead price changes is rejected for both Sweden and the USA.

7 Impact elasticities at the country level

At the next step, we utilized the error correction model versions of the VARX* representations to analyze the contemporaneous impacts of foreign variables on domestic counterparts. We also assume the weak exogeneity of the foreign variables. The estimation procedure in the GVAR framework maintains consistency, ensuring that the variables of each model interact in the long run. This analysis is particularly valuable at the global scale, as it allows us to investigate the feedback effects from the foreign variables (Pesaran and Smith 2006; Pesaran et al. 2004; Galesi and Lombardi 2009). Specifically, we focus on the impact elasticities, as discussed in Galesi and Lombardi (2009). These elasticities measure the immediate variation of a domestic variable resulting from a 1% change in the corresponding foreign variables.

[10] The lag orders of the weakly exogenous variables and the number of cointegrating relationships for country specific models are reported in Appendix 12.

Table 6 F-statistics for testing the weak exogeneity of the country-specific foreign and global variables

			Foreign variables		Global variables			
Country/region	F test	95% F-Stat. Critical value	Output	Inflation	Copper	Oil	Gold	Lead
Argentina	F(2,95)	3.09	0.44	1.09	2.45	1.41	1.38	0.06
Australia	F(3,99)	2.70	0.08	1.31	1.12	0.83	2.42	0.51
Brazil	F(2,97)	3.09	0.16	0.86	1.71	0.05	0.37	0.93
Canada	F(3,99)	2.70	0.75	2.47	2.15	1.44	0.86	1.56
China	F(2,97)	3.09	0.17	0.31	0.46	0.38	0.49	0.02
Chile	F(2,95)	3.09	1.64	0.37	0.68	0.27	0.38	1.38
Euro area	F(1,101)	3.94	0.45	0.02	0.41	1.83	1.12	1.19
India	F(2,100)	3.09	0.98	1.29	0.10	0.56	0.56	0.33
Indonesia	F(3,101)	2.69	0.62	0.55	2.72#	1.05	0.45	0.42
Japan	F(2,100)	3.09	2.29	1.37	1.26	0.31	0.45	3.08
Korea	F(3,99)	2.70	3.62#	0.71	0.72	0.41	0.91	1.01
Malaysia	F(2,101)	3.09	2.23	2.68	0.57	3.23#	0.01	1.28
Mexico	F(2,102)	3.09	1.34	0.29	0.14	0.52	0.33	0.61
Norway	F(3,99)	2.70	1.06	1.82	3.21#	1.51	1.30	1.44
New Zealand	F(3,99)	2.70	2.28	0.78	0.94	0.58	0.91	1.14
Peru	F(2,102)	3.09	1.83	0.75	0.42	0.05	0.61	0.63
Philippines	F(3,100)	2.70	0.49	2.20	2.96#	1.42	0.72	0.91
South Africa	F(2,100)	3.09	0.78	0.42	2.63	1.07	1.53	1.28
Saudi Arabia	F(1,104)	3.93	0.01	0.06	0.81	1.41	5.38#	0.36
Singapore	F(1,102)	3.93	1.07	0.85	0.20	0.41	1.56	0.37
Sweden	F(2,100)	3.09	0.11	1.62	4.41#	1.33	0.50	8.22#
Switzerland	F(3,99)	2.70	3.56#	0.97	1.25	0.71	0.09	0.90
Thailand	F(2,101)	3.09	0.03	0.48	1.71	0.14	2.88	0.35
Turkey	F(1,103)	3.93	0.08	0.96	0.60	0.39	0.93	1.81
UK	F(2,100)	3.09	1.49	1.35	2.06	2.52	1.06	0.44
USA	F(2,103)	3.08	1.04	1.87	2.90	1.50	0.51	4.38#

This table presents the F-statistics for testing the weak exogeneity of the country-specific foreign and global variables in our GVAR model. The # denotes the rejection of the null hypothesis of the weak exogeneity assumption at the 5% significance risk level

We examine the impact of a 1% increase in foreign-specific inflation on Argentina's domestic inflation, based on the research conducted by Pesaran et al. (2004). This analysis is crucial to evaluate the spillover effects originating from the foreign variables. Table 7 presents the results, showing that the estimated coefficients are predominantly positive, except for the inflation effects observed in Brazil, Chile, and Japan. Many of the countries/regions demonstrate statistically significant impact elasticities, indicating a notable influence of foreign variables. Additionally, all countries/regions exhibit statistically significant exchange rate elasticities. The statistical significance of the effects of foreign variables on domestic counterparts is particularly high for both the output and inflation. For output, the estimated coefficients range from 0 to 2, with Argentina showing the lowest value (0.15) and Turkey demonstrating the highest (2.01). Notably, the impact elasticity is statistically significant and exceeds that of Turkey (2.01), Sweden (1.247), Singapore (1.32), and Malaysia (1.12). This implies that the domestic output reacts more strongly to an increase in the output of major trading partners.

The estimated impact elasticity with respect to inflation ranges between -3 and 1. Additionally, the impact elasticity for the output effects is significant for Argentina (1.08) and India (1.02), indicating an overreaction of inflation relative to the increase in inflation of their main trading partners. On the other hand, statistically non-significant estimates suggest that the inflation dynamics would be independent of foreign countries' inflationary pressure. Furthermore, a statistically significant impact elasticity greater than one is observed for the real exchange rate in several countries such as Argentina (1.77), Canada (1.21), Euro area (1.18), Korea (1.05), Malaysia (1.01), Norway (1.08), Sweden (1.23), and Thailand (1.38). This indicates an overreaction or influence of an increase in the real exchange rate of major trading partners on the domestic real exchange rate. Overall, these findings align with the research conducted by e.g. Galesi and Lombardi (2009), which demonstrates that the foreign variables significantly impact the domestic macroeconomic performance in most countries.

8 Shock reactions

In this section, we employed the GIRFs (generalized impulse response functions) to analyze the response of global macroeconomic variables to the commodity price shocks. We obtained the point estimates for the simulation horizon, which covers a period of up to 40 periods (10 years). This allows us to examine the long-term effects of these shocks. Moreover, we also conducted a comparative analysis to highlight the differences between our findings and those of several other studies that have focused on somewhat similar kinds of sets of commodities as ours.

8.1 Real GDP

Figure 3 depicts the responses of real output to the shocks in the copper market price changes. Both the advanced economies (Panel A) and the emerging economies (Panel B) tend to experience an improvement in regional real output over an eight-quarter period (equivalent to two years) following a positive copper price change shock. The impact of the shock on regional output, ranging from approximately 0.10 to 0.60 basis points, is generally statistically significant throughout the simulation horizon for both the advanced and emerging economies (see Fig. 9 for detailed individual reactions with

Table 7 Contemporaneous effects of foreign variables on domestic counterparts

Country/region	Output	Inflation	Real exchange rate
Argentina	0.149 (0.44)	1.088* (3.49)	1.768* (3.26)
Australia	0.177* (2.32)	0.238 (1.28)	0.899* (4.05)
Brazil	0.657* (3.09)	− 3.72 (− 1.62)	–
Canada	0.520* (5.82)	0.714* (5.25)	1.207* (3.26)
China	0.997* (3.84)	0.243 (0.96)	–
Chile	1.075* (2.59)	− 0.212 (− 1.31)	0.713* (6.73)
Euro area	0.411* (5.04)	0.285* (4.95)	1.178* (5.06)
India	0.465 (1.35)	1.017* (2.65)	0.173* (0.13)
Indonesia	0.447 (1.80)	1.081 (1.58)	–
Japan	0.633* (3.45)	− 0.008 (− 0.07)	0.750* (4.29)
Korea	0.203 (1.04)	0.585* (3.77)	1.049* (6.64)
Malaysia	1.115* (5.92)	0.569* (3.06)	1.009* (7.07)
Mexico	0.202 (1.04)	0.540 (1.70)	–
Norway	0.895* (3.35)	0.630* (2.29)	1.085* (5.08)
New Zealand	0.336* (2.43)	0.512* (5.13)	0.604* (5.73)
Peru	0.914* (3.54)	2.982 (1.78)	–
Philippines	0.270 (1.67)	0.628* (2.75)	1.072* (7.76)
South Africa	0.092 (0.84)	0.268 (1.14)	0.767* (8.43)
Saudi Arabia	0.312 (1.37)	0.203* (3.02)	–
Singapore	1.328* (5.15)	0.019 (0.20)	0.992* (6.07)
Sweden	1.247* (6.90)	0.567* (3.08)	1.235* (4.07)

Table 7 (continued)

Country/region	Output	Inflation	Real exchange rate
Switzerland	0.219 (1.44)	0.225* (2.52)	0.905* (6.18)
Thailand	0.970* (2.28)	0.571* (3.08)	1.379* (0.18)
Turkey	2.016* (3.15)	0.790 (0.58)	–
UK	0.605* (5.72)	0.369* (3.39)	0.724* (0.06)
USA	0.450* (4.19)	0.267* (4.81)	–

White's heteroskedastic-robust t-ratios are given in parentheses

confidence bands[11]). These findings are consistent with the previous results reported in Table 5, which also demonstrated the positive responses in regional output. Interestingly, while some regions show modest reactions to copper price change shocks after two years, China and Africa (represented by South Africa) exhibit more pronounced effects even within the first two years. One possible explanation for China's persistence in reacting to these shocks could be its significant reliance on copper in industrial production. On the other hand, it is not immediately clear why Africa would display such strong reactions, considering that it is neither a major exporter nor importer of copper.

Our findings support and align with previous research. For instance, Stuermer (2018) confirms that the shifts in copper market prices have a stimulating effect on the global real GDP. Similarly, we observe a positive and statistically significant rise in world output following the price change shock, consistent with Stuermer's results. This boost typically persists for approximately five years. Furthermore, other studies, like Wen et al. (2019) as well as Marañon and Kumral (2020), have also documented a favorable and significant impact of international copper market price shocks on the key macroeconomic indicators across different regions. These indicators encompass the GDP, inflation, and exchange rates.

Figure 4 presents the impulse response functions (GIRFs) of a positive one standard error shock to changes in crude oil prices on the regional output components. On average, this shock leads to an increase in output ranging from 0.10 to 0.50 basis points. For the advanced economies (Fig. 4, panel A), the effect of the shock on regional output may persist for approximately six quarters before returning to the pre-shock levels or fading out completely. However, this pattern is not observed in some emerging economies (Fig. 4, panel B). In terms of the oil market price changes, the

[11] To gain a better understanding of the impact of shocks, please refer to Appendix A, Figs. 9, 10, 11, 12. These figures present detailed simulations of generalized impulse response functions (GIRFs) for the global macroeconomic variables. Additionally, we have included the 95% confidence bands to provide a measure of uncertainty. These simulations specifically illustrate the individual reactions of the macroeconomic variables to the commodity price change shocks.

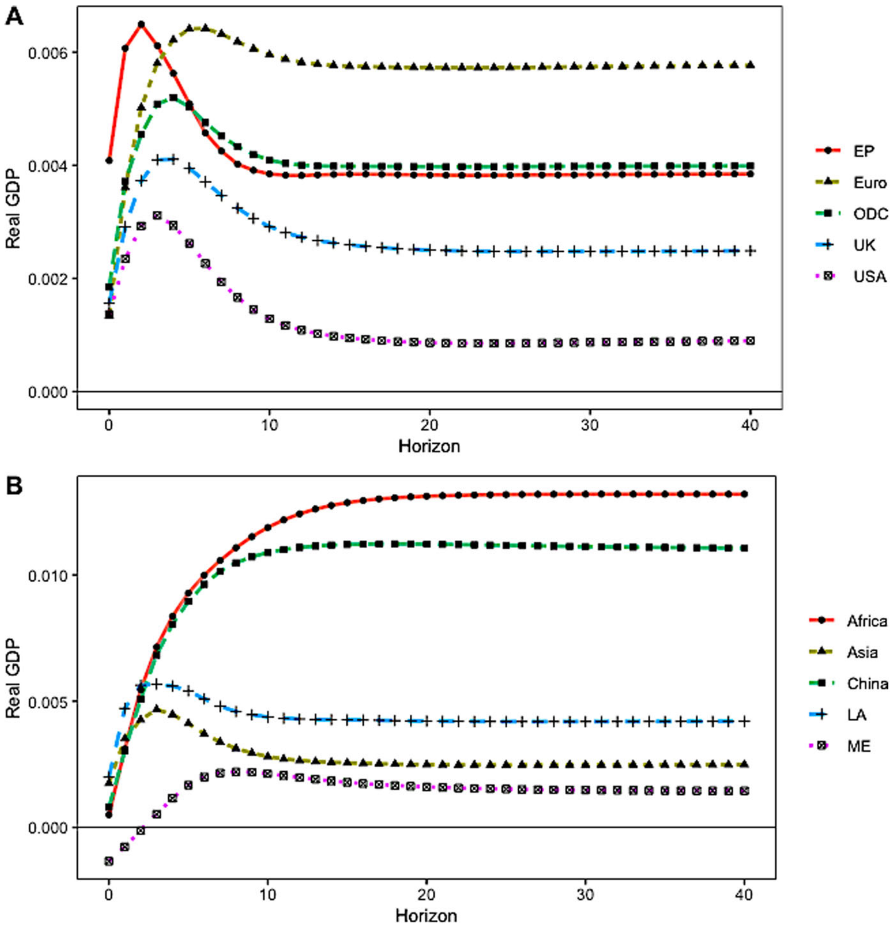

Fig. 3 GIRFs of a positive unit (one s.e.) shock to copper price changes for the advanced (panel **A**) and emerging economies (panel **B**). *Notes*: *EP* denotes other European countries, *Euro* is euro area, *LA* is Latin America, *ME* is Middle East, and *ODC* is other developed economies

impact of the shock is more pronounced for the emerging economies compared to the advanced economies. This is consistent with the findings presented in Table 5 and can also be seen in Fig. 10 in Appendix A.

These reactions align with the previous research (Boschi and Girardi, 2011) and indicate that regional output development is significantly influenced by the oil price shocks in both the short and medium terms. On the other hand, Chudik and Fidora (2012) examined the response of regional output to the negative oil supply shocks in advanced and emerging economies. Their findings suggest that both types of economies experience a decline in output following a negative oil supply shock. Specifically, emerging economies in Asia and Latin America tend to experience sharper declines in output growth on average.

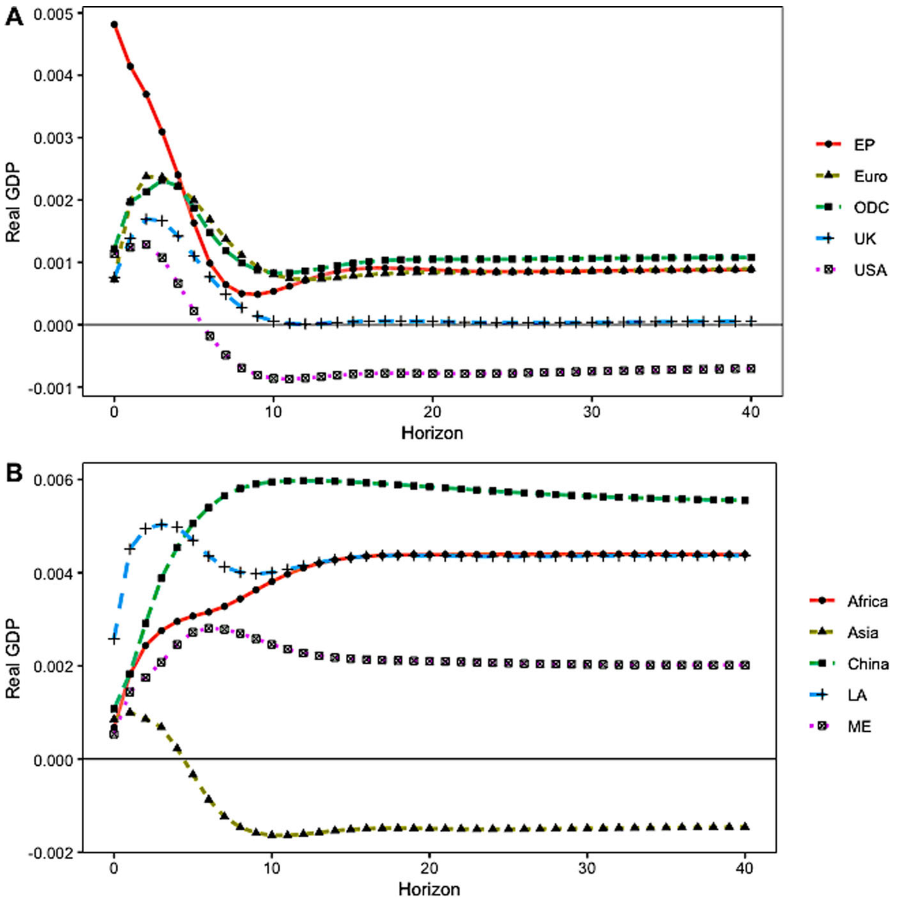

Fig. 4 GIRFs of a positive unit (one s.e.) shock to the crude oil price changes for advanced (panel **A**) and emerging economies (panel **B**). For the notations, see Fig. 3

8.1.1 Real exchange rate

From Fig. 5 we see the responses of the regional real exchange rates to a positive shock in gold price changes. These responses align with the negative effects on the real exchange rate reported also in Table 5. The results indicate that a positive shock to gold price changes leads to a depreciation in the real exchange rate across all regions. On average, this shock in gold price changes corresponds to a quarterly change of approximately − 0.01% to − 0.03% in the real exchange rate across the various regions. It is also worth noting that this shock is statistically significant for both the advanced (panel A) and emerging economies (panel B) throughout the entire simulation period. Overall, these findings suggest that an increase in the gold price change has a noticeable impact on the real exchange rate, resulting in a depreciation across all regions, regardless of their economic development level.

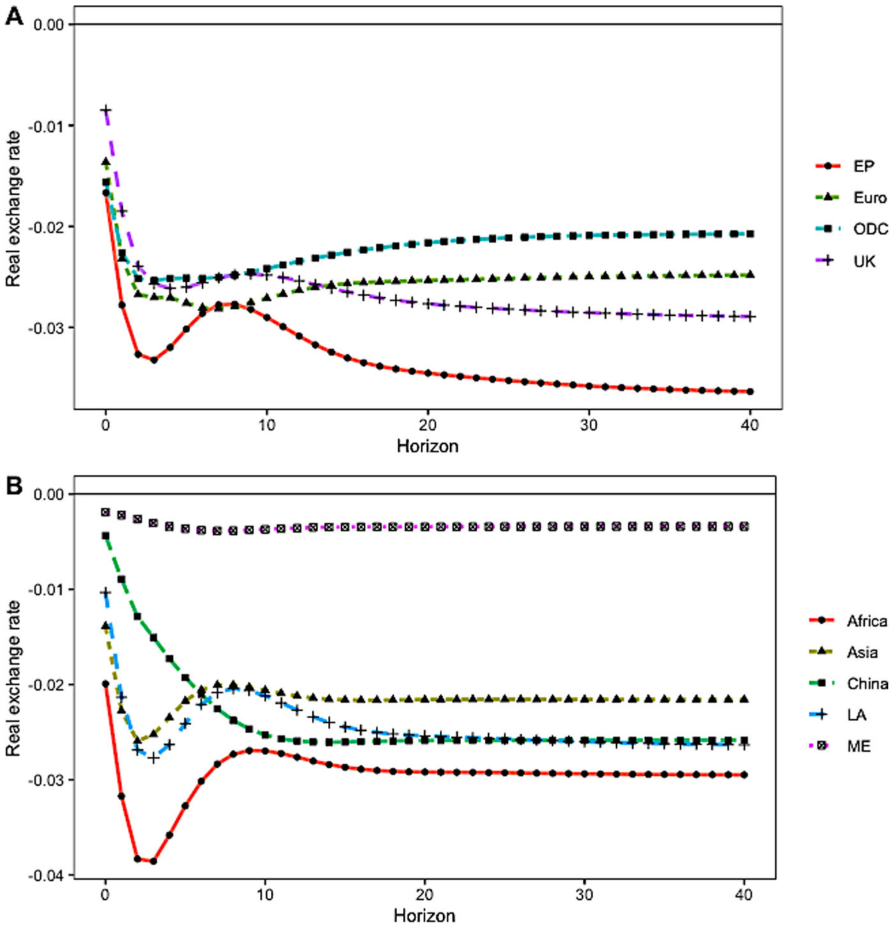

Fig. 5 GIRFs of a positive unit (1 s.e.) shock to gold price changes for advanced (panel **A**) and emerging economies (panel **B**). For the notations, see Fig. 3

For a comprehensive understanding of the significance of the shocks, please refer to the individual responses along with their respective confidence bands, which can be found in Appendix Fig. 11. The findings depicted in Fig. 5 align with previous research, reinforcing the notion that the gold market can be considered as hedge against economic recession and currency risk (Sui et al. 2021; Wang and Lee 2016). For instance, Wang and Lee (2021) utilized a TVR-VAR approach and affirmed the negative response of major currencies (such as USD, euro, and the British pound) to the shocks in the price of gold. Additionally, they indicated that gold acts as a hedge against currency depreciation in the short term, although this effect diminishes in the long run.

In Fig. 6, we present the reactions of the real exchange rate at the regional level to a lead price change shock. Our findings reveal that a positive one standard error shock

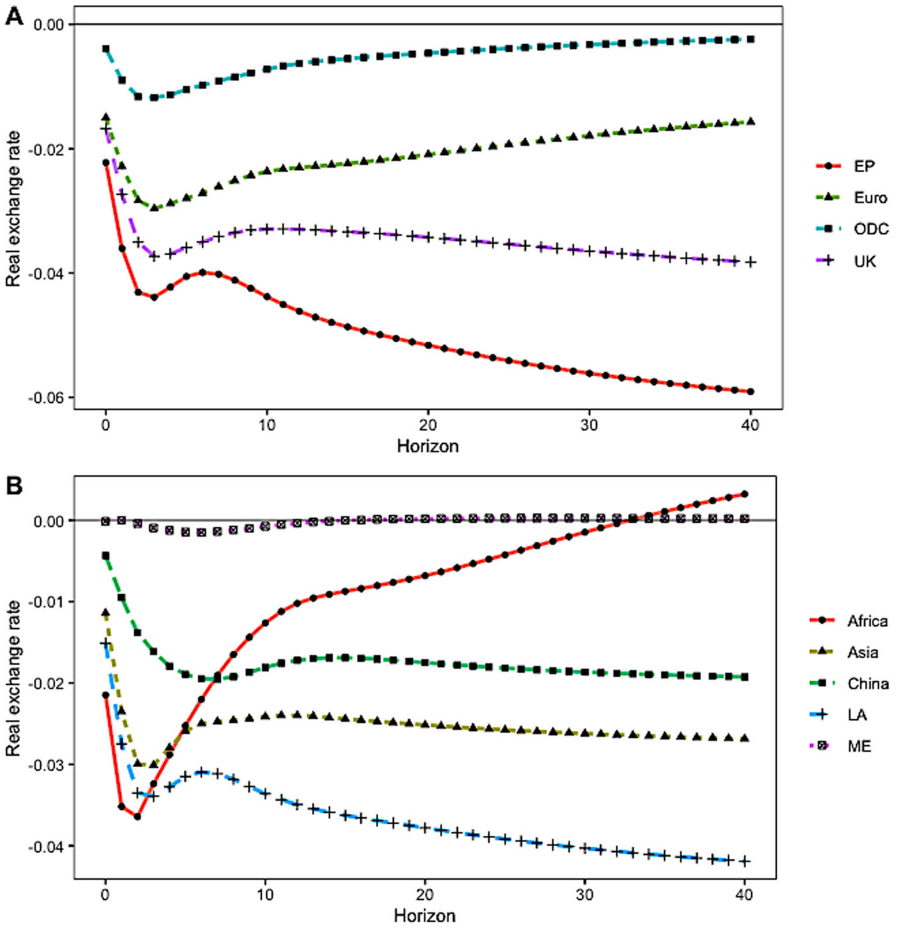

Fig. 6 GIRFs of a positive unit (one s.e.) shock to lead price changes for the advanced (panel **A**) and emerging economies (panel **B**). For the notations, see Fig. 3

in the lead price changes leads to a noticeable real exchange rate depreciation per quarter, ranging from − 0.01% to − 0.02%. These effects are particularly pronounced in several specific advanced and emerging economies. To the best of our knowledge, our study is the first to specifically examine the impact of global lead prices on the real exchange rate movements using the LASSO and GVAR approaches. However, it is worth noting that our results align with earlier studies, such as the one conducted by Brown and Hardy (2019), who identified a significant and robust relationship between the exchange rate movements and three base metal prices (copper, lead, and nickel), although they employed a somewhat different methodology.

Overall, our research contributes to the existing literature by shedding light on the relationship between the lead price change shocks and real exchange rate dynamics, offering new insights into the potential drivers of exchange rate movements.

8.1.2 Inflation

Figure 7 demonstrates the responses of regional inflation to a shock in crude oil price changes. Upon analyzing the data, it is evident that the reactions vary significantly, but the responses consistently become positive and stable within the first six quarters after the initial shock. The figure specifically depicts a clear inflationary effect resulting from the oil price shock, observable after the initial six quarters, for both the advanced and emerging economies. It is worth noting that the effect seems to dissipate relatively quickly for the advanced economies (panel A) compared to the emerging economies (panel B). However, it is important to highlight that the Middle Eastern countries exhibit a distinct negative impact on inflation as a consequence of the oil price shock, which deviates from the reaction seen in the other country groups.

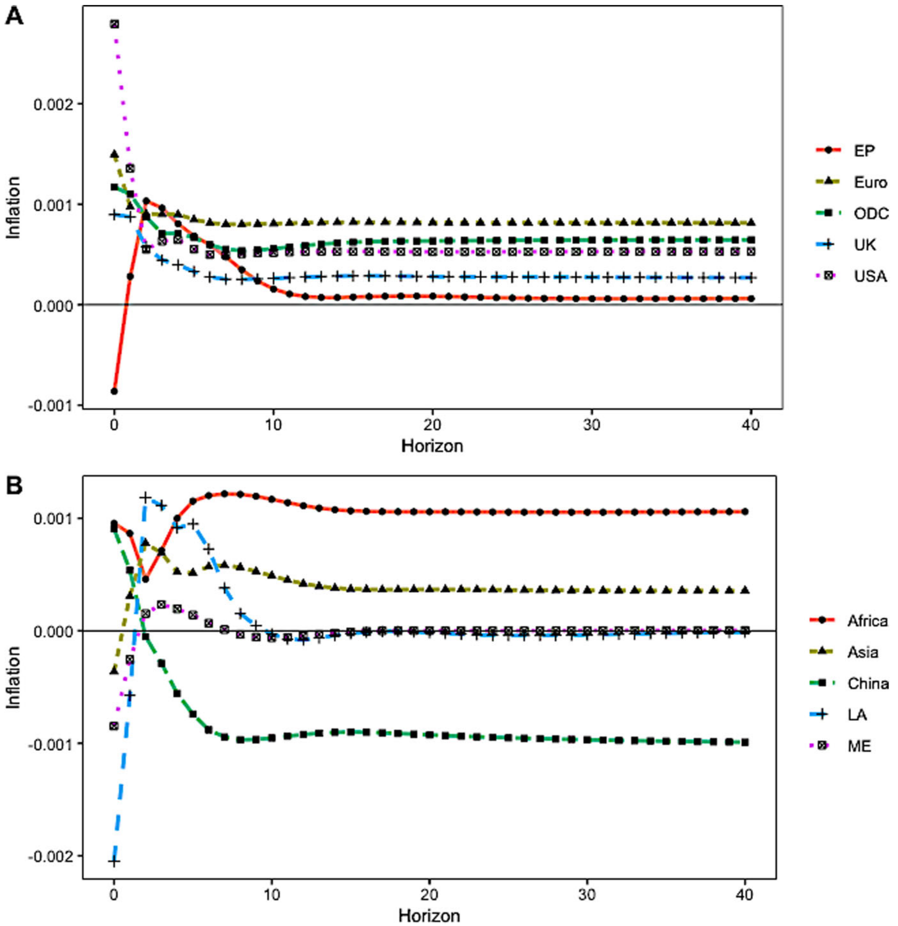

Fig. 7 GIRFs of a positive unit (one s.e.) shock to crude oil prices for advanced (panel **A**) and emerging economies (panel **B**). For the notations, see Fig. 3

The reactions depicted in Fig. 7 align with the current global economic conditions, providing clear evidence that significant historical oil price shocks transmit inflationary pressures worldwide. This observation corroborates with the findings of, e.g., Ha, Kose, and Ohnsorge (2022). For a more in-depth analysis of the shock reactions' significance, please refer to Fig. 12 in the appendix. In earlier studies, for example Galesi and Lombardi (2009) conducted a study examining the impact of oil price hikes on headline inflation. They found that the oil price shocks tend to exert inflationary pressures, particularly in advanced economies. Supporting the findings of our simulation, a recent analysis by Ha, Kose, and Ohnsorge (2022) also indicates that the global inflationary trends have been primarily driven by the increases in oil prices. This aligns with the results obtained from our Generalized Impulse Response Functions (GIRFs) regarding the effects of oil price change shocks. Notably, the events in Ukraine in 2022 have once again reaffirmed this causal relationship between the oil prices and aggregate inflation.

8.2 Generalized forecast error variance decompositions

To further assess the impact of fluctuations in the commodity prices on global macroeconomic activities over the next 10 years, we analyzed the variance in macroeconomic variables attributed to each specific commodity price shock. This analysis was performed over a 40-quarter period average using a methodology called generalized forecast error variance decompositions (GFEVDs). In Table 8, we present the proportion of macrovariable variances explained by the four globally most relevant commodity price change shocks for various regional and country settings. In general term, the results indicate that the shocks in copper market price changes may account for approximately from 1 basis point (for Africa) up to even 70 basis points

Table 8 Generalized forecast error variance decompositions (average in %)

	Real GDP		Real exchange rate		Inflation
Regions	Copper	Oil	Gold	Lead	Oil
Africa	0.01	0.01	0.33	0.04	0.45
Asia	0.24	0.34	0.09	0.11	0.33
China	0.70	0.68	0.18	0.06	0.04
Euro area	0.68	1.04	0.44	0.01	0.50
Other European countries	0.07	0.22	0.27	0.38	0.37
Latin America	0.25	0.84	0.14	0.06	0.34
Middle East	0.33	0.20	0.20	0.09	0.03
Other developed countries	0.16	0.15	0.22	0.25	0.64
UK	0.67	0.56	0.22	0.32	0.14
USA	0.02	0.50			0.20

The points estimate reported are the average of a 40-quarter-ahead forecast error variance (proportion) of the commodity price change explained by conditioning on contemporaneous and future innovations (for China) of the variability in the regional outputs. The strongest effects are observed in China, the euro area, and the UK, where the copper market price developments play a significant role in explaining the variation in the global economy. This finding aligns with our previously observed shock responses illustrated in Fig. 3.

Furthermore, we find that the increases in crude oil market price changes also contribute significantly to the regional output variability. For China, the crude oil price change hikes account for approximately 68 basis points, while in the euro area, Latin America, the UK, and the USA, the corresponding figures are 104, 84, 56, and 50 basis points, respectively. Similarly, there is notable variation in the way the different regions respond to the changes in the real exchange rate when it comes to the changes in the prices of gold and lead. These commodities contribute to anywhere between 1 to 44 basis points of the overall variance in the real exchange rate. When it comes to the variations in regional inflation, the crude oil price fluctuations have an impact of 4 to 64 basis points. However, the advanced economies, including the euro area, tend to experience more significant effects due to the oil market shocks. This aligns with the fact that the oil price increases have historically been a major factor in driving the inflationary pressures in recent years.

9 Concluding remarks and policy recommendations

In this study, we have employed the machine learning (LASSO) and GVAR approaches to analyze the relationship between key macroeconomic variables (output, inflation, and real exchange rate) and commodity market price developments in a globally comprehensive dataset. Our novel approach enabled us to assess the statistical significance of various commodities without any preconceived assumptions about their relevance. By considering at the start of our analyses a large set of 55 commodities, we identified the four globally most significant commodity market segments to be the crude oil, gold, copper, and lead markets. These markets seem to play a crucial role in influencing the global economic cycles in the contemporary context. In the second stage of our analysis, we investigated the dynamic impacts of price change shocks in these identified markets on the performance of economic regions in both the advanced and emerging countries.

Overall, our findings support the notion that the traditional commodity markets like copper, oil, and gold significantly contribute to the global economic performance. However, as a somewhat novel finding we revealed the important role of lead metal market in the global economic development, too. These findings have broader implications, suggesting the growing importance of these commodities in shaping the global economic trends.

Given the significant influence of crude oil, gold, copper, and lead markets on global economic cycles, policymakers should encourage the diversification of commodity market exposures in their political decisions. This can include promoting the development of other commodity markets, such as renewable energy sources or emerging technologies, to reduce the dependency on a few key commodities and mitigate the potential risks associated with their price volatility. Additionally, we propose that achieving optimal stabilization policies for output, inflation, and the development of real exchange rates requires meticulous forecasting exercises for the global commodity prices that hold the greatest significance in general. This is especially important for some individual economies in the group of more developed market economies.

Appendix A

See Figs. 8, 9, 10, 11, 12.

See Tables 9, 10, 11, 12, 13 and 14.

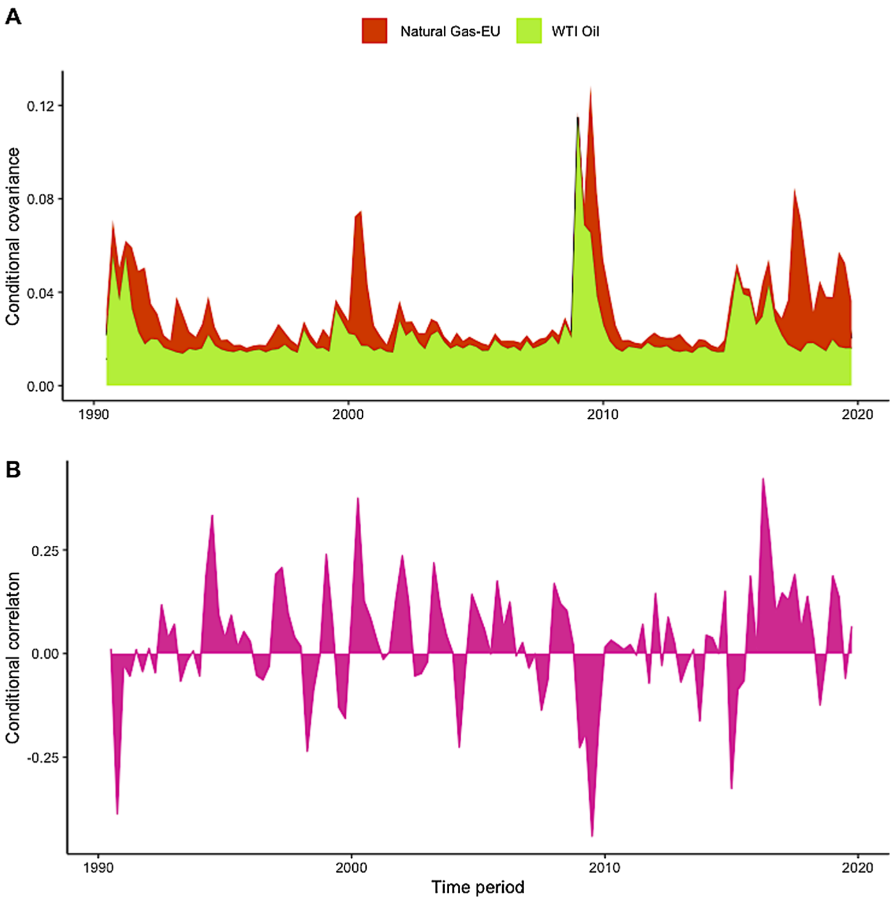

Fig. 8 The dynamic conditional covariance (panel **A**) and correlation (panel **B**) between the EU natural gas and WTI crude oil price changes. Note: Authors' estimations are based on the DCC-GARCH (1,1)-model for log price changes

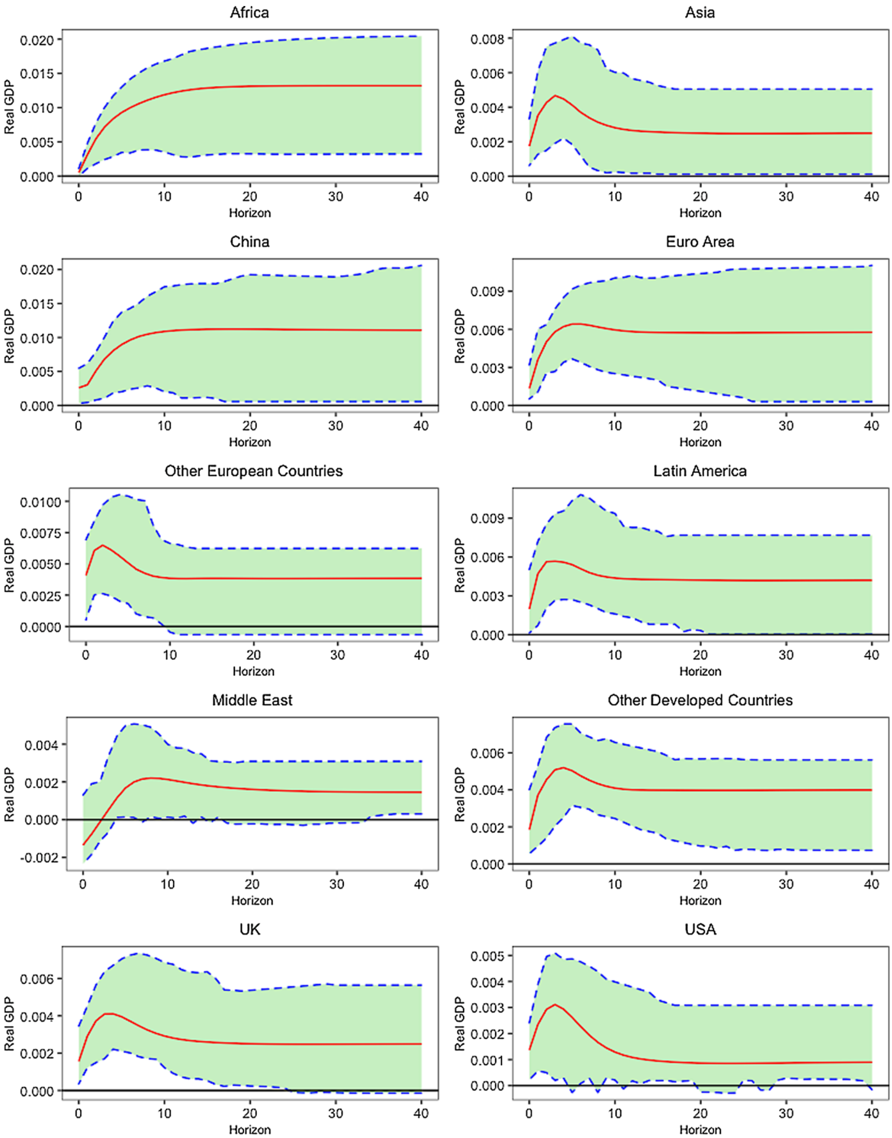

Fig. 9 The response of real GDP to a unit (one s.e.) copper price shock with the 95% confidence band for the regions

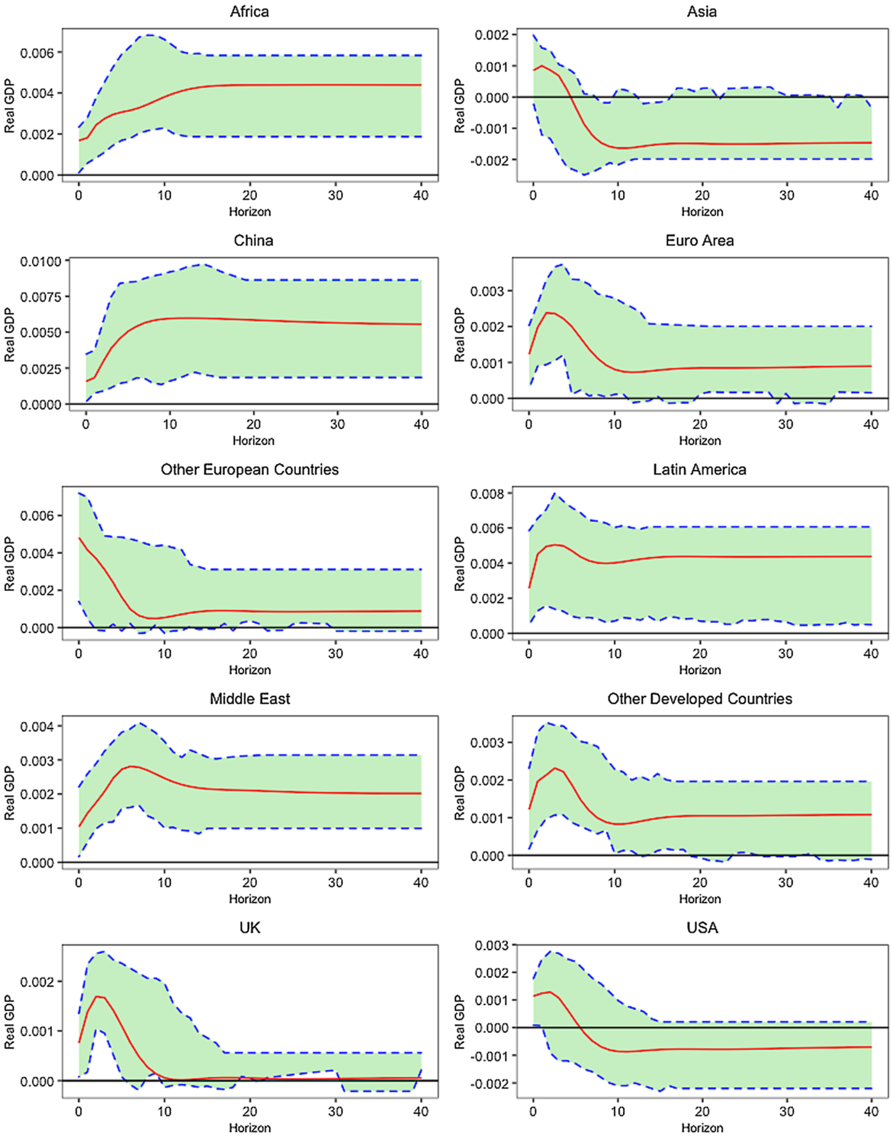

Fig. 10 The response of real GDP to a unit (one s.e.) oil price shock with the 95% confidence band for the regions

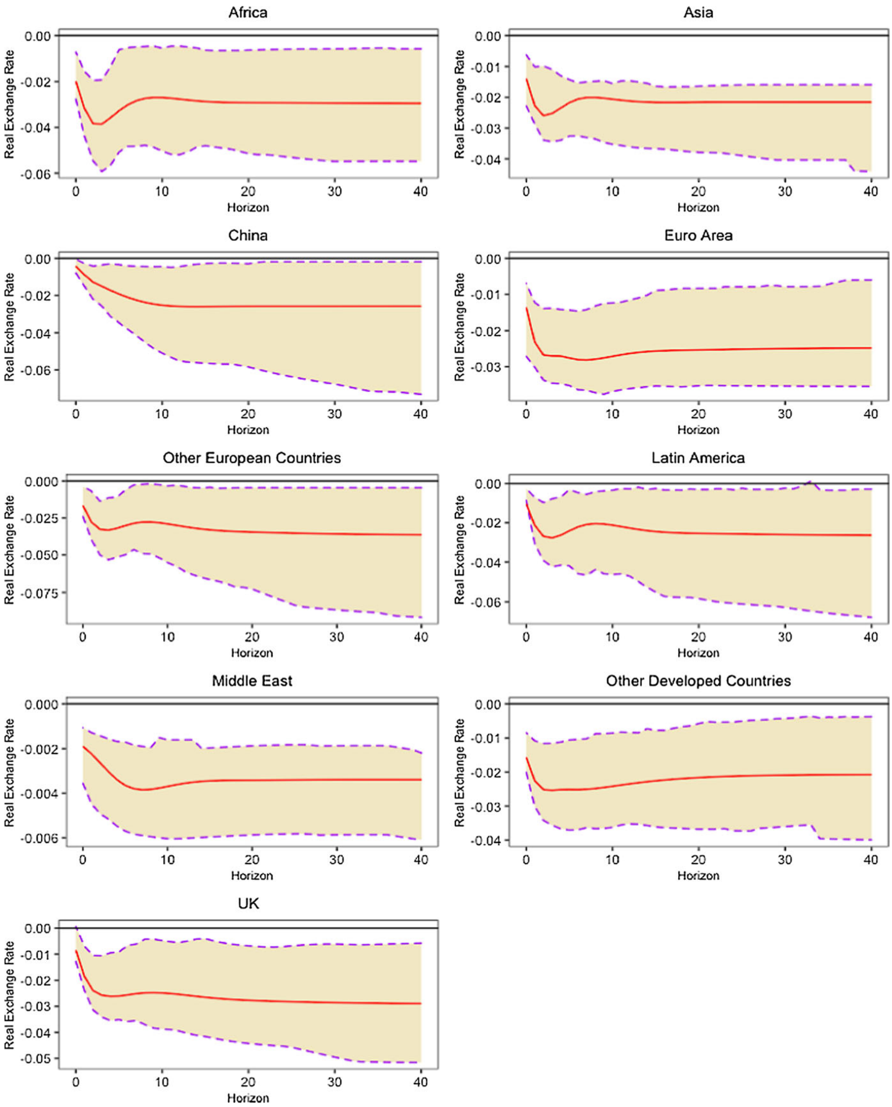

Fig. 11 The response of real exchange rate to a unit (one s.e.) gold price shock with the 95% confidence band for the regions

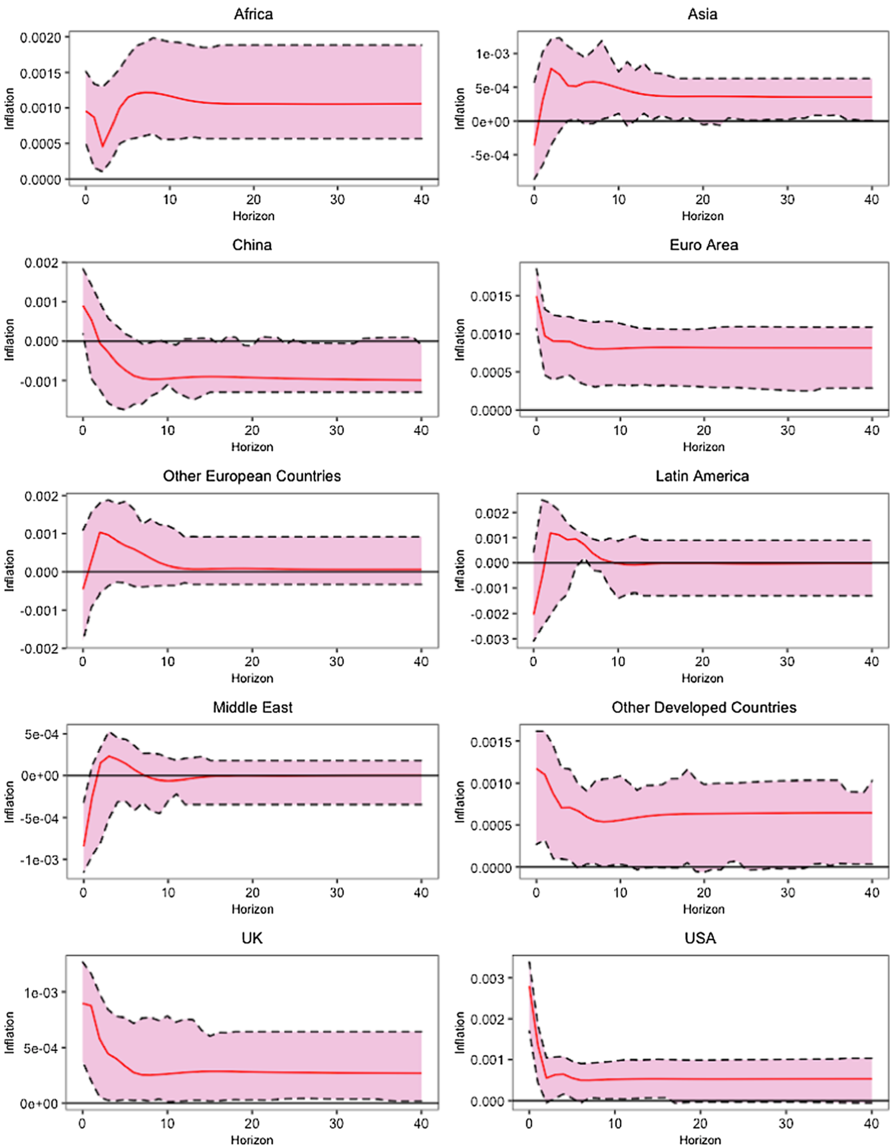

Fig. 12 The response of inflation to a unit (one s.e.) oil price shock with the 95% confidence band for the regions

Table 9 Estimates for the effects on macroeconomy from the LASSO-selected commodity market returns *– pre-crisis 1990Q1- 2006Q4*

	Output (real GDP)		Inflation	Real exchange rate	
Country	Copper	Oil	Oil	Gold	Lead
Argentina		0.02 (0.01) ***			
Australia				– 0.15 (0.04) ***	
Austria	0.01 (0.00) **		0.01 (0.00) ***		– 0.05 (0.02) **
Belgium	0.02 (0.00) **		0.01 (0.00) ***	– 0.15 (0.05) ***	– 0.23 (0.06) ***
Brazil				– 0.26 (0.08) ***	– 0.10 (0.03) ***
Canada		0.02 (0.01) ***	0.01 (0.00) **	– 0.15 (0.05) ***	
China					– 0.11 (0.04) ***
Chile	0.01 (0.01) *			– 0.18 (0.07) ***	– 0.09 (0.04) ***
Finland			0.02 (0.01) **	– 0.12 (0.05) **	
France		0.01 (0.00) **	0.01 (0.0) ***	– 0.18 (0.04) ***	
Germany	0.01 (0.00) *		0.02 (0.00) ***	– 0.13 (0.05) **	– 0.09 (0.02) ***
India	0.01 (0.01) *			– 0.11 (0.05) **	
Indonesia				– 0.22 (0.07) ***	– 0.08 (0.03) ***
Italy	0.02 (0.00) **			– 0.15 (0.05) ***	
Japan				– 0.30 (0.06) ***	– 0.14 (0.04) ***
Korea		0.02 (0.01) *			
Malaysia		0.01 (0.00) *	0.02 (0.00) **	– 0.20 (0.06) ***	
Mexico	0.02 (0.01) *				
Netherlands					
Norway	0.01 (0.01) **	0.02 (0.01) **		– 0.17 (0.06) ***	– 0.17 (0.04) ***
New Zealand			0.01 (0.00) ***	– 0.23 (0.07) ***	

Table 9 (continued)

	Output (real GDP)		Inflation	Real exchange rate	
Country	Copper	Oil	Oil	Gold	Lead
Peru					
Philippines		0.01 (0.00) *			– 0.20 (0.10) **
South Africa		0.01 (0.00) **		0.41 (0.15) ***	
Saudi Arabia		0.02 (0.00) ***		– 0.04 (0.01) ***	
Singapore	0.04 (0.01) ***		0.01 (0.00) *		
Spain			0.01 (0.00) ***	– 0.11 (0.05) **	– 0.09 (0.03) ***
Sweden				– 0.15 (0.04) ***	
Switzerland	0.02 (0.01) **	0.01 (0.00) *	0.01 (0.00) **	– 0.16 (0.05) ***	– 0.06 (0.02) ***
Thailand	0.02 (0.00) ***		0.02 (0.00) ***	– 0.35 (0.06) ***	
Turkey	0.01 (0.00) **	0.01 (0.01)			
UK					
USA			0.02 (0.00) ***		
# of significant effects/total # of countries	12/33	10/33	13/33	21/33	12/33

This table presents the LASSO-selected commodities (4 out of the 55 commodity indices in row 2), that have the strongest impact on global macroeconomic variables (real GDP, inflation, and real exchange rate) for the sub sample; pre-crisis 1990Q1- 2006Q4. The model is estimated using OLS (Eq. 4) with robust standard errors in parentheses. Here *, **, and *** denote the 10, 5, and 1% levels of statistical significance. For further notations, see Table 5

Table 10 Estimates for the effects on macroeconomy from the LASSO-selected commodity market returns *– post-crisis 2010Q1- 2019Q4*

	Output (real GDP)		Inflation	Real exchange rate	
Country	Copper	Oil	Oil	Gold	Lead
Argentina		0.03 (0.01) ***			
Australia			0.01 (0.00) ***	– 0.24 (0.04) ***	0.18 (0.04) ***
Austria	0.01 (0.00) **	0.02 (0.01) *	0.02 (0.00) ***	– 0.19 (0.05) ***	
Belgium	0.01 (0.00) **	0.01 (0.00) *	0.01 (0.00) ***	– 0.14 (0.05) ***	– 0.05 (0.02) **
Brazil		0.03 (0.01) ***		– 0.23 (0.08) ***	– 0.21 (0.06) ***
Canada			0.01 (0.00) **	– 0.18 (0.05) ***	– 0.10 (0.03) ***
China	0.00 (0.01)				
Chile	0.02 (0.01) **			– 0.21 (0.07) ***	– 0.14 (0.04) ***
Finland	0.02 (0.01) **	0.02 (0.01) **	0.02 (0.01) **	– 0.17 (0.05) ***	– 0.12 (0.04) ***
France	0.01 (0.00) **	0.01 (0.00) **	0.01 (0.0) ***	– 0.18 (0.04) ***	
Germany	0.01 (0.00) *		0.02 (0.00) ***	– 0.12 (0.05) **	– 0.09 (0.03) ***
India					– 0.05 (0.02) **
Indonesia	0.01 (0.00) *	0.01 (0.02)		– 0.39 (0.22) ***	
Italy	0.02 (0.00) **	0.02 (0.01) *	0.01 (0.00) *	– 0.16 (0.05) ***	– 0.012 (0.03) ***
Japan	0.02 (0.00) ***			– 0.32 (0.06) ***	0.09 (0.04) **
Korea	0.02 (0.01) *	0.02 (0.01) *		– 0.21 (0.07) **	– 0.15 (0.04) ***
Malaysia		0.02 (0.00) **	0.02 (0.00) **	– 0.21 (0.06) ***	
Mexico	0.02 (0.01) *		– 0.01 (0.01)		
Netherlands				– 0.19 (0.05) **	– 0.06 (0.03) **
Norway	0.02 (0.01) **	0.02 (0.01) **	0.01 (0.00) *	– 0.23 (0.06) ***	
New Zealand			0.01 (0.00) ***	– 0.23 (0.07) ***	– 0.19 (0.04) ***

Table 10 (continued)

	Output (real GDP)		Inflation	Real exchange rate	
Country	Copper	Oil	Oil	Gold	Lead
Peru	0.02 (0.01) *				
Philippines	0.02 (0.01) *	0.01 (0.00) *		– 0.09 (0.05) *	– 0.07 (0.03) **
South Africa	0.01 (0.01)	0.01 (0.00) **	0.00 (0.01)	0.39 (0.15) ***	– 0.21 (0.10) **
Saudi Arabia	– 0.00 (0.01)	0.01 (0.00) *		– 0.04 (0.01) ***	
Singapore	0.04 (0.01) ***		0.01 (0.00) *	– 0.16 (0.04) ***	– 0.015 (0.02)
Spain			0.02 (0.00) ***	– 0.12 (0.05) **	
Sweden	0.02 (0.01) *	0.01 (0.00) *		– 0.15 (0.04) ***	– 0.09 (0.03) ***
Switzerland	0.02 (0.01) **	0.01 (0.00) *	0.01 (0.00) **	– 0.16 (0.05) ***	
Thailand	0.02 (0.00) ***		0.02 (0.00) ***	– 0.30 (0.06) ***	– 0.06 (0.02) ***
Turkey	0.01 (0.00) **	0.02 (0.01) **			
UK			0.01 (0.01)		0.01 (0.07)
USA			0.01 (0.00) ***		0.03 (0.05)
Number (#) of significant effects/total # of countries	19/33	16/33	16/33	25/33	17/33

This table presents the LASSO-selected commodities (4 out of the 55 commodity indices in row 2), that have the strongest impact on global macroeconomic variables (real GDP, inflation, and real exchange rate) for the sub sample; post-crisis 2010Q1- 2019Q4. The model is estimated using OLS (Eq. 4) with robust standard errors in parentheses. Here *, **, and *** denote the 10, 5, and 1% levels of statistical significance. For further notations, see Table 5

Table 11 Summary statistics for the domestic variables

	Real GDP			Inflation			Real exchange rate		
Country/region	Mean	Std. dev	J. B	Mean	Std. dev	J. B	Mean	Std. dev	J. B
Argentina	4.77	0.31	9.16	0.06	0.16	16,761.50	− 4.22	0.30	1.84
Australia	4.72	0.28	8.21	0.01	0.01	404.69	− 4.46	0.33	11.22
Brazil	4.74	0.23	10.75	0.12	0.27	485.28	− 4.29	0.30	3.85
Canada	4.66	0.21	9.66	0.00	0.00	164.78	− 4.47	0.25	13.07
China	5.13	0.87	9.41	0.01	0.01	225.24	− 2.69	0.31	10.90
Chile	4.77	0.38	6.85	0.01	0.01	173.85	1.56	0.24	6.82
Euro area	4.63	0.12	9.31	0.00	0.00	4.87	− 4.90	0.19	5.51
India	4.92	0.59	8.06	0.02	0.01	11.30	− 1.07	0.32	13.20
Indonesia	4.88	0.39	7.11	0.02	0.03	2507.13	3.99	0.30	32.96
Japan	4.65	0.07	7.51	0.00	0.00	72.10	0.11	0.15	1.42
Korea	4.75	0.36	8.08	0.01	0.01	243.36	2.23	0.20	6.44
Malaysia	4.78	0.43	4.76	0.01	0.01	248.94	− 3.48	0.16	6.80
Mexico	4.66	0.23	7.41	0.02	0.02	769.47	− 2.34	0.21	12.18
Norway	4.57	0.20	9.59	0.01	0.01	88.50	− 2.75	0.21	7.54
New Zealand	4.98	0.22	5.48	0.01	0.00	143.68	− 4.27	0.33	10.84
Peru	4.86	0.42	8.79	0.06	0.23	16,342.79	− 3.58	0.25	3.66
Philippines	4.86	0.40	8.11	0.01	0.01	331.39	− 1.07	0.27	11.16
South Africa	4.76	0.25	11.94	0.02	0.01	10.66	− 2.92	0.19	31.87
Saudi Arabia	4.87	0.37	12.24	0.00	0.01	194.44	− 3.43	0.19	15.95
Singapore	4.76	0.46	7.92	0.00	0.01	8.05	− 4.27	0.25	9.96
Sweden	4.69	0.21	7.66	0.00	0.01	351.54	− 2.65	0.16	0.93

Table 11 (continued)

Country/region	Real GDP			Inflation			Real exchange rate		
	Mean	Std. dev	J. B	Mean	Std. dev	J. B	Mean	Std. dev	J. B
Switzerland	4.68	0.14	9.58	0.00	0.00	26.06	− 4.43	0.25	10.41
Thailand	4.81	0.31	5.59	0.01	0.01	29.56	− 1.19	0.24	10.06
Turkey	4.78	0.35	8.05	0.07	0.06	30.50	− 5.32	0.38	11.41
UK	4.66	0.17	10.26	0.01	0.00	533.81	− 5.16	0.20	8.66
USA	4.65	0.20	8.30	0.01	0.00	474.66			

This table presents the summary statistics for the domestic variables at levels, without taking the first difference. J.B denotes the Jarque–Bera test statistics for series normality at a 5% significance level; Std dev. = standard deviation

Table 12 Summary statistics for the country-specific foreign variables

Country/region	Real GDP*			Inflation*			Real exchange rate*		
	Mean	Std. dev	J. B	Mean	Std. dev	J. B	Mean	Std. dev	J. B
Argentina	4.77	0.32	9.24	0.04	0.09	448.1	− 3.23	0.23	9.74
Australia	4.85	0.43	8.40	0.01	0.01	53.4	− 2.04	0.22	12.85
Brazil	4.79	0.37	8.47	0.01	0.02	8614.5	− 2.96	0.18	10.10
Canada	4.70	0.26	7.89	0.01	0.01	134.2	− 2.86	0.20	12.67
China	4.71	0.24	7.60	0.01	0.01	387.1	− 2.14	0.19	9.75
Chile	4.80	0.38	8.76	0.02	0.03	953.1	− 2.78	0.21	12.89
Euro area	4.76	0.33	8.46	0.01	0.01	232.4	− 3.27	0.22	12.85
India	4.78	0.34	8.52	0.01	0.01	192.6	− 2.93	0.21	12.71
Indonesia	4.80	0.38	7.99	0.01	0.01	100.2	− 2.28	0.21	12.30
Japan	4.83	0.43	8.33	0.01	0.01	74.2	− 2.37	0.24	14.05
Korea	4.84	0.43	8.67	0.01	0.01	125.2	− 2.49	0.22	13.52
Malaysia	4.80	0.38	8.08	0.01	0.01	42.7	− 2.13	0.22	12.59
Mexico	4.71	0.27	7.93	0.01	0.01	172.3	− 2.78	0.21	13.61
Norway	4.68	0.21	8.64	0.01	0.01	118.8	− 4.21	0.18	8.74
New Zealand	4.80	0.38	8.29	0.01	0.01	27.3	− 2.84	0.24	13.23
Peru	4.78	0.36	8.53	0.02	0.02	776.1	− 2.71	0.21	13.04
Philippines	4.78	0.34	7.94	0.01	0.01	18.8	− 1.87	0.20	11.38
South Africa	4.79	0.35	8.59	0.01	0.01	182.2	− 3.12	0.21	13.37
Saudi Arabia	4.79	0.36	8.20	0.01	0.01	74.5	− 1.86	0.21	13.11
Singapore	4.81	0.39	7.41	0.01	0.01	22.6	− 1.71	0.21	11.61
Sweden	4.67	0.20	8.38	0.01	0.01	55.1	− 4.18	0.19	8.54
Switzerland	4.70	0.23	8.30	0.01	0.01	94.7	− 4.20	0.19	9.92
Thailand	4.79	0.36	8.12	0.01	0.01	95.1	− 2.08	0.20	11.54
Turkey	4.73	0.27	8.48	0.01	0.01	100.5	− 3.79	0.20	10.84
UK	4.70	0.23	8.32	0.01	0.01	46.4	− 4.02	0.20	9.10
USA	4.77	0.34	8.60	0.01	0.01	212.3	− 3.06	0.21	13.48

This table shows the summary statistics of the country-specific foreign variables at levels, excluding the first difference. For notes, see Table 9

Table 13 Summary statistics for the global variables

Global variables	Mean	Std. dev	Jarque–Bera
Crude Oil	4.51	0.63	9.02
Copper	4.31	0.61	12.15
Gold	3.88	0.64	14.34
Lead	3.94	0.65	11.35

Table 14 VARX*, weak exogeneity lag order and number of cointegrating relationships in the country-specific models

Country/region	VARX* lag order of individual models		Lag order of weak exogeneity regression		Cointegrating relations
	Domestic variables (p_i)	Foreign variables (q_i)	Domestic variables (p^*)	Foreign variables (q^*)	Number (#)
Argentina	2	1	2	1	2
Australia	1	1	1	1	3
Brazil	2	1	2	1	2
Canada	2	1	1	1	3
China	2	1	2	1	2
Chile	2	1	2	1	2
Euro area	2	1	1	1	1
India	2	1	1	1	2
Indonesia	2	1	1	1	3
Japan	2	1	1	1	2
Korea	2	1	1	1	3
Malaysia	1	1	1	1	2
Mexico	1	1	1	1	2
Norway	2	1	1	1	3
New Zealand	2	1	1	1	3
Peru	2	1	1	1	2
Philippines	2	1	1	1	3
South Africa	2	1	1	1	2
Saudi Arabia	2	1	1	1	1
Singapore	2	1	1	1	1
Sweden	2	1	1	1	2
Switzerland	1	1	1	1	3
Thailand	2	1	1	1	2
Turkey	2	1	1	1	1
UK	1	1	1	1	2
USA	2	1	1	1	2

This table shows the lag order (p, q) in the VARX* estimation of Eq. 5 and the weak exogeneity estimation of Eq. 7, respectively. The lag orders are selected based on the Akaike information criterion (AIC). The table also reports the number of cointegrating relations found for each country model in Eq. 7

Acknowledgements The authors are most grateful for the comments and suggestions from the Editor Robert M. Kunst and the associate editor of Empirical Economics along with two anonymous referees. We also thank the participants of JSBE XXXVIII Summer Seminar 2022 from the comments that greatly improved the quality of this paper. JyIMaF Research Group is also thankful for the financial support of the OP Group Research Foundation

Funding Open Access funding provided by University of Oulu (including Oulu University Hospital). This project was supported by OP Financial Group Research Foundation, Finland, for the first author. [Under Grant Numbers 20210078].

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