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Economic complexity and greenhouse gas emissions

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ABSTRACT

The contribution of the paper is twofold. First, it provides evidence that economic complexity contributes to reduce greenhouse gas emission intensity as well as per capita emissions. It is argued that the production of complex goods is associated with lower emission intensity due to the types of technologies used in the production of such goods and their high value-added characteristic. Using data for 67 countries between 1976 and 2012, the tests reported in the paper suggest that an increase of 0.1 in the economic complexity index generates a 2% decrease in next period's emissions of kilotons of CO_2e per billion dollars of output as well as in emissions per capita. Second, the paper proposes a Product Emission Intensity Index (PEII) associated with the production of 786 goods. The index is a weighted average of the emissions of the countries that export each given product with revealed comparative advantage. This index makes it possible to analyse specifically what products are associated with higher emission intensities, contributing to the formulation of policies aiming to reduce greenhouse gas emissions by shifting production away from high-emission intensity products as much as possible. The index corroborates that complex products are associated with lower emission intensities.

1. Introduction

Achieving the climate mitigation goals of the Paris Agreement (UNFCCC, 2015) as a coordinated global response to avoid the worst impacts of climate change requires deep structural transformations of productive systems worldwide. Global annual economic losses related to additional temperature increases of approximately 2 °C range between 0.2% and 2.0% of income (IPCC, 2014a), which are conservative estimates of costs of inaction due to methodological limitations in capturing multiple types of impacts, such as catastrophic changes, tipping points and loss of human lives, cultural heritage, and ecosystem services (IPCC, 2014a; Stern, 2016). Limiting warming to 1.5 °C requires a rapid, far-reaching and unprecedented transition in energy, land use, urban, infrastructure (including transport and buildings) and industry systems that substantially reduces emissions, based on a substantial increase in investments in a broad portfolio of mitigation options (IPCC, 2018).

For effective climate change mitigation, it is vital to understand how greenhouse gas (GHG) emissions can be associated with specific products, production processes and technologies. Nonetheless, sectoral-level data on GHG emissions for multiple countries are only available at highly aggregate levels (up to 29 sectors in the EDGAR database). Moreover, the sectoral classification used for emissions data is not the same as the ones used for sectoral output and trade data whereby it is required to create a correspondence to reach comparable sectoral units. These issues create challenges to assess detailed emission levels of different sectors and products.

The productive structure of each country reflects its technological and productive capabilities, defining its diversification trajectories and framing its possibilities for economic development (Hidalgo et al., 2007). More diverse economies tend to produce less ubiquitous goods, which indicates a higher level of complexity of the economy's productive structure. Following this approach, Hidalgo and Hausmann (2009) and Felipe et al. (2012) provided strong evidence suggesting that high economic complexity predicts high income per capita growth, while Hartmann et al. (2017) showed that economic complexity is negatively correlated with income inequality. Moreover, Lapatinas et al. (2019) and Mealy and Teytelboym (2020) provide evidence that economic complexity contributes to improve indicators of environmental performance and to reduce CO_2 emission as well.

As Hausmann et al. (2011, p. 27) stress, "economic complexity reflects the amount of knowledge that is embedded in the productive structure of an economy". In this paper we argue that the high

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amount of knowledge embedded in the productive structure of complex economies encompasses the knowledge required for cleaner production technologies. Hence, we argue that the economic complexity index reflects more than the structure of production of each economy.

In this paper, therefore, we investigate whether differences in countries' economic complexity can explain different levels of GHG emission intensity and per capita emissions. We explore the hypothesis that the production of complex goods is associated with lower emission intensity and lower emissions per capita as well. The possible explanation for these negative relationships is two-fold: (i) relatively high value added is obtained from each unit of pollution in more complex productive structures; and (ii) cleaner production technologies are used in countries that produce such goods, as found by Mealy and Teytelboym (2020). Moreover, we employ the methodology proposed by Hartmann et al. (2017) to calculate a Product Emission Intensity Index (PEII) for 786 products, which makes it possible to analyse in detail what products are associated with higher emission intensity. Hence, the present paper offers relevant insights regarding whether different types of goods are associated with different levels of GHG emissions.

This paper is organized as follows. Section 2 discusses the connection between GHG emissions and the process of economic development. Section 3 discusses data and methods employed in this paper. Section 4 reports and analyses the results of the regressions estimating the relationship between economic complexity and GHG emission intensity and GHG emissions per capita. Section 5 presents the Product Emission Intensity Index and discusses the characteristics of the goods associated with higher emissions, paying especial attention to the products position in the *Product Space* (Hausmann et al., 2011). Section 6 presents the concluding remarks of the paper.

2. Connecting GHG emissions, economic development, and economic complexity

2.1. GHG emissions and economic development

Economic development is intrinsically associated with structural changes. The common denominator of different development theories is that all approaches emphasize the crucial role of industrialization or structural change towards modern sectors for sustained economic growth (e.g. Rostow, 1956; Prebisch, 1962; Lewis, 1954; Furtado, 1964; Hirschman, 1958; Kaldor, 1966). Thus, a key difference between economic growth and economic development is the type of structural (qualitative) transformation taking place in the economy.

The increasing deterioration of natural capital and the climate emergency emphasize that it will not be possible to repeat the paths that developed economies followed in the past if the sustainability of development itself is considered. Consequently, economic development must be based on structural changes that lead simultaneously to the modernization of the productive apparatus and to the mitigation of climate change and its related risks. Ultimately, this will require a significantly high degree of technological progress to build efficient, low carbon, resilient and sustainable productive structures.

Economic growth and GHG emissions present a two-way relationship. On the one hand, GHG emissions exert an impact on growth as increasing concentrations of GHG in the atmosphere drive multiple climate change-related events that have net adverse effects on economic activity. The Stern (2007) Report asserts that climate change is the greatest and widest-ranging market failure ever seen. It estimated that climate change will incur, if no action is taken, costs ranging from 5% to 20% of global GDP annually. By creating a constraint for ever-increasing economic growth, increasing GHG concentrations also limit the possibilities of economic development. On the other hand, economic growth can have an impact on GHG emissions as well. However, the nature of this impact is not necessarily linear.

Past experiences of economic growth associated with increasing GHG emissions have led to the assumption that growth necessarily increases GHG emissions. Until 1970s, OECD countries experienced an economic growth path characterized by a fossil fuelled, energy-intensive industrialization process (IPCC, 2014b). Similarly, such argument finds resonance in China's recent coal-fuelled growth leap as well (Azadi et al., 2011).

The linear relationship implicitly or explicitly assumed between economic growth and GHG emissions has led to claims that policies to contain global warming are necessarily harmful to growth. Projections for net macroeconomic costs of mitigation have contributed to build the misleading perception that economies perform better when no explicit action to mitigate GHG emissions is taken and that mitigation policies are necessarily costly to the economy. For instance, the scenarios presented in the latest IPCC report that are consistent with warming below 2 °C result in net macroeconomic losses that range between 2% and 15% of global GDP in relation to a baseline without mitigation (IPCC, 2014b).

The assumption of such linearity implies a trade-off between economic growth and GHG emissions, which has been challenged by recent studies for underestimating both the costs of unmanaged climate change (e.g. catastrophic changes) and the benefits of the global low carbon transition, such as spillover-effects of green innovation and economies of scale (Burke et al., 2016; Dietz et al., 2018; Stern, 2016; Stoerk et al., 2018; Weitzman, 2009).

There is also debate about whether the relationship between GDP per capita growth and GHG emissions per capita presents an inverted U-shaped relation, known as the Environmental Kuznets Curve (EKC). The implicit economic concept in this debate is that environmental quality would be a luxury good, which only becomes affordable once income is increased, because either: (a) as income increases and basic needs are covered, there is increased attention to environmental quality; (b) higher income levels might be connected to higher levels of environmental awareness; or (c) higher income countries are more likely to be able to provide the resources necessary for tackling environmental issues (Azadi et al., 2011; Grossman & Krueger, 1995; Martínez-Alier, 1995; Munasinghe, 1999). The vast literature on the EKC hypothesis offers mixed empirical evidence is support of such relation for CO_2 emissions, although there is more foundation for other types of local pollutants, such as particulate pollution (Carvalho, 2013; He & Richard, 2010; Stern, 2004, 2015).

Whereas the precise shape of the relation between economic growth and emissions is unknown, it is becoming increasingly clear, however, that halting economic growth is not the solution to fight global warming, especially in the recent context of economic recovery from the impacts of the COVID-19 pandemic. As found by Le Quéré et al. (2020), GHG emissions reductions based on abrupt decreases of economic activity are only temporarily effective and sustaining mitigation in the future can only be achieved by structural changes in the economy. Hepburn and Bowen (2012) show that holding the current level of per capita GDP constant (i.e. without any additional investments in modern low carbon technologies) would not avoid dangerous climate change and would still require improvements in carbon intensity. Furthermore, less economic growth does not avoid the risk associated with using controversial mitigation technology options, such as carbon capture and storage, nor is it the most economically efficient way of reducing GHG emissions (Jakob & Edenhofer, 2014).

In addition, since the Great Recession of 2008–2009, a number of approaches have emerged that sustain that the right mix of climate policy instruments can be a driver of economic growth and job creation. These include the "green economy" debate in the lead up to Rio + 20 (UNEP, 2011a, 2011b), the "Green New Deal" discussions, which started in the United Kingdom in 2008 and are now gaining training traction in the United States and in the European Union (Barbier, 2019), and the "green growth" debate led by the OECD (OECD, 2011). In this context, it can be argued that there has been a shift from "there is trade-off between economic growth and GHG emissions" to "the transition to low-carbon, resilient economy can drive economic growth". Such formulations have been gaining impetus with green recovery packages announced worldwide to fight the present crisis of the COVID-19 pandemic.

Nonetheless, the policies that aim to reconcile economic growth with GHG emissions mitigation require the *decoupling* of economic growth from GHG emissions. According to UNEP (2011a, p. XV), "*decoupling means using less resources per unit of economic output and reducing the environmental impact of any resources that are used or economic activities that are undertaken*." Jackson (2009) distinguishes between relative and absolute decoupling. The first is defined as a reduction of environmental pressure per unit of economic output. Relative decoupling entails that the environmental impact might continuously increase if GDP grows faster than environmental depletion. Absolute decoupling is a stronger concept in that it implies a dissociation of absolute environmental impact from economic growth. Thus, achieving absolute decoupling of GDP growth from GHG emissions is critical to allow for economic development whilst meeting the climate goals of the Paris Agreement. It is important to note that reducing GHG emissions per capita does not necessarily translate into a reduction of absolute emissions, since population and total emissions could grow together. Nonetheless, if the rate of decrease of emissions per capita is higher than the rate of increase of population, reducing emissions per capita does translate into an absolute reduction of carbon emissions.[2]

In spite of the debates about the relationship between economic growth and GHG emissions, there is scarce literature on the relationship between structural change and GHG emissions. In other words, the relationship between economic development and GHG emissions has not received enough attention.

Considerable work has been carried out on system transitions, such as energy, transport and urban infrastructure (IPCC, 2018). For example, this literature addresses the shift of the energy system from fossil-fuel based generation to renewable energy sources, such as biomass, wind and solar generation. Even though a broad portfolio of mitigation options is available (ibid.), the relationship with structural change and economic development is less clearly established.

The Big Push for Sustainability is a noteworthy exception. It is an approach explicitly designed to address structural change and environmental sustainability with a focus on Latin American and Caribbean countries (ECLAC, 2016, 2018, 2020; Gramkow, 2020). The Big Push for Sustainability represents an articulation and coordination of policies (public and private, national and subnational, sectoral, tax, regulatory, fiscal, financing, planning, etc.) that leverage national and foreign investments to produce a virtuous cycle of economic growth, employment and income generation, inequalities and structural gaps reduction and promotion of the environmental sustainability of development. Built within the framework of ECLAC's thinking, the approach is explicitly focused on structural problems particularly relevant to the region such as structural heterogeneity, incorporation of technical progress and its benefits, trade specialization, high levels of inequality (social, gender, etc.), among other structural divides of development (Gramkow, 2019). By fostering the expansion of technological capabilities, the Big Push for Sustainability seeks to contribute to resilient, low-carbon solutions and to a more diversified, complex and competitive external insertion (ibid.). Nonetheless, significant work remains to be done on establishing the associated environmental impact of alternative productive structures in terms of their complexity.

This paper seeks to contribute to fill this gap in the existing literature, by taking the economic complexity literature as reference to understand the interconnections between structural change, economic growth and GHG emission intensities. More specifically, the paper explores the relationship between structural change and relative and absolute decoupling, investigating whether changing the sectoral composition of production impacts on the GHG emission intensity of the economy as well as on its emissions per capita. It is noteworthy that although reducing GHG emissions per capita might not necessarily lead to an absolute reduction of GHG emissions, if the decrease in emissions per capita is larger than the increase in population, reducing emissions per capita does indeed translate into an absolute reduction of carbon emissions.

2.2. Product Space

Exploring the idea that each country's productive structure influences its growth and development possibilities, Hidalgo et al. (2007) seminal paper investigated whether the sectoral composition of each country's competitive exports influences the path, the costs and the speed of change towards the production of more sophisticated goods.

As Hidalgo et al. (2007) stress, the competitive production of different types of goods requires different capabilities. Consequently, the capabilities present in a country determine the goods it can produce and how difficult it is for the country to start producing goods that require different (or additional) capabilities. Consequently, if this statement is correct, then the range of goods a country can produce competitively and the level of complexity of these goods indicates the capabilities a country possesses.

Hidalgo et al. (2007) used the index of Revealed Comparative Advantage (RCA), developed by Balassa (1965), to identify the efficiency of each economy in producing each product. Formally:

$$RCA_{cp} = \frac{x_{cp}/\sum_p x_{cp}}{\sum_c x_{cp}/\sum_c \sum_p x_{cp}} \tag{1}$$

where x denotes the export quantum, while subscripts c and p denote country and product, respectively. An index higher than one indicates that the country has high competitiveness in the production of the given good, while the opposite holds if the index is lower than one.

Hidalgo et al. (2007) established how close products are in terms of the capabilities required for their production using the conditional probabilities of exporting each pair of goods with RCA. In a nutshell, this method assumes that the probability of competitively producing two products that require similar capabilities is higher than the probability of competitively producing two goods that require different capabilities. Trade data from UN Comtrade is available at a highly disaggregated level (up to 8,000 product categories) for numerous countries and years. Hidalgo et al. (2007: 484) explored the large amount of information in the UN Comtrade database to calculate the *proximity* between goods as the probability of a country exporting product p with RCA given that it exports product k with RCA as well. Adopting a threshold value for proximity, the authors established linkages between products, creating a network that they called *Product Space.*

Hidalgo et al. (2007) showed that less developed countries tend to produce goods with a limited number of linkages, which hinders

[2] Note that, by definition: E=(E/L)*L, where E is GHG emission and L is population.

the possibilities for these countries to diversify their productive structure and move towards the production of more sophisticated products. The opposite holds true for developed countries. Thus, the authors provided three important empirical contributions to the economic development literature: (i) different countries face different opportunities for increasing their economic growth, given their distinct productive structures and associated capabilities; (ii) structural change is highly path dependent; (iii) achieving competitiveness in the production of sophisticated goods takes time, since this process requires learning new capabilities and less sophisticated goods are not associated with many other activities (Hidalgo et al., 2007: 487).

2.3. Economic complexity

Extrapolating Hidalgo et al.'s (2007) paper, Hidalgo and Hausmann (2009) proposed to calculate products' and countries' complexity based on information on the diversification of the countries' economies and on the ubiquity of the products. The level of diversification of each country, on the one hand, was defined as the number of products the country produces with RCA. The level of ubiquity of each good, on the other hand, was defined as the number of countries that produce the good with RCA. Formally:

$$Diversification = k_{c,0} = \sum\nolimits_p M_{cp} \tag{2}$$

$$Ubiquity = k_{p,0} = \sum\nolimits_c M_{cp} \tag{3}$$

where M is a *dummy* variable which equals one if country c exports the good p with RCA, and zero otherwise.

Using these measures, Hidalgo and Hausmann (2009) provided evidence that there is a strong positive correlation between each country's income per capita and its level of diversification. Moreover, they also showed that diversification and ubiquity are negatively correlated, which points out that countries that are more diversified tend to produce goods that are less ubiquitous.

Hidalgo and Hausmann (2009) explored the information contained in the diversification and ubiquity indexes to calculate a Product Complexity Index (PCI) and an Economic Complexity Index (ECI). The intuition for combining the two indexes is straightforward. On the one hand, a country with a high diversification is considered less complex if the products it produces competitively (with RCA) are highly ubiquitous. On the other hand, a product with a small ubiquity is considered less complex if it is produced by countries that are not very diversified. Hence, it is possible to perform continuous iterations between the two indexes in order to extract progressively more refined information about the economic complexity of each product and country. Formally:

$$k_{c,N} = (1/k_{c,0})\sum\nolimits_p M_{cp}k_{p,N-1} \tag{4}$$

$$k_{p,N} = (1/k_{p,0})\sum\nolimits_c M_{cp}k_{c,N-1} \tag{5}$$

where N denotes the number of iterations.

Substituting (4) into (5) yields:

$$k_{c,N} = \sum\nolimits_{c'} M_{cc'}k_{c',N-2} \tag{6}$$

where $M_{cc'} = \sum_p (M_{cp}M_{c'p})/(k_{c,0}k_{p,0})$ and c′ denotes other countries besides c.

Eq. (6) is satisfied when $k_{c,N} = k_{c,N-2} = 1$, which is the eigenvector associated with the highest eigenvalue of $M_{cc'}$. However, since this eigenvector is formed of ones, he is uninformative. Hence, the eigenvector associated with the second highest eigenvalue ($\vec{K}$) is used to capture highest part of the system's variance. Thus, ECI is calculated as:

$$ECI = (\vec{K} - < \vec{K} >)/sd(\vec{K}) \tag{7}$$

where < > denotes the average, and *sd* denotes the standard deviation.

The same procedure is used to calculate PCI, but now substituting (5) into (4) and using the eigenvector associated with the second highest eigenvalue ($\vec{Q}$) of $M_{pp'}$:

$$PCI = (\vec{Q} - < \vec{Q} >)/sd(\vec{Q}) \tag{8}$$

In terms of GHG emissions, it can be argued that economies with a broader and more interconnected range of products with RCA are more likely to present lower levels of GHG emission intensity and of emissions per capita as well. A well-developed productive system and a high number of productive capabilities offers better conditions for green innovations, i.e. for developing technological solutions that benefit the environment. Mealy and Teytelboym (2020) provide evidence that supports this argument. They find that economic complexity is positively correlated with green innovations.[3] The determinants of green innovations do not differ significantly from non-green innovations, which suggests that if a country is capable of producing innovations leading to sophisticated goods, it is also likely that this country will be able to produce green innovations leading to lower GHG emissions (Gramkow and Anger-Kraavi, 2018). Furthermore, there is also evidence that suggests that economic complexity contributes to increase technological absorption (Gala et al., 2018). Thus, it is also possible that the same applies to the absorption of green innovation.

Following Hausmann et al. (2011, p. 27), therefore, we argue that the high amount of knowledge embedded in the productive structure of complex economies encompasses knowledge required for cleaner production technologies. Consequently, the economic complexity index captures more than simply the sectoral composition of each economy.

3. Data and methods

3.1. Data

In order to estimate the impact of economic complexity on GHG emission intensity and on emissions per capita, two main datasources were used. Data relative to the Economic Complexity Index (ECI), calculated as discussed in the previous section, were obtained from MIT's Observatory of Economic Complexity (atlas.media.mit.edu). Data on total GHG emissions (in kilotons of CO_2 equivalent, CO_2e) were obtained from the World Development Indicator (WDI) database (databank.worldbank.org/data/reports.aspx?source = world-development-indicators#). WDI emissions are, in turn, calculated based on the Emissions Database for Global Atmospheric Research (EDGAR) data, version 4.3.2 (edgar.jrc.ec.europa.eu). This database comprises data on annual emissions of greenhouse gases, including CO_2 totals,[4] all anthropogenic CH_4 sources, N_2O sources and F-gases (HFCs, PFCs and SF_6), calculated for up to 29 sectors[5] in several countries over 1970–2012. The

[3] Part of the decrease in GHG emissions generated by increases in economic complexity could be explained by outsourcing of high-emission activities (Andersson & Lindroth, 2001). We would like to thank an anonymous referee for bringing up this point. Nonetheless, following the results of Mealy and Teytelboym (2020), the argument here is that higher economic complexity contributes to decrease the level of GHG emissions of each activity in addition to its sectoral composition effect. Nonetheless, since this is not explicitly tested in this paper, this can be a hypothesis to be explored in future research.

[4] Excluding short-cycle biomass burning (such as agricultural waste burning and Savannah burning) but including other biomass burning (such as forest fires, post-burn decay, peat fires and decay of drained peatlands).

[5] EDGAR 4.3.2 includes emissions from energy and agriculture. It does not include land use, land-use change and forestry.

EDGAR GHG data, however, is not presented under the same classification used for disaggregated trade (SITC) or output (ISIC) data. Hence, it is not straightforward to associate sectoral emission, production and trade data. The data relative to the control variables used in the econometric tests – trade openness (exports plus imports to GDP); urbanization (percentage of population living in urban areas); electricity consumption; GDP per capita (in constant 2010 USD)[6]; secondary school enrolment (% gross); population; agriculture share; manufacturing share, and patent applications by residents – were also gathered from WDI.

Combining the different databases mentioned above, the final sample used in this paper comprises data for 67 countries between 1976 and 2012. To illustrate the considerable variance in this sample, it is interesting to analyse the information related to GDP per capita, ECI, GHG emissions per capita and GHG emission intensities. The mean ECI of the sample is 0.130, the mean GDP per capita is 13,693 dollars, and the mean GHG emission intensity is 1,829 kilotons of CO_2e per billion dollars of output (kt $CO_2e/USD_{billion}$ output), while the mean GHG emissions per capita is 0.008. The lowest ECI in the sample is from Nigeria (−2.764) in the year of 2009, with a GDP per capita of 2,216 dollars, GHG emissions per capita of 0.002, and GHG emission intensity of 798. The highest ECI in the sample is from Japan (2.625) in the year of 1996, with a GDP per capita of 41,514 dollars, emissions per capita of 0.011 and a level of emission intensity of 273. The lowest emission intensity in the sample, however, is from Sweden (131) in 2012, with a GDP per capita of 52,520 dollars, emissions per capita of 0.007 and an ECI of 1.752. On the other end, the highest emission intensity is from Bolivia (30,039) in 2011, with a GDP per capita of 2,051 dollars, emissions per capita of 0.061 and an ECI of −0.940. The lowest GDP per capita in the sample is from China (263 dollars) in 1976, with a level of emission intensity of 9,502, emissions per capita of 0.002 and an ECI of 0.341. The highest GDP per capita is the sample is from Norway (91,617 dollars) in 2007, with an ECI of 0.661, emissions per capita of 0.015 and emission intensity of 168. When it comes to GHG emissions per capita, Sri Lanka in 1989 had the lowest level (0.001), with an ECI of −0.621, GDP per capita of 1,132 and emission intensity of 904. Finally, the country with the highest level of emissions per capita in the sample is Australis in 2001 (0.064), with an ECI of −0.066, GDP per capita of 44,565 dollars and GHG emission intensity of 1,435.

The same 67 countries and time period were used to calculate the Product Emission Intensity Index (PEII), described in Section 3.3. To this end, data relative to international trade was gathered from the UN Comtrade (wits.worldbank.org). Trade data are classified according to the Standard International Trade Classification (SITC), revision 2, 4-digits, comprising information for 786 product categories between 1976 and 2012. Similarly to Hartmann et al. (2017), countries with an average export value under 1 billion dollars were excluded from the analysis to avoid taking into account small countries. Thus, the final sample used to calculate RCAs comprised 147 countries.

Table 1 presents the correlations between the variables used to estimate Eq. (9). This table shows that ECI is highly correlated with urbanization, electricity consumption and GDP per capita, and is negatively correlated with emission intensity. Moreover, it also indicates that GDP per capita is strongly correlated with these same variables. This is not unexpected, since Hidalgo and Hausmann (2009) pointed out that ECI is an important predictor of GDP per capita growth. Nonetheless, these high correlations generate multicollinearity in the estimated regressions. Interestingly, the logarithms of emissions per capita and of emission inten-

[6] GDP per capita in constant 2010 USD was used instead of in constant PPP because of its wider coverage.

Table 1
Variables' correlations.

	Ln of Emissions per capita	Ln of Emission Intensity	ECI	Ln of Urbanization	Ln of Openness	Ln of Electricity Cons.	Ln of GDP per capita	Ln of Sec. School Enrollment	Ln of Population	Ln of Agric. Share	Ln of Manuf. Share	Ln of Patents
Ln of Emissions per capita	1.000											
Ln of Emission Intensity	−0.481	1.000										
ECI	0.635	−0.732	1.000									
Ln of Urbanization	0.708	−0.660	0.550	1.000								
Ln of Openness	0.201	−0.321	0.245	0.226	1.000							
Ln of Electricity Consumption	0.835	−0.788	0.797	0.783	0.344	1.000						
Ln of GDP per capita	0.869	−0.851	0.793	0.795	0.302	0.946	1.000					
Ln of Sec. School Enrollment	0.704	−0.683	0.642	0.717	0.351	0.822	0.807	1.000				
Ln of Population	−0.217	0.360	−0.105	−0.372	−0.436	−0.297	−0.333	−0.197	1.000			
Ln of Agriculture Share	−0.686	0.779	−0.733	−0.698	−0.399	−0.822	−0.850	−0.719	0.186	1.000		
Ln of Manufacturing Share	−0.089	0.210	0.032	−0.062	−0.134	−0.091	−0.167	−0.078	0.160	0.345	1.000	
Ln of Patents	0.639	−0.508	0.777	0.437	−0.020	0.708	0.670	0.611	0.329	−0.617	0.066	1.000

Source: Athors' elaboration.

sity are negatively correlated, and all the variables that are positively correlated with emission intensity are negatively correlated with emissions per capita and vice versa.

3.2. Estimation strategy

One of the objectives of this paper is to estimate the impact of structural change, more precisely the impact of changes in the economic complexity of each country, on GHG emission intensity and on GHG emissions per capita. As mentioned in the introduction, reducing GHG emissions to the levels required to meet international climate change mitigation goals requires deep structural transformations of productive structures worldwide. One mechanism by which an economy can reduce its GHG emissions is to adopt production techniques that reduce emissions in the production process of each good (Frondel et al., 2007). Another mechanism to reduce an economy's GHG emissions is to change the sectoral composition of the economy, by shifting the country's economic structure towards the production of goods that have, on average, lower levels of emission intensity. An example of the latter mechanism would be to progressively shift from fossil fuel-intensive sectors to renewable energy and energy efficient industries, which can mean creating entirely new industries in a given country. As mentioned earlier, an increase in economic complexity most likely contributes to reduce both types of emissions.

To test the effect of economic complexity on each country's emission intensity, the following equation was estimated:

$$lnEI_{c,t} = \beta_{01} - \beta_{11}ECI_{c,t} - \beta_{21}ECI_{c,t-1} + \beta_{i1}X_{c,t} + u_c + t + \varepsilon_{c,t} \tag{9}$$

where $EI = TGHG/Y$ denotes the GHG emission intensity (i.e. total GHG emissions per unit of output), ECI is the Economic Complexity Index, and X is a matrix of additional control variables. The regressions are carried out using pooled data for countries c at different time periods t. The ln indicates that the variable is in natural logarithms, βs are the estimated coefficients, u is the country fixed-effects, t is the time fixed-effects and ε is the error term. Current and lagged ECI are introduced in Eq. (9) to test whether the effect of ECI on GHG emission intensity works with a delay.

Similarly, to test the effect of economic complexity on each country's level of emissions per capita, the following equation was estimated:

$$lnEpc_{c,t} = \beta_{02} - \beta_{12}ECI_{c,t} - \beta_{22}ECI_{c,t-1} + \beta_{i2}X_{c,t} + u_c + t + \varepsilon_{c,t} \tag{10}$$

Taking Sharma's (2011) and Lapatinas's et al. (2019) works as reference, nine control variables were used: (i) trade openness; (ii) urbanization; (iii) electricity consumption; and (iv) GDP per capita; (v) population; (vi) education; (vii) agriculture share; (viii) manufacturing share; (viii) and patents. Trade openness is expected to increase emissions per capita and intensity because it might foster specialization in high-emission intensity products due to static comparative advantages. As with ECI, lagged openness is also included in Eqs. (9) and (10) to test whether its effect is actually delayed. Manufacturing share and GDP per capita are expected to impact positively on emissions per capita but should exert a negative impact on emission intensity. Education and patents are also expected to have negative impacts on emission intensity and on emissions per capita, while the remainder of the variables are expected to present positive effects.

The main difference between the study presented in this paper and the one carried out by Lapatinas et al. (2019) is that our dependent variables are GHG emission intensity, i.e. GHG emissions by unit of output, and emissions per capita instead of the Environmental Performance Index, as in their study. Moreover, this paper presents more comprehensive regression results than the ones provided by Mealy and Teytelboym (2020). Emission intensity is a measure of economic efficiency in the sense that it indicates how much pollution (in the form of GHG) a given country emits to produce one unit of GDP. Testing the impact of economic complexity on emissions per capita complements the investigation, assessing whether the variables impacts on the level of emissions as well.

As stressed in the Introduction, international climate change commitments ultimately require reaching absolute GHG emissions reductions, which implies an absolute decoupling of GDP growth from GHG emissions. Nonetheless, analysing emission intensity is important because, as a measure of relative decoupling, it represents a necessary step for absolute decoupling. Moreover, analysing and comparing sectors or products, which is one of the goals of this paper, requires the adoption of a common unit of measurement. Thus, the best option seems to be to analyse the intensity associated with the production of each unit of real output.

Two econometric issues must be addressed in order to estimate the impact of ECI on GHG emission intensity and on emissions per capita, as described in Eqs. (9) and (10). First, the presence of unobserved fixed effects (FE) that might be correlated with one or more of the explanatory variables. Thus, in order to remove this source of endogeneity, a FE estimator was employed. Moreover, dummies to control for time fixed effects were also included in all regressions. Second, because GDP per capita and GHG emission intensity are correlated by construction, and because ECI is a predictor of GDP per capita growth, these variables might be correlated with the error term, which would generate some endogeneity bias in the coefficients. To address this possible issue, a System Generalized Method of Moments (GMM) estimator was employed (Blundell & Bond, 2000; Roodman, 2009).

System GMM employs a system of equations in levels and in differences to estimate the parameters, using as instruments the lags of the variables in differences and in levels in each equation, respectively (Roodman, 2009: 114). This estimator is a Two-Step Feasible Efficient System GMM estimator, which controls for fixed effects via first differences. The two-step approach is used to obtain a feasible efficient GMM estimator, given that GMM is inefficient in the presence of heteroskedasticity. In the first step a Two-Stage Least Square is regressed. The residuals from the first stage are used to form the weighting matrix employed to eliminate heteroskedasticity. In the second step the parameters are estimated satisfying the orthogonality conditions of the instruments, i.e. minimizing the L moment conditions $E[Z_{ct}\varepsilon_{ct}] = 0$, where Z is the matrix that contains the L included and excluded instruments. Finally, the identification of the parameters using System GMM requires overidentification, tested using Hansen's J Test, and no autocorrelation, which is tested using Arellano and Bond's Autoregressive (AR) Test.

In order to keep the short-panel requirement of small time-dimension in relation to the number of units, non-overlapping averages were calculated for the periods 1976–79, 1980–83, 1984–87, 1988–91, 1992–95, 1996–99, 2000–03, 2004–07 and 2008–12, so that the final panel has 67 countries and 9 time periods, in a total of 603 observations.

3.3. Product Emission Intensity Index

The association of GHG emission intensity with the production of each type of product is carried out following the methodology proposed by Hausmann, Hwang and Rodrik (2007), and further explored by Hartmann et al. (2017). Hausmann, Hwang and Rodrik (2007) proposed a seminal measure of product sophistication by classifying goods according to the weighted average of income per capita of the countries that export each good competitively, i.e. with RCA. A decade later, Hartmann et al. (2017) used the same strategy to calculate the income inequality associated with the production of each commodity. In this paper this strategy is used to calculate the GHG emission intensity associated with each product.

The Product Emission Intensity Index (PEII) is defined as the weighted average of the GHG emission intensity of each product's exporters (with RCA), where the product's share in each country's total exports are used as weights. Formally, the PEII of product p is defined as:

$$PEII_p = (1/N_p)\sum_c M_{cp}s_{cp}EI_c \tag{11}$$

where M_{cp} is 1 if the country exports the product with RCA and 0 otherwise, s_{cp} is the share of the country's exports of the given product, and $N_p = \sum_c M_{cp}s_{cp}$ is a normalizing factor. Finally, EI_c is the average level of GHG emission intensity of each country over the period under analysis.

The Product Emission Intensity Index, therefore, assumes that the products that generate high emissions are the ones produced and exported by countries with high emission intensities. Evidently, this is an imperfect measure that infers the emissions associated with each product. Despite the limitations of such measure, however, its advantage is that it provides information on emission intensities for a highly disaggregated product level, based on real-world variables to guide policy decisions, in light of the limitation of the existing sectoral emissions data.

4. Estimating the impact of economic complexity on GHG emissions

4.1. Bivariate relationships

Fig. 1 shows the bivariate relationship between initial Economic Complexity and the natural logarithm of GHG emissions intensity (kt CO_2e/$USD_{billion}$ output). This figure illustrates that there is a strong negative correlation between economic complexity and the emission intensities within the 67 countries that comprise this paper's database. Fig. 1A shows the correlation between the variables taking into account the average of the whole period 1976–2012. Fig. 1B and C illustrate that this negative relationship is stable throughout the period of analysis, with similar coefficients both at the first and last decades of the period, respectively.

To illustrate the movements of some countries in the complexity-emission intensities plan, China, Brazil and Indonesia are marked in Fig. 1B and C. Fig. 1B shows that in the first decade of the sample (1976–1985) China had an initial economic complexity index slightly higher than that of Brazil (0.341 and −0.308, respectively). Nonetheless, China was generating a much higher level of CO_2e emissions per unit of output than Brazil (7,858 and 1,468, respectively). This difference is most likely due to the fact that the Chinese development leap has been coal-fuelled, following a pattern of "pollute first, clean-up later" (Azadi et al., 2011), whereas Brazil presents, compared to world average, a relatively clean energy matrix by generating most of its electricity from hydroelectric plants and presenting a significant share of biofuel used in transport. In this sense, therefore, the two countries were in the opposite ends of the spectre of the energy-related and agriculture-related emissions covered in this study.[7] Meanwhile, Fig. 1B also shows that over this period Indonesia had a much lower level of economic complexity (−1.823) and a high level of GHG emission intensity (4,826), not too far from China's.

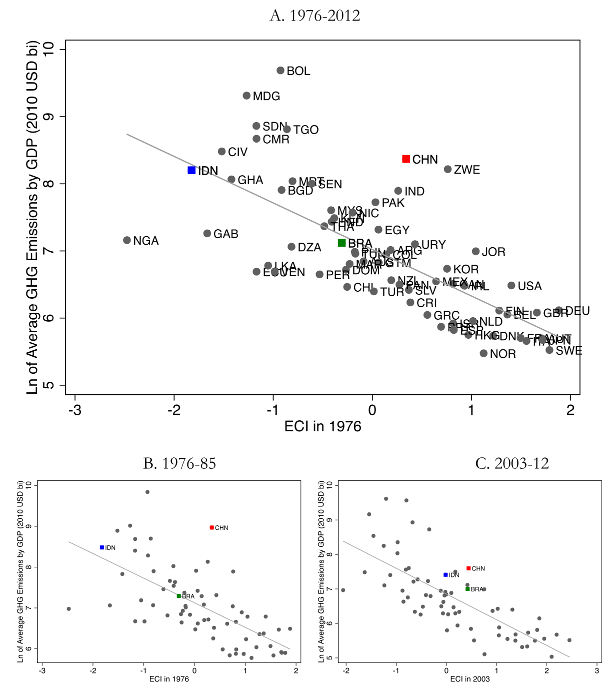

Fig. 1. Relating economic complexity and GHG emission intensity.

Fig. 1C indicates that, two decades later (from 2003 to 2012), although Brazil's GHG emission intensity has shown only a slight improvement, reaching 1,096, the country's ECI in the beginning of the period has increased to 0.423. China, on the other hand, has managed to increase its initial economic complexity to 0.442,

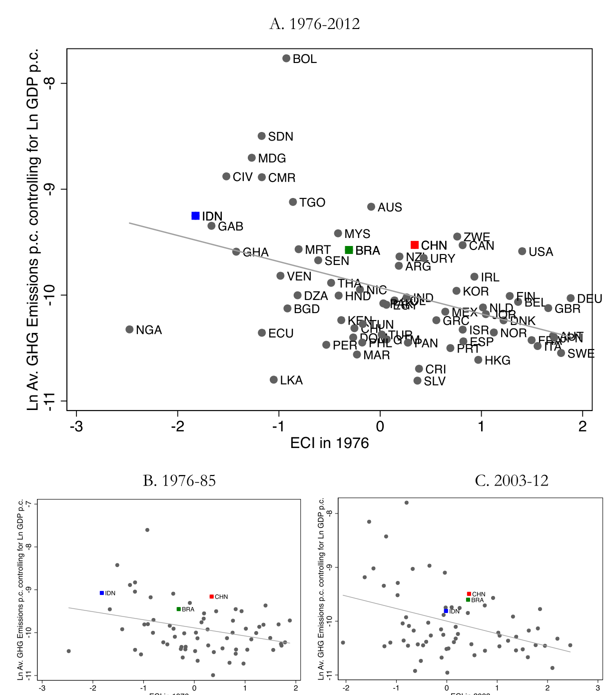

Fig. 2. Relating economic complexity and GHG emissions per capita. *Obs.:* The effect of the Ln of GDP per capita on the Ln of average GHG emissions per capita was controlled for using the parameter found in column (vii) of Table A5, in the Appendix. *Source:* Authors' elaboration based on data from MIT's Observatory of Economic Complexity and World Development Indicators.

[7] Land use, land-use change and forestry (LULUCF) emissions, which are not included in the database used in the present study, should have their relationship with economic complexity tested separately from other GHG emissions types, given their specificities. Namely, in contrast to other sectors, LULUCF is not covered by annual, statistical assessments of the goods, but needs geostatistical and/or remote sensing information (Janssens-Maenhout et al., 2019).

while considerably reducing its emission intensity to 1,995, getting much closer to Brazil's emission intensity level. It is noteworthy that the relative decoupling of China's CO_2e emissions from GDP growth happened in a context of accelerated CO_2e emissions increase, which has made China the largest GHG emitter worldwide, surpassing the United States in 2006, according to WDI data. The example of China, therefore, shows that reducing emission intensity can be achieved in a context of substantial increase in gross GHG emissions owing to faster-growing GDP. Indonesia, however, has made the most remarkable progress, by considerably increasing its initial economic complexity from −1.823 to −0.016 and reducing its GHG emission intensity from 4,826 to 1,654.

Fig. 2 shows the bivariate relationship between initial Economic Complexity and the natural logarithm of GHG emissions per capita after removing the effect of the logarithm of GDP per capita. This figure indicates that there is also a negative correlation between economic complexity and emissions per capita, although not as strong as the one between ECI and emission intensity.

Fig. 2B shows that in the first decade of the sample (1976–1985) Brazil had a slightly higher level of CO_2e emissions per capita (0.011) than China and Indonesia (0.003 and 0.006, respectively), partially due to the high populations of China and Indonesia.

Fig. 2C indicates that in the last decade of the sample (2003–2012), Brazil's GHG emissions per capita have remained unchanged (0.011) despite the improvement in its ECI. Meanwhile, China's emissions per capita have increased to 0.007 despite the increase in its initial ECI. Indonesia's impressive increase in the initial economic complexity, however, was accompanied by a reduction in the country's emissions per capita to 0.004.

4.2. Regression results for GHG emission intensity

Table 2 presents a set of regressions with different specifications of Eq. (9) using the Fixed Effects estimator, which explores the within-group dimension of the panel. Lagged ECI is negative and significant in all regressions except when manufacturing share is introduced. Current ECI is not significant in any of the regressions.

The fact that lagged ECI is significant is not unexpected. Similar results were found by Hausmann et al. (2011) when testing the impact of economic complexity on GDP per capita growth. According to Hausmann et al. (2011, p. 27), "countries whose economic complexity is greater than what we would expect, given their level of income, tend to grow faster than those that are "too rich" for their current level of economic complexity". The same logic applies to the results found in this paper, but with regard to GHG emission intensity.

The results reported in Table 2 indicate, therefore, that countries with complex productive structures relative to their income level tend to reduce their GHG emission intensity in the future.

Most importantly, lagged ECI remains significant at the 5% level in the regression including all the variables. The logarithm of GDP per capita is negative and significant in all the regressions. Agriculture share is significant in some of the regressions, but not in the regression with all the variables. Trade openness is positive and significant in most of the regressions, as expected. The rest of the variables are not significant, except for population and urbanization, that show up significant and with opposite signs in the complete specification of column (viii).

In sum, the results presented in Table 2 indicate that ECI exerts a negative and significant effect on subsequent GHG emission intensity even when controlling for the effect of GDP per capita and several other control variables. Moreover, similar results are found using pooled OLS (see Table A2 of the Appendix) and simple OLS with initial ECI as a regressor (see Table A4 of the Appendix).

Table 3 presents the main results of the panel regressions. Column (i) presents the regression of Eq. (9) including the variables found significant in the fixed effects regression with all the variables (column (viii) of Table 2) and including lagged openness to investigate if this variable presents a delayed effect on GHG emission intensity. The results indicate that lagged ECI and the logarithm of GDP per capita exert a negative impact on countries'

Table 2
Emission intensity fixed effects regressions.

Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
ECI	−0.0475	−0.0423	−0.0501	0.0676	−0.0709	−0.0840	0.0437	0.0912
	(0.119)	(0.136)	(0.125)	(0.0711)	(0.117)	(0.130)	(0.0879)	(0.0708)
Lagged ECI	−0.156**	−0.166*	−0.156**	−0.169**	−0.128*	−0.118	−0.166**	−0.137**
	(0.0763)	(0.0846)	(0.0777)	(0.0805)	(0.0749)	(0.0737)	(0.0721)	(0.0562)
Ln of GDP per capita	−0.470**	−0.450*	−0.472**	−0.628***	−0.438**	−0.491**	−0.382***	−0.408**
	(0.189)	(0.238)	(0.191)	(0.105)	(0.185)	(0.187)	(0.0956)	(0.172)
Ln of Agric. Share	0.172*	0.148	0.170*	0.138*	0.138	0.182*	0.143*	0.0678
	(0.0963)	(0.0994)	(0.0968)	(0.0792)	(0.0879)	(0.0931)	(0.0844)	(0.0778)
Ln of Openness	0.167**	0.171**	0.166**	0.151*	0.165**	0.174**	0.0594	0.0958
	(0.0768)	(0.0782)	(0.0736)	(0.0771)	(0.0742)	(0.0703)	(0.0626)	(0.0667)
Ln of Electricity Cons.		0.0112						0.158
		(0.125)						(0.110)
Ln of Urbanization			0.0280					−0.770***
			(0.247)					(0.232)
Ln of Sec. School Enrol.				0.0441				−0.00561
				(0.107)				(0.0922)
Ln of Population					0.253			0.419*
					(0.321)			(0.232)
Ln of Manuf. Share						0.114		−0.0526
						(0.0744)		(0.0660)
Ln of Patents							0.0000429	−0.00135
							(0.0217)	(0.0234)
Constant	9.977***	9.779***	9.900***	11.22***	5.635	9.774***	9.661***	4.991
	(1.589)	(1.690)	(1.769)	(0.847)	(5.466)	(1.725)	(0.836)	(3.752)
N. Obs.	485	469	485	439	485	469	383	344
Adj. R-sq.	0.358	0.359	0.357	0.515	0.361	0.406	0.636	0.728

Note: Dependent variable: Ln of GHG emissions (kilotons of CO2 equivalent) by units of output (billions of 2010 USD). Time dummies were included in all the regressions. Robust standard erros between brackets. Significance levels: *** = 1%; ** = 5%; * = 10%.
Source: Authors' elaboration.

Table 3
Emission intensity main results.

Estimator Model	FE (i)	FE (ii)	FE (iii)	FE (iv)	FE (v)	Sys-GMM (vi)
Lagged ECI	−0.196***		−0.256***	−0.199***	−0.195***	−0.227*
	(0.0678)		(0.0820)	(0.0691)	(0.068)	(0.130)
Ln of GDP per capita	−0.566***	−0.600***		−0.570***	−0.555***	−0.257*
	(0.180)	(0.178)		(0.181)	(0.170)	(0.137)
Ln of Openness	0.121	0.132	0.142*		0.148*	−0.149
	(0.0781)	(0.0823)	(0.0817)		(0.077)	(0.097)
Lagged Ln of Openness	0.0439	0.0358	−0.133	0.117		
	(0.103)	(0.103)	(0.126)	(0.0937)		
Constant	11.21***	11.46***	7.045***	11.43***	11.18***	9.519***
	(1.419)	(1.400)	(0.556)	(1.391)	(1.397)	(1.081)
N. Obs.	536	536	536	536	536	536
Adj. R-sq.	0.368	0.346	0.250	0.365	0.369	
N. of Instruments/Lags						24 / 2-
Arellano-Bond Test						0.095
Hansen J Test						0.126

Note: Dependent variable: Ln of GHG emissions (kilotons of CO2 equivalent) by units of output (billions of 2010 USD). Time dummies were included in all the regressions. Robust standard erros between brackets. Significance levels: *** = 1%; ** = 5%; * = 10%.
Source: Authors' elaboration.

GHG emission intensity. Both variables are significant at the 1% level. The logarithm of trade openness and its lag have no significant effect on GHG emission intensity.

In columns (ii) to (v), variables are excluded from the complete specification one at a time. The exercise indicates that GDP per capita is the variable that explains the largest percentage of the variance, 11.8%, according to the semi-partial correlation (the difference in the adjusted R-squared between the full model and the one in which GDP per capita is excluded). Nonetheless, the results show also that lagged ECI explains 2.2% of the variance, considerably more than trade openness, which explains only 0.3%. Moreover, it is important to note that ECI has also an indirect impact on GHG emission intensity, since it predicts higher GDP per capita growth. Lagged trade openness is not significant in any of the regressions. Column (v) indicates that lagged ECI, GDP per capita and trade openness alone explain a considerable portion of the variance in GHG emission intensity: 36.9%.

Finally, to address the possible simultaneity between GHG emission intensity and GDP per capita and ECI, column (vi) reports the results of regression (v) using the System-GMM estimator to control for the endogeneity of these variables. The coefficients of lagged ECI and of GDP per capita remain negative and statistically significant. Trade openness, however, enters with a negative sign and is no longer statistically significant. The number of instruments used in this regression is lower than the number of groups to avoid spurious significance. The Arellano-Bond and the Hansen J tests suggest the validity of the instruments.

In sum, the regression results reported in Table 3 indicate that an increase of 0.1 in the ECI generates a reduction in next period's level of GHG emissions per unit of output between 2 and 2.3%, *ce-*

Table 4
Emissions per capita fixed effects regressions.

Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
ECI	−0.0738	−0.0478	−0.0380	−0.0472	0.0634	−0.0811	0.0457	0.119
	(0.116)	(0.119)	(0.134)	(0.122)	(0.0715)	(0.129)	(0.0858)	(0.0736)
Lagged ECI	−0.133*	−0.148*	−0.163*	−0.152*	−0.161*	−0.114	−0.163**	−0.177***
	(0.0725)	(0.0753)	(0.0844)	(0.0776)	(0.0812)	(0.0735)	(0.0718)	(0.0660)
Ln of GDP per capita	1.004**	0.627	0.541**	0.517**	0.361***	0.493**	0.626***	0.507***
	(0.496)	(0.544)	(0.243)	(0.196)	(0.112)	(0.195)	(0.0967)	(0.161)
Ln of sqr. GDP per capita	−0.0333	−0.00717						
	(0.0299)	(0.0352)						
Ln of Agric. Share		0.163*	0.146	0.170*	0.139*	0.180*	0.142*	0.113*
		(0.0964)	(0.0981)	(0.0963)	(0.0798)	(0.0914)	(0.0831)	(0.0667)
Ln of Openness		0.168**	0.180**	0.172**	0.156**	0.180**	0.0682	0.0862
		(0.0786)	(0.0795)	(0.0755)	(0.0780)	(0.0721)	(0.0616)	(0.0646)
Ln of Electricity Cons.			0.00801					0.199*
			(0.125)					(0.109)
Ln of Urbanization				0.0215				−0.635***
				(0.243)				(0.222)
Ln of Sec. School Enrol.					0.0503			0.00641
					(0.107)			(0.0857)
Ln of Manuf. Share						0.109		−0.0220
						(0.0761)		(0.0710)
Ln of Patents							−0.00316	−0.00500
							(0.0218)	(0.0246)
Constant	−11.23***	−11.02***	−10.87***	−10.72***	−9.458***	−10.81***	−11.14***	−8.993***
	(2.284)	(2.292)	(1.714)	(1.758)	(0.881)	(1.768)	(0.845)	(1.169)
N. Obs.	536	485	469	485	439	469	383	344
Adj. R-sq.	0.186	0.197	0.205	0.197	0.235	0.197	0.376	0.432

Note: Dependent variable: Ln of GHG emissions (kilotons of CO2 equivalent) per capita. Time dummies were included in all the regressions. Robust standard erros between brackets. Significance levels: *** = 1%; ** = 5%; * = 10%.
Source: Authors' elaboration.

Table 5
Per capita emissions main results.

Estimator Model	FE (i)	FE (ii)	FE (iii)	FE (iv)	FE (v)	FE (vi)	FE (vii)	Sys-GMM (viii)
Lagged ECI	−0.186**		−0.179**	−0.199***	−0.190**	−0.182**	−0.181**	−0.275*
	(0.077)		(0.081)	(0.073)	(0.078)	(0.074)	(0.076)	(0.141)
Ln of GDP per capita	0.533**	0.525**		0.419*	0.537**	0.505**	0.514**	1.004***
	(0.247)	(0.246)		(0.222)	(0.248)	(0.202)	(0.188)	(0.206)
Ln of Agriculture share	0.152	0.164	0.0537		0.154	0.173*	0.173*	0.497*
	(0.102)	(0.109)	(0.110)		(0.104)	(0.0998)	(0.096)	(0.259)
Ln of Openness	0.163**	0.171**	0.169*	0.135*		0.150*	0.175*	−0.029
	(0.081)	(0.085)	(0.089)	(0.0771)		(0.080)	(0.079)	(0.115)
Ln of Energy Cons.	0.010	−0.003	0.256*	0.0558	0.00330			
	(0.123)	(0.128)	(0.131)	(0.121)	(0.129)			
Ln of Urbanization	−0.066	−0.128	−0.110	−0.005	−0.052	−0.010		
	(0.240)	(0.260)	(0.287)	(0.247)	(0.248)	(0.229)		
Lagged Ln of Openness	0.0348	0.027	0.111	0.0390	0.133	0.040		
	(0.116)	(0.117)	(0.119)	(0.109)	(0.100)	(0.107)		
Constant	−10.65***	−10.30***	−7.703***	−9.773***	−10.44***	−10.59***	−10.64***	−14.81***
	(1.787)	(1.783)	(1.254)	(1.667)	(1.769)	(1.671)	(1.573)	(2.073)
N. Obs.	469	469	469	520	469	485	485	485
Adj. R-sq.	0.203	0.180	0.142	0.201	0.196	0.197	0.199	
N. of Instruments/Lags								23 / 3-
Arellano-Bond Test								0.881
Hansen J Test								0.701

Note: Dependent variable: Ln of GHG emissions (kilotons of CO2 equivalent) per capita. Time dummies were included in all the regressions. Robust standard erros between brackets. Significance levels: *** = 1%; ** = 5%; * = 10%.
Source: Authors' elaboration.

teris paribus. This is a considerably large effect, which highlights the importance of structural change towards complex products in order to reduce emission intensity. Moreover, since economic complexity impacts also on GDP per capita growth, its net effect on GHG emission intensity is in fact larger that its direct effect.

4.3. Regression results for per capita GHG emissions

Table 4 presents a set of regressions with different specifications of Eq. (10) using the Fixed Effects estimator. The results found for GHG emissions per capita are in general very similar to the ones found for GHG emission intensity. Lagged ECI is negative and significant in all the regressions except when the logarithm of the manufacturing share is introduced. Current ECI is not significant in any of the regressions. Yet, Lagged ECI remains significant at the 1% level in the regression including all the variables.

The logarithm of GDP per capita is significant in all the regressions but now with a positive coefficient. In columns (i) and (ii) the square of the logarithm of GDP per capita is introduced to assess the Environmental Kuznets Curve (EKC) hypothesis. The coefficient is negative, but not significant, which suggests that the EKC is not valid for this sample.

Agriculture share is positive and significant in most of the regressions, including the regression with all the variables. Trade openness is positive and significant in most of the regressions, but not in the regression with all variables. The rest of the variables are not significant, except for electricity consumption and urbanization, that show up significant and with opposite signs in the complete specification of column (viii).

The results presented in Table 4 indicate that lagged ECI presents a negative and significant effect on GHG emissions per capita even when controlling for the effect of GDP per capita and several other control variables. Once again, similar results are found using pooled OLS (see Table A3 of the Appendix) and simple OLS with initial ECI as a regressor (see Table A5 of the Appendix).

Table 5 presents the main results of the panel regressions using GHG emissions per capita as the dependent variable. Column (i) presents the regression of Eq. (10) including the variables found significant in the fixed effects regression with all the variables (column (viii) of Table 3) and including lagged openness to investigate if this variable presents a delayed effect on GHG emissions per capita. The results indicate that lagged ECI and the logarithm of GDP per capita exert a negative impact on countries' GHG emissions per capita. Both variables are significant at the 1% level. The logarithm of trade openness is significant, but not the remainder of the variables.

In columns (ii) to (vii), variables are excluded from the complete specification one at a time. The exercise indicates that GDP per capita is the variable that explains the largest percentage of the variance, 6.1%, according to the semi-partial correlation. Lagged ECI explains 2.3% of the variance, once again considerably more than trade openness, which explains 0.7%. Agriculture share explains only 0.2%. The rest of the variables are not significant in any of the regressions. Column (vii) indicates that lagged ECI, GDP per capita, agriculture share and trade openness explain 19.9% of the variance in GHG emissions per capita.

Finally, to address the possible endogeneity between GHG emissions per capita, GDP per capita and Lagged ECI, column (viii) reports the results of regression (vii) using the System-GMM estimator controlling for the endogeneity of these variables. The coefficient of GDP per capita remains positive and statistically significant at the 1% level. Lagged ECI is still negative and significant at the 10% level, while the agriculture share is positive and significant. Trade openness, however, enters with a negative sign and not significant. The number of instruments used in this regression is lower than the number of groups to avoid spurious significance, and the Arellano-Bond and the Hansen J tests suggest the validity of the instruments.

The results reported in Table 5 indicate that an increase of 0.1 in the ECI leads to a reduction in next period's level of GHG emissions per capita of around 1.8–2.75%, holding all else constant. It is noteworthy to mention, however, that since economic complexity impacts also on GDP per capita growth, its net effect on GHG emissions per capita is in fact smaller that its direct effect.

The regression results reported in this section complement the results discussed in the previous section. The investigation suggests that increasing a country's economic complexity leads not only to a reduction in GHG emission intensity but also to a similar reduction in GHG emissions per capita. On the one hand, reducing emission intensity means that higher economic complexity leads to an increase in the energy efficiency of the production of each monetary unit of output. On the other hand, reducing emissions per capita reinforces that increasing economic complexity leads to the adoption of cleaner production technologies, as the results presented by Mealy and Teytelboym (2020) suggest.

5. Analysing the Product Emission Intensity Index

After examining the relationship between economic complexity and GHG emissions, this section discusses the estimated Product Emission Intensity Index (PEII), investigating how this index can be used to analyse the GHG emission intensity associated with each country's productive structure.

5.1. Product Emission Intensity Index: a descriptive analysis

Table 6 presents the 10 products with the highest and lowest PEIIs, amongst the 786 products in the SITC, revision 2, 4-digit classification. This table illustrates that different types of specialized machines are among the products with the lowest PEIIs, while minerals and other primary products figure among the goods with the highest PEIIs.

Table 7 shows the average PEII for each technological sector, following Lall's (2000) classification. This table shows that there is a high correlation between the level of GHG emission intensity, measured by the average PEII, and the technological content of the goods produced by the sector. Interestingly, this table indicates that medium-tech products are in fact the ones with lowest PEII, closely followed by high-tech products. Low-tech, resource-based, and other manufactures come next, with similar levels of emissions. Finally, primary products show up with a considerably higher level of emissions than the other sectors. Interestingly, a similar finding was obtained for Brazil (Gramkow, 2013).

Table 6
Top and bottom 10 products according to the Product Emission Intensity Index (PEII).

SITC	PEII	Product Description	Ranking
7187	302.3	Nuclear reactors and parts	1
7368	302.8	Work holders, self-opening dieheads and tool holders	2
7416	303.0	Machine plant and laborathory equipment involving a temperature change	3
7422	312.7	Centrifugal pumps	4
7412	317.7	Furnace burners for liquid fuel and parts	5
7452	323.0	Other non-electrical machine parts	6
7281	328.7	Machine tools for specialized particular industries	7
7373	338.7	Welding, brazing, cutting, soldering machines and parts	8
7361	339.3	Metal cutting machine-tools	9
7252	340.0	Machinery for making paper pulp, paper, paperboard; cutting machines	10
2879	6851.9	Ores and concentrates of other non-ferrous base metals	777
3414	7717.6	Petroleum gases and other gaseous hydrocarbons	778
6871	7897.3	Tin and tin alloys ,unwrought	779
2239	8074.0	Flours or meals, oil seeds, oleaginous fruit non defatted	780
752	8421.1	Spices (except pepper and pimento)	781
6872	8867.9	Tin and tin alloys, worked	782
2890	9342.9	Ores & concentrates of precious metals; waste, scrap	783
2875	9496.7	Zinc ores and concentrates	784
2923	9972.7	Vegetable plaiting materials	785
2876	13182.5	Tin ores and concentrates	786

Source: Authors' elaboration.

Table 7
Product Emission Intensity Index (PEII) by technological sector.

Technological Sectors	PEII	Ranking
Medium-tech	761.1	1
High-tech	785.5	2
Low-tech	1317.7	3
Resource-based	1426.7	4
Other manufacturing	1536.5	5
Primary products	2123.4	6

Source: Authors' elaboration.

5.2. Product Space and the Product Emission Intensity Index

Fig. 3A shows the distribution of products in the *Product Space* using PEII levels as reference. In this figure, the 786 products were ranked according to the PEII, and then divided in three categories: (i) the 262 products with lowest PEIIs were classified as low-emission intensity products (in green); (ii) the 262 products with the highest PEIIs were classified as high-emission intensity products (in red); and (iii) the 262 products between low- and high-emission intensity products were then classified as medium-emission intensity products (in yellow). Recall that the connections of the product space reflect the proximity of the products in terms of the capabilities used for their competitive production. Hence, machinery products are clustered at the centre of the network, presenting a high number of connections, while primary products are located at the boarders of the network (see Hausmann et al. (2011) for a detailed description of the product space).

Fig. 3A highlights that high-emission intensity products are located more towards the periphery of the network, while low-emission intensity products are located predominantly in the centre of the network. This distribution is not unexpected. Britto, Romero, Freitas, & Coelho, 2019 have shown that medium- and high-technology goods are located in the centre and centre-left parts of the network, while primary- and natural resource-based products are located in its fringes. Thus, low-emission intensity products are predominantly in the centre of the network due to the fact that most of those are medium- and high-tech products. As Table 7 shows, medium- and high-tech products are the ones with lowest emission intensities, while primary products are the ones with the highest emission intensities.

Fig. 3B to G illustrate the changes in the productive structures of Indonesia, China and Brazil in the first (1976–1985) and last (2003–2012) decades of the period under investigation. Hence, these figures shed some light into the processes of increase in economic complexity and reduction of emission intensities observed in the three countries, as shown in Fig. 1. Table 8 complements Fig. 3, presenting data on the level of diversification of these countries dividing products according to their levels of emission intensity.

Fig. 3B and C and Table 8 show that Indonesia has increased considerably the diversification of its economy, going from 69 industries with RCA in 1976–1985 to 144 in 2003–2012. Most importantly, this diversification has happened mostly in medium-emission intensity products. The number of industries with RCA in this group has increased from only 9 in 1976–1985, to 47 in 2003–2012. Nonetheless, the country has also increased the number of high-emission intensity products with RCA (60 to 86, respectively), while low-intensity products have increased only from 0 to 11. From this point on, therefore, in order to continue reducing its emission intensity, Indonesia will have to keep increasing the production of high-complexity and low-emission intensity products while start reducing the production of low-complexity and high-emission intensity ones.

Fig. 3D and E indicate that China has also underwent an intense transformation of its productive structure (79 to 206 products with

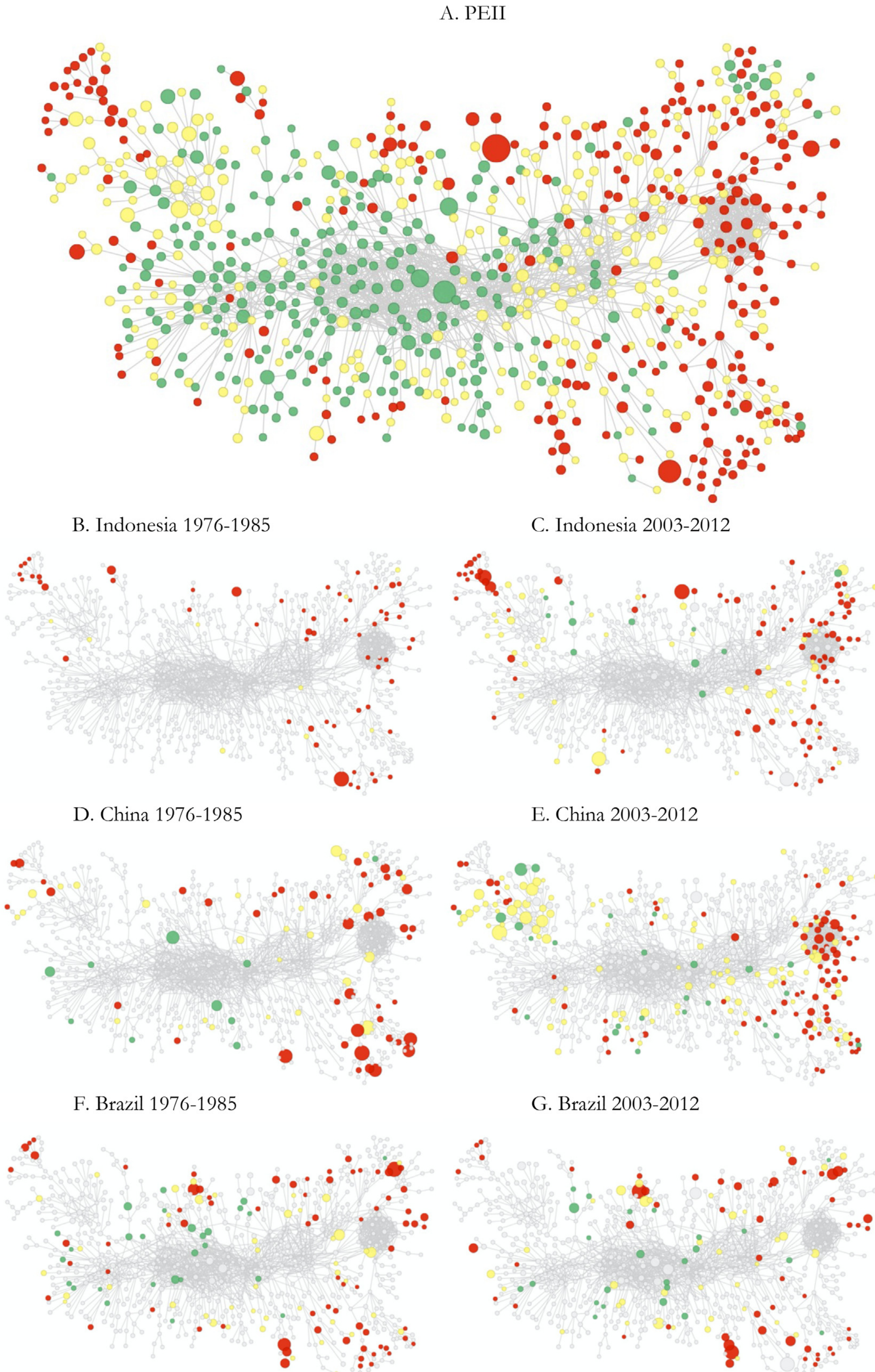

Fig. 3. Product Space and Product Emission Intensity Index. *Obs.:* Red = High emission Intensity; Yellow = Medium emission intensity; Green = Low emission intensity.

RCA), with a marked increase in the number of low- and medium-emission intensity products with RCA (10 to 25, and 26 to 96, respectively), located more towards the centre of the product space. Moreover, the number of high-emission intensity products with RCA (43 to 85), located at the fringes of the network, has increased less rapidly. These improvements notwithstanding, the

Table 8
Diversification according to emission intensity: selected countries.

		Average number of products with revealed comparative advantage			
Country	Period	High-emission intenisty	Medium-emission intensity	Low-emission intensity	Total
Brazil	1976–1985	77	43	27	147
	1986–2002	82	64	48	194
	2003–2012	55	37	24	116
China	1976–1985	43	26	10	79
	1986–2002	150	111	29	290
	2003–2012	85	96	25	206
Indonesia	1976–1985	60	9	0	69
	1986–2002	113	55	7	175
	2003–2012	86	47	11	144

Note: Emission intenisties: High-emission > 1238; Low-emission < 728.1. Averages: Hig-emission = 2119; Medium-emission = 936; Low-emission = 525.
Source: Authors' elaboration.

country can still improve its productive structure considerably, moving towards high-complexity and low-emission intensity products.

The structural changes in Brazil, however, have been characterized by moving backwards in terms of industries with RCA, which aggravates the unsustainability of development in the long term cha. The country has reduced the number of industries with RCA from 194 in 1986–2002 to 116 in 2003–2012, following a process of increased specialization in exports of primary and natural resource intensive goods (Britto, Romero, Freitas, & Coelho, 2019; Gramkow & Gordon, 2015). This sharp reduction in the number of products with RCA has occurred in high-emission intensity products (82 to 55) and in medium-emission intensity products (64 to 37), but the highest proportional decrease was actually in low-emission intensity products (48 to 24). Thus, despite the fact that the country has managed to marginally improve its emissions intensity and its economic complexity, as shown in Fig. 1, Table 8 calls attention to the fact that the country has been prematurely losing competitiveness in several industries, which makes the competitive production of high-complexity products more challenging in the future.

Finally, it is also interesting to mention a few examples of the types of products these countries produce competitively. Among the products with lower PEII (of 461) in Brazil during the first period is Organic chemical products (SITC 5983). At the other end is Soya bean oil (SITC 4232), with a PEII of 4180. Similarly, in the second period, at the lower end of emission intensities we find Wheeled tractors (SITC 7224), with a PEII of 456. At the high-emission intensity end, we find Tin ores and concentrates (SITC 2876), with a PEII of 13182. For China during 1976–85, among the products with lowest PEII (of 460) is Meat of swine (SITC 113), which shows that not all primary products present high-emission intensity. Among the products with highest PEII (of 2650) is Crude minerals (SITC 2789). For 2003–2012 we find Motorcycles, auto-cycles and cycles (SITC 7851) at the lower end of emission intensities (PEII of 553), and Raw silk (SITC 2613) at the higher end (PEII of 2249). In Indonesia, the products with lowest PEII in the first period are of medium-emission intensity, such as Copper ores and concentrates (SITC 2871), with a PEII of 1078. The highest PEII of the country's competitive products in 1976–85 is Tin ores and concentrates (SITC 2876), with a PEII of 13182. For the second period, among the country's lowest and highest PEIIs are Printing and writing paper (SITC 6412 and PEII of 475) and Tin and tin alloys (SITC 6872 and PEII of 8868).

6. Concluding remarks

Building economies that are less susceptible and more resilient to crises, especially in the context of the climate emergency, is one of the defining challenges of our time. In this paper, we investigated whether economic complexity leads not only to higher income per capita growth and lower income inequality, but also to climate change mitigation. Our results indicate that economic complexity presents a significant impact on the reduction of GHG emission intensity as well as on per capita GHG emissions.

The paper provides important evidence in support of the idea that the production of complex goods is associated with lower emissions for two main reasons. First, complex goods are frequently technologically sophisticated products that are related to large market values of output. This creates economic efficiency in the sense that more economic value is obtained for each unit of pollution emitted. In addition, complex economies are more prone to develop capabilities that can help reduce pollution and produce goods more efficiently, for instance by developing green innovations. Together with previous studies, these results underline that complex economies can present relevant prospects for sustainable development.

Using data for 67 countries between 1976 and 2012, the tests reported in the paper suggest that an increase of 0.1 in the economic complexity index generates a 2% decrease in next period's emissions of kilotons of CO_2e per billion dollars of output as well as in GHG emissions per capita. The tests showed that these results hold when fixed effects and System GMM estimators were used, and is robust to the introduction of several control variables, thereby indicating their statistical robustness.

Moreover, the methodology proposed by Hartmann et al. (2017) was used to calculate a Product Emission Intensity Index (PEII), which estimates the level of GHG (CO_2e) emissions per unit of output associated with the production of each of the 786 products in the SITC, revision 2, 4-digit classification. The estimates showed that medium- and high-tech products present lower PEIIs, while primary products present the highest PEII. Hence, this index confirms that structural change towards more complex high-tech goods leads to a reduction in aggregate GHG emission intensity.

This index makes it possible to analyse specifically what products are associated with higher emission intensities, contributing to the formulation of policies that aim to reduce GHG emissions. Measures associated with the economic complexity methodology are already being used to inform development policies (Hausmann and Chauvin, 2015; Hausmann et al., 2017). In face of the scarce data on emissions generated by industries at highly disaggregate levels, this index, despite its limitations, provides important information for policymakers seeking to generate environmentally sustainable economic development.

The policy implication of the evidence reported in this paper is that public policies should aim at increasing economic complexity, since in addition to evidence of its economic and social benefits, we now bring new evidence that it can also contribute significantly to both relative and absolute decoupling of economic growth and GHG emissions. This paper thus shows that policies that promote economic complexity can be an effective framework towards sustainable development in its tripod (social, economic and environmental dimensions). In sum, this paper highlights the importance of green industrial policies that seek to increase economic complexity.

Although further investigation is still required to understand more accurately the channels through which economic complexity influence GHG emissions, we believe this paper provides an important contribution to this fruitful research agenda.

CRediT authorship contribution statement

João P. Romero: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Visualization, Funding acquisition. **Camila Gramkow:** Conceptualization, Investigation, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
List of countries in the sample used in the econometric tests.

Algeria	Cote d'Ivoire	Hong Kong	Morocco	Sudan
Argentina	Denmark	India	Netherlands	Sweden
Australia	Dominican Republic	Indonesia	New Zealand	Thailand
Austria	Ecuador	Ireland	Nicaragua	Togo
Bangladesh	Egypt	Israel	Nigeria	Tunisia
Belgium	El Salvador	Italy	Norway	Turkey
Bolivia	Finland	Japan	Pakistan	United Kingdom
Brazil	France	Jordan	Panama	United States
Cameroon	Gabon	Kenya	Peru	Uruguay
Canada	Germany	Rep. of Korea	Philippines	Venezuela
Chile	Ghana	Madagascar	Portugal	Zimbabwe
China	Greece	Malaysia	Senegal	
Colombia	Guatemala	Mauritania	Spain	
Costa Rica	Honduras	Mexico	Sri Lanka	

Source: Authors' elaboration.

Table A2
Emission intensity pooled OLS regressions.

Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
ECI	0.0447	0.009	0.0496	0.126	0.058	0.0896	−0.206	−0.153
	(0.153)	(0.164)	(0.156)	(0.157)	(0.160)	(0.153)	(0.186)	(0.182)
Lagged ECI	−0.281*	−0.306*	−0.270*	−0.290*	−0.287*	−0.292*	−0.133	−0.143
	(0.151)	(0.165)	(0.153)	(0.153)	(0.153)	(0.150)	(0.173)	(0.181)
Ln of GDP per capita	−0.419***	−0.508***	−0.464***	−0.396***	−0.425***	−0.401***	−0.396***	−0.415***
	(0.035)	(0.062)	(0.048)	(0.041)	(0.043)	(0.0361)	(0.034)	(0.082)
Ln of Agriculture Share	0.015	0.014	0.026	0.0790*	0.013	0.0538	0.061	0.130**
	(0.049)	(0.049)	(0.048)	(0.043)	(0.050)	(0.0571)	(0.040)	(0.059)
Ln of Openness	−0.090**	−0.112**	−0.0866**	0.001	−0.105*	−0.0821*	0.002	0.085
	(0.043)	(0.044)	(0.043)	(0.048)	(0.060)	(0.0429)	(0.055)	(0.064)
Ln of Electricity Cons.		0.150***						0.094
		(0.056)						(0.076)
Ln of Urbanization			0.184*					0.134
			(0.110)					(0.092)
Ln of Sec. School Enrol.				−0.088				−0.089
				(0.093)				(0.088)
Ln of Population					−0.009			0.038
					(0.026)			(0.039)
Ln of Manuf. Share						−0.166**		0.004
						(0.067)		(0.098)
Ln of Patents							0.088***	0.076**
							(0.018)	(0.032)
Constant	10.92***	10.77***	10.56***	10.49***	11.19***	11.05***	9.76***	7.95***
	(0.432)	(0.427)	(0.457)	(0.436)	(0.947)	(0.470)	(0.455)	(1.103)
N. Obs.	485	469	485	439	485	469	383	344
Adj. R-sq.	0.705	0.695	0.706	0.736	0.704	0.703	0.717	0.770

Note: Dependent variable: Ln of GHG emissions (kilotons of CO2 equivalent) by units of output (billions of 2010 USD). Time dummies were included in all the regressions. Robust standard erros between brackets. Significance levels: *** = 1%; ** = 5%; * = 10%.
Source: Authors' elaboration.

Table A3
Emissions per capita pooled OLS regressions.

Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
ECI	0.030	−0.000	0.035	0.107	0.047	0.085	−0.223	−0.174
	(0.158)	(0.170)	(0.161)	(0.162)	(0.164)	(0.156)	(0.193)	(0.190)
Lagged ECI	−0.270*	−0.293*	−0.260*	−0.273*	−0.279*	−0.285*	−0.121	−0.125
	(0.155)	(0.171)	(0.157)	(0.158)	(0.157)	(0.153)	(0.180)	(0.190)
Ln of GDP per capita	0.582***	0.510***	0.539***	0.606***	0.574***	0.600***	0.607***	0.598***
	(0.035)	(0.066)	(0.048)	(0.041)	(0.043)	(0.036)	(0.034)	(0.086)
Ln of Agriculture Share	0.017	0.016	0.027	0.081*	0.014	0.061	0.063	0.138**
	(0.049)	(0.049)	(0.048)	(0.044)	(0.050)	(0.058)	(0.041)	(0.062)
Ln of Openness	−0.103**	−0.123***	−0.100**	−0.004	−0.122**	−0.096**	−0.007	0.087
	(0.044)	(0.045)	(0.0443)	(0.048)	(0.062)	(0.044)	(0.057)	(0.065)
Ln of Electricity Cons.		0.128**						0.0797
		(0.060)						(0.080)
Ln of Urbanization			0.172					0.145
			(0.112)					(0.093)
Ln of Sec. School Enrol.				−0.090				−0.088
				(0.093)				(0.089)
Ln of Population					−0.012			0.038
					(0.026)			(0.041)
Ln of Manuf. Share						−0.189***		−0.013
						(0.070)		(0.104)
Ln of Patents							0.087***	0.079**
							(0.019)	(0.034)
Constant	−9.751***	−9.914***	−10.09***	−10.23***	−9.407***	−9.567***	−10.93***	−12.82***
	(0.433)	(0.433)	(0.461)	(0.437)	(0.958)	(0.476)	(0.462)	(1.129)
N. Obs.	485	469	485	439	485	469	383	344
Adj. R-sq.	0.580	0.609	0.582	0.630	0.579	0.593	0.689	0.795

Note: Dependent variable: Ln of GHG emissions (kilotons of CO2 equivalent) per capita. Time dummies were included in all the regressions. Robust standard erros between brackets. Significance levels: *** = 1%; ** = 5%; * = 10%.
Source: Authors' elaboration.

Table A4
Emission intensity simple OLS regressions.

Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
ECI	−0.301***	−0.317**	−0.477**				
	(0.0959)	(0.123)	(0.139)				
Ln of GDP per capita	−0.572***	−0.575***	−0.694***				−0.443***
	(0.154)	(0.175)	(0.204)				(0.056)
Initial ECI				−0.316***	−0.307***	−0.343***	−0.216***
				(0.097)	(0.099)	(0.122)	(0.090)
Initial Ln of GDP per capita				−0.411***	−0.463***	−0.502***	
				(0.100)	(0.116)	(0.134)	
Ln of Openness	−0.157	−0.131	−0.048	−0.156	−0.338**	−0.262	
	(0.111)	(0.176)	(0.217)	(0.106)	(0.162)	(0.206)	
Ln of Urbanization	0.0587	0.0642	0.209	0.167	0.103	0.265	
	(0.291)	(0.294)	(0.351)	(0.351)	(0.334)	(0.409)	
Ln of Electricity Cons.	0.205	0.189	0.024	0.002	0.103	−0.017	
	(0.136)	(0.146)	(0.173)	(0.112)	(0.147)	(0.181)	
Ln of Sec. School Enrol.		0.091	0.238		−0.161	−0.063	
		(0.389)	(0.446)		(0.394)	(0.462)	
Ln of Population		0.014	−0.158		−0.088	−0.171	
		(0.073)	(0.129)		(0.073)	(0.125)	
Ln of Agriculture Share			−0.024			0.070	
			(0.133)			(0.127)	
Ln of Manuf. Share			−0.039			−0.189	
			(0.212)			(0.204)	
Ln of Patents			0.218**			0.131	
			(0.082)			(0.084)	
Constant	10.82***	10.23***	12.77***	10.29***	13.16***	14.00***	10.76***
	(0.682)	(2.241)	(3.848)	(0.873)	(2.156)	(3.892)	(0.489)
N. Obs.	65	64	59	65	64	59	67
Adj. R-sq.	0.701	0.682	0.681	0.675	0.668	0.633	0.720

Note: Dependent variable: Ln of GHG emissions (kilotons of CO2 equivalent) by units of output (billions of 2010 USD). OLS regressions taking the averages of the whole period. Robust standard erros between brackets. Significance levels: *** = 1%; ** = 5%; * = 10%.
Source: Authors' elaboration.

Table A5
Emissions per capita simple OLS regressions.

Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
ECI	−0.300***	−0.312**	−0.475***				
	(0.0966)	(0.124)	(0.142)				
Ln of GDP per capita	0.448***	0.443**	0.319				0.555***
	(0.165)	(0.182)	(0.208)				(0.056)
Initial ECI				−0.305***	−0.302***	−0.430***	−0.220**
				(0.096)	(0.099)	(0.116)	(0.091)
Initial Ln of GDP per capita				0.247**	0.249**	0.139	
				(0.117)	(0.123)	(0.120)	
Ln of Openness	−0.170	−0.151	−0.0639	−0.149	−0.151	−0.173	
	(0.115)	(0.184)	(0.224)	(0.108)	(0.170)	(0.213)	
Ln of Urbanization	0.0521	0.0521	0.209	0.040	0.022	0.157	
	(0.296)	(0.304)	(0.360)	(0.283)	(0.298)	(0.372)	
Ln of Electricity Cons.	0.183	0.167	−0.001	0.373***	0.340**	0.151	
	(0.148)	(0.159)	(0.187)	(0.134)	(0.160)	(0.165)	
Ln of Sec. School Enrol.		0.099	0.241		0.123	0.166	
		(0.391)	(0.446)		(0.356)	(0.391)	
Ln of Population		0.009	−0.166		−0.002	−0.212	
		(0.075)	(0.132)		(0.071)	(0.131)	
Ln of Agriculture Share			−0.018			−0.052	
			(0.138)			(0.132)	
Ln of Manuf. Share			−0.069			−0.171	
			(0.232)			(0.234)	
Ln of Patents			0.224***			0.214***	
			(0.083)			(0.074)	
Constant	−9.834***	−10.31***	−7.653*	−9.419***	−9.594***	−5.014	−9.948***
	(0.709)	(2.326)	(3.995)	(0.792)	(2.004)	(4.053)	(0.492)
N. Obs.	65	64	59	65	64	59	67
Adj. R-sq.	0.641	0.626	0.674	0.653	0.639	0.698	0.626

Note: Dependent variable: Ln of GHG emissions (kilotons of CO2 equivalent) per capita. OLS regressions taking the averages of the whole period. Robust standard erros between brackets. Significance levels: *** = 1%; ** = 5%; * = 10%.
Source: Authors' elaboration.

Table A6
List of products and associated PEIIs.

Low-emission intensity								Medium-emission intensity								High-emission intensity							
SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII
7187	302.3	7246	425.7	7911	536.4	5417	649.6	7712	728.2	6551	833.8	8510	949.1	980	1093.9	7433	1238.1	8994	1452.2	6549	1933.2	5225	2645.1
7368	302.8	7213	426.2	7126	537.7	574	651.7	6996	729.9	8812	834.8	7928	952.9	6123	1094.0	5629	1244.3	6536	1459.4	6612	1940.8	6522	2649.4
7416	303.0	7132	427.8	7421	538.1	8732	654.4	5835	731.1	6940	836.8	6252	956.7	8465	1094.0	2713	1247.8	1211	1465.2	7924	1941.4	2789	2650.7
7422	312.7	7499	431.2	452	539.5	1124	655.4	6538	731.3	5169	837.1	6674	957.7	7781	1099.2	8442	1249.3	6421	1469.0	2820	1947.9	2783	2682.2
7412	317.7	7248	433.9	7369	539.6	6259	655.7	2926	731.9	6863	837.5	6732	958.8	7631	1099.7	6516	1250.0	6589	1469.1	611	1948.3	9710	2734.1
7452	323.0	7491	434.0	6572	540.9	2666	656.2	5413	735.1	6417	840.7	7758	963.2	6951	1101.7	6535	1253.2	2659	1480.7	6114	1948.6	2640	2746.0
7281	328.7	121	434.2	6289	542.0	7762	657.0	5137	735.6	8219	842.0	8122	963.9	7933	1102.9	5530	1254.3	8960	1481.5	6513	1957.2	8928	2773.7
7373	338.7	5839	434.5	5331	546.3	5514	658.9	5163	736.2	7622	850.1	488	964.2	2686	1104.6	8741	1257.5	4313	1487.1	2479	1967.0	2114	2845.7
7361	339.3	7169	440.0	6415	546.9	6783	659.9	7912	742.6	6210	853.7	7512	965.6	819	1105.3	6960	1264.6	5121	1491.0	6716	1967.2	2771	2865.0
7252	340.0	5148	445.0	7751	547.1	2712	661.6	7144	746.4	6643	854.2	2860	966.6	6664	1109.4	2927	1266.2	5311	1495.2	7921	1979.5	2785	2930.1
7441	341.6	7212	446.0	576	548.6	6658	662.0	8211	751.0	224	854.4	8952	970.5	1123	1111.5	582	1270.7	8422	1496.6	2731	1981.8	8451	2965.2
7362	345.0	8745	449.9	8842	549.5	7931	662.6	9510	752.3	6912	858.5	6794	971.0	3231	1114.0	4243	1271.5	6577	1506.2	4244	2013.8	5722	3088.9
6631	345.5	7413	450.0	7842	549.6	230	665.0	6112	754.7	7831	859.4	5622	975.4	8463	1115.6	2733	1273.1	6852	1514.2	2784	2016.9	360	3094.5
7439	346.8	6745	450.3	5843	551.6	4235	665.9	9110	756.2	5411	862.0	7638	980.6	742	1119.5	111	1273.3	3341	1516.6	5222	2018.2	2683	3198.3
8821	350.3	7832	451.3	6419	553.1	6975	666.1	7162	756.5	5232	862.6	4113	982.4	6281	1119.7	5621	1274.7	6122	1518.2	4242	2018.7	8997	3206.6
7492	352.3	8822	454.3	7851	553.2	6665	666.1	7112	756.7	13	866.1	7211	982.6	5914	1122.5	1221	1275.6	8421	1540.3	6560	2033.5	4234	3215.0
7259	357.1	5825	454.8	7138	556.2	4111	666.3	7599	756.7	412	870.0	4311	982.7	2882	1123.1	3223	1275.9	741	1541.1	5721	2038.9	1212	3325.4
7449	357.2	7224	456.2	7919	556.7	6994	666.3	6727	759.8	5221	874.9	544	983.1	6651	1123.4	6812	1283.2	561	1547.8	4245	2059.3	6899	3344.4
8996	364.0	5821	458.6	5335	557.8	7245	667.1	7621	759.8	2665	877.5	6921	984.2	6978	1126.7	2714	1287.5	112	1549.0	8441	2067.6	6341	3430.8
7272	368.3	113	460.5	7754	558.4	5334	670.1	8731	760.1	3345	877.7	730	985.2	14	1128.0	2685	1289.0	6583	1551.0	8998	2071.6	542	3442.6
2120	369.2	5983	461.4	6991	559.4	7821	671.3	5113	762.0	1110	877.9	8981	988.5	8993	1128.9	8482	1296.0	2231	1555.7	8435	2076.4	721	3490.6
5838	374.6	5829	461.5	5826	560.6	7244	671.5	7524	762.7	5146	879.7	141	989.5	5828	1130.1	440	1299.7	3343	1557.1	6113	2095.1	612	3504.0
7372	375.1	7247	468.7	6543	563.2	5922	674.7	6741	765.5	5138	879.8	6514	992.3	579	1131.9	341	1309.4	8974	1565.0	2614	2107.1	4236	3532.4
6418	376.8	7129	469.8	5849	565.7	6821	675.2	6931	769.2	6645	886.8	149	998.2	7234	1131.9	421	1313.0	6584	1566.6	6342	2112.6	2924	3559.6
7423	377.2	5416	470.4	6251	570.4	5162	677.0	6542	769.6	8946	888.5	2482	1001.6	483	1132.6	7938	1313.8	8947	1567.9	711	2113.3	577	3580.8
6352	377.7	6750	472.0	7849	570.4	7591	677.4	5837	771.7	8931	889.2	6672	1002.5	460	1135.2	8434	1317.0	8429	1572.9	7861	2119.6	6129	3584.5
5824	379.2	6637	472.6	7723	572.4	6749	679.3	7411	772.4	5842	890.7	115	1002.6	589	1136.4	4233	1320.1	6974	1593.4	6349	2121.3	6597	3587.0
7268	382.2	6784	474.2	6639	575.0	8924	679.8	8972	774.7	7782	890.9	1122	1003.2	6594	1139.0	7233	1328.3	6724	1598.9	11	2133.9	2874	3623.6
7753	383.8	6412	475.0	575	576.0	5239	680.8	583	776.2	5542	892.4	8472	1003.3	8942	1140.3	2224	1329.1	6582	1602.0	2320	2139.1	2872	3691.6
7264	386.8	6649	475.4	8959	577.3	4239	681.0	6613	778.4	6770	892.5	8951	1004.8	7243	1144.0	8462	1329.9	9310	1603.5	19	2160.1	2631	3837.2
7133	387.1	5111	478.8	2331	578.1	7163	681.1	7649	778.4	5852	893.0	7768	1006.1	6593	1144.0	546	1330.5	712	1626.7	6118	2162.9	2112	3856.2
8744	387.4	8922	479.5	6911	579.9	8743	681.2	240	781.8	116	893.5	6935	1006.2	4312	1144.3	4249	1334.0	6999	1629.0	3232	2164.3	2632	3972.4

Table A6 (*continued*)

Low-emission intensity								Medium-emission intensity								High-emission intensity							
SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII	SITC	PEII
5836	388.1	5241	479.6	7914	579.9	8720	682.0	7711	782.8	481	896.1	129	1007.7	7763	1150.6	7223	1340.9	3351	1637.5	2111	2168.0	2634	4012.7
7251	390.1	1121	480.0	6641	590.3	6997	684.8	7841	785.1	6842	896.7	5982	1010.6	6532	1153.5	7239	1347.6	2815	1640.5	2223	2219.6	751	4049.7
6571	391.4	7283	481.4	7139	593.9	6747	687.7	2682	789.9	585	896.7	5981	1010.8	2873	1160.5	6531	1352.1	5723	1655.7	8433	2240.5	470	4082.0
2518	391.5	7188	484.9	6642	594.5	5822	687.9	7528	790.1	7868	897.3	8935	1011.0	6953	1160.9	7612	1356.6	2667	1658.3	4314	2242.7	6811	4166.4
6635	393.0	5989	486.0	7111	596.1	9610	691.4	7271	790.6	572	898.0	7757	1011.8	8212	1165.3	565	1362.6	5541	1662.2	8851	2242.8	4232	4180.3
7284	393.3	5156	487.2	7119	598.1	7915	692.9	7731	790.9	6666	898.5	482	1013.2	545	1168.0	6638	1367.4	3342	1665.2	2613	2249.2	6576	4199.6
7913	393.8	6760	487.3	7428	598.7	430	693.8	6973	791.9	2681	898.5	6343	1020.0	6552	1168.6	8452	1375.0	2633	1667.0	6831	2258.2	813	4219.7
8121	394.3	6623	500.5	7523	599.6	5419	694.4	5912	796.1	5312	905.2	541	1022.0	2519	1174.3	6712	1376.1	6518	1679.6	8443	2273.5	2238	4436.5
7742	395.4	7414	501.0	8983	606.7	7451	697.2	2671	797.3	7761	907.4	5543	1028.0	7431	1177.4	5122	1378.6	342	1682.7	2232	2278.0	9410	4479.5
6546	395.5	5155	502.8	6785	606.7	343	699.8	7611	797.3	6713	908.6	616	1030.9	6781	1180.1	7148	1380.6	3344	1694.7	6116	2291.5	6673	4617.9
7429	396.7	7161	503.3	6579	607.1	6992	700.2	8939	798.8	7764	910.4	2734	1033.8	7628	1181.6	2814	1383.2	3330	1695.5	2235	2313.3	12	4650.7
913	398.0	6595	504.9	6624	607.3	6793	700.3	5112	800.5	6851	914.2	2651	1033.9	573	1184.6	8464	1386.8	914	1723.7	6541	2317.7	2483	4668.4
7442	402.2	7783	505.1	8841	612.3	8483	701.7	6591	800.8	619	915.0	7415	1035.5	2919	1186.9	6611	1388.7	7131	1734.5	812	2334.8	2782	4740.7
7269	403.0	2516	506.3	6648	614.5	7721	701.8	5224	802.8	5823	919.2	5139	1037.9	2332	1190.3	5414	1395.2	3353	1746.6	6545	2344.0	2119	4780.7
6330	403.8	3224	506.6	5145	614.7	6130	702.1	4241	807.8	2471	921.5	3222	1039.7	8431	1191.9	118	1396.9	1223	1750.3	2772	2346.2	8471	4852.2
7149	406.2	5154	507.0	6782	615.0	5223	705.7	5323	814.1	6924	921.5	8989	1044.5	5114	1202.7	2742	1397.4	3221	1771.5	2911	2382.1	586	5121.7
7267	407.1	5833	511.0	2511	616.7	5157	706.9	484	815.3	8830	926.5	5921	1056.5	6671	1203.1	8459	1401.6	8484	1791.0	6521	2390.8	2922	5374.4
5415	407.9	6744	511.4	8748	622.3	6282	707.6	411	815.8	571	927.3	344	1058.3	6359	1203.7	6596	1405.0	422	1803.7	615	2404.8	2654	5700.6
6954	408.7	7367	512.0	6822	626.8	6733	708.6	8932	816.7	2655	927.9	7522	1060.4	6254	1204.6	7852	1408.2	6592	1810.2	6344	2419.5	459	5708.7
6632	409.8	5123	512.1	5851	627.3	6424	709.2	8941	816.7	7525	930.6	372	1060.7	5249	1205.1	8432	1408.6	6519	1840.3	6115	2439.5	2225	5711.5
7741	410.2	6647	513.3	2226	629.4	6861	709.4	2925	818.3	6539	932.9	2732	1061.0	6253	1207.5	6932	1409.0	8423	1841.9	1213	2451.5	2481	5885.4
7263	410.3	2440	515.2	7788	630.8	6832	710.2	6416	818.4	7722	933.2	2741	1061.7	3354	1207.8	5911	1410.5	7922	1845.6	6121	2462.3	5513	6390.6
7434	410.9	8813	517.4	6880	630.8	7643	712.6	5913	819.1	8124	933.3	620	1065.5	6731	1210.0	6646	1411.0	8424	1847.2	2450	2468.6	2879	6851.9
451	411.1	5332	518.1	3510	631.7	5834	713.0	2460	819.6	350	934.3	6517	1072.1	8852	1217.3	564	1411.8	2877	1867.4	2221	2519.1	3414	7717.6
7432	412.2	6411	518.3	15	632.9	5832	714.8	814	820.4	8811	934.9	2117	1073.3	6574	1218.2	6534	1413.2	3415	1879.1	2687	2525.9	6871	7897.3
7810	412.5	7932	519.5	8749	635.0	223	716.0	6652	820.8	2672	935.4	8310	1074.1	2816	1220.5	2690	1413.2	8999	1886.2	6581	2545.9	2239	8074.0
7371	415.5	8921	523.1	7648	637.5	2234	720.8	7518	821.9	6573	938.8	8982	1076.3	2652	1230.7	5322	1416.1	3413	1887.8	5233	2590.0	752	8421.1
7219	418.2	7435	524.6	2517	643.3	6993	724.4	7784	822.2	7822	941.4	2871	1078.3	3352	1231.7	6353	1421.5	8481	1898.6	2929	2612.5	6872	8867.9
8742	418.2	6633	528.7	252	643.7	7521	725.6	5623	825.1	6725	942.7	6351	1080.5	6423	1233.1	8933	1426.5	2711	1900.1	723	2617.1	2890	9342.9
6413	420.1	5841	529.0	6428	643.9	6891	727.6	8461	825.4	7642	943.0	114	1082.6	7853	1235.3	6841	1428.9	8991	1902.5	2222	2618.9	2875	9496.7
7493	420.4	142	529.2	7641	645.0	6422	727.9	6553	829.8	6544	943.1	2116	1083.8	6512	1235.7	6515	1435.1	722	1905.5	371	2625.6	2923	9972.7
7436	423.0	5161	531.6	5831	645.1	8710	728.0	7929	830.7	2786	944.0	251	1086.1	7511	1237.7	1222	1442.7	6354	1905.6	548	2628.5	2876	13182.5
5827	424.1	2512	533.1	7752	647.9			6644	833.2	6998	945.2	5231	1087.0			811	1443.7	8439	1924.9	6575	2631.9		
5147	425.0	6746	535.2	7732	649.0			2881	833.3	7923	946.8	6618	1089.8			6511	1450.4	8973	1928.4	2472	2642.4		

Source: Authors' elaboration.

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