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Evaluating the role of technology and technological spillovers on CO_2 emissions

João Gabriel Pio y Eduardo Gonçalves[a]

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Abstract. It is recognized in the literature that advances in technology are one of the main mechanisms to increase technical efficiency and production with less use of inputs. However, technological advancement can also lead to increased emissions due to rebound effects or the Jevons paradox phenomenon. The purpose of this study is to evaluate the role of technology and technological spillovers in CO_2 emissions. In a complementary way, the hypothesis of the inverted U-shaped relationship between CO_2 emissions and industrial value added is empirically evaluated in a panel of country-sector data. Results show that both the stock of R&D and domestic R&D spillovers play a significant role in reducing CO_2 levels. There is weaker evidence for foreign R&D spillovers.

Key Words: CO_2 emissions; Environmental Kuznets Curve (EKC); R&D stock; domestic technological spillovers; foreign technological spillovers; System-GMM.

Evaluación del papel de la tecnología y sus efectos indirectos sobre las emisiones de CO_2

Resumen. En la literatura se reconoce que los avances tecnológicos son uno de los principales mecanismos para aumentar la eficiencia técnica y la producción con un menor uso de insumos. Sin embargo, el avance tecnológico también puede provocar un aumento de las emisiones debido a los efectos rebote o la paradoja de Jevons. El objetivo de este estudio es evaluar el papel de la tecnología y sus efectos indirectos en las emisiones de CO_2. De forma complementaria, se evalúa empíricamente la hipótesis de la relación en forma de U invertida entre las emisiones de CO_2 y el valor añadido industrial en un panel de datos país-sector. Los resultados muestran que tanto el *stock* de I+D como los efectos indirectos de la I+D nacional desempeñan un papel significativo en la reducción de los niveles de CO_2. En el caso de los efectos indirectos de la I+D extranjera, los datos son menos concluyentes.

Palabras clave: emisiones de CO_2; curva de Kuznets ambiental (CKA); *stock* de I+D; efectos indirectos domésticos de la tecnología; efectos indirectos extranjeros de la tecnología; Sistema-GMM.

Clasificación JEL: Q5; Q16; O32; O33.

[a] Federal University of Juiz de Fora, Brasil. Email addresses: jpiogabriel@gmail.com and eduardo.goncalves@ufjf.br, respectively.

1. Introduction

The negative effects of pollutant emissions and climate change are critical global issues often attributed to carbon dioxide (CO_2) emissions, which are closely linked to economic activity (IPCC, 2013). The literature frequently addresses the challenge of reducing emissions while balancing economic growth, with researchers using the Environmental Kuznets Curve (EKC) to analyze the relationship between income levels and emissions. The EKC suggests that emissions rise with income until a certain point, after which they decrease as awareness of environmental issues grows (Beckerman, 1992; Dinda, 2004). Policy directions, therefore, often focus on industrialization as a pathway to environmental improvement.

While the EKC hypothesis has been widely debated, technological change plays a key role in reducing emissions by increasing efficiency. The literature consistently shows that innovation positively impacts labor productivity and total factor productivity (Dietzenbacher and Los, 2002; Hall *et al.*, 2010). Technological spillovers, both domestic and foreign, are crucial for expanding knowledge capital and technological capacity (Acharya, 2015; Coe and Helpman, 1995). Recent studies have explored the validity of the EKC across different sectors (Htike *et al.*, 2022; Erdogan *et al.*, 2020) and within regions of the same country (Costantini *et al.*, 2013; Jiao *et al.*, 2020). Others have examined the role of R&D or patent stock and their spillovers (Aldieri *et al.*, 2022; Rahko and Alola, 2024; Du *et al.*, 2019).

Although all these works have attempted to incorporate technological issues into their work, the results of empirical work have been inconclusive regarding the prediction of EKC. Moreover, not all studies consider the interrelations between sectors in terms of technological knowledge spillovers. As established by Erdogan *et al.* (2020), the pathways to carbon emission reduction differ across sectors, requiring analyses that consider their specificities. Additionally, the literature assumes that increasing technical efficiency improves production capacity and thus impacts emission levels. However, the effects of R&D spending on carbon emissions cannot be known in advance, just as the spillover effects of R&D spending from one sector to others cannot be predicted. This is because rebound effects and situations like Jevons paradox can increase the use of the input or good made efficient by innovation, nullifying the initial effects of carbon reduction.

This study contributes to the literature by incorporating domestic technological knowledge and spillovers, addressing endogeneity issues from omitting these variables. Using a country-sector panel for 23 countries and 14 sectors from 2002 to 2015, we employ System-GMM estimation. Our results indicate that domestic technological knowledge and spillovers significantly reduce emissions, though foreign R&D spillovers show weaker evidence. The traditional inverted U-shape of the EKC holds when sector-country data is analyzed.

In addition to this introduction, the article contains six more sections. In the second, a brief literature review is presented. The third describes the methodological strategy adopted, as well as the construction of the variables. The fourth specifies the database used and the descriptive statistics. In the fifth section the results are presented and discussed. Finally, in the sixth section, the conclusions are made.

2. Review of literature and hypotheses

The relationship between pollutant emissions, energy consumption, and economic growth has been extensively studied in recent decades (Al-Mulali *et al.*, 2015; Dogan and Seker, 2016; Huang *et al.*, 2008; Marrero, 2010; Menz and Welsch, 2012; Richmond and Kaufmann, 2006; Zhou and Liu, 2016). These studies mainly test the existence of the EKC, based on Kuznets (1955), which proposes an inverted-U relationship between income and environmental degradation. Initially, as income rises, environmental degradation increases due to intensified resource extraction and higher pollution levels. At this stage, natural resources are plentiful and waste production is low. However, as industrialization progresses, pollution rises. In a later phase, as the service sector expands and information and communication technologies diffuse, environmental degradation decreases. At higher income levels, increased awareness of quality of life and the adverse effects of environmental degradation lead to reduced emissions after reaching a certain income threshold (Dinda, 2004; Kaika and Zervas, 2013a).[1]

Critics argue that fast economic growth alone cannot solve environmental problems, and public policies are needed to protect the environment. Moreover, the EKC concept emphasizes production over consumption patterns.

[1] In this logical sequence of describing the economic growth process, the arguments implicitly assumes that the service sector is less polluting, that the growth process leads to a reduction in inequality, and that the causal relationship between income and environmental degradation is unidirectional. These are some theoretical limitations of the EKC concept (Kaika and Zervas, 2013a and 2013b).

However, these criticisms do not invalidate the EKC hypothesis; they merely highlight its limitations, particularly in its application to specific pollutants, such as CO_2 emissions in empirical studies (Kaika and Zervas, 2013b).

The Kuznets curve links technological progress and CO_2 emissions by suggesting that emissions rise with intensive energy use in early stages of development but decrease as advanced technologies and the service sector grow. Firms may adopt energy-efficient or environmentally friendly technologies, such as renewable energies or clean production methods, driven by market opportunities or stricter regulations (Ang, 2007; Du *et al.*, 2019). The literature debates whether general R&D reduces environmental impacts (Fernández *et al.*, 2018; Erdogan *et al.*, 2020) or if it must be targeted at green technologies (Costantini *et al.*, 2013; Aldieri *et al.*, 2022). Technological advancements can also increase emissions if focused on carbon-intensive sectors (Töbelmann and Wendler, 2020). Additionally, the rebound effect (Khazzoom, 1987; Brookes, 1992) suggests that energy efficiency can fuel economic growth, raising energy demand and offsetting initial CO_2 reductions (Jin *et al.*, 2018). Technological diffusion and spillovers between countries and sectors can reduce technological gaps, boosting productivity through trade (Coe *et al.*, 1997), but may also increase emissions due to the Jevons paradox, where increased efficiency lowers prices and raises demand (Alcott, 2005).

Within the empirical literature, several studies have tested the EKC hypothesis, as well as the effect of the use of energy inputs and the degree of openness. The EKC hypothesis has been reexamined in the context of innovation literature and technology spillovers, considering the relationships between innovation and CO_2 emissions. The innovation literature, which specifically addresses the effects of technological development, demonstrates that improving technical efficiency significantly impacts labor productivity and Total Factor Productivity (TFP), which in turn affects the income of countries and regions (Bascavusoglu, 2004; Grossman and Krueger, 2014).

Theoretical arguments and empirical literature provide us with an econometric specification (Eq. 1) that incorporates the stage of development of the country/sector, energy use, R&D expenditures as a proxy for technological advancement, and foreign trade as a mediating element of technological spillovers.

$$CO_2 = f(CO_{2_{t-1}}, V, V^2, EGY, Tech, Open) \tag{1}$$

In the Eq. (1) V refers to the income or production level of the country and V^2 the square of income/production. Besides, EGY refers to the use of energy, *Open* the degree of trade openness, $CO_{2\,t-1}$ the level of CO_2 emissions in the past, and *Tech* refers to the R&D expenditures.[2]

The EKC hypothesis is supported by some studies (Ang, 2007; Fodha and Zaghdoud, 2010; Galeotti *et al.* 2006 and 2009; Gökmenoğlu and Taspinar, 2016; Halkos, 2003; Richmond and Kaufmann, 2006; Seker *et al.*, 2015; Alola and Rahko, 2024), while others find no empirical evidence (Dogan and Seker, 2016; Halicioglu, 2009; Holtz-Eakin and Selden, 1995; Marrero, 2010). This discrepancy may arise from differences in country/region, time period, econometric methods (Dinda, 2004), development level (Aldieri *et al.*, 2022; Töbelmann and Wendler, 2020), or sector (Erdogan *et al.*, 2020). For example, Erdogan *et al.* (2020) find the EKC does not hold in sectors like energy and transport but does in industry. Htike *et al.* (2022) confirm this in only three of seven sectors, including electricity and public services, while the relationship does not hold in manufacturing, transport, or agriculture.

Research also examines the impact of R&D, green innovations, and spillovers on CO_2 emissions across regions (Costantini *et al.*, 2013; Jiao *et al.*, 2020) and countries (Aldieri *et al.*, 2022; Rahko and Alola, 2024; Du *et al.*, 2019). Generally, higher technological progress is linked to lower carbon emissions, as firms adopt cleaner technologies (Costantini *et al.*, 2013). Innovation in one sector can affect upstream and downstream industries (Jiao *et al.*, 2020), highlighting the need to analyze both spillover effects and internal R&D.

Studies show domestic technological development reduces emissions in Nordic countries but lacks statistical significance in Italy (Costantini *et al.*, 2013). In the USA and EU, R&D negatively correlates with emissions, while in China, general innovation increases emissions (Jiao *et al.*, 2020). However, R&D spending in Chinese provinces shows an inverted U-shaped relationship with emissions, indicating that high R&D is needed for reductions (Jiao *et al.*, 2018). Similarly, Sun *et al.* (2021) found that domestic patent stock lowers emissions in 24 countries, but general innovations may have no significant effect on emissions in Europe (Töbelmann and Wendler, 2020). Non-green innovations can even increase emissions through rebound effects (Jiao *et al.*, 2018; Erdogan *et al.*, 2020).

Given these divergent findings, investigating the EKC within a sector-country panel framework is crucial. Two possible relationships between techno-

[2] Although not all works that use the variable are time-lagged, most empirical work adopts the dynamic panel model, such as Al-Mulali *et al.* (2015); Gökmenoğlu and Taspinar (2016); Marrero (2010). A complete review of the work and strategy methodology used here is presented by Dinda (2004).

logical progress and CO_2 emissions emerge: either negative (H1a) or positive (H1b).

Hypothesis 1: Technological progress affects CO_2 emissions.
Hypothesis 1a: Technological progress negatively affects CO_2 emissions.
Hypothesis 1b: Technological progress positively affects CO_2 emissions.

Technological spillovers, which impact knowledge capital, are well-documented in innovation literature (Griliches, 1979). These spillovers occur when competitors absorb technological knowledge, limiting the original owner's benefits. Through trade, countries, sectors, and firms access technology developed by others (Silverberg *et al.*, 1988).

Spillovers can occur domestically (Griliches, 1979; De la Potterie, 1997; Dietzenbacher and Los, 2002) or internationally (Acharya, 2009 and 2015; Coe and Helpman, 1995; Keller, 2004), where importing intermediaries creates foreign knowledge capital that boosts technical efficiency. For example, Cole *et al.* (2005 and 2008) examined UK and China emissions, using current R&D expenditure as a proxy for innovation, but their approach didn't align with innovation literature, which prefers measuring R&D stock via the perpetual inventory method (Acharya, 2009 and 2015; Keller, 2004). Lei *et al.* (2012) also analyzed international spillovers using FDI as a proxy, though literature suggests R&D stock access is more robust (Acharya, 2009 and 2015; Keller, 2004). Similar methods were used by Apergis *et al.* (2013).

Recent research links R&D stock or patents and spillovers to the EKC hypothesis, showing spillovers reduce carbon emissions in small economies like Nordic countries (Alola and Rahko, 2024), Italian regions (Costantini *et al.*, 2013), and Chinese provinces (Jiao *et al.*, 2018). Vertical intersectoral spillovers can be more important than sectoral innovation itself in emission reduction (Jiao *et al.*, 2020). Long-term effects of spillovers have been confirmed for Nordic countries (Rahko and Alola, 2024) and across countries (Sun *et al.*, 2021). The literature emphasizes that vertical spillovers can drive emission reduction, particularly in technology-concentrated countries, though results vary by sector (Sun *et al.*, 2021; Jiao *et al.*, 2020). In China, the Kuznets curve holds, and FDI spillovers reduce emissions. Alola and Rahko (2024) validate the U-shaped Kuznets hypothesis in small, open, developed economies in the energy and industrial sectors.

Technology is key to boosting productivity and competitiveness, yet due to the rebound effect or Jevons paradox, the impact of domestic and foreign spillovers on energy efficiency and productivity is unpredictable. Based on these theoretical arguments, two additional hypotheses are tested:

Hypothesis 2: Domestic spillovers affect CO_2 emissions.
Hypothesis 2a: Domestic spillovers negatively affect CO_2 emissions.
Hypothesis 2b: Domestic spillovers positively affect CO_2 emissions.

Hypothesis 3: Foreign spillovers affect CO_2 emissions.
Hypothesis 3a: Foreign spillovers negatively affect CO_2 emissions.
Hypothesis 3b: Foreign spillovers positively affect CO_2 emissions.

This paper aims to evaluate the effects of technology and its spillovers on CO_2 emissions, using innovation and EKC literature as a basis. Unlike previous studies, it analyzes domestic and foreign intra- and inter-sectoral spillovers across country, sector, and time, addressing endogeneity issues in the methodology discussed in the next section.

3. METHODOLOGICAL STRATEGY

Empirical models and System-GMM

The methodology investigates the relationship between technology stock, technological spillovers, and CO_2 emissions using the EKC in 23 countries from 2002-2015. Unlike prior studies, we employ a three-dimensional panel (sector, country, and time), offering several advantages. First, it captures unobserved heterogeneity across sectors within countries. Second, it introduces more variation, improving parameter identification and reducing multicollinearity. Third, it allows for fixed or random effects by sector, country, and time, controlling for unobservable bias. Based on this approach, three models are estimated (equations 2-4).

$$\text{M1: } CO_{2_{hit}} = \beta_0 CO_{2_{hit-1}} + \beta_1 V_{hit} + \beta_2 V_{hit}^2 + \beta_3 EGY_{hit} + \beta_4 R\&D_{hit} + \alpha_h + \gamma_i + \delta_t + u_{hit} \quad (2)$$

$$\text{M2: } CO_{2_{hit}} = \beta_0 CO_{2_{hit-1}} + \beta_1 V_{hit} + \beta_2 V_{hit}^2 + \beta_3 EGY_{hit} + \beta_4 R\&D_{hit} + \beta_5 Spl_{hit}^{Dom} + \alpha_h + \gamma_i + \delta_t + u_{hit} \quad (3)$$

$$\text{M3: } CO_{2_{hit}} = \beta_0 CO_{2_{hit-1}} + \beta_1 V_{hit} + \beta_2 V_{hit}^2 + \beta_3 EGY_{hit} + \beta_4 R\&D_{hit} + \beta_5 Spl_{hit}^{Dom} + \beta_6 Spl_{hit}^{For} + \alpha_h + \gamma_i + \delta_t + u_{hit} \tag{4}$$

Where V_{hit} represents the value added, EGY_{hit} the energy use, $R\&D_{hit}$ the domestic R&D stock, Spl_{hit}^{Dom} the domestic spillovers, Spl_{hit}^{For} the foreign R&D spillovers and u_{hit} is the error term. In all models fixed effect term of country, sector and time were included for two reasons. First, to capture the measurement errors associated with the input-output matrices used, which is specific to the country (h), sector (i) and year (t). Second, other variables potentially important in determining CO_2 emissions, such as specific laws and production structure, are likely to be national, industry-specific, and year-specific. In addition, all variables are presented in natural logarithm.

In the first model, we capture effects using the "traditional" EKC structure. The second model includes a variable for domestic R&D knowledge stock. The third model adds variables for domestic and foreign technological spillovers in sectorial transactions.

The dataset combines time series and cross-sectional observations, providing more information and degrees of freedom compared to separate cross-sectional or time series data (Baltagi, 2008). Traditional panel data methods (fixed or random effects) are unsuitable for dynamic models due to endogeneity (Halkos, 2003; Marrero, 2010). The dynamic structure $\beta_0 CO_{2_{hit-1}}$ introduces bias as lagged emissions correlate with the error term.

To address this, the Generalized Method of Moments (GMM), specifically System-GMM by Arellano and Bover (1995) and Blundell and Bond (1998), is used. System GMM, with its simultaneous equations approach (levels with lagged first differences and first differences with lagged levels as instruments), increases efficiency and reduces finite sample bias by utilizing additional moment conditions (Blundell and Bond, 2000).

In summary, the main reasons for using System-GMM can be highlighted in three central aspects;

i) Treatment of the endogeneity of the lagged dependent variable (dynamic panel)
ii) Omitted variable bias
iii) Unobserved panel heterogeneity

The first case refers to the main gain when using the System-GMM estimator. Our proposed model structure indicates that the past effects of CO_2 emissions influence present values, in other words, a dynamic panel structure. In this case, System-GMM allows us to deal with possible endogeneity problems that arise when the lagged dependent variable is included as an explanatory variable.

The second reason is that it is possible to include other instruments, other than the lagged explanatory variables, to control endogeneity problems of some explanatory variable. In our work, the variable "income" (v_{hit}) is potentially endogenous, since unobservable factors simultaneously affect income and CO_2 emissions. Therefore, the System-GMM approach allows us to address endogeneity problems through the inclusion of "external" instruments (Roodman, 2009).

Finally, in the presence of heteroscedasticity and serial correlation, the two-step System-GMM uses a consistent estimate of the weighting matrix, taking the residuals of the one-step estimate (Davidson and MacKinnon, 2004). Furthermore, in the presence of biased standard errors, it is possible to use finite sample correction for the covariance matrix, which makes System-GMM estimates robust and efficient (Roodman, 2009).

In general, for the purpose of our work, the specificities of System-GMM render it the best estimator to be used, mainly with regard to the control of endogeneity problems.

Construction of variables

Variables of spillovers

Based on the Coe and Helpman (1995) and Acharya (2015), and Wolff (1997) specifications we define domestic and foreign technological spillovers.

Regarding domestic spillovers, the technical coefficients of production from input-output matrices are used as weights to estimate the amount of domestic spillovers, understood as the fraction of R&D expenditure "borrowed" from another sector. In general, this procedure assumes that the technological knowledge that sector i receives from sector j is proportional to the importance of sector j in the input structure of sector i (Wolff, 1997). We then calculate domestic spillovers based on equation (5):

$$spl_{hit}^{dom} = \ln\left(\sum_{j \in I, j \neq i} a_{hij} * R\&D_{hjt}\right) \tag{5}$$

Where:

spl_{hit}^{dom}: domestic spillovers received by sector i of country h at time t.

a_{hij}: technical production coefficient representing the proportion of purchases that sector i makes from sector j in country h. This reflects the dependence of sector i on sector j for production.

$R\&D_{hjt}$: R&D stock of sector j in country h at time t to represent technological knowledge.

Regarding foreign spillovers, the amount of R&D obtained in economic transactions is defined as a proportion of the quantity of products, or intermediate inputs, acquired by a country by means of importation. This variable aims to capture the diffusion of technological knowledge through the purchase of goods via international trade. New and advanced technology embodied in imported inputs and capital goods can reduce carbon emissions by two channels, directly reducing carbon emissions and indirectly by serving as a basis for carbon emission-reducing innovations. Equation (6) calculates intersectoral and intra-sectoral foreign spillovers.[3]

$$spl_{hit}^{for} = \ln\left(\sum_{\substack{h'\neq h \\ h'\in H}} \sum_{j\in I} \frac{M_{hh'jt}}{\sum_{h'\in H, j\in I, h'\neq h} M_{hh'jt}} R\&D_{h'jt}\right) \tag{6}$$

Where:

spl_{hit}^{for}: foreign spillovers received by sector i in country h at time t.

$M_{hh'jt}$: total imports from country h' to country h in sector j at time t.

$R\&D_{h'jt}$: R&D stock of sector j in country h' at time t.

The domestic stock of R&D or knowledge capital is measured using the perpetual inventory method;

$$R\&D_{hit} = (1-\delta)S_{hi,t-1} + RD_{hit} \tag{7}$$

[3] For example, intra-sectoral foreign spillovers are understood as a sector i in country j receiving spillovers from the same sectors in other countries, while inter-sectoral foreign spillovers are understood as a sector i in country j receiving spillovers from different sectors in other countries.

Where δ is the depreciation rate of knowledge obsolescence and RD_{hit} is the actual R&D expenditure. Based on the works of Coe and Helpman (1995), Nishioka and Ripoll (2012), the initial R&D stock is defined as follows;

$$R\&D_{hi0} = \frac{RD_{hi0}}{(\delta + g_{hi})} \tag{8}$$

In what g_{hi} is the growth rate of real R&D expenditure for sector i and country h evaluated for the available period. Following the works of Coe and Helpman (1995) and Nishioka and Ripoll (2012), $\delta = 0.15$ was adopted.

To verify whether absorptive capacity is necessary to assimilate foreign spillovers (Coe *et al.*, 2009), we will interact the foreign technological spillover variable from section "Variables of spillovers" with the domestic stock of R&D, our proxy for absorptive capacity.

4. Database

The data set comprises the period 2002 to 2015 and 23 countries: Australia, Austria, Belgium, Canada, Czechia, Germany, Spain, Finland, France, United Kingdom, Italy, Japan, Mexico, Norway, Poland, Portugal, Republic of Korea, Romania, Singapore, Slovenia, Turkey, Taiwan and United States. The choice of countries and period was mainly due to the data available. However, the analyses obtained are not impaired given that the set of countries are highly representative as it contributes more than 92% of CO_2 emissions among high-income countries.[4]

The data used in this research originate from two different sources: The Eora Global Supply Chain Database (Eora26) (intermediate inputs, product, value added, CO_2 emissions and energy); and Analytical Business Expenditure on Research and Development (ANBERD), for R&D investments.

As regards the composition effect and technological effect of the decomposition model of the EKC hypothesis, we focus only on the manufacturing sectors, selecting from the International Standard Industrial Classification (ISIC) rev. 3 (see table 1).

[4] According to World Bank data for the year 2018. Furthermore, Mexico's emissions data was excluded from the percentage since it is an upper-middle-income country.

Table 1. Description of Sector Aggregation

Description	*Cod.* ISIC *Rev. 3.0*
Food Products, Beverages and Tobacco	D10T12
Textiles, Wearing Apparel, Leather and Related Products	D13T15
Wood, Paper, Printing and Reproduction of Recorded Media	D16T18
Chemical, Rubber, Plastics, Fuel Products and Other Non-Metallic Mineral Products	D19T23
Basic Metals and Fabricated Metal Products, Except Machinery and Equipment	D24T25
Computer, Electronic and Optical Products, Electrical Equipment, Machinery, Motor Vehicles and Other Transport Equipment	D26T30
Furniture, Other Manufacturing and Repair and Installation of Machinery and Equipment	D31T33

Source: own elaboration.

As proxy for sector income level the value added of each sector was used.[5] This is measured in millions of dollars converted to purchasing power parity (PPP) at constant prices in 2010. In addition, R&D investment data has also been converted in the same order.

Emission relevant energy use (measured in *Terajoules*) by sector is used for the variable of energy use. These data are related to gross energy use, excluding the non-energy use of energy commodities and energy products for transformation. CO_2 emissions are measured in gigagrams. These data are obtained by applying the CO_2 emission coefficient to the energy use for emissions and then adding process-based emissions (Genty *et al.*, 2012). From the previous descriptions, table 2 specifies the variables used in this paper, the expected signal and the data source.

[5] It is not uncommon to use value added in the context of the EKC when dealing with industry data (Kiliç *et al.*, 2024; Trofimov, 2024). The regression of gross domestic product and squared gross domestic product on carbon emission levels implicitly hypothesizes structural changes that involve an increase in the productivity level of society. Similarly, the regression of value added and its squared value by sector against pollution levels is based on testing sectoral productivity changes, given that productivity levels depend on the sector's production level, according to the Kaldor-Verdoorn law (Kaldor, 1966).

Table 2. Description of Variables

	Variable	*Description*	*Signal expected*	*Source*
Inertial component	$CO_{2\ t-1}$	Log of CO_2 emissions (in gigagrams)	+	Eora
Scale effects	V	Log value added (millions of USD$ at 2010 and PPP prices)	+	Eora
Composition effect	V^2	Log of value added to the square (millions of USD$ at prices 2010 and PPP)	-	Eora
Energy input	EGY	Log of use of energy (in Terajoule)	+	Eora
Technical Effects	R&D	Log of R&D (millions of USD$ at prices 2010 and PPP)	-/+	ANBERD
Technical Effects	Spl^{dom}	Variables of domestic spillovers (millions of USD$ at prices 2010 and PPP)	-/+	Authors'calculation
Technical Effects	Spl^{for}	Variables of foreign spillovers (millions of USD$ at prices 2010 and PPP)	-/+	Authors'calculation

Source: own elaboration.

Table 3. Descriptive statistics in log, for the period from 2002 to 2015

Variables	*N*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
CO_2	2 254	8.29	1.65	1.65	13.15
EGY	2 254	11.04	1.89	5.90	17.55
V	2 254	2.78	1.42	-1.17	6.91
R&D	2 254	6.97	2.44	-9.32	13.55
Spl^{dom}	2 254	7.45	2.07	2.95	12.90
Spl^{for}	2 254	8.31	1.27	5.07	12.19

Source: own elaboration.

5. Results of the estimation and discussion

Diagnostic tests for GMM

As discussed in the previous section, the estimation of the panel data set using the traditional method (fixed and random effects) causes problems of endogeneity. In addition, the method proposed by Arellano and Bond (1991) (First-Difference GMM estimator) to correct this problem proved inefficient, as demonstrated in empirical studies by Huang *et al.* (2008) and Marrero (2010). Therefore, in this part of the research, only the results of the System-GMM method will be presented, which is the most efficient and consistent estimator.

In the System-GMM estimation process, the lagged levels of y and the endogenous regressor with *t-2* and earlier were used as instruments. In addition, lagged differences of *y* and all regressors for *t-1* were used as additional instruments in the estimation. A similar procedure was adopted by Marrero (2010). Table 4 shows the results based on the specifications M1 to M3 (Equations 2, 3, and 4). Specifications M4 up to M7 show the interactions among R&D, domestic spillovers, and foreign spillovers to test hypotheses 1 and 2 and their variants.

To validate the assumptions underlying the proposed System-GMM method, it is important to analyze the test results of *m1*, *m2* and Hansen test. The first two refer to the AR tests for the autocorrelation of residuals. The residuals of the deferred equation must have correlation in series, AR (1), and the differentiated residuals, AR (2), should not present significant behavior. That is, if the errors of the proposed models are not correlated in series, there must be evidence of first order serial correlation, captured by the m1 test, and no correlation evidence in second order series, m2. Both tests have as null hypothesis the absence of autocorrelation of residuals. The Hansen test, in turn, is a test of overidentifying constraints. The null joint hypothesis is that the instruments are valid, that is, not correlated with the error term, and that the instruments not included are correctly excluded from the estimated equation.

As can be seen in table 4, the m1 test for the all models proposed was statistically significant, indicating the presence of correlation in series, AR (1) in the residuals. On the other hand, the m2 test rejected the null hypothesis of correlation in series in the differentiated residues, AR (2). As expected, these results show that, for the estimated models, there is no significant evidence of the presence of serial autocorrelation in the residuals. Finally, the Hansen test, presented also in table 4, accepts the null hypothesis, with a high level of significance for all models. This indicates that the instrumentation process of System-GMM was adequate, that is, the instruments used are valid.

Econometric results: Discussion and comparison with literature

The results found in this research corroborate the empirical literature that validate EKC hypothesis, but bring interesting evidence regarding the magnitude of its effect when considering the technological aspect.

In the first estimated model (M1) the proposed "traditional" form for EKC curve was applied. The results are in agreement with those obtained by Al-Mulali *et al*. (2015), Halkos (2003), Du *et al*. (2019), Jiao *et al*. (2018), Töbelmann and Wendler (2020), some of them also made use of the System-GMM method which points to validation of the inverted U-shape of the relationship between income growth and CO_2. When considering the data disaggregated by sectors, these results show that the relationships pointed out in some of the literature are maintained. The time lag of dependent variable ($CO_{2\ t-1}$) represents the inertial component meaning that the CO_2 level depends on their own level in the past period, as Töbelmann and Wendler (2020) also found.

The coefficients of the variables energy (EGY) and manufacturing value added (V) are both positive and highly significant. Regarding energy, the result indicates that the burning of fossil fuels to generate energy has a significant effect on carbon emissions (Carattini *et al*., 2015) and this result is directly comparable with the findings of Töbelmann and Wendler (2020). When one observes manufacturing value added (V) it can be concluded that the presence of manufacturing industries is heavily associated with pollution. However, when the scale of value added increases the coefficient turns negative, indicating a similar U-inverted pattern for carbon emissions and manufacturing value added, similar to the pattern observed in traditional papers that associate a more aggregated measure of production such as GDP with carbon emissions. The estimated elasticities are higher for value added (V) in comparison with energy variable (EGY), which differs from that found by Töbelmann and Wendler (2020) that the effect of energy is much larger in comparison with the effect of GDP.

Although the results of the estimates, in terms of magnitude, cannot be compared directly with others, due to methodological differences such as sectorial dimension, distinct period and diverse sample of countries, the presented values are similar to other cases. Marrero (2010), for example, showed that the magnitude of the EKC curve variables (GDP and GDP squared) and energy use were 0.29, -0.05 and 0.90, respectively, considering the countries of the European Union between 1996 and 2016. Al-Mulali *et al.* (2015) showed that the magnitude of the EKC curve variables was 0.82 and -0.02, respectively, in the period from 1980 to 2006; Dogan and Seker (2016), in turn, reported 0.66 for use for energy from 1975 to 2011. Jiao *et al.* (2018) reported coefficient varying between 0.79 and 1.04 for per capita GDP of Chinese provinces and -0.09 and -0.16 for squared per capita GDP. Du *et al.* (2019) showed higher coefficients for per capita GDP and squared per capita GDP for their country sample, which were respectively 1.62 and -0.08.

The R&D variable (as shown in table 4) exhibits a negative association with CO_2 emission levels, thereby confirming H1a in specifications M1 through M5. However, in specifications M6 and M7, the inclusion of spillovers or the interaction terms removes the significance of the R&D variable. The literature shows that R&D stocks are one of the most important factors in increasing productivity (Bascavusoglu, 2004; Grossman and Krueger, 2014). Cole *et al.* (2005) found negative effects of R&D spending on emissions in the United Kingdom. And Lei *et al.* (2012), in turn, showed that the FDI produces negative impacts on emissions in China. Fernández *et al.* (2018) found a negative coefficient for R&D for the European Union and US economies.

Finally, in the third model (M2) up to the seventh (M7), the variables of technological spillovers are included step by step. The inclusion of these variables allows us to evaluate the effects of intersectoral relations both domestically and internationally, which are manifested in the buying and selling of intermediate inputs, that is, improving technical efficiency due to the technological absorption from others.

The first point to highlight is the effect of domestic spillovers. The inclusion of this variable shows a statistically significant elasticity of -0.177 (M2, table 4), reducing the elasticity of the R&D variable from -0.235 to -0.165. These results show that this variable is an important factor for reducing emissions. Acharya (2009) and Griliches (1979) show that domestic intersectoral relations are the main mechanisms of technological transfer and knowledge capital formation, since it allows access to technology developed by other sectors. Rent spillovers are a way to substitute internal effort in some cases, although their interaction with internal R&D can enhance a firm's absorptive capacity (Cohen and Levinthal, 1989). In our case, the interaction between the R&D variable and domestic spillovers, aimed at capturing the sector's domestic absorption capacity, is not significant in specification M4, although the interaction variable shows a negative sign. Nevertheless, the results from

Table 4. Determinants of CO_2 emissions between 2002 and 2015 for 23 OECD countries (System-GMM)

Variables	*M1*	*M2*	*M3*	*M4*	*M5*	*M6*	*M7*
Carbon emissions ($CO_{2\ t-1}$)	0.365***	0.404***	0.405***	0.401***	0.587***	0.405***	0.465***
	(0.134)	(0.111)	(0.107)	(0.116)	(0.060)	(0.109)	(0.091)
Value added (V)	0.576***	0.580***	0.490***	0.613**	0.136*	0.495***	0.466**
	(0.195)	(0.199)	(0.161)	(0.239)	(0.079)	(0.163)	(0.140)
Value added square (V^2)	-0.040*	-0.045**	-0.038**	-0.048*	-0.003	-0.039*	-0.041**
	(0.021)	(0.023)	(0.019)	(0.026)	(0.011)	(0.020)	(0.016)
Energy use (EGY)	0.463***	0.527***	0.523***	0.524***	0.383***	0.520***	0.389***
	(0.111)	(0.101)	(0.098)	(0.101)	(0.072)	(0.100)	(0.109)
R&D	-0.235**	-0.165**	-0.138**	-0.151**	-0.270*	-0.126	0.148
	(0.109)	(0.067)	(0.053)	(0.091)	(0.148)	(0.185)	(0.163)
Domestic spillovers		-0.177***	-0.128**	-0.172***		-0.127***	-0.175
		(0.059)	(0.053)	(0.060)		(0.055)	(0.164)
Foreign Spillovers			-0.033		-0.092**	-0.030	0.147
			(0.032)		(0.045)	(0.051)	(0.112)
R&D*Domestic spillovers				-0.03			0.023*
				(0.012)			(0.013)
R&D*Foreign spillovers					0.022	-0.001	-0.054**
					(0.014)	(0.017)	(0.014)
AR(1)	0.001	0.001	0.001	0.001	0.001	0.001	0.001
AR(2)	0.157	0.305	0.299	0.202	0.127	0.290	0.118
Hansen test (prob > chi2)	0.549	0.845	0.784	0.778	0.241	0.704	0.646
Hansen test excluding group (prob > chi2)		0.390	0.222	0.482	0.896	0.993	0.048
Difference-in-Hansen test (prob > chi2)	0.549	0.952	0.942	0.735	0.071	0.5916	0.860
Number of instruments	23	25	26	22	26	26	26
Observations	2 093	2 093	2 093	2 093	2 093	2 094	2 095

Notes: *$p < 0.1$; **$p < 0.05$; and ***$p < 0.01$.

Source: own elaboration.

specifications M2, M3, M4, and M6 allow us to assert that our evidence aligns with some findings that show domestic spillovers are more important than internal innovations in regions or sectors for reducing emissions (Constantini *et al.*, 2013; Jiao *et al.*, 2018 and 2020).

The foreign spillovers variable, slp^{For}, which captures technological transference mediated by international trade, was not significant in the specification that includes domestic spillovers (M3 column).[6] Specification M5, which does not include the domestic spillovers variable but adds foreign spillovers and their interaction with domestic R&D, provides evidence in favor of carbon emissions reduction when foreign spillovers are received. The same is true for specification M7. In this case, the absorptive capacity, captured by the interaction between R&D and foreign spillovers, seems to be important for mitigating the environmental impact of economic activity.

Regarding our hypotheses, table 4 seems to provide evidence supporting that R&D expenditures reduce carbon emissions (Hypothesis 1a) and that domestic spillovers decrease carbon emissions (Hypothesis 2a). This suggests that advancements in technical efficiency may prevent situations like the Jevons paradox or rebound effects. As for the influence of foreign spillovers, there is evidence that tends to support Hypothesis 3a, although in some cases, our estimates point to non-significant results, particularly when domestic spillovers act as reducers of emissions. In general, the results found in our models were expected and show the importance of R&D to reduce emissions, validating the EKC curve for a sector-country panel data.

6. Conclusion and policy implications

With a data set comprising 23 countries and seven aggregated manufacturing industries, analyzed for the period from 2002 to 2015, this work sought to analyze the contribution of technological advances on the reduction of levels of CO_2 emissions. In addition, in a complementary way, we sought to verify the validation of the EKC hypothesis and to analyze the relationship among emissions, energy use and R&D knowledge and its spillovers, both domestic and foreign. This article contributes to this literature by providing new evidence on the inconclusive debate between R&D spending and carbon emis-

6 We also estimate the influence of foreign spillovers originating from each country separately, *i.e.*, the USA, Germany, Japan, and G7 countries, but the results are not significant. The results are available upon request.

sions. It takes into account issues concerning endogeneity by using the GMM system and a country-sector panel data that considers specificities related to unobserved heterogeneity not only between countries and over time but also among different sectors within countries. The main contributions are associated with the empirical verification of the effects of technological development on environmental degradation. These effects cannot be anticipated a priori, as technologies may increase efficiency and productivity, but for these reasons, they may also increase resource use, nullifying the initial effects on carbon emissions.

The results found in this research bring important aspects to the interpretation of policy guidance described by the EKC hypothesis. As discussed in previous sections, the political orientation of the EKC hypothesis states that when a given country reaches a certain level of income, individuals become more aware of the negative effects of environmental degradation, and with this greater efforts are employed to control levels. Therefore, countries should focus on economic development, since it leads to environmental improvement in the medium and long term (Dinda, 2004). In our case, when the scale of sectoral production increases, the productivity level rises in line with the Kaldor-Verdoorn hypothesis, which contributes to reducing carbon emissions. This bears similarity to when the EKC is measured using national income metrics.

However, as discussed in the innovation literature, technological development is pursued mainly by developed countries, which direct a relatively high proportion of GDP to advanced R&D and research, for example nanotechnology, chemistry and others. Therefore, it is possible that the EKC hypothesis captures the greater effort of developed countries directed at the development of new technologies, with the aim of increasing productivity and competitiveness, not necessarily the increase in environmental "awareness" as proposed. Furthermore, greater productivity can increase the use of the input or good made efficient by innovation, nullifying the initial effects of carbon reduction.

Thus, our aim have contributed to understanding the effects of technology on CO_2 emission levels. In addition, they provide policy implications regarding measures that can be implemented to reduce emissions. First, considering sectoral characteristics, we have seen that the increase in the R&D stock negatively impacts CO_2 levels emitted. Besides, the effects of investment in technology are not restricted to the sector that conducts the R&D expenditure itself, meaning there are domestic technological spillovers that amplify the impact of technological improvement and then reducing CO_2 emission levels. Some evidence is obtained for foreign spillovers when this variable is interacted with domestic R&D expenditures, underscoring the importance of absorptive capacity. However, in comparison, domestic spillovers have proven to be more relevant in the various tests conducted. It is therefore advisable to subsidize R&D expenditure, given its direct and indirect connection to emission reduction through domestic spillovers and its role in enhancing absorptive capacity. To achieve this, governments should offer tax incentives, subsidies, and public-private financing programs for companies that invest in green technologies and energy efficiency. This absorptive capacity, combined with foreign spillovers from other countries, helps mitigate the effects of climate change. Additionally, since our results strongly associate energy use with carbon emissions, it is important to promote public policies that replace dirty energy sources with clean ones to reduce environmental impacts.

Furthermore, fostering international collaboration in R&D can maximize the benefits of technology transfer. Promoting bilateral and multilateral agreements, facilitating the creation of joint ventures, and encouraging participation in international research consortia are measures that can promote the reduction of CO_2 emissions and accelerate the technology transfer process. Additionally, investing in innovation infrastructure, such as technology parks and firm incubators, along with strengthening the educational system in technological areas, will increase the capacity to absorb new technologies.

Some of the main limitations of the research should be mentioned. The use of data in a dataset mainly composed of developed countries, members of the OECD, is a limitation on the effect of technology on emissions in developing countries. In addition, the innovation literature also addresses other aspects regarding the development of new technologies, such as patents, stock of human capital and technological infrastructure. Thus, as a suggestion for future research, it would be interesting to address these aspects.

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