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Summary

The decoupling of energy-related carbon emissions from economic growth has been mostly driven by reductions of the energy intensity of GDP, which can be attributed either to changes in countries' economic structure or within-sector energy-efficiency improvements. One question is whether observed reductions in energy intensity may stem from shifts to less energy-intensive sectors without equivalent changes in consumption patterns, raising uncertainty on their true impact on global decarbonization. This paper aims to empirically investigate this mechanism in a panel of 15 OECD countries. First, using an Index Decomposition Analysis (IDA) including an offshoring factor, we show that structural changes in the production side have generally been unmatched with similar changes in consumption patterns. We then proxy a "demand-invariant structural change" in a Bayesian Structural Panel VAR model, by exploiting a novel measure given by the divergence between consumption-based and production-based carbon emissions. We find that shocks in this divergence measure are efficiently associated with demand-invariant structural changes and persistently and significantly reduce national energy intensity. Taken together, our results support the thought that caution should be taken when using production-based indicators to assess a country's contribution to global carbon mitigation.

Keywords: Energy intensity; Emissions accounting; Offshoring; IDA analysis; Structural VAR; Panel data

JEL classification: C22, C33, F18, Q43, Q56

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Energy Intensity and Structural Changes: Does Offshoring Matter?*

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Abstract

The decoupling of energy-related carbon emissions from economic growth has been mostly driven by reductions of the energy intensity of GDP, which can be attributed either to changes in countries' economic structure or within-sector energy-efficiency improvements. One question is whether observed reductions in energy intensity may stem from shifts to less energy-intensive sectors without equivalent changes in consumption patterns, raising uncertainty on their true impact on global decarbonization. This paper aims to empirically investigate this mechanism in a panel of 15 OECD countries. First, using an Index Decomposition Analysis (IDA) including an offshoring factor, we show that structural changes in the production side have generally been unmatched with similar changes in consumption patterns. We then proxy a "demand-invariant structural change" in a Bayesian Structural Panel VAR model, by exploiting a novel measure given by the divergence between consumption-based and production-based carbon emissions. We find that shocks in this divergence measure are efficiently associated with demand-invariant structural changes and persistently and significantly reduce national energy intensity. Taken together, our results support the thought that caution should be taken when using production-based indicators to assess a country's contribution to global carbon mitigation.

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1 Introduction

Over the past decades, world energy–related carbon emissions[1] have steadily increased, albeit at a lower rate than global GDP.[2] To date, the decoupling between emissions and economic activity has been mostly driven by reductions in the energy intensity of GDP. In some economies, for instance in the European Union and the United States, the reduction of the energy intensity, leveraged by a slight decarbonization of the fuel mix, has allowed to achieve an absolute decoupling. Conversely, in emerging economies, notably in China and India, the reduction in energy intensity has proven largely insufficient to offset the impacts of sustained economic growth.

Generally speaking, reductions in energy intensity can be traced either to changes in the economic landscape, namely to structural shifts towards less energy-intensive activities (*structural effect*) or to within-sector technological improvements driving down the amount of energy used per unit of economic output (*sectoral effect*) (Metcalf, 2008; Voigt et al., 2014; Hardt et al., 2018). Although both processes bring down the national energy intensity, the consequences in terms of global emissions may vary depending on whether structural changes are mirrored by equivalent changes in domestic consumption patterns. If that does not occur, a reduction in the amount of energy used per unit of GDP may simply hide an increased offshoring of energy-intensive activities (Bhattacharya et al., 2020), without substantial benefits in terms of carbon emission mitigation (Fan et al., 2021).

The main objective of this paper is to investigate the effects of "demand-invariant structural changes" (i.e., changes in the production landscape that are not mirrored by equivalent changes in the sectoral composition of final demand) on the evolution of energy intensity in a sample of 15 OECD countries. In this sense, we intend to shed some light on the actual contribution of energy efficiency gains exhibited by developed countries on global decarbonization.[3]

Our empirical strategy is twofold. We first develop an Index Decomposition Analysis (IDA) of the change in energy intensity of GDP by including an offshoring factor among the structural change determinants. Afterwards, we estimate a Bayesian Structural Panel VAR model where we proxy demand-invariant structural changes with a shock in a novel measure given by a divergence measure between consumption-based and production-based carbon emissions. The demand-invariant nature of the shock is imposed, in the structural VAR, in a recursive identification strategy which assumes that the shock evaluated cannot affects the domestic demand on impact.

[1] Throughout the paper, "carbon emissions" will be used to refer to Kyoto greenhouse gases expressed in CO_2 equivalents, namely CO_2, CH_4, NO_2 and fugitive emissions (i.e., f-gases).

[2] Between 1990 (the baseline year of the Kyoto Protocol) and 2020, global emissions have increased by 127%, while global real GDP has increased by around 255% (IEA, 2023; UN Statistics Division, 2023). Temporary drops in global emissions have been detected only in 2009, during the Great Recession, and in 2020, during the Covid-19 outbreak.

[3] Here and in the following, we often refer to energy intensity reductions as energy efficiency gains or improvements. The two expressions are used as equivalent and the concept of energy efficiency should always be interpreted from a macroeconomic perspective.

The IDA results provide supporting evidence, in all the OECD countries in our sample, for structural changes that have not been historically mirrored by equivalent changes in domestic demand composition, mainly due to the role played by offshoring. Accordingly, the Panel VAR's structural impulse response functions (IRFs) suggest that shocks in the carbon emission divergence measure are associated with structural changes persistently affecting the evolution of energy intensity. Sub-sample estimations allow us to gain further interpretations of the results. Specifically, we find that the observed reduction in energy intensity is higher or more persistent in countries where structural changes have historically played an important role in dowsizing the national energy intensity, and in countries that rank higher in the Climate Change Performance Index's greenhouse gas (GHG) factor. In essence, our findings support the thought that economies displaying a better outlook in terms of production-based emissions are not necessarily contributing to global carbon emission mitigation.

Previous works have disentangled the role of structural and sectoral effects on the observed variations of energy intensity through IDAs (see, e.g., Metcalf, 2008; Voigt et al., 2014; Hardt et al., 2018). Relatedly, other papers have investigated the role of international trade by analyzing the divergence between production-based and consumption-based emissions under different settings (Liu et al., 2016; Cohen et al., 2018; Bhattacharya et al., 2020). To the best of our knowledge, this paper is the first empirical attempt to isolate in a multivariate econometric framework the impact of demand-invariant structural shocks on energy intensity at a country level. As a further novelty, our work firstly identifies structural changes through the exploitation of a divergence measure between consumption-based and production-based emissions.

The remainder is organized as follows. Section 2 summarizes the reference literature. Section 3 describes the adaptation of IDA used for the analysis of the historical evolution of national energy intensities. Section 4 delves into the multivariate macroeconometric framework developed for the dynamic analysis, by describing the Bayesian Panel VAR model and the identification strategy, as well as the structural IRFs results together with robustness checks. Section 5 concludes.

2 Related literature

The paper contributes to different strands of the literature with heterogeneous emphasis, regarding both our main objective and the empirical methodologies employed.

First, we join the literature that tries to qualify and quantify the drivers of the national and sectoral energy intensity. Several studies, using decomposition techniques, have analysed China's energy intensity, in order to investigate the role of structural changes in explaining the observed decline, as well as the role of inter-fuel substitution and energy efficiency (Zhang, 2003; Fisher-Vanden et al., 2004; Ma and Stern, 2008; Zhao et al., 2010; Wu, 2012). Similar analyses have been conducted for the United States, showing that, from the first oil crisis to the Great Recession, within-industry efficiency improvements contributed mostly to the experienced energy intensity reduction, and that, at the state level, per-capita income and energy prices were also significant drivers (Sue Wing, 2008; Metcalf, 2008). At the European level, Alcántara and Duarte (2004) using an input-output decomposition, showed that energy intensity heterogeneity among countries is mainly affected by sectoral changes and demand-side effects, rather than by structural changes. More recently, Voigt et al. (2014) analyzed the trend of energy intensity in 40 countries and performed a IDA to disentangle structural and technological changes from 1995 to 2007. Their country-specific results attribute most of the energy intensity reduction to technological improvements. As for the decomposition analysis of structural changes only, Hardt et al. (2018) acknowledged that the majority of energy savings in the United Kingdom have been driven by the offshoring of energy-intensive activities. IDAs of energy intensity have not led to conclusive evidence on the role of structural and sectoral effects on energy intensity evolution, probably because they rely on different data, both in terms of time window and of geographical extent. Our contribution to the IDA literature mainly builds on previous works, but we take a step further by adapting the methodology of Hardt et al. (2018) to a new empirical framework. Still, IDAs merely describe the historical evolution of energy intensity and its main drivers. In this sense, they represent a propedeutic step to the core of our analysis.

As a matter of fact, the main novelty of our study lies in the use of a Structural Panel VAR model to assess the dynamic evolution of energy intensity changes. Indeed, many factors that affect the environment vary over time and are bidirectionally interconnected (e.g., changing economic conditions, geopolitical pressures, legislation, natural disasters, and technologies), and this is particularly relevant when evaluating the long-run consequences of GHG emissions concentration. In this model, we build an original instrument to isolate structural changes using the divergence in carbon emission computation methods. Hence, from a methodological viewpoint, the paper enriches the empirical literature which exploits structural VAR models for the dynamic analysis of energy variables and the economy. Ajmi et al. (2015) relied on a SVAR model to capture the time variation of the relationship between energy consumption, CO_2 emissions, and GDP. Fan et al. (2021) estimated a VAR to analyze the relationship between emissions, energy consumption, international trade, and economic activity in China. Mohapatra et al. (2016) exploit a panel VAR model to disentangle the time-varying scale, technique, and composition effects – that are basically different terminologies for the economic growth, sectoral and structural effects, respectively – for the provinces of Canada. Indeed, it is likely that the magnitude of these effects is time-varying and that their relative weights can significantly affect the inferences on the nature of the observed effects of economic growth on the environment. Moreover, Jaunky (2011) uses a vector error correction mechanism (VECM) within a VAR framework to compare long-run and short-run income elasticities of emissions. This approach allows him to overcome the issue of multicollinearity that has burdened the empirical literature on the economic growth and environment nexus.

We also share part of our policy implications with a topical literature focused on the comparison between consumption-based and production-based emissions, as well as on the investigation of the role of international trade on emissions. To this end, one of the main strands relies on general or partial equilibrium models to assess the difference between consumption-based and production-based emissions. Liu et al. (2016) analyze the effects of trade liberalization through the quasi-natural experiment of China's accession to the World Trade Organization (WTO). Their results indicate that accession produced an increase in emissions embodied in Chinese exports, suggesting that emerging economies, subject to less stringent environmental regulations, have been assigned an important role in production for the global economy. Supporting evidence has also been provided on the other spectrum of the trade relationship. Naegele and Zaklan (2019) and Aichele and Felbermayr (2015) studied the effects of two cornerstones of environmental regulation on trade, namely the EU ETS and the Kyoto Protocol. While no evidence of trade effects has been recorded for the former, the latter has displayed an increase in embodied carbon imports in those countries that ratified the Kyoto agreement.

As for the differences that may arise from the adoption of different emissions accounting methodologies, Cohen et al. (2018), by analyzing the decoupling elasticities between emissions and GDP per capita for the world's top emitters, found that in the most developed countries, the evidence for decoupling weakens when considering consumption-based instead of production-based emissions. Bhattacharya et al. (2020) found that there is a higher difficulty in arranging climate change multilateral agreements based on carbon intensity (i.e., the ratio of CO_2 emissions to GDP) similarities between countries in a business-as-usual emissions forecasting scenario. When comparing emissions' trends in developed and emerging economies, it is advisable to rely on relative indices, as pointed out by Bhattacharya et al. (2020). In this regard, the choice of energy intensity as the main variable of interest to the analysis is also motivated by the need to achieve greater comparison between countries.

3 Index Decomposition Analysis

In this section of the work, using an extension of the renowned Kaya identity, we perform an IDA to assess the contribution of each energy intensity's driving factor to its historical evolution in 15 OECD countries.[4] Further breakdowns of the Kaya identity allow us to isolate the determinants of structural effects, in a way that enables the analysis of offshoring and demand-related effects.

3.1 Methodological framework and data

The determinants of fuel combustion carbon emissions at time t of a given country i can be described by the Kaya identity (Kaya and Yokoburi, 1997) that, in its simplest form, reads as follows:

$$C_{it} = \frac{C_{it}}{E_{it}} \cdot \frac{E_{it}}{Y_{it}} \cdot \frac{Y_{it}}{P_{it}} \cdot P_{it}. \tag{1}$$

Equation (1) highlights the main potential drivers of emissions changes: the carbon intensity of energy ($\frac{C_{it}}{E_{it}}$), the energy intensity of GDP ($\frac{E_{it}}{Y_{it}}$), the GDP per capita ($\frac{Y_{it}}{P_{it}}$) and the level of population (P_{it}). In this sense, the dynamics of emissions can be interpreted as the result of the changes in the Kaya identity factors. Among these factors, both in developed and emerging economies, reductions of the energy intensity have played a primary role in the in the reduction of the carbon intensity of GDP between 1971 and 2019 (see Figure 1).

In the following, we then restrict our focus to changes in the energy intensity of GDP[5], which may either result from within-sector variations in energy intensity (*sectoral effect*) or from structural adjustment of the economy towards more or less energy-intensive sectors (*structural effect*):

$$e_t = \frac{E_t}{Y_t} = \sum_i \frac{E_{it}}{Y_{it}} \cdot \frac{Y_{it}}{Y_t}. \tag{2}$$

This level of aggregation in the decomposition will be henceforth referred to as the baseline decomposition. Within the structural effect, it is worth investigating, through further analysis, any potential mismatch between changes on the production side and changes in the consumption mix (Jaunky, 2011). For this purpose, the structural effect can be split into three elements (Hardt et al., 2018)[6]:

$$\frac{Y_{it}}{Y_t} = \sum_i \left(\frac{Y_{it}}{XG_{it}}\right)\left(\frac{XG_{it}}{X_t}\right)\left(\frac{X_t}{Y_t}\right), \tag{3}$$

[4] The sample includes: Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, United Kingdom and United States.

[5] In the IDA, for sectoral decomposition purposes, by energy intensity of GDP it is meant the ratio between final energy consumption of all economic sectors excluding transport, storage and communication and residential uses, and their respective value added. In the SVAR analysis that will follow, the energy intensity is computed for the overall economy as the ratio between total primary energy supply (TPES) and GDP.

[6] The main difference with respect to Hardt et al. (2018), is that they aggregate what we will refer to as sectoral demand and demand-to-output factors into a composite changed-need effect.

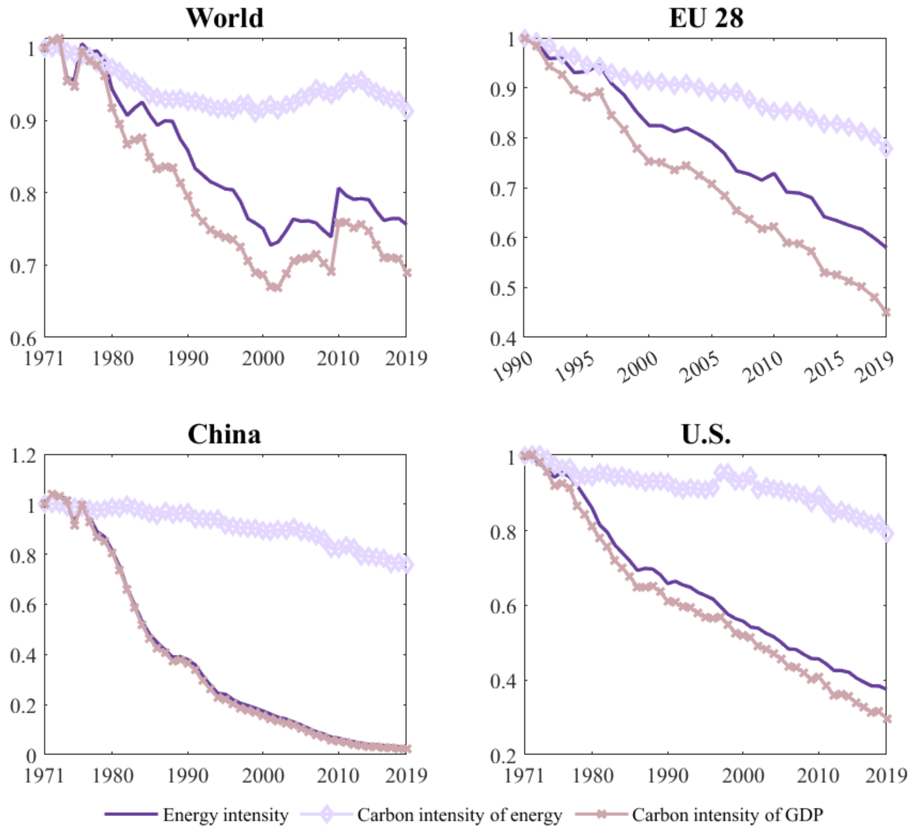

Figure 1 – Evolution of the carbon intensity of GDP and of its drivers: World, China, United States (1971 - 2019) and EU-28 countries (i.e., EU27 and the United Kingdom) (1990 - 2019). *Source*: authors' elaboration on IEA and UN data (2021).

where $\frac{Y_{it}}{XG_{it}}$ is an *offshoring factor*, given by the sectoral domestic output Y_{it} over the sectoral global output embodied in the domestic final demand XG_{it}, $\frac{XG_{it}}{X_t}$ is a *sectoral demand* factor, indicating the sectoral composition of global output embodied in domestic final demand, which can be interpreted as a structural change of consumption patterns in the reference economy, and $\frac{X_t}{Y_t}$ is the *demand to output* factor, defined as the ratio between total global output embodied in the reference economy's final demand and total domestic output, which can be interpreted as the ratio between a country's total demand and output.

To assess the role played by the above-mentioned driving factors, we use an Index Decomposition Analysis (IDA). In particular, we rely on the Fisher Ideal index methodology (Ang et al., 2004; Ang, 2015), which has the advantage of rendering perfect decomposition (i.e., without residuals) and of being suited to analyse the evolution of energy intensity and its drivers with respect to a base year.

For the IDA, we use data from the *IEA's World Energy Balances* to define the total final energy consumption, by country and by sector, while data from the *OECD Inter-Country Input-Output* (ICIO) Tables will be used for the definition of the global sectoral output embodied in domestic demand. The final demand by sectoral aggregates[7] is obtained from the final demands of households, non-profit institutions and governments, gross fixed capital formation, changes in inventories and valuables, and direct purchases abroad from residents. This level of analysis is country-specific, with a sample of 15 OECD economies that have experienced an appreciable reduction in national energy intensity over the past 50 years. The choice of developed economies that experienced a reduction in the national energy intensity is in line with the motivation of this work (i.e., to investigate further channels that can explain the achievement of energy efficiency improvements in developed economies). The time window for this analysis is 1995 to 2020, with 1995 chosen as the base year. This window is motivated both by data availability and the need for consistency between the two levels of decomposition, and by the fact that most of the impacts that are attributable to trade globalization are likely to be recorded after the beginning of the new millenium, with China entering the WTO in 2001.

3.2 IDA results

The baseline decomposition analysis shows that in the majority of countries the decline in the industrial energy intensity has been driven both by sectoral and structural changes (see Figure 2). Pushing the decomposition forwards allows us to break down the structural effect, in order to isolate the role of international trade. For this second layer of decomposition, we analyse the components of the evolution of the structural effect (see Figure 3).[8]

The resulting evidence roots for an important role played by offshoring. Indeed, on average in the past 25 years, offshoring has substantially contributed to the reduction in the industrial energy intensity in all the analysed countries with the exception of Germany, Finland, France and Japan. However, if the average contribution is computed after 2001 (i.e., after China's accession to WTO), offshoring determines structural changes that contribute to energy intensity reductions for all countries except for Japan. In other words, the domestic final demand for outputs of more energy-intensive sectors does not vary accordingly with domestic production. Indeed, the change in the demand to output ratio has increased the structural effect across countries, namely there has been an increase in overall domestic demand relative to domestic output. Finally, the sectoral composition of demand exerts an overall negative, although modest, contribution to the evolution of energy intensity across the time window of interest in all the sample economies with the exception of Japan. Putting these three factors together, what emerges is that, in the majority of the sample economies, there has been a shift in domestic final demand

[7]The sectors used for the decomposition are: "Agriculture, hunting, forestry, fishing", "Mining, Manufacturing, Utilities", "Construction", "Wholesale, retail trade, restaurants and hotels, and other activities".

[8]Following Ang (2015), some logarithmic transformations have been applied to obtain this graphical representation.

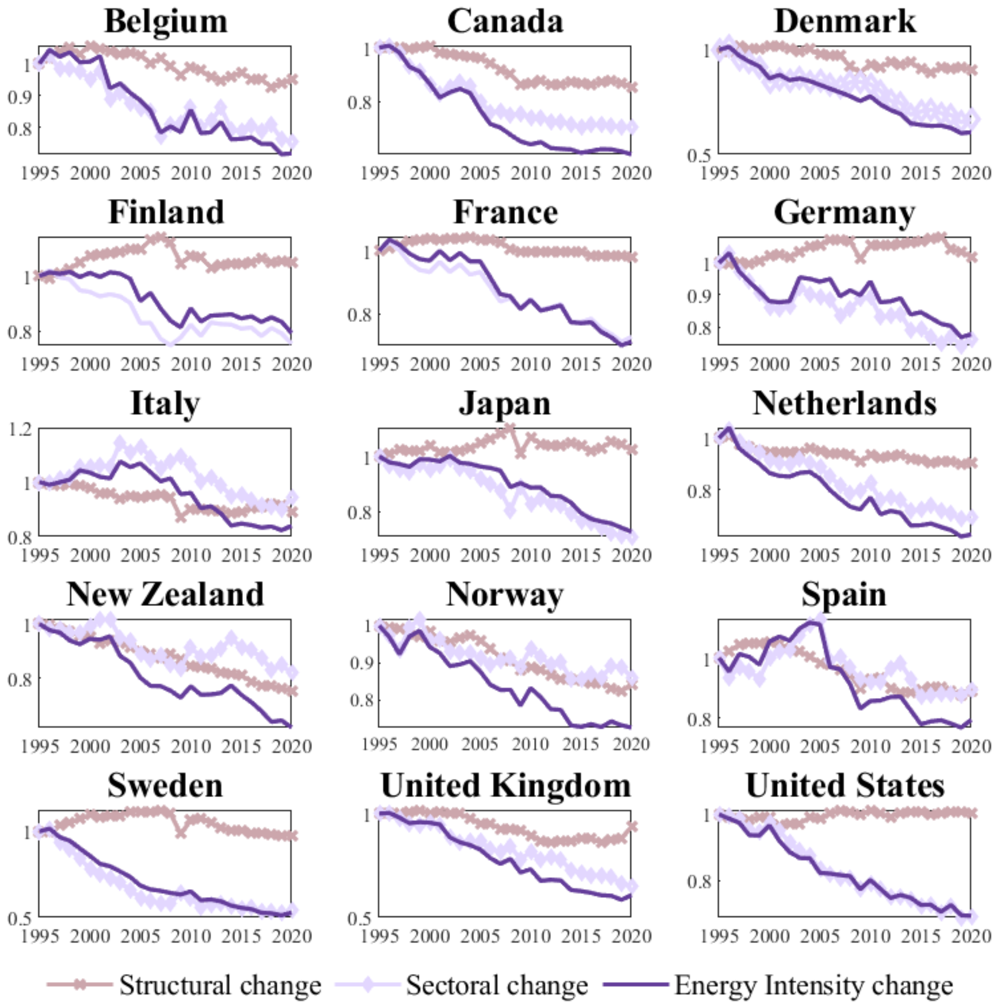

Figure 2 – Decomposition of the Change in Industrial Energy Intensity (1995 - 2020) for the full sample (reference year: 1995). *Source*: authors' elaboration on IEA and UN data (2021).

towards less energy-intensive productions. However, this has been coupled with an overall increase in domestic demand with respect to domestic production, both at the aggregate and at the sectoral level. To this extent, the overall shift in sectoral production (i.e. structural effect) is not exactly matched by that of the sectoral composition of final demand (i.e., sectoral demand). This evidence supports the existence of structural changes that are not mirrored by equivalent shifts in the composition of final demand. The role played by this type of shocks in the evolution of energy intensity is the main focus of our multivariate econometric analysis developed in Section 4. Although the IDA, by relying on an accounting identity, does not allow to draw causal conclusions, it seems to bring about sufficiently evocative evidence on the possible role that offshoring and structural changes that are not mirrored by demand may have played in the energy intensity reductions of

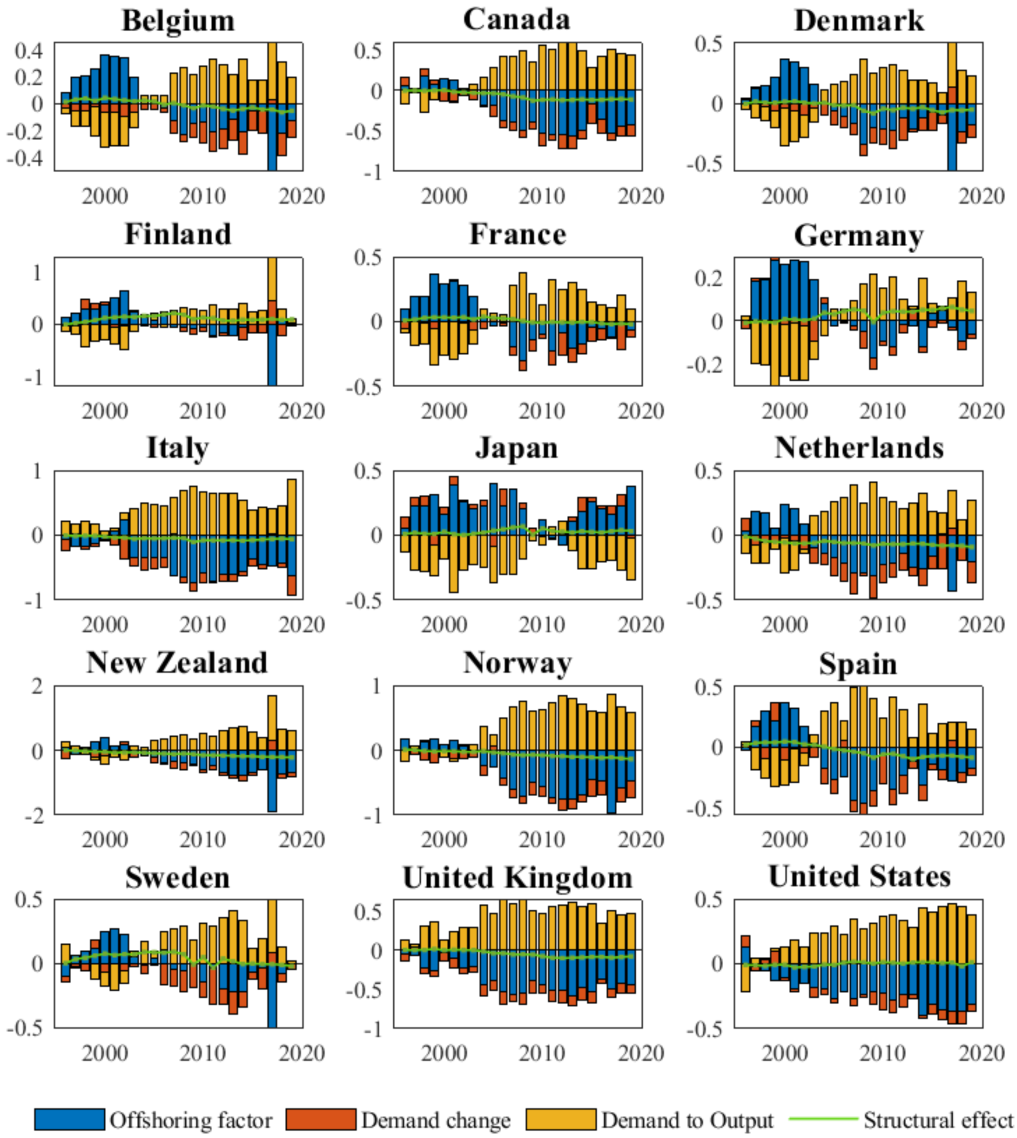

Figure 3 – Decomposition of the Structural Effect (1996 - 2019: reference year 1995), sample countries. *Source*: authors' elaboration on IEA, OECD ICIO and UN data (2021).

many developed economies. We dig deeper into the dynamic relationship between these factors by estimating a Structural Panel Vector Autoregression model, which enables a more comprehensive (and global) picture of the energy efficiency improvements that have been observed, at the country level, over the past 50 years.

4 Dynamic analysis: a Bayesian structural panel VAR

The previous section has highlighted the possible role that offshoring and structural changes that are not mirrored by demand may have played in the evolution of energy intensity.

Specifically, the former likely raises concerns on the overall global environment. As a matter of fact, if a reduction in the nation-wide energy intensity is obtained through a greater reliance on import for energy-intensive products, rather than on internal production, the overall impact on the environment remains uncertain and strictly depends on the carbon intensities of external productions. Therefore, it becomes of paramount importance to further investigate the nature of any possible dynamic relationship between nation-wide energy intensities and offshoring-related structural changes. In this section, we investigate the dynamic relationship between demand-invariant structural changes and the evolution of energy intensity, by washing out demand-related effects in order to retain structural effects that relate to the interplay between internal production and import. The analysis exploits a multivariate macroeconometric framework and employs annual data. Specifically, we estimate a Bayesian Structural Panel VAR model for the period 1970-2020 and we use a recursive identification strategy to guarantee the demand-invariant nature of the shock.

4.1 Methodology and data

To meet our objective, two key empirical issues need to be addressed. First, we need to identify a good proxy for structural changes and to include in the econometric model the right vector of endogenous variables, so as to avoid any omitted variable bias. Secondly, we need to design an identification strategy to efficiently disentangle a *demand-invariant* structural shock in the Panel VAR.

4.1.1 Measuring structural changes using carbon emissions computation methodologies

We proxy structural changes by using the divergence between production-based and consumption-based carbon emissions (OECD, 2016). Production-based emissions are associated with fossil-fuel combustion activities within the country, while consumption-based emissions are those associated with a country's final domestic demand (Wiebe and Yamano, 2016). Specifically, we build a statistical index tracking the time-varying divergence between these two variables, which therefore provides a measure of how much emissions associated with a country's final demand differ from those associated with its production over time. The underlying rationale is that the carbon effects of a structural variation in the economy are likely characterized by a change in the discrepancy between production-based and consumption-based emissions, which allows us to approximate the possible role of offshoring.

The direction of the effect is conditional on the nature of the shock and on the way in which the divergence measure is built. Technically, being consumption-based emissions $C^c_{i,t}$ and production-based emissions $C^p_{i,t}$ in the year t for a given country i, we compute the divergence measure simply as follows:

$$\gamma_{i,t} = \frac{C^c_{i,t}}{C^p_{i,t}}. \tag{4}$$

Hence, whenever $\gamma_{i,t} > 1$, the country i's final demand at time t is associated with more emissions than those of its production, while when $\gamma_{i,t} < 1$, the reverse occurs. Data for consumption-based and production-based emissions have been gathered from the Eora World multi-regional input-output database which traces global supply chains to make up the final demand of the country of interest.

The elasticity of domestic demand to the occurring structural change is crucial in this framework. Indeed, if a structural change occurs without any variation in the internal demand (e.g., a reduction in the volume of the industry sector in favour of an increase in the service sector is carried out without any changes in the domestic consumption attitude towards service and manufacturing) $\gamma_{i,t}$ will move up. In the opposite case, if consumption patterns precisely mirror structural changes, we would not expect any change in the emission divergence measure. Between these two cases, one can find an array of hybrid scenarios where a variation in domestic demand manifests alongside a structural change, though the two do not mirror each other precisely. These potential scenarios strictly depend on the extent and the variation of the sectoral composition of domestic consumption. For the sake of our research, however, we will only focus on completely *demand-invariant* structural changes, restricting the Panel VAR structure such that the structural change has no contemporaneous effect on the domestic demand of a country.

Figure 4 illustrates the average evolution of the emission divergence index for the sample of 15 OECD countries from 1970 to 2020, alongside the historical evolution of average energy intensity. Descriptive evidence indicates a noteworthy trend: alongside a decrease in energy intensity, the average level of consumption-based emissions has increased relative to production-based emissions over time. This is reflected in the upward trend of the emission divergence index, both on average and across all countries.

Although these are purely descriptive statistics and correlations, the historical data, along with the Index Decomposition Analysis (IDA) presented in Section 3, provide compelling motivation to empirically investigate the potential causal relationship between demand-invariant structural changes and the evolution of energy intensity.

4.2 Model description

We exploit a multivariate regression framework, by estimating a Structural Bayesian Panel VAR.[9] The panel is balanced for the period 1970-2021 and quite homogeneous in terms

[9] The sample of countries coincides with the one used in the IDA exercise developed in Section 3.

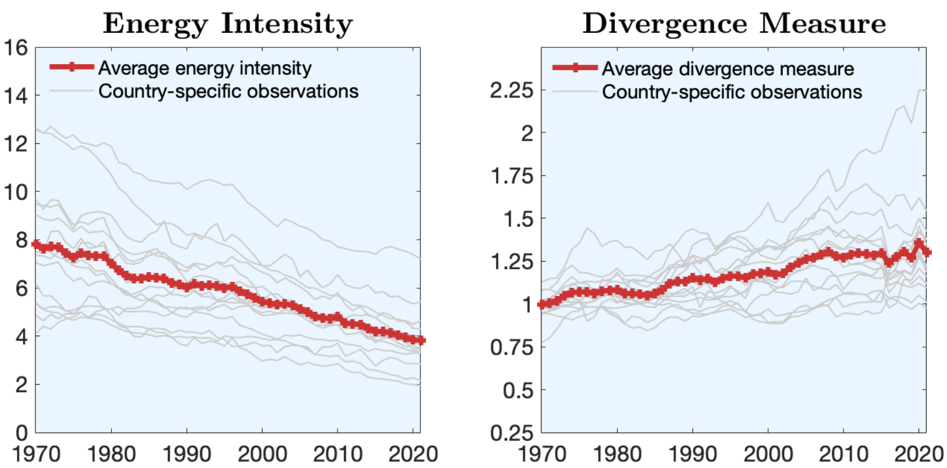

Figure 4 – Average energy intensity evolution and average emission divergence measure evolution in the period 1970-2021 for the 15 OECD countries in the sample.

of economic development and political institutions. We employ annual data due to the unavailability of carbon emissions and energy data at higher frequencies. However, the panel structure allows us to exploit the horizontal dimension of data reaching a consistent number of observations.

Given a country i in the year t, the reduced form Panel VAR equation reads as:

$$\boldsymbol{Y}_{i,t} = \boldsymbol{\alpha}_i + \boldsymbol{\theta_t} + \sum_{l=1}^{L} \boldsymbol{A}_{i,l}\boldsymbol{Y}_{i,t-l} + \boldsymbol{\epsilon}_{i,t}, \tag{5}$$

where $\boldsymbol{A}_{i,l}$ are the matrices of coefficients at each lag order l, $\boldsymbol{\alpha}_i$ and $\boldsymbol{\theta}_t$ are the matrices of dummies for country and time fixed-effects,[10] $\boldsymbol{\epsilon_{i,t}}$ is a vector of normal distributed zero-mean reduced-form shocks with variance-covariance matrix $\boldsymbol{\Sigma}_i$ and $\boldsymbol{Y}_{it}$ is the vector of endogenous variables included in the model. In our baseline estimation we include 4 lags as suggested by the Akaike criterion ($L = 4$). However, results are robust to the inclusions of less lags in the model specification (see the robustness checks in Section 4.4).

The correct identification of the shock can only be reached by controlling for other factors that are key drivers of the energy intensity. Specifically, together with the energy intensity ($ei_{i,t}$) and the emission divergence measure ($\gamma_{i,t}$), we include in the vector of endogenous variables of the model proxies for the other determinants of energy intensity according to the baseline decomposition of Equation (2). The sectoral effect $se_{i,t}$, which captures the within-sector energy intensity variations, is proxied with the energy intensity

[10]The idea behind the inclusion of time-fixed effects is to take into account any potential co movement across countries in the variables of interest which would otherwise be incorrectly attributed to our shocks (e.g., global business cycle). However, in our robustness checks we show that excluding time-fixed effects from the model specification does not significantly affect our results.

of the industry sector.[11] To account for the structural effect, we exploit the relative shares over total value added of the industry sector and the service sector (respectively $ind_{i,t}$ and $ser_{i,t}$), that are, respectively, the most and the least energy intensive sectors. The inclusion in the model of these structural components has also the key objective of assessing if our instrument efficiently works in capturing structural changes in the sample. Finally, in order to identify only structural changes that are demand invariant, we also include the domestic demand ($d_{i,t}$) in our econometric specification.[12] Formally, the vector of endogenous variables is:

$$\boldsymbol{Y}_{it} = [d_{i,t},\, \gamma_{i,t},\, se_{i,t},\, ind_{i,t},\, ser_{i,t},\, ei_{i,t}]'. \tag{6}$$

All variables are included in log-level form, such that the IRFs may be easily interpret as percent variations. Only the value added of the industry and service sector are in ratio of the total valued added of GDP, therefore one must read the results as percentage of GDP variations. Carbon emissions and energy data have been downloaded from the IEA and the Eora World multi-regional input-output database, while data for the domestic demand have been gathered from the OECD official data warehouse.

4.3 Model estimation and shock identification

The model estimation requires careful assumptions on the reduced form equation. First, we assume both dynamic and static homogeneity. This implies that the matrix of parameters is the same across all units (countries), i.e., $\boldsymbol{A}_{i,l} = \boldsymbol{A}_l \;\forall\; i$, and that the variance-covariance matrix of the reduced-form disturbances is also country-independent, i.e., $\boldsymbol{\Sigma}_i = \boldsymbol{\Sigma} \;\forall\; i$, with the country-fixed effect smoothing this homogeneity for not explicit country's characteristics. Second, we assume that the reduced-form shocks $\boldsymbol{\epsilon_{i,t}}$ are serially and cross-sectionally uncorrelated. Under these assumptions, a pooled fixed-effects estimation of the matrices of parameter $\boldsymbol{A_l}$ is the best approach to estimate the Panel VAR (Canova and Ciccarelli, 2013). However, while assuming no serial correlation is common practice in multi-variate estimations, both the no cross-sectional correlation and the dynamic homogeneity assumption can pose challenges. Regarding the former, it is known that spillovers are generally not negligible, especially in homogeneous panels of developed countries. Thus, assuming that in Equation (5) the residuals are not cross-sectionally correlated may produce biased estimation of the parameters. Secondly, if countries are actually characterized by different dynamics, which is reasonable in macroeconomic frameworks, assuming common slope

[11]Here and for the rest of the paper, when we mention the industry sector we refer to the Mining, Manufacturing and Utilities sector, which is typically the most energy intensive sector in all the considered economies.

[12]In our robustness check we test the sensibility of the results to the use of different proxies for the domestic demand.

produces a biased and inconsistent fixed-effect estimator, even when the cross-sectional dimensions and the time span are sizable (Pesaran and Smith, 1995).

We address the two problems separately. First, to reliably assume no cross-sectional correlation of the reduced-form residuals, in the spirit of Global Vector AutoRegression models (Pesaran et al., 2004), we include in the reduced form equation a global exogenous regressor accounting for any spillovers between countries.[13] Specifically, for this purpose, we exploit the Monthly World Industrial Production (WIP) index developed by Baumeister and Hamilton (2019), aggregating data at annual frequency. Secondly, the dynamic homogeneity assumption – implied by a pooled estimation as ours – is forced by data availability.[14] The best we can do is to partially relax this assumption by performing sub-sample estimations according to specific countries' characteristics. In so doing, we avoid the imposition of a unique macroeconomic dynamics structure across the whole sample a priori, allowing the matrices of parameters to vary at least for different groups of countries and gaining information about the potential heterogeneity of our results.

The Panel VAR model is estimated using Bayesian techniques, which impose prior beliefs on the parameters to overcome the curse of dimensionality. In particular, we rely on the modified version of the Minnesota prior proposed by Bańbura et al. (2010) to deal with large scale VARs.[15] We approximate the posterior distribution exploiting a Gibbs sampling algorithm which conducts 25,000 replications, using the last 10,000 to do inference. The prior distribution involves an hyper-parameter λ which conveys the weight attached, within the estimation, to prior beliefs with respect to the information contained in the data. Given that our system of equations is not too large we impose $\lambda = 1$.[16] However, in our robustness analysis we will change the value of λ to assess the sensibility of the results to different prior's tightness.

The identification of structural shocks is reached by exploiting the demand-invariant nature of the structural change of interest as key condition to employ zero contemporaneous restrictions. As already pointed out, to meet our objective we need the shock in our dispersion measure to have a null net impact on the domestic demand, so that the contribution of offshoring can be detected. Therefore, the impact matrix employed to recover structural shocks is the lower triangular of the standard Cholesky decomposition

[13]A similar empirical strategy to overcome the downturn of assuming no cross-sectional between residuals is exploited by Ciccarelli and Marotta (2024).

[14]Since only annual data are available for the variables of interest, the number of observations in each single country is to little to perform different type of estimation which involve dynamic heterogeneity (e.g., mean-group estimator).

[15]The main modifications of the Minnesota priors concerns the moments of the parameter's distribution, which are imposed – for better suiting the behavior of macroeconomic variables – to be white noise and with the variance covariance matrix following a normal inverted Wishart distribution. For further technical details about the Bayesian prior and how it is implemented please refer to Bańbura et al. (2010), which we rigorously follow.

[16]For $\lambda \to 0$ the posterior tends to the prior beliefs and data informs less the estimation, while for $\lambda \to \infty$ the weight attached to the posterior is zero and the predictions replicates the OLS estimate.

of the variance-covariance matrix of the reduced-form residuals with the domestic demand ordered first in the recursive identification. This ensures that – on impact – shocks in the divergence measure have a zero effect on the level of demand. Formally, we order the domestic demand as first in a recursive VAR structure and we retreive the structural shocks $\boldsymbol{\varepsilon_t}$ are obtained as:

$$\boldsymbol{\varepsilon_t} = \boldsymbol{\Omega}\boldsymbol{\epsilon_t} \quad \text{where} \quad \boldsymbol{\Sigma} = \boldsymbol{\Omega}\boldsymbol{\Omega}', \tag{7}$$

where $\boldsymbol{\Sigma}$ is the variance-covariance matrix of the reduced-form residuals.

4.4 Panel VAR Results

Once the structural shocks of the Panel VAR have been identified, we can analyse the impact of structural changes on the evolution on energy intensity by retrieving the structural impulse response functions (IRFs) to a positive shock in the emission divergence measure in our panel of countries. Structural IRFs to a 10 % increase in the emission divergence measure are reported in Figure 5 for all the endogenous variables of the model. The size of the shock is equivalent, on average among countries, to around two standard deviation. The blue lines are the median IRFs, while the shaded areas are the 68 percent (darker) and 95 percent (lighter) Bayesian credible intervals. In the remainder, we will refer to results as significant if the zero-line is not included in at least the 68 area. However, some of our results hold even at the 95 percent level.

The produced shock in the emission divergence measure is quite persistent, meaning that the distance between consumption-based and production-based emissions tends to take the form of a structural rather than a temporary variation. As expected from the identification strategy exploited, the effect of the shock on the domestic demand is zero on impact. Moreover, it is also not significant for the whole time horizon considered. This guarantees that all the results can be interpreted by taking into account that the demand remains roughly constant over time.

A key result is that a demand-invariant shock in our emission dispersion measure leads to a significant decrease in the share over total value added of the industrial sector, together with an increase in the corresponding figure for the services sector. This finding is consistent with the intuition that a positive shock in our emissions divergence measure can efficiently capture structural changes, namely shifts away from energy-intensive activities. Indeed, a positive shock in γ_t represents a relative increase in consumption-based emissions with respect to the production-based ones. The positive shock in the emission divergence measure also brings to an increase in the proxy that we employ for the sectoral effect, namely the industry's energy intensity. This is possibly motivated by the fact that the energy use in this sector has declined, but not as much as the value added by this sector.

As for the main variable of interest, the produced shock in the divergence measure induces a significant decrease in the nation-wide energy intensity, with peak by almost -2% on impact, which persists over time up to 8 years. Therefore, changes in the production structure of an economy that are not matched by the domestic demand can partly explain the declines that have been observed in national energy intensities of the sample economies.[17]

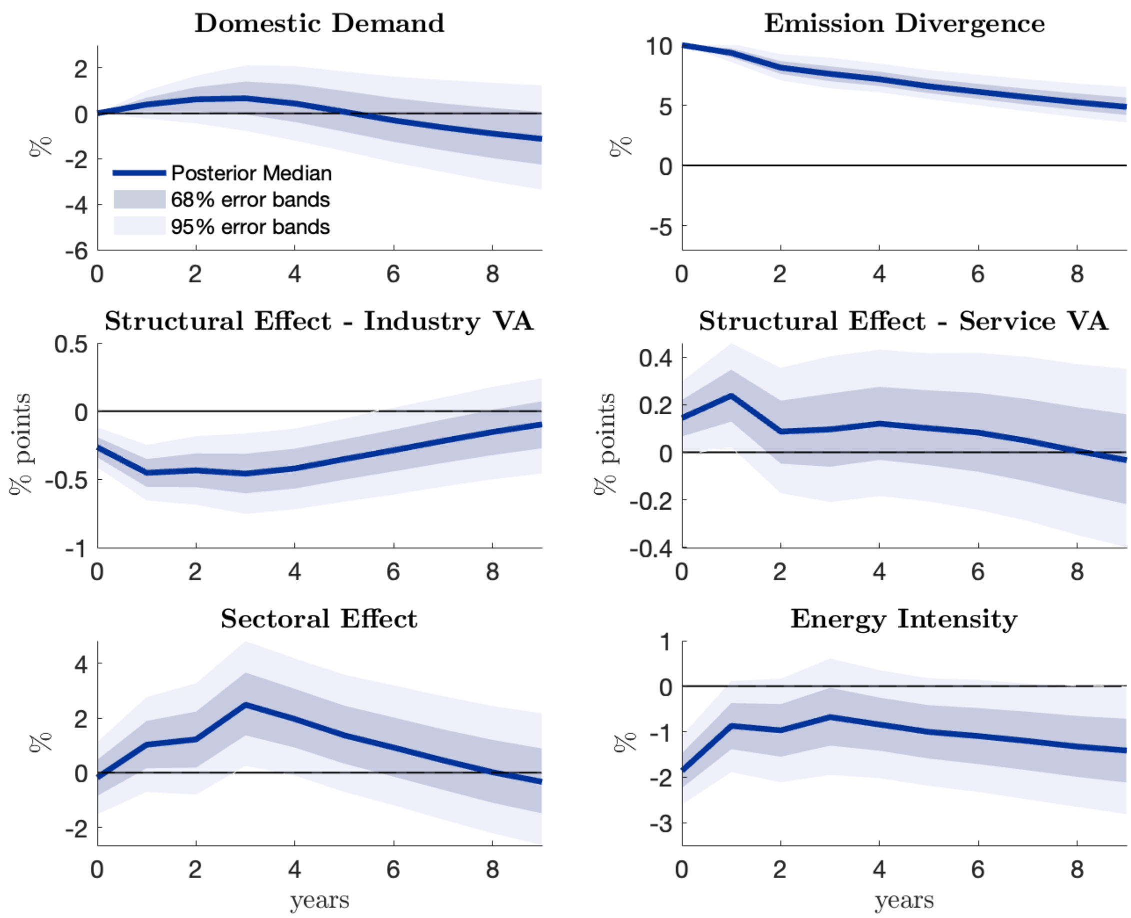

Figure 5 – Results of Structural IRFs to a 10% shock in the emission divergence measure. Shocks have been identified using zero contemporaneous restrictions ordering the domestic demand first in the Cholesky decomposition to ensure the demand-invariant nature of the shock on impact. Both 68 % and 95 % Bayesian credible intervals are reported.

[17]Note that, even if theoretically a VAR historical decomposition analysis would have helped us in explaining the contribution of emission divergence shock to the decreasing in energy intensity, practically this type of exercise is not really useful when trying to explain observed variable's dynamics that are significantly trended over time. Indeed, the stationarity assumption behind the estimation of any VAR model implies that historical decomposition analysis would only be able to explain the contribution of structural shocks to the historical cycle of the series around the observed trend.

We tested the robustness of the results to a series of different factors. Specifically, we changed the number of lags employed in the Panel VAR estimation (from 1 to 4 lags), we moved the value of the hyper-parameter exploited in the Bayesian prior, which conveys the degree to which the estimates depend on the data-driven information with respect to the prior belief, we excluded the time-fixed effect from the model specification and we exploited different proxies to capture domestic demand (i.e., real GDP, total consumption expenditure, external balance of goods and services). Figure 6 reports all the robustness exercises on the structural IRFs to a 10 percent shock in the divergence measure of energy intensity. Results prove to be robust to different specifications, suggesting that the kind of shock identified significantly impacts (i.e., reduces) the energy intensity over time also under different specifications.

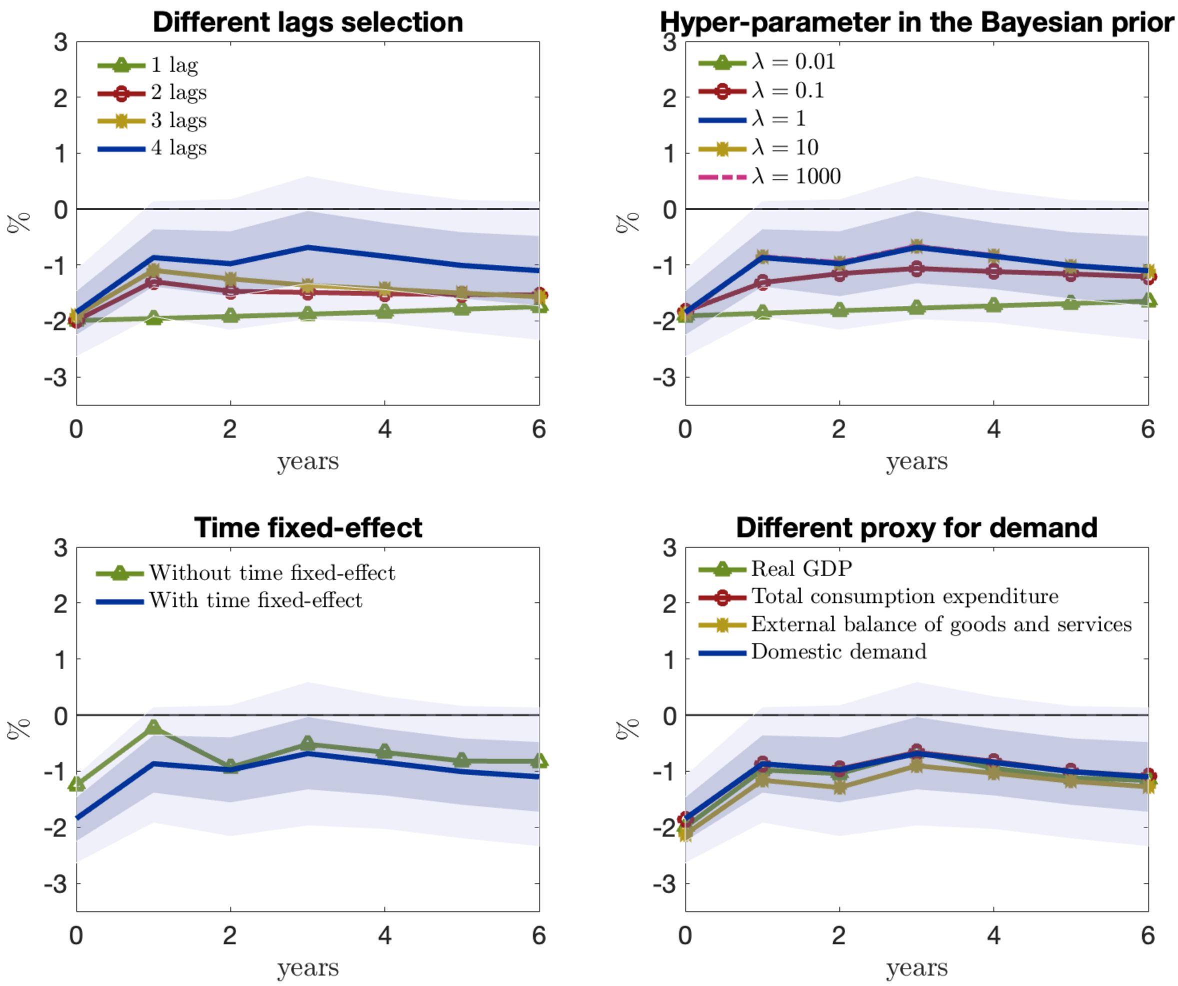

Figure 6 – Robustness checks on the structural IRF to a 10 % increase in the divergence measure on energy intensity. (a) Different lags selection (baseline in 4 lags). (b) Changing the tightness of the hyper-parameter in the Bayesian prior (baseline is $\lambda = 1$). (c) Including or not the time-fixed effects (baseline is the former). (d) Using different proxies for domestic demand, broader (e.g., real GDP) or more specific (e.g. total consumption expenditure).

4.4.1 Sub-sample estimations

In order to strengthen the results and to comply with the strict identification assumption for dynamic homogeneity, we perform two sub-sample estimations of the Panel VAR. Specifically, the Panel VAR model is estimated for smaller groups of countries according to some specific designed characteristics, allowing therefore the matrices of parameters $\boldsymbol{A_l}$ to vary at least for two different pools of units. Besides relaxing the cross-sectional homogeneity assumption, this empirical exercise also allows us to test the heterogeneity of our main results to peculiar features of the sample economies.

Results for the structural IRFs of energy intensity to a 10% shock in the emission divergence measure in two different sub-sample estimations is reported in Figure 7. First, in Panel (a), we split the sample between countries which have experienced an average positive or negative contribution of the offshoring factor to the energy intensity evolution over the past 25 years. Results suggest that the reduction of energy intensity induced by impact of structural changes on energy intensity is only persistent in the latter case. On a different note, in countries in which offshoring has contributed to the reduction in energy intensity, the impact of structural changes is quite temporary and vanishes after three years. Secondly, Panel (b) reports the results of the structural IRF when we perform sub-sample estimations according the the Climate Change Performance Index (CCPI) ranking, focusing exclusively on the GHG component of the index.[18] We find that the effect of demand-invariant structural changes on energy intensity persists and is significant only in countries that are better ranked in the CCPI index's factor for emissions, while it disappears for the rest of countries. This is not surprising considering that the CCPI is based on production-based measures of emissions, which neglect the divergence between the two accounting measures of emissions. Taken together, the sub-sample estimations suggest that the evolution of energy intensity from a national perspective can be misleading and not always representative of a country's actual contribution to global decarbonization. Indeed, countries that overperform when looking at production-based GHG emissions display a greater responsiveness of national energy intensity to demand-invariant changes.

[18]The Climate Change Performance Index (CCPI) serves as a tool to promote transparency in both national and international climate policies. The CCPI employs a standardized framework to evaluate and compare the climate performance of 63 countries and the EU, which collectively contribute to over 90% of global greenhouse gas emissions. The assessment of climate mitigation performance is divided into four categories: GHG Emissions, Renewable Energy, Energy Use, and Climate Policy.

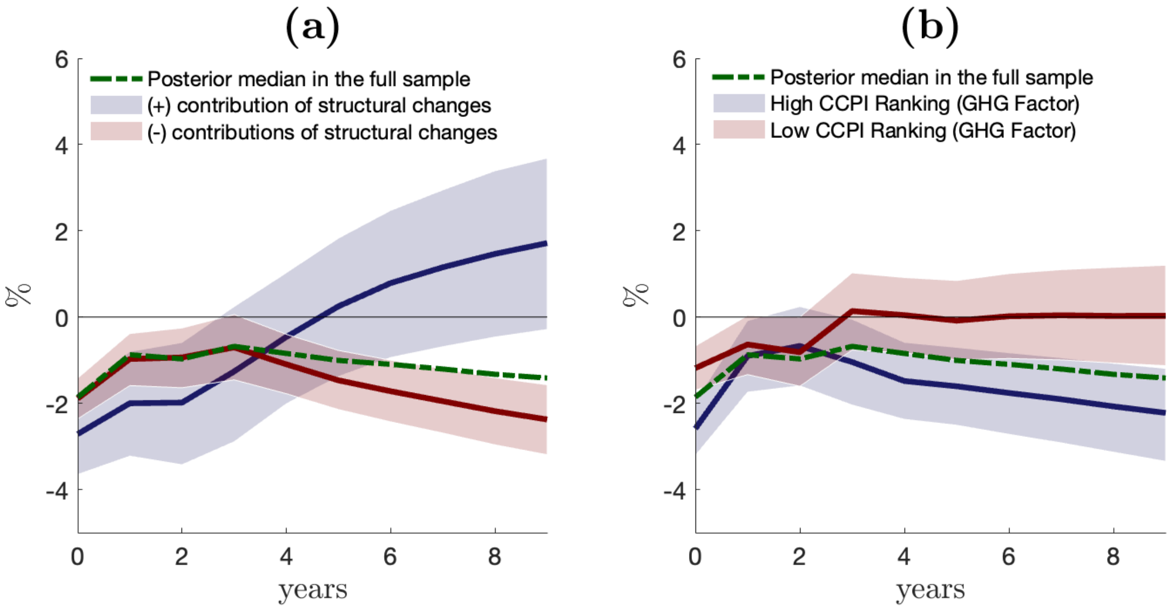

Figure 7 – Sub-sample estimations: structural IRFs of energy intensity to a 10% shock in the emission divergence measure according to different countries' characteristics. (a) Positive/negative contribution of the structural changes to the energy intensity's evolution in the IDA. (b) Countries' CCPI raking according to the GHG emission factor. Color shaded areas are the 68 % Bayesian credible intervals.

5 Final remarks

We developed a two-fold empirical strategy to disentangle the possible role of offshoring in the decline of the energy intensity of GDP observed in several developed economies over the past decades. We first performed an Index Decomposition Analysis, including an offshoring factor, to assess the contribution of structural changes unmatched by equivalent changes in consumption patterns to national energy-intensity trends. The IDA provides suggestive evidence of the role of offshoring in downsizing the energy-intensity of GDP in most analysed countries. Then, to get further insights, we have looked at the dynamic relationship between demand-invariant structural shocks and the evolution of national energy intensity. By estimating a Panel Structural VAR model, where shocks are proxied through the divergence between consumption-based and production-based carbon emissions, we found that the impact of offshoring is generally strong and long-lasting.

In essence, our results suggest that part of the reduction of the energy intensity, and therefore carbon intensity of GDP, exhibited by developed economies, has been triggered by the offshoring of energy-intensive activities. Therefore, caution should be applied when using production-based indicators, rather than an appropriate combination of production and consumption-based data, to assess a country's contribution to global carbon mitigation.

Clearly, it is not straightforward to find a single measure telling apart structural changes that are not matched by equivalent changes in final demand. Still, the divergence between production and consumption-based carbon emissions, used in our econometric analysis, may help to dissect any departure in the trends of national consumption and production-based emissions, in a way that is purged by overall shifts in domestic demand. A possible avenue for future research lies in the possibility to disentangle the "pure" final demand vis-à-vis domestic production shifts from the carbon-intensity effect. In other words, part of the divergence might be attributed to the fact that, even with final demand remaining fixed, energy-intensive imported goods can still bring about a greater emissions' content, due to less energy-efficient production technologies or more carbon-tilted fuel mixes of exporting countries.

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