THE EFFECTS OF POPULATION, TECHNOLOGY AND AFFLUENCE ON CO_2 EMISSIONS IN THE GLOBAL ECONOMY

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Overview

This paper investigates the response of the carbon dioxide emissions to unanticipated changes in the size of population, real economic activity and technological innovations at the world level and it relates to the strand of the literature explaining the emissions dynamics by the IPAT framework (Liddle, 2015, 2013). Carbon emissions, which have been identified as the main driver of global warming, need to be reduced in order to limit the average temperature increase, as outlined at COP26, in the Glasgow Climate Pact in 2021. However, despite the general trend of lower carbon intensities across advanced economies, less advanced countries exhibit a significant increase in carbon emissions based on their strong economic growth. Thus, understanding the fundamental drivers of worldwide emissions is important both for policy makers as well as for the well-being of society in order to deal with future global climate change and to implement efficient policies that react to climatic events (Hsiang, 2016). This paper contributes to the existing literature by shedding some light on several directions. First, our study proposes a Structural Vector Autoregressive (SVAR) model that allows to identify the effects of shocks arising from the global economy on the level of carbon dioxide emissions. Our main idea is that carbon emissions can be modelled as a part of the endogenous transmission of population, world real economic activity and technology shocks. Most studies investigate the relationship between human activities and global environment with reduced-form specifications that cannot identify the causes of environmental impacts shocks. With this respect, the studies applying the STIRPAT (Stochastic Impacts by Regression on Population, auence and Technology) framework to carbon emissions typically do not account for the interdependence relationship of the variables (Dietz and Rosa, 1997, 1994). In contrast our study allows us to account for the endogeneity of carbon dioxide emissions with respect to macroeconomic variables. Second the empirical approach applied to our study is based on a revised version of the Bayesian SVAR model developed by Baumeister and Hamilton (2015). The Bayesian approach allows us to summarize and express the degree of beliefs about the ecological elasticities estimates that can be obtained from other studies.

Methods

This analysis is based on annual aggregate global data, covering the period 1963-2016 sourced from the World Bank. The set of endogenous variables includes (i) the population size (P); (ii) the energy efficiency, which is a proxy for the technology index (T); (iii) the Gross Domestic Product (GDP) per capita, which is a measure of auence (A) and (iv) the CO_2 emissions (I). Specifically, the population size is represented by the number of persons in billion. The technology index is derived by the inverse of energy intensity. The GDP per capita is a measure of consumption (or production). Finally, the CO_2 emissions represent a measure of environmental degradation. All these variables are converted to the natural logarithm, so that the structural coefficients can be directly interpreted as elasticities. Thus, the vector of endogenous variables is $\boldsymbol{y_t} = [p_t, t, a_t, i_t]'$.
The representation of the SVAR model can be written as a system of four equations:

$$\begin{cases} p_t = \boldsymbol{b_1}'\boldsymbol{x_{t-1}} + v_{1,t} & (1) \\ t_t = \alpha_{ta} s_t + \boldsymbol{b_2}'\boldsymbol{x_{t-1}} + v_{2,t} & (2) \\ a_t = \alpha_{ap} p_t + \alpha_{at} t_t + \alpha_{ai} i_t \, \boldsymbol{b_3}'\boldsymbol{x_{t-1}} + v_{3,t} & (3) \\ i_t = \beta_{ip} p_t + \beta_{it} t_t + \beta_{ia} a_t + \boldsymbol{b_4}'\boldsymbol{x_{t-1}} + v_{4,t} & (4) \end{cases}$$

where $\boldsymbol{x_{t-1}}$ is a $(k \times 1)$ vector, (with $k = 4m + 1$) containing a constant and m lags of the endogenous variables and $\boldsymbol{b_1'}, \boldsymbol{b_2'}, \boldsymbol{b_3'}, \boldsymbol{b_4}'$ are row vectors containing the lagged structural coefficients to the first-four equations. Equation (1) says that the global population is weakly exogenous. In equation (2) the green technology is instantaneously affected by the GDP per capita, via α_{ta}. Equation (3) models the determinants of the real economic activity, with the contemporaneous effect of population, technology and CO_2 emissions, given by α_{ap}, α_{at} and α_{ai}, respectively. Equation (4) describes the behaviour of the IPAT identity and it says that the CO_2 emissions have contemporaneous relationships with population, technology and CO_2 emissions, given by α_{ap}, α_{at} and α_{ai}, respectively. In order to achieve the identification of the structural coefficients we follow the algorithm proposed by Baumeister and Hamilton

(2015), which is based on two main steps. The first step consists of a specification of informative prior beliefs about the structural parameters of the model. The second step is designed to generate draws from the posterior distribution of the structural coefficient through the Random Walk Metropolis Hastings algorithm.

Results

By analyzing the forecast error variance decomposition[1], we see that 88% of the variability in CO_2 is contemporaneously explained by carbon emissions shocks. The economic activity accounts for 9% of variability in CO_2 emissions, on impact. In the long-run, on average, technology and economic activity shocks play a key role in explaining the CO_2 emission with around 14% and 40%, respectivley. The explanatory power of technology shock for the energy efficiency is on average large (around 60%). It is worth nothing that the economic activity shocks are relevant in explaining 30% of variability of energy efficiency in the long-run. In contrast shocks to population and carbon emissions explain a small variation in the energy efficiency, with 4% and 8%, repectively. Finally, 88% of the variation of the economic growth is driven by the economic activity shock, followed by carbon emission shock with 8%, technology shock 3% and population shock 1%, on impact. In the long-run, technology and carbon emissions shocks together explain up to 35% of economic growth. The impulse response functions (IRFs) are in line with the results obtained by the forecast error variance decomposition. Specifically, the IRFs estimates show that an unexpected increase in population has negligible effects on CO_2 emissions. Conversely, a positive technology shock causes a rise in the technology energy efficiency, a reduction in the auence and in the CO_2 emissions, on impact. The technology shock induces persistent reduction in the CO_2 emission up to 10 years. A positive economic activity shock causes a simultaneous rise in affluence, and technology, accompanied by an hump-shape response of CO_2 emissions. It is worth nothing that our findings are expected to be more grounded on the economic theory with respect to estimates which are derived from reduced-form panel data and time-series models. Moreover, our results are obtained from a structural identify model that takes into account the economic motivation behind each shock.

Conclusions

We study the effects of population, technology, and economic activity shocks on CO_2 emissions at the global level. Two main conclusions emerge from this analysis. First, there is evidence that population, affuence and technology are endogenous with respect to CO_2 emissions, suggesting the importance of capturing the multitude of shocks that jointly shape the carbon emissions dynamics. Second, the main drivers of carbon emissions play a different role depending on the horizon of interest. Specifically, in the short-run CO_2 emissions are mainly explained by their own idiosincratic shock. Instead, in the long-run, technology and economic growth are relevant factors in driving the CO_2 emissions and, consequently, environmental degradation.

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[1] The forecast error variance decomposition tells us how much of the forecast error variance or prediction mean squared error of the variable of interest, at any given horizon, is accounted for by each structural shock (Kilian and Lütkepohl, 2017).