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► **To cite this version:**

Alexandra-Anca Purcel. Developing states and the green challenge. A dynamic approach. Romanian Journal of Economic Forecasting, 2020, XXIII (2), pp.173-193. hal-03182341

HAL Id: hal-03182341

<https://uca.hal.science/hal-03182341>

Submitted on 28 Oct 2021

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Developing states and the green challenge. A dynamic approach

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Abstract: This paper studies the effects of output, urbanization, energy intensity, and renewable energy on aggregated and sector-specific CO₂ emissions for a rich sample of developing states. We employ the recently developed GMM panel VAR technique, which allows us to tackle the potential endogeneity issue and capture both the current and future impact of indicators on CO₂ via the impulse-response analysis. On the one hand, robust to several alternative specifications, the findings indicate that output, urbanization, and energy intensity increase the aggregated CO₂ emissions, while renewable energy exhibits an opposite effect. Moreover, regarding the CO₂ responsiveness to output and urbanization shocks, the pattern may suggest that these countries are likely to attain the threshold that would trigger a decline in CO₂ emissions. We also reveal heterogeneities related to both countries' economic development and Kyoto Protocol ratification/ascension status. On the other hand, the sectoral analysis unveils that the transportation, buildings, and non-combustion sector tend to contribute more to increasing the future CO₂ levels. Overall, our study may provide useful insights concerning environmental sustainability prospects in developing states.

Keyword: CO₂ emissions; urbanization; energy efficiency; renewable energy; developing countries; environmental Kuznets curve; GMM panel VAR.

JEL Classification: Q01, Q53, Q56, O13

Acknowledgments: I am indebted to the Editor (Corina Saman), two anonymous referees, participants at "The Thirteen International Conference on Economic Cybernetic Analysis: Sustainable Growth in The Current Socio-Political Context (SGSP2018)" held at The Bucharest University of Economic Studies, and Dorina Lazăr and Alexandru Minea for valuable comments and fruitful discussions. All remaining errors are mine. Usual disclaimers apply.

I. Introduction

As a global and stock pollutant with the highest share in greenhouse gasses, carbon dioxide (CO₂) emissions are considered the main driving force of environmental degradation. According to Olivier et al. (2017) report, developing countries such as Indonesia and India have recorded the highest absolute increase in CO₂ emissions in 2016 (6.4% and 4.7% respectively), followed closely by Malaysia, Philippines, and Ukraine.

Indeed, having the fastest-growing economies, most developing countries experience complex structural changes that reflect in the mix of various socio-economic processes such as industrialization and urbanization. For example, according to the United Nations World Urbanization Prospects (2014)¹, the urban population in 2014 accounted for 54% of the total world population, and it is expected to rise at about 66% by 2050. Additionally, considering the worldwide ongoing urbanization process, Asia and Africa seem to exhibit the fastest rate of urbanization. Overall, these changes strongly connected with the industrialization process also imply an intensification and a shift of economic activities towards urban conglomerates, demanding the use of more energy resources, which in turn may reflect in higher pollution. Consequently, some of the key factors that can help mitigate pollution include the gradual replacement of classic fossil fuels with more carbon-neutral alternatives, the increase of renewable sources in the energy mix, and the improvements in energy efficiency. In this regard, the renewable energy and energy efficiency projects implemented between 2005 and 2016 in developing economies, and supported at the international level, are expected to reduce greenhouse gas (GHG) emissions by 0.6 gigatons of CO₂ per year by 2020 (United Nations Environment Programme, 2017)². Likewise, based on the same report, approximately 75 developing or emerging economies have implemented policies or programs that incorporate renewable energy and energy efficiency technologies.

Looking at developing countries' positions vis-à-vis the global environmental challenges and the main related tools designed to address them, they differ in certain features from developed countries. On the one hand, developing states being Non-Annex I parties of the Kyoto Protocol do not have binding commitments to reduce or limit their emissions, compared to their industrialized counterparts. Nonetheless, they may voluntarily comply, and the advanced economies that choose to support them in fighting global warming may also benefit in terms of the fulfillment of their commitments. For example, the Kyoto Protocol's

¹ <https://population.un.org/wup/publications/files/wup2014-highlights.pdf>

² https://wedocs.unep.org/bitstream/handle/20.500.11822/22149/1_Gigaton_Third%20Report_EN.pdf?sequence=1&isAllowed=y

well-known Clean Development Mechanism (CDM) is designed to jointly involve developing and developed economies in fighting climate change through the implementation of various green projects.³ On the other hand, following the Paris Agreement's adoption under the umbrella of the United Nations Framework Convention on Climate Change (UNFCCC), both developing and developed economies are required to put the efforts and fight together against the imminent threats of climate change. As such, the Paris Agreement may represent one of the most powerful instruments adopted so far concerning developing countries and their active role in combating and mitigating the harmful effects of global warming.

Taking stock of the above mentioned, the goal of this paper is to assess the responsiveness of CO₂ emissions following external disturbances to output and urbanization, assuming a transmission channel that incorporates two of the key elements used in mitigating environmental degradation, namely the renewable energy and energy efficiency. In doing so, we employ the recently-developed Generalized Method of Moments (GMM) panel Vector Auto-Regression (VAR) approach of Abrigo & Love (2016), which allows us to explore the essential dynamics and tackle the potential endogeneity between indicators. The technique is applied for a comprehensive group of developing countries, within a modified Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) framework, which along with the Environmental Kuznets Curve (EKC) hypothesis⁴ helps us to provide the necessary economic foundation for the assumed innovations' transmission mechanism required to identify the key structural shocks. Furthermore, opposite to a sizeable empirical strand of literature that independently examines the nexus between CO₂ and growth (urbanization) via the classical (urbanization-related) EKC hypothesis, we jointly test these two well-known hypotheses. Indeed, building on the general belief that a vast majority of developing economies have not yet reached the maximum level of growth (urbanization) that would ensure a decrease in pollution, this approach via the computation of impulse response functions (IRFs) allows us to assess whether this will be feasible or not in the future. As well, motivated by the ongoing structural changes that developing countries experience, we focus on aggregated and sector-specific CO₂, as they may provide us with complementary insights.

³ As a result of the CDM green projects (i.e., projects aimed at reducing emissions) implemented in developing countries, the Annex I parties can buy Certified Emission Reduction (CER) units, which in turn help them to meet some of their commitments of emission reduction (Carbon Trust, 2009).

⁴ The classical EKC hypothesis states that the relationship between environmental degradation and economic growth follows a bell-shaped pattern (Grossman & Krueger, 1991).

Our findings can be summarized as follows. First, although output and urbanization shocks trigger a rise in the current and future levels of CO₂, the effect may reverse, and in the long-run, a bell-shaped pattern seems to be at work in terms of the CO₂ responsiveness. Moreover, the green actions that developing countries have taken in the last decades, in particular those related to renewable energy sources, seems to reduce the cumulated CO₂ emissions both on the short- and long-term horizon. However, considering that the positive disturbances to energy intensity are associated with an increase in CO₂, more attention should be paid to energy efficiency, by attracting and implementing more related projects. Also, while the results confirm the persistence in CO₂, a permanent shock to its dynamics causes only a small increase in the future emissions levels.

Second, we examine the robustness of these findings by changing the order of variables into the transmission channel, altering the sample in several ways concerning both N and T dimensions, and controlling for an extensive set of exogenous factors. According to IRFs, the shocks to output, urbanization, energy intensity, and CO₂ have the same cumulated increasing effect on CO₂, opposite to positive disturbances to renewables that trigger a cumulated decrease in CO₂. Likewise, the CO₂ response to GDP and urbanization shocks tends to exhibit a bell-shaped pattern in the long-run, indicating that the related EKC hypothesis may be validated.

Third, we find that the results are sensitive to both countries' level of development and the Kyoto Protocol ratification/ascension status. On the one hand, overall, the IRFs show that low income economies might experience a more moderate increase in pollution in the long-run than lower-middle income states. Besides, in low income states, the results seem to be compatible with the EKC hypothesis, especially for urbanization. On the other hand, the countries that ratified or acceded to the Kyoto Protocol before it entered into force may also be those which have been more actively engaged in combating pollution, given that both output and urbanization are more likely to display a threshold effect on CO₂ (i.e. validate the EKC hypothesis in the long-run). Indeed, this may also suggest that these states faced the effects of increasing pollution earlier and, thus, decided to become more actively involved in combating climate change sooner than their counterparts.

Finally, despite the positive response of aggregate CO₂ to output and urbanization shocks, when the sectoral components of CO₂ are taken into account, the findings appear to be much more diverse. In particular, we find opposite results for the other industrial combustion and power industry sector, namely external disturbance to both GDP and urbanization lead to a cumulated decrease in associated CO₂. Thus, overall, the disaggregated

CO₂ analysis indicate that transportation followed by construction and non-combustion sector are more prone to contribute to increasing CO₂ pollution in developing economies.

The remainder of the paper is organized as follows. Section 2 reviews the related empirical literature. Section 3 provides the STIRPAT framework, discusses the research methodology, and describes the data used in the analysis. Section 4 presents the baseline empirical findings. Section 5 examines the robustness of these findings. Section 6 explores their sensitivity. Section 7 analyzes the sector-specific CO₂ dynamics following exogenous shocks to other system variables, and the last section presents the concluding remarks.

II. Literature review

In the light of the vast body of empirical literature on the environmental degradation determinants, this section aims to review some of the most recent empirical studies that tackle the impact of output, urbanization, (non-) renewable energy, among other explanatory factors, on environmental degradation. More precisely, we mainly focus on works that explore this nexus for developing⁵ economies in the context of STIRPAT and/or EKC hypothesis (both the classical and urbanization related ones). As well, given that the output appears in almost all studies as one of the main determinants of environmental degradation, we split the literature into two main parts, namely the (i) output-urbanization-environmental degradation nexus, and (ii) output-(non-)renewables-environmental degradation nexus.⁶

First, regarding the impact of economic growth and urbanization on environmental pollution, we further split the studies into two sub-categories. Thus, the first strand of literature tackles the papers that extend the baseline STIRPAT equation and/or EKC hypothesis to capture the effects of the urbanization process. In this fashion, researchers such as Lin et al. (2009), Li et al. (2011), Wang et al. (2013), Wang & Lin (2017), among others, using time-series data on China reveal that, overall, both urbanization and economic growth exacerbate the environmental degradation. The authors employ techniques such as ridge regression, partial least-squares regression, or VAR model. Likewise, the findings of Talbi (2017) for Tunisia and Pata (2018) for Turkey show that urbanization increases CO₂ pollution, while economic growth exhibits a nonlinear effect on CO₂, validating the EKC hypothesis.

⁵ The term “developing” is used with double connotation, meaning that it refers to both developing and emerging countries.

⁶ We note that the studies that comprise, along with the output, both urbanization and (non-) renewable energy as explanatory factors of environmental degradation, are included in the category that we consider most suitable.

Furthermore, making use of STIRPAT framework, several works (see e.g. Poumanyong & Kaneko, 2010; Liddle, 2013; Iwata & Okada, 2014; Sadorsky, 2014a; Wang et al., 2015; among others) examine the effects of growth and urbanization on environmental degradation, using either samples of developing countries or mixed samples comprising both developing and developed economies. However, in most cases, the findings unveil that both variables have a positive effect on environmental degradation. Also, it is worth noted that concerning economic growth, Liddle (2013) and Wang et al. (2016) find evidence in favor of the EKC hypothesis. Also, scholars such as Li et al. (2016), Awad & Warsame (2017), Joshi & Beck (2018), among others, study the relationship between pollution and growth in the context of the EKC hypothesis, while controlling for the effects of the urbanization process. The authors apply either parametric or semi-parametric panel data techniques, and, most frequently, environmental degradation is proxied by CO₂ emissions. Overall, the findings seem to be mixed with respect to the EKC hypothesis's validity, whereas urbanization tends to increase the pollution levels.

The second strand of literature focuses on testing the urbanization-related EKC hypothesis, whether or not this is done within the STIRPAT context. In this manner, the findings provided by Martínez-Zarzoso & Maruotti (2011) support the urbanization-pollution EKC for 88 developing states spanning over the period 1975-2003. Opposite, Zhu et al. (2012) and, more recently, Wang et al. (2016) find little evidence in favor of urbanization-CO₂ and urbanization-SO₂ EKC hypothesis, respectively. Besides, employing the panel VAR analysis, Lin & Zhu (2017) study the dynamic relationship between industrial structure, urbanization, energy intensity, and carbon intensity for 30 provinces of China spanning over the period 2000-2015. Concerning the carbon intensity response following external shocks to the other variables, the IRFs reveal that both urbanization and industrial structure decrease the carbon intensity, while energy intensity disturbances increase (decrease) on impact (after three years) the carbon intensity. According to twenty years horizon FEVDs' results, only urbanization exhibits a bell-shaped pattern on carbon intensity. Also, the findings provided by Chen et al. (2019) and Xie & Liu (2019) show that urbanization exhibits nonlinear effects on CO₂ for 188 Chinese prefecture-level cities and 30 Chinese provinces, respectively.

Second, the present study is also related to the body of literature that investigates the effects of economic growth, non-renewable energy (especially energy intensity), and/or renewable energy on environmental degradation. In this regard, Shahbaz et al. (2015) investigate for 13 Sub Saharan African states the link between energy intensity and CO₂, while additionally test the EKC hypothesis. On the one hand, the long-run panel findings

unveil that the energy intensity has a positive impact on CO₂, while a bell-shaped pattern characterizes the CO₂-GDP nexus. On the other hand, the country-specific long-run results reveal that energy intensity significantly increases CO₂ in countries such as Botswana, Congo Republic, Gabon, Ghana, South Africa, Togo, and Zambia. Besides, an inverted U-shaped (U-shaped) relationship between CO₂ and GDP is found in South Africa, the Congo Republic, Ethiopia, and Togo (Senegal, Nigeria, and Cameroon). Antonakakis et al. (2017) employ the panel VAR approach to investigate the dynamic interrelationship between output, energy consumption (and its subcomponents, namely electricity, oil, renewable, gas, and coal) CO₂. In doing so, the authors concentrate on a large panel of 106 states spanning over the period 1971-2011. Overall, for low income group, the findings (based on cumulative generalized IRFs) reveal that CO₂ respond significantly and positively only to output and oil consumption shocks. On the contrary, for lower-middle income countries, the CO₂ seems to react significantly and positively to output, aggregated energy consumption, electricity consumption, and oil consumption. Likewise, Naminse & Zhuang (2018) examine for China the link between economic growth, energy intensity (in terms of coal, oil, gas, and electricity), and CO₂, over the period 1952-2012. The results based on the IRFs analysis show that coal, electricity, and oil consumption have a positive impact on the future levels of CO₂. In contrast, gas consumption seems to decrease future levels of CO₂. The regression analysis also indicates an inverted U-shaped relationship between growth and CO₂, in line with EKC. Also, Charfeddine & Kahia (2020) investigate the impact of renewable energy and financial development on both CO₂ emissions and growth for 24 Middle East and North Africa (MENA) states. The computed IRFs unveil a cumulative negative effect of renewables on CO₂, suggesting that renewable energy sources may reduce CO₂ pollution.

Moreover, some authors assess the impact of (non-) renewable energy consumption and output on CO₂ pollution using the EKC framework for European Union (EU) states. As such, the results of Bölük & Mert (2014) for a sample of 16 EU countries indicate that the consumption of renewables has a positive impact on CO₂ emissions, while the EKC hypothesis is not validated. Conversely, based on a sample of 27 developing and developed EU states, the findings of López-Menéndez et al. (2014) show, on the one hand, that renewables have a negative effect on greenhouse gas emissions. On the other hand, the results suggest that the EKC hypothesis may be at work for those economies which exhibit high intensity with respect to renewable energy sources. Likewise, for a sample of EU economies, Dogan & Seker (2016) show that renewable (non-renewable) energy decreases (increases) the

CO2 emission, and the EKC hypothesis is supported. As an empirical methodology, the authors employ panel data techniques robust in the presence of cross-sectional dependence.⁷ Bearing in mind the present study's objective, we previously review some studies that directly or indirectly tackle the effects of output, urbanization, and (non-) renewable energy, among others, on environmental degradation. However, given that we aim at addressing the potential endogenous behavior between variables and, thus, consistent with the recursive order that we impose among them (see subsection 4.2 for details), the study could also be linked with the strand of research that examines the relationship between (i) output and urbanization (see e.g. Brückner, 2012; Bakirtas & Akpolat, 2018; among others), (ii) output and (non-) renewable energy (see e.g. Sadorsky, 2009; Salim & Rafiq, 2012; Liu, 2013; Apergis & Payne, 2015; Doğan & Değer, 2018), (iii) urbanization and (non-) renewable energy (see e.g. Shahbaz & Lean, 2012; Sadorsky, 2014b; Wang, 2014; Kurniawan & Managi, 2018; among others), and as well the papers that focus on efficiency of (non-) renewable energy (see e.g. Aldea et al., 2012; Jebali et al., 2017; Gökgöz et al., 2018; among others).

III. STIRPAT framework, research strategy, and data

3.1. STIRPAT framework

STIRPAT is an analytical framework introduced in the literature by Dietz & Rosa (1994, 1997) as the stochastic counterpart of IPAT identity proposed by Ehrlich & Holdren (1971). According to the I=PAT accounting equation, the environmental impacts denoted by (I) are determined in a multiplicative way by demographic-economic forces such as population (P), affluence (A), and technology (T). Nonetheless, over the years, to meet the needs of different research questions the baseline IPAT/STIRPAT model has encountered many alternative specifications (see e.g. Kaya, 1990; Schulze, 2002; Waggoner & Ausubel, 2002; Xu et al., 2005; Martínez-Zarzoso et al., 2007; Lin et al., 2009; Shafiei & Salim, 2013; among others). First, the classical IPAT equation written for panel data with $i = \overline{1, N}$ observed countries over the period $t = \overline{1, T}$ takes the following for

$$I_{it} = \alpha \cdot P_{it}^{\beta_1} \cdot A_{it}^{\beta_2} \cdot T_{it}^{\beta_3} \cdot \varepsilon_{it} \quad (1)$$

⁷These findings are also partially supported by the more recent study of Inglesi-Lotz & Dogan (2018) for a sample that comprises the top 10 electricity generators states from Sub-Saharan Africa. Specifically, the results show that renewable (non-renewable) decreases (increases) the CO2, but the validity of the EKC hypothesis over the period 1980-2011 is not supported.

Second, the stochastic counterpart of the above accounting identity is obtained by applying natural logarithm on equation (1). Also, along with this transformation, we approximate the environmental impacts I with a well-known global pollutant, namely the CO2 emissions. Likewise, we proxy P with the share of the urban population in total population (URB), A with the gross domestic product (GDP), while T it is captured through both energy intensity (EINT) and the share of renewable energy in total energy consumption (RENG). Subsequently, our modify STIRPAT model can be specified as follows

$$CO2_{it} = \alpha_i + \beta_1 GDP_{it} + \beta_2 URB_{it} + \beta_3 EINT_{it} + \beta_4 RENG_{it} + \varepsilon_{it} \quad (2)$$

In the above equation, all the variables are expressed in natural logarithm form, while α_i and ε_{it} captures the potential country-specific fixed effects and the error term, respectively. Moreover, given that the affluence term is usually expressed via GDP, its square (cubic) term into the equation allows for testing the well-known EKC hypothesis in its traditional (extended form). Indeed, the same holds for any explanatory factor, namely adding higher-order polynomial terms, allows for testing a potential nonlinear effect of the respective variable on environmental degradation (e.g. the urbanization-EKC hypothesis).

3.2. Methodology

To explore the CO2 responsiveness to other system variables shocks, we draw upon the novel panel VAR methodology. In this regard, we follow the work of Love & Zicchino (2006) and Abrigo & Love (2016) and estimate a homogeneous panel VAR model using the GMM approach. Indeed, this technique gives us the possibility to treat all the variables endogenously and also to account for the unobserved individual heterogeneity.

The reduced-form specification of a homogeneous panel VAR with individual fixed effects can be written as follows

$$Y_{it} = W_0 + W_1(L)Y_{it} + v_i + \varepsilon_{it} \quad (3)$$

Where Y_{it} represents the vector of our four stationary endogenous variables, namely the GDP, URB, EINT, RENG, and CO2, and $w_1(L)$ stands for associated matrix polynomial in the lag operator (i.e. the autoregressive structure). w_0 is the vector of constants, while v_i and ε_{it} denotes the vector of unobservables country-specific characteristics and idiosyncratic errors, respectively. The unobservables may capture the cultural, institutional, and historical individual country characteristics that are time-invariant. Likewise, we assume that the vector of idiosyncratic errors ε_{it} possesses the following features: $E[\varepsilon_{it}] = 0$, $E[\varepsilon'_{it}\varepsilon_{it}] = \Sigma$ and $E[\varepsilon'_{it}\varepsilon_{is}] = 0$, $\forall t > s$. Put differently, the innovations have zero first moment values, constant

variances, and do not exhibit individual serial and cross-sectional correlation (see Abrigo & Love, 2016).

Furthermore, in line with Holtz-Eakin et al. (1988), the panel VAR model described above assumes that the parameters are common across all panel members (Abrigo & Love, 2016). Indeed, this seems to be quite a strong restriction that may not hold when working with a large number of countries, which are prone to exhibit certain particularities. Thus, the country-specific fixed effects are introduced into the model to overcome the parameters' homogeneity assumption. In this regard, the model may be estimated via the fixed effects or ordinary least squares approach, but the coefficients are likely to suffer from Nickell's bias (Nickell, 1981)—when estimating dynamic panels, the fixed-effects are correlated with the regressors, given the lags of endogenous variables (Abrigo & Love, 2016). To alleviate this issue, we use the Helmert procedure described in Arrelano & Bover (1995), and remove the mean of all future available country-time observations, by applying forward mean-differencing (orthogonal deviations). Also, in this manner, we refrain from eliminating the orthogonality between transformed variables and lagged regressors. Consequently, the coefficients are consistently estimated by GMM, using instruments the lags of independent variables (Abrigo & Love, 2016).

3.3. *Data*

The study concentrates on 68 countries classified by World Bank (2017) as economies with low and lower-middle income. The list of countries included in the analysis, grouped by geographic region, is displayed in Table 1 in the Supplementary Material. Moreover, the data are annual and cover the period from 1992 to 2015, while the sample is constructed according to data availability and in such a way to omit to deal with missing observations for the main variables. Also, by focusing on this period, we avoid the instabilities triggered by the fall of the Communist Bloc and the end of the Cold War, which may equally distort our analysis.

On the one hand, our primary data source is the World Bank, given that four out of five variables included in the empirical analysis come from World Bank Indicators (WDI, 2018). These variables are the GDP (constant 2011 international \$, purchasing power parity), EINT (energy intensity of GDP), URB (urban population as % of the total population), and RENG (renewable energy consumption as % of total final energy consumption).

On the other hand, the data for CO₂ emissions (kton per year) are collected from Janssens-Maenhout et al. (2017), Emissions Database for Global Atmospheric Research (EDGAR). For the baseline model, we use the aggregate CO₂ emissions, computed as the

sum of emissions from transport, other industrial combustion, buildings, non-combustion, and power industry sector. Nonetheless, in the heterogeneity section, we estimate the model for each sector separately, using disaggregated CO2 emissions. Furthermore, to capture the overall dynamics' magnitude between variables (especially between CO2 and GDP), we refrain from working with their per capita versions. Indeed, this allows us to further investigate, in the robustness section, if potential changes in the population alter the baseline findings. Also, for modeling purposes, all the variables are express in natural logarithm. Table 2 and Table 3 in the Supplementary Material illustrates the variables definition and their descriptive statistics before applying any transformation.

IV. Empirical results

4.1. Some preliminary data evaluations

Prior to modeling the dynamic relationship between variables, we check some univariate properties of our data, such as the cross-sectional dependence, the critical assumption of stationarity required by a stable VAR model, and the potential cointegration of variables.

First, we check the presence of cross-sectional dependence by employing the Breusch-Pagan (1980) LM, Pesaran (2004) scaled LM, Pesaran (2004) CD, and Baltagi et al. (2012) Bias-Corrected (BC) scaled LM test. The findings depicted in Table 1 show that all variables are characterized by cross-sectional dependence.

Table 1

Cross-sectional dependence tests

| Test/Variable | CO2 | GDP | EINT | RENG | URB |
|-------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| Breusch-Pagan LM | 34483.67*** (0.000) | 44405.60*** (0.000) | 19907.45*** (0.000) | 18059.67*** (0.000) | 43539.82*** (0.000) |
| Pesaran scaled LM | 477.134*** (0.000) | 624.129*** (0.000) | 261.184*** (0.000) | 233.808*** (0.000) | 611.303*** (0.000) |
| Pesaran CD | 141.464*** (0.000) | 202.439*** (0.000) | 55.523*** (0.000) | 59.380*** (0.000) | 110.153*** (0.000) |
| BC scaled LM | 475.655*** (0.000) | 622.651*** (0.000) | 259.705*** (0.000) | 232.330*** (0.000) | 609.824*** (0.000) |

Notes: The Breusch-Pagan (1980) LM, Pesaran (2004) scaled LM, Pesaran (2004) CD, and Baltagi et al. (2012) Bias-Corrected (BC) scaled LM test. H0 is "no cross-section dependence (correlation)". P-values in brackets. ***, **, *, denotes significance at the 1%, 5% and 10% level, respectively.

Second, taking into account the presence of cross-sectional dependence and the large dimension of N (i.e., N=68 and T=24), we employ the Harris-Tzavalis (1999) panel unit root test. In particular, this test allows us to alleviate the effects of cross-sectional dependence by subtracting the cross-sectional means from the variables, while imposing small-sample adjustment to T. Besides, bearing in mind that unit root/stationarity tests are usually sensitive to the number of lags included in the equation, we also consider the Pesaran's (2003) CADF

test by augmenting the equation with one and two lags, respectively. Also, for both tests, we include in the equation a constant and a trend for the variables in levels, whereas only the constant for their first difference. Table 2 and Table 3 show the associated results. Overall, we can observe that all variables are stationary on their first difference and integrated of order one in levels, with the notable exception of URB and CO2 for Pesaran's (2003) test augmented by one lag.

Table 2

| Stationarity analysis I | | | | |
|--------------------------------|----------------------|---------|-----------------|---------|
| Test/ Variable | Harris-Tzavalis test | | | |
| | Level (cons & trend) | | Δ (cons) | |
| | rho | p-value | rho | p-value |
| GDP | 0.748 | (0.983) | 0.235*** | (0.000) |
| URB | 0.853 | (1.000) | 0.839** | (0.033) |
| EINT | 0.685 | (0.258) | -0.007*** | (0.000) |
| RENG | 0.675 | (0.145) | -0.056*** | (0.000) |
| CO2 | 0.686 | (0.271) | 0.004*** | (0.000) |

Notes: We remove cross-sectional means and apply small sample adjustment to T. H0 is "panels contain unit roots". P-values in brackets. ***, **, *, denotes significance at the 1%, 5% and 10% level, respectively.

Table 3

| Stationarity analysis II | | | | | | | | |
|---------------------------------|--------------------------------|---------|-----------|---------|---------------------------------|---------|-----------|---------|
| Test/ Variable | Pesaran's CADF test | | | | | | | |
| | Level (cons & trend) | | | | Δ (cons) | | | |
| | Augmented by one lag (average) | | | | Augmented by two lags (average) | | | |
| | t-bar | p-value | t-bar | p-value | t-bar | p-value | t-bar | p-value |
| GDP | -2.263 | (0.663) | -2.819*** | (0.000) | -1.969 | (0.999) | -2.139*** | (0.000) |
| URB | -2.620*** | (0.003) | -1.674 | (0.740) | -2.325 | (0.446) | -1.965** | (0.034) |
| EINT | -2.185 | (0.865) | -2.962*** | (0.000) | -1.866 | (1.000) | -2.114*** | (0.001) |
| RENG | -1.884 | (1.000) | -3.017*** | (0.000) | -1.740 | (1.000) | -2.036*** | (0.008) |
| CO2 | -2.597*** | (0.005) | -3.234*** | (0.000) | -2.166 | (0.899) | -2.630*** | (0.000) |

Notes: H0 is "all series are non-stationary". P-values in brackets. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Third, given that the stationarity analysis suggests mixed results, especially for URB and CO2 variable, and to be sure that variables do not exhibit a long-term relationship, we check for a potential cointegration between variables. Indeed, if the variables are cointegrated in levels, only taking their first difference to satisfy the stationarity condition of the VAR model would eventually bias the estimates. To this end, we employ the error-based panel cointegration tests of Westerlund (2007), which allow us to control for the presence of cross-sectional dependence via the bootstrap procedure. The findings depicted in Table 4 show that the null hypothesis of no cointegration is strongly accepted across all four tests when using both 100 and 800 replications for the bootstrap procedure. Consequently, estimating the panel VAR by differencing the data seems to be the most appropriate decision in our case, since the model will be consistent, and the inference will hold. Besides, taking the first difference of

the log-transformed data facilitate the modeling between variables by allowing us to work with their growth rates.

Table 4

| Panel cointegration tests | | | | |
|----------------------------------|---------------------------------|----------------|---------------------------------|----------------|
| Westerlund (2007) | | | | |
| Statistic | Z-value | Robust p-value | Z-value | Robust p-value |
| | bootstrap with 100 replications | | bootstrap with 800 replications | |
| Gt | 0.669 | 0.271 | 0.669 | 0.271 |
| Ga | 13.271 | 1.000 | 13.271 | 1.000 |
| Pt | 10.714 | 0.591 | 10.714 | 0.591 |
| Pa | 9.670 | 0.684 | 9.670 | 0.684 |

Notes: H0 is "no cointegration". The equation includes the constant term, one lag, and one lead. The width of the Bartlett kernel window is set to three. ***, **, *, denotes significance at the 1%, 5% and 10% level, respectively.

4.2. Identification and estimation of the structural panel VAR model

4.2.1. Identification

A crucial aspect of the VAR approach involves the assumptions imposed to estimate the associated system of simultaneous equations consistently. Indeed, converting the classical VAR into a structural VAR (SVAR) approach by setting specific restrictions, allow us to achieve the necessary causal inference, and have a meaningful economic interpretation of the parameters. In other words, the identification in SVAR of all structural parameters requires that some theory-based economic restrictions are imposed. In doing so, we draw upon a recursive panel SVAR model, meaning that we do not impose any restriction on the matrix that captures the impact effects⁸, i.e. we use exclusion restrictions. Effectively, this can be done by imposing a particular causal order between variables, which plays a vital role in the computation of both the Cholesky decomposition of the innovations' variance-covariance matrix and the IRFs (Abrigo & Love, 2016). Correspondingly, we further detail the rationale behind the causal ordering we impose on the systems' variables.

First, according to the EKC hypothesis and STIRPAT framework, we argue that the GDP exhibits the highest levels of exogeneity, while CO2 the highest level of endogeneity. More specifically, we consider that CO2, namely the variable ordered last into our transmission channel, responds more quickly following exogenous shocks to economic activity. Thus, the exogenous structural disturbances to output have both a contemporaneously and lagged impact on the CO2. Opposite, the GDP being ordered first into the system may have only a delayed response to any exogenous shocks to CO2 (i.e. is restricted to respond within the period).

⁸ The matrix of impact effects or impact multipliers matrix, stands for the matrix that contains the immediate responses of the variables following a structural shock.

Second, the three remaining variables, namely the urbanization, energy intensity, and renewable energy, enter the transmission channel at the right- (left) side of the GDP (CO₂). The reasoning for this choice is straightforward. On the one hand, as previously mentioned, the related literature ranks these factors among the most important determinants of CO₂ emission. On the other hand, regarding the sample's particularities (discussed more in detail in the Introduction section), they may easily explain the ongoing urbanization process, along with the efforts made by developing economies to combat climate change. In this manner, for example, the active involvement in the CDM of the Kyoto Protocol may mirror some of the countries' efforts aiming to reduce environmental degradation. However, what remains ambiguous so far, is the causal ordering of these factors in the transmission channel, given that it may influence our results. Indeed, we may have less information than the underlying economic foundation of CO₂-GDP nexus, but the economic intuition could equally help us in this regard.

Subsequently, we assume that any exogenous shocks to output may impact the urbanization degree, which may further influence the energy intensity, renewable energy share, and the CO₂. The same logic is preserved for the other variables, namely the external disturbances to energy intensity may affect renewables, which in turn may reflect on the CO₂ emissions levels. Thus, the CO₂ emissions are ultimately allowed to react within the period to any exogenous shocks to the other system's variables. In contrast, all the variables respond within the period following exogenous shocks to output.

Taken collectively, our previous economic rationale may be linked with the fast growth of developing economies, which may impact the scale of the urbanization process. As a result, we expect that the intensification of economic processes to increase the energy use, but at the same time, at least from a sustainability perspective, to foster the advance in energy efficiency and renewables. Notably, we postulate that efforts to promote energy efficiency and the renewable energy share are a by-product of the pressures caused by urbanization and, in any case, economic activity. Indeed, these efforts may also suggest the countries' willingness to get involved in pollution mitigation activities.

Nonetheless, the Granger (1969) causality Wald test can also help us verify the underlying economic reasoning. In this regard, we note that the associated results depicted in Table 5 in the Supplementary Material overwhelmingly endorse the assumed transmission channel between variables. Specifically, the findings show that each factor separately Granger-causes the CO₂ (except the renewable energy), while all four variables jointly Granger-cause the CO₂. Besides, GDP, along with all the excluded variables taken together,

Granger-cause the equation variable. Also, as a counterfactual, the causality towards the GDP runs only from the renewable energy share, but its statistical significance is considerably low.

4.2.2. Estimation

A key primary step in estimating the panel SVAR involves setting the optimal lag length of the model. Therefore, we choose the appropriate order of our panel SVAR, according to moment and model selection criteria (MMSC) proposed by Andrews & Lu (2001) based on Hansen's (1982) J statistic. Table 6 in the Supplementary Material presents the associated results. Overall, the MMSC statistics indicate that the first-order panel SVAR is the most suitable, compared with the other two alternatives, namely the second- and third-order specifications.⁹

Accordingly, we estimate the first-order panel SVAR model through the GMM estimator. The results displayed in Table 8 in the Supplementary Material show the following.¹⁰ On the one hand, the output has a significant positive one-lag impact on itself, urbanization, and CO₂, while a negative one on the energy intensity and renewable energy. On the other hand, urbanization, renewable energy, and CO₂ respond positively and significantly to a one-lag impact of urbanization. Moreover, the energy intensity seems to have a significant increasing delayed effect only on CO₂ emissions. Also, given that renewable energy displays a significant negative one-lag impact on GDP, there is a negative feedback effect at work between the indicators.

The first-order panel SVAR-GMM findings give us an original resolution on the dynamic behavior between variables. Indeed, it also represents the leading basis for the crucial IRFs and forecast-error variance decompositions (FEVDs), which may be retrieved following its multivariate estimation. As such, being mainly interested in the CO₂ response following shocks to other system variables, let us now discuss the associated orthogonalized

⁹ Along with MMSC (i.e. Bayesian, Akaike, and Hannan-Quinn information criterion) also the overall coefficient of determination (CD) which shows the share of the variation explained by the model and Hansen's (1982) J statistic of over-identifying restrictions are reported (see Abrigo & Love, 2016). However, we rely predominantly on MMSC in choosing the optimal lag length, given that the Hansen's (1982) J statistic has no correction for the degrees of freedom and, thus, may provide biased results. Also, we mention that the chosen model accepts Hansen's overidentification restriction at a 1% level of significance.

¹⁰ Post estimation, we examine the stability condition of the panel SVAR-GMM model. As such, we note that all eigenvalues lie inside the unit root circle, proving that the model is correctly specified and exhibits a high accuracy (see Table 7 and Figure 1 in the Supplementary Material).

cumulative IRFs¹¹ and FEVDs, both generated based on 1000 Monte Carlo simulations, and depicted in Figure 1 and Table 5, respectively.

First, the IRFs indicate that one standard deviation exogenous positive shock to GDP triggers a persistent increase in CO₂ emissions, both immediately and cumulated over the twenty years horizon. More specifically, the CO₂ increases with about two percentage points (pp) on impact, following a positive shock to output. Although it shows a smooth evolution over time, the upward trend seems to be slightly bent to the right. Likewise, its magnitude almost triples in the long-run, reaching and even exceeding five pp. From an economic perspective, these findings suggest that developing countries under examination are situated on the EKC's growing side. However, depending on their economic context, the results may suggest that they are likely to reach the crucial GDP turning point in the long-run sooner or later. Overall, these findings are expected, considering that the developing countries exhibit among the highest GDP growth rates, which are often incompatible with lower levels of environmental pollution. For example, a positive exogenous technology shock may induce the well-known phenomena of "catch-up growth" and, thus, trigger the intensification of industrial processes, which would eventually reflect at first in higher pollution. Indeed, as the nations' economic welfare grows, they can more easily acquire advanced green technologies, which, along with the increase in household income, may equally promote environmental sustainability. Thus, over time these may help in flattening the pollution curve. In this fashion, judging from the perspective of a future potential validity of EKC, our findings may complement the work of Liddle (2013), Shahbaz et al. (2015), Dogan & Seker (2016), Li et al. (2016), Wang et al. (2016), Talbi (2017), Naminse & Zhuang (2018), Pata (2018), among others.

Second, one standard deviation permanent positive shock to urbanization triggers an increase in CO₂, which may attain almost five pp after twenty years from impact. Also, we note that the cumulated effect becomes statistically significant only after two years. This may imply that the adverse effects of the urbanization process are not reflected immediately on the environment, but rather with a delay. Additionally, the overall pattern of the CO₂ response seems to mirror to a certain extent the CO₂ response to GDP shocks, suggesting that states will be able to reach the urbanization threshold that would lead to a decrease in CO₂ in the future. In this regard, the results are similar to studies that unveil a bell-shaped pattern

¹¹ We also recovered the simple orthogonalized IRFs, given that they are useful in evaluating the overall stability of our model. In this regard, Figure 2 in the Supplementary Material shows that the CO₂ responses move towards zero over time, supporting both the variables' stationarity condition and the overall stability of the model.

between urbanization and environmental degradation (see e.g. Martínez-Zarzoso & Maruotti, 2011; Lin & Zhu, 2017; Chen et al., 2019).

Third, a positive one standard deviation shock to energy intensity raises the CO₂ by about three pp on impact. As well, the cumulate CO₂ response exhibits a sharp increase over roughly the first one year and a half, then stabilizes and very slowly increases until it reaches nearly four pp following a permanent shock to energy intensity. This result is in line with the study of Sadorsky (2014a), Shahbaz et al. (2015), and Naminse & Zhuang (2018), but opposes the one of Martínez-Zarzoso & Maruotti (2011).

Fourth, in terms of the overall pattern displayed, the response of CO₂ following a positive exogenous shock to renewables seems quite similar to the cumulate effect produced by an exogenous shock to energy intensity. However, one standard deviation positive shock to RENG induces an opposite effect, namely a decrease of about two pp in CO₂ at the moment of the impact. Moreover, the cumulate magnitude of the negative response diminishes significantly after the initial impact, and then stabilize and gravitate around the same value for the rest of the period. We note that the permanent shock, projected twenty years ahead, still causes a drop in CO₂, even if the magnitude is slightly lower (i.e. around one and a half pp). These findings corroborate the ones of López-Menéndez et al. (2014), Dogan & Seker (2016), and Charfeddine & Kahia (2020) while contrasting those of Bölük & Mert (2014).

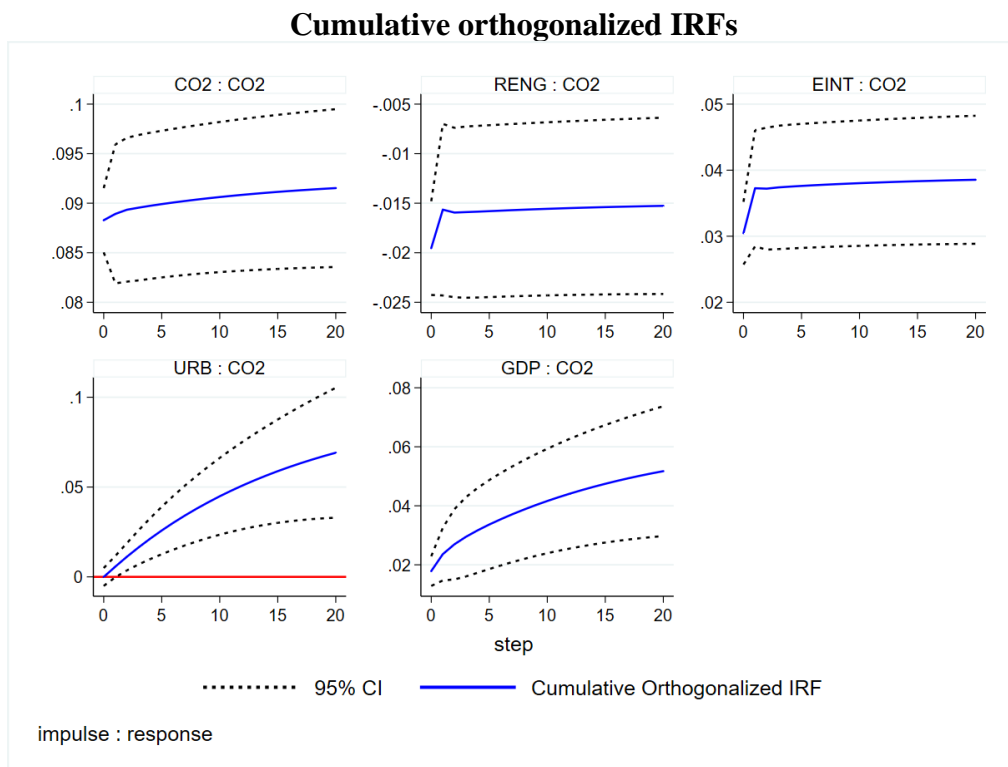
Finally, the CO₂ increases at about nine pp in the aftermath of a permanent exogenous positive shock to itself. However, the increasing of the cumulative response in the long-run is almost imperceptible, pointing out a low magnitude of CO₂ persistence (see the top-left plot in Figure 1). Overall, this finding supports the one of Martínez-Zarzoso & Maruotti (2011), Sadorsky (2014a), and Acheampong (2018), among others, who find persistence effects in CO₂ emissions.

Concerning FEVDs, on the one hand, as expected, the largest share of the variables' variation is explained by their dynamics (see the principal diagonal of Table 3). Furthermore, energy intensity seems to explain, twenty years ahead, about 9.99% of the variation in CO₂, followed by renewable energy (4.06%), output (3.99%), and urbanization (2.01%). Indeed, the findings seem to uphold the energy as the primary contributor of CO₂ in our group of developing economies. Also, the results indicate that the renewables have a more significant long-term contribution to CO₂, compared to output and urbanization. Overall, this is a quite exciting and promising result, which may suggest, yet again, that these states have made substantial efforts to switch towards more environmentally friendly energy sources, and, among others, that the CDM related projects have had the desired outcomes. Likewise, this

result is also supported by the large share of renewable energy variation, following a shock to energy intensity.

On the other hand, we remark that the external shocks to output explain, twenty years ahead, a large share of variation in the other macro factors. These findings are also not unexpected, considering that the exogenous disturbances propagate first through output and then to its related macro components. Besides, it seems that any exogenous shocks to the remaining column variables, do not exhibit a large magnitude in explaining the fluctuations in the row variables.

Figure 1



Observations: 1428 • Groups: 68

Notes: Considering two generic variables A and B, “A: B” denotes the response of B following shocks to A. The continuous line denotes the impulse response functions. The dashed lines stand for the associated 95% confidence interval computed based on 1000 Monte Carlo simulations.

Table 5**Twenty years horizon forecast-error variance decompositions**

| Response variables | Impluse variables | | | | |
|--------------------|-------------------|-------|-------|-------|-------|
| | GDP | URB | EINT | RENG | CO2 |
| GDP | 99.36 | 0.21 | 0.19 | 0.19 | 0.02 |
| URB | 12.31 | 87.54 | 0.02 | 0.01 | 0.09 |
| EINT | 21.59 | 0.14 | 78.14 | 0.04 | 0.07 |
| RENG | 0.89 | 0.37 | 8.17 | 90.47 | 0.08 |
| CO2 | 3.99 | 2.01 | 9.99 | 4.06 | 79.92 |

Notes: The numbers (in percentages) show the variation in the row variable that is explained by the column variables.

V. Robustness

We assess the robustness of our baseline SVAR specification in several ways. Also, we focus on reporting the associated findings with respect to the crucial IRFs, retrieved after running the panel SVAR-GMM model.

5.1. Alternative ordering

Considering that we use a recursive ordering strategy to achieve identification in our SVAR, we check the stability of the underlying economic rationale by implementing alternative transmission schemes. On the one hand, we check the soundness of our economic intuition behind the ordering of the factors positioned at the right-side (left-side) of GDP (CO2) within the transmission scheme, namely URB, EINT, and RENG. In this manner, we switch their initial position by running a five-time rotation between them, until we consider all available options. On the other hand, we order each of these three factors at the top of the transmission channel, namely before the output. Therefore, we can observe if changing the variable which exhibits the highest level of exogeneity alters the baseline findings. It should be mentioned that these new restrictions imposed among the system variables are even more consistent with the literature that positions urbanization, energy intensity, and renewables as the main determinants of CO2.

As shown by Figure 3 in the Supplementary Material, using distinct ordering scenarios does not qualitatively alter the baseline findings. Indeed, as expected, small changes in the magnitude of the responses are present. In this fashion, we note that a more visible difference is at work for CO2 response following external shocks to EINT, especially in the model where EINT is ordered first into the transmission channel. In particular, the cumulative response of CO2 due to a positive shock to EINT seems to follow a downward trend after reaching the peak, that is, approximately after one year and a half after the impact. One possible explanation could be related to the fact that manifesting the highest level of

exogeneity, the effect of energy intensity on CO₂, does not also include the effect of disturbances to GDP and urbanization. As such, the energy intensity may appear much lower, thus, having a lower impact on CO₂.

5.2. Altering the sample

To check whether our baseline findings are robust under certain economic or political distress conditions, we account for some well-known related events which can be seen in relation to both T and N dimensions of our sample. First, to control for the potential (delayed) effects of the global financial crisis, we restrict the period of analysis to (1992-2010) 1992-2008. Furthermore, the exclusion of the period following 2008 coincides with the starting point of the Kyoto Protocol's first commitment phase (i.e. 2008-2012). Thus, if there were specific changes in the environmental behavior of developed countries as a result of potential pressures to achieve their binding targets, we would expect them to reflect on developing countries as well. Second, we drop the period immediately following the end of the Cold War, namely 1992-1996, since the economies affected by this quite prominent geopolitical distress could have encountered difficulties in terms of economic recovery. Indeed, if our assumption hold, the fluctuations in their primary macro aggregates may alter the baseline findings. Third, having in mind the Arab Spring, which involves several developing states, we also check whether its effects reflected on our results. In doing so, we drop from the sample all the economies affected to some extent by this major political unrest episode. Finally, it is generally recognized that the petroleum industry has major implications on the environment. In this fashion we exclude all states ranked by the Central Intelligence Agency (CIA)¹² among the top thirty economies regarding the crude oil exports. Overall, the associated cumulative IFRs, depicted in Figure 4 in the Supplementary Material, shows that independent of the restriction imposed on the sample, the baseline results are preserved both in terms of pattern and statistical significance.

5.3. Exogenous control factors

We exogenously introduce, along with the main SVAR endogenous variables, several additional explanatory factors into the model to control for a potential bias caused by omitted variables. These variables are related to changes in the size of the economy¹³ (population),

¹² For more details, see <https://www.cia.gov/library/publications/the-world-factbook/fields/262rank.html>

¹³ With respect to possible changes in countries' population, we estimate two alternative models using (i) GDP and CO₂ in per capita terms, and (ii) GDP, EINT, and CO₂ in per capita terms (i.e. their growth rates in per

sectoral output composition (agriculture, industry, and services as % of GDP), trade (trade as % of GDP), environmental prospects (forest rents as % of GDP), external financing (remittances in % GDP), and private sector financial conditions (domestic credit to the private sector as % GDP) (see Table 2 and Table 3 in the Supplementary Material for variables definition and descriptive statistics, respectively). Also, to maintain the stability conditions of the SVAR model and consistency between variables, we transformed them into growth rates, by taking the first difference of their log-transformed values. Overall, the cumulative IRFs illustrated by Figure 5 in the Supplementary Material indicate that the findings are comparable with those of the baseline model, especially judging based on the significance and long-term trajectory of CO₂ response due to different innovations shocks.

IV. Heterogeneity

This section explores the sensitivity of CO₂ responses following external shocks to other factors, depending on the income level group and the ratification or ascension date of states to the Kyoto Protocol.

6.1. The level of economic development

The economic development stages that a country crosses imply that different effects such as scale, structural, or technological, are at work during different periods and may cause substantial fluctuations in environmental conditions (see e.g. Grossman & Krueger, 1991). Thus, to explore the possible difference of CO₂ responses with respect to countries' income level, we construct two sub-samples of low and lower-middle income economies, based on the World Bank classification (2017) (see Table 4 in the Supplementary Material for summary statistics). Panel (a) and panel (b) in Figure 6 in the Supplementary Material depicts the cumulative IRFs for both income sub-samples. First, as expected, following external shocks, the GDP exhibits a positive effect on CO₂ but with higher magnitude in lower-middle income economies. Moreover, the cumulated CO₂ response over the first two years displays a sharp increase in lower-middle income states, compared to the low income ones. Likewise, the increasing long-run trajectory seems to be more accentuated in wealthier countries.

capita terms, computed as the difference of log-transformed values). As shown by the panel (e)-(f) in Figure 4 in the Supplementary Material, the cumulative IRFs are almost identical to those revealed by the baseline model.

Second, CO₂ emissions significantly and positively react due to innovations shocks to urbanization only in low income countries, and with a delay of around four years. Besides, the CO₂ response path tends to display a bell-shaped pattern in the long-term, supporting the urbanization-EKC hypothesis. Conversely, the lack of significance in the lower-middle income countries may suggest that the urbanization process is at a more advanced stage, leading to a more abundant flow of sophisticated ecological practices that help in combating pollution.

Third, following a positive shock to energy intensity (renewables), the CO₂ emissions respond in a positive (negative) way in both income groups. As well, the cumulated effect shows a sharp increase after the impact in both sub-samples (except CO₂ response following renewables shocks in low income states, where the increase seems to be smoother and lower in magnitude). However, starting approximately with the second year, the IRFs indicate that the cumulated effect stabilizes and preserves its positive linear trajectory up to twenty years in low income states. In contrast, it follows a monotonically increasing pattern in lower-middle income ones. On the whole, this may confirm that in countries where the industrialization process is more pronounced, it also becomes more challenging to maintain low levels of pollution.

Finally, an exogenous positive shock to CO₂ leads to an increase in its levels, and the magnitude of impact seems to be comparable in both groups. Nonetheless, in low income countries, the cumulated response starts to decline after the impact, and then quickly readjust (after about two years) to a linear path that remains stable in the long-run. Opposite, in lower-middle income economies, the cumulated response keeps an increasing trajectory over the twenty years horizon.

6.2. The Kyoto Protocol status

We split the main sample taking into account the date of the ratification/accession of individual states to the Kyoto Protocol based on the United Nations Treaty Collection¹⁴. Thus, the first sub-sample (Kyoto Protocol group A) comprises the nations which ratified or acceded before the year in which it entered into force (i.e. 2005), while in the second group (Kyoto Protocol group B) we include the remaining countries for which the ratification/accession date is 2005 onwards (see Table 4 in the Supplementary Material for

¹⁴https://treaties.un.org/Pages/ViewDetails.aspx?src=TREATY&mtsg_no=XXVII-7-a&chapter=27&clang=en.

summary statistics). The cumulative IRFs are illustrated by panels (c) and (d) in Figure 6 in the Supplementary Material.

On the one hand, the findings indicate that for the states which ratified or acceded to the Kyoto Protocol before 2005, the evolution of cumulated CO₂ response following output and urbanization shocks seems to switch its increasing trend in the long-run. In particular, this suggests that this group of countries may attain the peak in CO₂ more rapidly and for lower levels of GDP and URB, compared to the economies which ratified /acceded to the Protocol after it entered into force. As such, the traditional and urbanization-EKC hypothesis seems to be more realistic for the Kyoto Protocol group A. Moreover, for the Kyoto Protocol group A states, the urbanization exhibits a delayed cumulated effect on CO₂. In contrast, for the members of group B, the effect loses its significance in the long-term.

On the other hand, an exogenous increase in energy intensity (renewables) triggers a cumulated positive (negative) effect on CO₂ in both groups of economies. However, at the moment of the impact, the magnitude of CO₂ response is higher due to energy intensity (renewable energy) disturbances for the states which ratified/acceded to the Kyoto Protocol before (after) it entered into force. Also, in the next two years after the impact, the cumulated magnitude of CO₂ response following both energy intensity and renewables shocks increases sharply, but then stabilizes and raises very slowly for the group A economies. For the group B states, the cumulated response of CO₂ (i) raises abruptly after the impact due to EINT disturbances, but then stabilizes to a new high and follows a linear path until the end of the period, (ii) remains roughly at the same level recorded at the time of the impact following renewable energy shocks. Besides, a positive one standard deviation shock to CO₂ has a positive effect on its levels for both groups. However, the cumulated effect increases (decreases) slowly over the years across the states of the Kyoto Protocol group A (B). Overall, the findings may suggest that the states which ratified or acceded to the Protocol before 2005 are the ones that have undergone significant changes in their economic development (e.g. have experienced a more intense process of industrialization and urbanization, among others). Thus, they were committing much faster in actions to counteract the potential adverse effects on the environment.

VII. Sectoral CO2 emissions

To have a more in-depth look at the potential changes in pollution dynamics in the relationship with our macro indicators, we substitute aggregated CO2 with its sector-specific counterparts (see Table 2 and Table 3 in the Supplementary Material for variables definition and summary statistics, respectively).¹⁵ In doing so, we estimate the GMM-SVAR model considering the CO2 related to each of the following sectors: transport, buildings, other industrial combustion, non-combustion, and power industry. Figure 2 displays the CO2 sector-specific cumulative orthogonalized IRFs.

First, considering the presumed differences in the magnitude, an external shock to output and urbanization has a cumulative significant positive effect on CO2 from transport, buildings, and non-combustion sector—with the notable exception of CO2 from buildings which do not significantly respond to urbanization disturbances. Besides, the significant positive cumulated paths over the twenty-year horizon suggest that the related EKC hypothesis may be at work in the very long-run, both for output and urbanization. Also, in line with the baseline findings, the CO2 emissions respond with a delay of about two years following urbanization shocks. On this last point, given that the construction industry has a substantial contribution to the urbanization process, the lack of significance of the buildings-related CO2 response following external shocks to urbanization may indicate that a substantial number of green projects are implemented in this sector, thus, helping to reduce the associated pollution.

Second, an exogenous increase in output and urbanization reduce the CO2 from other industrial combustion and power industry sector both on impact and cumulated over twenty years. However, industrial combustion- and power industry-related CO2 emissions do not respond immediately to output shocks, but rather with roughly ten and eighteen years of delay. Moreover, regarding the disturbances to urbanization, they seem to cause a U-shaped pattern in cumulative CO2 emissions' evolution, opposite to the bell-shaped pattern postulated by the traditional EKC hypothesis.

Third, the CO2 related to each of the five sectors react positively (negatively) to one standard deviation energy intensity (renewables) shocks, both on impact and cumulated over the twenty years, thus, backing up the baseline findings. However, the effect of renewables

¹⁵ We test the cross-sectional dependence and stationary properties of CO2 sector variables using the same tests as for the baseline model. The findings confirm the presence of cross-sectional dependence, while the unit root test shows that variables are stationary in levels (see Supplementary Material Table 9-11). However, in empirical analysis, we use the first difference of the variables in order to work with growth rates and have all the variables in the system at the same level.

on CO₂ from non-combustion and power industry is not statistically significant. Indeed, these two similar results may go hand in hand, given that access to energy in developing countries is a significant issue, mainly alleviated, among others, by the transition to off-grid renewable energy systems [International Renewable Energy Agency (IRENA), 2015]. More precisely, the off-grid renewables technologies (e.g. solar, micro-hydro, wind, biomass, among others), whose leading market is concentrated in developing economies, represent the more environmentally-friendly and cost-effective alternative to classical non-renewable energy sources, such as the fossil fuels used for electricity generation via combustion processes [see e.g. IRENA, 2015; Renewable Energy Policy Network for the 21st Century (REN21), 2015]. Additionally, the results also corroborate with the negative effect of output and urbanization on power industry-related CO₂.

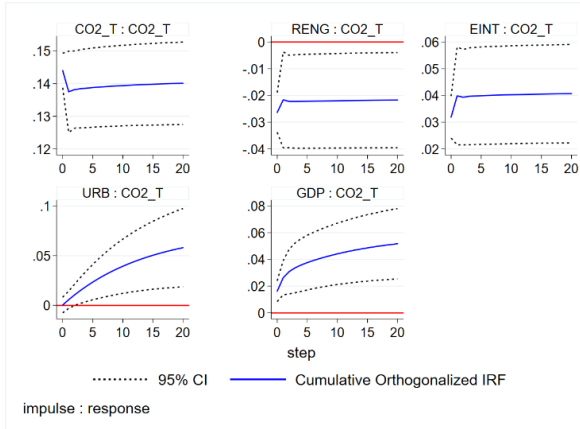
Fourth, an external increase in the sector-specific CO₂ emissions triggers a statistically significant increase in its levels. At the same time, the magnitude at the moment of impact ranges from about 14.5 pp (CO₂ from transport) to 30 pp (CO₂ from other industrial combustion). Furthermore, the cumulated effect starts to decay immediately after the impact (except CO₂ associated with other industrial combustion), and then quickly stabilizes and follows an almost linear path until the end of the analyzed period. In particular, the results may highlight, yet again, the inertial behavior of CO₂ pollution levels.

Overall, the findings illustrate, on the one hand, the complexity of the relationship between sector-specific CO₂ and the several related key economic aggregates, highlighting which sector is more likely to be associated in the future with higher pollution levels. On the other hand, the results strengthen the vital role of non-combustion energy sources and energy efficiency projects (e.g. the rapidly growing off-grid renewable systems, the use of sustainable technologies in the construction industry, among many others) in promoting green growth and urbanization, and ultimately in reducing the environmental degradation.

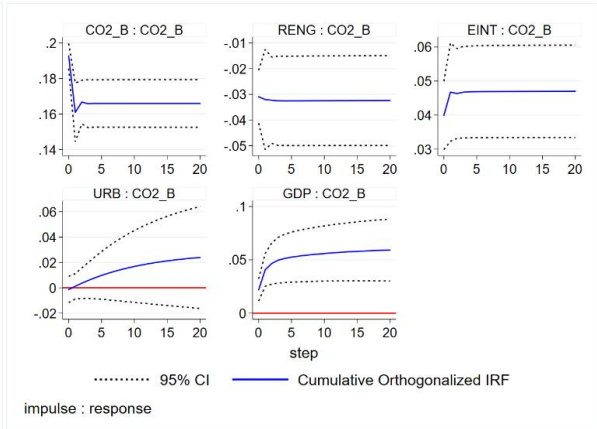
Figure 2

Cumulative orthogonalized IRFs: sectoral CO2 emissions

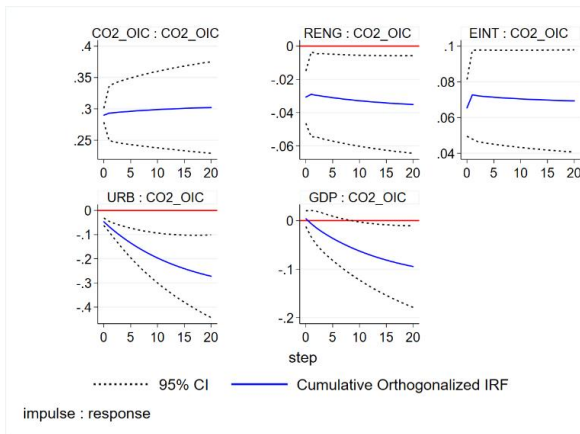
(a) CO2 from transport



(b) CO2 from buildings



(c) CO2 from other industrial combustion



(d) CO2 from non-combustion

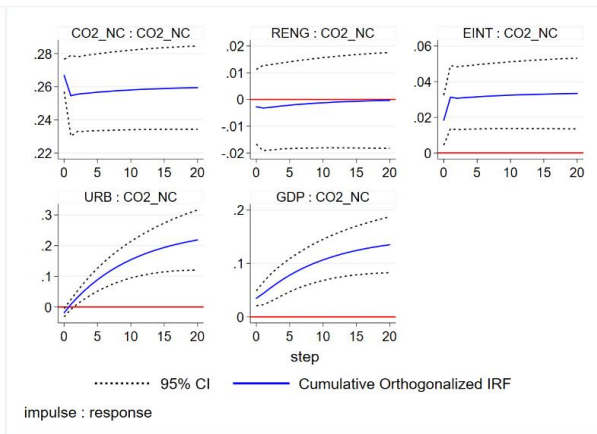
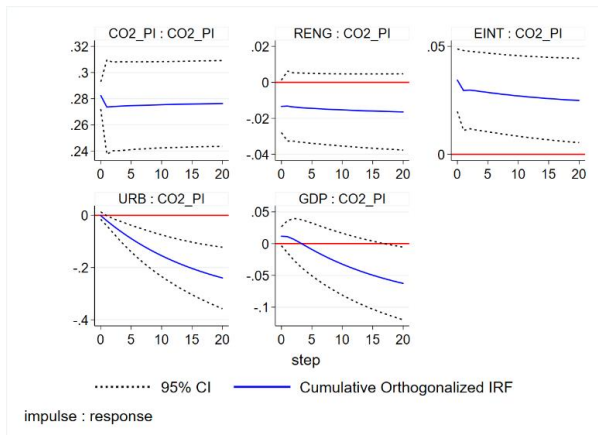


Figure 2**(continued)****(e) CO2 from power industry**

Observations: 1422 • Groups: 68

Notes: The continuous line denotes the impulse response functions. The dashed lines stand for the associated 95% confidence interval computed based on 1000 Monte Carlo simulations.

VIII. Conclusion and policy implications

This paper explored the impact of external changes in output, urbanization, energy intensity, and renewable energy on aggregated and sector-specific CO₂, within a modified STIRPAT analytical framework. To this end, motivated by the potential endogenous behavior between variables, we employed the novel panel GMM-VAR technique for a rich sample of 68 developing states over 1992-2015.

The results showed, on the one hand, that an exogenous increase in output, urbanization, energy intensity and CO₂ led to a significant increase in CO₂, both on impact and cumulated over the twenty years horizon. Besides, the CO₂ response following disturbances to output and urbanization, suggest that a threshold effect, compatible with the classical and urbanization EKC hypothesis, might be at work in the long-run for our group of countries. Conversely, we found that a positive shock to renewables cumulatively and significantly decreases the current and future levels of CO₂. In sum, these findings may imply that in the context of rapid industrialization and urbanization, renewable energy is one of the most powerful tools in mitigating environmental degradation. Nonetheless, more considerable attention must also be paid to energy efficiency, especially as increasing it can further enhance the beneficial effects of renewable energy on the environment. These results are supported by several robustness tests, including an alternative Cholesky ordering of variables, when altering the sample, and controlling for a series of exogenous factors. On the other hand, the findings are found to be sensitive concerning both countries' level of

development and their Kyoto Protocol ratification/ascension status. Besides, the disaggregated CO₂ analysis unveiled essential differences regarding the contribution of various sectors to the overall CO₂ pollution. In particular, the results may suggest that the CO₂ emissions related to transportation, construction, and non-combustion sector are more likely to increase in the future, compared to other industrial combustion and power industry sector.

The findings could be transposed in some valuable policy recommendations. First, developing countries should pay more attention to the implications that the process of urbanization, as well as the growth-promoting policies, have on CO₂ pollution. Moreover, the urban planning and development policy requires an appropriate design to accommodate better any potential negative impacts on the quality of the environment. Second, although countries make outstanding efforts to invest as much as possible in renewable energy sources and minimize energy dependency, these investments should be continuously adapted to cope with the dynamics of their particular economic environment. Likewise, adequate monitoring during project implementation may increase their efficiency and signal beforehand any potential nonconformities. Third, to counterbalance and mitigate the overall pollution, additional efforts should be directed towards the sectors where CO₂ emissions are more likely to increase. Finally, the ongoing international cooperation and assistance from developed nations may represent a central pillar in ensuring environmental sustainability in developing economies. Future work could consider a more detailed breakdown of energy sources in assessing their impact on CO₂ (see e.g. Antonakakis et al., 2017; Naminse & Zhuang, 2018). However, this is strictly conditioned by data availability, especially for this group of developing economies. As well, an analysis of the impact of various types of crises on CO₂, by making use of complementary techniques such as the local projection method (see e.g. Jalles, 2019), could provide additional insights regarding the future behavior of CO₂ emissions.

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Supplementary Material

Table 1

List of countries

| Geographic region | | |
|----------------------------------|-----------------------------|---------------------------------------|
| East Asia and Pacific (10) | Europe and Central Asia (6) | Latin America and Caribbean (5) |
| Indonesia | Armenia | Bolivia |
| Kiribati | Georgia | El Salvador |
| Lao PDR | Kyrgyz Republic | Guatemala |
| Mongolia | Tajikistan | Honduras |
| Myanmar | Ukraine | Nicaragua |
| Papua New Guinea | Uzbekistan | |
| Philippines | | |
| Solomon Islands | | |
| Vanuatu | | |
| Vietnam | | |
| Middle East and North Africa (5) | South Asia (6) | Sub-Saharan Africa (36) |
| Egypt, Arab Rep. | Bangladesh | Angola |
| Jordan | Bhutan | Benin [‡] |
| Morocco | India | Burkina Faso [‡] |
| Tunisia | Nepal [‡] | Burundi [‡] |
| Yemen, Rep. | Pakistan | Cabo Verde |
| | Sri Lanka | Cameroon |
| | | Central African Republic [‡] |
| | | Chad [‡] |
| | | Comoros [‡] |
| | | Congo, Dem. Rep. [‡] |
| | | Congo, Rep. |
| | | Côte d'Ivoire |
| | | Ethiopia [‡] |
| | | Gambia [‡] |
| | | Ghana |
| | | Guinea [‡] |
| | | Guinea-Bissau [‡] |
| | | Kenya |
| | | Lesotho |
| | | Liberia [‡] |
| | | Madagascar [‡] |
| | | Malawi [‡] |
| | | Mali [‡] |
| | | Mauritania |
| | | Mozambique [‡] |
| | | Nigeria |
| | | Rwanda [‡] |
| | | Senegal [‡] |
| | | Sierra Leone [‡] |
| | | Sudan |
| | | Swaziland |
| | | Tanzania [‡] |
| | | Togo [‡] |
| | | Uganda [‡] |

Zambia

Zimbabwe[‡]Notes: [‡] denotes that the respective country belongs to the low income group.**Table 2****Variables definition**

| Variable | Defintion | Source | |
|----------|---|---|--|
| CO2 | CO2 emissions totals of fossil fuel use and industrial processes (ktonnes) | The European Commission, Joint Research Centre (EC-JRC)/Netherlands Environmental Assessment Agency (PBL). Emissions Database for Global Atmospheric Research (EDGAR), release EDGARv4.3.2_FT2016 (1970 - 2016). Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Olivier, J.G.J., Peters, J.A.H.W., Schure, K.M., Fossil CO2 and GHG emissions of all world countries, EUR 28766 EN, Publications Office of the European Union, Luxembourg, 2017, ISBN 978-92-79-73207-2, doi:10.2760/709792, JRC107877 (http://edgar.jrc.ec.europa.eu/overview.php?v=booklet2017&dst=CO2emi) | |
| CO2_T | CO2 emission from transport | | |
| CO2_B | CO2 emission from buildings | | |
| CO2_OIC | CO2 emission from other industrial combustion | | |
| CO2_NC | CO2 emission from non-combustion | | |
| CO2_PI | CO2 emission from power industry | | |
| GDP | GDP based on purchasing power parity (PPP) (constant 2011 international \$) | | The World Bank, World Bank Indicators (https://databank.worldbank.org/data/home.aspx) |
| URB | Urban population (% of total population) | | |
| RENG | Renewable energy consumption (% of total final energy consumption) | | |
| EINT | Energy intensity level of primary energy computed as total primary energy supply over GDP measured in constant 2011 US dollars at PPP (MJ/\$2011 PPP GDP) | | |
| POP | Total midyear population | | |
| AGRI | Agriculture, value added (% of GDP) | | |
| IND | Industry, value added (% of GDP) | | |
| SERV | Services, value added (% of GDP) | | |
| TRADE | Trade (% of GDP) | | |
| FRENTS | Forest rents (% of GDP) | | |
| CREDIT | Domestic credit to private sector (% of GDP) | | |
| GDPc | GDP per capita based on purchasing power parity (PPP) (constant 2011 international \$) | | |
| REM | Migrant remittance inflows (nominal US\$ million) | The World Bank staff calculation based on data from IMF Balance of Payments Statistics database and data releases from central banks, national statistical agencies, and World Bank country desks (https://www.worldbank.org/en/topic/labormarkets/brief/migration-and-remittances) | |
| CO2c | CO2 per capita emissions totals of fossil fuel use and industrial processes (ktonnes) | | |
| | | Authors' computation based on The European Commission, Joint Research Centre (EC-JRC)/Netherlands Environmental Assessment Agency (PBL) (CO2 emissions: http://edgar.jrc.ec.europa.eu/overview.php?v=booklet2017&dst=CO2emi) and World Bank Indicators data (population: https://databank.worldbank.org/data/home.aspx) | |

| | | |
|-------|--|--|
| EINTc | Energy intensity level of primary energy per capita computed as total primary energy supply over GDP measured in constant 2011 US dollars at PPP (MJ/\$2011 PPP GDP) | Authors' computation based on the World Bank Indicators data (energy intensity level of primary energy and population: https://databank.worldbank.org/data/home.aspx) |
|-------|--|--|

Table 3

Descriptive statistics (full-sample)

| Variable/Statistic | Mean | Std. dev | Median | Min | Max | Observations |
|------------------------------|-----------|-----------|-----------|-----------|----------|--------------|
| baseline analysis | | | | | | |
| GDP | 1.54e+11 | 5.49e+11 | 2.52e+10 | 1.43e+08 | 7.54e+12 | 1632 |
| URB | 36.97067 | 15.85659 | 35.3225 | 6.288 | 83.679 | 1632 |
| EINT | 8.732009 | 6.978321 | 6.149098 | 1.91032 | 57.98816 | 1632 |
| RENG | 59.00502 | 29.2848 | 63.37218 | 0.600592 | 98.34261 | 1632 |
| CO2 | 45506.02 | 185879.9 | 4161.842 | 20.6217 | 2419637 | 1632 |
| robustness analysis | | | | | | |
| GDPc | 2815.427 | 2185.772 | 2085.198 | 180.4062 | 12152.17 | 1632 |
| CO2c | 0.0008181 | 0.0012382 | 0.0003974 | 0.0000311 | 0.012404 | 1632 |
| POP | 4.17e+07 | 1.38e+08 | 1.03e+07 | 74769 | 1.31e+09 | 1632 |
| AGRI | 23.93044 | 12.40996 | 22.88478 | 2.706677 | 79.04237 | 1559 |
| IND | 24.93198 | 10.76102 | 24.15961 | 2.073173 | 77.41367 | 1540 |
| SERVI | 45.03406 | 9.706143 | 45.77348 | 12.43525 | 77.02007 | 1485 |
| TRADE | 72.59632 | 32.94223 | 67.26805 | 0.1674176 | 311.3553 | 1565 |
| FRENTS | 4.593966 | 6.052195 | 2.429323 | 0.0000 | 40.42677 | 1616 |
| REM | 2072.407 | 6065.007 | 204.5626 | 0.0095628 | 70388.64 | 1340 |
| CREDIT | 21.92812 | 18.57499 | 15.66249 | 0.4103563 | 114.7235 | 1521 |
| CO2 sector-specific analysis | | | | | | |
| CO2_T | 7117.286 | 20936.74 | 1244.581 | 15.26836 | 257301.2 | 1632 |
| CO2_B | 5187.247 | 17222.53 | 561.6689 | 0.407881 | 180733.1 | 1632 |
| CO2_NC | 5724.411 | 18873.11 | 476.8578 | 0.046156 | 206595.6 | 1632 |
| CO2_OIC | 10202.23 | 42005.12 | 636.099 | 0.0000 | 529105.3 | 1608 |
| CO2_PI | 17424.87 | 91486.77 | 608.0745 | 0.0000 | 1245902 | 1632 |

Table 4**Descriptive statistics (sub-samples)**

| Variable/Statistic | Mean | Std. dev | Median | Min | Max | Observations |
|-------------------------------|----------|----------|----------|----------|----------|--------------|
| low income economies | | | | | | |
| GDP | 1.97e+10 | 2.16e+10 | 1.36e+10 | 5.13e+08 | 1.53e+11 | 576 |
| URB | 29.17297 | 11.52414 | 30.2355 | 6.288 | 59.632 | 576 |
| EINT | 11.83926 | 8.449231 | 9.401523 | 1.91032 | 57.98816 | 576 |
| RENG | 81.83385 | 14.57414 | 86.66449 | 40.46676 | 98.34261 | 576 |
| CO2 | 2391.314 | 2914.064 | 1306.94 | 45.36593 | 18988.19 | 576 |
| lower-middle income economies | | | | | | |
| GDP | 2.27e+11 | 6.71e+11 | 4.27e+10 | 1.43e+08 | 7.54e+12 | 1056 |
| URB | 41.22395 | 16.2794 | 40.0925 | 12.977 | 83.679 | 1056 |
| EINT | 7.037145 | 5.31305 | 5.425794 | 1.992982 | 38.33533 | 1056 |
| RENG | 46.55294 | 27.75466 | 51.01571 | .600592 | 95.85808 | 1056 |
| CO2 | 69023.13 | 227689 | 8254.396 | 20.6217 | 2419637 | 1056 |
| Kyoto Protocol status group A | | | | | | |
| GDP | 1.90e+11 | 6.53e+11 | 2.88e+10 | 1.43e+08 | 7.54e+12 | 1104 |
| URB | 38.34527 | 17.04287 | 36.327 | 6.288 | 83.679 | 1104 |
| EINT | 8.284522 | 6.528194 | 5.964056 | 1.91032 | 57.98816 | 1104 |
| RENG | 53.47162 | 30.03119 | 57.21445 | .600592 | 97.29142 | 1104 |
| CO2 | 59523.13 | 222856.2 | 5533.39 | 20.6217 | 2419637 | 1104 |
| Kyoto Protocol status group B | | | | | | |
| GDP | 7.91e+10 | 1.77e+11 | 2.00e+10 | 6.37e+08 | 9.47e+11 | 528 |
| URB | 34.09649 | 12.56938 | 33.7425 | 9.585 | 65.526 | 528 |
| EINT | 9.667664 | 7.759983 | 6.990818 | 2.056564 | 50.13474 | 528 |
| RENG | 70.57486 | 23.83922 | 78.07493 | 5.554171 | 98.34261 | 528 |
| CO2 | 16197.52 | 41380.69 | 2583.84 | 43.01915 | 227542 | 528 |

Table 5

Panel SVAR-Granger causality Wald test

| [Equation] \ Excluded variable | chi2 | df | prob > chi2 |
|--------------------------------|-----------|----|-------------|
| [GDP] | | | |
| URB | 1.083 | 1 | (0.298) |
| EINT | 1.531 | 1 | (0.216) |
| RENG | 2.812* | 1 | (0.094) |
| CO2 | 0.469 | 1 | (0.493) |
| ALL | 5.921 | 4 | (0.205) |
| [URB] | | | |
| GDP | 10.608*** | 1 | (0.001) |
| EINT | 0.167 | 1 | (0.683) |
| RENG | 2.247 | 1 | (0.134) |
| CO2 | 1.989 | 1 | (0.158) |
| ALL | 16.152*** | 4 | (0.003) |
| [EINT] | | | |
| GDP | 22.044*** | 1 | (0.000) |
| URB | 0.149 | 1 | (0.699) |
| RENG | 0.563 | 1 | (0.453) |
| CO2 | 0.805 | 1 | (0.370) |
| ALL | 23.092*** | 4 | (0.000) |
| [RENG] | | | |
| GDP | 11.287*** | 1 | (0.001) |
| URB | 5.934** | 1 | (0.015) |
| EINT | 2.131 | 1 | (0.144) |
| CO2 | 1.273 | 1 | (0.259) |
| ALL | 23.727*** | 4 | (0.000) |
| [CO2] | | | |
| GDP | 4.828** | 1 | (0.028) |
| URB | 15.787*** | 1 | (0.000) |
| EINT | 6.179** | 1 | (0.013) |
| RENG | 1.313 | 1 | (0.252) |
| ALL | 22.787*** | 4 | (0.000) |

Notes: H0 is "Excluded variable does not Granger-cause equation variable", while according to H1 "Excluded variable Granger-causes equation variable. ***, **, *, denotes significance at the 1%, 5% and 10% level, respectively.

Table 6

| Panel SVAR selection order criteria | | | | | | |
|-------------------------------------|-------|--------|-----------|----------|---------|----------|
| Lag | CD | J | J p-value | MBIC | MAIC | MQIC |
| 1 | 0.988 | 70.449 | 0.019 | -270.824 | -25.550 | -117.853 |
| 2 | 0.988 | 48.099 | 0.033 | -179.417 | -15.900 | -77.435 |
| 3 | 0.988 | 17.601 | 0.345 | -96.156 | -14.398 | -45.166 |
| Observations | 1224 | | | | | |
| Panels | 68 | | | | | |

Notes: Model and moment selection criteria are computed using the first four lags of variables.

Table 7

| Model stability condition | | |
|---------------------------|-----------|---------|
| Eigenvalue | | |
| Real | Imaginary | Modulus |
| 0.940 | 0 | 0.940 |
| 0.372 | 0 | 0.372 |
| -0.081 | 0 | 0.081 |
| -0.045 | 0 | 0.045 |
| 0.022 | 0 | 0.022 |

Notes: All the eigenvalues lie inside the unit circle. The GMM panel SVAR model satisfies stability condition.

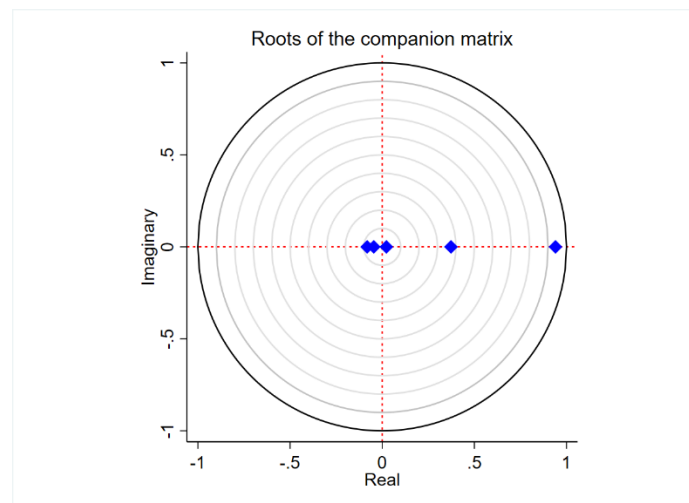
Figure 1**Inverted roots of AR characteristics polynomial (GMM-SVAR)**

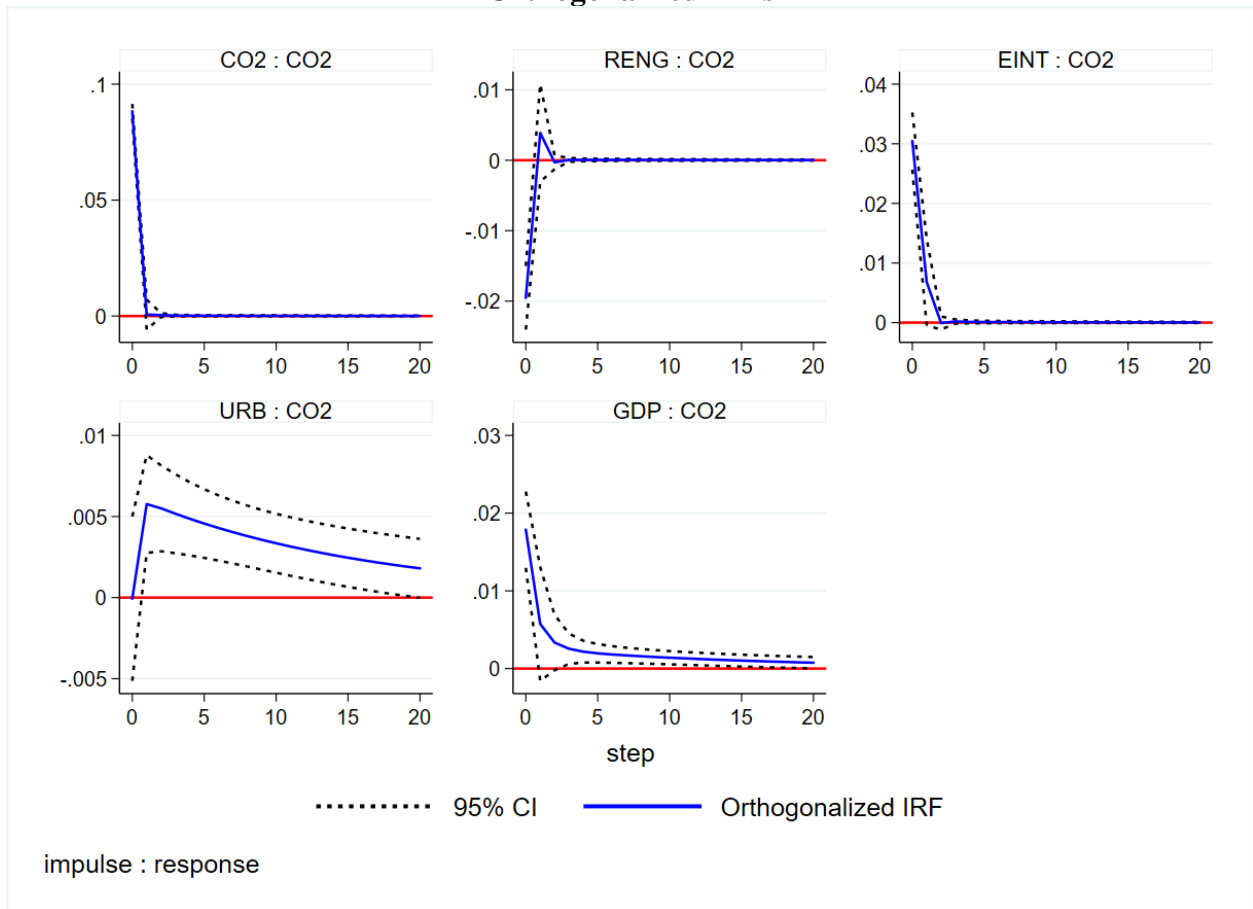
Table 8**First-order panel SVAR-GMM estimates**

| Response of | Response to | | | | |
|-------------------------------|------------------------|-----------------------|----------------------|----------------------|---------------------|
| | GDP _{t-1} | URB _{t-1} | EINT _{t-1} | RENG _{t-1} | CO2 _{t-1} |
| GDP | 0.3746*** (0.0436) | -0.2343 (0.2251) | 0.0190 (0.0154) | -0.0292* (0.0174) | 0.0083 (0.0122) |
| URB | 0.0066*** (0.0020) | 0.9398*** (0.0241) | 0.0002 (0.0007) | 0.0010 (0.0007) | 0.0011 (0.0007) |
| EINT | -0.2868*** (0.0610) | 0.1219 (0.3158) | -0.0517 (0.0427) | 0.0271 (0.0362) | 0.0246 (0.0274) |
| RENG | -0.1375*** (0.0409) | 0.4409** (0.1810) | -0.0481 (0.0329) | -0.0618 (0.0497) | -0.0263 (0.0233) |
| CO2 | 0.1628** (0.0741) | 1.9181*** (0.4827) | 0.1078** (0.0433) | 0.0536 (0.0468) | 0.0072 (0.0367) |
| Observations ($N \times T$) | 1428 | | | | |
| Countries | 68 | | | | |

Notes: The five-variable one lag panel SVAR is estimated by GMM, using first four lags of the variables as instruments. The country-specific fixed effects are removed during estimation via the Helmert transformation. Reported numbers display the coefficients of regressing the row variables on first lag of the column variables. Standard errors robust to heteroskedasticity and serial correlation in brackets. ***, **, *, denotes significance at the 1%, 5% and 10% level, respectively.

Figure 2

Orthogonalized IRFs



Observations: 1428 • Groups: 68

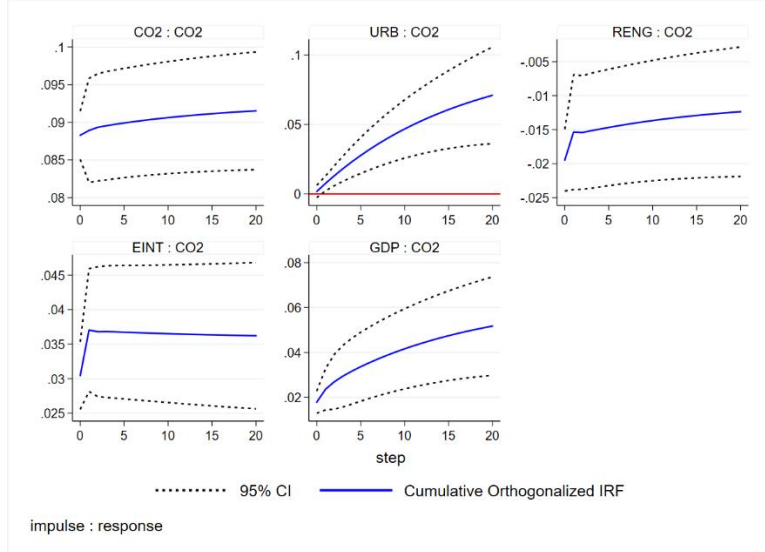
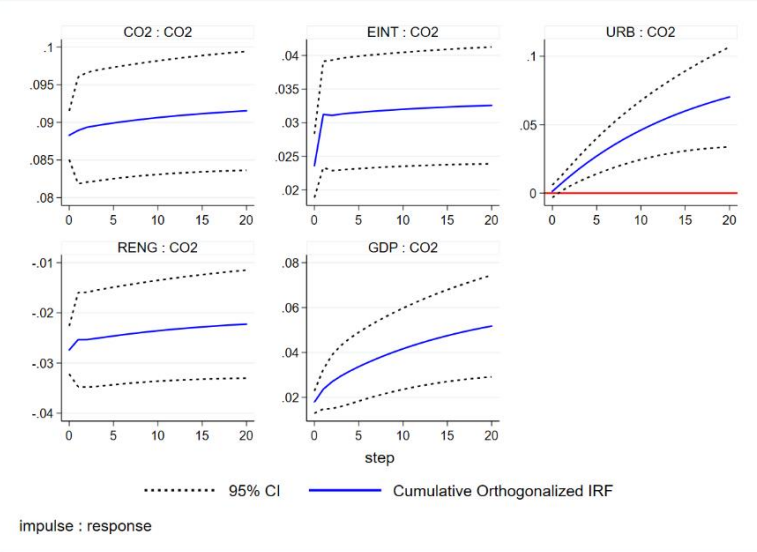
Notes: The continuous line denotes the impulse response functions. The dashed lines stand for the associated 95% confidence interval computed based on 1000 Monte Carlo simulations.

Figure 3

Cumulative orthogonalized IRFs: robustness (alternative ordering)

(a) (GDP → RENG → URB → EINT → CO2)

(b) (GDP → EINT → RENG → URB → CO2)

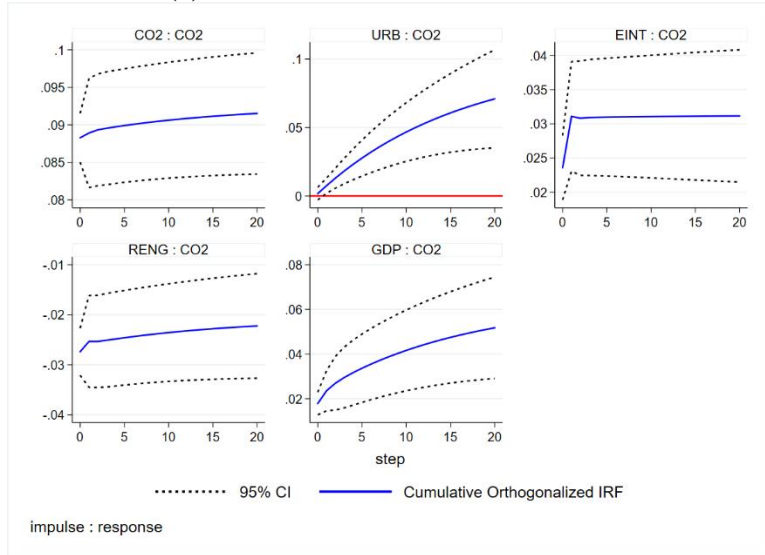
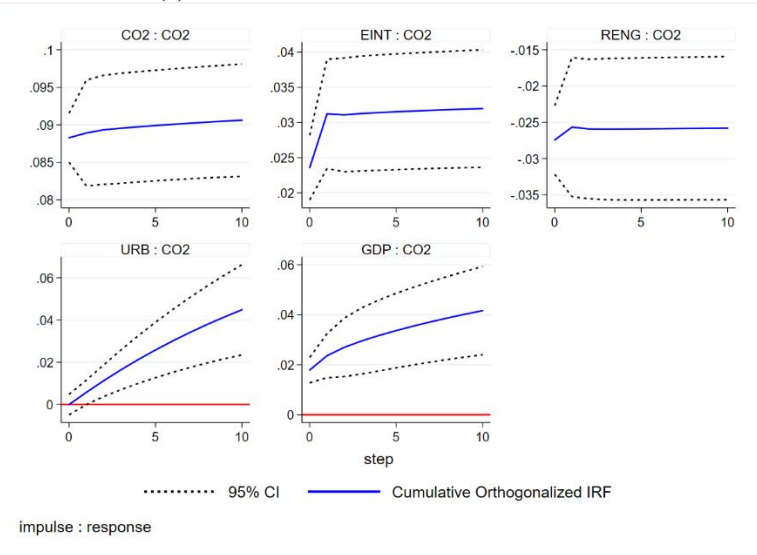


Observations: 1428 • Groups: 68

Observations: 1428 • Groups: 68

(c) (GDP → URB → RENG → EINT → CO2)

(d) (GDP → RENG → EINT → URB → CO2)



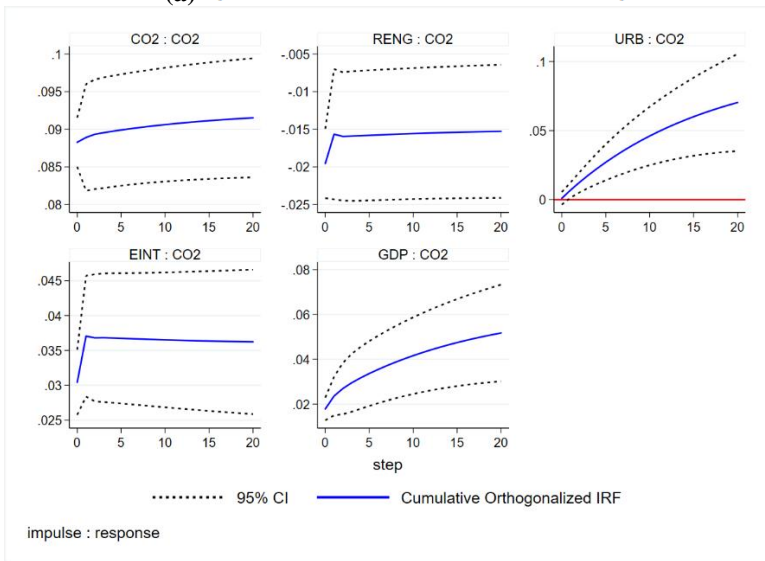
Observations: 1428 • Groups: 68

Observations: 1428 • Groups: 68

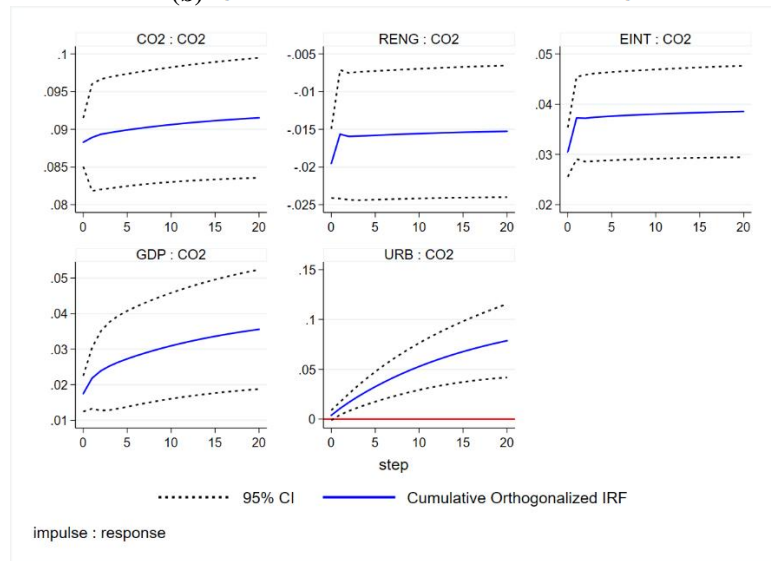
Figure 3

(Continued)

(a) (GDP → EINT → URB → RENG → CO2)



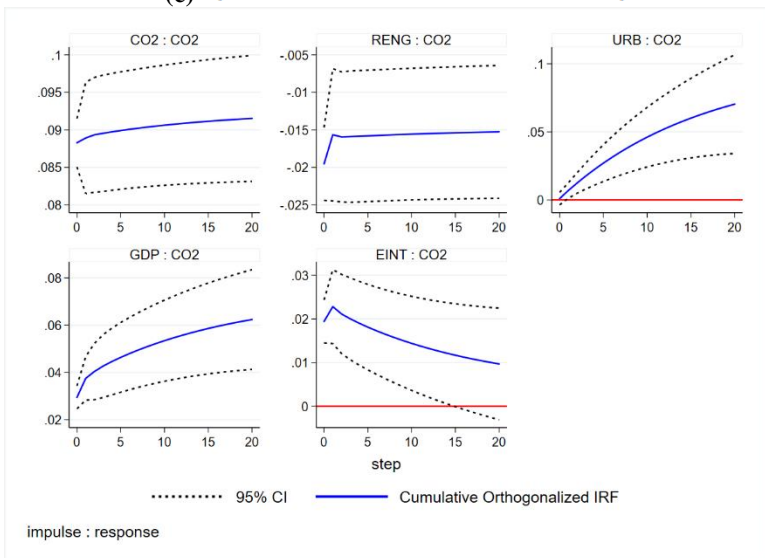
(b) (URB → GDP → EINT → RENG → CO2)



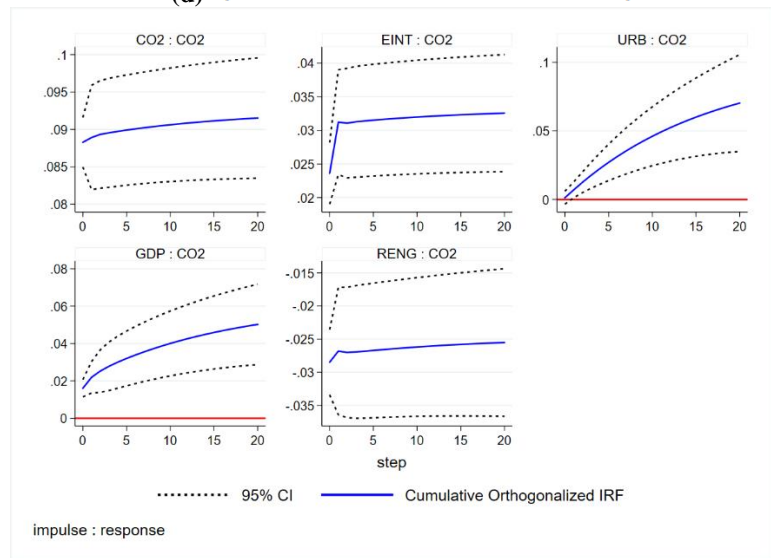
Observations: 1428 • Groups: 68

Observations: 1428 • Groups: 68

(c) (EINT → GDP → URB → RENG → CO2)



(d) (RENG → GDP → URB → EINT → CO2)



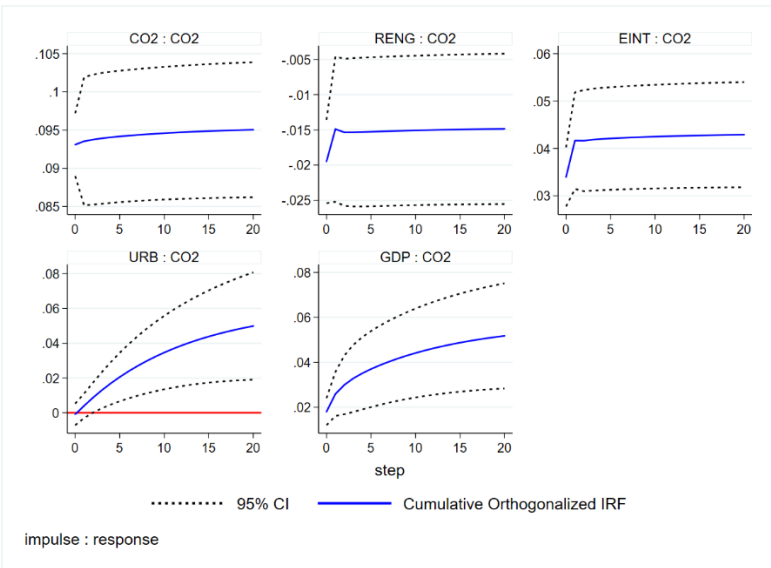
Observations: 1428 • Groups: 68

Observations: 1428 • Groups: 68

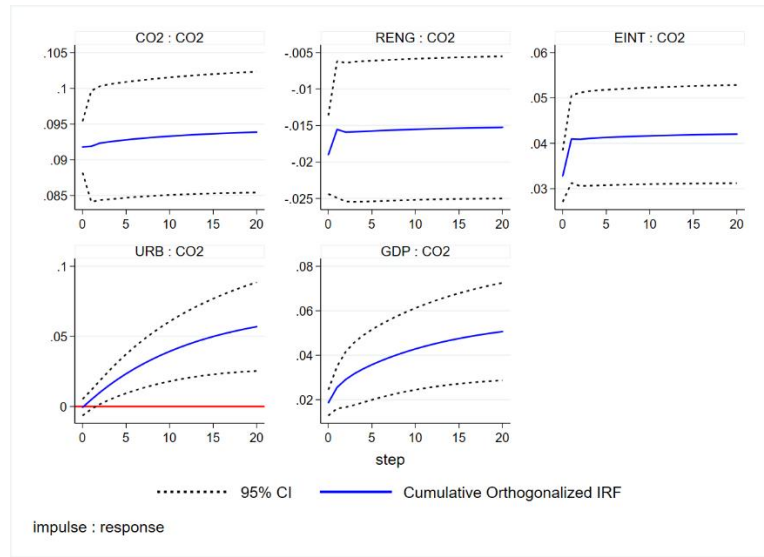
Notes: The continuous line denotes the impulse response functions. The dashed lines stand for the associated 95% confidence interval computed based on 1000 Monte Carlo simulations.

Figure 4
Cumulative orthogonalized IRFs: altering the sample & variables in per capita terms

(a) period: 1992-2008



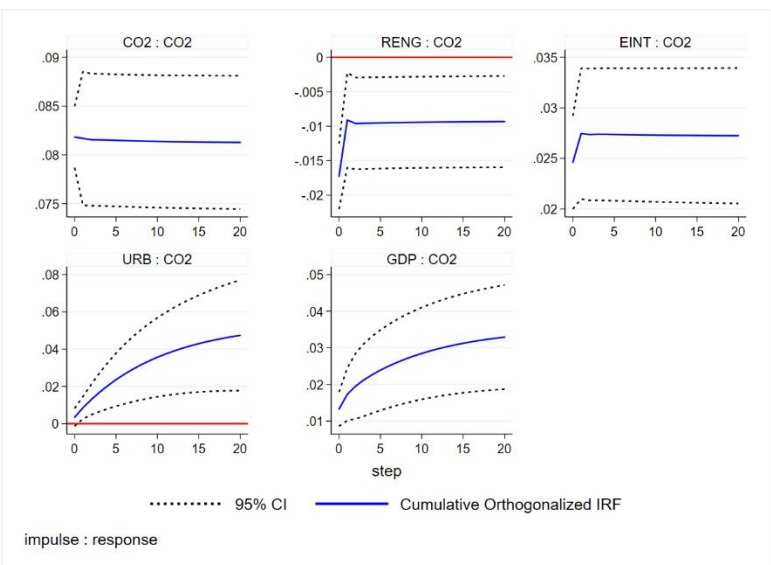
(b) period: 1992-2010



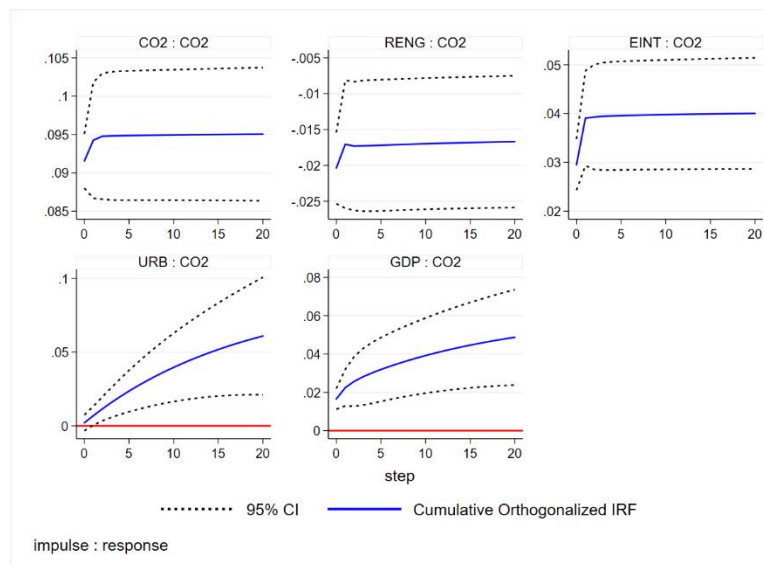
Observations: 1020 • Groups: 68

Observations: 1156 • Groups: 68

(c) period: 1996-2015



(d) without: Egypt, Jordan, Mauritania, Morocco, Sudan, Tunisia, Yemen



Observations: 1292 • Groups: 68

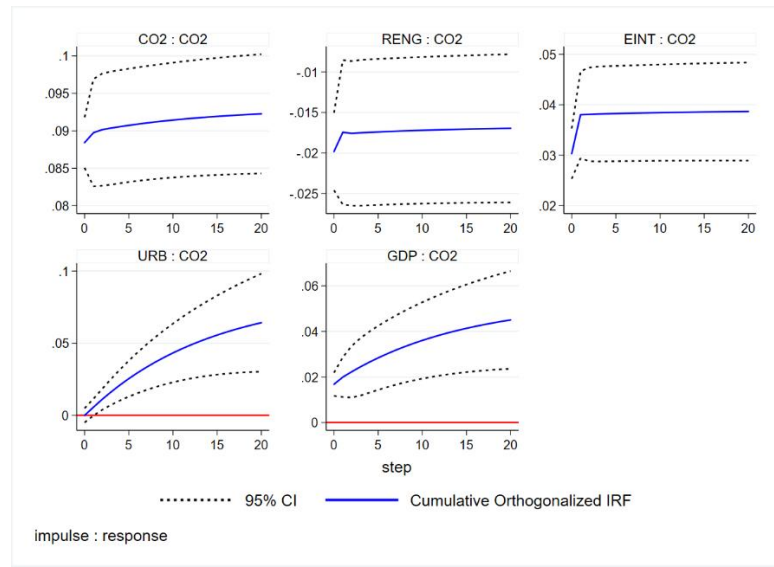
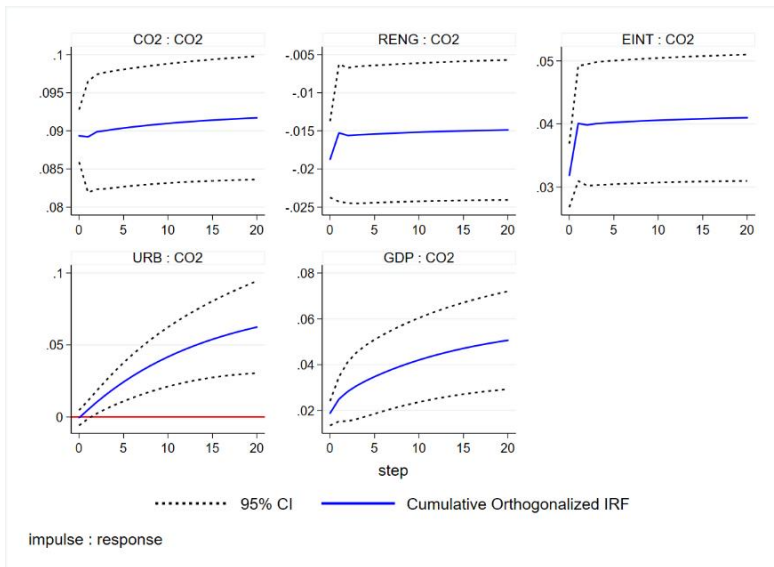
Observations: 1281 • Groups: 61

Figure 4

(Continued)

(e) without: Angola, Congo Rep., Egypt, Indonesia, Nigeria, Vietnam

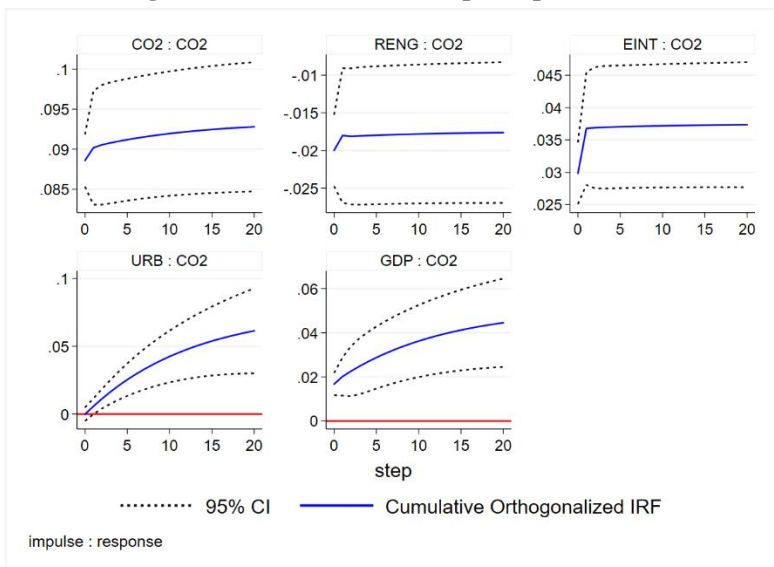
(f) GDP and CO2 in per capita terms



Observations: 1302 • Groups: 62

Observations: 1428 • Groups: 68

(g) GDP, EINT, and CO2 in per capita terms



Observations: 1428 • Groups: 68

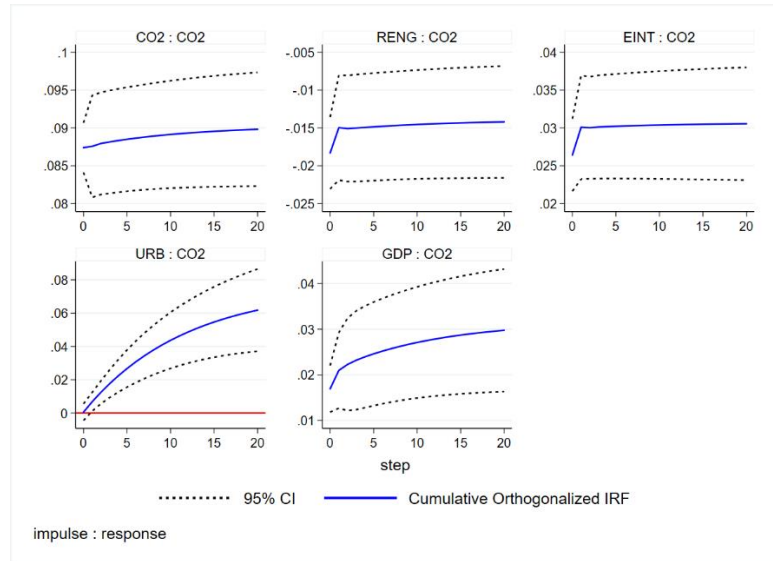
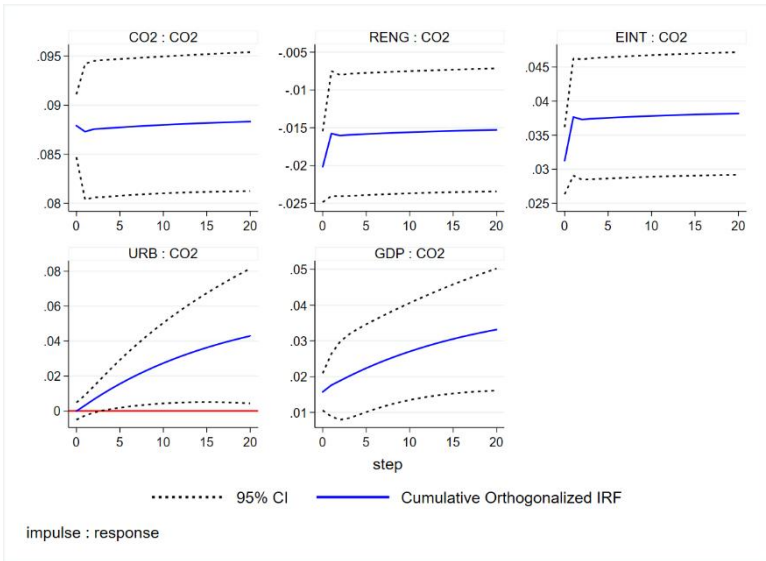
Notes: The continuous line denotes the impulse response functions. The dashed lines stand for the associated 95% confidence interval computed based on 1000 Monte Carlo simulations.

Figure 5

Cumulative orthogonalized IRFs: exogenous additional controls

(a) population

(b) agriculture



(c) industry

(d) services

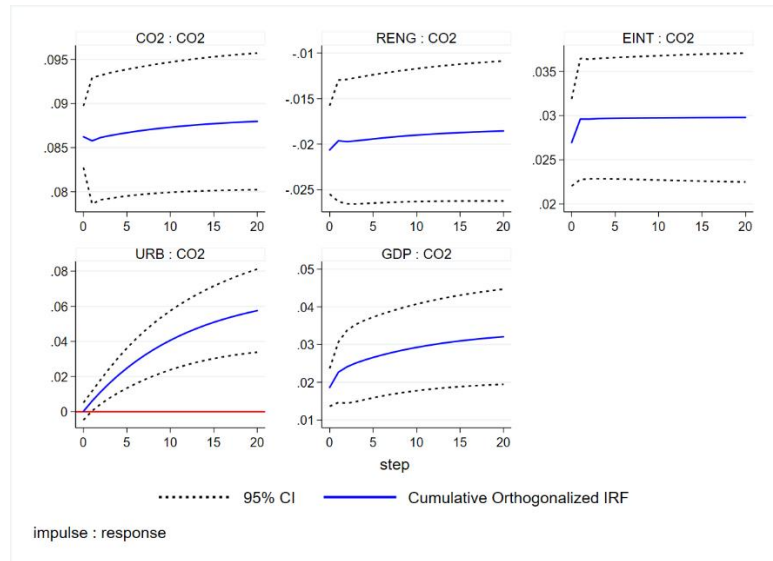
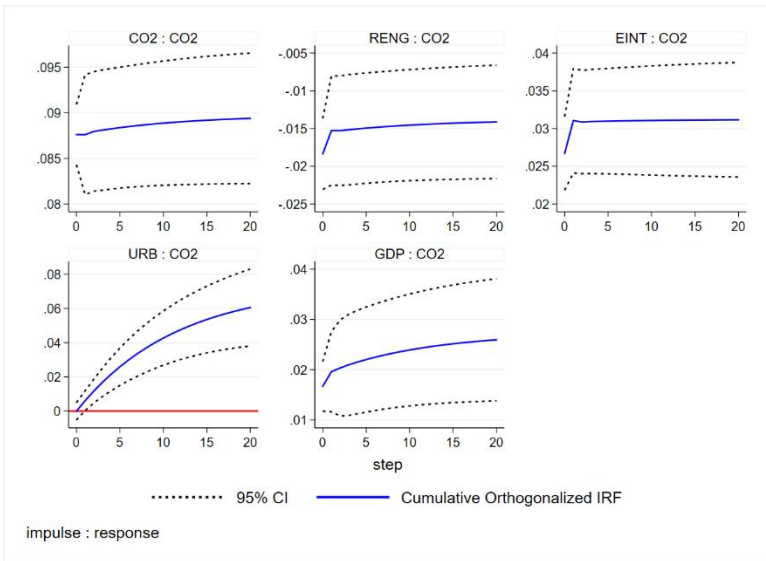
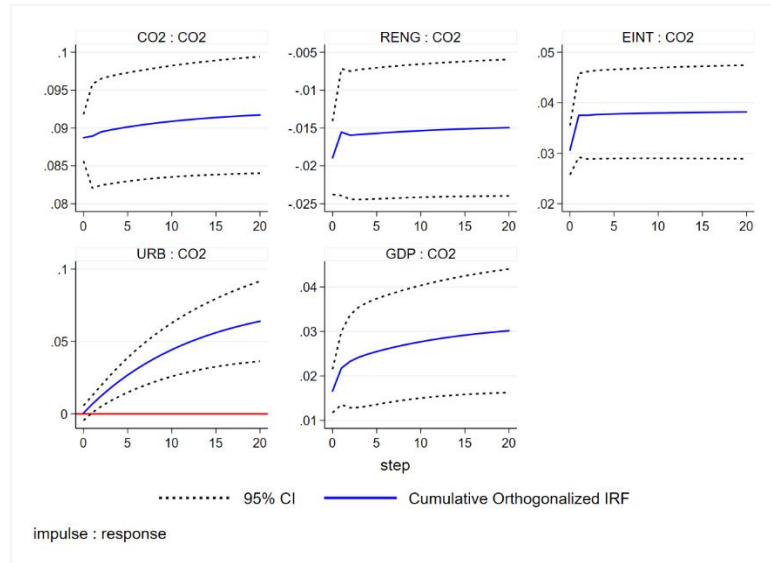
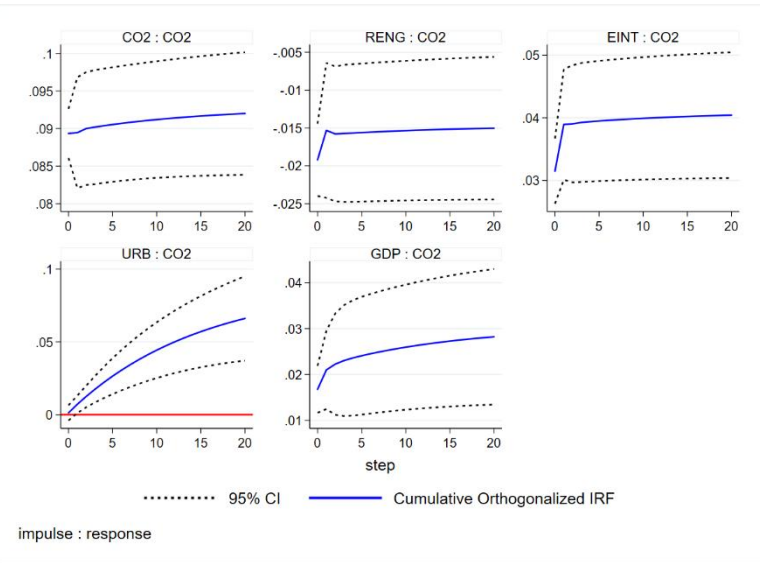


Figure 5

(Continued)

(a) trade

(b) forest rents

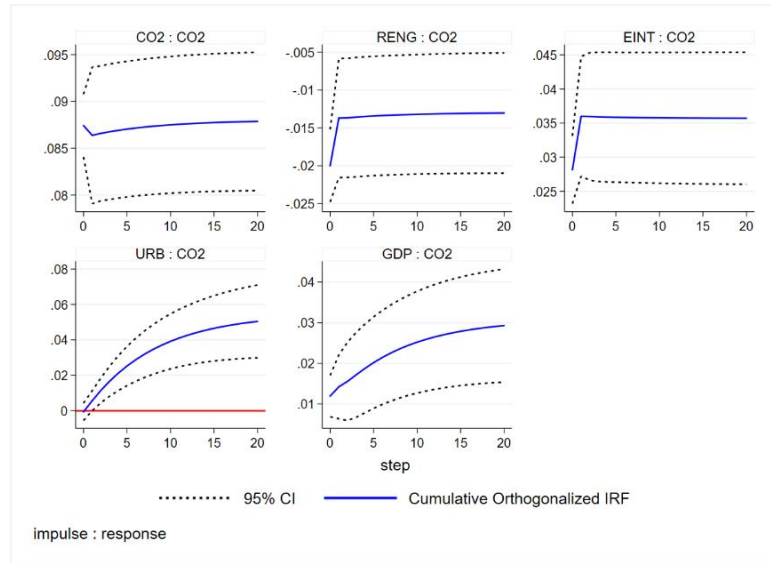
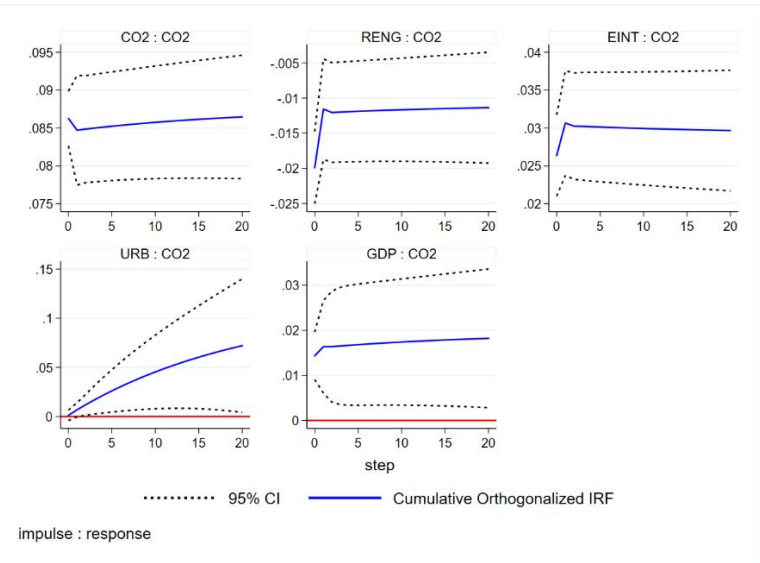


Observations: 1365 • Groups: 68

Observations: 1414 • Groups: 68

(c) remittances

(d) domestic credit to private sector



Observations: 1155 • Groups: 68

Observations: 1326 • Groups: 68

Notes: The continuous line denotes the impulse response functions. The dashed lines stand for the associated 95% confidence interval computed based on 1000 Monte Carlo simulations.

Table 9**Cross-sectional dependence tests**

| Test/Variable | CO2_T | CO2_B | CO2_NC | CO2_OIC | CO2_PI |
|-------------------|------------------------|-------------------------|------------------------|------------------------|------------------------|
| BC scaled LM | 508.921*** (0.000) | 172.403*** (0.000) | 259.421*** (0.000) | 188.111*** (0.000) | 456.459*** (0.000) |
| Pesaran CD | 168.292*** (0.000) | 22.035*** (0.000) | 77.171*** (0.000) | 46.489*** (0.000) | 93.698*** (0.000) |
| Pesaran scaled LM | 510.399*** (0.000) | 173.882*** (0.000) | 260.899*** (0.000) | 189.568*** (0.000) | 457.938*** (0.000) |
| Breusch-Pagan LM | 36729.01*** (0.000) | 14014.72 *** (0.000) | 19888.26*** (0.000) | 14816.93*** (0.000) | 33187.98*** (0.000) |

Notes: The Breusch-Pagan (1980) LM, Pesaran (2004) scaled LM, Pesaran (2004) CD, and Baltagi et al. (2012) Bias-Corrected (BC) scaled LM test. H0 is "no cross-section dependence (correlation)". P-values in brackets. ***, **, *, denotes significance at the 1%, 5% and 10% level, respectively.

Table 10**Stationarity analysis I**

| Test/ Variable | Harris-Tzavalis test | | | |
|-------------------|----------------------|------------|-----------------|------------|
| | Level (cons & trend) | | Δ (cons) | |
| | rho | p_value | rho | p_value |
| CO2_T | 0.629 | (0.001)*** | -0.028 | (0.000)*** |
| CO2_B | 0.667 | (0.075)* | -0.150 | (0.000)** |
| CO2_NC | 0.643 | (0.006)*** | -0.083 | (0.000)*** |
| CO2_OIC | 0.512 | (0.000)*** | -0.225 | (0.000)*** |
| CO2_PI | 0.618 | (0.000)*** | -0.010 | (0.000)*** |

Notes: We remove cross-sectional means and apply small-sample adjustment to T. H0 is "Panels contain unit roots". Tajikistan and Togo (for CO2_OIC), and Congo Rep. And Ghana (for CO2_PI) are excluded from the sample due to missing values. P-values in brackets. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 11**Stationarity analysis I**

| Test/ Variable | Pesaran's CADF test | | | | | | | |
|-------------------|--------------------------------|---------|------------|---------|---------------------------------|---------|------------|---------|
| | Level (cons & trend) | | | | Δ (cons) | | | |
| | Augmented by one lag (average) | | | | Augmented by two lags (average) | | | |
| | t-bar | p-value | t-bar | p-value | t-bar | p-value | t-bar | p-value |
| CO2_T | -2.533** | (0.024) | -3.359*** | (0.000) | -2.697*** | (0.000) | -2.803*** | (0.000) |
| CO2_B | -2.105 | (0.966) | -3.287*** | (0.000) | -1.964 | (0.999) | -2.486*** | (0.000) |
| CO2_NC | -2.255 | (0.686) | -3.433*** | (0.000) | -2.123 | (0.951) | -2.475*** | (0.000) |
| CO2_OIC | -8.874*** | (0.000) | -20.063*** | (0.000) | 2.369 | (0.991) | -6.841*** | (0.000) |
| CO2_PI | -4.375*** | (0.000) | -14.658*** | (0.000) | -1.947** | (0.026) | -10.466*** | (0.000) |

Notes: Pesaran (2003) H0 is "all series are non-stationary". For the unbalanced panels, namely for CO2_OIC and CO2_PI, we report the standardized t-bar statistic. P-values in brackets. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Additional References for the Supplementary Material

Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Olivier, J.G.J., Peters, J.A.H.W. and Schure, K.M., 2017. Fossil CO₂ and GHG emissions of all world countries. EUR 28766 EN, Publications Office of the European Union, Luxembourg, ISBN 978-92-79-73207-2, doi:10.2760/709792, JRC107877.