# Assessing Regional Convergence of Greenhouse Gas Emissions in Spain: Insights from Economic Activities

## Abstract

In recent decades, Spain has undergone a strong economic expansion; however, it has not made a robust response to fulfil the international greenhouse gas Paris Agreement targets. Thus, understanding the dynamics of the environmental performance of the Spanish regions is essential for policymakers. We explore the convergence process of emissions intensity at the regional level during 1990 - 2018, differentiating between direct and diffuse emission sector, based on the degree of energy intensity of economic activities, which is the most novel aspect of our analysis. Our results recognize several convergence clubs; predominantly, the determining factors are income level and added value breakdown, the energy mix of renewable power, as well as the temperature of the climate. In any event, the dispersion of behaviours and the existence of different factors driving the convergence process highlight the need for customized policies at the regional scale.

Keywords: Emission intensity • Convergence • Clubs/Clusters • Sectors • Spain

## Key Policy Highlights

- Customized environmental policies are vital for regions in Spain with varying emissions levels.
- National consensus is needed to reduce emissions across industries, transportation, businesses, households, and agriculture.
- Targeted development can mitigate environmental impact, aiding policymakers.
- Regions that are falling behind should prioritize renewable energy promotion.
- Energy conservation laws must be mandatory henceforth.

## 1. Introduction

There is growing recognition, as highlighted by the Intergovernmental Panel on Climate Change (IPCC), of the significant role that regional governments play in the fight against climate change. Regional governments are increasingly implementing policies that seek to strike a balance between economic growth and the reduction of greenhouse gas (GHG) emissions in order to mitigate the impact of climate change (IPCC, 2014). As such, efforts across the regions to reduce ecological damage should include mechanisms aimed to achieving zero GHG emissions or, at the very least, a balance between emissions and mitigation. Recent studies (Otero et al. 2020) affirm that achieving absolute decoupling of economic growth from environmental harm, whether through top-down or bottom-up governance, remains a theoretical aspiration and can only be realized in the near future with significant transformations in our economic systems. In fact, current levels of resource efficiency do not permit a simultaneous increase in GDP and a zero increase in GHG emissions.

One of most reliable indicators of productive activity efficiency from an environmental perspective, as recognized by the World Business Council for Sustainable Development (WBCSD) (Verfaillie and Bidwell 2000), is emission intensity (Huppes and Ishikawa, 2005), measured as the ratio of GHG emissions to GDP. A decreasing emission intensity reflects improved efficiency and a commendable environmental performance. However, in recent decades, emission intensity has been on the rise, suggesting that economic growth has been largely driven by increased GHG emissions, with minimal environmental efficiency gains. Nonetheless, this pattern is not uniform across countries. Differences in emission intensity and a more favourable international climate for emissions reduction agreements have prompted researchers to explore two key aspects. Firstly, whether economic growth inherently leads to an increase in country’s GHG emissions. This has been a focus of literature, primarily centered around the Environmental Kuznets Curve (EKC) hypothesis, which posits an initial increase in emissions intensity as a country develops, followed by a decrease with an inverted U-shaped relationship between emissions and income (Kaika and Zervas 2013; Jaunky 2011; Al-Mulali et al. 2015). Secondly, the idea of emissions convergence among countries has gained support in empirical literature, with studies such as those by Pettersson et al. (2014), Ahmed et al. (2017) and Runar, Amin, and Patrik (2017).

Empirical findings suggest that various socioeconomic factors underlie the heterogeneity of GHG emissions convergence clubs, including development factors (Liu et al. 2019), energy factors (González-Álvarez, Montañés, and Olmos 2020), technology research and development (R&D) factors (Fernández Fernández, Fernández López, and Olmedillas Blanco 2018), globalization factors (Kim, Wu, and Lin 2020), demographic factors (Dong et al. 2018), and climate factors (Du, Zhao, and Huang 2017), among others.

However, a comprehensive global analysis faces limitations due to the substantial heterogeneity among countries. Many prior studies rely on assumptions that may distort overall evidence. Key critiques include the failure to account for intra-country variations inherent in social and economic structures, as well as limitations in the availability and quality of cross-country aggregate data (Payne, 2020). A selected few studies have explored the EKC and environmental convergence using within-country panel data (Apergis 2016), providing sub-national evidence for regions within countries. In recent years, analyses at the individual country level have emerged, including studies in the United States (Kounetas, Polemis, and Tzeremes, 2021), Australia (Ivanovski and Awaworyi Churchill, 2020), Canada (Hamit-Haggar, 2019), and China (Zhao, Wesley Burnett, and Lacomb,e 2015). These studies employ various methodologies and definitions of EKC and convergence.

Over the past three decades, Spain has experienced robust economic growth, positioning itself as a leading European country. Economic prosperity has been distributed among Spanish regions through a transfer system and the political autonomy.

Additionally, this growth has facilitated the adoption of ecological measures and the development of sustainable activities, notably in the renewable energy sector, where Spain has emerged as a global leader thanks to its abundant natural resources, particularly wind and solar energy. The primary objective of this research is to quantify the convergence process of emissions intensity at the regional level in Spain during the period 1990 – 2018. We distinguish between the direct and diffuse sector based on the energy intensity of economic activities. The emissions within these sectors arise from economic activities characterized by significantly different levels of energy-intensity utilization, consequently resulting in varying degrees of ecological impact. This differentiation allows us to provide more precise policy recommendations to optimize costs and efforts among regions, which represents a novel aspect of our analysis.

Within this context, we undertake an analysis utilizing three distinct metrics of emission intensity to assess the environmental efficiency of economic activities based on emission reduction regulations. Another noteworthy aspect is the nation itself; Spain is of particular interest due to its regions possessing a high degree of decentralization in political decision-making. Despite the introduction of uniform policies by the national government, all regions exhibit substantial differences.

The paper is structured as follows: Section 2 provides details on the data and introduces the methodology used. Section 3 presents the results, while Section 4 discusses concluding remarks and policy recommendations.

## 2. Materials and methods

### *2.1. Materials*

The GHG data came from open data sources provided by the Spanish National Inventory System within the Ministry of Ecological and the Demographic Challenge. This data is published in accordance with the IPCC-CRF (Common Reporting Format) control methodology, established by the United Nations Framework Convention on Climate

Change (UNFCCC) for all signatory nations of the Kyoto Protocol in 1992 and the Paris Agreement in 2015. The inventory submission illustrates the correspondence of CRF categories with economic activities and emissions generation, including energy production and distribution, energy use in industry, transport, commercial, institutional and households, industrial processes and product use; agriculture, and waste.

The dataset is measured in thousand metric tonnes of carbon dioxide equivalents (ktCO2 eq) for each economic activity. The period covers the years from 1990 to 2018, with data reported on an annual basis. It encompasses the 17 Spanish regions: Andalucía (AND), Aragón (ARA), Asturias (AST), Islas Baleares (BAL), Islas Canarias (CAN), Cantabria (CAB), Castilla y León (CYL), Castilla – La Mancha (CLM), Cataluña (CAT), Comunidad Valenciana (CVA), Extremadura (EXT), Galicia (GAL), La Rioja (RIO), Madrid (MAD), Murcia (MUR), Navarra (NAV), and País Vasco (PVA). The data also include the two autonomous cities of Ceuta and Melilla,[i] both small cities located in North Africa and part of the territorial organization of Spain. Additionally, GDP data by region are expressed in 2016 constant prices.

To assess environmental efficiency, we propose three indicators for emissions intensity. First, we define Direct Emissions Intensity (DREI) as the ratio between economic activities of the direct emissions sector (energy production and distribution, and energy use in industry) and GDP. We also define Diffuse Emissions Intensity (DFEI) as the ratio between economic activities of the diffuse emissions sector (transport, commercial, institutional and households, industrial processes and product use, agriculture, and waste) and GDP. In this context, DREI represents activities with a high degree of energy dependence, and therefore, they are more polluting than DFEI activities. Finally, Total Emissions Intensity (TEI) is the ratio between all economic activities and GDP. In all cases, a lower ratio indicates lower emissions generated per unit of output, indicating higher efficiency. A detailed description of each economic activity can be found in supplementary Table A.1 of the Appendix A.

Table 1 presents descriptive statistics for the three ratios across the regions. AND shows the highest mean value for the direct emissions sector, with an average of 25,422.06 ktCO2 eq, followed by AST. Subsequently, the regions of CYL, CAT, and GAL follow with the rest of the regions falling behind. For the diffuse emissions sector, the standard deviation across the entire panel indicates greater dispersion of regional performance. In this case, CAT represents the highest level at 29,871.19 ktCO2 eq, closely followed by AND. After these, CYL, MAD, GAL, CVA, and CLM have the highest emissions. Therefore, the regions with the highest total emissions are AND, CAT and CYL, while the rest of the regions follow. However, when discussing regional performance in terms of GDP, the situation is reversed. Regions with high emissions levels have lower economic development than one might assume: CYL and AST are good examples of this, ranking seventh and thirteenth, respectively. Conversely, regions with minimal pollution and strong economic growth, such as, MAD, CVA, and PVA, rank second, fourth and fifth, respectively.

[Table 1 near here]

### *2.2. Methods*

Measuring economic convergence involves assessing the extent to which regions or countries are closing the gap in terms of their economic well-being and development. Researchers have often used statistical tools like sigma-convergence and beta-convergence to quantify the dispersion or narrowing of factors disparities among regions or countries (Barro and Sala-i-Martin, 1991; Barro and Sala-i-Martin, 2004). Beta convergence focuses on the speed or rate of convergence. It examines whether initially less-developed regions or entities tend to grow at a faster pace, in terms of economic indicators compared to more prosperous ones. Sigma convergence, on the other hand, concentrates on the reduction of absolute disparities in economic indicators among regions or entities. It looks at whether the variation or spread in economic performance is decreasing over time, indicating a reduction in inequality. These approaches help economists and policymakers understand how regions or entities are evolving and whether policies should be tailored to address specific types of convergence or divergence.

In addition to the traditional concepts of beta and sigma convergence, the concept of club convergence has attracted increasing interest in the literature. Club suggests that economies or regions tend to cluster into distinct groups based on their economic performance. It implies that there might be different convergence patterns or steady-state levels of development for different groups of regions or entities. Two distinct methodological strategies appear in the literature on the analysis of convergence clubs. The first approach, inspired by Quah (1993, 1997), examines convergence clubs by studying how the distribution of a specific variable changes over time. This method uses tools like stochastic kernel density functions and Markov chains without making strict assumptions. The second approach involves using parametric models, specifically beta convergence models, while considering differences between individual economies. When we account for these differences, we can explore whether economies tend to one or more common equilibria. If they do, it suggests the existence of different convergence clubs. This method has been influenced by the work of Azariadis and Drazen (1990) and Galor (1996).

More recently, Phillips and Sul (2007) and Phillips and Sul (2009) introduced a novel econometric approach involving a nonlinear factor model with a growth component and a time- varying idiosyncratic component. This approach enables the identification of the relative transitions in heterogeneity, along with temporal series regression test for convergence. Notably, this approach circumvents the challenges posed by unit root cointegration tests and avoids the imposition of specific assumption about the time properties of the variables.

The logarithmic t-convergence test serves as the foundation for a stepwise clustering algorithm designed to identify convergence clusters in panel data, and analyse differential transitional behaviours among these clusters. In essence, this allows us to distinguish groups of economies that converge to different equilibria from those that deviate from the rest without reaching a stationary equilibrium. Recent research, including studies by Herrerias (2013), Apergis and Payne (2017) and Haider and Akram (2019), has leveraged these features to explore the formation of groups of nations exhibiting similar emissions intensity patterns, as well as those exhibiting unique and distinct behaviour.

Following the methodology of Phillips and Sul (2009) and Phillips and Sul (2007), we consider Xit as the variable under analysis (DREI, DFEI or TEI) with i and t representing the indicators for Spanish regions and time, respectively. This variable can be decomposed as Xit = $\delta_{it}\mu_t$ where $\delta_{it}$ is the time- varying factor measuring the idiosyncratic difference between common trend components $\mu_t$ and Xit . This framework suggests the presence of convergence if $\delta_{it}$ converges toward a common value $\delta$. It is important to note that $\delta_{it}$ may trace out transition paths to substantially different steady states across regions. Thus, the first step can be interpreted as a relative transition parameter ($h_{it}$), defined as follows (Phillips and Sul, 2007):

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N} \delta_{it}} \tag{1}$$

This transition path captures the individual relative deviation of each region relative to the panel average, effectively removing the trend component. In cases of convergence, the element $\delta_{it}$ converges towards $\delta$, and as a result, $h_{it}$ should converge towards 1, with cross-sectional variation ($H_{it}$) defined as follows (Phillips and Sul, 2007):

$$H_{it} = N^{-1}\sum_{i=1}^{N}(h_{it} - 1)^2 \rightarrow 0, \qquad as \qquad t \rightarrow \infty \tag{2}$$

This value approaches 0 as time approaches infinite in the presence of convergence, whereas it converges to a non-zero constant or diverges when convergence is absent.

The test for convergence hypothesis, following Phillips and Sul (2007) for this type of dataset, can be empirically estimated through the following log-t regression equation, where r equals the value 0.3:

$$log\frac{H_1}{H_2} - 2log[log(t)] = \alpha + \beta log(t) + u_t, \qquad t = [rT] + 1, \dots, T \tag{3}$$

The null hypothesis of convergence ($\beta = 0$), is rejected at the 5% level when the t-statistic takes values lower than – 1.65. Thanks to equation (3), autocorrelation and heteroskedasticity issues are addressed, leading the t-ratio to converge towards a standard N(0,1) distribution when the convergence hypothesis is rejected.

In cases where the hypothesis of convergence is rejected, the authors propose a clustering algorithm to group regions that converge to the same steady state, thereby identifying clubs within the sample. One piece of advice from their paper is to examine the possible merging of clubs, using equation (3) to prevent an overestimation of the number of clusters. To address this issue, our results includes a club-merging analysis for convergence between two adjacent clubs when there are two or more clubs. In line with the recommendation of Phillips and Sul (2007), we extracted the trend components for the series of our analysed variable (Xit ) using the Hodrick and Prescott (1997) filter, applying the standard value $\lambda$ = 400. [ii]

## 3. Results

Our three ratios for measuring the environmental efficiency of the entire sample are depicted in Figure 1. As observed, there is a declining trend from 1990 onwards. Specifically, DREI, DFEI, and TEI have decreased by 69.0%, 26.5% and 44.4%, respectively. While it might initially appear that TEI inertia is driven by the direct emissions sector, this is not the case. In the initials years, GHG emissions are equally distributed between both sectors. However, from 2008 onwards, diffuse emissions surpass direct emissions in significance. It is noteworthy that during the 2008 to 2009 period, coinciding with the shock of the Great Recession, the most substantial rate decreases in total emissions were recorded at 9.3% and 8.5%, respectively. In 2008, diffuse emissions declined by 5.4%, and in 2009, direct emissions decreased by 17.9%; both of which represent record year-on-year figures for all datasets. In any case, it is evident that the decline in TEI has been more rapid in the last decade than in the previous one, and this trend is still faster than earlier decades.

[Figure 1 near here]

It becomes clear from the available evidence that our TEI measures for all regions are lower at the end of the period, as shown in Figure 2. In other words, all regions have increased their output value while simultaneously managing to reduce their total emissions. This indicates that all regions have improved the efficiency of their productive activities from an environmental perspective. Therefore, we can observe evidence of the Environmental Kuznets Curve (EKC) hypothesis, where economic growth does not necessarily lead to greater environmental damage. The trajectory of this intensity is more crucial for our analysis than the actual level reached by this ratio, although it is true that not all regions, as not all have achieved the same level of efficiency.

When we closely examine the results by emissions sector, the variability in behaviours becomes even more pronounced. DREI and DFEI patterns exhibit varying rates and deviations across regions. Figure 3 illustrates the change in direct emissions intensity is illustrated for the entire sample. Most regions have achieved gains in environmental efficiency in energy-intensive economic activities. Even regions with a substantial volume of direct emissions have made efforts to enhance their efficiency, such as AND (– 39.6%) and AST (– 83.3%). However, there is a group of four regions (CYM, EXT, RIO, and MUR) whose efficiency has notably worsened, despite having lower emissions in activities related to energy production, distribution, and energy use in industry. Thus, the regions with higher GHG emissions are making greater efforts to reduce them.

Similarly, in Figure 4, variations in diffuse emissions intensity are presented for the entire dataset. On this occasion, the generation of efficiency gains in DFEI is shared by all regions, albeit at a slower rate than DREI. In this category of economic activities related to  the diffuse sector, regions appear to exhibit more erratic behaviour. The most polluting regions are not doing enough to improve their efficiency in activities such as transport, households, industrial processes, and agriculture. CAT and AND are the GHG emissions leaders in transport, but their efficiency improvements (– 47.5% and – 22.0% respectively) do not align with the environmental challenge. In commercial, institutional, and household activities, the region of MAD is the largest polluter; however, the efforts to improve efficiency remain inadequate (– 29.4%). Similarly, CYL is the largest emitter of GHGs in agriculture but does not top the list in terms of environmental efficiency (– 15.8%). A notable case is ARA, which ranks last (– 3.8%) despite being a significant player in the diffuse sector, specifically, in agriculture.

[Figure 2 near here]

[Figure 3 near here]

[Figure 4 near here]

In summary, the evidence aligns with the EKC hypothesis for the Spanish regions. Starting from the year 2008, the Great Recession resulted in two outcomes: an economic downturn and a further decline in GHG emissions. This suggests the emergence of a sustainable path following an external economic shock. Additionally, we observe a shift in the sources of pollution, transitioning from economic activities that are more energy-intensive to other types of activities.

### *3.1. Club convergence*

The t-statistic's significance in the analysis of convergence for our measures of emissions intensity (DREI, DFEI, and TEI) concerning  environmental efficiency is presented in Tables 2, 3, and 4.

Table 2 presents the results for the club-clustering algorithm applied to DREI. The first row in Panel A displays the log-t regression for all eighteen regions in Spain, clearly demonstrating the rejection of the null hypothesis of convergence, as the t-stat is less than – 1.65 (i.e., – 31.213 < – 1.65). Subsequently, no common behavioural pattern is observed, prompting the application of the clustering algorithm to investigate the presence of distinct of clubs. The results reveal the existence of only one convergent club, encompassing all regions except AST and MAD, with latter constituting a non-convergent (divergent) club.

It is essential to emphasize the cases of AST and MAD. AST stands out as the region with the second-highest levels of direct emissions, attributed to an economic structure heavily reliant on energy-intensive activities like coal mining and the iron and steel industry. Nevertheless, its evolution has significantly reduced such emissions by 32.4% in absolute terms, bringing it closer to closing the DREI gap compared to other regions in the sample. Conversely, MAD has the lowest emission ratio, with activities such as energy production, distribution, and energy use in industry holding negligible weight in terms of emissions. This region has maintained a nearly stagnant direct emissions sector, resulting in stable DREI values over the years. MAD has transitioned into an almost entirely service-based economy and serves as the country's capital, housing its central administration. Panel C in Table 2 presents the final results in a map.

To better understand the obtained results, Figure 5 presents the average values of the DREI ratio for estimated Club 1, in conjunction with the values of the non-convergent regions (AST and MAD). There is a general decline in all paths of the DREI ratio, indicating efficiency gains from an environmental perspective. Additionally, it is important to note that the deviation among them is lower at the end of the sample period than at the beginning. In other words, all regions demonstrate efforts to reduce GHG emissions, with historically more-polluting regions shouldering the greatest Notably, the timing of correction varies. AST saw a significant drop in the early 2000s, from 2000 to 2008, with an average decrease of 7.7%, followed by a more modest 1.5% decline thereafter. In contrast, Club 1 and MAD experienced a more substantial decline after the Great Recession, with drops of 5.0% and 5.5%, respectively.

[Table 2 near here]

[Figure 5 near here]

Secondly, when we consider the DFEI ratio, the results for club convergence findings are presented in Table 3. The null hypothesis is again rejected for all regions since the t-stat (– 50.215) is lower than – 1.65. After accounting for various regional performances, convergence analysis yields new club estimations listed in Panel A. The evidence reveals four convergence clubs and one non-convergent club. Club 1 comprises AST, CLM and CYL. Club 2 includes ARA and CAB. Club 3 contains RIO and NAV, while Club 4 is the largest group, consisting of AND, BAL, CAN, CAT, CYM, CVA, MUR and PVA. In contrast, divergent regions are EXT, GAL and once again MAD. Panel B reveals the club-merging analysis, considering possible aggregations between clubs with adjacent estimated figures. In Panel C, a geographic representation of the final classification highlights more varied behaviours according to DFEI than to DREI. The heterogeneity in DFEI patterns is explained in the next section through an analysis of the forces that drive club formation.

We now focus on the non-convergent regions, EXT, GAL and MAD. Initially, EXT may seem to have no reason to show a divergent performance, given its normalized emissions level in the diffuse emissions sector. However, it stands out as the only region where more than half of GHG emissions originate from cereal agriculture and livestock, particularly sheep and Iberian swine cattle. GAL, historically distant from other Spanish regions due to its location surrounded by the Atlantic Ocean and Portugal, exhibits a different performance driven by emissions in transport and agriculture. High emissions in transport are attributed to a higher percentage of dispersed population settlements compared to other territories. Additionally, emissions in agriculture are largely attributed to cattle farming for milk and meat. In addition to the factors previously mentioned for MAD, considerable emissions in transport are due to its role as a core region with national road and rail radial networks, and the Spain's main airport, which serves as the most significant hub for domestic aviation.

Figure 6 displays the average values of the DFEI ratio for all estimated convergence clubs, as well as the values of non-convergent regions (EXT, GAL and MAD). A clear downward trend is observed, although not as steep as in the case of DREI Interestingly, the onset of the Great Recession does not appear to accelerate the downward trajectory compared to previous years, except for MAD. It is worth emphasising that both Club 4 and GAL exhibited a consistent decline both before and after the Great Recession. Thus, all clubs achieve gains in environmental efficiency, but the effort is not evenly distributes across regions. The deviation in differences between the average values of the clubs remains relatively constant over the years. Consequently, the degree of heterogeneity remains stable at the end of the sample period, with no indication that these differences will disappear in the near future.

[Table 3 near here]

[Figure 6 near here]

Table 4 reports the club convergence analysis for the TEI ratio. The null hypothesis of convergence for all regions is once again rejected because the t-statistic is equal to – 55.866, lower than – 1.65. In this case, there is no common behavioural pattern; therefore, we apply clustering algorithms to investigate the existence of clubs. Panel A reveals two convergent clubs and one divergent club. Convergent Club 1 comprises AND, ARA, BAL, CAN, CAB, CLM, CYL, CVA, EXT, GAL, RIO, MUR and NAV. Club 2 includes CAT and CYM, while the divergent club consist of AST (for the second time), MAD (which has consistently appeared as a non-convergent region), and PVA. Similarly, Panel B in Table 4 illustrates the merging estimation between adjacent clubs.

Our final club classification is presented in Panel C, with Club 1, Club 2, and three divergent regions. Similar to the DFEI ratio, we explain the underlying factors driving this heterogeneity in various patterns for TEI in the following section. The cases of AST and MAD have been previously explained; that is, one of the two emission sectors (direct and diffuse) dominates in each region . For all years, the direct emissions sector accounts for an average of 75.6% of total GHG emissions in AST, while the diffuse emissions sector contributes 80.4% in MAD. Since 1990, PVA has maintained a consistent GHG emissions mix between the direct and diffuse sector. Its economy relies on more energy-intensive activities, such as petroleum refining and natural gas exploration, production, storage, and distribution, leading to significant increases in GHGs from transport and residential activities. Transport emissions have risen due to increased personal and industrial mobility, with minimal reliance on public transport. Residential emissions have increased due greater energy consumption. PVA is not a leading region in pollution but has made substantial efforts, surpassing other regions, to improve environmental efficiency over the years (with a value of – 77.1%, it is the second-best region for reducing the DFEI ratio).

Regarding TEI, Figure 7 illustrates the transition paths for estimated Club 1 and Club 2, along with the non-convergent regions (AST, MAD and PVA). The results confirm our previous findings, showing an overall downward trend in the TEI ratio, indicating improvements in environmental efficiency. Notably, the deviation in performance decreases for all regions towards the end of the period, although future trajectories remain uncertain. In terms of total emissions, the Great Recession appears to have spurred efforts to improve environmental efficiency, as Club 1, Club 2, and the divergent regions have more than doubled their rate of descent, aligning with the TEI ratio.

[Table 4 near here]

[Figure 7 near here]

In summary, our results differ depending on the emissions intensity measure considered. The analysis of the convergence hypothesis for the DFEI ratio reveals more disparities than the other two ratios: DREI and TEI. The greater diversity of behaviours within the DFEI groupings suggests more complex reasons for these differences compared to TEI. The following section is dedicated to examining the underlying factors in more detail. The results of the club analysis of the DREI are very similar, with minimal differences among all regions.

### *3.2. Factors driving the clubs*

We further analyse the factors influencing the clustering convergence of DFEI and TEI measures, excluding DREI as it only has one convergence club. The heterogeneity in performance patterns across Spanish regions in the diffuse emissions sector and total emissions reflects the forces driving the creation of these clubs. However, the primary focus should be on emissions from the diffuse sector, as these emissions contribute significantly to overall pollution. A deeper understanding of these factors can help promote emissions efficiency.

To confirm the factors behind the clubs, we employ suitable methodologies for each ratio. We estimate an ordered logistic model for DFEI and a binary for TEI, this approach is highly similar to that taken by Panopoulou and Pantelidis (2009) and Burnett (2016). We employ a model selection approach, progressively removing statistically insignificant explanatory variables. Additionally, we check for multicollinearity or heteroskedasticity but find no evidence of these issues. It should be noted that due to limited data availability, we have only 18 possible observations. This sample size would be even smaller if we considered only the club estimations from DFEI and TEI ratios. Nevertheless, our results are robust.

For DFEI, we employ an ordered logistic regression model based on the ordinal classification of the clubs. The dependent variable corresponds to the number of clubs estimated, and its values represent the preference or ranking of the clubs. We model the cumulative probabilities of the ordinal response, where $Y_i$ represents the results of the club-clustering algorithm for DFEI, $X_i$ is the vector of the explanatory factors, and $F_{ic}$ is the probability that region i belongs to convergence club c of the DFEI ratio. The model is defined as (Panopoulou and Pantelidis, 2009; Burnett, 2016):

$$F_{ic} = Pr(Y_i \leq y_c X_i),\ c = 1, \dots, C \tag{4}$$

$$log\left(\frac{F_{ic}}{1-F_{ic}}\right) = \beta X_i + \varepsilon_c,\ \beta X_i = \beta_1 X_{i1} + \dots + \beta_k X_{ik} \tag{5}$$

where ß is the estimate of the coefficient, $\varepsilon$ is the error term, and k is the number of explanatory factors. This model helps us investigate the factors affecting GHG emissions in the diffuse sector and the differences among regions.

For the two clubs of the TEI ratio, we employ a logistic model with a binary dependent variable: zero if a region belongs to Club 1 and one if it belongs to Club (6)
2. The model is defined as:

$$Y_i = \begin{cases} 0\ if\ Y_i^* \leq 0 \\ 1\ if\ Y_i^* > 0 \end{cases} \tag{6}$$

$$Y_i^* = \alpha + \beta X_i + \varepsilon_i \tag{7}$$

Where $\alpha$ is the constant, $X_i$ is a set of determinants of convergence for each region, and $\varepsilon$ is the error term. This model helps us examine the driving forces behind total GHGs in the regions.

Following the literature (Panopoulou and Pantelidis, 2009; Burnett, 2016), we evaluate the emissions intensity using selected variables, explaining differences among the Spanish regions. The explanatory variables finally used are:

- Development factors. We consider average annual net household income, INCOME (Source: National Statistical Institute (INE) of Spain), and INCOME squared (INCOME2) to reflect economic progress.
- We also examine the proportion of regional GDP generated by primary sector (PRIMARY). Source: National Statistical Institute (INE) of Spain.
- Proportion of regional GDP generated by industry and manufacturing sector, INDUSTRY. Source: National Statistical Institute (INE) of Spain.
- We assess the renewable power capacity installed, represented by ENERGY MIX as a percentage of the total regional power generating facilities. Source: Red Eléctrica Group of Spain (REE).
- We include average temperature in degree Celsius (ºC) for period 1981 - 2010 by region (TEMPERATURE) to examine the impact of climate on emissions.. Source: State Meteorological Agency (AEMET) of Spain.

Positive coefficients for these variables indicate lower emissions intensity, contributing to environmental efficiency gains. Negative coefficients suggest lower efficiency due to increased emissions. The results obtained for the DFEI and TEI measures of emissions intensity are presented in Table 5.

For DFEI, the variables INCOME2 and PRIMARY have a reducing effect on emissions intensity, while INCOME and ENERGY MIX have the opposite effect. The development drivers support EKC evidence at the 1% level of significance. Higher income levels represent initially lead to higher GHG emissions, but regions eventually reach a turning point where emission reduction outpaces economic growth, supporting the Environmental Kuznets Curve (EKC) hypothesis, result that is consistent with previous studies such as Balaguer and Cantavella (2016). Moutinho, Varum, and Madaleno (2017) argue that there is no evidence that all types of activities of the Spanish economy have yet reached the turning point.

However, the analysis should consider the components of regional GDP to pinpoint reductions in emissions through less-polluting activities. The variable PRIMARY's positive sign indicates that a higher share of primary activities in GDP reduces the DFEI ratio. Notably, some regions, such as CLM and ARA, with high primary shares in their economies, do not exhibit expected environmental efficiency gains, which may require further investigation. Laso et al. (2018) estimate that in Spain, approximately 70% of the energy-saving potential for food production and processing lies within the agricultural stage. Consequently, if the system were to operate efficiently, it would be possible to reduce GHG emissions related to this sector in a similar proportion. In the case of ARA, Baccour, Albiac, and Kahil (2021) have revealed that there is still considerable significant room for introducing mitigation measures to reduce emissions and promote sustainable agriculture. Similar conclusions have been drawn for CLM in agriculture (Ortega, de Juan, and Tarjuelo 2005) and dairy production (Morantes et al. 2017).

Surprisingly, the ENERGY MIX variable shows a negative relationship with the DFEI measure, challenging the intuitive idea that a higher proportion of renewable energy resources would reduce emissions and improve environmental efficiency. Montoya, Aguilera, and Manzano-Agugliaro (2014) illustrate how renewable energies have contributed to alleviate the energy shortfall that Spain has experienced in recent years. This is attributed to differences in energy production and consumption across regions, where some regions with surplus renewable energy transfer it to others, resulting in environmental efficiency losses.

For TEI, the results again support the EKC hypothesis, with higher income levels associated with lower emissions. The variable INDUSTRY, representing a high share of industry in regional GDP, increases the TEI ratio, indicating that emissions from energy-intensive industries should be addressed to achieve significant emission reductions. As suggested by Tarancón and del Río (2007), addressing CO2 emissions in more energy-intensive products, such as non-metallic minerals (cement, bricks, lime, and glass), metallurgy, and chemicals, is crucial for achieving significant reductions in total emissions. However, Cansino, Román, and Ordóñez (2016) emphasize that Spain did not transition to less carbon-intensive production until the onset of the Great Recession, which poses a challenge in reducing emissions from energy-intensive activities. Notably, regions such as NAV and RIO, characterized by a substantial industrial presence in their economies, belong to Club 1.

ENERGY MIX continues to have a significant effect on the TEI ratio, with regions like CYL, GAL, CLM, and EXT in Club 1, benefiting from surplus renewable energy produced in these regions. Nearly two-thirds of their energy production originates from renewable sources. However, these regions do not fully consume the energy they generate and transfer their excess energy to others, which, in turn, results in environmental efficiency losses.

Moreover, a higher average temperature increases the probability of belonging to Club 1, as warmer climates lead to increased electricity demand for cooling. This is a concern for Spanish regions, particularly those reliant on tourism, where uncontrolled growth in energy consumption from cooling systems may impact environmental efficiency. Economic activities such as retail, hotels, and restaurants, among others, play an important role in the level of total emissions, but this is often overlooked (Alcántara and Padilla, 2009; Du and Ng, 2028).

[Table 5 near here]

In summary, the factors driving the DFEI and TEI clubs exhibit similarities but with distinct implications. Economic development positively influences environmental efficiency through multiplier effects, while an inferior distribution grid for renewable energy sources in high-demand regions counteracts efficiency gains.

## 4. Conclusions and policy recommendations

The aim of this paper has been to identify the convergence process of greenhouse gas emissions in the Spanish regions using several measures of emissions intensity. We implement club convergence, based on the methodology proposed by Phillips and Sul (2007), for the 18 regions in Spain, including the union of the two autonomous cities of Ceuta and Melilla, spanning the period from 1990 to 2018. Prior research provides valuable foundation for evaluating environmental efficiency of economic output. In this study, we employ three ratios to assess emissions efficiency, with the advantage of distinguishing emissions between the direct and diffuse sectors. The primary distinction lies in the level of energy intensity. Historically, more energy-intensive activities have faced stringent environmental regulations, while other sectors have encountered more flexible regulations. Consequently, policymakers may have influenced the severity or mitigation of climate change effects.

We link our emissions intensity ratios to the examination of the Environmental Kuznets hypothesis in Spain. Our goal is to investigate whether economic growth inevitably leads to increased GHG emissions. Our analysis reveals that emissions intensity results for all regions were lower at the end of the period, indicating a decoupling between economic growth and pollution.

The Great Recession did not significantly accelerate this trend, as each additional unit of gross economic value led to a marginal increase in total pollution of less than one. Another consequence of this economic shock was a change in the emissions pattern, with the diffuse emissions sector driving the increase in total emissions. At the regional level, there is substantial heterogeneity in performance, with efficiency gains differing between regions. Regions where the direct emissions sector dominates have been more successful in improving environmental efficiency. Conversely, regions with a greater share of diffuse emissions have made slower progress.

Thus far, environmental policy guidelines have not effectively distributed efforts to reduce GHG emissions equitably among all regions. This imbalance in regulation does not appear to be rectified in the near future. As the importance of the diffuse emissions sector grows, there is a need for increased efforts to reduce emissions in the most polluting regions, coupled with mechanisms that promote efficiency improvements in transport, commerce, households, industrial processes, agriculture, and waste management.

From the convergence analysis, the empirical evidence rejects the null hypothesis for all intensity measures. The evidence against convergence is stronger in the cases of the diffuse emissions sector and total emissions. In a subsequent step, we conduct a clustering study, which yields different results depending on the chosen emissions intensity ratio. When examining diffuse emissions intensity, we identify the largest number of clubs, totalling four. On the other hand, there are two clubs for total emissions intensity and only one for direct emissions intensity.

We extend our analysis to determine the drivers behind the formation of these clubs. In this process, we consider the estimated clubs for the total and diffuse emissions sectors, with a particular focus on the latter. The results suggest that income level, breakdown of value adding, and the energy mix of renewables power are the primary determinants of GHG emissions in the Spanish regions. In the case of the diffuse emissions sector, the results also highlight to the importance of climate temperature, in addition to the previously mentioned factors. While these findings support the EKC hypothesis, they should be interpreted with caution. The relationship between income and emissions depends on multiple factors, and our analysis cannot determine the exact income level at which the tipping point occurs.

Several policy recommendations emerge from our study, although further research is necessary. Firstly, our results suggest the need for a national-level agreement among all Spanish regions to equitably share efforts to reduce emissions, particularly in the diffuse emissions sector. Secondly, this agreement should acknowledge the diverse behaviours across the regions, prompting regional governments to develop climate change strategies to combat climate change encompassing territorial development, transportation, education, and household initiatives, among others. Thirdly, regions should prioritize long-term environmental efficiency improvement, focusing on (1) promoting zero-emissions solutions across all economic activities, (2) advocating for renewable energy adoption in all regions, not solely those with abundant resources, and (3) capitalizing on the growing consumption trend to design sustainable energy-saving standards for citizens.

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## Appendix A

**Table A.1.** Definitions for economic activities emissions

| Economic activity | Description |
|---|---|
| Energy production and distribution | ▪ Fuel combustion activities.<br>▪ Exploration, production, transport, refining/storage, and distribution for solid fuels and oil and natural gas. |
| Energy use in industry | ▪ Mineral industry, such as, production of cement, lime, and glass.<br>▪ Other process uses of carbonates.<br>▪ Manufacturing industries (i.e., iron and steel, non-ferrous metal, pulp and paper, etc.) and construction. |
| Transport | ▪ Domestic aviation.<br>▪ Road transportation.<br>▪ Railways.<br>▪ Domestic navigation.<br>▪ Other transportation. |
| Commercial, institutional and households | ▪ Commercial retail.<br>▪ Institutional buildings.<br>▪ Stationary and mobile residential.<br>▪ Farms of all types (agriculture, forestry, and fishing).<br>▪ Other non-specified. |
| Industrial processes and product use | ▪ Chemical industry.<br>▪ Metal industry.<br>▪ Other non-energy products from fuels.<br>▪ Industrial and domestic refrigeration (stationary and mobile).<br>▪ Other product manufacture and use, for example, electric equipment and medical applications.<br>▪ Pulp and paper industry.<br>▪ Food and beverages industry.<br>▪ Other (i.e., fireworks, tobacco, etc.). |
| Agriculture | ▪ Dairy and non-dairy cattle.<br>▪ Livestock of sheep, swine and other (i.e., poultry, goats, horses, mules, and asses).<br>▪ Manure management.<br>▪ Agricultural soils, cultivation of irrigated crops and cereals, with application of inorganic and organic fertilizers.<br>▪ Field burning and residues. |
| Waste | ▪ Managed waste disposal sites.<br>▪ Composting and biogas facilities.<br>▪ Incineration and open burning of biogenic and non-biogenic waste.<br>▪ Domestic and industrial wastewater treatment and discharges.<br>▪ Other non-specified. |

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i The figures for the autonomous cities are not shown individually because of their low degree of representation. In this manner, our subsequent analysis always has 18 regions, the last one being the combination of Ceuta and Melilla (CYM).

ii The smoothing parameter, $\lambda$, of the Hodrick-Prescott filter should be adjusted when changing the frequency of observations which can affect the results of filtering (Ravn and Uhlig 2002). We have defined $\lambda = 400$ as noted (Phillips and Sul 2009). Results do not change significantly with $\lambda=100$ for annual data.

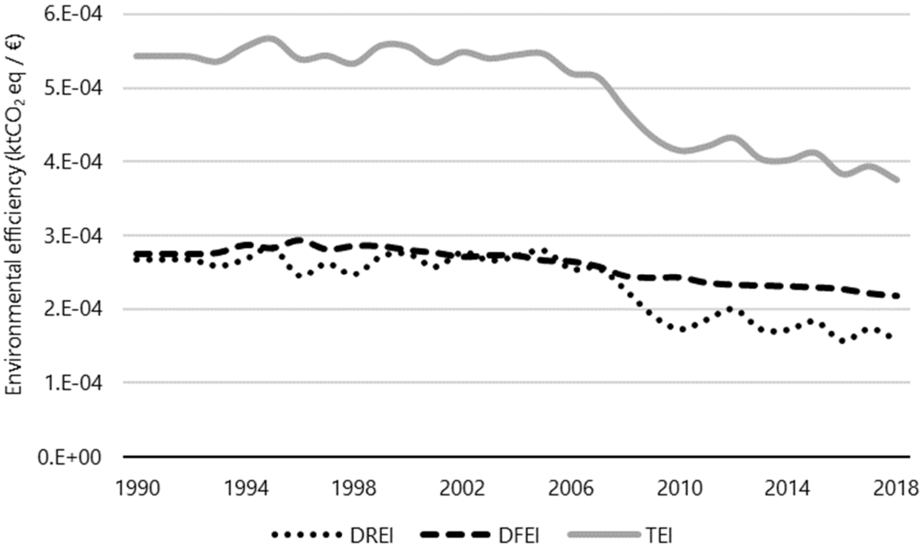


**Figure 1**. Average Direct Emissions Intensity (DREI), Diffuse Emissions Intensity (DFEI), and Total Emissions Intensity (TEI): 1990-2018.

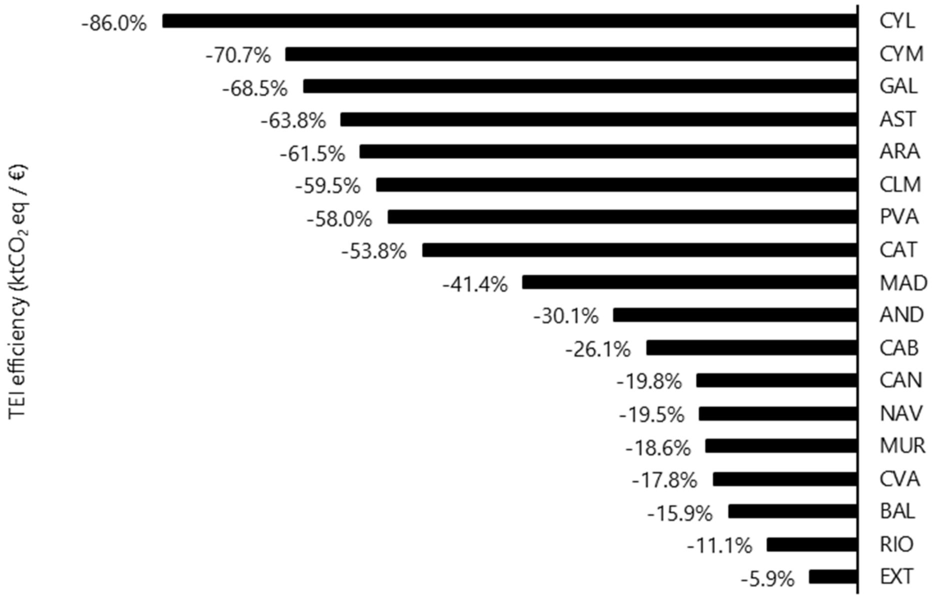


**Figure 2**. Percentage change of Total Emissions Intensity (TEI): 1990 - 2018.

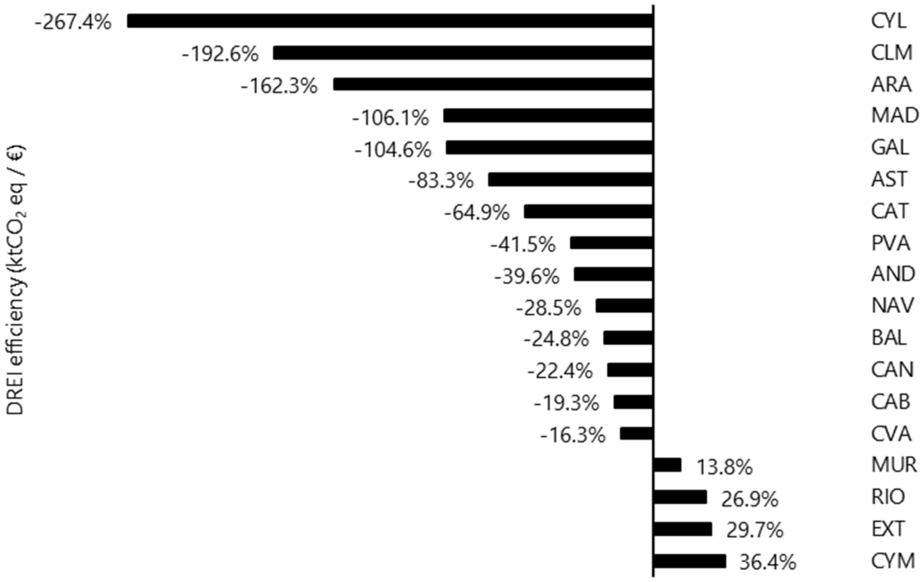


**Figure 3.** Percentage change of Direct Emissions Intensity (DREI: 1990 - 2018.

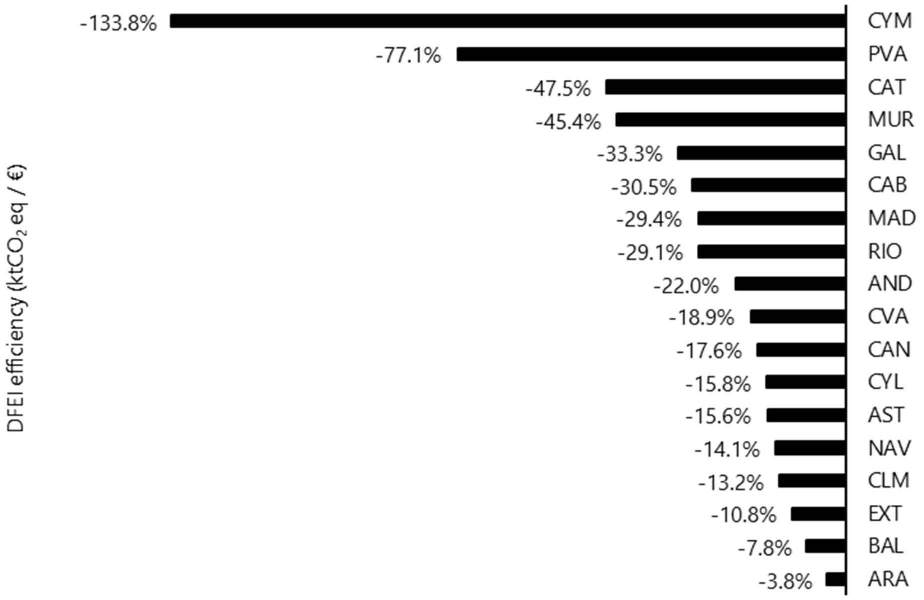


**Figure 4.** Percentage change of Diffusive Emissions Intensity (DFEI): 1990 - 2018.

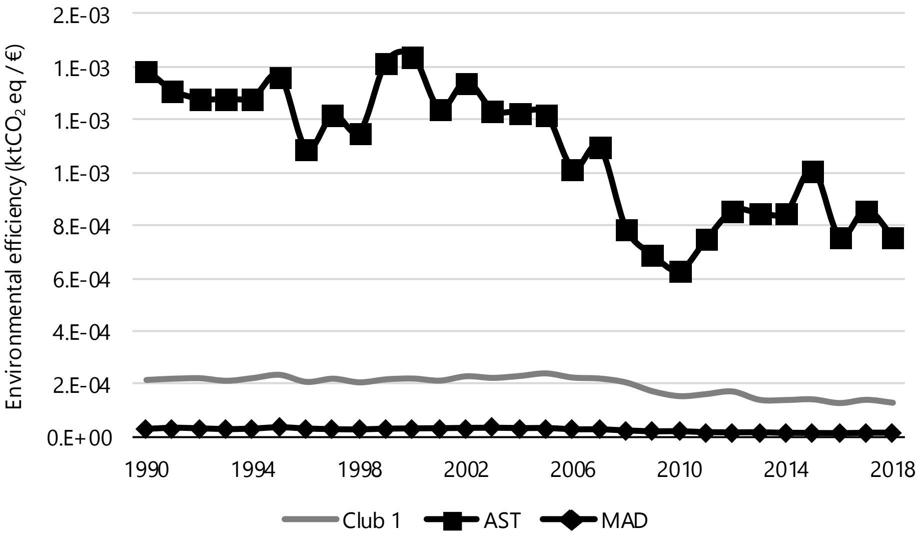


**Figure 5.** Average Direct Emissions Intensity (DREI) by club and non-convergent regions.

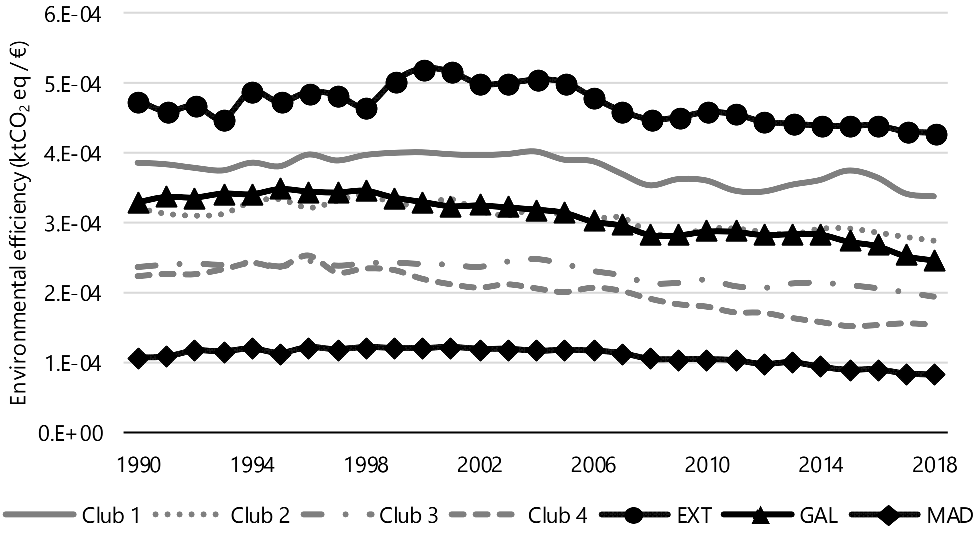


**Figure 6.** Average Diffuse Emissions Intensity (DFEI) by club and non-convergent regions.

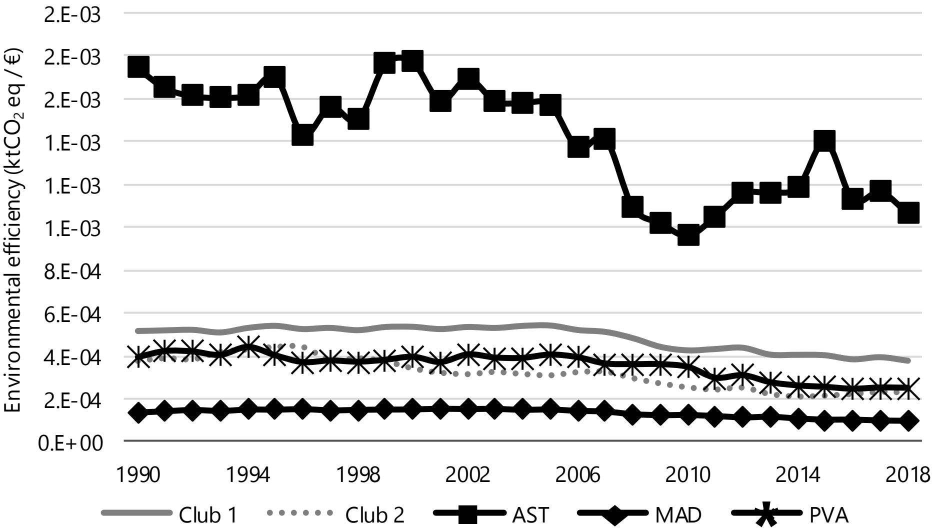


**Figure 7.** Averages Total Emissions Intensity (TEI) by club and non-convergent regions.

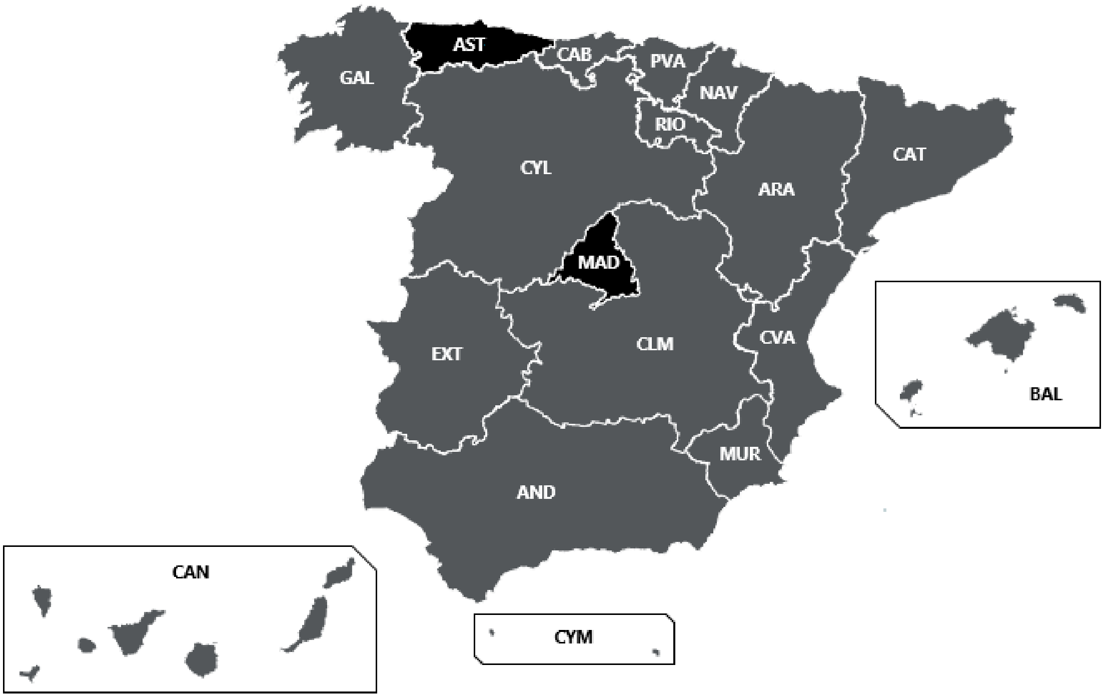
**Table 1.** Descriptive statistics: emissions sector and GDP

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| Direct emissions sector | | | | |
| AND | 25,422.06 | 4,855.09 | 18,933.55 | 36,384.94 |
| ARA | 9,305.89 | 1,892.00 | 5,710.80 | 12,152.75 |
| AST | 21,720.59 | 3,999.75 | 14,429.22 | 28,194.88 |
| BAL | 4,559.84 | 986.51 | 2,968.54 | 5,950.98 |
| CAN | 5,867.10 | 1,228.22 | 3,929.45 | 7,632.23 |
| CAB | 2,459.82 | 473.75 | 1,649.00 | 3,191.93 |
| CYL | 17,511.83 | 5,366.69 | 5,638.13 | 25,167.56 |
| CLM | 8,729.87 | 2,569.48 | 4,219.29 | 12,868.99 |
| CAT | 17,962.31 | 3,241.18 | 13,474.85 | 25,254.29 |
| CVA | 11,304.59 | 2,200.50 | 7,391.06 | 15,078.83 |
| EXT | 795.97 | 323.08 | 459.75 | 1,559.48 |
| GAL | 17,076.65 | 3,070.00 | 10,934.69 | 22,197.15 |
| RIO | 800.96 | 553.68 | 327.83 | 2,240.36 |
| MAD | 4,329.55 | 1,101.72 | 2,792.93 | 6,444.00 |
| MUR | 3,408.55 | 1,317.58 | 1,855.60 | 7,403.62 |
| NAV | 2,554.62 | 848.96 | 1,448.56 | 4,284.15 |
| PVA | 10,391.63 | 2,188.23 | 7,476.23 | 15,076.26 |
| CYM | 245.92 | 79.66 | 116.89 | 365.70 |
| *Panel* | 9,135.99 | 7,985.46 | 116.89 | 36,384.94 |
| Diffuse emissions sector | | | | |
| AND | 26,843.84 | 4,241.63 | 19,467.21 | 33,600.15 |
| ARA | 8,689.02 | 1,214.14 | 6,224.57 | 10,573.65 |
| AST | 6,851.41 | 833.07 | 5,468.89 | 8,277.57 |
| BAL | 4,325.47 | 636.74 | 2,949.23 | 5,247.80 |
| CAN | 7,581.45 | 1,694.97 | 4,507.04 | 10,123.65 |
| CAB | 3,546.67 | 416.63 | 2,721.80 | 4,207.12 |
| CYL | 19,251.04 | 2,227.05 | 15,427.07 | 22,372.33 |
| CLM | 12,690.94 | 1,987.21 | 9,260.27 | 15,807.95 |
| CAT | 29,871.19 | 2,812.65 | 23,634.58 | 34,841.46 |
| CVA | 14,502.88 | 2,469.13 | 10,214.01 | 19,014.83 |
| EXT | 7,290.52 | 1,254.22 | 5,118.40 | 8,592.11 |
| GAL | 14,985.79 | 1,428.95 | 11,808.55 | 17,128.94 |
| RIO | 1,567.00 | 208.80 | 1,216.86 | 1,883.15 |
| MAD | 17,870.30 | 3,118.28 | 11,560.66 | 22,450.06 |
| MUR | 4,931.69 | 621.65 | 3,794.10 | 6,093.34 |
| NAV | 3,476.07 | 526.35 | 2,499.33 | 4,126.78 |
| PVA | 9,283.68 | 911.28 | 7,993.59 | 11,126.12 |
| CYM | 673.22 | 172.83 | 331.96 | 937.84 |
| *Panel* | 10,790.68 | 8,348.25 | 331.96 | 34,841.46 |
| Total emissions sector | | | | |
| AND | 52,265.90 | 8,666.90 | 38,400.76 | 69,985.09 |
| ARA | 17,994.91 | 2,122.90 | 15,238.43 | 22,198.17 |
| AST | 28,572.00 | 4,097.07 | 21,983.61 | 35,247.97 |
| BAL | 8,885.32 | 1,578.57 | 6,018.19 | 10,931.09 |
| CAN | 13,448.56 | 2,794.65 | 8,533.50 | 17,622.46 |
| CAB | 6,006.50 | 855.38 | 4,370.81 | 7,393.76 |
| CYL | 36,762.88 | 5,583.94 | 26,777.49 | 46,364.46 |
| CLM | 21,420.81 | 3,475.11 | 16,822.45 | 28,676.94 |
| CAT | 47,833.51 | 5,676.18 | 38,641.91 | 57,340.79 |
| CVA | 25,807.48 | 4,485.59 | 17,605.08 | 32,721.72 |
| EXT | 8,086.50 | 1,514.46 | 5,594.99 | 10,151.60 |
| GAL | 32,062.45 | 3,213.98 | 27,420.78 | 37,919.70 |
| RIO | 2,367.96 | 716.41 | 1,544.69 | 4,047.19 |
| MAD | 22,199.86 | 3,752.06 | 14,975.26 | 28,306.11 |
| MUR | 8,340.25 | 1,838.40 | 5,649.71 | 13,018.97 |
| NAV | 6,030.69 | 1,291.32 | 4,063.21 | 8,289.19 |
| PVA | 19,675.32 | 2,947.98 | 16,352.97 | 25,056.56 |

| | | | | |
|---|---|---|---|---|
| CYM | 919.15 | 124.96 | 650.05 | 1,162.41 |
| *Panel* | 19,926.67 | 15,118.27 | 650.05 | 69,985.09 |
| GDP | | | | |
| AND | 126,160.89 | 23,904.08 | 88,272.06 | 155,839.12 |
| ARA | 29,462.34 | 5,024.43 | 21,743.70 | 36,135.36 |
| AST | 20,417.13 | 2,470.95 | 16,325.44 | 24,535.35 |
| BAL | 24,684.44 | 4,316.07 | 17,339.86 | 31,496.94 |
| CAN | 35,898.07 | 6,652.54 | 24,038.93 | 44,585.13 |
| CAB | 11,323.80 | 1,766.45 | 8,647.36 | 13,596.32 |
| CYL | 48,495.18 | 6,850.57 | 37,694.30 | 57,074.84 |
| CLM | 32,566.19 | 6,077.87 | 23,564.00 | 40,613.06 |
| CAT | 179,349.32 | 31,186.68 | 127,439.11 | 222,939.48 |
| CVA | 89,431.81 | 16,099.28 | 63,798.87 | 109,961.66 |
| EXT | 15,656.82 | 2,990.69 | 11,060.95 | 19,541.39 |
| GAL | 49,330.86 | 8,312.03 | 35,963.34 | 61,209.87 |
| RIO | 6,957.29 | 1,203.64 | 4,920.13 | 8,557.17 |
| MAD | 169,108.02 | 37,654.89 | 109,876.40 | 226,766.51 |
| MUR | 23,222.57 | 5,163.87 | 15,628.25 | 30,603.24 |
| NAV | 15,558.77 | 2,961.99 | 11,035.11 | 19,920.67 |
| PVA | 56,545.71 | 9,699.65 | 41,889.53 | 70,088.72 |
| CYM | 2,584.23 | 491.33 | 1,814.19 | 3,258.54 |
| *Panel* | 52,041.86 | 54,238.35 | 1,814.19 | 226,766.51 |

**Table 2.** Testing for convergence: DREI

| | | $\hat{\beta}$ coef. | t-stat |
|---|---|---|---|
| *Panel A: Club convergence tests* | | | |
| All regions | | – 0.415 | – 31.213 |
| Club 1 | AND, ARA, BAL, CAN, CAB, CYL, CLM, CAT, CVA, EXT, GAL, RIO, MUR, NAV, PVA, CYM | 0.453 | 13.084 |
| Non-convergent | AST, MAD | – 0.777 | – 83.976 |
| *Panel B: Merging analysis* | | | |
| No clubs can be merged | | | |
| *Panel C: Convergence map* | | | |

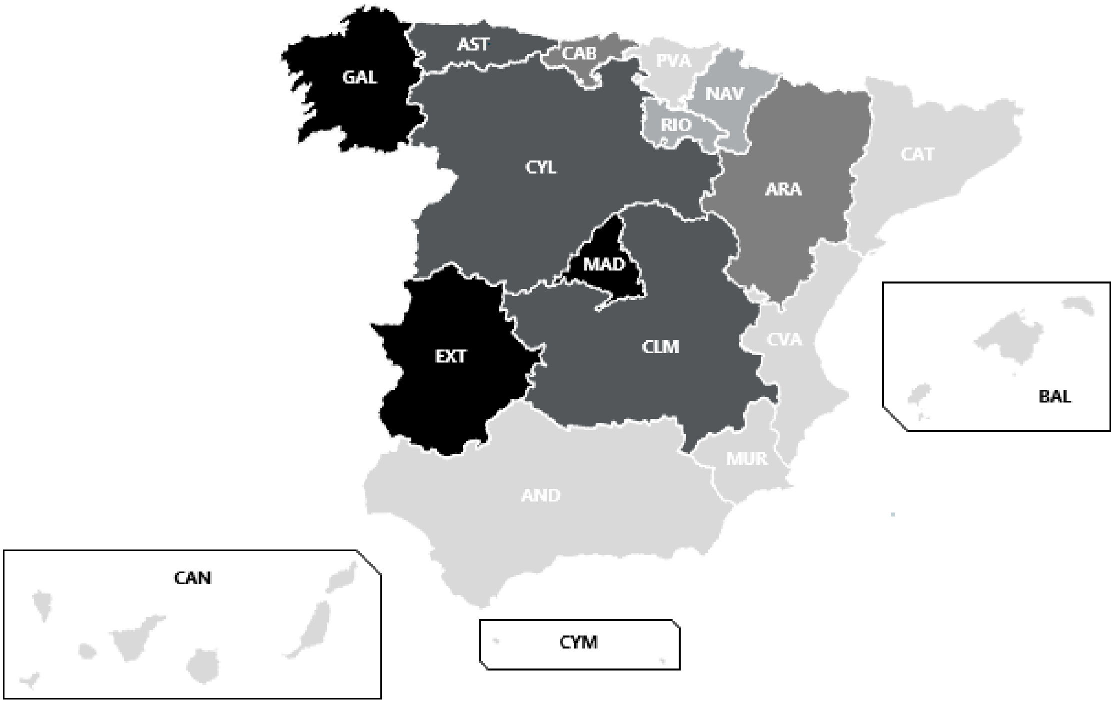


The table reports the estimated coefficient $\hat{\beta}$ and the convergence test t-statistic, which supposes a critical value at the 5% level $t_{0.05} = -1.65$, to reject the null hypothesis of convergence across all cases. Colour codes in the Spanish regions map are dark grey (convergence of Club 1) and black (non-convergent).

**Table 3.** Testing for convergence: DFEI

| | | $\hat{\beta}$ coef. | t-stat |
|---|---|---|---|
| *Panel A: Club convergence tests* | | | |
| All regions | | – 1.052 | – 50.215 |
| Club 1 | AST, CLM, CYL | 1.210 | 8.279 |
| Club 2 | ARA, CAB | 2.503 | 4.166 |
| Club 3 | RIO, NAV | – 1.071 | – 0.468 |
| Club 4 | AND, BAL, CAN, CAT, CYM, CVA, MUR, PVA | 0.066 | 0.771 |
| Non-convergent | EXT, GAL, MAD | – 0.887 | – 110.354 |
| *Panel B: Merging analysis* | | | |
| Club 1 + Club 2 | | – 0.390 | – 7.822 |
| Club 3 + Club 4 | | – 0.604 | – 7.386 |
| Club 4 + Non-convergent group | | – 0.836 | – 46.037 |

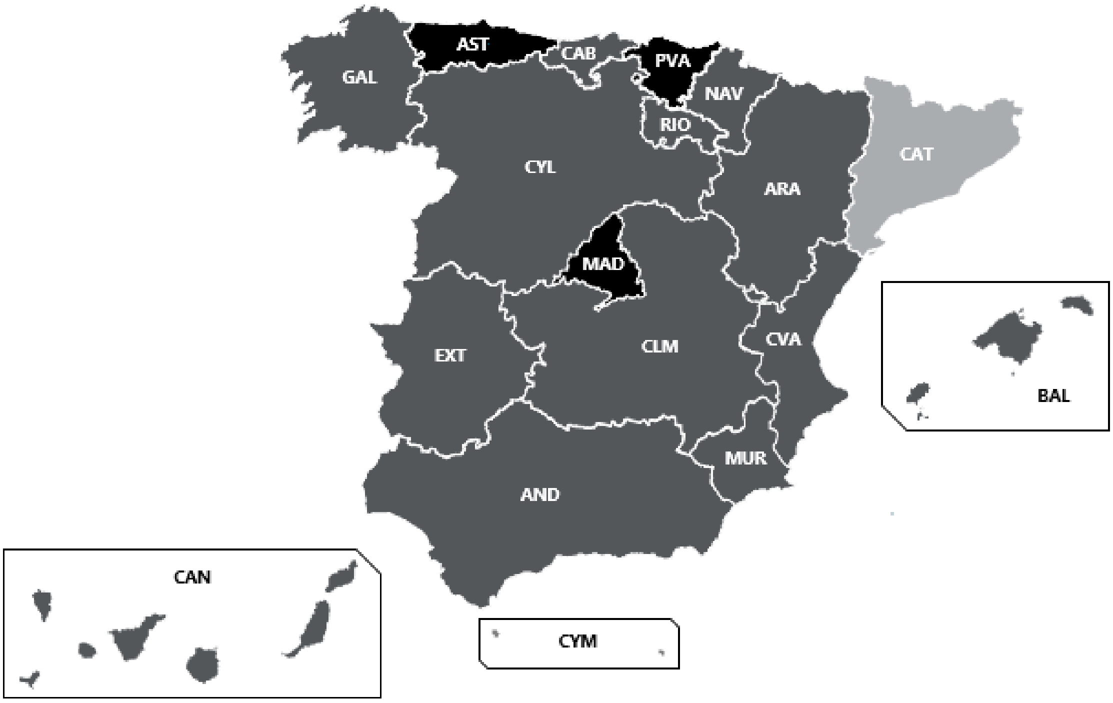
*Panel C: Convergence map*



The table reports the estimated coefficient $\hat{\beta}$ and the convergence test t-statistic, which supposes a critical value at the 5% level $t_{0.05} = -1.65$, to reject the null hypothesis of convergence across all cases. Colour codes in the Spanish regions map are dark grey (convergence of Club 1), grey (Club 2), light grey (Club 3), almost white (Club 4) and black (non-convergent).

**Table 4.** Testing for convergence: TEI

| | | $\hat{\beta}$ coef. | t-stat |
|---|---|---|---|
| *Panel A: Club convergence tests* | | | |
| All regions | | – 0.582 | – 55.866 |
| Club 1 | AND, ARA, BAL, CAN, CAB, CLM, CYL, CVA, EXT, GAL, RIO, MUR, NAV | – 0.026 | – 1.510 |
| Club 2 | CAT, CYM | 0.350 | 6.784 |
| Non-convergent | AST, MAD, PVA | – 0.647 | – 57.664 |
| *Panel B: Merging analysis* | | | |
| Club 1 + Club 2 | | – 0.391 | – 49.985 |
| Club 2 + Non-convergent group | | – 0.648 | – 63.101 |
| *Panel C: Convergence map* | | | |



The table reports the estimated coefficient $\hat{\beta}$ and the convergence test t-statistic, which supposes a critical value at the 5% level $t_{0.05} = -1.65$, to reject the null hypothesis of convergence across all cases. Colour codes in the Spanish regions map are dark grey (convergence of Club 1), grey (Club 2) and black (non-convergent).

**Table 5.** Factors driving the clubs. Estimation results for logit models

| | DFEI | TEI |
|---|---|---|
| INCOME | – 0.018 ***<br>(– 3.21) | – 0.024 *<br>(– 1.78) |
| INCOME$^2$ | 0.000000879 ***<br>(3.16) | 0.00000121 *<br>(1.86) |
| PRIMARY | 158.852 *<br>(1.60) | |
| INDUSTRY | | – 164.266 ***<br>(– 3.71) |
| ENERGY MIX | – 37.669 **<br>(– 2.28) | – 8.650 ***<br>(– 2.64) |
| TEMPERATURE | | – 4.012 ***<br>(– 3.06) |
| *Pseudo R$^2$* | 0.460 *** | 0.553 *** |
| *Log pseudolikelihood* | – 9.661 | – 2.631 |

The table reports the estimated coefficient of the logit models, using White-Huber standard errors. The test statistics are in parenthesis.

*** Denotes statistical significance at the 1% level.

** Denotes statistical significance at the 5% level.

* Denotes statistical significance at the 10% level.