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CO_2 Emissions and GDP: A Revisited Kuznets Curve Version via a Panel Threshold MIDAS-VAR Model in Europe for a Recent Period

Sarah Goldman
Lux-SIR (Scientific International Research), Luxembourg, and CRIISEA, University of Picardie, Amiens, France
E-mail: chairmanship@lux-sir.com

Virginia Zhelyazkova
VUZF University, Sofia, Bulgaria
E-mail: vzhelyazkova@vuzf.bg

Abstract
Since the 2015 Paris Agreements that pledged a global reduction of CO2 emissions, almost all European countries have started to define and implement diverse climate change regulation measures to tackle the tragedy of the commons. In this context, the need to investigate the relationship between CO2 emission and economic growth in terms of GDP has increased for a deeper understanding of macroeconomic developments while applying carbon reduction policies to be reached. The link between growth and CO2 is not obvious and it continues to be widely discussed. The current paper aims to identify the specificities of the relationship between CO2 emissions and GDP growth by applying panel VAR specifications in Europe (for a time span of 1995-2022). We have chosen to introduce two kinds of frequencies. The main result resulted from estimations is the existence of two different thresholds. Unsurprisingly, there is a positive long-term CO2 emission in case of GDP shocks for both regimes. However, regarding the CO2 emissions shocks, regime 1 depicts a continuous decrease in GDP growth whereas in regime 2 there is a continuous rise in GDP. This output reinforces the idea of a non-linear relationship between the CO2 emissions and the GDP.

Keywords: CO2 emissions, Economic growth, Environment Kuznets Curve (EKC), Panel MIDAS-VAR and Thresholds

JEL classification: B22, B23, C33, N55, Q48

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1. Introduction

Environmental concerns have become pressing for the past 20 years and have given rise to a plethora of scientific literature aiming at investigating their relationship with a number of economic variables. As a central subject matter naturally emerges the question of how CO2 emissions impact economic growth, and, if a relationship is proven, what its specificities are. This topic began to stand out, especially after the Paris Agreement in 2015 when signatory countries agreed on an ambitious common practical approach to taming CO2 emissions and achieving global climate neutrality by 2050. However, in this process, a number of impediments occur that pose difficulties to research. Thus, while economic growth is traditionally measured by the gross domestic product

(GDP), and there is largely consensus to date on its composition and quantification, this is not the case for CO2 emissions. Indeed, we have to bear in mind that, for a number of valid reasons, the current CO2 emissions database is underestimated, not reliable enough, and therefore disputable. One important reason for this is that the reporting of Scope 3 emissions (i.e., all indirect emissions of companies) is by present not mandatory for economic agents; therefore, the quality of the CO2 emissions data is low. Also, there is no harmonization in terms of definitions of acceptable CO2 emissions thresholds as well as of other important specificities of this indicator. Having said that, these real limitations should not prevent us from exploring the relationship between CO2 emissions and GDP growth. Understanding it is vital for both designing proper relevant macroeconomic policies and for digging deeper into the interplay of CO2 emissions with other important macroeconomic variables.

In the quest for answers, the recent period has been characterized by the emergence and application of numerous econometric tools and approaches targeting the evaluation of the impacts of CO2 emissions on economic growth. Diverse methods, geographical areas, and periods have been analyzed. The VAR specification seems to be a preferred tool used by central bankers despite its limitations (Jeffers and Goldman, 2021). This is explained by some relevant characteristics of the method. This could be attributed to the fact that the VAR model is simple, easily reproducible, and provides forecast quality equivalent to existing short-term models. It also generally improves the forecasting exercises at longer horizons. Thus, as noted by Stock and Watson (2001), VAR processes have today become "a reference for judging new forecasting systems", in particular for evaluating the predictive quality of stochastic intertemporal general equilibrium models (Zhang and Lin, 2019).

There are several versions run for the couple CO2 emissions and GDP that introduced mixed frequency (Jia et al., 2022) or distinct thresholds. However, the thresholds mixed frequency models are very rare. The current paper attempts to overcome this failure. It studies the interconnection of CO2 emissions and GDP by applying VAR specifications on data for selected European countries which the authors deem representative for illustrating the interplay of CO2 and GDP (Austria, Belgium, Germany, Denmark, Spain, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherland, Norway, Portugal and Sweden) for the period 1995-2022 – the longest one for which relevant data exists.

The paper is structured as follows. The first section provides a brief survey of the related literature. Many VAR specifications have been tested to describe the EKC; however, the diverse VAR approaches do not take into account neither the multiple frequencies nor the thresholds. Consequently, we make use of the Threshold MIDAS-VAR models to reduce the gap in terms of methodologies (Section 2). The last section concludes.

2. Empirical literature survey: CO2 emissions and Growth

As already underlined, CO2 pollution seems to be one of the most important concerns for the future of human beings since it is responsible for the global warming. The International Panel on Climate Change (IPCC) has reiterated its findings on the anthropogenic causes of climate change in its latest, Fifth Assessment Report. This provides a strong reason for investigating further the relationship between CO2 emissions and economic growth.

A number of studies relative to the relationship of this couple have used the well-known environment Kuznets Curves popularized by Krueger and Grossman (1991) (e.g., Selden and Song, 1994; Vincent, 1997; Stern and Common, 2001; Stern 2003, 2004; Hasanov et al., 2021; González and Montañés, 2023). In a simple manner, the EKC explores the idea that during the first step of economic growth, there is a degradation of the environment; it also demonstrates that after an optimal threshold, there is an improvement of social welfare. The World Bank Development Report published in 1992, based on Shafik, and Bandyopadhyay's studies, by using an EKC approach (Goldman et al., 2023a) concludes that economic development inevitably damages the planet. The Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model is often used to assess the impact of other technical-socio-economic variables on CO2 emissions. A number of authors have attempted to measure with accuracy the consequences of the evolution of different variables, such as population, renewable energy, income; green policies, etc. on the CO2 trajectory (Bargaoui et al., 2014; Yu et al., 2023; Cevic and Jalles, 2023). They all have concluded that the CO2 emissions are largely impacted by the above-cited variables and they have recommended taking into consideration their findings for the definition of transition policies.

Other empirical specifications are run to evaluate the relationship between GDP and CO2 emissions, most of the time they are based on VAR models mainly exposed by the central banks to build their regulation actions. Indeed, for decades and particularly since 2015 with the Paris Agreement, policymakers have searched to evaluate the size of CO2 emissions in order to be able to manage and reduce it in the very short term. The goal is to reach net zero emissions in 2030 for most of countries except for China and India, where the target is designed for a later period (respectively 2060 and 2070). Kharas et al. (2022) have developed a VAR model for 180 countries to better measure the position of each country in terms of CO2 emissions for different sectors (energy, industry, transport, buildings, agriculture and forestry). Complex VAR models have emerged to tackle the limits of simple structural VAR specifications. They have introduced mixed frequencies or several thresholds (endogenously or exogenously defined). The link between growth and CO2 is not obvious and it continues to be widely discussed (Fávero et al., 2022; Khan et al., 2022; Qui et al., 2023). Indeed, the relationship is not linear and multiple studies have provided contrary results, however, the link is at times positive (Li et al., 2022; Goldman et al., 2023b) at other negative (Yılmaz, 2020; Acaroğlu et al., 2023). The negative link that is observed could be explained by the threshold existence related to the initial dotation. Hence, it is obvious that the empirical models should introduce distinct states. Based on a MIDAS model associated to back propagation, Zhao et al. (2014) have concluded that the impacts of CO2 emissions on GDP are both positive and negative. According to Xu and Lio (2022), the MIDAS approach applied to Chinese CO2 emissions of power industry outperforms the autoregressive distributed lag (ARDL). Moreover, the link between GDP and carbon emissions of industries is narrow and positive; meaning that the pollution continues and will continue to increase despite the damaging consequences on the planet. According to our knowledge, presently, no MIDAS-VAR models associated with thresholds are used to investigate the relationship between CO2 emissions and economic growth. The aim of this paper is to fill that shortfall.

3. A panel MIDAS-VAR approach applied to European database

3.1. Methodology description

The data collection has brought several different scopes for the empirical studies and different frequencies are often available. The unique frequency analysis is very limited when the aim is to capture the nature of the economic issues. A more sophisticated approach could largely improve the content of the co-movement such as simple structural VAR estimations (Ghysels, 2016; Bacchiocchi et al., 2018; Carreira and Gueddoudj, 2021).

The mixed frequency (MF) data has been applied in several studies for years. MF approach has aimed to provide new tools to analyzing the macroeconomic outlook. Forecasting macroeconomic variables and measuring the impacts of monetary policies are key tasks for all national and international institutions, especially for Central Banks. Nevertheless, most of important macroeconomic indicators are not sampled at the same frequency. A notorious example is the forecasting of gross domestic product (GDP). Indeed, this indicator is sampled at a quarterly frequency but it is in connection with other variables such as inflation, which is a monthly sample or interest rate, which is daily sampled. The simplest solution is to change the frequency by reducing the frequency of the highest frequency variables and run estimations but this solution is not optimal since it erases the inner processes of the variables as well as any informative content of the variables coming from their nature (for example for daily variables the volatility is reduced or has even vanished). To avoid criticism on this matter, Ghysels et al. (2006) propose a general framework called mixed data sampling (MIDAS). Due to the flexibility of the model and simplicity of use, this approach has been substantially used and improved. Indeed, Clements and Galvão (2008) introduced a common factor to the Midas model with an autoregressive (AR) component. Kuzin et al. (2009) incorporated a vector auto-regression (VAR) to improve the AR-Midas model. The Midas approach and in particular its importance for forecasting exercises continues to be a topic of dissertations and to be improved. Since 1980, the use of VAR specification to exploring the co-movements of economic, monetary and financial variables has skyrocketed. This is typically done with some real activity databases (GDP, industrial production index), some price variables (inflation or commercial/ residential real estate prices) and some monetary data fluctuations (monetary aggregates, interest rates). The recent spur in global environmental concerns has contributed to introducing some environmental variables in order to measure the correlation between pollution and economic growth often assessed using the GDP[1]. This idea has been largely described by the works of Kuznet (1955) that use the CO2 emissions and tend to demonstrate that there is inverted U-shape relationship between CO2 emissions and growth. Different studies have attempted to define Kuznet curves per country (Luzzati et al., 2018; Hannesson, 2022) and have found diverse results amongst jurisdictions or during the analyzed periods (Arouri et al., 2012; Barra and Zotti, 2017; Mitić et al., 2023). The complexity of the relationship and the variety of the conclusions tend to demonstrate that the links between the variables are not obvious. Furthermore, given the plurality of empirical approaches, data sources, countries etc., it may be delicate to compare them all and get the same conclusions. The aim of this section is to provide another approach that will feed the debates relative to the impact of CO2 emissions on GDP growth. The rest of the section is organized as follows. We first present the data used for the purpose of the specifications of the estimation, then we expose and justify the choice of our model. The last

[1] Even if this variable choice is disputable (Piketty, 2014).

paragraph is dedicated to the discussions of the results given the main limitations of the selected approach.

In this section we present in general the background of the selected model. We use the standard k-dimensional process associated with different frequencies (years and quarters). The vector process $x_L(t_L)$ where L is low frequency- is only observed at m fixed period and the $x_H(t_L, k_H)$ process, with $K_H = K - K_L$, series -where H is high frequency- and , is observed during t_L periods. We note, $x_L(t_L)$ the low frequency bivariate process and $x_H(t_L, k_H)$ the high frequency bivariate process.

$$\begin{pmatrix} x_H(t_L,1) \\ \\ . \\ . \\ . \\ x_H(t_L,q) \\ \\ x_L(t_L) \end{pmatrix} = A_0 + \sum_1^p A_j \begin{pmatrix} x_H(t_L-j) \\ \\ . \\ . \\ . \\ x_H(t_L-j,q) \\ \\ x_L(t_L-j) \end{pmatrix} + \varepsilon(t_L) \tag{1}$$

The dimension is $K_L + q \times K_H$ and the lag is p. The interpretation of the matrix is the following, for illustration, based on the annual data, we stack the quarter (Q1, Q2, Q3, Q4) with the first-year low frequency data, and similarly for the rest of the components of the vector. The aim is to predict the next year's high and low frequency data given the previous year's high and low frequency.

Ghysels (2016) has largely discussed plausible implementations of mixed frequency VAR models and has suggested to study the link between real-time predictions and policy response functions and this point is particularly relevant to capture the relationship between CO2 emissions and GDP growth. Following Krolzig (1996), we modify (1) to allow for different regime changes that follows a VAR process that depends on the value of an unobserved discrete state variable S_t. In a general manner, we suppose that there are r possible regimes $(m = 1, \dots r)$. He proposes two specifications, namely switching intercept or switching mean. For the second alternative, (1) becomes:

$$\begin{pmatrix} x_H(t_L,1) - \mu(t_{L1}, S^m_{t_{L,1}}) \\ \\ . \\ . \\ . \\ x_H(t_L,q) - \mu(t_L, S^m_{t_{L,q}}) \\ \\ x_L(t_L) - \mu(t_L, S^m_{t_{L,}}) \end{pmatrix} = A_0 + \sum_1^p A_j \begin{pmatrix} x_H(t_L-j) - \mu(t_{L-j}, S^m_{t_{L-j}}) \\ \\ . \\ . \\ . \\ x_H(t_L-j,q) - \mu(t_{L-j,q}, S^m_{t_{L-j,q}}) \\ \\ x_L(t_L-j) - \mu(t_{L-j}, S^m_{t_{L-j,}}) \end{pmatrix} + \varepsilon\left(t_L, S^m_{t_L}\right) \tag{2}$$

As common in such empirical works, we report the impulse response functions (IRFs) in order to visualize the dynamic transmission of uncorrelated structural shocks among the variables (CO2 emissions and GDP growth). Based on the MIDAS-VAR model proposed in (1) and (2), under the assumption of stationarity, the IRFs can be easily obtained through the MIDAS-VAR representation (Figure 1) and the threshold MIDAS-VAR specification (Figure 2). In our case and given the pre-test and post-test, we have assumed two regimes (regime 1 and regime 2) and the lag selection is based on the AIC criteria (lag=1). In a nutshell - there are diverse VAR specifications that analyse the interconnectedness of the variables and the most sophisticated specifications introduce multiple frequencies and thresholds. The choice for using a threshold MIDAS-VAR model is threefold: (1) it allows us to use the database without transforming the frequency that characterise the inherent process of the variable. Moreover, by mixing frequencies we have a better understanding of the relationships between the variables (Bacchiocchi et al., 2018). (2) For forecasting exercises, the non-linearity threshold models are essential. The Granger causality is often bi-directional and this means that we should introduce a threshold in our specification. Based on the Kuznets curve literature, it is possible to conclude that the link between the couple CO2 emissions and GDP growth is characterized by the existence of thresholds (Goldman et al., 2023a). (3) As already demonstrated through the literature survey and to our knowledge, in the current literature, there is no threshold MIDAS-VAR specification to materialized the Kuznets curve approach.

3.2. Data and pre-tests presentation

We have chosen to run a panel bi-variate model (Table 1), the GDP that is assumed to measure the wealth, and the CO2 emissions for a set of 15 countries (Austria, Belgium, Germany, Denmark, Spain, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherland, Norway, Portugal and Sweden), for two reasons. Firstly, in a general manner, the VAR process is based on the parsimony rules (Ghysels, 2016). Secondly, as already underlined, the selection of the variables is related to the Kuznets curves scope and to the quality of the database for the selected countries panels. Indeed, they are harmonized and the countries are similar in terms of economic growth in order to partially avoid the countries' biases. Outliers' analyses are run and we have decided not to withdraw outliers or transform the database by using filters (before testing the stationarity assumption) to keep the countries and times specificities.

Table 1 - Variables for the estimation

Variables	Periods	Frequencies	Sources
GDP GROWTH (GDP_G, %)	1995-2022	Quarters	European Central Bank- Statistical Data Warehouse (ECB-SDW)
CO2 emissions (CO2, Tonnes)[2]	1998-2019	Years	OECD

Source: Authors.

Given the different frequencies (quarters and years) and the scope of the analysis in terms of repercussions, we make use of a panel MIDAS-VAR model to assess the impact of CO2 emissions

[2] The CO 2 emissions should be interpreted with caution since they do not take into account the scope 3 and there is a data gap in the CO2 assessment that should be sooner or later overcome. Moreover, data harmonization does not yet exist (OECD Report, Annual Climate Action monitor, 2021)

on GDP. The VAR specification is often used and it completes optimally the theoretical growth model, such as Dynamic Stochastic General Equilibrium (DSGE) models (Giacomini, 2013).

Table 2 reports the preliminary statistics and it shows that the variables are not normally distributed.

Table 2 - Skewness and Kurtosis statistics

Variables	Skewness	Kurtosis	Observations
GDP_G	-0.441	6.266	1440
CO2	2.156	8.891	330

Source: Authors.

The VAR specification requires respecting the stationarity hypothesis for all variables taken into account. Since the pioneering works of Levin and Lin (1992, 1993) and Quah (1994), the notion of stationarity has been developed to respond to the increasing econometrics needs. To guarantee the stationarity assumption, we use common tests (Levin, Lin and Chu, LLC, Augmented Dickey Fuller, ADF and Philipps-Peronn, PP) in level and in first differences in case that the variable is not stationary. All these tests have some advantages and limits (Hurlin and Mignon, 2007); however, here, we will not insist on the limitations since it is outside of the scope of our research. Table 3 summarizes the main results in first differences, if the variable is not stationary in level.

Table 3 - Stationary tests

Variables	LLC p-value ()	ADF p-value ()	PP p-value ()	Filter
GDP_G	-3.780 (0.0001)	56.929 (0.0021)	53. 300 (0.0055)	I(0)
CO2	-7.568 (0.0000)	96.663 (0.0000)	155.023 (0.0000)	I(1)

Source: Authors.

The variable CO2 has been filtered to get the stationary hypothesis. We have tried several specifications and we have chosen to expose the best specification in terms of statistics (no residuals autocorrelation and heteroscedasticity). For the Lag, we have taken into account the AIC criteria (0.817690) and we have therefore chosen lag=1. We run the bi-variate specification[3] and get the following shocks trajectories[4].

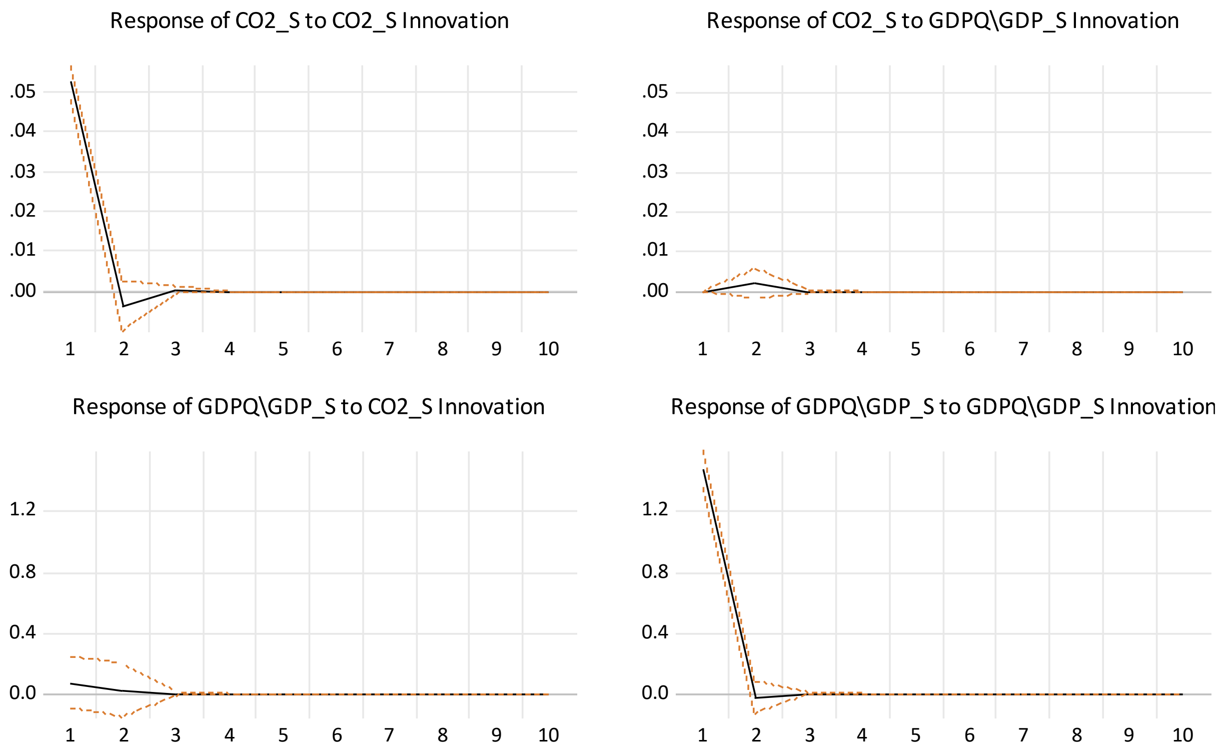
3.3. IRFs Results

As already underlined in the previous paragraph and following the current literature review, only IRFs graphs are presented hereafter.

[3] Method: Standard VAR. Sample (adjusted): 2000-2019. Number of observations:300 (20×15).

[4] All the post-tests (autocorrelation and heteroscedasticity) are satisfying. For more details, see Appendices A (Tables A1-A4).

Response to Cholesky One S.D. (d.f. adjusted) Innovations
± 2 analytic asymptotic S.E.s



Source: Authors.

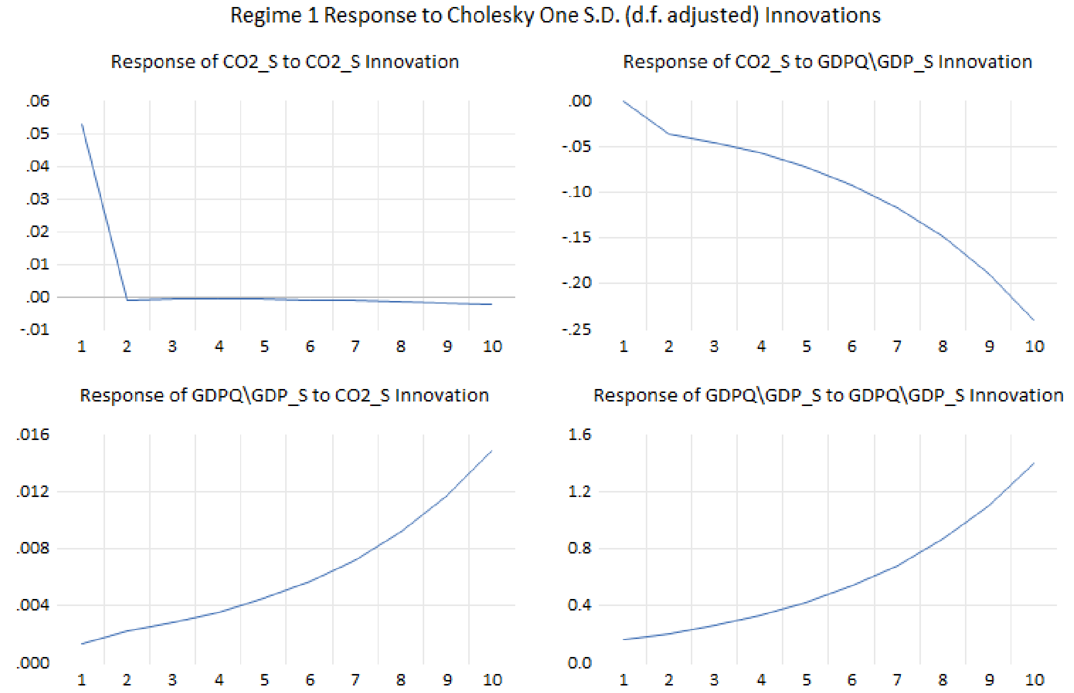
Figure 1 - Impulses functions

In Figure 1, the impulse functions provide interesting trajectories that may suggest the existence of different thresholds since the impacts of shocks are relatively weak. Another explanation for the weakness of the shocks could be related to the fact that most of the selected countries have low carbon emissions levels. A simple causality test has demonstrated the bidirectional causality tests that are in line with several research studies (Barassi and Spagnola, 2012; Huaping et al., 2020). According to the Granger Causality test, there is a bidirectional causality between the variables (Appendices A, Table A5); this means that there are different regimes. We explore this possibility. The finding is common since other studies have found a bi-directional relationship (Pejović et al., 2021). However, the two-ways Granger causality is not always the case for all countries. Indeed, according to Jia et al. (2022) for Canada, UK, and US databases, the GDP growth shows a one-way causal link to CO2 emissions. In that respect, this point raises the question of countries' specificities.

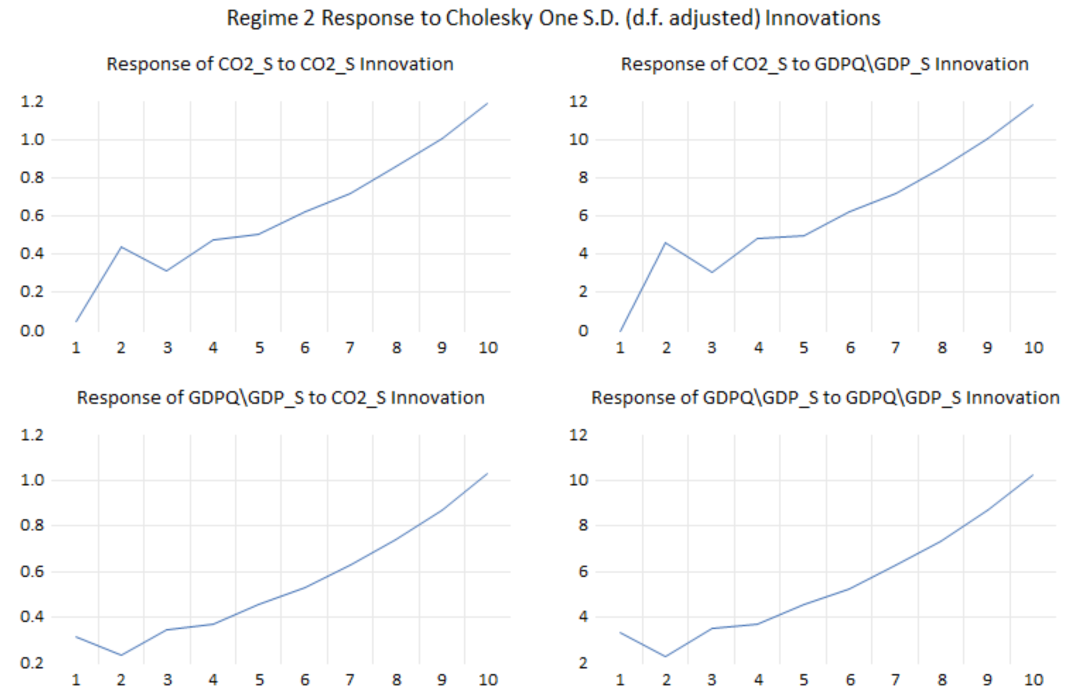
The next paragraphs are devoted to the panel MIDAS-VAR model associated to multiple thresholds[5]. The graphs below (Figure 2) depict two states: Regime 1 and Regime 2[6].

[5] Included observations: 300 (20×15). The model converged after 26 iterations. Random search.
[6] All post-tests are reported in Appendices B (Tables B1-B2).

Regime 1



Regime 2



Source: Authors.

Figure 2. Thresholds models impulse functions

Based on the trajectories of the responses, several relevant conclusions have emerged towards the relationship between GDP and CO2 emissions. Unsurprisingly, there is a positive long-term CO2 emission in case of GDP shocks for both regimes, meaning that an increase in GDP creates CO2 emissions. Regarding the CO2 emissions shocks, regime 1 depicts a continuous decrease in GDP growth whereas in regime 2 there is a continuous rise in GDP. The constant transition probability to be in regime 1 is approximatively 0.8 and the expected duration is roughly 5.2 years (in regime 2, 0.2, more than 1 year).

Despite the interest of such models, several limitations should be debated. The bi-variate approach could be limiting for capturing the complexity of the CO2 emissions and GDP interlinkages. However, our purpose is to validate (or not) the KC hypothesis thanks to more sophisticated models. As regards the simple threshold VAR approach, it is well known that the transition probabilities do not depend on the original state and the number of thresholds is exogenous. In general, the database underestimates the importance of CO2 emissions since scope 3 reporting is not yet mandatory t for all entities. In addition, the number of observations should be larger to ensure plausibility of results.

4. Conclusion

The ecological concerns are more and more central in the theoretical and empirical model determination. The introduction of environment variables has enhanced the traditional macroeconomic framework and has enriched the debates. This has actively contributed to improving our knowledge on the impacts of pollution and particularly on the influence of CO2 emissions on GDP which has then contributed largely to the discussions on the Kuznets curve.

The VAR model is a good empirical tool for estimations related to the couple CO2 emissions and economic growth and they have been largely used by the central banks to assess the macroeconomic impacts of monetary policy (Bagliano and Favero, 1998; Evans and Kuttner, 1998). Hence, we have investigated MIDAS-VAR models because most of the time the variables do not have the same frequency. Based on the Granger causality results that show a bi-directional link, we have made use of thresholds MIDAS-VAR specifications. We have found out that the shocks related to the relationship between pollution and GDP could be positive or negative; it depends on the state where the economy is. This result is relevant for policy makers that aim at tackling the climate change because this means that climate change policies should be calibrated to the countries' specificities. A general climate change policy framework is therefore doomed to failure.

Lastly, it is worth noting that with the data revolution, the proposed method should be reviewed and users of traditional methodologies should introduce some more adapted empirical instruments to tackle the problem of overwhelming information. Artificial intelligence is a key tool to manage big data. Indeed, big data and Machine Learning have provided new possibilities to understand how economic activity is impacted by increasing pollution by using spatial information over cities, urban and rural areas and regions, and how this information can shape monetary, financial and economic processes and related policies. To deeply understand the climate change scope, very granular sustainable big data are required for the researchers that utilise empirical models, since the results could be biased by the quality of the database, in other words, the empirical results (outputs) are conditioned by the databases' nature (inputs).

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Appendix

A. Simple MIDAS VAR

A-1 Pormanteau Tests

VAR Residual Portmanteau Tests for Autocorrelations
Null Hypothesis: No residual autocorrelations up to lag h
Sample: 1998 2022
Included observations: 300

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	Df
1	0.752611	---	0.755129	---	---
2	1.604983	0.8079	1.613220	0.8064	4

*Test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution
*df and Prob. may not be valid for models with exogenous variables

A-2 LM tests

VAR Residual Serial Correlation LM Tests
Sample: 1998 2022
Included observations: 300

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	Df	Prob.
1	3.804036	4	0.4332	0.952472	(4, 586.0)	0.4332
2	0.844422	4	0.9324	0.210898	(4, 586.0)	0.9324

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	Df	Prob.
1	3.804036	4	0.4332	0.952472	(4, 586.0)	0.4332
2	4.380066	8	0.8213	0.546745	(8, 582.0)	0.8213

*Edgeworth expansion corrected likelihood ratio statistic.

A-3 VAR Residual Heteroscedasticity Tests (Levels and Squares)

Sample: 1998 2022
Included observations: 300

Joint test:

Chi-sq	Df	Prob.
26.63246	18	0.0862

Individual components:

Dependent	R-squared	F(6,293)	Prob.	Chi-sq(6)	Prob.
res1*res1	0.072505	3.817433	0.0011	21.75144	0.0013
res2*res2	0.006290	0.309125	0.9320	1.887116	0.9298
res2*res1	0.006410	0.315017	0.9289	1.922852	0.9267

A-4 VAR Residual Heteroscedasticity Tests (Including cross terms)

Sample: 1998 2022
Included observations: 300

Joint test:

Chi-sq	Df	Prob.
29.93096	27	0.3173

Individual components:

Dependent	R-squared	F(9,290)	Prob.	Chi-sq(9)	Prob.
res1*res1	0.079163	2.770102	0.0040	23.74894	0.0047
res2*res2	0.006309	0.204586	0.9935	1.892752	0.9931
res2*res1	0.007604	0.246894	0.9871	2.281189	0.9862

A-5 Causality tests

VAR Granger Causality/Block Exogeneity Wald Tests Included observations: 300			
Dependent variable: CO2_S			
Excluded	Chi-sq	Df	Prob.
GDPQ_S	1.192442	1	0.2748
All	1.192442	1	0.2748
Dependent variable: GDPQ_S			
Excluded	Chi-sq	Df	Prob.
CO2_S	0.069013	1	0.7928
All	0.069013	1	0.7928

B Threshold MIDAS-VAR

B-1 Lag analysis

Regime Specific AR Roots
Regime 1

Roots of Characteristic Polynomial Endogenous variables: CO2_S GDPQ\GDP_S Exogenous variables: C Lag Specification: 11	
Root	Modulus
0.033493	0.033439
-0.015503	0.015503
No root lies outside the unit circle. VAR satisfy the stability condition	

Regime 2

Roots of Characteristic Polynomial Endogenous variables: CO2_S GDPQ\GDP_S Exogenous variables: C Lag Specification: 11	
Root	Modulus
0.439351	0.439351
0.003089	. 0.003089
No root lies outside the unit circle. VAR satisfy the stability condition	

B-2 Portmanteau tests

VAR Residual Portmanteau Tests for Autocorrelations
Null Hypothesis: No residual autocorrelations up to lag h
Sample: 1998 2022
Included observations: 300

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	0.838310	---	0.841114	---	---
2	1.686610	0.7931	1.695107	0.7916	4

*Test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution

VAR: BIVAR
Transition summary: Constant simple switching transition probabilities and expected durations
Sample (adjusted): 2000 2019
Included observations: 300 after adjustments

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = k)

	1	2
1	0.809413	0.190587
2	0.809413	0.190587

Constant expected durations:

1	2
5.246937	1.235464