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Research article

Tracking the change in Spanish greenhouse gas emissions through an LMDI decomposition model: A global and sectoral approach

Q1 *Paula Fernández González**, *María José Presno*, *Manuel Landajo*

Department of Applied Economics, University of Oviedo, Avda del Cristo, s/n 33011 Oviedo, Spain

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ABSTRACT

The reduction of GHG emissions to reverse the greenhouse effect is one of the main challenges in this century. In this paper we pursue two objectives. First, we analyze the evolution of GHG emissions in Spain in 2008–2018, at both the global and sectoral levels, with the variation in emissions decomposed into a set of determining factors. Second, we propose several actions specifically oriented to more tightly controlling the level of emissions. Our results showed a remarkable reduction (18.44%) in GHG emissions, mainly due to the intensity effect, but also to the production-per-capita effect. We detected somewhat different patterns among the various sectors analyzed. While the intensity effect was the most influential one in the Agricultural, Transport, and Others sectors, the production-per-capita effect was predominant in the case of Industry. The carbonization effect was revealed as crucial in the Commerce sector. The above findings highlight the importance of the energy efficiency measures taken in recent years in the Spanish economy, also pointing to the need to deepen those strategies and to propose new measures that entail greater efficiency in emissions. Additional efforts in areas like innovation, R&D, diffusion of more eco-friendly technologies, and a greater use of greener energies all prove to be essential reduction actions to fight the greenhouse effect.

1. Introduction

Greenhouse gases (GHGs) are emitted from both natural and human-related sources, and it is now well known that their accumulation in the atmosphere derives both from absorption of infrared rays emitted by the Sun and from increases of the heat in the atmosphere, significantly contributing to global warming. That increase in the average temperature of the planet is known to cause extreme weather phenomena with dramatic consequences, including acidification of the oceans, floods, increases in the sea levels, reduction in water resources, heat waves, wildfires, droughts, changes in ecosystems, extinction of animal species, famines, spread of diseases, poverty, and inequality. As pointed out by the IPCC (2014), the role of humans in the increase of emissions is indisputable. Although climate change has naturally occurred throughout history (with oscillations between glaciation and tropical periods), those shifts typically were slow, requiring long periods of time. Human action, especially after the

* Corresponding author.
E-mail: pfgonzal@uniovi.es (P.F. González).

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Industrial Revolution, seemingly altered that situation, with economic and demographic growth having a magnifying effect on global warming.

Given the current situation, the study of the historic patterns and future perspectives of greenhouse gas emissions, as well as of the forces that motivate their variations, has become a topic of high relevance. The goal of this paper is twofold: to analyze the change in GHG emissions in Spain in the last decade, and to understand the driving forces underlying their evolution. To do this, we decomposed the variation in GHG emissions into four determining factors: population, activity, intensity, and carbon intensity effects. We considered two levels of disaggregation (global and sectoral). The results of this analysis will be useful in designing actions and measures specifically adapted to each sector, with a view to pursuing a reduction in emissions that helps fight global warming.

We rely on the Index Decomposition Analysis (IDA). This is one of the most heavily employed index-based decomposition techniques, with an impressive range of applications in the fields of energy and environmental analysis. IDA is a leading choice because of its useful features, which include the advantage of not requiring large amounts of information.

From a methodological standpoint, many authors have developed a conceptual framework that has both enabled the theoretical formulation of Divisia-index-based methods and validated their practical application: Hulten, 1973; Boyd et al.; 1987; Liu et al., 1992; Ang (1995, 2005); Ang and Lee, 1994; Ang and Choi, 1997; Sun, 1998; Sun and Ang, 2000; Ang and Liu, 2001; Albrecht et al., 2002; Fernández and Fernández, 2008; Fernández González et al., 2013; Choi and Oh, 2014; Fernández González, 2015; and Zhang and Wang, 2021.

In recent years, numerous authors have applied IDA to decompose the variations of various energy aggregates in several countries. Instances include Wang et al., 2017; Chong et al., 2019, Wang et al., 2014; Chai et al., 2018; Moutinho et al., 2018; De Oliveira-De Jesús, 2019; Chontanawat et al., 2020; Chen and Lin 2020; Yang et al., 2020; Hasan and Chongbo 2020; Liu et al., 2021; Li et al., 2019; and Tenaw 2021; Li et al., 2021; and Gao et al., 2019.

The objective of this work is to identify and analyze the driving forces underlying GHG emission changes. To accomplish this goal, we shall rely on so-called *Divisia IDA* methodology, which possesses a number of useful features to be detailed below. The paper is structured as follows. Section 2 outlines the methodology—relying on the Logarithmic Mean Divisia Index (LMDI) decomposition method—which we employed to analyze the evolution of GHG emissions in Spain during 2008–2018. Section 3 reports and analyzes our results, both globally and at a sectoral level. This analysis will make it possible to study the contribution of the various determining factors of the overall variation. Finally, Section 4 summarizes the main conclusions and provides some useful guidelines for environmental action policies.

2. Methodology

In order to decompose the change in GHG emissions into a set of predetermined factors, in this section we will carry out a revision and adaptation of the multiplicative LMDI method (first proposed by Ang and Choi (1997)). The use of index-based methods comes with the advantage that (1) they do not require a large amount of information, unlike others like Structural Decomposition Analysis (SDA), (2) they offer results of great interest, and (3) they allow estimation of the effects that certain magnitudes (such as energy efficiency and decarbonization) have on the changes in gas emissions. In addition, using Divisia specifically provides important advantages over other indices, including that they deliver an exact decomposition and, under certain conditions of data homogeneity, they fulfill some useful properties like the circular test (Sun and Ang, 2000).

As for the determinant factors taken into account in the decomposition, the following driving forces will be considered:

(a) *Population effect*, that is, the impact of population growth.
(b) *Activity effect*, encompassing the impact of economic growth. Assuming a constant (average) coefficient between GDP and CO_2 emissions, this effect may be regarded as the theoretical CO_2 emissions coming from economic activities (Sun, 1998).
(c) *Intensity effect*, that is, the impact on emissions of energy requirements per unit of value added. It involves the energy consumption related to some variables like energy prices, energy conservation and energy-saving investments, structure and efficiency of the energy systems, technological choices, and socioeconomic behavior.
(d) *Energy carbon intensity effect*, which is defined as the impact on the mass of emitted gas from each unity of fuel consumed. It is also called carbonization effect.

The factors included are the most relevant ones when decomposing changes in gas emissions because they encompass, respectively, the effects of changes in energy mix, energy efficiency, economic growth, and population.

Within the general LMDI framework, two main approaches have been developed in the last two decades: the one proposed by Ang and Liu (2001), named LMDI-I, and the one put forward by Sato (1976) and Vartia (1976), named LMDI-II. In this paper we focused on the latter as it has the advantage of involving a geometric mean that ensures that the weights add up to one.

Another issue is the type of decomposition to be carried out (multiplicative or additive). We preferred the multiplicative approach because the decomposition in this case has a ratio (index number) form that is readily interpretable.

Finally, we implemented a so-called time-series (i.e., multiperiod) decomposition instead of period-wise (single-period) decomposition, as the former allows the information from intermediate periods to be exploited and the cumulative impacts from the first to the last period to be readily computed.

In a generic setting with k economic sectors, following Fernández González et al. (2014), the total GHG emissions (C) can be expressed as follows:

$$C = \sum_{j=1}^{k} C_j = \sum_{j=1}^{k} P\left(G_j E_j C_j\right)/\left(P_j G_j E_j\right) = \sum_{j=1}^{k} PY_j I_j F_j \quad (1)$$

where C_j denotes GHG emissions in sector j, G_j represents production of sector j, P is population, E_j denotes sectoral energy consumption, $Y_j = G_j/P_j$ represents sectoral production

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per inhabitant, $I_j = E_j/G_j$ is the energy intensity in sector *j*, and $F_j = C_j/E_j$ represents the emission intensity (i.e., the mass of gas emitted per unity of energy consumed, both referred to sector as *j*).

Taking logarithmic derivatives with respect to time in Eq. (1) we have

$$d\ ln\ C/dt = \sum_{j=1}^{k} P\left(Y_j I_j F_j / C\right)\left(d\ ln\ P/dt + d\ ln\ Y_j/dt + d\ ln\ I_j/dt + d\ ln\ F_j/dt\right) \quad (2)$$

Integrating Eq. (2)

$$ln\ (C_T/C_0) = \sum_{j=1}^{k} \int_0^T w_j (t) \begin{pmatrix} (d\ ln\ P(t)/dt) + \left(d\ ln\ Y_j(t)/dt\right) + \left(d\ ln\ I_j(t)/dt\right) + \\ + \left(d\ ln\ F_j(t)/dt\right) \end{pmatrix} dt \quad (3)$$

where

$$w_j(t) = P(t)\ Y_j(t)\ I_j(t)\ E_j(t)/C(t) = P(t)\ Y_j(t)\ I_j(t)\ F_j(t) / \sum_{j=1}^{k} P(t)\ Y_j(t)\ I_j(t)\ F_j(t) \quad (4)$$

and applying the exponential function to Eq. (3) the following expression is readily obtained:

$$C_T/C_0 = \exp\left(\sum_{j=1}^{k}\int_0^T w_{jr}(t)\left(d\ ln\ P_j(t)/dt\right)dt\right) \exp\left(\sum_{j=1}^{k}\int_0^T w_j(t)\ \left(d\ ln\ Y_j(t)/dt\right)dt\right) \exp\left(\sum_{j=1}^{k}\int_0^T w_j(t)\left(d\ ln\ I_j(t)/dt\right)dt\right) \exp\left(\sum_{j=1}^{k}\int_0^T w_j(t)\left(d\ ln\ F_j(t)/dt\right)dt\right) \quad (5)$$

By employing a discrete approximation to Eq. (5) above, a standard formula for the logarithmic change is obtained as follows:

$$C_T/C_0 = \exp\left(\int_0^T ln\ (P_T/P_0)dt\right) \exp\left(\sum_{j=1}^{k}\int_0^T w_j(t^*) ln\ \left(Y_{j,T}/Y_{j,0}\right)dt\right) \exp\left(\sum_{j=1}^{k}\int_0^T w_j(t^*) ln\ \left(I_{j,T}/I_{j,0}\right)dt\right) \exp\left(\sum_{j=1}^{k}\int_0^T w_j(t^*) ln\ \left(F_{j,T}/F_{j,0}\right)dt\right) \quad (6)$$

where $w_j\ (t^*)$ is the weight function given by Eq. (4), evaluated at point $t^* \in [0,\ T]$. Since that point is unknown, several weight functions may be considered, each leading to a different decomposition method. Early proposals were based on Laspeyres (Park 1992) and Marshall–Edgeworth indices (Boyd et al. 1987; Ang and Lee 1994). Subsequently, Liu et al. (1992); Ang (1995); Ang et al. (1998) and Sun (1998), developed the methodology, proposing weighting functions that both adapt to changes in the magnitudes and lead to perfect decompositions. Sun and Ang (2000) proved some interesting properties of exact decomposition methods.

In the case of the exact decomposition method of Ang and Choi (1997), the following expression is obtained for the weights:

$$w_j(t^*) = L\left(w_{j,0}, w_{j,T}\right) / \sum_{j=1}^{k} L\left(w_{j,0}, w_{j,T}\right) \quad (7)$$

where $w_{j,0} = C_{j,0},\ w_{j,T} = C_{j,T}$, and $L(.)$ is the weight function proposed by Sato (1976).

Thus,

$$\tilde{w}_j(t^*) = L\left(C_{j,0}, C_{j,T}\right)/L(C_0, C_T) \quad (8)$$

By inserting Eq. (8) in Eq. (6):

$$\frac{C_T}{C_0} = \exp\left(\sum_{j=1}^{k}\int_0^T ln\ (P_T/P_0)\ dt\right) \exp\left(\sum_{j=1}^{k}\int_0^T \tilde{w}_j\ (t^*) ln\ \left(Y_{j,T}/Y_{j,0}\right)\ dt\right) \exp\left(\sum_{j=1}^{k}\int_0^T \tilde{w}_j\ (t^*) ln\ \left(I_{j,T}/I_{j,0}\right)dt\right) \exp\left(\sum_{j=1}^{k}\int_0^T \tilde{w}_j\ (t^*) ln\ \left(F_{j,T}/Fj,0\right)dt\right) \quad (9)$$

or equivalently

$$R_{tot} = R_{pop} R_{ypc} R_{int} R_{eci} \quad (10)$$

where R_{pop} represents the population impact (*population effect*), R_{ypc} collects the influence of economic growth per capita (*production per capita effect*), R_{int} denotes the influence of energy intensity (*intensity effect*), and R_{eci} represents the impact of energy carbon intensity (*energy carbon intensity* or *carbonization effect*). Their expressions are as follows:

$$R_{pop} = P_T/P_0 \quad (11)$$

$$R_{ypc} = \exp\left(\sum_{j=1}^{k}\left(L\left(C_{j,0}, C_{j,T}\right)/L(C_0, C_T)\right) ln\ \left(Y_{j,T}/Y_{j,0}\right)\right) \quad (12)$$

$$R_{int} = \exp\left(\sum_{j=1}^{k}\left(L\left(C_{j,0}, C_{j,T}\right)/L(C_0, C_T)\right)\ ln\ \left(I_{j,T}/I_{j,0}\right)\right) \quad (13)$$

$$R_{eci} = \exp\left(\sum_{j=1}^{k}\left(L\left(C_{j,0}, C_{j,T}\right)/L(C_0, C_T)\right)\ ln\ \left(F_{j,T}/F_{r,0}\right)\right) \quad (14)$$

Finally, the multiplicative time-series decompositions for the cumulative effects have the following expressions:

$$C_{tot0,T} = R_{tot0,1} R_{tot1,2} \ldots R_{totT-1,T} \quad (15)$$

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Table 1 – Estimated effects with respect to the previous year (2008–2018).

Years	R_{tot}	R_{pop}	R_{ypc}	R_{int}	R_{eci}	R_{rsd}
2008	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2009	0.9034	1.0125	0.8768	0.9896	1.0282	1.0000
2010	0.9610	1.0053	0.9969	0.9896	0.9690	1.0000
2011	0.9976	1.0039	0.9913	0.9434	1.0625	1.0000
2012	0.9800	1.0032	0.9568	1.0144	1.0065	1.0000
2013	0.9266	0.9981	0.9868	1.0026	0.9382	1.0000
2014	1.0096	0.9954	1.0138	0.9753	1.0257	1.0000
2015	1.0357	0.9987	1.0353	0.9277	1.0798	1.0000
2016	0.9691	0.9998	1.0072	1.0054	0.9572	1.0000
2017	1.0407	1.0019	1.0604	0.9627	1.0176	1.0000
2018	0.9835	1.0028	1.0467	0.9545	0.9815	1.0000

where *Rrsd* denotes the residual effect. Since the LMDI method provides exhaustive decompositions, *Rrsd* =1 automatically holds true in the multiplicative case.

$$C_{pop0,T} = R_{pop0,1}R_{pop1,2}....R_{popT-1,T} \tag{16}$$

$$C_{ypc0,T} = R_{ypc0,1}R_{ypc1,2}....R_{ypcT-1,T} \tag{17}$$

$$C_{int0,T} = R_{int0,1}R_{int1,2}....R_{intT-1,T} \tag{18}$$

$$C_{eci0,T} = R_{eci0,1}R_{eci1,2}....R_{eciT-1,T} \tag{19}$$

3. Decomposition of the change in Spanish GHG emissions

In this section, we present a multiplicative LMDI-II decomposition of the change in Spanish GHG emissions, with the following driving factors: population effect, production per capita effect, intensity effect, and energy carbon intensity effect (carbonization effect). The decomposition is implemented at two levels (global and sectoral). The study period, namely 2008–2018, encompasses both a period of worldwide financial and economic crisis and its subsequent recovery. We obtained time series data on population (in millions), GHG emissions by sector (in thousands of tons), and gross domestic product by sector (in millions of euros), respectively, from the Population and Housing Census, Air Emissions accounts, Annual Spanish Economic Accounts, and Energy Consumption Survey, all of them elaborated by the Spanish Statistical Office (INE, 2021a, 2021b, 2021c). We obtained time series data on energy consumption by sector (in ktoe) from the Ministry for Ecological Transition and Demographic Challenge of Spain (MITECO, 2021). We considered the following sectors: agriculture (including agriculture, forestry, and fishing), industry (including construction), transport, commerce, and others (which includes public administration and other services).

3.1. *Results and discussion*

Table 1 shows the estimated effects of the decomposition of the change in emissions in Spain (2008–2018) with respect to the previous year.

Table 2 – Estimated effects with respect to base year 2008.

Years	C_{tot}	C_{pop}	C_{ypc}	C_{int}	C_{eci}	C_{rsd}
2008	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2009	0.9034	1.0125	0.8768	0.9896	1.0282	1.0000
2010	0.8682	1.0179	0.8741	0.9793	0.9964	1.0000
2011	0.8661	1.0219	0.8665	0.9239	1.0587	1.0000
2012	0.8488	1.0252	0.8291	0.9372	1.0655	1.0000
2013	0.7864	1.0232	0.8182	0.9397	0.9997	1.0000
2014	0.7940	1.0185	0.8295	0.9165	1.0254	1.0000
2015	0.8223	1.0171	0.8588	0.8502	1.1072	1.0000
2016	0.7969	1.0169	0.8650	0.8548	1.0598	1.0000
2017	0.8293	1.0188	0.9172	0.8229	1.0785	1.0000
2018	0.8156	1.0217	0.9601	0.7855	1.0586	1.0000

where C_{rsd} denotes the cumulative residual effect.

Due to the great variability of the results, the need for homogenization, and ease of interpretation, Table 2 below presents the cumulative results, with year 2008 employed as the common base.

GHG emissions in Spain showed a strong decrease from 2008 to 2018, with an 18.44% overall drop. Nevertheless, that trend did not continually decrease throughout the period, and a slight rise was observed in the last part of it. The results of the decomposition (Table 2) reveal two fundamental points:

(a) There was an opposite evolution of the intensity and carbonization factors. The higher the energy efficiency (defined as energy consumption per unit of output), the greater the carbonization effect (i.e., higher emissions per unit of energy consumed). Seemingly, energy efficiency measures such as increases in the use of less-energy-intensive technologies and a growing production and consumption of less-energy-intensive goods did not translate into a reduction in GHG emissions. Therefore, it could be interesting to formulate complementary measures to enhance further reductions in GHG emissions. Certainly, these would include research and promotion of greener energies; development of technologies for the capture and storage of CO2, methane and other gases; recovery and recycling of gases; and stronger actions oriented towards a more circular economy.

(b) The per capita production effect had a strong influence, which, excepting the last year, displayed the same pattern as the total effect. The variations in per capita production significantly marked the evolution of GHG emissions throughout the study period, which clearly reinforces the conclusions obtained by Fernández González et al. (2014), showing the importance of implementing alternative measures that simultaneously favor economic growth and a healthier atmosphere.

Likewise, when analyzing Fig. 1 below two distinct phases may be observed: first, a period of acute economic crisis and its inertia (2008–2013), and second, a phase of gradual recovery (2014–2018).

In the first phase (2008–2013), a period of severe economic recession, GHG emissions experienced a sharp drop by 21.36%. The per capita production effect was the most influential fac-

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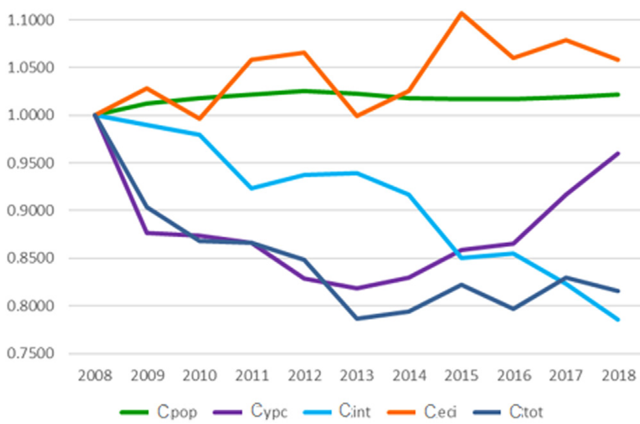

Fig. 1 – Total cumulative effects from 2008 to 2018.

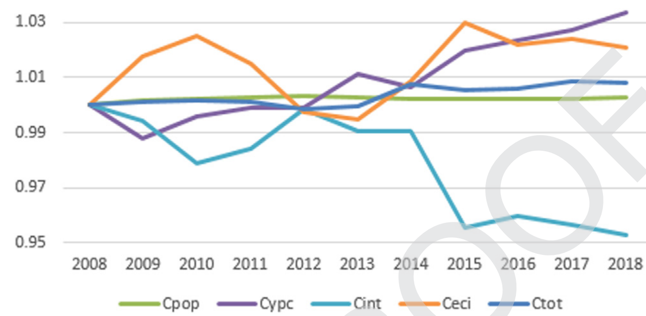

Fig. 2 – Cumulative effects in Agriculture from 2008 to 2018.

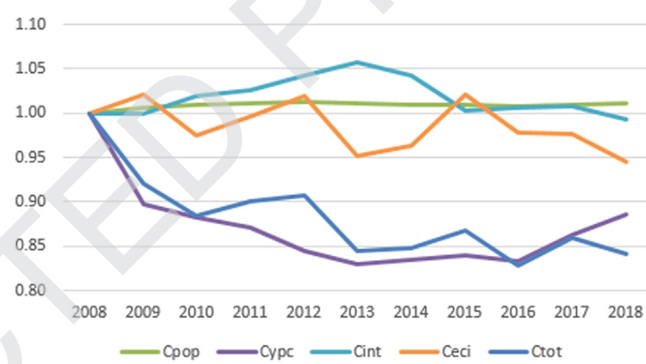

Fig. 3 – Cumulative effects in Industry from 2008 to 2018.

tor, significantly contributing to the fall in emissions (19.18%). As expected, lower production led to a reduction in GHG emissions into the atmosphere. In that period, the intensity effect was significantly negative, contributing to the GHG emissions reduction by 6.03%. In other words, certain energy efficiency actions contributed (albeit only slightly) to reducing emissions. This may be a consequence of both the inertia of the previous period and the inevitable lag between the time R&D investments were made and results obtained. When an economic crisis comes, economic agents try to reduce costs to survive, and this adjustment process can also lead to forced energy savings.

In the second phase (a period in which there was some economic recovery), GHG emissions slightly increased (by 3.71% in 2013). The per capita production effect and, to some extent, the carbonization effect pushed the level of emissions upward. In contrast, the intensity effect turned out to be negative, contributing to a reduction in pollutant gas emissions. It was precisely in this phase that the intensity effect acquired vital importance as a determining factor in controlling emissions. The previous stage allowed the most efficient economic agents to survive, and the economic growth in the current phase favored investments both in new and more efficient technologies and in the search for greener energies.

In 2018, both the carbonization and intensity effects moved in the same direction (reducing GHG emissions) and were sufficiently important to counteract the production per capita and population effects. This means that all the efforts made to increase energy efficiency, as well as the investments in CO_2 capture systems and in promotion of green energies jointly managed to keep at bay the effect caused by the economic recovery. Further study would be needed to know whether this tendency will finally consolidate itself and Spain is able to strongly grow while reducing its GHG emissions.

Previous studies, applying different methodologies to closely related aggregates, have reached results similar to those displayed in this paper. More specifically, González-Sánchez and Martín-Ortega (2021), based on multiple linear regression models, concluded that both GDP and the energy intensity effect have been the main driving forces in GHG emission reductions in Spain. Serrano-Puente (2021), relying on an Input-Output LMDI method, found technical energy efficiency to be a leading contributor to GHG emissions reduction, whereas Román-Collado and Colinet (2018), employing a similar (Input-Output LMDI) methodology, detected the intensity effect as the most important driving force in reducing energy consumption and therefore GHG emissions.

When analyzing the results by economic sector (see Figs. 2–5 below), we observed that the intensity effect has been the protagonist in almost all areas, with the exceptions of the industrial sector (where the per capita income effect played the leading role) and the commercial sector (mainly influenced by the carbonization effect).

In the case of the agricultural sector (Fig. 2), during the period analyzed there was a slight, gradual increase in emissions, mainly due to the carbonization effect and (to a lesser extent) to the per capita production effect. The population effect was slightly positive but had no great influence on the result. Only the intensity effect was negative, also being the only one that partially offset the increase in emissions. In the agricultural sector, the use of more efficient technologies was fundamental, but insufficient to reduce GHG emissions. This clearly suggests that the use of greener energies and gas capture systems may be indispensable in the future. Another relevant issue is the promotion of a change in consumer preferences toward greener products, with a reduction in the consumption of emission-intensive agricultural products such as meat.

Regarding the industrial sector (Fig. 3), there was a sharp (29.74%) decrease (with slight rebounds) in GHG emissions throughout the study period. All effects, except the population effect, contributed to this decrease. The most relevant

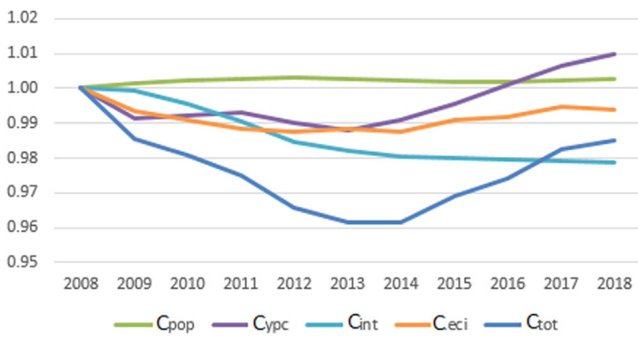

Fig. 4 – Cumulative effects in Transport from 2008 to 2018.

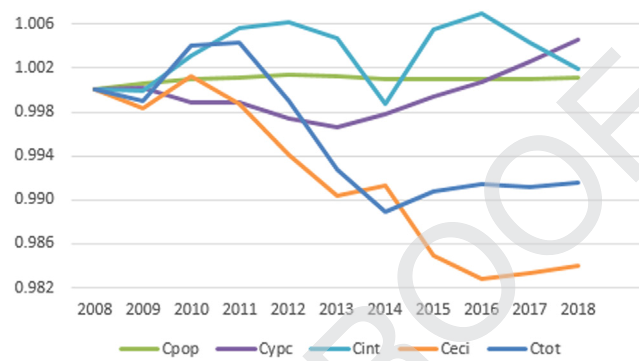

Fig. 5 – Cumulative effects in Commerce from 2008 to 2018.

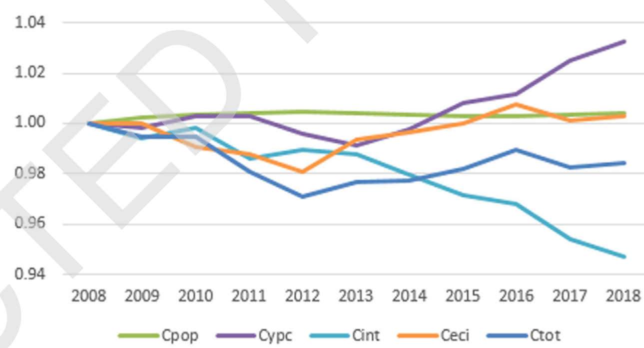

Fig. 6 – Cumulative effects in Others from 2008 to 2018.

factor was the per capita production effect. The decline in production (a consequence of the severe economic crisis suffered in 2008), the loss of industrial fabric (especially small- and medium-sized enterprises), and a slow recovery of that sector, all led to a significant decrease in GHG emissions. Only in the last years of the study period, because of the economic recovery, did this effect lose some importance as a driver of emissions reduction.

Another effect that had a negative (albeit small) impact was the carbonization effect. Its pattern of behavior was similar to that of the total effect. The use of greener energies and the shift toward the production of fewer emission-intensive goods also contributed to the reduction of gas emissions. However, this effect experienced ups and downs (with no clear trend) throughout the study period.

Finally, the intensity effect (to some extent) was also negative overall, although there were some periods (namely those with stronger economic impact of the economic shock) in which this effect contributed to increased emissions. As commented above, in a crisis, industrial companies need a period of adaptation to the new situation. At first, they increase emissions because they are possibly trying to reduce costs, whereas in a latter period they invest in technology to improve their productivity and efficiency, and thus they are able to compete in the market.

As for the Transport sector (Fig. 4), there has also been a reduction of 1.49% in emissions, favored by the intensity effect and, to a lesser extent, by the carbonization effect. The per capita production effect, whose behavior pattern was similar to that of the total effect, also contributed to that reduction until 2013, but after that date it boosted the increase in emissions, and its overall effect at the end of the study period was positive. This partly offset the influence of the intensity and carbonization effects, although the overall figure was still negative. That is, this sector has seen a reduction in its GHG emissions. The increasing use of electric and hybrid vehicles (replacing combustion vehicles), more efficient engines (resulting from technological innovation), improved communication networks, the promotion of public transport, and the use of nonmotorized vehicles such as bicycles and scooters have all contributed to the reduction in emissions.

Regarding the commercial sector (Fig. 5), there was only a 0.84% reduction in emissions. While that reduction is certainly mild, it is interesting to analyze it to better understand the performance of that sector. In this case, emission reductions came exclusively from the carbonization effect. The intensity effect was positive during almost the entire period, and the per capita production effect—although negative (because of the recession) in the first years studied—was also positive overall. However, these two effects were unable to offset the reduction in emissions driven by the carbonization effect. Issues like the greener attitudes of consumers and producers and the use of trading platforms and recycled products, among others, were sufficient merely to avoid increases in emissions. However, it remains a concern that the intensity effect was positive, so further innovation and promotion of more efficient technologies could be of great interest.

Regarding the last of the sectors considered (Fig. 6), we observed a 1.57% reduction in emissions, driven exclusively by the intensity effect. The other effects, especially the per capita production effect, were positive but insufficient to offset the influence of the intensity effect. In this case, the development of new technologies and, above all, access to and dissemination of administrative information by telematic means could be key points in reducing GHG emissions into the atmosphere.

Finally, it should be noted that the various sectors have unequal weights in terms of their importance as GHG emitters and, therefore, the consequences of their functioning have different grades of relevance in reducing GHG emissions. Specifically, Fig. 7 shows their respective levels of involvement and their evolution.

During the period analyzed, Industry was the most relevant sector, followed by Others and Agriculture, while Commerce was the least influential one. When considering two dif-

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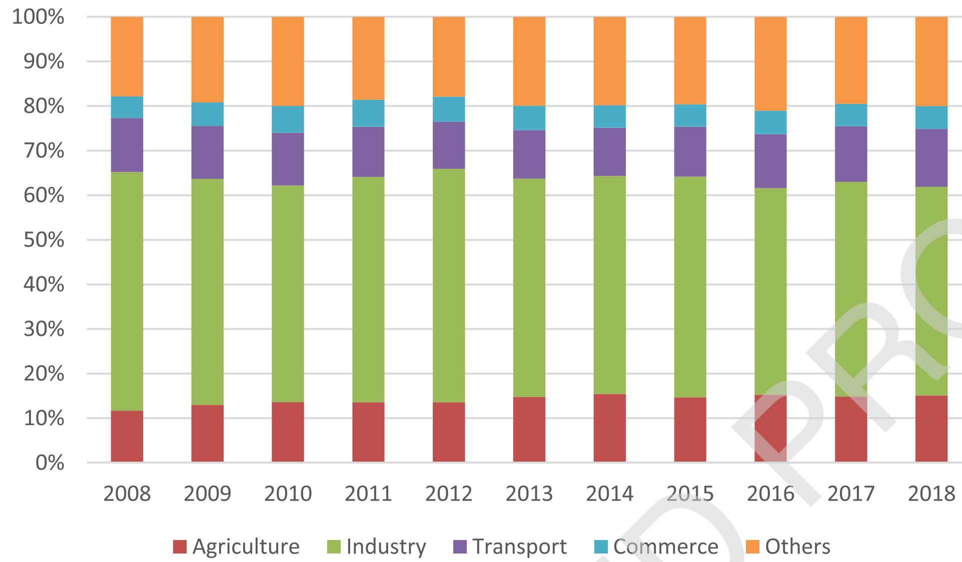

Fig. 7 – Evolution of sector weights as contributors to the global count of GHG emissions in Spain (2008-2018).

ferent phases (namely 2008–2013 and 2014–2018), in the first period (the economic crisis phase), Agriculture gained importance against Transport, while in the second period (the economic recovery phase), the Others sector grew as compared to Industry. In any event, the latter was the most relevant sector throughout the whole period, and therefore it was (and remains) crucial in reducing emissions.

4. Discussion and conclusions

The greenhouse effect and the need to control the level of GHG emissions into the atmosphere is a serious concern for both national and international organizations. In this paper we studied the evolution of GHG emissions in Spain in 2008–2018, proposing environmental actions that contribute to reduce the level of emissions.

For this purpose, we outlined a methodology, based on logarithmic weighted average index numbers, that accurately decomposed the changes experienced by the aggregate into a set of predetermined factors. These factors are population effect, per capita production effect, intensity effect, and carbonization effect.

The result showed a significant (18.44%) reduction in overall GHG emissions to the atmosphere. There were ups and downs during the period, but the total effect was clearly negative. While the per capita production effect was not the most important factor when the complete period is considered, it was clearly one of the main determinants, particularly in the first part of the period, and its behavior pattern was similar to that of the total effect. In times of economic crisis, downward production adjustments naturally contribute to reducing the level of emissions, while the production increases contribute to make them rise when the recovery arrives.

Another vitally important effect (the most relevant when considering the whole period) was the intensity effect, which was particularly negative in the first years of the severe economic crisis period and in the economic recovery phase. In 2008, when the crisis hit, the effects of previous R&D investments (which tend to come with a delay) were still noticeable. After a period of poor investments and adaptation of the production systems to the new situation, economic recovery finally arrived and made it affordable to invest again in innovation and in the search for more efficient technologies, eventually leading to a GHG emissions reduction.

The carbonization effect was positive during most of the study period, thus contributing to an increase in GHG emissions by 5.86%. Moreover, its evolution was opposite to that of the intensity effect most of the time. The growing use of green energies, gas capture, and storage systems, and the promotion of a more circular economy certainly remain pending tasks for the country.

The population effect drove emissions slightly upward throughout the entire study period, especially in recent years. In the early period, because of the economic crisis, and although with a certain delay, the lower number of births and a lower migratory pressure reduced the Spanish population and lessened the positive influence of this effect on the level of emissions.

Our analysis of the evolution of GHG emissions by sector of activity revealed that the intensity effect was noticeable, especially in the last years of the study (which coincided with an economic recovery), in the Agriculture, Transport, and Other Services sectors, contributing to reduce GHG emissions by a range between 2% and 6% depending on the sector. The intensity effect was almost neutral in Commerce. In that sector, there seems to have been a lack of sufficient measures to promote innovation, research and development of more efficient technologies, the dissemination of more environmentally friendly management models, and changes in consumer preferences toward green products.

The carbonization effect was negative in most of the sectors analyzed, particularly in Industry. In some others, like Agriculture and Other Services, it was a burden for the reduc-

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tion of GHG emissions, so some sectors might benefit from a more intense promotion of green energies, a greater use of gases and waste, and, in general, a more circular economy.

The per capita production effect was strongly negative in Industry and slightly positive in all the other economic sectors. The crisis particularly hit the industrial sector, reducing its production and therefore its GHG emissions. However, it is also evident that, to achieve a negative per capita effect without weakening economic growth, a change in the attitudes of consumers toward more eco-friendly products and a shift of producers to lower emitting sectors will be needed. In this regard, advertising and promotion of green attitudes, a change in the education of the population (both being matters that would fall mainly in the sphere of the government), and the promotion of less-polluting sectors could greatly help reduce emissions.

The above breakdown of the variations in GHG emissions to the atmosphere by the Spanish economy highlights the importance of implementing decarbonization measures, but it also shows the need to deepen and take additional energy efficiency measures oriented to promoting further reductions in the level of emissions. Among others, these would include the following.

i) In the case of the agriculture sector: methane gas capture, heat and power generation from manure and agricultural waste, reduction in fertilizer inputs, and promotion of more energy-efficient technologies.
ii) In the commerce and industrial sectors: energy audits and energy management teams to develop, implement, and evaluate a strategic energy saving plan; the use of LED and solar lighting; optimizing air compressors, development and use of more energy-efficient technologies; carbon capture and storage; and industrial waste heat recovery.
iii) In the construction, public buildings, and household sectors: increasing material efficiency; using low pollutant machinery, suitable insulation, and ventilation systems; using green energies (microgrids), smart buildings, and renovation of appliances; and electrification of heating systems.
iv) In the case of the transport sector: change from fossil-fuel motors to hybrid or electric vehicles, reduction of the transport demand by promoting nonmotorized vehicles like bikes and public transport, promotion of vehicle sharing, use of less-polluting engines, switch in preferences from air transport to high-speed trains, and even the use of greener energies.

Starting with the need of a clear and transparent regulation for favoring fair competition and avoiding market failures, some useful political measures that may be implemented would include: (a) the establishment of financial incentives to invest and encourage the use of more efficient technologies, (b) the use of hydrogen made with zero-carbon electricity, (c) the use and advertising of “information labeling,” (d) the setting down of rigorous certification systems for both appliances and buildings (Leadership in Energy and Environmental Design), (e) incorporation of new performance standards (on buildings, equipment, and transportation), (f) inducement of changes in consumer preferences (e.g., by shifting demand to low carbon footprint goods and services), (g) promotion of green attitudes (recycle and re-use), and (h) encouragement of investment in and diffusion of more efficient and less polluting technologies.

In short, innovation, R&D, and transmission of more eco-friendly technologies—together with promotion and use of green energies, a more circular economy, and consumer green attitudes—have all revealed themselves as the best strategies to reduce GHG emissions, and therefore to combat climate change. (Eqn 7, 9-19).

Uncited References

González-Sánchez and Martín-Ortega, 2020, Hulten, 1987, Ang and Liu, 2007

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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