Article:

Smith, L. Vanessa orcid.org/0000-0003-0489-047X, Tarui, Nori and Yamagata, Takashi orcid.org/0000-0001-5949-8833 (2021) Assessing the impact of COVID-19 on global fossil fuel consumption and CO2 emissions. Energy economics. 105170. ISSN 0140-9883

https://doi.org/10.1016/j.eneco.2021.105170

Assessing the impact of COVID-19 on global fossil fuel consumption and CO_2 emissions *

L. Vanessa Smith†
DERS, University of York

Nori Tarui‡
Department of Economics, University of Hawaii

Takashi Yamagata§
DERS, University of York & ISER, Osaka University

January 2021 (2nd version)

Abstract

We assess the effect of the COVID-19 pandemic on global fossil fuel consumption and CO_2 emissions over the two-year horizon 2020Q1-2021Q4. We apply a global vector autoregressive (GVAR) model, which captures complex spatial-temporal interdependencies across countries associated with the international propagation of economic impact due to the virus spread. The model makes use of a unique quarterly data set of coal, natural gas, and oil consumption, output, exchange rates and equity prices, including global fossil fuel prices for 32 major CO_2 emitting countries in 1984-2019. We produce forecasts of coal, natural gas and oil consumption, conditional on GDP growth scenarios based on alternative IMF World Economic Outlook forecasts that were made before and after the outbreak. We also simulate the effect of a relative price change in fossil fuels, due to global scale carbon pricing, on consumption and output. Our results predict fossil fuel consumption and CO_2 emissions to return to their pre-crisis levels, and even exceed them, within the two-year horizon despite the large reductions in the first quarter following the outbreak. Our forecasts anticipate more robust growth for emerging than for advanced economies. The model predicts recovery to the pre-crisis levels even if another wave of pandemic occurs within a year. Our counterfactual carbon pricing scenario indicates that an increase in coal prices is expected to have a smaller impact on GDP than on fossil fuel consumption. Thus, the COVID-19 pandemic would not provide countries with a strong reason to delay climate change mitigation efforts.

JEL Classifications: C33,O50,P18,Q41,Q43,Q47

Keywords: COVID-19, CO_2 emissions, fuel consumption, Global VAR (GVAR), conditional forecasts

*We are grateful to Julia Touza-Montero, Joao Madeira and Ron Smith for helpful discussions. We thank Sara Elsayed, Rui Lin and Ryo Mikami for excellent research assistance.

†Corresponding author. Address: Heslington, York YO10 5DD, UK. E-mail: vanessa.smith@york.ac.uk

‡nori@hawaii.edu.

§takashi.yamagata@york.ac.uk. This author gratefully acknowledges support from JSPS KAKENHI (18K01545, 15H05728).

1 Introduction

Since the first case of pneumonia with unknown cause in Wuhan, China, in December 2019, the spread of the novel coronavirus (COVID-19) has been causing a worldwide public health emergency. Governments enforced social isolation and lockdown to slow down the virus spread, leading to a virtual halt of major economic activities. The World Economic Outlook, published in April 2020 by the International Monetary Fund (IMF, 2020b), predicts that the global economy will shrink by 3 per cent in 2020. This forecast was further revised downwards to a 4.9 per cent decline in June 2020 (IMF, 2020c), then slightly upwards to a 4.4 per cent fall in October (IMF, 2020d). This means that the shock to the global economy from COVID-19 could be more severe than the 2008 global financial crisis and even the Great Depression.

According to latest research, the sharp drop in economic activity due to the enforced confinement has dramatically reduced energy use, and hence carbon dioxide (CO_2) emissions. Le Quéré et al. (2020) estimated daily changes in global CO_2 emissions taking account of the levels of the confinement policy. Based on the emissions data for six economic sectors across 69 countries, their results indicated a 17% decline in daily global CO_2 emissions by early April 2020 relative to the mean level in 2019. Liu et al. (2020) report a decrease of 7.8% in global CO_2 emissions due to fossil fuel use during the first quarter of 2020 relative to the first quarter of 2019.

Despite such evidence of the instantaneous impacts, longer-term effects on energy consumption and CO_2 emissions have not been well understood. Studying such effects is important because related evidence will provide policy makers with essential information to prepare post-COVID-19 economic recovery packages given the emission targets as many countries agreed at the 2015 United Nations Climate Change Conference (COP21 in Paris). Some energy experts express concerns that the slowdown in CO_2 emissions may be temporary. IEA (2019) states that "the unprecedented decline in emissions in 2020 may only be temporary without structural changes. Recoveries from past crises have caused immediate rebounds in CO2 emissions, including the highest year-on-year increase on record in 2010." The United States Energy Information Administration forecasts that energy-related CO2 emissions will increase by 6% in 2021 from the 2020 level as the economy recovers and energy use increases.

Here we assess the impact of the global economic shock from COVID-19 on fossil fuel consumption and CO_2 emissions over the two-year horizon 2020Q1-2021Q4. For this purpose, we employ the global vector autoregressive (GVAR) model (Pesaran et al., 2004; Dees et al., 2007). As a large-scale multi-country, spatial-temporal model, GVAR controls for unobserved global or foreign shocks that affect each country. This approach is critical for assessing the impact of COVID-19 because of the global scale of its spread and the associated economic effects. The spread of the virus that first hit China induced significant economic disruptions in Asia, Europe, North America and beyond. While the spread of the virus itself reduced domestic economic activities in each country, it also disrupted the global supply chain (Ivanov, 2020), which in turn amplified the negative economic effects across countries. The GVAR model takes into account such cross-country dependencies and dynamic macroeconomic effects. For reliable estimation of such a large dimensional model, we apply the GVAR model to a sufficient number of time-series observations across countries that cover a major part of the world economy.

A related strand of literature investigates the relationship between energy consumption and growth; see Kahouli (2019) for an extensive survey. Many of these studies employ a single country analysis, adopting VAR models and vector error correction (VEC) models (e.g., Bloch et al., 2012; Akpan and Akpan, 2012; Bozkurt and Akan, 2014), due to the relatively small number of observations (annual data since 1960). Recently, studies using panel data analysis have emerged in the literature. Omri and Kahouli (2014) and Saidi and Hammami (2015), among others, use cross-country panel data with a relatively large number of countries (around 60) for 22-23 years of observations. They estimate short dynamic panel data models with generalised method of moments (GMM). Coers and Sanders (2013) and Antonakakis et al. (2017) employ panel VAR models whilst Shahbaz et al. (2013) employ the autoregressive distributed lag (ARDL) bounds testing approach using longer panel data with around 40 observations. These panel data studies permit country heterogeneity only in a limited way without controlling for global common shocks or spatial dependence despite both of these featuring prominently in the recent panel data econometrics literature. Notably, our econometric approach can address all of these issues. Thus it is suitable for studying the intermediate-term economic impact of COVID-19, which must take into account the different transmission channels of the economic effects of the virus across countries, over time.

Our analysis applies a unique quarterly data set of coal, natural gas and oil consumption, output, exchange rates, equity prices and global fossil fuel prices for 32 countries spanning the period 1984Q1-2019Q4. To the best of our knowledge, no such compiled quarterly disaggregated consumption data set is publicly available for the period of our interest.[1] According to the BP data for the year 2018, 81% of global CO_2 emissions due to fossil fuel combustion was released by the 32 countries in our sample. To predict CO_2 emissions, it is important to decompose the fossil fuel sources into coal, natural gas and oil because of the different CO_2 intensity among fuel sources. Furthermore, among the fossil fuels, the share of coal consumption within emerging economies is much higher than in advanced economies. Our forecasts indicate how CO_2 emissions evolve in the emerging and advanced economies as the fuel mix changes across countries within these groups.

In order to assess the impact of the global economic shock from the COVID-19 spread, we produce conditional forecasts of coal, natural gas and oil consumption, for the advanced and the emerging economies, separately, conditional on GDP forecast trajectories (scenarios) over eight quarters. These trajectories are based on the IMF forecasts for 2020Q1-2021Q4 published in IMF (2020b), the World Economic Outlook, April 2020. IMF (2020b) publishes the quarterly forecast figures, while the IMF update (2020c) does not. We compare the results of three scenarios to identify the effects of: (0) no outbreak; (1) one virus spread in 2020Q1-Q2; (2) two waves of virus spread in 2020Q1-Q2 and 2021Q1-Q2. We assess the effects on the above two country groups individually, as well as on the world as a whole.

Our second main objective is to investigate the effect of changes in the relative fossil fuel prices on output and consumption. Policy to mitigate climate change, such as carbon pricing, will increase the relative (end-user) price of coal because coal is more carbon intensive than natural gas. The effect of such relative price changes on output is critical when assessing the trade-off between the reduction of emissions and the negative effect on the economy, which can be an important issue during the time of depression.

The above counterfactuals will allow us to assess the following for each country group (advanced and emerging): (i) relative emission resilience to the negative economic shock; (ii) relative sensitivity of emissions to carbon pricing; and (iii) relative robustness of output to carbon pricing. The finding could be useful for the countries to pursue emissions targets beyond their intended nationally determined contributions under the Paris Agreement.

We find that fossil fuel consumption and CO_2 emissions are expected to return to their pre-crisis levels, and even exceed them, within the two-year horizon despite large reductions in the first quarter following the outbreak. Our forecasts anticipate more robust recovery and growth for the emerging economies than for the advanced. Recovery to pre-crisis levels is expected even if another wave of pandemic takes place within a year. We argue that this result may be due to (i) the IMF forecasts predicting GDP recovery for the advanced economies in the two-year period, with faster recovery for the emerging economies, and (ii) limited responsiveness of fossil fuel consumption to income changes, as indicated in existing empirical studies.

The fuel prices demonstrate a sharp decline over the first quarters before exhibiting recovery. Importantly, different fuels have different trajectories of price recovery. The coal and oil prices first increase then drop sharply before recovering in the second year. The fuel prices are expected to return to their pre-crisis level within the two-year period, but the price recovery may be slower if a second pandemic wave occurs within a year. Turning to the effect of carbon pricing, our counterfactual analysis suggests that (i) a permanent rise in the price of coal relative to natural gas and oil will reduce fossil fuel consumption in advanced and emerging economies by a similar magnitude; (ii) the negative effects on GDP are smaller than those on coal consumption; and (iii) the magnitude of the negative GDP effect on the emerging economies is only around half of what the advanced economies experience. These results suggest that, while emerging economies appear to be more resilient to carbon pricing policy, such policy is as effective in reducing emissions for these economies as it is for the advanced ones.

Our research is not the first to employ the GVAR model in the area of energy economics. Cashin et al. (2014) apply a GVAR model for 38 countries/regions over the period 1979Q2–2011Q2 to show that the economic consequences of a supply-driven oil-price shock are very different from those of an

[1] Annual data provided by British Petroleum (BP) and the World Bank are typically used in the literature to date.

oil-demand shock driven by global economic activity. Mohaddes and Pesaran (2016) develop a GVAR-oil model that integrates a model for the global oil market within that of the global economy to identify country-specific oil-supply shocks. Mohaddes and Pesaran (2017), using a global VAR model for 27 countries/regions over the period 1979Q2 and 2013Q1, find that a fall in oil prices lowers interest rates and inflation in most countries and increases global real equity prices. Mohaddes and Raissi (2019) use a similar GVAR model to Cashin et al. (2014) to investigate the global macroeconomic consequences of falling oil prices due to the oil revolution in the USA.

A few studies apply the GVAR model to investigate how fossil fuel use is related to CO_2 emissions in China. Zhou et al. (2019) apply a GVAR model to sector-level data of six industries in China to study cross-sectoral linkages of carbon emission efficiency in China's construction industry including industry coal consumption and total-factor carbon emission efficiency. Cui and Zhu (2016) investigate how dual constraints of energy consumption and carbon emission affect China's economic growth by applying a GVAR model that takes into account fuel switch between non-renewable renewable energy sources. Zhang et al. (2018) apply the GVAR model to quarterly data in 1979-2008 for 33 countries in a way closer to ours. They study the effects of growth in China's building industry on energy consumption and carbon emissions in 33 countries. They find that the responses of energy consumption in most countries are positive though they are negative in Japan and the Euro area, indicating heterogeneous effects of growth in a country's sector on its trading partners' emissions. Our model incorporates energy consumption by fuel type, demonstrating different changes in the energy mix in different country groups. Our approach also addresses the impacts of relative price changes among fossil fuels due to carbon pricing.

In what follows, Section 2 describes the data. Section 3 discusses the econometric model and estimation method. Section 4 explains the implementation of the conditional forecasting, conditional on the GDP scenarios after the COVID-19 spread. Section 5 discusses the experiment associated with a higher relative coal price, followed by a conclusion in Section 6. The details of the data sources, the GVAR model, and additional empirical results can be found in Appendices A-C.

2 Data

We employ a unique quarterly data set of coal, natural gas and oil consumption, output, exchange rates, equity prices, and global fossil fuel prices for 32 countries spanning the period 1984Q1-2019Q4 (1). According to the BP data for the year 2018, China, India and the US emitted 28.7%, 15.7% and 7.6% of CO_2, totaling 51.9% of the 81% of world CO_2 emissions released by the 32 countries in our sample.

Following IMF, we partition the countries into two groups, the 'advanced economies' and the 'emerging market and developing economies,' as shown in Table 1. To be concise, we refer to the latter group simply as 'emerging economies'. Within the advanced economies, we also consider the subset EU^+, which consists of ten European Union (EU) member countries plus Norway and Switzerland. We add these two countries due to their historically close relationship with the EU. This group has been severely hit by the pandemic and is subject to the most stringent carbon pricing policy.

We analyse spatial-temporal interactions among nine variables. Let $coal_{it}, gas_{it}$ and oil_{it} represent the logarithms of per capita consumption of coal, natural gas and crude oil (in Mtoe) for country i in quarter t. The logarithm of the associated global prices, $pcoal_t, pgas_t$ and $poil_t$, are based on the Australian coal price (US dollars per mt), European Natural Gas price (US dollars per mmbtu) and Brent crude oil (US dollars per bbl), respectively. The remaining three domestic variables are gdp_{it}, ep_{it} and eq_{it}, which are the logarithms of the (real) gross domestic product, the real exchange rate in terms of US dollars for country i in quarter t and the real equity price, respectively.[2] Details of the construction and sources of the data are available in Appendix A.1. The consumption data were first tested for seasonality. We adjusted those series that exhibited significant seasonal effects for temperature and/or season. In some cases where temperature adjustment induced spurious volatility, only seasonal adjustment was performed. Temperature adjustment is based on the heating and cooling degree days as well as their 30-year average between 1981 and 2010 (the 'climate normals,' see Elkhafif

[2]Studies find linkages between the degree of financial development and energy consumption (Sadorsky, 2010; Shahbaz et al., 2013). We include real equity prices as a regressor by following the practice of Mohaddes and Pesaran (2016, 2017), who find equity prices to be closely related with fossil fuel prices.

Table 1: 32 countries and associated groups within the sample

Advanced Economies		**Emerging Economies**
EU$^+$		
Austria	Australia	Argentina
Belgium	Canada	Brazil
France	Japan	China
Finland	Korea	Chile
Germany	New Zealand	India
Italy	Singapore	Indonesia
Netherlands	United States	Malaysia
Norway		Mexico
Spain		Philippines
Sweden		South Africa
Switzerland		Saudi Arabia
United Kingdom		Thailand
		Turkey

1996 and Won et al. 2016 for recent applications). Appendix A.2 explains the procedures for performing temperature and seasonal adjustment as well as for assessing seasonal effects. Energy prices as well as the remaining variables (in the case of eq and ep the underlying Consumer Price Indices) were seasonally adjusted where required.

3 Modelling Framework

We employ the global vector autoregressive (GVAR) modelling framework of Pesaran et al. (2004), which is further developed in Dees et al. (2007). The GVAR model is a multi-country model that links country-specific models in a coherent manner using time series and panel techniques. To explain how the model works, we define the $k_i \times 1$ vector of energy consumption and economic variables of country i in quarter t by $\mathbf{x}_{it} = (coal_{it}, gas_{it}, oil_{it}; gdp_{it}, ep_{it}, eq_{it})'$, as well as the $m_d \times 1$ vector of energy prices by $\mathbf{d}_t = (pcoal_t, pgas_t, poil_t)'$. Stacking $\mathbf{x}_{it}$ for $i = 0, 1, ..., N$ for our 32 countries yields the $k \times 1$ global variable vector, $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, ..., \mathbf{x}'_{Nt})'$ with $k = \sum_{j=0}^{N} k_i$, and country 0 taken as the numeraire country (the United States). The pth-order GVAR model of our 181×1 global variable vector[3] and energy prices at t, $\mathbf{y}_t = (\mathbf{x}'_t, \mathbf{d}'_t)'$, is given by

$$\mathbf{y}_t = \mathbf{c}_0 + \mathbf{c}_1 t + \mathbf{C}_1 \mathbf{y}_{t-1} + ... + \mathbf{C}_p \mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t, \ t = 1, ..., T, \tag{1}$$

where contemporaneous correlations in the error term are permitted. The GVAR model of equation (1) is a large model that, despite its simple overall structure, allows for a rich set of dynamics including a high degree of interdependencies. It is not directly estimable due to the curse of dimensionality and possible existence of cointegrated variables. To avoid these problems, estimation and specification of the GVAR model involves two-steps. In the first step, a vector error correction model for the domestic variables, $\mathbf{x}_{it}$, is estimated for each i, augmented with the global variables, $\mathbf{d}_t$, and the foreign variables of country i, $\mathbf{x}^*_{it}$, which are specified below. Based on these parameter estimates as well as those of an estimated model for $\mathbf{d}_t$, in the second step the estimated version of equation (1) is obtained. The two-step estimation approach is explained in detail below. Appendix B.1 provides further details on the variables included in the GVAR model.

[3]See Table B.1(ii) in Appendix B.1.

3.1 The country-specific VARX* models

Consider the following VARX*(p_i, q_i) structure for the i^{th} country-specific model

$$\begin{aligned}\mathbf{x}_{it} &= \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \boldsymbol{\Phi}_{i1}\mathbf{x}_{i,t-1} + ... + \boldsymbol{\Phi}_{ip_i}\mathbf{x}_{i,t-p_i} + \boldsymbol{\Lambda}_{i0}\mathbf{x}^*_{it} + \boldsymbol{\Lambda}_{i1}\mathbf{x}^*_{i,t-1} + ... + \boldsymbol{\Lambda}_{iq_i}\mathbf{x}^*_{i,t-q_i}, \\ &\quad + \boldsymbol{\Psi}_{i0}\mathbf{d}_t + \boldsymbol{\Psi}_{i1}\mathbf{d}_{t-1} + ... + \boldsymbol{\Psi}_{iq_i}\mathbf{d}_{t-q_i} + \mathbf{u}_{it},\end{aligned} \tag{2}$$

for $i = 0, 1, ..., N$ where $\mathbf{x}_{it}$ and $\mathbf{d}_t$ are the $k_i \times 1$ vector of domestic variables and the $m_d \times 1$ vector of common global variables, respectively, given above, and $\mathbf{x}^*_{it}$ is a $k^*_i \times 1$ vector of foreign variables. The foreign variables are constructed as weighted averages across all domestic variables in the model such that $\mathbf{x}^*_{it} = \sum_{j=0}^{N} w_{ij}\mathbf{x}_{jt}$, where $w_{ii} = 0$ and $\sum_{j=0}^{N} w_{ij} = 1$, and can be considered as proxies for unobserved common factors. These variables are expected to 'soak up' most of the cross-section correlation leaving only a modest degree in the estimated residuals. The weights, w_{ij}, are computed here based on the trade relationship (average of imports and exports) of the individual countries with their corresponding trading partners.[4] The common global variables in each country model are treated similar to the foreign 'star' variables, which includes sharing the same lag order, q_i.

As discussed in Pesaran et al. (2004), GVAR modeling allows for interactions among different countries through three separate but interrelated channels:

1. Contemporaneous dependence of $\mathbf{x}_{it}$ on $\mathbf{x}^*_{it}$ and on its lagged values, where as mentioned earlier the star variables can be considered as proxies for common unobserved factors such as, for example, the diffusion of technological progress or global upheaval in the case of COVID-19.

2. Dependence of the country-specific variables $\mathbf{x}_{it}$ on common global variables $\mathbf{d}_t$ and on its lagged values, which are the global fuel prices in our context.

3. Nonzero contemporaneous dependence of shocks in country i on the shocks in country j, measured via the cross-country covariances, $\boldsymbol{\Sigma}_{ij} = cov(\mathbf{u}_{it}, \mathbf{u}_{jt})$ for $i \neq j$. Such 'residual' interdependencies (after global unobserved factors have been taken into account) could be due, for example, to policy and trade spillover effects.

In the presence of possible $I(1)$ variables and cointegration the corresponding vector error correction form of equation (2), the VECMX*, assuming for expositional purposes that $p_i = q_i$, can be written as

$$\Delta\mathbf{x}_{it} = \mathbf{c}_{i0} - \boldsymbol{\alpha}_i\boldsymbol{\beta}'_i[\widetilde{\mathbf{z}}_{i,t-1} - \boldsymbol{\gamma}_i(t-1)] + \boldsymbol{\Lambda}_{i0}\Delta\mathbf{x}^*_{it} + \boldsymbol{\Psi}_{i0}\Delta\mathbf{d}_t + \sum_{j=1}^{p_i-1}\boldsymbol{\Gamma}_{z,ij}\Delta\widetilde{\mathbf{z}}_{i,t-j} + \mathbf{u}_{it}, \tag{3}$$

where $\mathbf{z}_{it} = (\mathbf{x}'_{it}, \mathbf{x}^{*\prime}_{it})'$, $\widetilde{\mathbf{z}}_{i,t-1} = (\mathbf{z}'_{i,t-1}, \mathbf{d}'_{t-1})'$, $\boldsymbol{\alpha}_i$ is a $k_i \times r_i$ matrix of rank r_i and $\boldsymbol{\beta}_i$ is a $(k_i + k^*_i + m_d) \times r_i$ matrix of rank r_i. By partitioning $\boldsymbol{\beta}_i$ as $\boldsymbol{\beta}_i = (\boldsymbol{\beta}'_{ix}, \boldsymbol{\beta}'_{ix*}, \boldsymbol{\beta}'_{id})'$ conformable to $\tilde{\mathbf{z}}_{it} = (\mathbf{x}'_{it}, \mathbf{x}^{*\prime}_{it}, \mathbf{d}'_t)'$, the r_i error correction terms defined by the above equation can be written as

$$\boldsymbol{\beta}'_i\left(\widetilde{\mathbf{z}}_{it} - \boldsymbol{\gamma}_i t\right) = \boldsymbol{\beta}'_{ix}\mathbf{x}_{it} + \boldsymbol{\beta}'_{ix*}\mathbf{x}^*_{it} + \boldsymbol{\beta}'_{id}\mathbf{d}_t - \left(\boldsymbol{\beta}'_i\boldsymbol{\gamma}_i\right)t,$$

which allows for the possibility of cointegration both within $\mathbf{x}_{it}$ and between $\mathbf{x}_{it}$, $\mathbf{x}^*_{it}$ and $\mathbf{d}_t$, and consequently across $\mathbf{x}_{it}$ and $\mathbf{x}_{jt}$ for $i \neq j$.

For the estimation of each country model (3), the foreign and common global variables are treated as weakly exogenous with respect to the long run parameters $\boldsymbol{\alpha}_i$ and $\boldsymbol{\beta}_i$ of the model, an assumption testable by the data. This assumption implies that there are no feedback effects from the domestic variables to these variables in the long-run without precluding short-term interactions between the two. The rank of the cointegrating space for each model is computed using Johansen's (1991) trace statistic as set out in Pesaran et al. (2000) for models with weakly exogenous $I(1)$ regressors. This way, the number of cointegrating relations of each country, r_i, the speed of adjustment coefficients, $\boldsymbol{\alpha}_i$, and the cointegrating vectors $\boldsymbol{\beta}_i$ for each country model are obtained. Conditional on a given estimate of $\boldsymbol{\beta}_i$, the remaining parameters in equation (3) are consistently estimated by ordinary least squares (OLS). From the estimated VECMX* models we can then recover the estimated version of equation (2).

[4]In principle, any type of weights could be used including different weights for different variables, as well as weights that change over time, as long as they satisfy the 'smallness' condition given in Pesaran et al. (2004).

Unit root tests applied to our variables suggested that on the whole these are $I(1)$. The lag orders of the individual country VARX* models were selected using the Akaike information criterion (AIC) setting a maximum for p_i and q_i of 3 and 2, respectively. The choice of these maximum values was based on the available number of observations and the desire to reduce serial correlation. The testable assumption of weak exogeneity of the foreign and global variables was supported by the data. Weak exogeneity test results for all countries, along with the individual country lag orders, number of cointegrating relations and other related output can be found in Section S.2 of the supplementary material. The construction of the weight matrix is based on a three year average of the trade relationships between the countries over the years 2014-2016.

3.2 Modelling the global prices

While estimation of the individual country VECMX* models in the presence of the weakly exogenous regressors does not require separately specifying a model for the global prices, for the purpose of forecasting in what follows this is required.

The modelling procedure for the global prices proceeds in two steps. Since the global prices, $\mathbf{d}_t$, were found to be $I(1)$ in order to allow for the possibility of cointegration, in the first step the following error correction model that includes a restricted intercept is estimated

$$\Delta \mathbf{d}_t = -\boldsymbol{\alpha}_d \boldsymbol{\beta}_d' [\mathbf{d}_{t-1} - \boldsymbol{\mu}] + \textstyle\sum_{j=1}^{p_d-1} \boldsymbol{\Gamma}_{d,j} \Delta \mathbf{d}_{t-j} + \boldsymbol{\eta}_t, \tag{4}$$

where $\boldsymbol{\alpha}_d$ and $\boldsymbol{\beta}_d$ are $m_d \times$ r_d vectors, and r_d denotes the number of cointegrating relations. Using the trace statistic of the Johansen cointegration approach one cointegrating relationship was found among the global prices, with $p_d = 3$ selected based on the AIC and no remaining serial correlation.

The cointegrating vector, $\boldsymbol{\beta}_d$, was estimated subject to one overidentifying restriction which was supported by the data. Let $\widehat{EC}_{d,t-1} = \hat{\boldsymbol{\beta}}_d' [\mathbf{d}_{t-1} - \hat{\boldsymbol{\mu}}]$ be the estimated error correction term which is given by

$$\widehat{EC}_{d,t-1} = 0.320 coal_{t-1} + 1.000 gas_{t-1} - 1.000 oil_{t-1} - 1.552. \tag{5}$$

In the second step the error correction specification in equation (4) is augmented with additional feedback effects computed as a weighted average of the domestic variable vector, $\mathbf{x}_{it}$. Specifically,

$$\Delta \mathbf{d}_t = \mathbf{c} + \boldsymbol{\delta} \widehat{EC}_{d,t-1} + \textstyle\sum_{j=1}^{\widetilde{p}-1} \boldsymbol{\Theta}_{d,j} \Delta \mathbf{d}_{t-j} + \textstyle\sum_{j=1}^{\widetilde{q}-1} \boldsymbol{\Theta}_{x,j} \Delta \widetilde{\mathbf{x}}_{t-j} + \boldsymbol{\eta}_t. \tag{6}$$

where $\widehat{EC}_{d,t-1}$ is taken as given (estimated in the first step), $\widetilde{\mathbf{x}}_t = \sum_{i=0}^{N} \widetilde{w}_i \mathbf{x}_{it}$ is a $k \times 1$ vector of feedback effects, with the weights $\widetilde{w}_i$ such that $\sum_{i=0}^{N} \widetilde{w}_i = 1$, which are computed based on PPP-GDP figures averaged over the years 2014-2016.

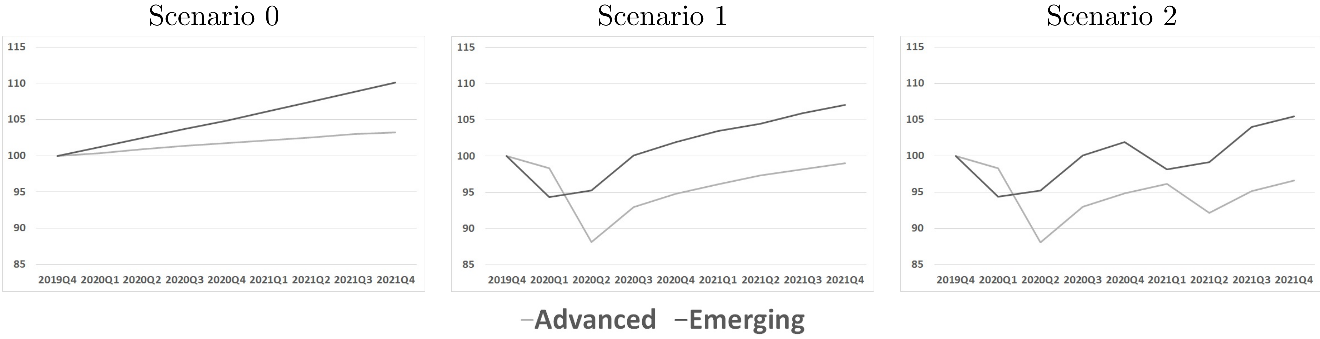
We further allow for separate lag orders, namely $\widetilde{p}_\ell$ and $\widetilde{q}_\ell$ with $\ell = 1, 2, 3$, to be selected by the AIC for each of the individual price equations using a maximum lag order of 3 for both. Having estimated equation (6) the VAR form for $\mathbf{d}_t$ is given by

$$\mathbf{d}_t = \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 t + \boldsymbol{\Phi}_{d,1} \mathbf{d}_{t-1} + ... + \boldsymbol{\Phi}_{d,\widetilde{p}} \mathbf{d}_{t-\widetilde{p}} + \boldsymbol{\Lambda}_{x,1} \widetilde{\mathbf{x}}_{t-1} + ... + \boldsymbol{\Lambda}_{x,\widetilde{q}} \widetilde{\mathbf{x}}_{t-\widetilde{q}} + \boldsymbol{\eta}_t. \tag{7}$$

Combining the estimated versions of models (2) and (7), we obtain the estimated GVAR model of equation (1) in terms of $\mathbf{y}_t$. Appendix B.2 details how to solve for the GVAR model based on equations (2) and (7).

4 Conditional forecasts of fossil fuel consumption and carbon emissions

In what follows, we produce forecasts for coal, natural gas and oil consumption conditional on three different eight-quarter horizon GDP growth rate paths (scenarios) for the advanced and emerging economies. These trajectories are based on the forecasts published in the IMF World Economic Outlook. We consider three GDP scenarios (Figure 1). Scenario 0 is the GDP forecast published by the IMF in January 2020, IMF (2020a), i.e., without the effect of the economic shock from the COVID-19 pandemic. Period zero corresponds to 2019Q4 and the value is normalised to 100. Scenario 1 is identical to the updated IMF forecast in April 2020 (IMF, 2020b, Figure 1.6, p.9), which clearly shows the effect of the economic shock from COVID-19's hit to Asia during January-February 2020 and to Europe and the US during March-April 2020. This trajectory asserts that the world economy returns to the long-run growth path in around 2020Q4, in the absence of a second outbreak. Scenario 2 assumes a second wave of pandemic around 2021Q1 and Q2 with an associated decline in GDP growth, which is slightly smaller in magnitude than that of the first wave.



Note: Scenarios 0 and 1 are based on the forecast in IMF (2020a,b). Scenario 2 assumes another wave of pandemic in 2021Q1.

Figure 1: Three GDP scenarios with and without the global economic shock from COVID-19

A few remarks are warranted on this method of constructing the conditioning GDP scenarios. First, naturally, the estimated GDP trend of our model and the IMF's hypothesised GDP trend in the advanced and emerging groups may be slightly different.[5] Second, even though the GDP growth rates would differ across individual countries, we assume a common GDP growth trend across countries within each of the two groups following the available published IMF forecasts. This assumption may be innocuous to the extent that our primary aim is to assess the impact of the (almost) simultaneous spread of COVID-19 to the advanced and emerging economies by comparing the conditional forecasts under Scenario 0 to those under Scenarios 1 and 2. We partially address this concern by further comparing the conditional forecasts with the unconditional forecasts from the GVAR model (1) in Appendix C.1. Finally, the IMF published revised GDP forecasts on 24 June 2020 (IMF, 2020c; Figure 1), in which the drop in 2020Q2 is larger for both the advanced and emerging groups compared to their April 2020 forecasts (IMF, 2020b). This was further revised slightly upwards in October (IMF, 2020d).Unfortunately, unlike IMF (2020b), the revised quarterly forecast figures are not publicly available and we could not update our exercise. However, because the IMF's (2020c,d) revised GDP forecasts fall between our Scenario 1 and Scenario 2 forecasts, it is likely that the forecasts of fossil fuel consumption and CO_2 emissions under this revised Scenario 1 would be lower than those under Scenario 1 but higher than those under Scenario 2. Therefore, the general results in this paper would still hold with the revised scenarios in IMF (2020c,d).

4.1 Conditional forecasting: method

Consider the estimated GVAR(3) model given by

$$\mathbf{y}_t = \hat{\mathbf{c}}_0 + \hat{\mathbf{c}}_1 t + \hat{\mathbf{C}}_1\mathbf{y}_{t-1} + \hat{\mathbf{C}}_2\mathbf{y}_{t-2} + \hat{\mathbf{C}}_3\mathbf{y}_{t-3} + \hat{\boldsymbol{\varepsilon}}_t, \tag{8}$$

$t = 1, ..., T$. We produce conditional forecasts from model (8) for each quarter $T+h$, for $h = 1, 2, ..., 8$ conditional on the IMF forecasted GDP growth paths of 2020Q1-2021Q4 implied by each of the Scenarios 0-2.

The GDP growth paths are applied to the *gdp* variable of all countries in model (8) starting from the last quarterly observation of our sample, T. This results in eight quarterly values for the *gdp* variable for every country: namely, $gdp_{i,T+j}$, $j = 1, ..., H(= 8)$ (two different sets of values for the advanced and emerging economies). These can be written compactly as

$$\mathbf{S}\mathbf{y}_{T+j} = \mathbf{g}_{T+j}, \; j = 1, 2, ..., H, \tag{9}$$

[5] As an alternative the GDP trend of 2019Q4 could be used.

where $\mathbf{S}$ is a suitably defined $(N+1)\times(k+3)$ matrix with 1 in the position of $gdp_{i,T+j}$ for each country i, 0 elsewhere; $\mathbf{g}_{T+j}$ is a $(N+1)\times 1$ vector that contains the values for the gdp variable corresponding to quarter $T+j$ for a given scenario; and H denotes the conditioning horizon, which is equal to eight (the same as the forecast horizon). The forecast for every quarter, $T+h$, is then obtained by conditioning on all eight quarterly values for gdp defined by (9) across all countries simultaneously.

The conditional point forecasts of $\mathbf{y}_{T+h}$ are given by

$$\boldsymbol{\mu}_h^* = E\left(\mathbf{y}_{T+h}\left|\mathcal{I}_T, \mathbf{S}\mathbf{y}_{T+j} = \mathbf{g}_{T+j},\ j=1,2,...,H\right.\right),\ \text{ for } h=1,2,...,H, \tag{10}$$

where $\mathcal{I}_T$ is the information set at time T. In deriving the expectations it is assumed that conditioning on the GDP growth paths does not affect the GVAR model parameters, $\mathbf{C}_i$, $i=1,2,3$ and the covariance matrix, $\boldsymbol{\Sigma}_\varepsilon$, associated with $\boldsymbol{\varepsilon}_t$, which is also assumed to be jointly normally distributed.

We further define the unconditional point forecasts of $\mathbf{y}_{T+h}$ given by

$$\boldsymbol{\mu}_h = E\left(\mathbf{y}_{T+h}\left|\mathcal{I}_T\right.\right),\ \text{ for } h=1,2,...,H. \tag{11}$$

While these forecasts condition on the information set $\mathcal{I}_T$, we define them as unconditional to distinguish them from the conditional forecasts in (10), which in addition condition on the gdp values given by $\mathbf{S}\mathbf{y}_{T+j} = \mathbf{g}_{T+j}$, $j=1,2,...,H$.

We use the latter forecasts to construct the difference, $\boldsymbol{\delta}_h = \boldsymbol{\mu}_h^* - \boldsymbol{\mu}_h$. Obtaining the probability distribution of this difference then allows us to compute the probability, for example, that consumption is lower in view of Scenarios 1 and 2, and to check whether these probabilities are in line with the differences of the point forecasts obtained between Scenarios 1-0 and 2-0. It is the probabilities associated with $\boldsymbol{\delta_h}$ that are given in Appendix C.1 referred to earlier. Further technical details related to the derivation of the conditional and unconditional forecasts, as well as the difference between the two, are available in Section S.3 of the supplementary material.

4.2 Conditional forecasting: results

In this subsection we report the conditional forecast results of the total amount of energy consumption and CO_2 emissions for the different groups (see Table 1) under the different GDP scenarios.

4.2.1 Energy consumption

Figure 2 summarizes the conditional forecasts of the total amount of energy consumption. The horizontal axis represents the quarters over the two-year forecast horizon and the vertical axis reports the forecasts of the amount of consumption. We first focus on the results for Scenario 0 (no COVID-19 effects). In the initial period (the observed 2019Q4 data point), the EU^+ and the advanced groups have a similar composition of energy consumption. In 2019Q4 the shares of coal, natural gas and oil for the advanced economies are 14.4%, 41.4% and 44.3%, respectively. For the EU^+ countries, perhaps reflecting their stringent emission policy, the coal share is smaller (9.3%) while the natural gas share is larger (44.9%). In contrast, coal is the major energy source in the emerging group, which accounts for 54.3% of the total. Under Scenario 0, total fuel consumption in the emerging economies rises much faster than in the advanced over the eight-quarter horizon. This reflects the different average GDP growth rate of the two groups. The fuel mix for these two groups stay similar over the horizons.

We next turn to the results of Scenario 1, which assumes a one-time spread of COVID-19. The EU^+ group appears to be hit much harder than the advanced group as a whole in the first quarter (2020Q1), displaying large negative drops in oil and natural gas consumption, simultaneously. Advanced economies as a whole follow a similar, but less pronounced pattern compared to EU^+. This is followed by fast recovery of consumption in the subsequent quarter(s), and a further up and down movement in consumption. This implies that the observed effects of the COVID-10 outbreak in the first year may continue during the second forecast year even though patterns from this GDP scenario are stable at the end of the first year. The emerging economies exhibit a notable negative hit in the first quarter (2020Q1), but then start growing at a similar pace as under Scenario 0. Under Scenario 2, which assumes a resurgence of the corona virus, the consumption patterns in EU^+ are similar over the first year (2020). The plunge in the fifth quarter (2021Q1) is deeper and the recovery in the subsequent quarter is much weaker than in Scenario 1. A similar observation applies to the advanced economies. For emerging economies, the second wave of negative GDP shocks push down consumption in the fifth quarter (2021Q1), which drags down consumption growth.

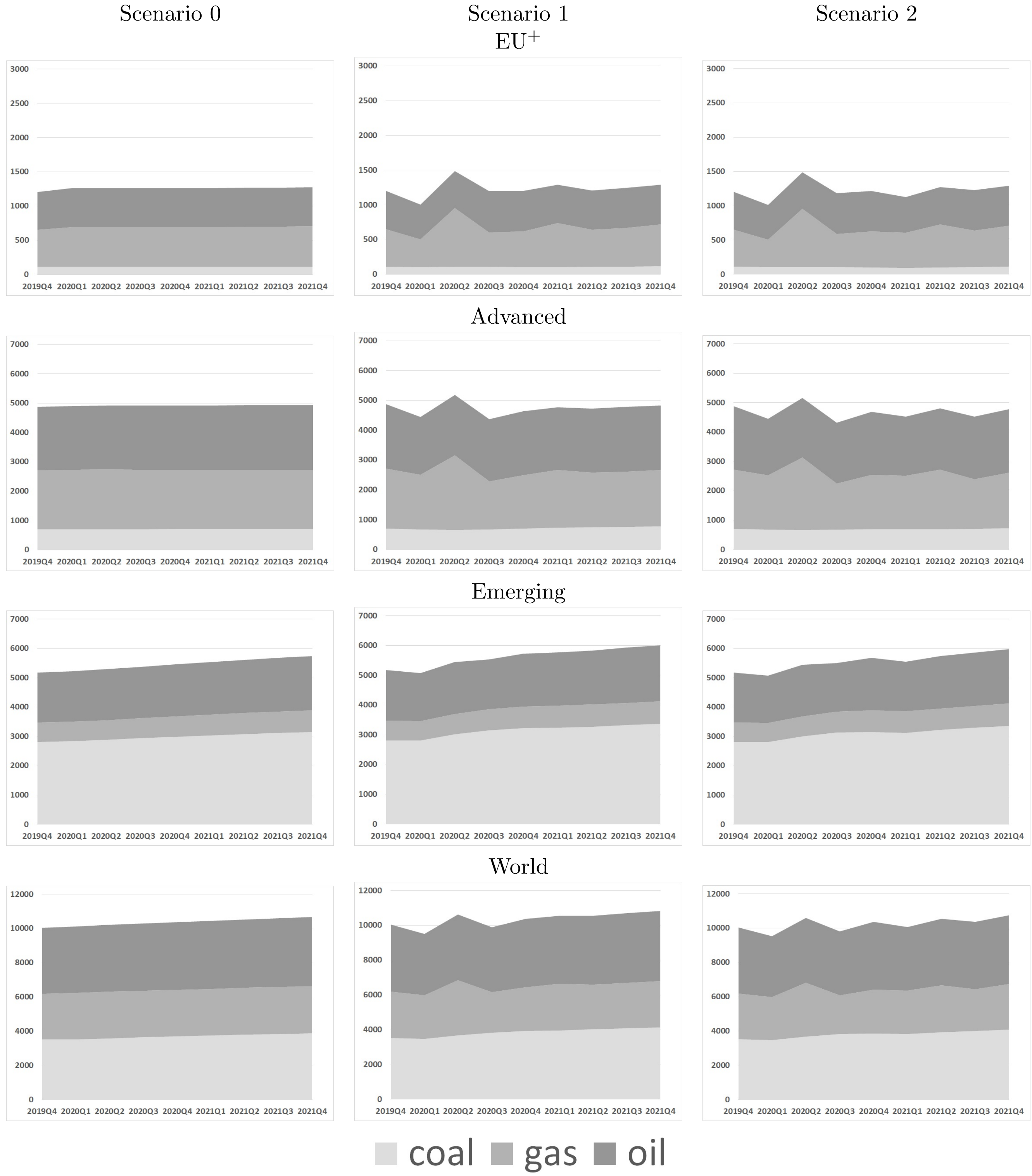


Figure 2: Forecasts of consumption of coal, natural gas, and oil by country group (annualised, in Mtoe)

4.2.2 CO_2 emissions

Based on the forecast energy consumption levels, we estimate the amount of emissions due to fossil fuel combustion. We use the simple emission factors which were used in the BP report. Specifically, a tonne of oil equivalent (toe) coal, natural gas and oil is converted to 3.96, 2.35 and 3.07 tonnes of CO_2.[6]

[6]We found that this simple method produces larger emission estimates compared to the BP estimates by 8.0%-10.1%, which is in line with BP's note. See Appendix A.3 for the comparison of our estimates with BP's and related details.

As expected, the emissions forecasts are qualitatively similar to the consumption forecasts as the former are a scaled version of the latter, weighted by the above emission factors. To save space, the emission forecasts are reported in Figure C.2 in Appendix C.2. Here we focus on investigating the effect of COVID-19's negative economic shock on emissions for the different country groups. We measure the effect by the change in the emissions by fuel source implied by Scenario 1 or 2 (with a COVID-19 shock) over Scenario 0 (without the shock), which is reported in Figure 3. The figures in the first row report the difference between the emissions in Scenario 1 and 0. For the advanced economies, the Scenario 1 GDP shock reduces emissions due to oil and gas use across all eight quarters, except the sharp increase for gas use in the second quarter (2021Q2). The emissions due to coal decrease during 2020, then increase continuously over the quarters in 2021. It is clear that oil and gas are the main contributor to the reduction of emissions. Table 2 reports the changes of the emissions for Scenarios 1 and 2 against Scenario 0. On average, over the eight quarters, the Scenario 1 GDP shock reduces emissions by 3.9% in advanced economies. On the other hand, in the emerging economies, apart from the drop in the first quarter, the emissions in the rest of the quarters are greater in Scenario 1 than in Scenario 0. The increase in emissions is mostly due to higher coal consumption. The average change in emissions for Scenario 1 over 0 is +3.4%. (see first panel of Table 2). Consequently, despite the massive 5.7% decrease of world emissions in the first quarter, the average emission changes over the two-year horizon, shown in the same panel of Table 2, is +0.4%, which is very small. This is because the decline in emissions in advanced economies is offset by the increases in emissions in emerging economies. We next turn to the second row of Figure 3 and the second panel of Table 2, which report the change in emissions for Scenario 2 over 0. Due to the second negative shock to GDP, emissions are more negatively affected compared to Scenario 1, particularly in the second forecast year. This reduces the growth in emissions in both the advanced and the emerging economies. The average changes in the advanced and in the emerging economies are -5.4% and +2.3%, respectively. Consequently, the average world emission changes is -0.9%.

Why does our analysis forecast relatively small effects of COVID-19 on fossil fuel consumption and CO_2 emissions over a two-year period? Several factors can explain the result. First, although the IMF (2020b) forecasts predict a large and immediate negative impact on GDP across countries that is unforeseen in the recent history, they indicate that the advanced economies' output recovers to the pre-pandemic level in the two-year period, while the emerging economies' output recovers even quicker. Second, existing cross-country studies on energy demand indicate that energy consumption may not be highly responsive to income changes.[7] Figure 1 indicates a decline in GDP by more than 5% for the emerging economies under Scenario 1 relative to Scenario 0 in the first quarter; and more than a 10% decline for the advanced economies in the second quarter. Table 2, on the other hand, suggests that CO_2 emissions decline by a smaller magnitude in both country groups in the initial quarters. These observations are consistent with the income elasticity estimates in the literature. As the income level increases over the later quarters, the fossil fuel consumption catches up, resulting in a fast recovery of CO_2 emissions.

To sum up, under Scenario 1 where the COVID-19 shock negatively affects the world economy in early 2020 but not in late 2020 to 2021, advanced economies will struggle to restore their energy consumption growth to the no COVID-19 levels until the end of 2021. In contrast, the emerging economies may recover faster from the drop in early 2020 and consume more energy than for the case without COVID-19. Consequently, total emissions in the world during 2020-2021 may not be affected much by the COVID-19 shock. However, if a second COVID-19 outbreak takes place, then energy consumption in advanced and emerging economies will go down further. As a result, the world CO_2 emissions level could be slightly less than that under the no-COVID-19 scenario.

4.3 Forecasting fossil fuel prices after the COVID-19 spread

We have seen that the global negative shock due to COVID-19 has different impacts on fuel consumption, and hence CO_2 emissions, in different countries. Our model also forecast fossil fuel prices by

[7] Huntington et al. (2019) reviews income elasticity estimates for liquid fuels in the literature, indicating a wide range of estimates that average at around less than 1. They find little evidence that countries with higher income levels have lower income responses.

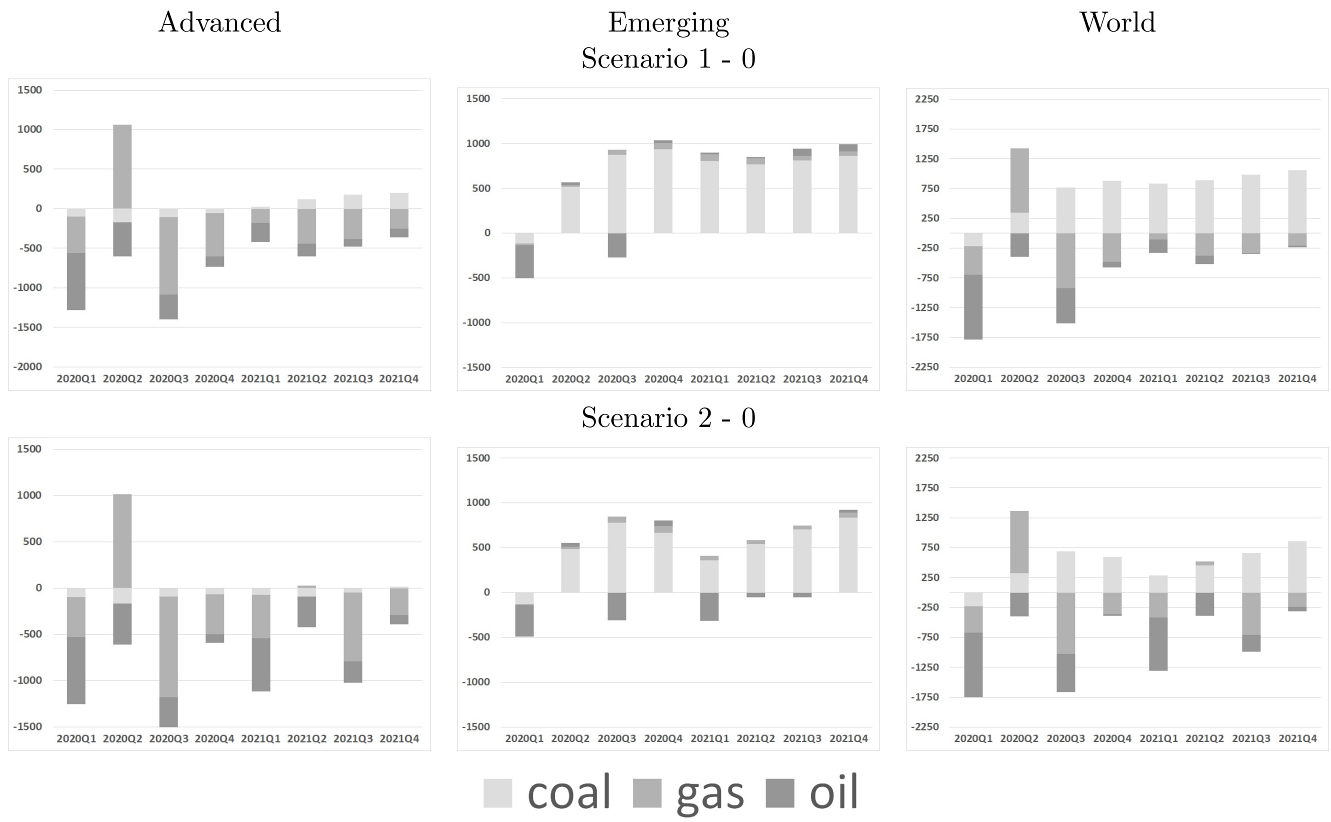


Figure 3: Difference in CO_2 emissions (annualised in $MtCO_2$)

Table 2: Changes in CO_2 emissions under Scenerios 1 and 2

	Scenario 1 to 0				Scenario 2 to 0			
Horizon	EU^+	Advanced	Emerging	World	EU^+	Advanced	Emerging	World
2020Q1	-20.4%	-9.5%	-2.8%	-5.7%	-20.1%	-9.2%	-2.8%	-5.6%
2020Q2	13.1%	3.2%	3.0%	3.1%	13.3%	2.8%	3.0%	2.9%
2020Q3	-4.1%	-10.3%	3.5%	-2.3%	-4.8%	-11.2%	2.9%	-3.0%
2020Q4	-4.1%	-5.3%	5.4%	0.9%	-3.2%	-4.2%	4.2%	0.6%
2021Q1	0.7%	-2.8%	4.6%	1.5%	-11.6%	-8.1%	0.5%	-3.1%
2021Q2	-4.8%	-3.4%	4.3%	1.1%	-0.9%	-2.8%	2.7%	0.4%
2021Q3	-1.6%	-2.1%	4.7%	1.9%	-3.0%	-7.4%	3.5%	-1.0%
2021Q4	1.2%	-1.2%	4.9%	2.4%	1.4%	-2.7%	4.5%	1.6%
Average	**-2.5%**	**-3.9%**	**3.4%**	**0.4%**	**-3.6%**	**-5.4%**	**2.3%**	**-0.9%**

taking into account (short-term) feedback effects of the domestic variables on the fuel prices as seen in equation (7).

Figure 4 lists the conditional forecast of prices using the GDP shock scenarios. Under Scenario 1, the prices of coal and gas first increase then drop sharply, and exhibit a gradual recovery thereafter. The oil price drop first then increases towards the common peak in the second quarter, then drop sharply. Under Scenario 2, over the first four quarters during 2020 the prices move similarly to those under Scenario 1, but during 2021 coal prices exhibit a sharper rise-and-drop. Importantly, the exogenous shocks can change the relative prices of coal, natural gas and oil, which would affect the future consumption of these fuels.

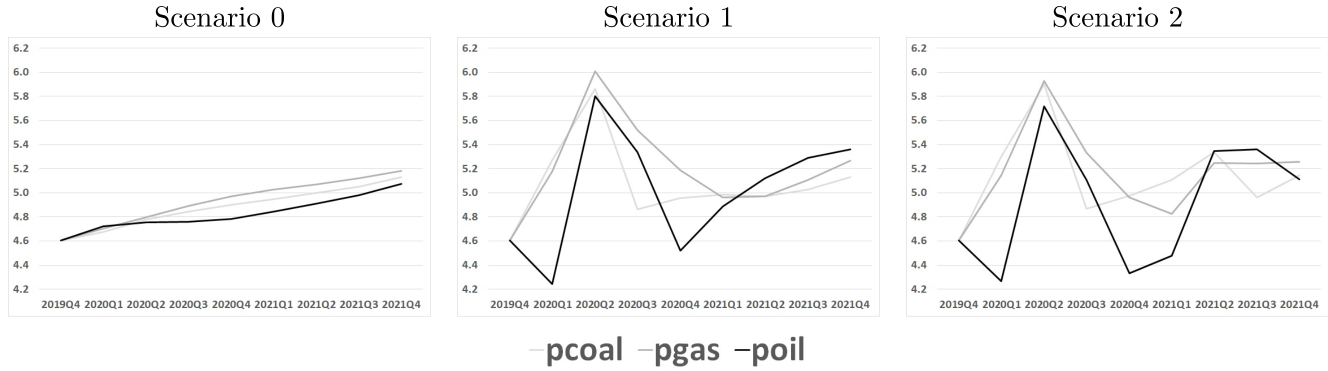


Figure 4: Conditional forecasts of fossil fuel prices conditional on GDP scenarios after the COVID-19 spread

4.4 Forecast performance evaluation

The primary interest of this paper is assessing a potential impact of the tight COVID-19 prevention measures by conditional forecasting rather than choosing the best forecasting models. However, investigating the efficacy of our forecasting approach is also useful because it may affect the quality of such an assessment. Here we inspect forecast performance of our approach. The efficacy of the conditional forecasts of energy consumption during 2020-2021, conditioned on the GDP projection for 2020Q1-2021Q4 by IMF, depends on two factors: the quality of the GDP forecast by IMF and the forecast ability of our global model. Here we aim to disentangle and examine the effects of these two factors, separately. Unfortunately, we cannot inspect out-of-sample forecasts during 2020-21, as we do not observe the actual consumption. Instead, we investigate out-of-sample forecasting errors during the most recent sharp economic fall around the 2008-09 financial crisis. Specifically, we estimate the model using the sample for the estimation period, from 1984Q1 to 2008Q4, and obtain the out-of-sample (conditional) forecast errors for energy consumption during the forecasting period, from 2009Q1 to 2010Q4.[8] For the forecast comparison, we employ the test for multi-horizon superior predictive ability (SPA), proposed by Quaedvlieg (2019). This serial correlation robust test considers all horizons of a forecast jointly, which is the desirable property for evaluation of our forecasts. We report the average SPA test scores based on mean squared forecast errors. The SPA test is upper one-tailed: for forecasts C and D, define the associated loss (here mean squared forecast errors over the horizon), L_C and L_D. The null is H_0: $E(L_C - L_D) = 0$ whilst the alternative is H_{A1}: $E(L_C - L_D) > 0$. We report the test results for H_{A1}: $E(L_C - L_D) > 0$ (Forecast D outperforms C) and H_{A1}: $E(L_D - L_C) > 0$ (Forecast C outperforms D), since the test results of these are different in general. Following Quaedvlieg (2019), we employ a bootstrap test.[9] First, to investigate the effects of choice of the GDP projections we implement the SPA test to compare the conditional forecasts based on the IMF projection of GDP and the actual GDP for the forecasting horizon 2009Q4-2010Q4. The forecast GDP is based on the IMF (2009) World Economic Outlook, January 2009 and OECD (2008), The OECD Economic Outlook, December 2008. The latter is employed when IMF (2009) does not contain the necessary information. We interpolated the quarterly GDP from the annual projections. The test is implemented for each of coal, gas and oil consumption for the 32 countries. In total, 89 test results are obtained. At the 5% significance level, the null of equal forecast performance is rejected in favour of the alternative that the conditional forecast with the actual GDP projection is better for 23 series out of the 89 (26%), whereas for all the 89 series the null is not rejected for the alternative that the conditional forecast with the IMF GDP projection is better. The full results are available in Table S.3.1 of the supplementary material. This can be seen as evidence that the choice of the GDP projection can affect the quality of the conditional forecast, which might be expected. Second, to examine the forecast ability of our global VAR model, we conduct the average SPA test to compare the unconditional forecast of our global VAR model with that of a benchmark model. For the latter, we have chosen country specific

[8] We are grateful to a referee for suggesting this exercise.

[9] See Quaedvlieg (2019) for more details.

vector autoregression models of coal, gas and oil consumption.[10] At the 5% significance level, the null hypothesis of equal forecast performance is rejected in favour of the alternative that the naïve VAR is better only for 4 series out of the 89 series (4.5%) whilst the null is rejected for the alternative that our unconditional forecast is better only for 2 series (2.2%). The full results are available in Table S.3.2 of the supplementary material. Since both portions of the rejections are less than the significance level, neither of the benchmark model or our global model outperforms the other. Provided that our global model can capture far more complicated spatial-dynamic dependencies, essentially this result reveals the promising forecast ability of our global model.[11] To sum up, the evidence in this subsection suggests that: (i) the accuracy of the conditional forecast depends on the quality of the projection conditioned upon, and; (ii) the forecast performance of our global model is as reliable as other benchmark models. We emphasise that the primary aim of this paper is assessing potential impact of the tight COVID-19 prevention measures on the global carbon emissions by conditional forecasting, rather than choosing the best forecasting models. The GDP scenarios 0-2 for 2020Q1-2021Q4 that we employ may not be very accurate ex post, however, they reflect the ex ante stylised economic impacts and suite the research aim of this paper.

5 The effect of changes in the fossil fuel prices on fuel consumption and output

Our analysis so far indicates that the effect of COVID-19 on the global CO_2 emissions would be close to zero over the two-year time horizon though the fossil fuel prices are expected to have sizeable fluctuations (5% or more) during this period. In particular, it shows that (i) an exogenous shock can change the relative prices of fossil fuels; and (ii) COVID-19 will not alleviate the urgency to reduce more CO_2 emissions globally. What does the model predict as the effect of carbon pricing on CO_2 emissions? In this section, we investigate the effect of changes in the relative prices of coal, natural gas and oil on fuel consumption and output.

Since coal is the most carbon intensive among the three fossil fuels, we implement a counterfactual experiment that raises the coal price. The unconditional forecast prices serve as the benchmark. We restrict the GVAR model so that contemporaneous and lagged feedback from the domestic variables (energy consumption, GDP, exchange rates and equity prices) to the fossil fuel equation are shut off and do not confound the interpretation of the experiment. Under this restriction, given the value of the prices, forecasts are produced from the following model

$$\mathbf{x}_t = \hat{\mathbf{b}}_0 + \hat{\mathbf{b}}_1 t + \hat{\mathbf{F}}_1\mathbf{x}_{t-1} + \hat{\mathbf{F}}_2\mathbf{x}_{t-2} + \hat{\mathbf{F}}_3\mathbf{x}_{t-3} + \hat{\mathbf{\Upsilon}}_0\mathbf{d}_t + \hat{\mathbf{\Upsilon}}_1\mathbf{d}_{t-1} + \hat{\mathbf{\Upsilon}}_2\mathbf{d}_{t-2} + \hat{\mathbf{v}}_t, \tag{12}$$

where the estimated coefficients embody the internal and external linkages and dynamics resulting from the estimation of the country-specific models in Section 3.1 (see Section B.2 of the Appendix for further details). In what follows, the unconditional forecast refers to the forecasts from the above model for $\mathbf{x}_t$, with the given global prices obtained as forecasts from the estimated VAR(3) representation of model (4) that includes the error-correction term given in (5). Under the counterfactual scenario, the forecasts for $\mathbf{x}_t$ are obtained subject to an increase in the price of coal by 12.5%. We refer to these forecasts as the conditional forecasts. In order to describe long-run effects, we consider forecasts over forty quarters.

Figure 5 reports the unconditional and conditional forecasts. Each panel displays average per capita log fuel consumption and per capita log GDP for each country group. The solid lines are the unconditional forecasts and the dashed lines are conditional on higher coal prices. The first panel shows that coal consumption in the advanced economies declines over the horizon, whereas it increases in the emerging economies. The second panel indicates that natural gas consumption increases worldwide, but much faster in the emerging economies. The third panel shows that oil consumption in the advanced economies stays almost constant over 10 years while it increases rapidly in the emerging economies. Finally, GDP grows faster in the emerging economies than in the advanced economies as

[10] Specifically, we estimate the VAR(2) for first-differenced logarithms of coal, gas and oil consumption with an intercept for the estimation period 1984Q1-2008Q4.

[11] Pesaran et al. (2009) demonstrate an extensive forecasting exercise of the GVAR model against typical benchmarks; and find that a double-averaged GVAR model forecast performs better than the benchmark competitors, particularly for output and inflation.

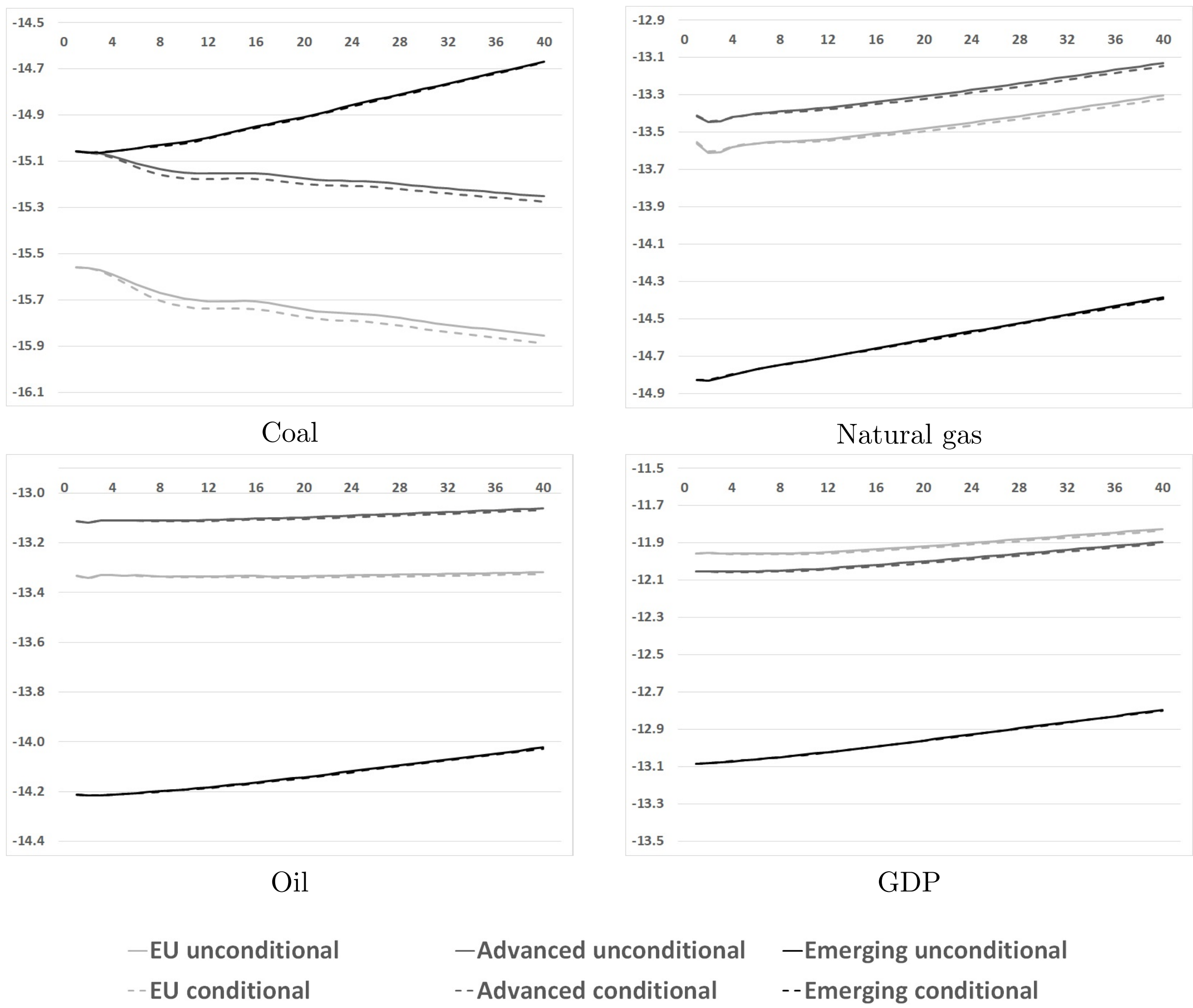


Figure 5: Forecasts of fuel consumption and GDP for benchmark and higher coal price cases

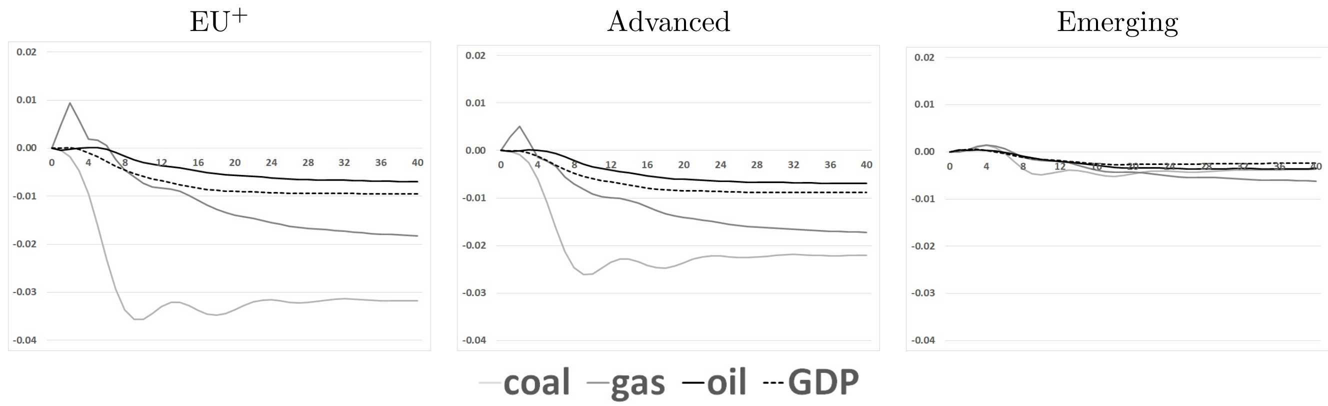


Figure 6: Difference in forecasts of fuel consumption and GDP between benchmark and higher coal price cases

illustrated in the last panel. These trajectories are remarkably similar under the scenario with higher coal prices. However, the negative effects of the higher coal price appear to be larger for EU$^+$ and the advanced economies than for the emerging ones.

In order to assess the effect of the higher coal price more clearly, we report the difference in consumption and GDP with and without the 12.5% coal price increase in Figure 6. The properties of the differences in consumption and GDP for the baseline and for the higher coal price are similar

Table 3: The forecast elasticity of fossil fuel consumption and GDP per capita with respect to coal price

	EU$^+$			
	coal	gas	oil	GDP
average change (annual)	-2.6%	-1.9%	-0.5%	-0.8%
s.e.(autocorrelation robust)	2.0%	0.7%	0.2%	0.3%
t-ratio	-1.30	-2.88	-2.64	-2.64
p-value	0.097	0.002	0.004	0.004
	Advanced			
	coal	gas	oil	GDP
average change (annual)	-1.8%	-1.6%	-0.6%	-0.7%
s.e.(autocorrelation robust)	1.5%	0.6%	0.2%	0.3%
t-ratio	-1.20	-2.90	-2.63	-2.54
p-value	0.115	0.002	0.004	0.006
	Emerging			
	coal	gas	oil	GDP
average change (annual)	-0.3%	-0.5%	-0.3%	-0.2%
s.e.(autocorrelation robust)	0.4%	0.2%	0.1%	0.1%
t-ratio	-0.73	-2.19	-2.65	-1.79
p-value	0.234	0.014	0.004	0.037

Note: The average annual change refers to the annualized average (over 40 quarters) of the quarterly change due to a 100% increase in the relative price of coal.

for EU$^+$ and the advanced economies, but the former group is more sensitive to the coal price hike. Eventually the higher coal price reduces energy consumption and GDP while the gap under the two scenarios widens. Though natural gas consumption increases in the initial two years, it decreases thereafter.

Table 3 reports the 'elasticity' of fossil fuel consumption and GDP per capita due to a 100% increase in the price of coal. The elasticity estimates are small across the board. The estimated own price elasticity of coal consumption in EU$^+$, which is weakly significant at the 10% level. The estimates for Advanced and Emerging economies are not significant. The figures for gas and oil are within the range of estimated price elasticity of energy demand in the literature.[12] Why does the elasticity estimate exhibit such a small magnitude, in particular for coal? The coal consumption has been decreasing over the past decade in many advanced countries including the U.S. and EU, accompanied by increased shares of natural gas and renewable energy in the energy mix (IEA, 2019). China, in contrast, has been increasing its coal consumption while some researchers estimate that its demand for coal is very inelastic (Ma and Stern, 2016). These factors may explain the weak association between the observed coal price and consumption.

For the emerging economies, the negative effect of the higher coal price on coal consumption is much smaller than that of the advanced economies and insignificant. The effects on GDP and natural gas consumption are much smaller for emerging than for advanced economies. The results also indicate that, relative to the fuel consumption, the negative impact of a higher coal price on GDP is smaller.

Overall, the above simulation reveals that a substantial increase in the coal price can significantly reduce fossil fuel consumption across the world. The effects on GDP are smaller than those on coal consumption. The negative effect on GDP due to a higher coal price is more limited in the emerging than in the advanced economies.

[12]According to a meta analysis by Huntington et al. (2019), estimated short-run price elasticity of oil demand varies substantially in the literature, averaging at -0.07 for developing countries and -0.11 for OECD countries among the reviewed studies. Note that our estimate is not the price elasticity of energy demand, so it is not directly comparable to the elasticity estimates in the literature.

6 Concluding remarks

We employ a global vector autoregressive (GVAR) model, which captures cross-sectional and time series interdependencies across countries, to study the global energy impacts of the COVID-19 pandemic and its global propagation. Its application based on data for 32 countries, which generate 81% of the global CO_2 emissions due to fossil fuel use, indicates that the negative effect of COVID-19 on global fossil fuel consumption, and hence CO_2 emissions, is large in the first quarter but limited over the two-year horizon. On one hand, the advanced economies will barely restore their energy consumption growth by the end of the two years to the level under the counterfactual scenario without COVID-19. On the other hand, the emerging economies may recover from the drop in early 2020 rather quickly and consume more energy than for the case of no COVID-19 outbreak. Consequently, total emissions in the world during 2020-2021 may not be affected much by the COVID-19 shock. However, if the world economy is further negatively affected, such as by a second wave of the coronavirus, energy consumption in the advanced and the emerging economies will decline further. The CO_2 emissions could be substantially lower than in the case of no COVID-19 shock for the advanced economies, but the impact is more limited for the emerging economies. Overall, our GVAR analysis indicates that the pandemic and the resulting economic shut down will not lead to a sizeable reduction in CO_2 emissions over a two-year time horizon. Thus COVID-19 would not provide countries with a reason to delay climate-change mitigation efforts.

What will happen if these economies adopt carbon pricing which increases the relative price of coal? Our conditional forecast analysis reveals that higher coal prices lead to lower fossil fuel consumption with less-than-proportional decreases in GDP. In particular, the impact on fossil fuel consumption and GDP is smaller for the emerging economies.

This result indicates that continued efforts to reduce CO_2 emissions, through an expanded introduction of carbon pricing in other countries, may not be too costly in terms of the magnitude of the GDP impacts. As the effects on GDP are expected to be more limited in the emerging than in the advanced economies, global application of carbon pricing may not exacerbate distributional impacts across countries with different income levels.

With regard to the impact of the economic shock from COVID-19 on the advanced versus emerging economies, the following caveats are in order: our analysis does not study the effects on each country separately; and stringent financing restrictions in emerging economies may drag down their recovery from the pandemic's negative economic effects (IMF, 2020b). Considering a global model that can reflect differences in sovereign credits across countries is left for future research.

Our analysis also demonstrates differential impacts of slower GDP growth due to COVID-19 on different fossil fuel sources in different parts of the world. The simulation associated with a higher coal price also indicated different effects on natural gas and oil consumption. In the context of climate change mitigation, it would be useful to consider the impact on renewable energy integration, which this paper does not address due to data availability. Future research could address how the pandemic's negative economic shocks influence the speed of renewables integration.

Appendix A: Further Description of the Data

A.1 Data Sources

A.1.1 Macroeconomic variables, PPP-GDP and trade data

Real GDP, the real exchange rate and real equity price for all countries, as well as PPP-GDP figures and the trade data for construction of the trade matrix (used in computing the foreign variables of the GVAR model) were taken from the GVAR 2019 Vintage available at https://www.mohaddes.org/gvar. This is an updated version of the 2016 Vintage, updated by Kamiar Mohaddes and Mehdi Raissi. The PPP-GDP data are from the World Development Indicator database of the World Bank. The trade data is from the IMF Direction of Trade statistics constructed based on the average of Exports and Imports (c.i.f.) at the annual frequency. Further details including the source of the macroeconomic variables for each country can be found there.

A.1.2 Population

Population data are from the World Bank website https://data.worldbank.org/indicator/SP.POP.TOTL available at the annual frequency. The annual data were interpolated to obtain the quarterly values using the approx function in R selecting the method "linear." Figures for 2018Q1-2019Q4 were set equal to the annual 2018 figure, the last available annual data point for all countries.

A.1.3 Energy consumption

Energy consumption data were obtained from Oxford Economics (https://www.oxfordeconomics.com/) whose provider is the International Energy Agency (IEA). The Lisman and Sandee (1964) method was used for interpolation where required.

Data for coal consumption (domestic demand, annualised, Mtoe) for all countries are constructed from the IEA World Energy Balances service, Summary and Extended Energy Balances database which contains annual data. Quarterly values were interpolated from the annual series.

Data for natural gas consumption (domestic demand, annualised, Mtoe) for all OECD countries are constructed from the IEA Natural Gas Monthly service, Natural Gas Balance database. Monthly figures were summed to obtain the quarterly values. Quarterly data for non-OECD countries were interpolated from annual data which were constructed from the IEA World Energy Balances service, Summary and Extended Energy Balances database.

Data for oil consumption (domestic demand, annualised, Mtoe) for all OECD countries, and non-OECD countries over the period 1991-2019, are from the IEA Monthly Oil Service. Monthly figures are summed to obtain the quarterly data. Quarterly values for non-OECD data for the period 1991Q1-2019Q4 were interpolated from the annual data of the IEA World Energy Balances service.

A.1.4 Global energy prices

The coal, natural gas and oil quarterly prices are computed from the monthly prices obtained from the World Bank Commodity Price Data ('Pink Sheet' Data).

A.1.5 Temperature data

Daily temperature data from monitoring stations across the countries of interest were extracted from the Global Historical Climatology Network- Daily (GHCN) hosted by the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA) over the period 1981-2014. GHCN daily is an integrated database of daily climate summaries from land surface stations across the globe that have been subjected to a common suite of quality assurance reviews. It contains records from over 100,000 stations in 180 countries and territories. NCEI provides numerous daily variables, including maximum temperature (Tmin) and minimum temperature (Tmax), total daily precipitation, snowfall, and snow depth. Both the record length and period of record vary by station and cover intervals ranging from less than a year to more than 175 years.

For each monitoring station, all available data that fulfilled the following criteria were retained: (i) both Tmax and Tmin were available for each day and (ii) no quality assurance or quality control issues were identified for either Tmax or Tmin. For those countries with missing data over the period of interest, namely Canada, Germany, Singapore and UK, data from the monitoring stations of the top three largest metropolitan areas based on population were included. Similarly for the US, data from the monitoring stations of the top three largest states in terms of population were included namely California, Texas and New York.

A.2 Temperature and Seasonal Adjustment

Temperature adjustment and/or seasonal adjustment of the energy consumption data was initially performed on the 2016 Vintage (ending in 2014). The 2016 Vintage was subsequently updated by forward extrapolation using the seasonal adjusted (where appropriate) growth rate of the 2020 Vintage. Gas consumption for 2019 for Argentina, China, India, Indonesia, Malaysia, Philippines, Saudi Arabia, Singapore, South Africa, and Thailand, were replaced with forecasts produced by Oxford Economics, as these were not yet available. This was also the case for coal consumption for all countries except Brazil.

A.2.1 Construction of HDD and CDD

The daily temperature data were converted from degree Fahrenheit to Celsius and heating and cooling degree days, $HDD_{i\tau d}$ and $CDD_{i\tau d}$ respectively, were construted for each country i and each day d of each year τ as follows

$$HDD_{i\tau d} = \begin{cases} \quad 18\ ^\circ C\ -\ \text{mean daily temperature of country } i \\ 0, \quad \text{if } 18^\circ C\ >\ \text{mean daily temperature of country } i \end{cases}$$

$$CDD_{i\tau d} = \begin{cases} \quad \text{mean daily temperature of country } i\ -\ 21\ ^\circ C \\ 0, \quad \text{if } 21\ ^\circ C\ <\ \text{mean daily temperature of country } i \end{cases}$$

where mean daily temperature was computed as (Tmin+Tmin)/2.

The corresponding quarterly data for HDD_{it} and CDD_{it} for $t = 1, 2, ..., T$ were constructed by taking the average daily $HDD_{i\tau d}$ and $CDD_{i\tau d}$ values for each of the four quarters. Missing values of no more than six consecutive values were encountered for HDD for Germany and for CDD for Germany, Indonesia and Malaysia. These gaps were filled using a simple linear interpolation method.

A.2.2 Temperature adjustment

Let y_{it} be quarterly energy consumption for country i. Following common practice (see for example Elkhafif, 1996) temperature adjustment of energy consumption was performed as follows:

1. Run the regression based on the quarterly data

$$y_{it} = b_{0i} + b_{1i}HDD_{it} + b_{2i}CDD_{it} + \varepsilon_{it},\ t = 1, 2, ..., T. \tag{A.1}$$

   Equation (A.1) may consist of only HDD_{it} or CDD_{it} see Table A.2.

2. Construct the correction factor as

$$CORR_{i\tau q} = \hat{b}_{1i}(HDD_{i\tau q} - NHDD_{iq}) + \hat{b}_{2i}(CDD_{i\tau q} - NCDD_{iq})$$

   where τ is the year ($\tau = 1984, 1985, ..., 2014$) and q is the quarter ($q = Q1, Q2, Q3, Q4$),

$$NHDD_{iq} = \text{the 30 year average of } HDD_i \text{ for the } q^{\text{th}} \text{ quarter (1981-2010)}$$
$$NCDD_{iq} = \text{the 30 year average of } CDD_i \text{ for the } q^{\text{th}} \text{ quarter (1981-2010),}$$

   are climate normals, typically computed over a three consecutive ten-year period the most recent being 1981-2010, see Won et al. (2016) for a discussion of climate normals.

3. The temperature adjusted consumption series is then

$$(y_{it})_{ta} = y_{it} - CORR_{i\tau q}.$$

A.2.3 Seasonal adjustment

Joint significance of seasonal components was tested for all consumption and price series based on the procedure described in Section A.2.4. For consumption, seasonal effects were not significant for any of the annual series namely all coal series and the natural gas non-OECD series. Significant seasonal effects were found for all natural gas OECD series with the exception of Norway and for all oil series with the exception of Indonesia[13] and Malaysia. No temperature and/or seasonal adjustment was performed for the natural gas series of Norway and the oil series of Malaysia nor for the coal and non-OECD natural gas series. For prices, only the natural gas prices exhibited seasonal effects and was seasonally adjusted.

[13] For the oil series of Indonesia we did peform seasonal adjustent despite the non-significant finding of the seasonality test as the high volatility of the series appeared to obscure the clear seasonal pattern in the less volatile part of the series

To seasonally adjust the data we start from $\log(y)$ (where y here is either the original consumption series or the temperature adjusted one, or the natural gas price series) and take the first difference, $\Delta\log(y)$. This is seasonally adjusted using the X-12 quarterly seasonal adjustment method under the additive option to obtain $\Delta\log(y)_{sa}$. Then using the first observation of the raw series $\log(y)$ (levels, not seasonally adjusted) the seasonally adjusted log changes, $\Delta\log(y)_{sa}$, are cumulated to obtain the log adjusted series $\log(y)_{sa}$. Finally, the seasonal adjusted level series, $(y)_{sa}$, is obtained by taking the exponential of $\log(y)_{sa}$.

Table A.2 summarises all adjustments to the energy consumption series for each country for the Vintage 2016 (ending 2014). It also includes information on the available HDD and CDD series for each country, with a 'no' indicating that the corresponding series was zero throughout the sample period 1984-2014 and was therefore not included in the temperature adjustment procedure (if performed), yes indicating otherwise.

Table A.2: Summary of adjustments to energy consumption of each country

	Coal	Natural Gas	Oil	HDD	CDD
Argentina	original data	original data	sa	yes	yes
Australia	original data	ta & sa	ta & sa	yes	yes
Austria	original data	ta & sa	sa	yes	yes
Belgium	original data	ta & sa	sa	yes	yes
Brazil	original data	original data	sa	yes	yes
Canada	original data	sa	sa	yes	yes
Chile	original data	sa	sa	yes	yes
China	original data	original data	sa	yes	yes
Finland	original data	ta & sa	ta & sa	yes	no
France	original data	ta & sa	sa	yes	yes
Germany	original data	sa	ta & sa	yes	yes
India	original data	original data	sa	yes	yes
Indonesia	original data	original data	sa	no	yes
Italy	original data	sa	ta & sa	yes	yes
Japan	original data	sa	ta & sa	yes	yes
Korea	original data	-	sa	yes	yes
Malaysia	original data	original data	original data	no	yes
Mexico	original data	sa	sa	yes	yes
Netherlands	original data	sa	sa	yes	yes
New Zealand	original data	ta & sa	sa	yes	yes
Norway	original data	original data	sa	yes	no
Philippines	original data	-	sa	no	yes
Saudi Arabia	-	original data	sa	yes	yes
Singapore	-	original data	sa	no	yes
South Africa	original data	-	sa	yes	yes
Spain	original data	sa	ta & sa	yes	yes
Sweden	original data	-	ta & sa	yes	no
Switzerland	original data	ta & sa	sa	yes	yes
Thailand	original data	original data	sa	no	yes
Turkey	original data	-	sa	yes	yes
UK	original data	sa	ta & sa	yes	yes
US	original data	ta & sa	ta & sa	yes	yes

Note: 'original data' signifies that the no temperature and/or seasonal adjustment was performed on the corresponding series. 'ta' and 'sa' signifies temperature adjusted and seasonally adjusted respectively. For the oil series any 'ta' and/or 'sa' for non-OECD countries was performed over the period 1991Q1-2014Q4 as prior to 1991 the series are interpolated from annual data. 'no' for any HDD or CDD series signifies that all values for the corresponding series were zero throughout the sample for the associated country and was therefore not included in the temperature adjustment procedure (if performed), 'yes' signifies otherwise. Post 2014 the consumption series were extrapolated using the seasonal adjusted (where appropriate) growth rate of the 2020 Vintage.

A.2.4 Assessing the joint significance of seasonal effects

To assess the joint significance of the seasonal components for a series y we consider its natural logarithm denoted by $\log(y)$, and use the following procedure:

1. Let S_1, S_2, S_3 and S_4 be the usual seasonal dummies, such that S_i, $i = 1, 2, 3, 4$, takes the value of 1 in the i^{th} quarter and zero in the remaining three quarters.

2. Construct $S_{14} = S_1 - S_4$, $S_{24} = S_2 - S_4$, $S_{34} = S_3 - S_4$.

3. Run a regression of $\Delta \log(y)$ (where the lower case denotes the natural logarithm of the corresponding variable) on an intercept and S_{14}, S_{24}, S_{34}. Denote the OLS estimates of S_{14}, S_{24} and S_{34} by a_1, a_2 and a_3.

4. Asses the joint significance of the seasonal components by testing the hypothesis that $a_1 = a_2 = a_3 = 0$ using the F-statistic.

5. In cases where the null hypothesis was rejected at the 10% level, seasonal adjustment was performed on the log-difference of the original series using the X-12 procedure as described above.

A.3 Comparison of Consumption and Emissions Data with BP Data

Our CO_2 emissions were calculated by applying the single emission factor used by BP[14] to each of the coal, natural gas and oil series. These emission factors are based on standard global average conversion factors compiled on the basis of average carbon content: coal at 94,600 kg CO_2 per TJ (3.96 tonnes per tonne of oil equivalent); natural gas at 56,100 kg CO_2 per TJ (2.35 tonnes per tonne of oil equivalent); and oil at 73,300 kg CO_2 per TJ (3.07 tonnes per tonne of oil equivalent).

We compared our CO_2 emission data with published BP data, `bp-stats-review-2019-consolidated-dataset-panel-format.xlsx`. The comparison is based on 2014Q4 annualised consumption and the 2014 BP data file[15] for the four country groups of Table 1: (i) EU^+, (ii) Advanced, (iii) Emerging, (iv) Total. The CO_2 emissions and consumption of coal, natural gas and oil per Mtoe is given in the table that follows.

Table A.3: CO_2 emissions and consumption of coal, natural gas and oil per Mtoe

	(i) Advanced				(ii) Emerging			
	coal	gas	oil	total	coal	gas	oil	total
(a) Our consumption	851.1	1725.1	2108.9	4685.1	2683.7	533.4	1472.5	4689.6
(b) BP consumption	866.5	1201.9	1935.7	4004.1	2596.0	597.4	1431.3	4624.8
(c) Emission Factors	3.96	2.35	3.07		3.96	2.35	3.07	
(d) CO_2 (a)×(c)	3370.2	4054.1	6474.4	13898.6	10627.5	1253.4	4520.7	16401.6
(e) CO_2 (b)×(c)	3431.3	2824.5	5942.6	12198.3	10280.2	1403.9	4394.2	16078.4
(f) BP CO_2				11023.9				14988.2
(g) log((d)/(e)) (%)	-1.8%	36.1%	8.6%	13.0%	3.3%	-11.3%	2.8%	2.0%
(h) log((e)/(f)) (%)				10.1%				7.0%
(i) log((d)/(f)) (%)				23.2%				9.0%

	(iii) EU^+				Total (i) + (ii)			
	coal	gas	oil	total	coal	gas	oil	total
(a) Our consumption	164.3	480.5	553.5	1198.3	3534.8	2258.5	3581.5	
(b) BP consumption	165.7	288.5	517.4	971.6	3462.5	1799.3	3367.0	8628.8
(c) Emission Factors	3.96	2.35	3.07		3.96	2.35	3.07	
(d) CO_2 (a)×(c)	650.8	1129.2	1699.2	3479.1	13997.7	5307.5	10995.1	30300.2
(e) CO_2 (b)×(c)	656.2	677.9	1588.5	2922.6	13711.5	4228.4	10336.8	28276.7
(f) BP CO_2				2651.6				26012.1
(g) log((d)/(e)) (%)	-0.8%	51.0%	6.7%	17.4%	2.1%	22.7%	6.2%	6.9%
(h) log((e)/(f)) (%)				9.7%				8.3%
(i) log((d)/(f)) (%)				27.2%				15.3%

Note: The difference between our CO_2 emission estimates (d) and those of BP (f) for total emissions is 15.3%. This discrepancy is wider for advanced economies (23.2%) than for emerging economies (9.0%). This difference can be decomposed into two parts: that from converting energy consumption into emissions (h) and that associated with the calculation of consumption (g). Our simple conversion method using the factor (c) tends to overestimate emissions by 7.0%-10.1%, which is in line with BP's note according to footnote 11 below. The other source of discrepancy related to consumption calculation is negligible for coal and moderate for oil, but substantial for natural gas. The difference between our natural gas consumption figures (a) and those of BP (b) are reported in (g) as 36.1%, -11.3%, and 22.7% for the Advanced, Emerging and Total groups, respectively. Since natural gas is far more used by the advanced group, the discrepancy in emission estimates due to the difference in energy consumption is larger for this group: these (g) are 13%, 2.0% and 6.9% for advanced, emerging and total, respectively.

[14] These are the emission factors that BP used to estimate carbon emissions from energy consumption prior to revising their process for the 2016 edition of the Statistical Review.2016.

[15] While these figures are based on BP's revised methodology for constructing CO_2 emissions since 2016, it is mentioned in their note that applying their emission factors we use here would result in CO_2 emissions about 8% higher than those derived from their revised methodology.

Appendix B: Further Description and Results of the GVAR Model

B.1 Country-specific Variables

Table B.1(i) Summary of domestic and foreign variables included in the country-specific models

	All Countries Excluding US		US	
Variables	Endogenous	Weakly Exogenous	Endogenous	Weakly Exogenous
Coal consumption	$coal_{it}$	$coal^*_{it}$	$coal_{US,t}$	$coal^*_{US,t}$
Nat. gas consumption	gas_{it}	gas^*_{it}	$gas_{US,t}$	$gas^*_{US,t}$
Oil consumption	oil_{it}	oil^*_{it}	$oil_{US,t}$	$oil^*_{US,t}$
GDP per capita	gdp_{it}	gdp^*_{it}	$gdp_{US,t}$	$gdp^*_{US,t}$
Real exchange rate	ep_{it}	-	-	$ep^*_{US,t}$
Real equity price	eq_{it}	eq^*_{it}	$eq_{US,t}$	-
Coal price	-	$pcoal_t$	-	$pcoal_t$
Nat. gas price	-	$pgas_t$	-	$pgas_t$
Oil price	-	$poil_t$	-	$poil_t$

Table B.1(ii) Composition of country variables

Variables	# Countries	
Coal consumption	30	Excluding: Saudi Arabia and Singapore
Nat. gas consumption	27	Excluding: Korea, Philippines, South Africa, Sweden, Turkey
Oil consumption	32	
GDP per capita	32	
Real exchange rate	31	Excluding: US
Real equity price	26	Excluding: Brazil, China, Indonesia, Mexico, Saudi Arabia, Turkey

Note: The excluded consumption series had at least some part of the series equal to zero.

B.2 Solving for the GVAR model

We solve for the GVAR model in terms of $\mathbf{y}_t = (\mathbf{x}'_t, \mathbf{d}'_t)'$, using the the estimated VECMX* models (2) and the global price model (7). We initially obtain the global model associated with the individual country equations given by (2), expressed in terms of the $k \times 1$ global variable vector $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, ..., \mathbf{x}'_{Nt})'$ with $k = \sum_{i=0}^{N} k_i$. To this end, by setting $\mathbf{z}_{it} = (\mathbf{x}'_{it}, \mathbf{x}^{*\prime}_{it})'$ (2) can be expressed in terms of $\mathbf{z}_{it}$ as follows

$$\begin{aligned} \mathbf{G}_{i0}\mathbf{z}_{it} &= \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{G}_{i1}\mathbf{z}_{i,t-1} + ... + \mathbf{G}_{ip_i}\mathbf{z}_{i,t-p_i} \\ &+ \mathbf{\Psi}_{i1}\mathbf{d}_{t-1} + ... + \mathbf{\Psi}_{iq_i}\mathbf{d}_{t-q_i} + \mathbf{u}_{it}, \end{aligned} \tag{B.1}$$

where $\mathbf{G}_{i0} = (\mathbf{I}_{k_i}, -\mathbf{\Lambda}_{i0})$ and $\mathbf{G}_{ij} = (\mathbf{\Phi}_{ij}, \mathbf{\Lambda}_{ij})$, for $j = 1, ..., p_i$. Then using the identity $\mathbf{z}_{it} = \mathbf{W}_i\mathbf{x}_t$, for $i = 0, 1, ..., N$, where $\mathbf{W}_i$ are the link matrices defined by the trade weights w_{ij}, (B.1) can be written as

$$\begin{aligned} \mathbf{G}_{i0}\mathbf{W}_i\mathbf{x}_t &= \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{G}_{i1}\mathbf{W}_i\mathbf{x}_{t-1} + ... + \mathbf{G}_{ip_i}\mathbf{W}_i\mathbf{x}_{t-p_i} + \mathbf{\Psi}_{i0}\mathbf{d}_t + \\ &+ \mathbf{\Psi}_{i1}\mathbf{d}_{t-1} + ... + \mathbf{\Psi}_{iq_i}\mathbf{d}_{t-q_i} + \mathbf{u}_{it}. \end{aligned} \tag{B.2}$$

The individual models in (B.2) are then stacked to yield the model for $\mathbf{x}_t$ given by

$$\mathbf{G}_0\mathbf{x}_t = \mathbf{a}_0 + \mathbf{a}_1 t + \mathbf{G}_1\mathbf{x}_{t-1} + ... + \mathbf{G}_p\mathbf{x}_{t-p} + \mathbf{\Psi}_0\mathbf{d}_t + \mathbf{\Psi}_1\mathbf{d}_{t-1} + ... + \mathbf{\Psi}_q\mathbf{d}_{t-q} + \mathbf{u}_t, \tag{B.3}$$

where $p = \max(p_i)$, $q = \max(q_i)$, and

$$\mathbf{G}_j = \begin{pmatrix} \mathbf{G}_{0j}\mathbf{W}_0 \\ \mathbf{G}_{1j}\mathbf{W}_1 \\ \vdots \\ \mathbf{G}_{Nj}\mathbf{W}_N \end{pmatrix}, \ \boldsymbol{\Psi}_s = \begin{pmatrix} \boldsymbol{\Psi}_{0s} \\ \boldsymbol{\Psi}_{1s} \\ \vdots \\ \boldsymbol{\Psi}_{Ns} \end{pmatrix}, \quad \begin{matrix} j = 0, 1, ..., p; \\ s = 0, 1, ..., q, \end{matrix}$$

$$\mathbf{a}_0 = \begin{pmatrix} \mathbf{a}_{00} \\ \mathbf{a}_{10} \\ \vdots \\ \mathbf{a}_{N0} \end{pmatrix}, \ \mathbf{a}_1 = \begin{pmatrix} \mathbf{a}_{01} \\ \mathbf{a}_{11} \\ \vdots \\ \mathbf{a}_{N1} \end{pmatrix}, \mathbf{u}_t = \begin{pmatrix} \mathbf{u}_{0t} \\ \mathbf{u}_{1t} \\ \vdots \\ \mathbf{u}_{Nt} \end{pmatrix}.$$

Setting $\widetilde{\mathbf{x}}_t = \sum_{i=0}^{N} \widetilde{w}_i \mathbf{x}_{it} = \widetilde{\mathbf{W}}\mathbf{x}_t$,[16] and assuming that $p = \widetilde{p} = \widetilde{q} = q$ for ease of exposition, (B.3) and (7) can be written in terms of $\mathbf{y}_t = (\mathbf{x}_t', \mathbf{d}_t')'$ as

$$\mathbf{H}_0\mathbf{y}_t = \mathbf{h}_0 + \mathbf{h}_1 t + \mathbf{H}_1\mathbf{y}_{t-1} + ... + \mathbf{H}_p\mathbf{y}_{t-p} + \boldsymbol{\zeta}_t, \tag{B.4}$$

where

$$\mathbf{H}_0 = \begin{bmatrix} \mathbf{G}_0 & -\boldsymbol{\Psi}_0 \\ \mathbf{0}_{m_d \times k} & \mathbf{I}_{m_d} \end{bmatrix}, \ \mathbf{h}_0 = \begin{bmatrix} \mathbf{a}_0 \\ \boldsymbol{\mu}_0 \end{bmatrix}, \ \mathbf{h}_1 = \begin{bmatrix} \mathbf{a}_1 \\ \boldsymbol{\mu}_1 \end{bmatrix},$$
$$\mathbf{H}_j = \begin{bmatrix} \mathbf{G}_j & \boldsymbol{\Psi}_j \\ \boldsymbol{\Lambda}_{xj}\widetilde{\mathbf{W}}_j & \boldsymbol{\Phi}_{dj} \end{bmatrix}, j = 1, ..., p, \quad \boldsymbol{\zeta}_t = \begin{bmatrix} \mathbf{u}_t \\ \boldsymbol{\eta}_t \end{bmatrix}.$$

Assuming that $\mathbf{H}_0$ is invertible, premultiplying (B.4) by $\mathbf{H}_0^{-1}$ we arrive at the GVAR model

$$\mathbf{y}_t = \mathbf{c}_0 + \mathbf{c}_1 t + \mathbf{C}_1\mathbf{y}_{t-1} + ... + \mathbf{C}_p\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t, \tag{B.5}$$

with $\mathbf{c}_j = \mathbf{H}_0^{-1}\mathbf{h}_j$, $j = 0, 1, \mathbf{C}_j = \mathbf{H}_0^{-1}\mathbf{H}_j$, $j = 1, ..., p$, and $\boldsymbol{\varepsilon}_t = \mathbf{H}_0^{-1}\boldsymbol{\zeta}_t$, which is the model used for forecasting. In general, the lag order of $\mathbf{y}_t$ will be determined by the maximum lag order $\max(\max(p, \widetilde{p}), \max(q, \widetilde{q}))$. In our case the final estimated GVAR model is of order 3. Related output on the stability of model (B.5) can be found in the supplementary material.[17]

For the purpose of forecasting when the global prices are taken as given (and no feedback effects are considered) as in the experiment of Section 5, forecasts are based on the model

$$\mathbf{x}_t = \mathbf{b}_0 + \mathbf{b}_1 t + \mathbf{F}_1\mathbf{x}_{t-1} + ... + \mathbf{F}_p\mathbf{x}_{t-p} + \boldsymbol{\Upsilon}_0\mathbf{d}_t + \boldsymbol{\Upsilon}_1\mathbf{d}_{t-1} + ... + \boldsymbol{\Upsilon}_q\mathbf{d}_{t-q} + \mathbf{v}_t, \tag{B.6}$$

which follows from model (B.3) above with $\mathbf{b}_j = \mathbf{G}_0^{-1}\mathbf{a}_j$, $j = 0, 1, \mathbf{F}_j = \mathbf{G}_0^{-1}\mathbf{G}_j$, $j = 1, ..., p$, $\boldsymbol{\Upsilon}_j = \mathbf{G}_0^{-1}\boldsymbol{\Psi}_j$, $j = 0, 1, ..., q$ and $\mathbf{v}_t = \mathbf{G}_0^{-1}\mathbf{u}_t$, where $\mathbf{G}_j$ $j = 0, 1, ..., q$, with p and q equal to 3 and 2 respectively.

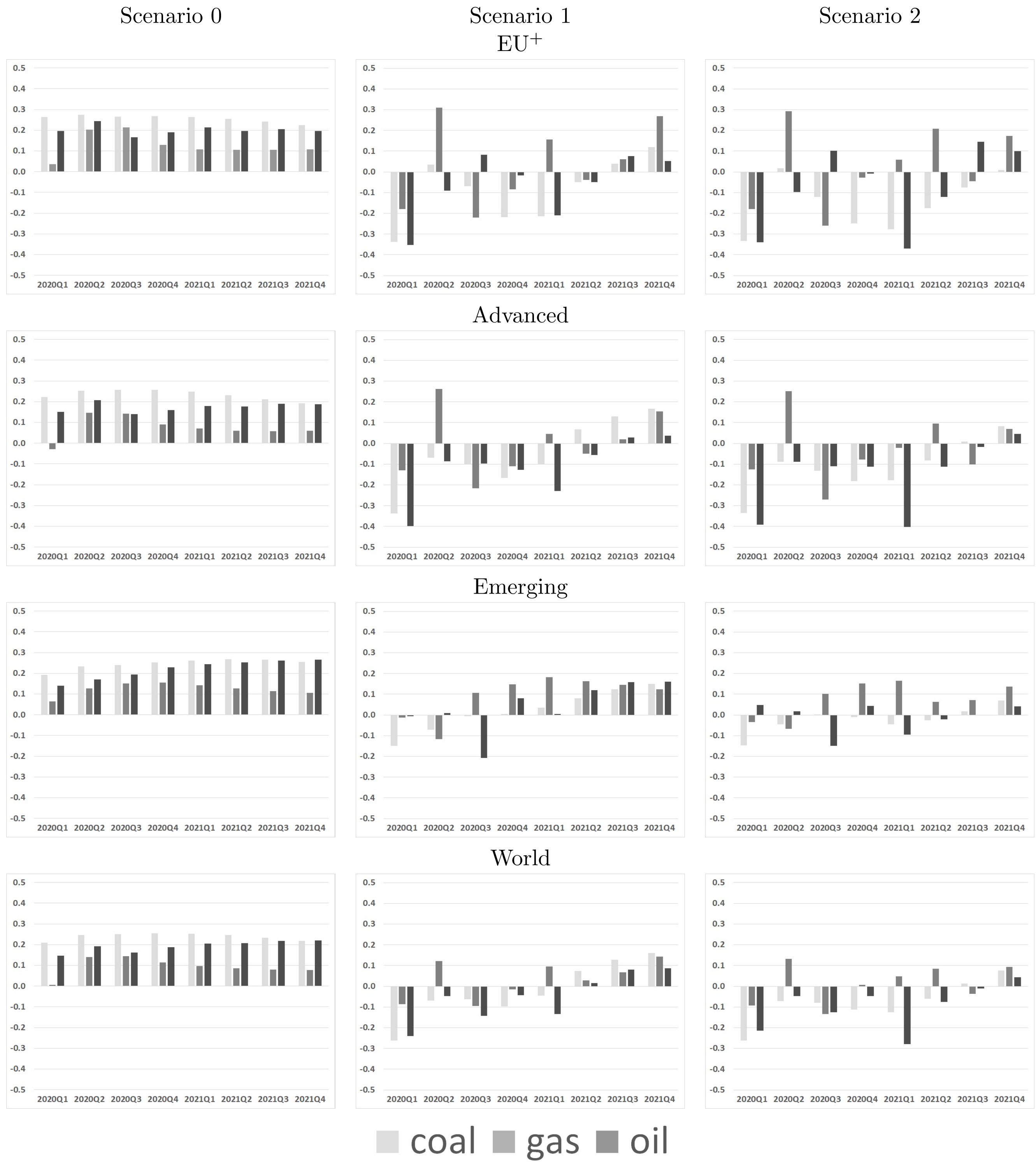
Appendix C: Additional Empirical Results

C.1 Conditional Forecast Probabilities

There are discrepancies between the estimated GVAR model and the assertions implied by the forecast scenarios, mainly due to the difference in the estimation periods. To address these, we compare the conditional forecasts based on the implied GDP changes in Scenarios 0 to 2 with the unconditional forecasts obtained from the estimated GVAR model. Figure C.1 reports the probabilities of positive consumption of the difference between the conditional and unconditional forecast of coal, natural gas,

[16] Note that for expositional simplicity we are assuming that the PPP-GDP weights in $\widetilde{\mathbf{W}}$ are the same for all variables. In practice, as in our case, these can be somewhat different if, for example, a certain variable is excluded from the estimation of the country-specific models for certain countries (see Table B.1(ii)), as the weights then get re-weighted in order to sum to one. The same holds true for the trade weights in $\mathbf{W}_i$.

[17] All GVAR-related output in this paper has been obtained using the GVAR Toolbox 2.0 of Smith and Galesi (2014) Smith and Galesi (2014) with modifications and additions to the existing functions.



Note: The vertical axis measures the probability that consumption under the conditional forecast exceeds that under the unconditional forecast in deviation from 0.5.

Figure C.1: Conditional forecast probabilities of changes in relative consumption by country group and oil by country group. The reported probabilities are the deviations from 0.5. When the figure is positive (negative), the chance of the conditional forecast of consumption being larger (smaller) than the unconditional forecast is more than 50/50. For Scenario 0, all figures are positive and show an increasing trend over time. For the advanced and EU^+ countries, the figure is not very large, well below 0.2. On the other hand, the figures for the emerging economies are mostly larger than 0.2. These results suggest that, on average, the scenario growth rate is mostly higher than the estimated rate, and the discrepancy is higher for the emerging economies. With this in mind, we turn to the conditional forecast probability for Scenario 1 (against the unconditional forecast). For the EU^+ and advanced countries, in most quarters the chance of having negative consumption is higher. The chance of negative consumption is the highest in the first quarter with a high chance maintained over the first year, easing somewhat towards the second half of the year. For the emerging economies, after the first quarter's negative figure, chance evens out in the second and third quarters, with the figures exceeding 0.1 thereafter and rising, mainly led by coal and oil. Hence, for emerging economies the Scenario 1 effect of COVID-19 on consumption is limited to the first quarter. The result for the world is a combination of that of advanced and emerging economies. The effect of COVID-19 on the world in Scenario 1 is largely pronounced in the first quarter, with small negative effects in quarters two until four, and consumption starting to grow thereafter, in the second year. Turning to the results for Scenario 2, compared to Scenario 1 the figures for EU^+ and advanced countries are similarly negative during the first year but much more negative during the second year. In Scenario 2, the positive figures for the emerging economies are much smaller, especially in the second year. Consequently, the world figures are mostly negative.

C.2 Forecasts of CO_2 Emissions

The conditional forecasts of the total amount of CO_2 emissions for the different country groups is summarised in Figure C.2. The horizontal axis represents the quarters over the two-year forecast horizon and the vertical axis reports the forecasts of the amount of emissions. See the discussion in Section 4.2.

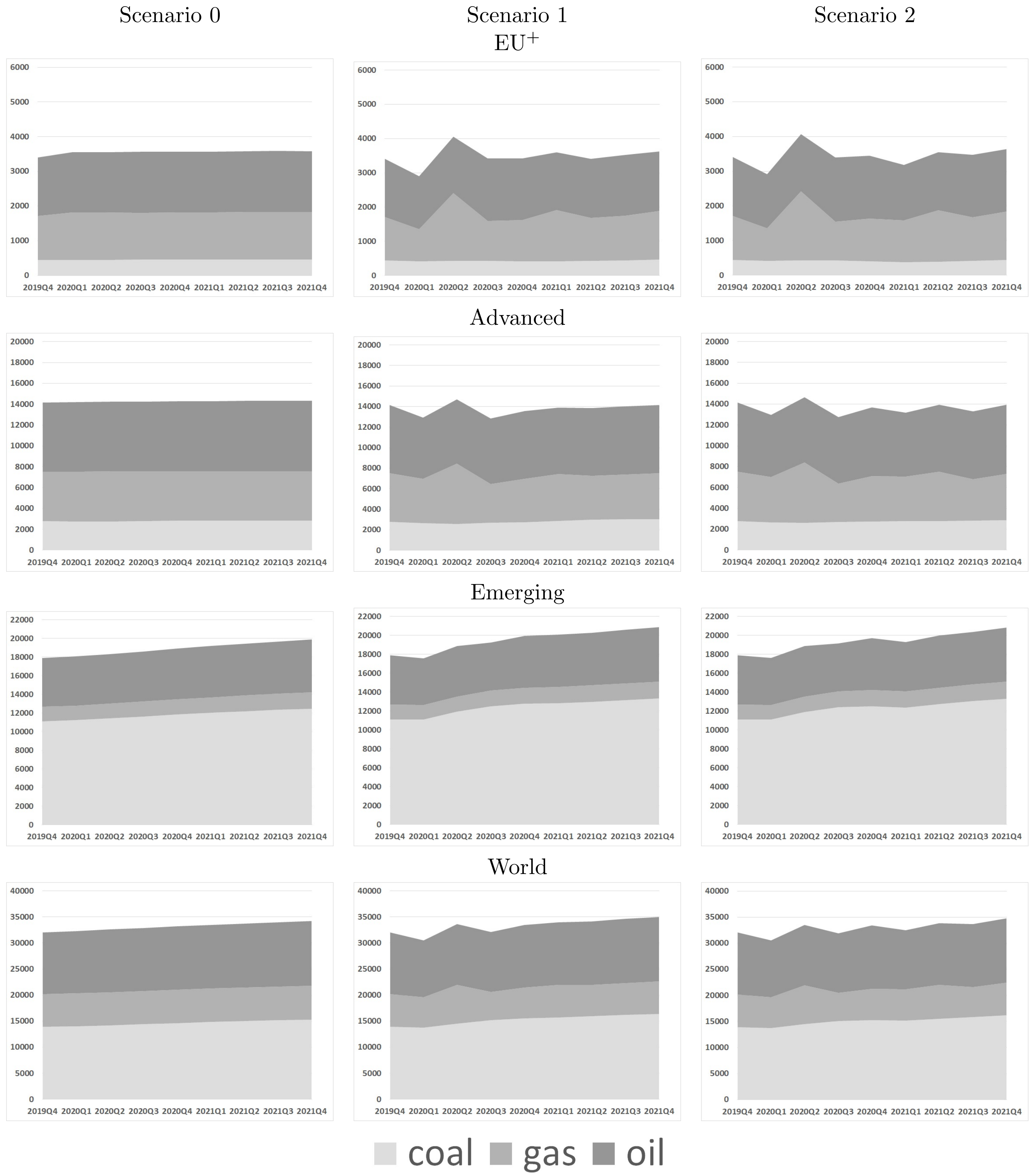


Figure C.2: Forecasts of CO_2 emissions due to fossil fuel use by country group (annualised in $MtCO_2$)

References

Akpan, G. E. and Akpan, U. F. (2012). Electricity consumption, carbon emissions and economic growth in nigeria. *International Journal of Energy Economics and Policy*, 2(4):292.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2017). Energy consumption, co2 emissions, and economic growth: An ethical dilemma. *Renewable and Sustainable Energy Reviews*, 68:808–824.

Bloch, H., Rafiq, S., and Salim, R. (2012). Coal consumption, co2 emission and economic growth in China: Empirical evidence and policy responses. *Energy Economics*, 34(2):518–528.

Bozkurt, C. and Akan, Y. (2014). Economic growth, co2 emissions and energy consumption: the turkish case. *International Journal of Energy Economics and Policy*, 4(3):484.

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

Coers, R. and Sanders, M. (2013). The energy–gdp nexus; addressing an old question with new methods. *Energy Economics*, 36:708–715.

Cui, B. and Zhu, L. (2016). Research on economic growth and carbon abatement under the energy consumption controlling objective based on endogenous growth theory and gvar model [j]. *Chinese Journal of Management Science*, 24(1):11–20.

Dees, S., Mauro, F. d., Pesaran, M. H., and Smith, L. V. (2007). Exploring the international linkages of the euro area: a global var analysis. *Journal of applied econometrics*, 22(1):1–38.

Elkhafif, M. A. (1996). An iterative approach for weather-correcting energy consumption data. *Energy economics*, 18(3):221–230.

Huntington, H. G., Barrios, J. J., and Arora, V. (2019). Review of key international demand elasticities for major industrializing economies. *Energy Policy*, 133:110878.

IEA (2019). *World Energy Outlook 2019.* International Energy Agency, Paris.

IMF (2020a). *World Economic Outlook Update, January 2020.* International Monetary Fund, Washington, DC.

IMF (2020b). *World Economic Outlook, April 2020.* International Monetary Fund, Washington, DC.

IMF (2020c). *World Economic Outlook Update, June 2020.* International Monetary Fund, Washington, DC.

IMF (2020d). *World Economic Outlook Update, October 2020.* International Monetary Fund, Washington, DC.

Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (covid-19/sars-cov-2) case. *Transportation Research Part E: Logistics and Transportation Review*, 136:101922.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. *Econometrica*, 59(6):1551–80.

Kahouli, B. (2019). Does static and dynamic relationship between economic growth and energy consumption exist in oecd countries? *Energy Reports*, 5:104–116.

Le Quéré, C., Jackson, R. B., Jones, M. W., Smith, A. J., Abernethy, S., Andrew, R. M., De-Gol, A. J., Willis, D. R., Shan, Y., Canadell, J. G., et al. (2020). Temporary reduction in daily global co 2 emissions during the covid-19 forced confinement. *Nature Climate Change*, pages 1–7.

Lisman, J. H. C. and Sandee, J. (1964). Derivation of quarterly figures from annual data. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 13(2):87–90.

Liu, Z., Deng, Z., Ciais, P., Lei, R., Davis, S. J., Feng, S., Zheng, B., Cui, D., Dou, X., He, P., et al. (2020). Covid-19 causes record decline in global CO2 emissions. *arXiv preprint arXiv:2004.13614.*

Ma, C. and Stern, D. I. (2016). Long-run estimates of interfuel and interfactor elasticities. *Resource and Energy Economics*, 46:114–130.

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

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

Mohaddes, K. and Raissi, M. (2019). The us oil supply revolution and the global economy. *Empirical Economics*, 57(5):1515–1546.

Omri, A. and Kahouli, B. (2014). Causal relationships between energy consumption, foreign direct investment and economic growth: Fresh evidence from dynamic simultaneous-equations models. *Energy Policy*, 67:913–922.

Pesaran, M. H., Schuermann, T., and Smith, L. V. (2009). Forecasting economic and financial variables with global vars. *International journal of forecasting*, 25(4):642–675.

Pesaran, M. H., Schuermann, T., and Weiner, S. M. (2004). Modeling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business & Economic Statistics*, 22(2):129–162.

Pesaran, M. H., Shin, Y., and Smith, R. J. (2000). Structural analysis of vector error correction models with exogenous i (1) variables. *Journal of Econometrics*, 97(2):293–343.

Quaedvlieg, R. (2019). Multi-horizon forecast comparison. *Journal of Business & Economic Statistics*, pages 1–14.

Sadorsky, P. (2010). The impact of financial development on energy consumption in emerging economies. *Energy policy*, 38(5):2528–2535.

Saidi, K. and Hammami, S. (2015). The impact of co2 emissions and economic growth on energy consumption in 58 countries. *Energy Reports*, 1:62–70.

Shahbaz, M., Khan, S., and Tahir, M. I. (2013). The dynamic links between energy consumption, economic growth, financial development and trade in china: fresh evidence from multivariate framework analysis. *Energy economics*, 40:8–21.

Smith, L. and Galesi, A. (2014). The GVAR Toolbox 2.0. `https://sites.google.com/site/gvarmodelling/gvar-toolbox`. Accessed: 2021-01-10.

Won, S. J., Wang, X. H., and Warren, H. E. (2016). Climate normals and weather normalization for utility regulation. *Energy Economics*, 54:405–416.

Zhang, H., Chen, J., Li, Y., and Seiler, M. J. (2018). Does the development of China's building industry influence the global energy consumption and carbon emissions? an analysis based on the gvar model. In *Proceedings of the 21st International Symposium on Advancement of Construction Management and Real Estate*, pages 641–649. Springer.

Zhou, Y., Liu, W., Lv, X., Chen, X., and Shen, M. (2019). Investigating interior driving factors and cross-industrial linkages of carbon emission efficiency in China's construction industry: Based on super-sbm dea and gvar model. *Journal of Cleaner Production*, 241:118322.

An Online Supplement for
Assessing the Impact of COVID-19 on Global Fossil Fuel Consumption and CO_2 Emissions

L. Vanessa Smith
University of York

Nori Tarui
University of Hawaii

Takashi Yamagata
University of York and Osaka University

January 2021

S.1 Introduction

This supplement is organised as follows: Section S.2 provides a selected set of results related to the estimated GVAR(3) model and the associated country-specific models. Section S.3 give the technical details associated with the GVAR forecasting discussed in Section 4.1 of the main paper.

S.2 Country Specific and GVAR results

The estimated GVAR(3) model in $\mathbf{y}_t = (\mathbf{x}_t', \mathbf{d}_t')'$, where $\mathbf{x}_t$ is the global variable vector and $\mathbf{d}_t$ is the vector of global prices, has 181 endogenous variables (3 of which correspond to the global prices), 112 stochastic trends (2 corresponding to the global prices) and 69 cointegrating relations (1 corresponding to the global prices). All the roots of the global VAR model in the 32 countries either lie on or inside the unit circle. The moduli of the largest non unit eigenvalue is 0.96. The lag orders for the domestic variables, p_i, and foreign variables, q_i, are selected based on the Akaike criterion with $p_{\max i} = 3$ and $q_{\max i} = 2$. The individual country models are estimated subject to reduced rank restrictions as described in Dées et al. (2007) and the cointegrating relations obtained are based on the trace statistic at the 95% critical value.[18] For estimation, $\mathbf{x}_{it}^*$ are treated as "long-run forcing" or $I(1)$ weakly exogenous with respect to the parameters of the conditional model. This assumption can be tested by regressing $\mathbf{x}_{it}^*$ on the error correction terms for country i and testing whether these terms are statistically significant. Tables S1-S4 and Figures S1 below provide a selected set of results related to the estimated GVAR(3) and the associated country-specific models. Additional results are available upon request.

[18]The number of cointegrating relations is determined for the case where unrestricted constants and restricted trend coefficients are included in the individual country error correction models.

Specification of Individual Country VARX*(p,q) Models

The table below shows the VARX* order and number of cointegrating relationships in the country specific models.

Table S1: VARX* order and number of cointegrating relationships

Country	VARX*(p_i, q_i)		# Cointegrating Relationships
	p_i	q_i	
ARGENTINA	3	1	1
AUSTRALIA	3	1	2
AUSTRIA	2	2	3
BELGIUM	3	2	2
BRAZIL	3	2	2
CANADA	3	2	2
CHILE	3	1	1
CHINA	3	1	1
FINLAND	3	1	1
FRANCE	3	2	3
GERMANY	2	2	3
INDIA	3	1	1
INDONESIA	3	1	3
ITALY	1	2	4
JAPAN	3	1	1
KOREA	3	2	2
MALAYSIA	3	1	3
MEXICO	3	2	2
NETHERLANDS	2	1	2
NEW ZEALAND	2	1	4
NORWAY	3	2	3
PHILIPPINES	3	1	1
SAUDI ARABIA	3	1	0
SINGAPORE	1	1	2
SOUTH AFRICA	2	1	1
SPAIN	2	2	4
SWEDEN	3	1	2
SWITZERLAND	3	1	3
THAILAND	3	1	3
TURKEY	3	2	2
UNITED KINGDOM	3	2	3
USA	2	1	1

Note: The lag orders for the domestic variables, p_i, and foreign variables, q_i, are selected based on the Akaike criterion with $p_{\max i} = 3$ and $q_{\max i} = 2$. The individual country models are estimated subject to reduced rank restrictions as described in DdPS and the cointegrating relations obtained are based on the trace statistic at the 95% critical value. The number of cointegrating relations was reduced for certain countries based on the performance of the persistence profiles of the GVAR.

Figure S1: Persistence profiles

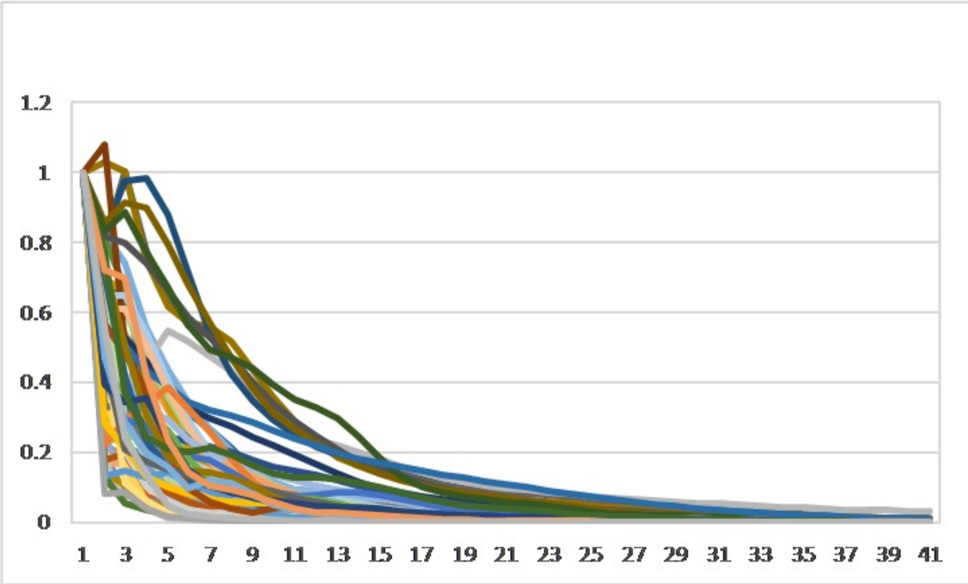


Table S2: Number of rejections of the null of parameter constancy per variable across the country specific models at the 1 percent level

Alternative Test Statistics	*coal*	*gas*	*oil*	*gdp*	*ep*	*eq*	Numbers(%)
	Domestic Variables						
PK_{sup}	0(0.0)	1(3.7)	1(3.1)	1(3.1)	0(0.0)	0(0.0)	3(1.7)
PK_{msq}	0(0.0)	3(11.1)	1(3.1)	2(6.3)	0(0.0)	0(0.0)	6(3.4)
N	11(36.7)	2(7.4)	2(6.3)	1(3.1)	2(6.5)	1(3.8)	19(10.7)
robust-N	2(6.7)	2(7.4)	1(3.1)	0(0.0)	1(3.2)	0(0.0)	6(3.4)
QLR	18(60.0)	5(18.5)	5(15.6)	5(15.6)	7(22.6)	3(11.5)	43(24.2)
robust-QLR	3(10.0)	0(0.0)	1(3.1)	0(0.0)	4(12.9)	1(3.8)	9(5.1)
MW	14(46.7)	5(18.5)	6(18.8)	3(9.4)	5(16.1)	2(7.7)	35(19.7)
robust- MW	3(10.0)	1(3.7)	2(6.3)	0(0.0)	5(16.1)	1(3.8)	12(6.7)
APW	18(60.0)	6(22.2)	5(15.6)	7(21.9)	7(22.6)	3(11.5)	46(25.8)
robust- APW	3(10.0)	0(0.0)	1(3.1)	0(0.0)	4(12.9)	1(3.8)	9(5.1)

Note: The test statistics PK_{sup} and PK_{msq} are based on the cumulative sums of OLS residuals, N is the Nyblom test for time-varying parameters and QLR, MW and APW are the sequential Wald statistics for a single break at an unknown change point. Statistics with the prefix robust denote the heteroskedasticity robust version of the tests. All tests are implemented at the 1% significance level.

Table S3. Contemporaneous effects of the foreign variables on their domestic counterparts in the country-specific models

Country	*coal*	*gas*	*oil*	*gdp*	*eq*
ARGENTINA	0.21 [0.32]	0.05 [0.10]	0.41 [0.29]	0.24 [0.39]	1.34† [0.43]
AUSTRALIA	-0.06 [0.19]	-0.20 [0.54]	0.25 [0.14]	0.28† [0.09]	0.84† [0.12]
AUSTRIA	0.40† [0.18]	0.11 [0.12]	0.55† [0.14]	0.79† [0.12]	1.04† [0.13]
BELGIUM	1.46† [0.41]	0.17 [0.16]	1.14† [0.25]	0.87† [0.14]	1.02† [0.07]
BRAZIL	0.34† [0.12]	-0.01 [0.10]	0.17 [0.15]	-0.27 [0.35]	-
CANADA	0.74† [0.09]	0.37† [0.15]	0.63† [0.17]	0.53† [0.09]	0.86† [0.06]
CHILE	0.26 [0.24]	0.48 [0.80]	-0.05 [0.24]	1.04† [0.33]	0.78† [0.10]
CHINA	0.10† [0.03]	-0.05 [0.04]	-0.04 [0.24]	0.61 [0.31]	-
FINLAND	0.46† [0.21]	0.38† [0.18]	0.45† [0.20]	1.30† [0.22]	1.10† [0.17]
FRANCE	0.07 [0.23]	0.93† [0.34]	0.61† [0.13]	0.60† [0.07]	1.06† [0.04]
GERMANY	0.23† [0.05]	0.30 [0.19]	1.38† [0.28]	1.51† [0.23]	1.11† [0.04]
INDIA	-0.02 [0.03]	-0.10 [0.07]	0.13 [0.22]	0.51 [0.40]	0.71† [0.14]
INDONESIA	0.57 [1.07]	-0.10 [0.15]	1.00 [0.84]	0.16 [0.32]	-
ITALY	0.14 [0.72]	0.60† [0.13]	0.52† [0.13]	0.88† [0.10]	1.08† [0.09]
JAPAN	0.10† [0.04]	0.08 [0.21]	0.59† [0.22]	0.44† [0.21]	0.85† [0.11]
KOREA	0.44† [0.21]	-	0.33 [0.29]	0.34 [0.20]	1.10† [0.21]
MALAYSIA	1.13† [0.52]	0.07 [0.06]	0.24 [0.27]	0.90† [0.18]	0.99† [0.18]
MEXICO	0.13 [0.12]	0.07 [0.11]	0.14 [0.18]	0.63† [0.22]	-
NETHERLANDS	0.20 [0.14]	0.71† [0.14]	0.06 [0.13]	0.37† [0.10]	1.01† [0.04]
NEW ZEALAND	0.27 [0.49]	-0.22 [0.38]	0.91† [0.32]	0.20 [0.14]	0.69† [0.08]
NORWAY	0.70 [0.46]	0.63 [0.74]	0.74† [0.35]	0.52† [0.26]	1.18† [0.09]
PHILIPPINES	0.02 [0.20]	-	0.45 [0.30]	0.01 [0.29]	1.06† [0.12]
SAUDI ARABIA	-	-0.01 [0.09]	-0.26 [0.16]	0.46 [0.27]	-
SINGAPORE	-	-1.29† [0.63]	0.53† [0.22]	1.20† [0.23]	1.19† [0.08]
SOUTH AFRICA	-0.04 [0.13]	-	0.07 [0.26]	0.32† [0.11]	0.87† [0.12]
SPAIN	0.60† [0.28]	0.41† [0.17]	0.68† [0.14]	0.05 [0.08]	1.11† [0.06]
SWEDEN	-0.01 [0.14]	-	1.05† [0.24]	0.98† [0.13]	1.15† [0.06]
SWITZERLAND	0.35 [0.45]	0.18 [0.18]	0.70† [0.28]	0.73† [0.16]	0.91† [0.05]
THAILAND	0.03 [0.11]	0.01 [0.06]	0.77† [0.21]	0.62† [0.31]	1.26† [0.18]
TURKEY	0.24† [0.11]	-	0.51 [0.32]	0.95 [0.61]	-
UNITED KINGDOM	0.64† [0.31]	0.51† [0.18]	0.63† [0.14]	0.51† [0.11]	0.88† [0.06]
USA	0.47† [0.12]	0.41 [0.23]	0.20 [0.12]	0.38† [0.09]	-

Note: White's heteroskedastic-robust standard errors are given in square brackets. † denotes statistical significance at the 5% level.

Table S4: F Statistics for testing the weak exogeneity of the country-specific foreign variables and global prices

Country	F test	$coal^*$	gas^*	oil^*	gdp^*	ep^*	eq^*	$pcoal$	$pgas$	$poil$
ARGENTINA	F(1,123)	2.21	0.08	0.06	2.14	-	2.64	0.00	0.04	0.85
AUSTRALIA	F(2,122)	2.34	0.37	0.26	0.31	-	1.41	0.25	2.86	0.02
AUSTRIA	F(3,105)	1.79	1.78	0.22	0.20	-	0.65	1.01	0.10	0.61
BELGIUM	F(2,106)	2.66	0.55	1.31	0.15	-	1.21	1.55	1.51	1.16
BRAZIL	F(2,123)	1.37	1.00	1.43	0.43	-	0.09	0.96	0.38	1.16
CANADA	F(2,122)	1.57	0.07	0.63	1.69	-	1.06	0.06	2.07	2.23
CHILE	F(1,107)	0.08	0.81	0.13	0.00	-	0.64	2.81	0.78	0.55
CHINA	F(1,124)	1.40	0.32	0.13	0.12	-	1.76	0.29	0.05	0.28
FINLAND	F(1,113)	2.75	0.32	1.73	2.26	-	0.46	0.26	0.75	0.26
FRANCE	F(3,105)	0.20	0.80	0.09	0.91	-	0.79	0.50	1.04	1.32
GERMANY	F(3,101)	1.41	1.34	1.08	$3.01^{\dagger}$	-	0.19	0.84	0.03	2.18
INDIA	F(1,123)	4.07	1.62	0.08	0.38	-	0.51	0.26	0.55	0.16
INDONESIA	F(3,107)	3.05	1.48	0.77	0.86	-	0.82	1.73	1.36	1.51
ITALY	F(4,110)	0.64	0.19	0.85	0.23	-	1.24	0.21	0.29	1.44
JAPAN	F(1,123)	1.52	1.15	0.05	0.14	-	0.11	1.04	1.81	0.11
KOREA	F(2,108)	1.59	0.07	0.20	0.75	-	0.29	0.37	2.52	0.14
MALAYSIA	F(3,114)	0.63	1.06	0.80	0.27	-	1.51	0.53	1.61	1.59
MEXICO	F(2,123)	2.23	0.73	0.79	2.31	-	1.48	1.65	1.54	2.39
NETHERLANDS	F(2,112)	0.99	0.37	1.07	0.07	-	1.14	2.34	0.37	0.36
NEW ZEALAND	F(4,120)	0.53	0.77	0.82	0.14	-	1.37	1.41	0.30	0.10
NORWAY	F(3,121)	6.19	2.01	3.95	1.63	-	0.31	0.10	1.13	0.60
PHILIPPINES	F(1,109)	0.26	0.33	0.22	2.47	-	0.94	$6.42^{\dagger}$	1.82	0.13
SAUDI ARABIA	F(0,126)	-	-	-	-	-	-	-	-	-
SINGAPORE	F(2,108)	1.73	0.48	0.24	2.60	-	0.71	0.27	0.64	0.03
SOUTH AFRICA	F(1,124)	1.01	0.34	0.02	0.20	-	0.04	0.06	0.00	0.60
SPAIN	F(4,110)	1.87	0.27	0.82	0.50	-	0.96	0.65	1.56	0.57
SWEDEN	F(2,113)	2.28	0.64	0.55	1.45	-	0.77	0.17	1.58	0.77
SWITZERLAND	F(3,121)	4.16	0.33	0.96	0.85	-	0.95	1.35	0.33	1.91
THAILAND	F(3,121)	1.78	2.02	0.64	0.36	-	0.57	0.31	0.17	0.27
TURKEY	F(2,124)	0.06	0.30	0.52	0.42	-	0.43	0.34	0.62	0.88
UNITED KINGDOM	F(3,111)	1.64	1.92	1.69	0.28	-	0.58	0.63	1.35	2.63
USA	F(1,116)	0.53	0.77	0.05	0.24	0.55	-	0.31	0.43	1.40

Note: These F statistics test zero restrictions on the coefficients of the error correction terms in the error-correction regressions for the country-specific variables. The lag orders for the domestic variables and those for the foreign and global price variables were selected based on the Akaike criterion with the maximum value for both set to two. Increasing the lag orders further reduced the number of statistically significant outcomes. † denotes statistical significance at the 5% level.

S.3 Forecasting using the GVAR

S.3.1 Unconditional forecasts

The unconditional forecasts based on the estimated GVAR(3) model in (8) are computed recursively by

$$\mu_h = \hat{\mathbf{c}}_0 + \hat{\mathbf{c}}_1 (T+h) + \hat{\mathbf{C}}_1 \mu_{h-1} + \hat{\mathbf{C}}_2 \mu_{h-2} + \hat{\mathbf{C}}_3 \mu_{h-3}, \text{ for } h = 1, 2, ..., H. \tag{S.1}$$

with initial values $\mu_0 = \mathbf{y}_T$, $\mu_{-1} = \mathbf{y}_{T-1}$ and $\mu_{-2} = \mathbf{y}_{T-2}$, where h is the forecast horizon.

Equivalently expressed in terms of the GVAR(1) companion form we have

$$\begin{pmatrix} \mathbf{y}_t \\ \mathbf{y}_{t-1} \\ \mathbf{y}_{t-2} \end{pmatrix} = \begin{pmatrix} \mathbf{C}_1 & \mathbf{C}_2 & \mathbf{C}_3 \\ \mathbf{I}_{k+m_d} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{k+m_d} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{y}_{t-1} \\ \mathbf{y}_{t-2} \\ \mathbf{y}_{t-3} \end{pmatrix} + \begin{pmatrix} \mathbf{b}_0 + \mathbf{b}_1 t \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix},$$

or

$$\mathbf{Y}_t = \mathbf{C}\mathbf{Y}_{t-1} + \mathbf{D}_t + \mathbf{E}_t \tag{S.2}$$

where recall $k + m_d$ is the total number of domestic variables and global prices in the GVAR model.

Hence

$$\mathbf{Y}_{T+h} = \mathbf{C}^h \mathbf{Y}_T + \textstyle\sum_{\ell=0}^{h-1} \mathbf{C}^\ell \mathbf{D}_{T+h-\ell} + \sum_{\ell=0}^{h-1} \mathbf{C}^\ell \mathbf{E}_{T+h-\ell}, \tag{S.3}$$

and

$$\mathbf{y}_{T+h} = \boldsymbol{\mathcal{F}} \mathbf{Y}_{T+h}, \tag{S.4}$$

where

$$\boldsymbol{\mathcal{F}} = \begin{pmatrix} \mathbf{I}_{k+m_d} & \mathbf{0}_{k+m_d \times k+m_d} & \mathbf{0}_{k+m_d \times k+m_d} \end{pmatrix}. \tag{S.5}$$

Conditional on the initial values, $\mathbf{Y}_T$, the point forecasts μ_h equivalently to (S.1) are given by

$$\mu_h = \boldsymbol{\mathcal{F}} \mathbf{C}^h \mathbf{Y}_T + \textstyle\sum_{\ell=0}^{h-1} \boldsymbol{\mathcal{F}} \mathbf{C}^\ell \mathbf{D}_{T+h-\ell}. \tag{S.6}$$

S.3.2 Conditional forecasts

Under joint normality of the GVAR shocks we have that $\mathbf{y}_{T+h}\left|\mathcal{L}_T\right.$ is normally distributed

$$\mathbf{y}_{T+h}\left|\mathcal{L}_T\right. \sim N(\mu_h, \boldsymbol{\Omega}_{hh}),$$

where $\mu_h = E\left(\mathbf{y}_{T+h}\left|\mathcal{L}_T\right.\right)$ and $\boldsymbol{\Omega}_{hh}$ is given by

$$\boldsymbol{\Omega}_{hh} = \boldsymbol{\mathcal{F}}\sum_{\ell=0}^{h-1}\mathbf{C}^{\ell}\boldsymbol{\Sigma}\mathbf{C}'^{\ell}\boldsymbol{\mathcal{F}}', \tag{S.7}$$

with

$$\boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\Sigma}_{\varepsilon} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix}, \tag{S.8}$$

and $\boldsymbol{\Sigma}_{\varepsilon}{=}Cov(\varepsilon_{T+h-i})$, and $\mathbf{C}$ and $\boldsymbol{\mathcal{F}}$ are given by (S.2) and (S.5), respectively. The covariance of ε_t can be estimated using the residuals of (8) as $\hat{\boldsymbol{\Sigma}}_{\varepsilon} = \frac{1}{T}\hat{\varepsilon}_t\hat{\varepsilon}_t'$.

Furthermore we have

$$\mathbf{y}_{T+h} = \mu_h + \xi_{T+h}, \tag{S.9}$$

where

$$\xi_{T+h} = \textstyle\sum_{\ell=0}^{h-1}\boldsymbol{\mathcal{F}}\mathbf{C}^{\ell}\mathbf{E}_{T+h-\ell},$$

with $\xi_{T+h}\left|\mathcal{L}_T\right.$ normally distributed as $N(\mathbf{0}, \boldsymbol{\Omega}_{hh})$, and $\mathbf{E}_{T+h-\ell}$ is defined by (S.2).

From (9) and (S.9) it follows that

$$\mathbf{S}\xi_{T+j} = \mathbf{g}_{T+j} - \mathbf{S}\mu_j \text{ for } j = 1, 2, ..., H, \tag{S.10}$$

and setting $\mathbf{q}_{T+j} = \mathbf{g}_{T+j} - \mathbf{S}\mu_j\ \forall j$, (S.10) can be written as

$$(\mathbf{I}_H{\otimes}\mathbf{S})\xi_H{=}\ \mathbf{q}_H,$$

where $\xi_H{=}\ (\xi_{T+1}', \xi_{T+2}', ..., \xi_{T+H}')'$ and $\mathbf{q}_H{=}\ (\mathbf{q}_{T+1}', \mathbf{q}_{T+2}', ..., \mathbf{q}_{T+H}')'$.

Under joint normality of the shocks and surpressing the dependence of ξ_{T+h} on H we have

$$\begin{aligned} &E\left(\xi_{T+h}\left|\mathcal{L}_T, \mathbf{S}\mathbf{y}_{T+j} = \mathbf{g}_{T+j},\ j = 1, ..., H\right.\right) \\ &= E\left(\xi_{T+h}\left|\mathcal{L}_T, (\mathbf{I}_H{\otimes}\mathbf{S})\xi_H{=}\ \mathbf{q}_H\right.\right) \\ &= (\mathfrak{s}_{hH}'{\otimes}\mathbf{I}_{k+m_d})\boldsymbol{\Omega}_H(\mathbf{I}_H{\otimes}\mathbf{S}')[(\mathbf{I}_H{\otimes}\mathbf{S})\boldsymbol{\Omega}_H(\mathbf{I}_H{\otimes}\mathbf{S}')]^{-1}\mathbf{q}_H, \end{aligned}$$

where $\mathfrak{s}_{hH}$ is a $H \times 1$ selection vector with unity as its h^{th} element and zeros elsewhere, and $\boldsymbol{\Omega}_H$ is the $kH \times kH$ matrix

$$\boldsymbol{\Omega}_H = \begin{pmatrix} \boldsymbol{\Omega}_{11} & \boldsymbol{\Omega}_{12} & \cdots & \boldsymbol{\Omega}_{1H} \\ \boldsymbol{\Omega}_{21} & \boldsymbol{\Omega}_{22} & \cdots & \boldsymbol{\Omega}_{2H} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{\Omega}_{H1} & \boldsymbol{\Omega}_{H2} & \cdots & \boldsymbol{\Omega}_{HH} \end{pmatrix}. \tag{S.11}$$

The diagonal elements of $\boldsymbol{\Omega}_H$, that is $\{\boldsymbol{\Omega}_{ii}\}_{i=1}^{H}$, are given by (S.7), while the off-diagonal elements can be expressed as

$$\boldsymbol{\Omega}_{ij} = \begin{cases} \boldsymbol{\mathcal{F}}(\sum_{\ell=0}^{i-1}\mathbf{C}^{\ell}\boldsymbol{\Sigma}\mathbf{C}'^{\ell})\mathbf{C}'^{(j-i)}\boldsymbol{\mathcal{F}}', & i < j \\ \boldsymbol{\mathcal{F}}\mathbf{C}^{(i-j)}(\sum_{\ell=0}^{j-1}\mathbf{C}^{\ell}\boldsymbol{\Sigma}\mathbf{C}'^{\ell})\boldsymbol{\mathcal{F}}', & i > j \end{cases}$$

where $\boldsymbol{\Sigma}$ is defined by (S.8).

Hence, the conditional point forecasts are given by

$$\mu_h^* = \mu_h + (\mathfrak{s}_{hH}'{\otimes}\mathbf{I}_{k+m_d})\boldsymbol{\Omega}_H(\mathbf{I}_H{\otimes}\mathbf{S}')[(\mathbf{I}_H{\otimes}\mathbf{S})\boldsymbol{\Omega}_H(\mathbf{I}_H{\otimes}\mathbf{S}')]^{-1}\mathbf{q}_H.$$

S.3.3 Probability distribution of the difference between conditional and unconditional forecasts

Let $\mathbf{y}_{T+h}^*$ be the values of $\mathbf{y}_{T+h}$ conditional on a given GDP growth path scenario given by

$$\mathbf{y}_{T+h}^* = \mu_h + \xi_{T+h}^*,\ h = 1, 2, ..., H,$$

where μ_h is given by (S.1) and ξ_{T+h}^* is the random variable defined by the probability distribution of ξ_{T+h} conditional on $(\mathbf{I}_H{\otimes}\mathbf{S})\xi_H{=}\ \mathbf{q}_H$, that is

$$\xi_{T+h}^* = \textstyle\sum_{\ell=0}^{h-1}\boldsymbol{\mathcal{F}}\mathbf{C}^{\ell}\mathbf{E}_{T+h-\ell}\left|\ (\mathbf{I}_H{\otimes}\mathbf{S})\xi_H{=}\ \mathbf{q}_H\right.. \tag{S.12}$$

The difference between $\mathbf{y}_{T+h}^*$ and $\mathbf{y}_{T+h}$ is given by

$$\delta_{T+h} = \mathbf{y}_{T+h}^* - \mathbf{y}_{T+h} = \xi_{T+h}^* - \xi_{T+h}.$$

The mean difference is

$$E\left(\delta_{T+h}\left|\mathcal{L}_T\right.\right) = \mu_h^* - \mu_h.$$

The variance $\mathbf{V}\left(\delta_{T+h} \mid \mathcal{L}_T\right)$ is given by

$$\mathbf{V}\left(\delta_{T+h} \mid \mathcal{L}_T\right) = \mathbf{V}\left(\xi^*_{T+h} \mid \mathcal{L}_T\right) + \mathbf{V}\left(\xi_{T+h} \mid \mathcal{L}_T\right) - Cov\left(\xi^*_{T+h}, \xi_{T+h} \mid \mathcal{L}_T\right) - Cov\left(\xi_{T+h}, \xi^*_{T+h} \mid \mathcal{L}_T\right) \tag{S.13}$$

where[19]

$$\mathbf{V}\left(\xi^*_{T+h} \mid \mathcal{L}_T\right) = \mathbf{\Omega}^*_{hh} \tag{S.14}$$

with

$$\mathbf{\Omega}^*_{hh} = \mathbf{\Omega}_{hh} - (\mathfrak{s}'_{hH} \otimes \mathbf{I}_{k+m_d})\mathbf{\Omega}_H(\mathbf{I}_H \otimes \mathbf{S}')[(\mathbf{I}_H \otimes \mathbf{S})\mathbf{\Omega}_H(\mathbf{I}_H \otimes \mathbf{S}')]^{-1}(\mathbf{I}_H \otimes \mathbf{S})\mathbf{\Omega}_H(\mathfrak{s}_{hH} \otimes \mathbf{I}_{k+m_d}). \tag{S.15}$$

To obtain $Cov\left(\xi^*_{T+h}, \xi_{T+h} \mid \mathcal{L}_T\right)$, recall that conditional on $\mathcal{L}_T$ the $(k+m_d) \times 1$ random vector ξ^*_{T+h} defined by (S.12) is dependently distributed with mean μ^*_h and variance $\mathbf{V}\left(\xi^*_{T+h} \mid \mathcal{L}_T\right) = \mathbf{\Omega}^*_{hh}$. Let $\mathbf{S}'_H = \mathbf{\Omega}_H^{1/2}(\mathbf{I}_H \otimes \mathbf{S}')$ and note that (S.15) can alternatively be expressed as

$$\mathbf{\Omega}_{hh} - \mathbf{\Omega}^*_{hh} = (\mathfrak{s}'_{hH} \otimes \mathbf{I}_{k+m_d})\mathbf{\Omega}_H^{1/2}\mathbf{P}_H^{1/2}\mathbf{\Omega}_H^{1/2}(\mathfrak{s}_{hH} \otimes \mathbf{I}_{k+m_d}),$$

where $\mathbf{P}_H = \mathbf{S}'_H \left(\mathbf{S}_H \mathbf{S}'_H\right)^{-1} \mathbf{S}_H$ is a projection matrix which is symmetric, idempotent and positive semi-definite. Hence, $\mathbf{\Omega}_{hh} - \mathbf{\Omega}^*_{hh}$ is a positive semi-definite matrix.

Under the assumption that[20]

$$Cov\left(\xi_{T+h}, \xi^*_{T+h} \mid \mathcal{L}_T\right) = \mathbf{V}\left(\xi^*_{T+h} \mid \mathcal{L}_T\right), \tag{S.16}$$

using this result in (S.13) the variance of δ_{T+h} is derived as

$$\mathbf{V}\left(\delta_{T+h} \mid \mathcal{L}_T\right) = \mathbf{\Omega}_{hh} - \mathbf{\Omega}^*_{hh} \geq 0$$

which is a positive semi-definite matrix. Hence,

$$\delta_{T+h} \mid \mathcal{L}_T \sim N(\mu^*_h - \mu_h,\ \mathbf{\Omega}_{hh} - \mathbf{\Omega}^*_{hh}). \tag{S.17}$$

[19] The dependence of $\mathbf{\Omega}^*_{hh}$ on H is supressed.here.

[20] For a similar assumption and related argument see Pesaran et al. (2007).

Table S5. Average superior predictive ability (SPA) test results, comparison of conditional forecasts upon actual GDP and IMF projection GDP

		H_{A1}: CF_{Actual} better than CF_{IMF}			H_{A2}: CF_{IMF} better than CF_{Actual}		
country	consumption	SPA	p-value	pvalue<5%	SPA	p-value	pvalue<5%
Algentina	coal	7.157	0.031	1	-7.157	0.971	0
Algentina	gas	1.290	0.199	0	-1.290	0.788	0
Algentina	oil	3.446	0.026	1	-3.446	0.982	0
Australia	coal	2.000	0.121	0	-2.000	0.889	0
Australia	gas	0.911	0.217	0	-0.911	0.766	0
Australia	oil	2.027	0.040	1	-2.027	0.971	0
Austria	coal	9.520	0.016	1	-9.520	0.987	0
Austria	gas	-0.249	0.569	0	0.249	0.386	0
Austria	oil	2.725	0.151	0	-2.725	0.854	0
Belgium	coal	2.063	0.130	0	-2.063	0.867	0
Belgium	gas	7.577	0.000	1	-7.577	1.000	0
Belgium	oil	2.624	0.051	0	-2.624	0.957	0
Brazil	coal	2.910	0.098	0	-2.910	0.930	0
Brazil	gas	2.538	0.085	0	-2.538	0.911	0
Brazil	oil	8.230	0.008	1	-8.230	0.994	0
Canada	coal	2.436	0.097	0	-2.436	0.882	0
Canada	gas	2.704	0.062	0	-2.704	0.942	0
Canada	oil	1.303	0.137	0	-1.303	0.864	0
China	coal	2.186	0.114	0	-2.186	0.869	0
China	gas	2.897	0.102	0	-2.897	0.906	0
China	oil	10.975	0.025	1	-10.975	0.963	0
Chile	coal	0.885	0.289	0	-0.885	0.712	0
Chile	gas	7.115	0.029	1	-7.115	0.969	0
Chile	oil	1.515	0.063	0	-1.515	0.917	0
Finland	coal	0.432	0.372	0	-0.432	0.593	0
Finland	gas	4.731	0.109	0	-4.731	0.903	0
Finland	oil	1.892	0.171	0	-1.892	0.842	0
France	coal	-1.568	0.821	0	1.568	0.190	0
France	gas	1.350	0.147	0	-1.350	0.828	0
France	oil	0.821	0.240	0	-0.821	0.741	0
Germany	coal	-1.777	0.875	0	1.777	0.134	0
Germany	gas	2.934	0.000	1	-2.934	1.000	0
Germany	oil	1.219	0.171	0	-1.219	0.846	0
India	coal	2.804	0.104	0	-2.804	0.897	0
India	gas	-0.380	0.616	0	0.380	0.384	0
India	oil	4.033	0.011	1	-4.033	0.980	0
Indonasia	coal	18.980	0.000	1	-18.980	1.000	0
Indonasia	gas	3.724	0.075	0	-3.724	0.916	0
Indonasia	oil	0.114	0.469	0	-0.114	0.586	0

(Table S5 continued)

country	consumption	HA1: CF_{Actual} better than CF_{IMF}			HA2: CF_{IMF} better than CF_{Actual}		
		SPA	p-value	pvalue<5%	SPA	p-value	pvalue<5%
Italy	coal	1.324	0.198	0	-1.324	0.790	0
Italy	gas	4.075	0.147	0	-4.075	0.845	0
Italy	oil	3.444	0.003	1	-3.444	0.998	0
Japan	coal	6.114	0.019	1	-6.114	0.987	0
Japan	gas	3.360	0.138	0	-3.360	0.846	0
Japan	oil	10.374	0.003	1	-10.374	0.996	0
South Korea	coal	2.843	0.087	0	-2.843	0.904	0
South Korea	oil	-0.163	0.544	0	0.163	0.445	0
Malaysia	coal	2.374	0.135	0	-2.374	0.878	0
Malaysia	gas	4.195	0.092	0	-4.195	0.934	0
Malaysia	oil	1.980	0.112	0	-1.980	0.907	0
Mexico	coal	3.798	0.095	0	-3.798	0.923	0
Mexico	gas	3.752	0.061	0	-3.752	0.941	0
Mexico	oil	1.389	0.145	0	-1.389	0.849	0
Netherland	coal	3.627	0.158	0	-3.627	0.826	0
Netherland	gas	0.015	0.486	0	-0.015	0.515	0
Netherland	oil	5.125	0.069	0	-5.125	0.922	0
Norway	coal	2.374	0.084	0	-2.374	0.894	0
Norway	gas	2.943	0.000	1	-2.943	1.000	0
Norway	oil	1.677	0.037	1	-1.677	0.956	0
Newzealand	coal	2.810	0.104	0	-2.810	0.895	0
Newzealand	gas	2.367	0.120	0	-2.367	0.894	0
Newzealand	oil	4.329	0.038	1	-4.329	0.970	0
Phllipines	coal	2.707	0.136	0	-2.707	0.878	0
Phllipines	oil	18.738	0.010	1	-18.738	0.990	0
South Africa	coal	1.001	0.234	0	-1.001	0.774	0
South Africa	oil	11.877	0.000	1	-11.877	1.000	0
Saudi Arabia	gas	-0.704	0.683	0	0.704	0.326	0
Saudi Arabia	oil	-3.185	0.916	0	3.185	0.078	0
Singapore	gas	0.462	0.266	0	-0.462	0.729	0
Singapore	oil	2.935	0.137	0	-2.935	0.863	0
Spain	coal	2.051	0.057	0	-2.051	0.931	0
Spain	gas	2.327	0.142	0	-2.327	0.857	0
Spain	oil	1.422	0.232	0	-1.422	0.791	0
Sweden	coal	0.999	0.262	0	-0.999	0.743	0
Sweden	oil	3.385	0.012	1	-3.385	0.985	0
Switzerland	coal	5.810	0.106	0	-5.810	0.903	0
Switzerland	gas	4.597	0.077	0	-4.597	0.923	0
Switzerland	oil	0.299	0.333	0	-0.299	0.673	0
Thailand	coal	1.865	0.191	0	-1.865	0.802	0
Thailand	gas	2.079	0.131	0	-2.079	0.883	0
Thailand	oil	2.170	0.130	0	-2.170	0.851	0
Turkey	coal	3.058	0.117	0	-3.058	0.893	0
Turkey	oil	16.927	0.003	1	-16.927	0.998	0
UK	coal	2.756	0.076	0	-2.756	0.929	0
UK	gas	2.107	0.085	0	-2.107	0.923	0
UK	oil	8.566	0.015	1	-8.566	0.985	0
USA	coal	0.427	0.377	0	-0.427	0.624	0
USA	gas	2.329	0.074	0	-2.329	0.914	0
USA	oil	6.746	0.000	1	-6.746	1.000	0

Table S6. Average superior predictive ability (SPA) test results, comparison of unconditional forecasts of naïve country VAR and GVAR

		H_{A1}: CF_{Actual} better than CF_{IMF}			H_{A2}: CF_{IMF} better than CF_{Actual}		
country	consumption	SPA	p-value	pvalue<5%	SPA	p-value	pvalue<5%
Algentina	coal	7.157	0.031	1	-7.157	0.971	0
Algentina	gas	1.290	0.199	0	-1.290	0.788	0
Algentina	oil	3.446	0.026	1	-3.446	0.982	0
Australia	coal	2.000	0.121	0	-2.000	0.889	0
Australia	gas	0.911	0.217	0	-0.911	0.766	0
Australia	oil	2.027	0.040	1	-2.027	0.971	0
Austria	coal	9.520	0.016	1	-9.520	0.987	0
Austria	gas	-0.249	0.569	0	0.249	0.386	0
Austria	oil	2.725	0.151	0	-2.725	0.854	0
Belgium	coal	2.063	0.130	0	-2.063	0.867	0
Belgium	gas	7.577	0.000	1	-7.577	1.000	0
Belgium	oil	2.624	0.051	0	-2.624	0.957	0
Brazil	coal	2.910	0.098	0	-2.910	0.930	0
Brazil	gas	2.538	0.085	0	-2.538	0.911	0
Brazil	oil	8.230	0.008	1	-8.230	0.994	0
Canada	coal	2.436	0.097	0	-2.436	0.882	0
Canada	gas	2.704	0.062	0	-2.704	0.942	0
Canada	oil	1.303	0.137	0	-1.303	0.864	0
China	coal	2.186	0.114	0	-2.186	0.869	0
China	gas	2.897	0.102	0	-2.897	0.906	0
China	oil	10.975	0.025	1	-10.975	0.963	0
Chile	coal	0.885	0.289	0	-0.885	0.712	0
Chile	gas	7.115	0.029	1	-7.115	0.969	0
Chile	oil	1.515	0.063	0	-1.515	0.917	0
Finland	coal	0.432	0.372	0	-0.432	0.593	0
Finland	gas	4.731	0.109	0	-4.731	0.903	0
Finland	oil	1.892	0.171	0	-1.892	0.842	0
France	coal	-1.568	0.821	0	1.568	0.190	0
France	gas	1.350	0.147	0	-1.350	0.828	0
France	oil	0.821	0.240	0	-0.821	0.741	0
Germany	coal	-1.777	0.875	0	1.777	0.134	0
Germany	gas	2.934	0.000	1	-2.934	1.000	0
Germany	oil	1.219	0.171	0	-1.219	0.846	0
India	coal	2.804	0.104	0	-2.804	0.897	0
India	gas	-0.380	0.616	0	0.380	0.384	0
India	oil	4.033	0.011	1	-4.033	0.980	0
Indonasia	coal	18.980	0.000	1	-18.980	1.000	0
Indonasia	gas	3.724	0.075	0	-3.724	0.916	0
Indonasia	oil	0.114	0.469	0	-0.114	0.586	0

(Table S6 continued)

		H_{A1}: CF_{Actual} better than CF_{IMF}			H_{A2}: CF_{IMF} better than CF_{Actual}		
country	consumption	SPA	p-value	pvalue<5%	SPA	p-value	pvalue<5%
Italy	coal	1.324	0.198	0	-1.324	0.790	0
Italy	gas	4.075	0.147	0	-4.075	0.845	0
Italy	oil	3.444	0.003	1	-3.444	0.998	0
Japan	coal	6.114	0.019	1	-6.114	0.987	0
Japan	gas	3.360	0.138	0	-3.360	0.846	0
Japan	oil	10.374	0.003	1	-10.374	0.996	0
South Korea	coal	2.843	0.087	0	-2.843	0.904	0
South Korea	oil	-0.163	0.544	0	0.163	0.445	0
Malaysia	coal	2.374	0.135	0	-2.374	0.878	0
Malaysia	gas	4.195	0.092	0	-4.195	0.934	0
Malaysia	oil	1.980	0.112	0	-1.980	0.907	0
Mexico	coal	3.798	0.095	0	-3.798	0.923	0
Mexico	gas	3.752	0.061	0	-3.752	0.941	0
Mexico	oil	1.389	0.145	0	-1.389	0.849	0
Netherland	coal	3.627	0.158	0	-3.627	0.826	0
Netherland	gas	0.015	0.486	0	-0.015	0.515	0
Netherland	oil	5.125	0.069	0	-5.125	0.922	0
Norway	coal	2.374	0.084	0	-2.374	0.894	0
Norway	gas	2.943	0.000	1	-2.943	1.000	0
Norway	oil	1.677	0.037	1	-1.677	0.956	0
Newzealand	coal	2.810	0.104	0	-2.810	0.895	0
Newzealand	gas	2.367	0.120	0	-2.367	0.894	0
Newzealand	oil	4.329	0.038	1	-4.329	0.970	0
Phllipines	coal	2.707	0.136	0	-2.707	0.878	0
Phllipines	oil	18.738	0.010	1	-18.738	0.990	0
South Africa	coal	1.001	0.234	0	-1.001	0.774	0
South Africa	oil	11.877	0.000	1	-11.877	1.000	0
Saudi Arabia	gas	-0.704	0.683	0	0.704	0.326	0
Saudi Arabia	oil	-3.185	0.916	0	3.185	0.078	0
Singapore	gas	0.462	0.266	0	-0.462	0.729	0
Singapore	oil	2.935	0.137	0	-2.935	0.863	0
Spain	coal	2.051	0.057	0	-2.051	0.931	0
Spain	gas	2.327	0.142	0	-2.327	0.857	0
Spain	oil	1.422	0.232	0	-1.422	0.791	0
Sweden	coal	0.999	0.262	0	-0.999	0.743	0
Sweden	oil	3.385	0.012	1	-3.385	0.985	0
Switzerland	coal	5.810	0.106	0	-5.810	0.903	0
Switzerland	gas	4.597	0.077	0	-4.597	0.923	0
Switzerland	oil	0.299	0.333	0	-0.299	0.673	0
Thailand	coal	1.865	0.191	0	-1.865	0.802	0
Thailand	gas	2.079	0.131	0	-2.079	0.883	0
Thailand	oil	2.170	0.130	0	-2.170	0.851	0
Turkey	coal	3.058	0.117	0	-3.058	0.893	0
Turkey	oil	16.927	0.003	1	-16.927	0.998	0
UK	coal	2.756	0.076	0	-2.756	0.929	0
UK	gas	2.107	0.085	0	-2.107	0.923	0
UK	oil	8.566	0.015	1	-8.566	0.985	0
USA	coal	0.427	0.377	0	-0.427	0.624	0
USA	gas	2.329	0.074	0	-2.329	0.914	0
USA	oil	6.746	0.000	1	-6.746	1.000	0

Reference

Pesaran, M.H., Smith, L.V., Smith, R.P. (2007). What if the UK or Sweden had joined the Euro in 1999? An empirical evaluation using a global VAR. *International Journal of Finance and Economics*, 12, 55-87.