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WORKING PAPER

Beyond Uniformity: Measuring the Stringency of Climate Policy Mixes Across Sectors and Countries

Coline METTA-VERSMESSEN [1*2*]

Environmental Policy Stringency (EPS) scores are increasingly used in econometric studies to analyze the effects of climate policy mixes on reducing greenhouse gas (GHG) emissions. These studies often rely on single indicators, such as the OECD measure, as neutral and stable proxies over time and across countries. However, econometric results obtained with such indicators may depend on the aggregation choices of these composite indicators. This study examines this issue by introducing sectoral EPS indicators with country-year specifications, based on the Climate Actions and Policies Measurement (CAPMF) database. These indicators capture national differences and extend sectoral coverage, including diffuse emissions. We test two key hypotheses: 1) the Proxy assumption, which considers EPS a neutral and robust proxy for climate policy stringency over time and across countries and sectors; 2) the Effectiveness assumption, which posits that stringency is associated with the effectiveness of policy mixes, implying a causal link between EPS and emissions reduction. Using two-way fixed effects panel regression with a Shift-Share Instrumental Variable (SSIV), we confirm the Effectiveness assumption: higher EPS is generally associated with reduced GHG emissions. However, we find that all indicators exhibit small regional and temporal instabilities, raising concerns about their reliability, with country-year-specific EPS outperforming indicators with equal weighting. Lastly, we demonstrate that aggregation choices in EPS construction are not neutral and directly influence regression results. These findings underscore the importance of using multiple indicators to enhance the robustness and comparability of EPS measures across sectors and national contexts.

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1* Paris Dauphine-PSL University, LEDa, France.
2* Climate Economics Chair (CEC) – IEF/ILB, France.

KEYWORDS

Environmental policy stringency | Policy mix | CAPMF | Policy interaction | Macroeconometrics

Executive summary

As countries worldwide strive to combat climate change, measuring the effectiveness of environmental policies has become crucial. Policymakers and researchers increasinlgy rely on Environmental Policy Stringency (EPS) indicators to assess the impact of climate policy mixes on reducing greenhouse gas (GHG) emissions. However, widely used EPS indicators, such as the OECD index, may overlook critical sectoral and national differences, raising concerns about their reliability and effectiveness as policy assessment tools.

This study introduces new sectoral EPS indicators, incorporating country-year specifications based on the Climate Actions and Policies Measurement Framework (CAPMF) database. By testing two key assumptions—the **Proxy assumption** (which assumes EPS is a neutral and robust policy measure over time and across countries) and the **Effectiveness assumption** (which assumes higher EPS leads to lower emissions). This research evaluates the reliability of EPS indicators and their influence on GHG emissions. Using advanced econometric techniques, including two-way fixed effects regression and a Shift-Share Instrumental Variable (SSIV) approach, we analyze how different EPS construction methods affect econometric results.

Key Findings

1. **EPS indicators are not fully neutral:** The way EPS is constructed significantly impacts econometric results, suggesting that aggregation choices influence policy effectiveness assessments.
2. **EPS is generally effective at reducing emissions:** Stricter environmental policies are associated with lower GHG emissions, particularly in the transport and industry sectors. However, their effectiveness in the electricity and building sectors varies depending on measurement choices.
3. **Sectoral coordination is key:** Policy mixes covering multiple sectors simultaneously, particularly the transport, electricity, and building sectors, enhance emission reduction effectiveness.
4. **EPS indicators exhibit regional and temporal instability:** The lack of enforcement considerations in EPS construction may contribute to inconsistencies across time and regions.
5. **No single EPS measure is sufficient:** A combination of methodologies is needed to provide a comprehensive and reliable assessment of policy stringency and effectiveness.

Policy Recommendations

- **Adopt a multi-indicator approach:** Relying on a single EPS measure can be misleading. Policymakers should use multiple indicators to gain a more accurate picture of environmental policy effectiveness.
- **Incorporate enforcement criteria:** Developing EPS indicators that include policy enforcement levels would improve their reliability and reduce regional and temporal inconsistencies.
- **Enhance sectoral coordination:** Climate policies should be designed with cross-sectoral complementarities in mind, particularly integrating transport, electricity, and building sector policies to maximize emission reductions.

This study underscores the complexity of measuring climate policy stringency and highlights the importance of refining existing indicators to better inform policy decisions. By improving the accuracy and sectoral specificity of EPS indicators, policymakers can design more effective strategies to reduce emissions and accelerate the transition to a low-carbon economy.

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1 Introduction

As the need to transition to a low-carbon economy grows more urgent, countries around the world are adopting a wide range of climate policy instruments targeting different emission sources and sectors. For instance, to achieve carbon neutrality, the European Union is developing a broad policy framework covering all emission sectors, including cap-and-trade mechanisms to manage emissions from transportation and buildings. The rising importance of environmental policies has sparked debates about their impact on both economic growth and climate goals. Consequently, there is a strong need to develop reliable measures of environmental policy stringency (EPS) (Brunel and Levinson, 2016; Galeotti et al., 2020), recognizing that a fast transition must also be an effective one. A solid indicator for EPS is essential to support meaningful comparisons across and within countries, although building such a tool poses significant challenges.

A booming literature is dedicated to formulating indicators quantifying Environmental Policy Stringency, defined as "an elevated, explicit or implicit, cost associated with polluting or environmentally deleterious behaviors" by Botta and Koźluk (2014, p.14), and on analyzing their impact on emission levels. One of the most prevalent among these indicators is the one created by the OECD (Kruse et al., 2022). However, this composite indicator overlooks the concept of policy interaction within the mix, instead considering the aggregated effects of isolated individual instruments. Furthermore, it tends to focus on energy sector policies, neglecting the intricate challenges posed by diffuse emission sectors due to their link with end consumers and their limited price elasticities. Finally, the OECD indicator employs a fixed equal aggregation approach that applies the same criteria across all countries, disregarding national specificities. While this methodology may appear more agnostic, it can bias the stringency score, assigning higher scores to policy mixes with a diverse set of instruments across sectors while undervaluing policy mixes focused on specific sectors or instruments.

This study aims to gain deeper insights into the measurement of the stringency of policy mixes. We contribute to the literature by, first, providing new Environmental Policy Stringy (EPS) indicators encompassing country-year specificities as well as sectoral coverage of climate policies. Second, we explore how EPS construction choices affect econometric results on the effect of policy mix on GHG reduction. By doing so, our analysis aims at testing two assumptions often implied and yet not confirmed by previous econometrical analysis. Firstly, EPS indicators are good proxies of environmental policy stringency, allowing for pertinent comparison between countries and years. We call it the Proxy assumption. Second, they are associated to the effectiveness of a policy mix in reducing emission. We call it the Effectiveness assumption.

To accomplish this, we use the Climate Actions and Policies Measurement Framework (CAPMF) database (Nachtigall et al., 2022) to construct four distinct metrics: EPS_OECD, EPS_GHG, EPS_GDP and EPS_BOD. Each indicator offers a unique perspective by varying the weighting approach. While the first one, following the OECD methodology, uses uniform equal sectoral weighting, the three others apply country-specific weighting. EPS_GHG and EPS_GDP adjust weights based on greenhouse gas emissions and GDP contribution respectively. EPS_BOD has the most flexible weighting through the Benefits-of-the-Doubt method. These variations allow us to capture the nuances of policy rigor across sectors and reflect both economic and environmental contexts. Then, we measure the influence of these indicators on emission levels using two-way fixed effects panel regression. In order to examine the influence of regulations within each emission sector and the interplay between regulatory frameworks across sectors, we employ national and sectoral emissions data. To ascertain causality in the relationship, we use a Shift-Share Instrumental Variable (SSIV). This instrument allows to better understand the effect of global shock in policy regulations on national policy mixes.

To address the shortcomings of relying on a single indicator, our Proxy assumption analysis reveals significant differences in results obtained with varying EPS indicators. Additionally, While EPS_OECD struggles with precision, and EPS_BOD suffers from high multicollinearity, EPS_GDP demonstrates greater stability and explanatory power for the effects of EPS on GHG emissions. However, all indicators suffers regional and temporal instability, likely due to the absence of the enforcement criteria in the scoring methodology. These findings highlight the limitations of individual measures and suggest that a combination of methodologies provides a more balanced and comprehensive assessment of environmental policy impacts. Our findings support the Effectiveness assumption, indicating that stricter EPS is generally associated with reduced emissions, particularly in the transport and industry sectors. However, EPS effects are not always consistent among EPS indicators, in particular in the building and electricity sectors. These findings underscore the need for an integrated approach to accurately capture the complexities of climate policy stringency across different sectors and contexts. Notably, the results highlight synergies between sectoral climate policy coverage, with the simultaneous presence of policies in the electricity, building and transport sectors being significantly associated with emission reductions whatever the EPS indicator used.

Our study contributes to the literature on Environmental Policy Stringency (EPS) by refining the construction of policy indicators and addressing existing limitations in regional and temporal comparisons. While prior studies on EPS index and GHG reduction yield varied findings on its relations with emissions reduction, our approach enhances the methodological framework by integrating sector-specific considerations and alternative aggregation techniques. In line with recent studies using the CAPMF framework, we emphasize the importance of policy mix effects. Our findings reinforce the notion that stringent policies are more effective when designed with cross-sectoral complementarities in mind, particularly between the transport and electricity or building sectors. By highlighting the role of sectoral synergies in emissions reduction, our study offers both methodological advancements for researchers and practical insights for policymakers, underscoring the need for coordinated and comprehensive climate policy design.

The paper is organized as follows. In Section 2, we provide the background and motivation for our analysis by reviewing the literature on Environmental Policy Stringency (EPS). Section 3 outlines the construction of each EPS indicator and details our empirical strategy, including the use of a two-way fixed effects model and a Shift-Share Instrumental Variable (SSIV) approach. In Section 4, we present the results, structuring the analysis around the two key assumptions—the proxy and Effectiveness assumptions—each examined separately. Finally, Section 5 provides our conclusions and discusses implications for future research.

2 Environmental Policy Stringency: A Literature Review

The growing importance of environmental policies has given rise to debates concerning their impact on both economic development and climate protection. Consequently, there is a compelling need to develop rigorous measures of environmental policy stringency (EPS) (Brunel and Levinson, 2016; Galeotti et al., 2020) defined as "a higher, explicit or implicit, cost of polluting or environmentally harmful behavior" by Botta and Koźluk (2014, p.14). A solid indicator to assess this EPS is essential to facilitate empirical comparisons between and within countries.

In his literature review about induced innovation, Popp (2019) notes a growing trend in international and cross-country comparisons. Their objective is to validate research findings across diverse contexts and, consequently, formulate more universally applicable policy recommendations. Furthermore, these measures allow for the examination of spillover effects between countries, enabling analyses of how one country's regulatory actions influence variables such as green innovation in other nations (Dechezleprêtre and Glachant, 2014). With regard to within-country analyses, they allow comparisons between different policy instruments or policy mixes that can be relevant in the ongoing debate opposing market-based instruments and command-and-control approaches (Li and Ramanathan, 2018; Ren et al., 2018; Zhu et al., 2021).

As emphasized by Botta and Koźluk (2014), the quality of empirical studies assessing environmental policy effectiveness largely depends on the accuracy of the chosen proxy. The complexity of the task extends beyond data collection challenges (Brunel and Levinson, 2013). The primary obstacle lies in obtaining measures allowing "all thing being equal" comparison. Brunel and Levinson (2013) identifies four major obstacles to measuring environmental policy stringency, which are frequently referenced in environmental policy literature (Herman and Shenk, 2021), namely:

1. Multi-dimensionality: Environmental policy stringency encompasses multiple facets, including diverse aspects of stringency and environmental pollution, as well as varying sectoral coverage.

2. Simultaneity: Policy stringency, which impacts pollution levels, may simultaneously be influenced by current pollution levels.

3. Industrial Composition: Ricardo's concept of "comparative advantage" implies variations in policy stringency based on a country's industrial composition.
4. Capital Vintage: Regulatory requirements may differ for new capital investments compared to existing ones, leading to variations in policy stringency.

2.1 How to measure Environmental Policy Stringency?

2.1.1 Typology of instruments and their limitations

We adopt here the classification of Galeotti et al. (2020) who have sorted out the different measures of environmental policy stringency into four category of indicators. This is similar to the classification proposed by Brunel and Levinson (2013) but with the merging of private and public investments into one category.

- **Pollution Abatement Effort:** This category includes two major types of instruments. Firstly, the Pollution Abatement Cost Effort (PACE), which has been used in the primary studies of the field (Popp, 2019), represents the private sector's efforts. Secondly, research and development (R&D) support, such as investments in renewable energy, as employed by Dechezleprêtre and Glachant (2014), reflects the public sector's actions. Criticisms of these measures include issues related to causality and difficulties in measurement, especially in cases of market failures.
- **Direct Assessment of Regulations:** This category has been widely used in literature. For instance, Bel and Joseph (2018) use oversupply of allowances in the EU Emissions Trading System (EU-ETS) and changes in EU-ETS regulations as proxies, demonstrating correlations with patenting activity and policy stringency. Additionally, Hille et al. (2020) compare the effectiveness of various instruments in supporting renewable energy, highlighting public R&D support's significant impact on solar-panel patenting. While efficient for specific regulations, this category faces challenges when applied to a broader range of policy instruments. Finding suitable proxies can be problematic.
- **Output-Based or Emission-Based Indices:** Researchers have relied on energy consumption or emission levels to gauge policy stringency. However, this approach confronts causality issues. Brunel and Levinson (2013) enhance this approach by creating an indicator based on the discrepancy between predicted and actual emission levels, which is used in the comparison of environmental policy stringency (EPS) indicators by Galeotti et al. (2020). This indicator shares similarities with the one devised by Sauter (2014). Building on the methodology outlined by OECD (2008), the authors developed a carbon emissions performance indicator per sector, based on GDP and emissions shares of the application sector.

- **Composite Indicators:** Researchers have devised composite indicators, such as the "Regional Environmental Regulation" indicator by Jiang et al. (2018), which combines public R&D support and an index of current regulatory practices in China or the Environmental Policy Stringency Index from OECD. These composite indicators, however, may raise concerns about objectivity and completeness, a topic explored further in the subsequent subsection.

Several authors have underscored the limitations of existing indicators (Brunel and Levinson, 2016; Galeotti et al., 2020; Herman and Shenk, 2021). In a 2014 study, Sauter (2014) criticized previous policy stringency indicators used in the literature, contending that they lacked a rigorous construction methodology. Herman and Shenk (2021) suggested employing Principal Component Analysis (PCA) and machine learning techniques for more precise indicators. This is precisely what Galeotti et al. (2020) accomplished in their work. They employed these four categories of environmental policy stringency measures to construct 13 different indicators, subsequently evaluating their accuracy through PCA. Their findings revealed disparities among indicators, occasionally yielding contradictory results. However, they demonstrated greater convergence between composite indices and emissions-based indicators, while others exhibited less reliability. Specifically, their research indicated a confirmation of the Porter hypothesis and a significant relationship between energy efficiency and composite indices or emissions-based indicators. Brunel and Levinson (2016) founded equivalent results in their study on correlation between EPS instrument. They argue that an effective indicator should possess qualities such as ease of computation, accessibility to yearly data, and cardinality, which enables comparative studies.

2.1.2 From the EPS index to the CAPMF Database

This analysis focus especially on OECD's work to score policy stringency.The development of policy stringency measurement by the OECD began with the Environmental Policy Stringency (EPS) index, an annual national rating system that ranges from 0 (indicating the absence of climate policy) to 6 (representing the highest stringency among observations). It covers specifically climate and air pollution mitigation measures. It was first designed by Botta and Koźluk (2014), then readjusted by Kruse et al. (2022). This composite score is built by aggregating the scores associated with the different policies considered. To encompass the multidimensionality inherent to climate regulation, the EPS Index adopts a specific policy categorization framework. In fact, the first version followed the taxonomy of Serres et al. (2010), emphasizing that an efficient policy mix should be balanced between Command and Control (CAC) tools and the Market Based Instrument (MBI). With extension by Kruse et al. (2022), the categorization was tripartite with the inclusion of the "Technology Support Policies". In each of these subcategories, 13 types of policies were categorized within which individual policies and instruments are scored and aggregated with equal weighting.

While this EPS index lacks sectors representation, with a focus on energy policies, an enlarged database was constructed. Called Climate Actions and Policies Measurement Framework (CAPMF) and presented by Nachtigall et al. (2022), it is an extended version of the scoring framework taking account of policies covering around 85% of national emissions. While the EPS index only covers "Market-Based instrument" (MBI), "Non-Market-Based instruments" (NMBI) and "Technology Support", the CAPMF covers three blocks: sectoral, cross-sectoral, and international policies. In this customizable dataset, the coverage of sectoral policies was extended to four distinct sectors (Electricity, Industry, Buildings, and Transport), for which the score is an aggregation of the score obtained for the MBIs (i.e., tax and certificates), and NMBIs (i.e., performance standard). Eventually, 130 policy variables grouped into 56 policy instruments are scored in the index. To score them on a common scale, an empirical approach has been used, using data from 1990 to 2020 for 50 countries. Each policy score for a particular country is determined on the basis of its relative stringency within the overall distribution of policy levels observed. Specifically, policies that fall between the 90th and 100th percentiles (representing the highest level of stringency for the given policy) receive a score of 10. The absence of a policy is assigned a score of 0, while intermediate scores are determined by thresholds of the percentiles of observations.

In total, the CAPMF enables straightforward country-specific scoring. Its ease of use makes it particularly valuable for both within-country and cross-country analyses. In particular, the tool is easily accessible on the OECD data explorer[1]. Through a user-friendly interface, the aggregation of scores can be customized to fit specific research needs. Researchers have the flexibility to selectively include or exclude variables or policies, thus creating new composite indices tailored to their research objectives.

2.2 EPS scores and policy mix effectiveness

Numerous studies have examined the relationship between the Environmental Policy Stringency (EPS) index from OECD and its influence on emissions reduction–for a non-exclusive literature review, see Albulescu et al. (2022). If the econometric approaches used can differ from a study to another, they mainly used the same EPS index which is the first one provided by the OECD and yet obtained variety of results.

The prevailing consensus in a majority of these studies underscores a significant and advantageous association between EPS and carbon emissions. For instance, de Angelis et al. (2019), through a comprehensive analysis distinguishing Market-Based Instruments from Non-Market-Based Instruments within EPS, have underscored the latter's more substantial influence on reducing carbon emissions. Additionally, they have highlighted variations in the strength of this relationship between European and non-European countries, with European nations benefiting more from EPS. Similarly, Sezgin et al. (2021), employing a cointegration model including carbon emissions, EPS, and Human Development, have revealed a significant decrease in carbon emissions correlated with EPS for G7 and BRICS economies.

[1]Last visited 24/01/24.

Although these two studies have elucidated a straightforward relationship between EPS and carbon emissions, the majority of studies reveal a non-linear relationship. Ahmed and Ahmed (2018), in their analysis of EPS within the Chinese context, have identified a beneficial relation between EPS and carbon emissions reduction. However, they have also acknowledged a slight adverse impact on economic productivity. Expanding the scope, Wolde-Rufael and Mulat-Weldemeskel (2021), utilizing panel cointegration techniques, have elucidated a compelling inverted U-shaped relationship between environmental policy stringency and CO2 emissions in BRIICTS countries. Their findings imply that stringent environmental policies lead to improved environmental quality beyond a certain threshold, suggesting that the effects of EPS may require time to materialize. This complex relationship has been reaffirmed by Albulescu et al. (2022), who, through a quantile fixed-effect panel data approach, have demonstrated an asymmetric relationship between carbon emissions and EPS. Specifically, they contend that the efficacy of policy stringency hinges on country's initial pollution levels.

On a broader scale, Chu and Tran (2022) have demonstrated the heterogeneous impact of EPS on ecological footprint. Employing panel quantile regression, they have identified a divergent relationship between EPS and ecological footprint depending on quantile threshold and the type of activity. While EPS has a positive effect on consumption ecological footprint below the 80th quantile, it yields negative and extreme effects for higher quantiles. In contrast, a favorable relationship between the EPS index and production footprint has been established.

However, to the best of our knowledge, three studies have reported contradictory results compared to those mentioned above. Yirong (2022), employing a non-linear AutoRegressive Distributed Lag (ARDL) approach, have reported mixed results for highly polluted countries. They have observed that an increase in EPS leads to long-term reductions in carbon emissions. Surprisingly, they have also noted that negative shocks to EPS have beneficial long-term effects on carbon emissions. In a more categorical way, Alexandersson (2020); Demiral et al. (2021) have demonstrated either a lack of a significant relationship or a detrimental one. Alexandersson (2020), utilizing panel data, did not detect a substantial impact of higher policy stringency on carbon emissions. Nevertheless, they observed effects on fuel consumption and prices. Notably, all regressions were conducted concurrently with fuel prices, fuel consumption, and EPS, potentially raising concerns of endogeneity and multicollinearity. Demiral et al. (2021), employing panel data regression, reported no discernible effect of stronger EPS on carbon emissions. Paradoxically, they found that higher EPS levels were associated with a significant increase in carbon emissions across the entire sample and for middle-income countries.

Four studies specifically analyzing the effect of policy mix on GHG emissions using the CAPMF framework are closely related to our analysis and present more consistent findings. First, Nachtigall et al. (2024) demonstrate through a two-way fixed effects regression that the CAPMF score is associated with a reduction in both GHG and carbon emissions. However, while they aggregate the 56 policy scores into a general mean, they neither focus on sectoral coverage nor distinguish between different sectors. Additionally, they do not explore alternative methods of score aggregation. Second, the cluster analysis by D'Arcangelo et al. (2024) confirms this negative relation between the CAPMF score and emissions while introducing the concept of synergies within climate policy mixes. Their findings indicate that the link between CAPMF and GHG emissions is stronger for mitigation strategies incorporating a diverse set of policy instruments. The study by Stechemesser et al. (2024) further supports the greater effectiveness of policy mixes over individual policies. Using a two-way fixed effects difference-in-differences approach, they agnostically identify emissions reductions associated with effective policies and policy mixes. While their results highlight the transport sector as having the highest potential for policy complementarity, their analysis remains confined within individual emissive sectors without considering potential synergies across sectors. Finally, Steinebach et al. (2024) review various climate policy databases and conclude that while all indicators consistently show an increase in policy activity over time, they diverge in their assessment of stringency levels. By comparing the stringency indicator from CAPMF with that of the CLIMAPP dataset, they argue that capturing the nuanced effects of policy mix stringency within a single indicator is challenging, reinforcing the findings of our study.

3 Method and Data

Our study makes several contributions to the existing literature regarding the relationship between Environmental Policy Stringency (EPS) and greenhouse gas emissions, addressing three key aspects. Firstly, we calculate four different sector-based indicators, allowing us to compare the effect of construction choices on empirical results, using panel data regressions. Secondly, we take into account the effect of the regulatory coverage of national economic sectors in our indicator, in order to analyze their impact on the effectiveness of the rigor of the policy mix as a whole. Thirdly, we use the updated EPS scores from the Climate Actions and Policies Measurement Framework database presented by Nachtigall et al. (2022), which allows for a comprehensive panel data analysis covering five additional years regarding to previous studies (2015-2020) and a total of 50 countries.[2]

3.1 Sectoral EPS indicators

Using the OECD CAPMF database we constructed four distinct sectoral EPS indicators, namely EPS_OECD, EPS_GHG, EPS_GDP and EPS_BOD. Since the focus of this study is the sectoral decomposition of climate regulation within the national climate policy mix, we concentrate on sector-specific policies. Cross-sectoral policies[3] (such as targets and governance) and international policies

[2]The database includes OECD members and candidates as well as remaining G20 countries, excluding the United States.

[3]To account for policy instruments classified as "Cross-sectoral policies" that are in fact sector-specific, we reclassified them according to the appropriate sector and type. For instance, bans and phase-outs of fossil fuel extraction have been reclassified as non-market-based instruments in the energy production sector. As such, the electricity sector in our study is more representative of energy sector as a whole (including hydrogen

are not considered in our analysis. With these indicators, our primary objective is to compare the effects of construction choices on the results, and secondarily, to address the imperfections of previous EPS indices.

Indeed, this sector-based approach addresses two main imperfections of the EPS index. First, it allows for a broader scope of analysis. A fundamental aspect of the first EPS index revolves around regulations within the energy sector, as explained in the initial version by Botta and Koźluk (2014). Although the subsequent version by Kruse et al. (2022) expanded its coverage slightly, the index remains predominantly focused on energy policies. As a result, it omits key sectors, particularly those with diffuse emissions, which often require specific regulations.[4] To achieve efficient decarbonization of the economy, efforts must be made across all sectors, as they are inherently complementary. Decarbonizing electricity production alone, for example, is insufficient to decarbonize the transport sector if there are no incentives to switch to electric transportation.

Second, our approach addresses biases in the aggregation of scores. In the OECD's EPS index, the total score is not adjusted to reflect the specific characteristics of each country. This can result in biased outcomes that favor countries whose policy mix aligns closely with the OECD methodology, while potentially underestimating the efforts of other countries. To explore if this scoring methodology can affect econometric results, we construct four distinct indicators with varying aggregation methods.

To ensure meaningful comparisons, we follow the "all else being equal" approach in constructing these indicators. This approach ensures that the indicators share common characteristics. First, they are all based on the same OECD rating of climate policies and actions. Second, they cover the same sectors: power generation, industry, buildings, and transport. Finally, they adhere to a consistent hierarchical structure, similar to that proposed by the OECD, where the total indicator is divided into the four sectors of activity, each further subdivided equally between market-based and non-market-based instruments. From this common foundation, only one element—the weighting method—varies across the indicators, enabling a targeted assessment of the impact of different scoring approaches.

3.1.1 Construction of EPS_OECD, EPS_GHG and EPS_GDP

To create EPS_OECD, as no aggregated score is proposed by the CAPMF database, we followed the methodology employed by the OECD for their EPS index, meaning an equitable decomposition of weights between each module, i.e. across each sector (with a weight of 1/4). Within each sector, we further divided the weight equally between market-based instruments (MBI) and non-market-based instruments (NMBI). The aggregation of policies' scores within each type (MBI and NMBI) was achieved by computing the average of their respective scores. This EPS is a baseline type.

production for instance) but we kept the electricity terminology for coherence with the original dataset.

[4]Such as those covered by the Effort Sharing Regulation in Europe, for instance.

EPS_GHG shares similarities with EPS_OECD but introduces a key modification related to sector weighting. Instead of equal weights for all sectors, we associated the final score of each sector with its greenhouse gas (GHG) emissions proportion within the national mix for each country annually. This adjustment allows us to emphasize the impact of GHG-intensive sectors on the overall EPS score.

EPS_GDP follows a similar structure to EPS_GHG but replaces the GHG proportion with the share of each sector's contribution to the Gross Domestic Product (GDP). To achieve this, we utilized proxies for certain sectors, specifically "Real estate activities" and "Distributive trade, repairs; transport; accommodation, food service," as classified in the OECD's GDP framework. An illustration of the structure of our indicators is presented in figure 1, showing the EPS_GDP structure and the proxies used.

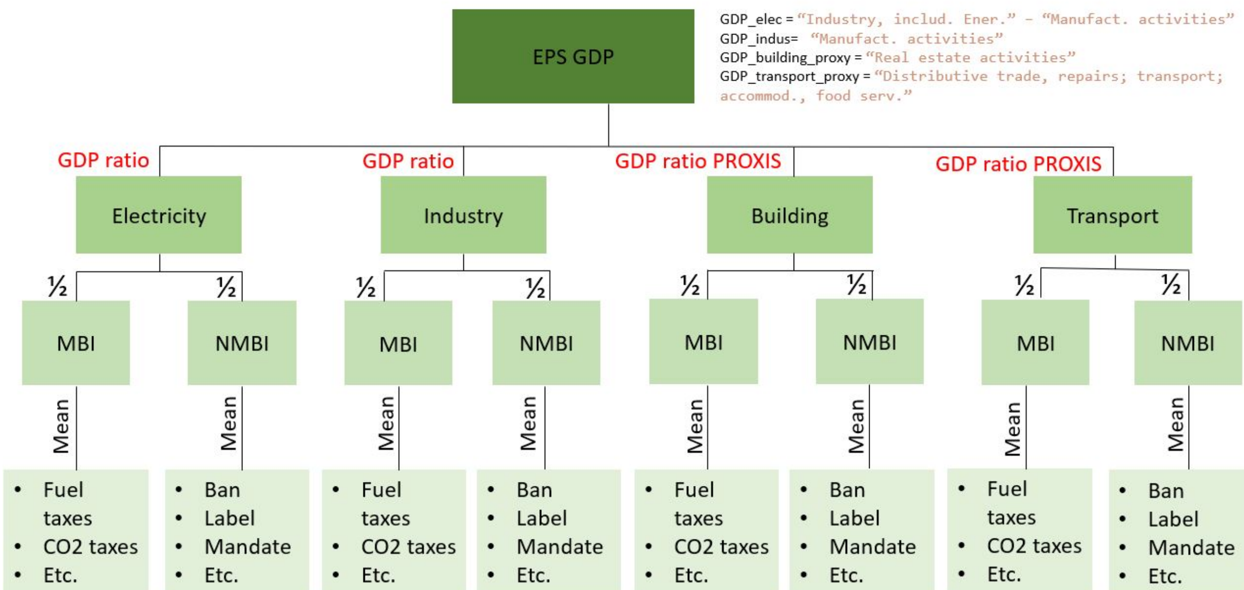

Figure 1: EPS_GDP Structure

3.1.2 Construction of EPS_BOD

For the construction of the EPS_BOD indicator, we employ the Benefits of the Doubt (BOD) method, which comes from the Data Envelopment Analysis literature (see Cherchye et al. (2007) for a comprehensive review and method specifics). The fundamental idea behind the BOD method is to account for the inherent specificities of each country during score construction. While the other three indicators equally score all policies inside each type (market-base or non-market-based instrument) within each sector, the BOD method acknowledges that different strategies may be necessary based on country-specific factors. For instance, some countries may choose to implement a carbon tax instead of a cap-and-trade to mitigate industrial emissions. As so, the core assumption of the BOD method is that each country's government is best positioned to understand its unique needs and construct effective policies. Therefore, if a country allocates more effort to a particular instrument, it is likely because it is more effective.

To achieve this, the BOD method maximizes the score for each country and each year subject to known constraints. Specifically, we maintained constraints ensuring that each sector has equal weight and that each type (MBI and NMBI) has also equal weight (following the 'all else being equal' method), leading to a maximum weight of 1/8 for each type. Naturally, weights cannot be negative. To prevent a country with only one policy in place from obtaining an aberrant score, we introduced a dispersion constraint within the EPS_BOD score. This constraint ensures that extreme scores are avoided, promoting a more balanced assessment. Therefore, during the maximization process, we additionally consider the minimization of weight variance within a type, multiplied by an argument α. Through sensitivity tests conducted with the data, we calibrated the value of α to achieve the most meaningful EPS score (as detailed in Appendix A). Specifically, we set $\alpha = 100$ and solve the following program:

For a country ($c \in [1, n]$), a sector ($s \in [1, 4]$), and a type ($t \in [1, 2]$), where ($p_{c,s,t,i}, i \in [1, m]$) represents the i-th policy, and the set of weights is denoted as ($w_{c,s,t} = \{w_{c,s,t,1}, w_{c,s,t,m}\}$)

$$EPS\_BOD_c = \sum_s \sum_t S_{c,s,t}$$

$$S_{c,s,t} = \sum_i w_{c,s,t,i} \; p_{c,s,t,i}$$

$$w_{c,s,t} = \arg\max_{w_{c,s,t}} S_{c,s,t} - \alpha \mathrm{VAR}(S_{c,s,t})$$

s.t.

1. Positivity constraint:

$$w_{c,s,t,i} \geqslant 0 \quad \forall \quad c, s, t, i$$

2. Distribution constraint:

$$\sum_i w_{c,s,t,i} \leqslant \frac{1}{8} \quad \forall \quad c, s, t$$

3.1.3 Graphical comparison of the indicators

The four indicators share a similar upward trend, with similar variations, such as the pronounced increase in 2007, as outlined in Figure 2. EPS_BOD has naturally higher total values, related to the maximization of scores for each country. However, as presented in Figure 3, the sectoral decomposition is distinct among the indicators. Notably, we observe that the building sector has a higher score for the BOD indicator than for the other three, indicating that countries make more pronounced and less distributed policy choices in this sector. Additionally, we notice that the electricity sector's score is highly sensitive to the indicator's construction choices. It plays a significant role in greenhouse gas emissions, which increases its weight in EPS_GHG, even though it does not constitute a major input, leading to a decrease in its weight in EPS_GDP.

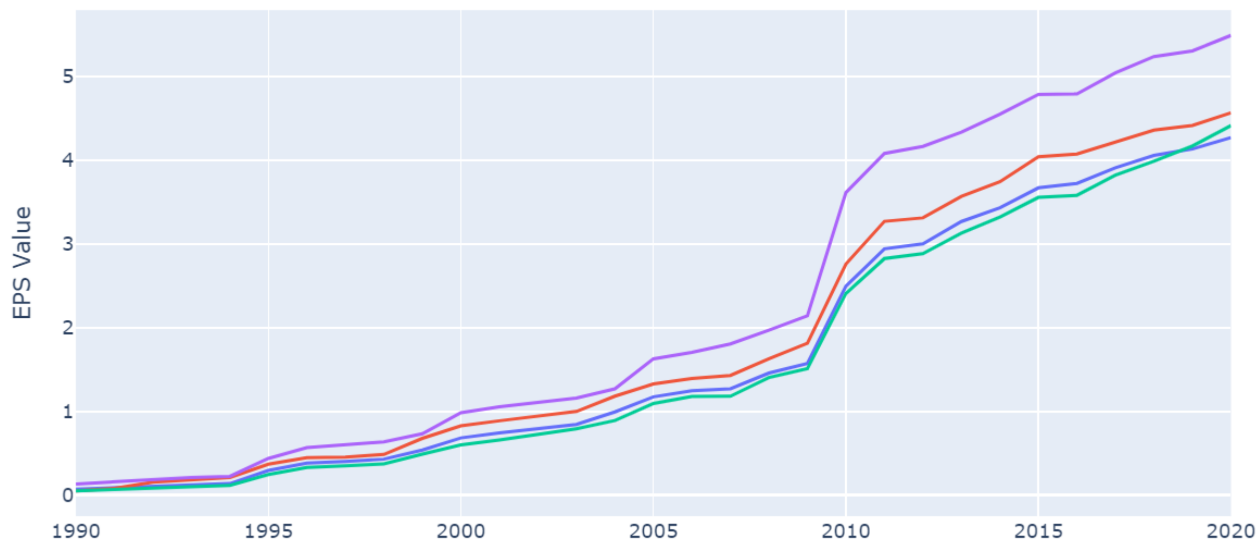

Figure 2: Comparison of the EPS total score

Legend: These curves represent the averaged EPS score for every countries, per year. In blue, the score of EPS_OECD; in red the GHG one, in green the GDP one and in purple the BOD one.

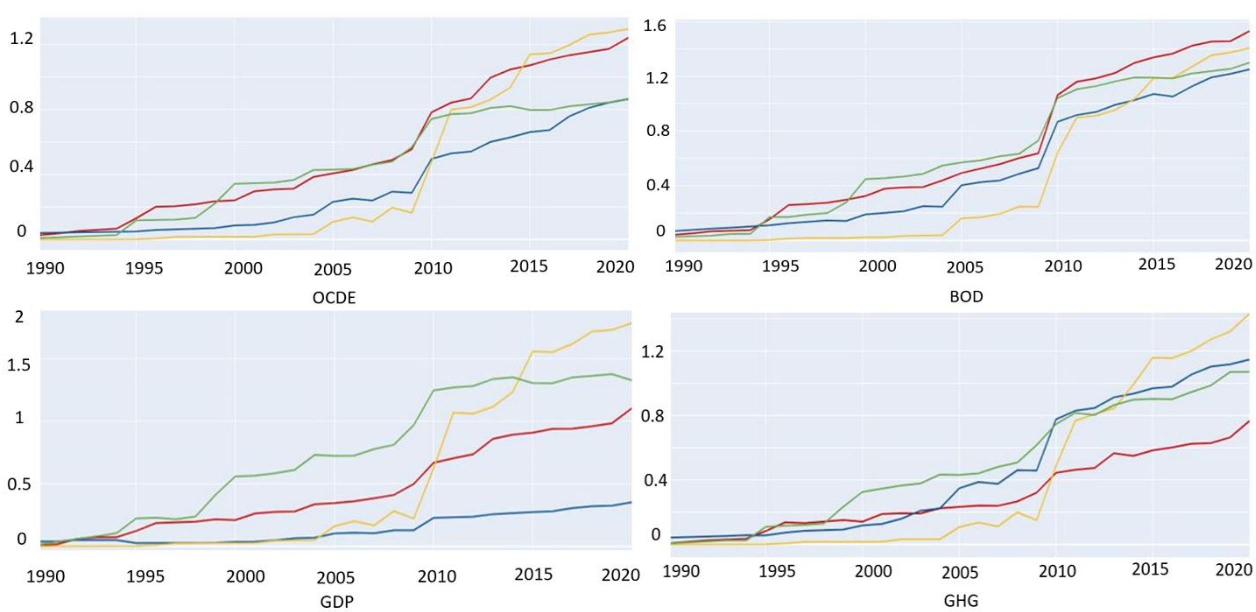

Figure 3: Comparison of the EPS sectoral decomposition

Legend: In red, the building value of the EPS score; in blue, the electricity one; in yellow, the industry one; and in green, the transport one.

3.2 Empirical strategy and data

3.2.1 A data-driven exploration of the Proxy and Effectiveness assumptions

EPS indicators are increasingly used in the literature to assess the effectiveness of policy mixes over time and across countries. However, the underlying Proxy and Effectiveness assumptions remain difficult to test.

The Proxy assumption posits that the chosen indicator serves as a reliable proxy for the stringency of climate policy mixes, enabling meaningful comparisons across countries and time. To function as a good proxy, the indicator should be unbiased and stable, reflecting only the constant stringency of a policy mix. However, just as real monetary values are unsuitable for temporal and regional comparisons—-where constant or Purchasing Power Parity-adjusted values are preferred—-a uniform EPS measure that ignores country-year specificities may introduce bias.

The Effectiveness assumption asserts that policy stringency is genuinely associated with the effectiveness of policy mixes, implying a causal relationship between EPS and emission reductions. However, validating this assumption is challenging due to endogeneity and omitted variable bias. This challenge becomes even more pronounced if results are sensitive to EPS measurement choices or if the chosen indicator suffers regional or temporal instability.

Given these concerns, this study examines how different EPS measurement choices influence GHG estimations based on these indicators. More specifically, we assess how these variations affect both the Proxy and Effectiveness assumptions.

3.2.2 An unbalanced panel database

We utilize data from the Organization for Economic Co-operation and Development (OECD) for policy scores, greenhouse gas (GHG) emissions (measured in thousands of tonnes of CO_2 equivalent), Gross Domestic Product (GDP) (expressed in million constant 2015 US dollars at constant exchange rates), and population figures. Additionally, we incorporate data from the World Bank to capture urban growth dynamics and the share of agriculture, fishery and forestry used for the Instrument Variable.

To ensure consistent observations across all models, we reduced the dataset to match the smallest subset, as the number of observations for EPS based on GDP and GHG is lower than for the other two indicators.[5] For the purpose of our analysis, logarithm values are used for GHG, GDP and POP, as illustrated by Figures 4 and 5. Our final unbalanced panel database encompasses 45 countries, spanning annual observations from 1990 to 2020. Tables 1 and 2 provide descriptive statistics of our data sample.

[5] This is because calculating them requires a sectoral breakdown of GHG emissions or GDP by year and country, for which there is less data available.

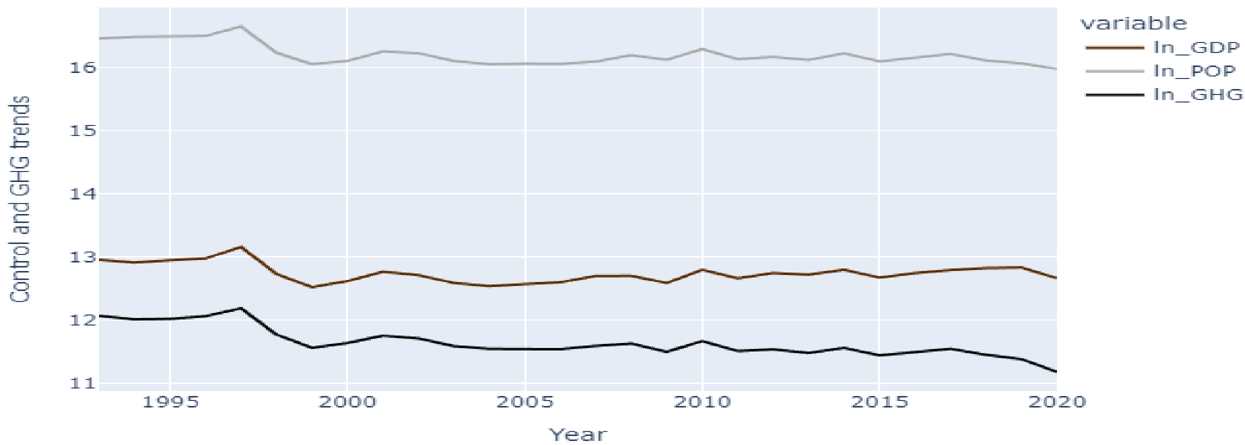

Figure 4: Trends of GHG and control variables

Legend: These curves represent the averaged logarithmic values for every countries, per year.

Table 1: Summary Statistics for Key Variables

Variable	Count	Mean	Std. Dev.	Min	50%	Max
ln_GDP (10^6 USD_{2015})	1119	12.50	1.55	8.80	12.56	15.34
ln_POP (Count)	1119	16.27	1.51	12.50	16.15	21.01
urban_growth (percentage)	1119	0.83	1.02	-3.45	0.78	5.09
ln(GHG) (10^3 $CO2_{eq}$)	1119	11.61	1.52	7.52	11.32	14.86
EPS_BOD (0-10 score)	1119	2.69	2.20	0.00	2.07	7.87
EPS_OECD (0-10 score)	1119	2.02	1.70	0.00	1.50	6.23
EPS_GHG (0-10 score)	1119	1.88	1.65	0.00	1.39	6.24
EPS_GDP (0-10 score)	1119	2.08	1.75	0.00	1.51	6.75

In our study, we address the issue of missing data, resulting in an unbalanced dataset. While non-balanced datasets are not inherently problematic for panel econometric studies, the key consideration lies in the randomness of the missing data. Notably, we observe that the missing data predominantly occur during the years 1990 to 1995 and primarily affect countries with less advanced climate protection measures. To ensure the robustness of our results, we conducted tests on balanced subsets of the dataset. Specifically, we created three distinct subsets: a subset capturing the maximum number of years; another subset maximizing country representation; a third subset capturing the maximum number of observations using the Python package from Joly (2024). The results of these tests are consistent with those obtained from the unbalanced dataset[6], confirming the representativeness of our panel.

[6]While the values and significance of the coefficients differ slightly, the signs remain the same. These differences are attributed to the reduction in the number of observations.

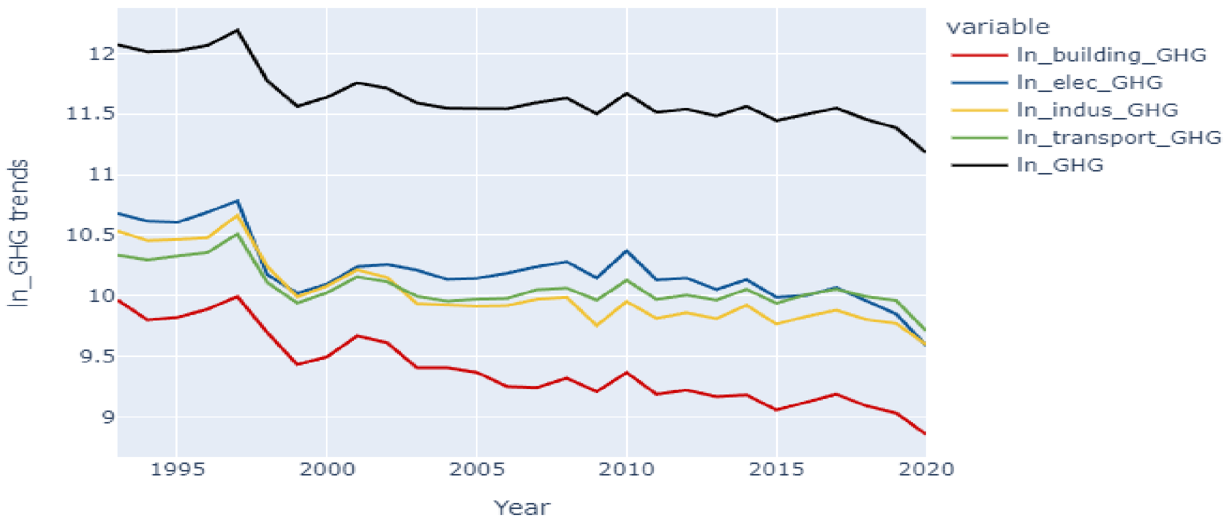

Figure 5: Trends of GHG and its sectoral decomposition
Legend: These curves represent the averaged logarithmic values for every countries, per year.

3.2.3 Estimation Strategy: a two-way fixed effects model

First, tests for heteroskedasticity (White Test, Breusch-Pagan Test) and autocorrelation (Durbin-Watson test) were conducted, ruling out the pooled data hypothesis. Next, a generalized Hausman test identified the Fixed Effect modeling as the best fit. AIC and BIC analysis confirm this result and specifically identified the two-way fixed effects model was identified as the best fit. Finally, after testing for heteroskedasticity, autocorrelation, and cross-sectional dependence, the Clustered covariance estimator was selected (see Appendix B.1 for a detailed description of this part and tests results).

Let $\ln(GHG_{cy})$ be the natural logarithm of greenhouse gas emissions for country c and year y. The model can be expressed as follows:

$$\ln(GHG_{cy}) = \beta_0 + \beta_\mathbf{1}\mathbf{X_{cy}} + \beta_\mathbf{2}\mathbf{Y_{cy}} + \alpha_c + \gamma_y + \varepsilon_{cy}$$

where:

- $\mathbf{X_{cy}}$ is the vector of exogenous control variables, including:
  - $\ln(GDP_{cy})$: the natural logarithm of GDP,
  - $\ln(GDP_{cy})^2$: the natural logarithm of GDP squared to account for non-linearity of GDP relation to emissions,
  - $\ln(POP_{cy})$: the natural logarithm of population size,
  - urban_growth$_{cy}$: the urban growth rate.

Table 2: Summary Statistics for Sectoral Decomposition of EPS by Model

Variable	Count	Mean	Std. Dev.	Min	50%	Max
BOD Model						
EPS_BOD_building	1119	0.80	0.61	0.00	0.67	2.32
EPS_BOD_elec	1119	0.62	0.52	0.00	0.48	2.09
EPS_BOD_indus	1119	0.52	0.63	0.00	0.24	2.18
EPS_BOD_transport	1119	0.76	0.56	0.00	0.70	2.33
OECD Model						
EPS_OECD_building	1119	0.64	0.48	0.00	0.55	1.72
EPS_OECD_elec	1119	0.38	0.37	0.00	0.27	1.48
EPS_OECD_indus	1119	0.47	0.57	0.00	0.16	1.90
EPS_OECD_transport	1119	0.53	0.40	0.00	0.50	1.74
GHG Model						
EPS_GHG_building	1119	0.35	0.33	0.00	0.26	1.94
EPS_GHG_elec	1119	0.53	0.57	0.00	0.30	2.60
EPS_GHG_indus	1119	0.44	0.58	0.00	0.14	3.01
EPS_GHG_transport	1119	0.56	0.49	0.00	0.45	2.19
GDP Model						
EPS_GDP_building	1119	0.51	0.44	0.00	0.39	1.96
EPS_GDP_elec	1119	0.15	0.21	0.00	0.08	1.92
EPS_GDP_indus	1119	0.60	0.82	0.00	0.18	5.49
EPS_GDP_transport	1119	0.82	0.62	0.00	0.77	2.65

- $\mathbf{Y_{cy}}$ is the vector of exogenous explanatory variables, such as EPS_OECD_{cy}.
- α_c and γ_y represent the entity-specific and time-specific fixed effects, respectively.
- ε_{cy} is the error term.

If the main model considers the absolute values of the variables, additional tests have been conducted using per capita values and GHG/GDP ratios. These tests confirm the results obtained with absolute values. Furthermore, tests using the logarithm of EPS+1 have also been performed, confirming the results. Other model specifications, while confirming the findings, exhibit lower significance and are therefore included in the appendix. For detailed results, see Appendix B.4 for per capita values, B.5 for emissions per GDP, and B.7.3 for the logarithm of EPS+1.

Given the intricate nexus between greenhouse gas emissions (GHG) and environmental policies, rigorous consideration of endogeneity is essential. More specifically, plausible endogeneity of the explanatory variables, the EPS indicators, arises due to simultaneity. Specifically, governments may implement climate regulations in response to the current state of their emissions, potentially biasing the results. This bias can manifest in two ways: first, if a reduction in emissions makes it easier for governments to introduce climate policies due to increased social acceptability, leading to a form of "greenwashing"; second, if high emissions levels compel governments to adopt stricter climate policies to mitigate their adverse effects. To address these concerns and ensure the robustness of the results, two strategies are employed, as detailed in Appendix B.3.

The first approach involves lagging the explanatory variable, which helps mitigate simultaneity by ensuring that past values of EPS influence current policy decisions rather than the other way around. The results of this lagging test confirm the robustness of the model, reinforcing the validity of the findings (see Appendix B.3.1). However, to further strengthen causal inference, an instrumental variable (IV) approach is implemented.

For this purpose, a shift-share instrumental variable (SSIV) approach is utilized, focusing on the shift component, as detailed in the Appendix B.3.2. The chosen shift is the global shock on the EPS indicator, operationalized using the leave-one-out mean. Several factors justify this choice. Firstly, from an economic perspective, the global state of climate policies can significantly influence national policy decisions, either through trade competitiveness pressures or public opinion dynamics concerning governance. Secondly, the construction of the EPS scores supports this approach, as each country's policy score is calculated relative to other observations. As a result, an increase in the global mean EPS score tends to lower a given country's relative score, which is confirmed by the first-stage regression results.

4 Empirical Results

4.1 Decoding Policy Stringency: The Proxy assumption

To evaluate the effectiveness of Environmental Policy Stringency (EPS) indicators as tools for policy assessment, we introduce the "Proxy assumption." This assumption tests whether an EPS indicator reliably serves as an unbiased, consistent measure of policy stringency across different countries and time periods. A robust proxy should meet two criteria: (1) it should provide a comparable measure of policy rigor regardless of country-specific conditions, and (2) it should maintain temporal stability, ensuring that scores reflect true policy variations rather than changes in the indicator's sensitivity over time.

Our analysis particularly examines the baseline EPS_OECD indicator, developed following the OECD methodology for their EPS index, which is widely used for cross-national and longitudinal comparisons. While the EPS_OECD is a cornerstone in assessing policy stringency, its standardized construction may introduce biases that do not account for unique national characteristics or evolving policy contexts. Consequently, we challenge the EPS_OECD by comparing it against three alternative indicators—EPS_BOD, EPS_GHG, and EPS_GDP—that modify the original methodology to address potential limitations in capturing policy effectiveness consistently across different countries and time periods.

The EPS_BOD, for example, adapts the EPS by allowing more flexibility based on each country's specific economic and environmental needs, which could potentially reduce the one-size-fits-all bias inherent in EPS_OECD. Similarly, EPS_GHG and EPS_GDP weight policy stringency based on each country's greenhouse gas emissions profile and economic output, respectively, providing a sector-sensitive approach that may better capture differences in policy impact across varied national contexts.

Through this comparison, we aim to determine whether the EPS_OECD and its alternatives—EPS_BOD, EPS_GHG, and EPS_GDP—are equally valid as unbiased proxies, or if their designs introduce discrepancies that could alter policy analysis. This exploration reveals not only the strengths and weaknesses of each indicator but also highlights the broader implications of selecting an EPS measure that best aligns with the empirical objectives of cross-national and inter-temporal policy studies.

4.1.1 Precision or Overlap? Tracking measurement choices effects

While our four EPS indicators generally yield similar results at the total score level, differences emerge in coefficients and significance levels, as shown in Table 3. For instance, EPS_BOD shows a lower coefficient and significance, likely due to its inherently higher values. These results are confirmed by the SSIV results (Tables B.8 and B.9), showing a slightly smaller coefficient for EPS_BOD.

Table 3: Total EPS Effects on GHG Emissions

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG)			
Cov. Est	Clustered			
No. Observations	1152			
R^2 (Within)	0.4359	0.0487	0.3522	0.4667
R^2 (Overall)	0.9170	0.9047	0.9161	0.9187
Log-likelihood	1263.6	1228.3	1253.8	1284.0
F-statistic	248.05	220.58	240.26	264.75
const	2.3136	0.8602	1.9494	2.7117
	(1.5069)	(0.5425)	(1.2771)	(1.8444)
ln(GDP)	-0.4454***	-0.2922*	-0.4330***	-0.4263***
	(-3.4578)	(-2.2033)	(-3.3965)	(-3.4048)
$\ln(GDP)^2$	0.0421***	0.0371***	0.0413***	0.0419***
	(7.7665)	(6.6155)	(7.6714)	(7.9063)
ln(POP)	0.5151***	0.5333***	0.5345***	0.4790***
	(7.9075)	(7.8432)	(8.1759)	(7.5818)
urban_growth	-0.0457***	-0.0476***	-0.0461***	-0.0470***
	(-6.8966)	(-6.8159)	(-6.7643)	(-7.1460)
EPS	-0.0750***	-0.0378***	-0.0676***	-0.0765***
	(-10.514)	(-7.1395)	(-9.7377)	(-12.314)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

The VIF tests, as shown in Table B.3 from the Appendix B.2, reveal a quite logical multicollinearity in ln(GDP)and ln(GDP)^2 across all models, with VIF values exceeding 20. The correlation analysis (See appendix, Table B.5) further supports this, highlighting high correlations between ln(GDP)and ln(POP)with ln(GHG)(0.918 and 0.950, respectively). This underscores the predictive influence of these economic variables on emissions and points to potential multicollinearity concerns, particularly in EPS_BOD and EPS_OECD, where EPS variables moderately correlate with economic indicators like ln(GDP)(0.2–0.35). This overlap suggests that these indicators may partially reflect economic conditions rather than strictly capturing environmental policy stringency. However, there is no multicollinearity issue in other variable, especially in EPS ones, with VIF values below 2. Interestingly, despite the construction of EPS_GHG and EPS_GDP to account for emissions and economic output respectively, they show the lowest multicollinearity levels. This observation suggests that these indicators may offer a more distinct representation of policy stringency with less overlap from economic variables, indicating potential robustness as proxy indicators.

At the sectoral level of emissions or regulation, distinction between EPS is even clearer. At the level of total national emissions, the regression analysis across the four models reveals varying impacts of sectoral regulation on emission reduction, suggesting distinct narratives depending on the indicator used. As presented in Table 4, regulatory stringency in the building sector shows inconsistent effects on emissions: the EPS_OECD and EPS_BOD indicators does not yield neither significant nor negative coefficients, while the EPS_GHG and EPS_GDP indicators exhibit a strong, significant negative relationship with emissions. This trend holds in models with interaction terms, as seen in Table 8. These discrepancies raise questions about their origins: whether they stem from a more accurate representation of regulatory stringency in the EPS_GHG and EPS_GDP indicators (evidenced by higher R^2, log-likelihood, and F-statistics) or whether they are misleading due to multicollinearity issues.

The Variance Inflation Factor (VIF) test supports the robustness of the EPS_GHG and EPS_GDP models, highlighting higher multicollinearity in the EPS_BOD and EPS_OECD models. This is specially true for EPS_building and EPS_elec, indicating potential interdependencies among sector-specific predictors. In contrast, EPS_GHG and EPS_GDP models exhibit lower VIF values, suggesting that these indicators better isolate the impacts of sector-specific instruments with minimal overlap. Specifically, EPS_GDP allow for clearer attribution of each sector's contribution to overall emissions, likely due to their design to capture national characteristics. Correlation analysis (Appendix B.2, Table B.6) further underscores this finding, showing moderate correlations between EPS sector metrics and ln_GDP and ln_POP within EPS_BOD and EPS_OECD models, particularly for the building and electricity sectors. This suggests that EPS_BOD and EPS_OECD may capture socioeconomic trends alongside policy stringency, while EPS_GHG and EPS_GDP maintain a more targeted focus on policy effects.

When breaking down the analysis by emission sectors, the results confirm that the EPS_BOD indicator is the least suitable, while EPS_GDP and EPS_GHG demonstrate the strongest explanatory power. For the overall effect of EPS, the EPS_GDP indicator shows the most substantial impact

Table 4: Sectoral EPS Effects on GHG Emissions

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable		ln(GHG)		
Cov. Est		Clustered		
No. Observations		1119		
R^2 (Within)	0.4315	0.0470	0.4415	0.4879
R^2 (Overall)	0.9224	0.9086	0.9300	0.9289
Log-likelihood	1228.9	1209.0	1240.5	1244.8
F-statistic	154.04	144.12	160.01	162.21
const	2.6795	0.6129	0.6378	2.7743
	(1.7408)	(0.3718)	(0.4109)	(1.8869)
ln(GDP)	-0.4934***	-0.2958*	-0.2647*	-0.3634**
	(-3.8606)	(-2.1963)	(-2.0789)	(-2.9162)
ln(GDP)^2	0.0438***	0.0364***	0.0325***	0.0387***
	(8.1390)	(6.4081)	(6.0315)	(7.2756)
ln(POP)	0.5118***	0.5558***	0.5718***	0.4573***
	(7.5738)	(7.8163)	(8.3257)	(6.7293)
urban_growth	-0.0482***	-0.0525***	-0.0391***	-0.0492***
	(-7.0423)	(-7.0958)	(-6.0421)	(-7.4979)
EPS_building	0.0241	0.0764***	-0.1395***	-0.0950***
	(1.0546)	(4.0007)	(-7.9003)	(-5.6734)
EPS_elec	-0.0779**	-0.0366*	-0.0353**	0.0149
	(-3.1460)	(-1.9754)	(-2.9959)	(0.6580)
EPS_indus	-0.1302***	-0.1243***	-0.0168	-0.0765***
	(-7.7360)	(-7.9372)	(-1.2799)	(-9.7827)
EPS_transport	-0.1115***	-0.0576**	-0.1351***	-0.0826***
	(-4.6648)	(-2.7776)	(-7.7816)	(-5.4661)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

on emissions in the building, electricity, and transport sectors. Meanwhile, for industrial emissions, EPS_OECD performs slightly better, closely followed by EPS_GHG and EPS_GDP. When examining the sector-specific effects of EPS, both EPS_GHG and EPS_GDP emerge as the most significant indicators across all emission sectors.

These divergences highlight the importance of selecting the appropriate EPS indicator depending on the sector and policy context, while no single indicator fully captures inter-country or inter-temporal variations in policy effectiveness. Overall, the EPS_BOD is the less reliable indicator. While EPS_OECD provides valuable insights, its multicollinearity with economic variables highlights limitations as standalone proxy. Conversely, the lower multicollinearity levels in and EPS_GDP models as well as their precision imply this indicator may serve as stronger proxy particularly when aiming to isolate the effect of policy stringency from economic influences across sectors and countries.

4.1.2 A Cross-Country Stable Indicator? An Analysis of Developed vs. Developing Countries

In order to analyze the cross-country stability of the Environmental Policy Stringency (EPS) indicator, the dataset was divided into two subsets: developed and developing countries. This division allows for a comparative analysis of the impact of EPS on greenhouse gas (GHG) emissions across different economic contexts.

Table 5: Total EPS Effects on GHG Emissions (Developed vs Developing Countries)

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG)			
Cov. Est	Clustered			
Developed countries (714 obs.)				
R^2 (Within)	0.2585	-0.9936	-0.0665	0.3502
R^2 (Overall)	0.9067	0.9104	0.9172	0.8838
Robust F-statistic	69.961	53.353	64.155	83.806
EPS	-0.0620***	-0.0139*	-0.0466***	-0.0681***
	(-5.7625)	(-2.0557)	(-4.4559)	(-7.6352)
Developing countries (438 obs.)				
R^2 (Within)	0.5086	0.3971	0.4853	0.5575
R^2 (Overall)	0.9357	0.9354	0.9363	0.9375
Robust F-statistic	113.35	100.86	105.93	121.60
EPS	-0.0376***	-0.0170*	-0.0356***	-0.0452***
	(-3.5111)	(-2.1370)	(-3.5488)	(-4.9237)
Signif. codes	0.001 '***'	0.01 '**'	0.05 '*'	

Note: Results come from a two-way fixed effects OLS with control variables, including ln(GDP), ln(GDP)^2, ln(POP) and urban growth.

The results on national emissions, presented in Table 5, reveal a slight degree of cross-country instability, as the effect of EPS varies between developed and developing countries. A stable EPS score would imply consistent effects on emissions across countries. One possible explanation for this observed instability is the disparity in the number of observations between the two subsets: developed countries have 714 observations, compared to 438 for developing countries. Notably, in the developed countries subset, the models exhibit lower significance (F-statistics and R-squared) levels across all specifications.

Developed countries demonstrate a stronger impact of policy stringency across the EPS_OECD, EPS_GHG, and EPS_GDP indicators.[7] The coefficients for developed countries are consistently larger in magnitude and significance. This pattern holds when decomposing emissions per GDP

[7] The EPS_BOD indicator does not yield statistically significant results across any specification, suggesting its limited explanatory power in emission reduction efforts. Thus, we focus on the other indicators.

(Table B.17) and per capita (Table B.13). Interestingly, EPS_GDP demonstrates again the best adjustment, with both higher significance and lower instability.

This regional instability across all indicators may be attributed to several factors. First, it could stem from the construction of the proxy, which is based on a *de jure* measure of stringency rather than a *de facto* one. EPS scores reflect enacted policies, regardless of implementation or enforcement levels. If policy enforcement is weaker in developing countries, this could explain the lower observed effect. Second, the lag in climate policies adoption in developing countries may play a role. Since these countries have adopted policies more recently, their effects may not yet be fully realized.

4.1.3 Temporal Stability of the Indicator: An Analysis Across Time Periods

To assess the temporal stability of the Environmental Policy Stringency (EPS) indicator, the dataset was divided into three distinct time periods: 1991-2000 (Period 1), 2001-2010 (Period 2), and 2011-2020 (Period 3). he selection of these periods is based on observed variations in policy adoption, with the first period characterized by a slow increase in policy measures, the second period by a moderate expansion, and the third period by a high intensity of policy adoption. This decomposition allows for a comparative analysis of the impact of EPS over time.

Table 6: Time-period Decomposition, Effect of Total EPS on GHG emissions

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
	Period 1 (1991-2000) - 293 obs			
R^2 (Within)	-0.3946	-0.3085	-0.3387	-0.4154
Robust F-statistic	34.18	34.39	34.28	34.17
EPS	-0.0036	-0.0117	-0.0003	-0.0106
	(-0.1340)	(-0.6929)	(-0.0110)	(-0.4643)
	Period 2 (2001-2010) - 416 obs			
R^2 (Within)	0.0366	-0.0303	0.0536	0.0560
Robust F-statistic	63.08	62.10	64.15	64.37
EPS	-0.0468***	-0.0284***	-0.0469***	-0.0481***
	(-4.3961)	(-4.1823)	(-4.8513)	(-4.8498)
	Period 3 (2011-2020) - 429 obs			
R^2 (Within)	0.0722	-0.2465	0.1748	-0.0375
Robust F-statistic	22.22	20.38	24.45	21.56
EPS	-0.0301**	0.0016	-0.0407***	-0.0204*
	(-2.5525)	(0.2093)	(-3.3879)	(-2.4409)

Note: Results come from a two-way fixed effects OLS with control variables, including ln(GDP), ln(GDP)^2, ln(POP) and urban growth.

The results, presented in Table 6, indicate notable variations in the impact of EPS across different time periods. In the first period (1991-2000), the EPS indicators show low statistical significance across all emission specifications, with coefficients close to zero and t-values indicating no significant relationship. This suggests that during the early years, environmental policy measures had limited influence on emissions reduction.

In contrast, the second period (2001-2010) reveals a substantial increase in the explanatory power of the EPS indicators. The coefficients for EPS_OECD, EPS_GHG, and EPS_GDP become statistically negative. This trend, confirmed with per capita and GDP emissions, indicates that environmental policies implemented during the early 2000s had a meaningful impact on emissions reduction.

However, the results for the most recent period (2011-2020) suggest a small decline in the significance and magnitude of the EPS indicators. Despite these fluctuations, the overall pattern across different specifications of emissions-GHG emissions per unit of GDP (Table B.18), and GHG emissions per capita (Table B.14)- remains consistent. This suggests potential shifts in policy effectiveness or external factors influencing emissions trends.

Overall, the results highlight that while the EPS indicator demonstrated a notable impact in the mid-2000s, its influence appears to have diminished in recent years. These findings suggest that policy effectiveness may not be constant over time and could depend on evolving economic and regulatory conditions. Further investigation into potential structural changes or policy adaptations is warranted to better understand the factors influencing the temporal stability of the EPS indicator.

4.2 Effectiveness assumption

4.2.1 A negative impact of total EPS on GHG

Results on total national emissions remain stable across the four models, supporting the Effectiveness assumption, as shown in Table 3. First, regarding control variables, our findings align with existing literature. The results confirm the non-linearity of the relationship between GHG emissions and GDP, while highlighting the positive effect of population size and the negative effect of the urbanization rate.

Second, across all four EPS indicators—EPS_OECD, EPS_BOD, EPS_GHG, and EPS_GDP—a significant and negative relationship is observed between EPS and greenhouse gas emissions,[8] with EPS coefficients ranging from -0.038 (EPS_BOD) to -0.077 (EPS_GDP). This relationship holds consistently across all specifications (GHG/cap, GHG/GDP), even when statistical significance weakens in certain models. Notably, although the logarithmic specifications exhibit lower within-group significance, the coefficients remain significant and suggest an overall elasticity of GHG to EPS between -0.5 and -0.12. These results are perfectly in line with the literature. For instance, Nachtigall et al. (2024) find a 12% reduction of GHG and carbon emissions associated to their CAPMF score.

Third, this relationship appears to be causal, as evidenced by results obtained using lagged variables (see Appendix B.3.1) and the Shift-Share Instrumental Variable (SSIV). Indeed, findings remain

[8]Measured using its natural logarithm, ln(GHG).

robust even when applying a Bartik Instrument, as detailed in Appendix B.3.2,[9] reinforcing the negative effect of total EPS on GHG across various indicators.

Results on sectoral emissions further support the Effectiveness assumption (see Appendix B.6). Similar effects of EPS across the four indicators are observed for all sectoral emissions, with coefficients ranging from -0.10 to -0.06 for EPS_GDP. However, while the within R-squared is significant for three sectors, it is not significant for emissions in the building sector. Additionally, EPS has a stronger effect in the electricity sector. To better understand this sectoral differences, we explore the effects of sectoral EPS is the next part.

4.2.2 Sectoral EPS Effects on GHG Emissions

To deepen our understanding of the relation between EPS and policy mix effectiveness, we decompose sectoral effects across building, electricity, industry, and transport sectors. Table 4 shows that results vary across sectors. Notably, the effect of EPS score for transport and industry are the most significant, both in terms of statistical significance and coefficient magnitude. EPS in the electricity sector has a small yet negative coefficient for most of the types of EPS, however, it is insignificant for EPS_GDP. In contrast, the effect of the building sector score is not statistically significant for EPS_OECD while associated to a negative coefficient for EPS_GHG and EPS_GDP. Potential explanations include inadequate regulations, rebound effects, low price elasticity, or behavioral factors.

While a clear causal relationship exists between EPS indicators and GHG emissions at the national level, results for sectoral emissions reveal a more nuanced picture, as detailed in Table 7.[10]

Table 7: Summary of Sectoral EPS effects on Sectoral GHG across model

	GHG_building	GHG_elec	GHG_indus	GHG_transport
EPS_building	+	+/-	+/-	-
EPS_elec	/	+/-	-	-
EPS_indus	-	-	-	-
EPS_transport	-	-	-	-

Note: This table shows the signs of EPS coefficients, from two-way fixed effects OLS on the logarithm of secotral emissions with control variables, including ln(GDP), $\ln(GDP)^2$, ln(POP) and urban growth. Results are summarized across the four EPS type: +/- means that the coefficient is changing from positive to negative or insignificant depending on the EPS' type.

Results on emissions from the industrial and transport sectors strongly support the Effectiveness assumption, showing significant negative coefficients across all EPS indicators, both in terms of

[9] Robust F-statistics exceed 48 in the first-stage and 119 in the second-stage, confirming the strength of the IV. However, we acknowledge a potential endogeneity issue with the instrument, as suggested by the autocorrelation test from van Kippersluis and Rietveld (2018), while Borusiak's IV test confirms the instrument's temporal instability.

[10] Detailed tables summarizing these sectoral results can be found in Appendix B.6.

sectoral coverage and indicator's type. At the sectoral level of policy stringency, EPS_indus and EPS_transport are associated with emission reductions across all sectors, reinforcing the idea of potential regulatory synergies between sectors.

However, results for the building and electricity sectors are more nuanced. First, within the building sector, the EPS_building indicator is positively correlated with emissions, whereas EPS_transport and EPS_indus exhibit negative correlations. However, this result should be interpreted with caution due to low within-group R-squared and F-statistic (approximately 30), indicating limited explanatory power of the model in this sector. This aligns with findings on total national emissions, where EPS_building is not statistically significant.

Second, while EPS for the electricity sector is negatively correlated with emissions (or insignificant) across all emitting sectors, the relations within the electricity sector itself is less stable. EPS_OECD exhibits a negative coefficient, whereas EPS_GDP shows a positive one. Since EPS_GDP is the best-adjusted proxy, it may be considered more reliable in this context. However, the discrepancy between EPS_OECD and EPS_BOD may stem from the regional instability of EPS_elec. As detailed in Table B.24 in the appendix, the EPS score in this sector has a significant effect only in developed countries, while it remains insignificant in developing ones.

4.2.3 A strong effect of sectoral policy interactions on GHG emissions

Building on the previous section, we hypothesize potential interactions between policies across different sectors. To better understand these dynamics, we test the effect of interactions between EPS from various sectors on total national emissions.

Following a general-to-specific approach, we initially included all possible interaction terms and then progressively removed the insignificant ones to enhance the F-statistic and improve the model's log-likelihood. This analysis is based on EPS_GDP for two key reasons. First, models incorporating other EPS types exhibit high multicollinearity.[11] Second, EPS_GDP is the best-adjusted EPS measure for this data-driven analysis. The final model, derived through this process, is detailed in Table 8.[12]

Including interaction terms between sectoral policy scores improves the consistency of results across EPS indicators and enhances the overall significance of the models. We find that these interaction terms largely absorb the effects of individual EPS scores, except for EPS_indus, which remains the only sectoral EPS with a standalone effect even when interaction terms are included. Its impact is notably strong, both in terms of coefficient magnitude and statistical significance.

However, this model also reveals that the stringency of policies targeting the electricity sector has mixed effects on emission levels. Its interaction with EPS_transport exhibits a negative offset-

[11] VIF tables can be found in Appendix B.7.2

[12] While the model includes insignificant standalone EPS, robustness tests without these variables yields the same results. We let these variables in the model to assure statistical coherence.

Table 8: Sectoral EPS Effects on GHG Emissions with Interaction Terms

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable		ln(GHG)		
Cov. Est		Clustered		
No. Observations		1119		
R-Squared (Within)	0.4762	0.1170	0.4480	0.4904
F-statistic	133.21	118.24	140.00	143.28
EPS_building	-0.0426	0.0339	-0.0878**	0.0326
	(-1.4803)	(1.1030)	(-2.6000)	(1.1280)
EPS_elec	0.1112**	0.0964**	0.0387*	0.0479
	(2.8445)	(2.7152)	(1.9898)	(0.8119)
EPS_transport	0.0124	0.0430	0.0290	0.0054
	(0.4145)	(1.4475)	(1.1906)	(0.3223)
EPS_indus	-0.1588***	-0.1870***	-0.0487**	-0.1033***
	(-7.6148)	(-5.8820)	(-2.5406)	(-10.719)
Average effect	-0.0765	-0.0725	-0.0183	-0.0670
EPS(Elec*Indus)	0.0809***	0.0700**	0.0420**	0.1856***
	(2.8874)	(2.5762)	(2.3266)	(4.1428)
Average effect	0.0315	0.0273	0.0137	0.0333
EPS(Elec*Transport)	-0.3167***	-0.1783***	-0.1629***	-0.1842***
	(-7.1652)	(-4.7306)	(-7.1064)	(-4.9505)
Average effect	-0.0753	-0.0800	-0.0467	-0.0322
EPS(Building*Transport)	0.0478	0.0384	-0.0507*	-0.0939***
	(1.5667)	(1.6188)	(-1.8671)	(-5.5326)
Average effect	0.0049	0.0358	-0.0332	-0.0527
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

Note: Results come from two-way fixed effects OLS with control variables, including ln(GDP), ln(GDP)^2, ln(POP) and urban growth.

ting effect, highlighting the importance of integrated sectoral policy approaches. Conversely, its interaction with EPS_indus yields small but positive and significant coefficients.

Finally, the results underscore the strong potential of transport policies to complement other sectoral regulations. Specifically, when combined with electricity or building EPS, the interaction term coefficient is significant and negative (except for EPS_BOD, the least reliable indicator). This finding aligns with Stechemesser et al. (2024), who identified the transport sector's high potential for policy complementarity, while also extending the analysis to cross-sectoral synergies.
In conclusion, the Effectiveness assumption holds across most sectors, especially in industry and transport, where either total or sectoral EPS results indicate significant emissions reductions with increased policy stringency. However, in the building and electricity sectors, the Effectiveness assumption appears less robust, underscoring first the importance of considering the broader policy mix and second the need of robust proxy.

5 Conclusion

As nations worldwide endeavor to mitigate climate change, there is a growing need to assess the effectiveness of environmental policies. This study seeks to contribute to this effort by examining the development of comprehensive Environmental Policy Stringency (EPS) indicators. Specifically, it aims to address two key research questions: firstly, how can robust EPS indicators be constructed to encompass the nuanced complexities of sectoral climate policy mixes? And secondly, how measurement choices effects empirical results regarding climate policy mixes effectiveness?

Leveraging the OECD Climate Actions and Policies Measurement Framework database, we devised four distinct metrics—EPS_OECD, EPS_BOD, EPS_GHG, and EPS_GDP—to evaluate the rigor of environmental policies across different sectors. Using a two-way fixed effects panel regression model combined with a Shift-Share Instrumental Variable (SSIV) approach, we were able to conduct a nuanced analysis of policy effectiveness, accounting for both time-invariant factors specific to each country and sector as well as broader temporal trends. This methodology enabled us to isolate the impacts of regulatory stringency within each sector while also examining interactions across sectors, providing insight into how policies covering one sector may influence outcomes in another.

The analysis of the Proxy assumption reveals significant differences in the reliability of EPS indicators as tools for assessing policy stringency. The EPS_OECD indicator, which follows the methodology of the widely used OECD EPS Index, does not fully account for national differences and exhibits variability over time, suggesting it may be less effective as a consistent proxy. While the standardized construction of the OECD indicator lacks precision, the Benefits-of-the-Doubt (BOD) method, by contrast, demonstrates multicollinearity issues with national trends. In comparison, EPS_GDP shows greater stability and lower multicollinearity, making it a more robust indicator for regional and temporal comparisons. However, at the sectoral level, while results confirm that EPS_GDP provides stronger adjustments than EPS_BOD, EPS_GHG, and EPS_OECD, the discrepancies between these indicators suggest that using a combination of measures may be necessary to better capture the nuanced effects of policy mixes. Additionally, although EPS_GDP appears more stable overall, all indicators suffer from regional and temporal instability, likely due to differences in the enforcement of policies across countries and over time.

Our results largely support the Effectiveness assumption at the total EPS level, confirming that increased EPS is associated with reduced GHG emissions. This negative relationship holds across all four EPS indicators. However, at sectoral level our study underscores a significant effect of measurement choices on EPS relation to GHG. In transport and industry sectors, sector-specific EPS scores significantly impact emissions reductions regardless of the chosen indicator. However, in building and electricity sectors, EPS effects are less consistent among indicators, likely due to rebound effects, low price elasticity, and complex sectoral interactions. Additionally, policy effectiveness appears to strengthen with sectoral coordination, as evidenced by the significant interaction between EPS_transport and EPS_elec or EPS_building. These findings suggest that while EPS indicators generally support emissions reduction, this relation depends on the chosen indicator and varies by sector, underscoring the need for integrated policy approaches and tailored proxies that account for national and sectoral specificities.

No single indicator is perfect on its own. As this analysis has shown, capturing the full complexity of climate policy mixes within a single measure is challenging and may result in misleading conclusions. In particular, our different types of sectoral EPS appear to lack temporal and regional stability. Further research could focus on adding an enforcement dimension to see if it helps coping with this issue. In the meantime, we recommend using a panel of methodologies, as demonstrated in this study, to offset the limitations of individual indicators and provide a more balanced and comprehensive view of environmental policy stringency.

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Appendix

A The choice of the dispersion parameter for EPS_BOD

In this part, we use the complete dataset for EPS_BOD, rather than the shortened database used in the EPS comparison, to achieve the best parameter adjustment.

Table A.1: Effect of the variance on the total EPS_BOD

	BOD_10var	BOD_50var	BOD_100var
Dep. Variable		ln(GHG)	
No. Observations	1308	1308	1308
R^2 (Within)	-0.6575	-0.1209	0.0487
Log-likelihood	1199.5	1216.8	1228.3
F-statistic	199.37	212.01	220.58
const	-2.6399	-0.8789	0.8602
	(-1.7010)	(-0.5698)	(0.5425)
ln(GDP)	0.0863	-0.0710	-0.2922*
	(0.6504)	(-0.5458)	(-2.2033)
$\ln(GDP)^2$	0.0226***	0.0291***	0.0371***
	(4.0046)	(5.2601)	(6.6155)
ln(POP)	0.5952***	0.5480***	0.5333***
	(8.7237)	(8.1315)	(7.8432)
urban_growth	-0.0518***	-0.0493***	-0.0476***
	(-7.1216)	(-6.9844)	(-6.8159)
EPS	-0.0109**	-0.0293***	-0.0378***
	(-2.7367)	(-5.8227)	(-7.1395)

As shown in Table A.1, the BOD indicator with the best adjustment is obtained for $\alpha = 100$. With this specification of the argument, the model demonstrates both a better general significancy and significancy of the parameter EPS.

B Econometrics tests

B.1 Diagnostic Tests and Model Selection

Based on the results of diagnostic tests, selecting the appropriate model specification is essential for ensuring the robustness and reliability of the regression analysis. Here, we present the test results for EPS_OECD with sectoral decomposition, which are representative of the findings for other indicators, with and without sectoral decomposition.

First, the White and Breusch-Pagan tests were conducted to assess heteroskedasticity and contemporaneous correlation in the pooled OLS regression. The significant LM-Stat values of 407 and 28, with corresponding p-values of approximately 2e-65 and 2e-4, indicate the presence of both heteroskedasticity and contemporaneous correlation in the model. Additionally, the Durbin-Watson test statistic of 2.20 suggests a small negative autocorrelation in the residuals of the pooled OLS model.

Next, the Hausman test was used to compare the fixed effects (FE) and random effects (RE) models to address potential endogeneity. The test produced a chi-squared statistic of 106 with 9 degrees of freedom resulting in a p-value of approximately 1e-18. These results indicate that we can reject the hypothesis that there is no correlation between the exogenous variables and the error terms. This confirm the economic intuition of a correlation between time trends and the exogenous variables, which was confirmed by the correlation matrix and the Variance Inflation Factor (VIF) test, revealing moderate multicollinearity. AIC and BIC analyses were performed, confirming that the two-way fixed effects model was the best fit for our data, as shown in Table B.2.

Finally, additional tests were conducted on the FE model for heteroskedasticity, autocorrelation, and cross-sectional dependence. The Breusch-Pagan test confirmed heteroskedasticity (p-value = 3e-13), while the Breusch-Godfrey test identified autocorrelation (p-value = 1e-9). However, Pesaran's test for cross-sectional dependence was not significant (p-value = 0.7). To address both heteroskedasticity and autocorrelation, the Clustered covariance estimator was applied. Tests were perform on the model with Discroll-Kraay estimator, confirming that the clustered estimator was the most conservatory.

Table B.2: Model Comparison

	RE	FE Entity	FE Time	FE Entity/Time
Dep. Variable		ln(GHG)		
No. Observations		1152		
Cov. Est.		Clustered		
R^2	0.7758	0.5385	0.9409	0.5462
R^2 (Within)	0.5380	0.5385	0.1821	0.4298
R^2 (Between)	0.9382	0.9331	0.9489	0.9312
R^2 (Overall)	0.9300	0.9256	0.9402	0.9186
AIC	-2311.02	-2359.89	982.82	-2533.31
BIC	-2265.58	-2314.45	1028.26	-2487.86

Note: Results come from a two-way fixed effects OLS with control variables, including ln(GDP), $\ln(GDP)^2$, ln(POP) and urban growth, and sectoral decomposition of EPS_OECD as explanatory variables.

B.2 Multicolinearity tests

Table B.3: VIF Comparison Across Models

Variable	**EPS_OECD**	**EPS_BOD**	**EPS_GHG**	**EPS_GDP**
ln(GDP)	21.61	21.94	22.02	20.99
$\ln(GDP)^2$	22.68	23.20	22.95	22.14
ln(POP)	1.20	1.21	1.19	1.21
urban_growth	1.05	1.06	1.06	1.05
EPS	1.17	1.20	1.18	1.14

The primary concerns are moderate multicollinearity in ln(GDP)and $\ln(GDP)^2$ across all models. However, this quite logical multicollinearity in these control variable does not affect the reliability of other variables of the model. Indeed, with the presence of $\ln(GDP)^2$ confidence intervals of coefficients for variable,s excluding the GPD ones, are actually reduced. Furthermore, at this level of aggregation for EPS variables, we note no multicollinearity issue for all type of EPS. This results is confirmed with the sectoral decomposition, as detailed in table B.4

Table B.4: VIF Comparison Across Sectoral Models

Variable	**EPS_OECD**	**EPS_BOD**	**EPS_GHG**	**EPS_GDP**
ln(GDP)	22.30	23.45	24.33	21.49
$\ln(GDP)^2$	23.65	24.26	25.61	22.94
ln(POP)	1.24	1.23	1.23	1.31
urban_growth	1.11	1.10	1.11	1.10
EPS_building	1.91	2.48	1.24	1.42
EPS_elec	1.84	2.21	1.21	1.24
EPS_indus	1.74	2.07	1.29	1.22
EPS_transport	1.51	1.73	1.21	1.33

With the sectoral decomposition of EPS variables, it appears more clearly that EPS_GDP has the lowest issues with multicollinearity. Indeed, if all VIF values are lower than 5 for EPS variables, they are the lowest for EPS_GDP, suggesting a better adjustment of this indicator.

Table B.5: Correlation Table of Control, Endogenous, and EPS Variables

	ln(GHG)	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
ln(GDP)	**0.908**	0.271	0.276	0.272	0.256
ln(POP)	**0.950**	0.098	0.102	0.095	0.0819
urban_growth	0.052	-0.028	-0.051	-0.032	-0.049
ln(GHG)	1	0.100	0.107	0.094	0.085

High correlations between ln(GDP)and ln(POP)with ln(GHG)(0.908 and 0.950) underscore their strong predictive influence on emissions. In contrast, urban_growth shows limited direct correlation (0.052) with ln_GHG.

EPS variables, aggregated or sectoral, show moderate correlations with GDP variables (0.2–0.35). This suggests that while EPS metrics capture emissions standards, they may overlap with economic variables, as demonstrated with the VIF test. Interestingly, EPS_GDP is the one with the lowest correlation with both GDP and GHG variables while EPS_BOD has the highest correlation with both of these variables.

Table B.6: Correlation of EPS Variables with Control and Endogenous Variables

	EPS_building	**EPS_elec**	**EPS_indus**	**EPS_transport**
		EPS_OCDE		
EPS_Building	1.0000	0.8535	0.8724	0.8325
EPS_Elec	0.8535	1.0000	0.8494	0.8001
EPS_Indus	0.8724	0.8494	1.0000	0.7124
EPS_Transport	0.8325	0.8001	0.7124	1.0000
		EPS_BOD		
EPS_Building	1.0000	0.9049	0.8990	0.8907
EPS_Elec	0.9049	1.0000	0.8804	0.8749
EPS_Indus	0.8990	0.8804	1.0000	0.8035
EPS_Transport	0.8907	0.8749	0.8035	1.0000
		EPS_GHG		
EPS_Building	1.0000	0.4899	0.6848	0.6681
EPS_Elec	0.4899	1.0000	0.6412	0.4413
EPS_Indus	0.6848	0.6412	1.0000	0.6465
EPS_Transport	0.6681	0.4413	0.6465	1.0000
		EPS_GDP		
EPS_Building	1.0000	0.5131	0.6293	0.7339
EPS_Elec	0.5131	1.0000	0.3472	0.4307
EPS_Indus	0.6293	0.3472	1.0000	0.5828
EPS_Transport	0.7339	0.4307	0.5828	1.0000

Additionally, inter-correlations among EPS sector metrics, detailed in Table B.6 highlight the potential for multicollinearity. The lowest levels of correlation between sectoral EPS variables are obtained for EPS_GDP (except for EPS_building for which variable EPS_GHG has lower correlation), which may explain the better adjustment of this indicator .

B.3 A causal relation

B.3.1 EPS lagged

Table B.7: Lagged Sectoral EPS Effects on GHG Emissions

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable		ln(GHG)		
Cov. Est		Clustered		
No. Observations		1078		
R^2 (Within)	0.3638	0.1166	0.1960	0.3595
R^2 (Overall)	0.9283	0.9259	0.9324	0.9166
Log-likelihood	1204.6	1190.9	1189.7	1182.4
F-statistic	124.29	118.00	115.08	124.76
EPS_building_lag	0.0129	0.0480*	-0.1283***	-0.0657***
	(0.5450)	(2.3491)	(-6.8722)	(-3.7268)
EPS_elec_lag	-0.0576*	-0.0048	-0.0410*	0.0464
	(-1.9996)	(-0.2252)	(-3.1150)	(1.9158)
EPS_indus_lag	-0.1072***	-0.1198***	0.0102	-0.0681***
	(-5.0549)	(-5.9609)	(0.6670)	(-6.9836)
EPS_transport_lag	-0.1459***	-0.0886***	-0.1087***	-0.0959***
	(-6.0642)	(-4.4767)	(-6.4564)	(-6.5120)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

Note: Results come from a two-way fixed effects OLS with control variables, including ln(GDP), ln(GDP)^2, ln(POP) and urban growth.

B.3.2 A Shift-Share Instrumental Variable

Total IV In our estimation strategy, we implement a Shift-Share Instrumental Variable (SSIV) approach to address endogeneity concerns when estimating the impact of Environmental Policy Stringency (EPS) on national greenhouse gas (GHG) emissions. This method, designed to isolate exogenous variation, combines both a "shift" and a "shock" component. Also known as a Bartik instrument, it leverages country-specific economic exposure and external, global policy shocks to isolate exogenous variation in EPS.

The share component is derived from each country's initial sectoral exposure, specifically the share of GDP from agriculture and forestry in 1990. This historical data captures a fixed economic characteristic that reflects each country's structural reliance on sectors impacted by environmental policy, while remaining exogenous to the current variation in GHG emissions. Therefore, we use data only from 1991 onward for other observations, ensuring that the shift component predates our panel data and remains uninfluenced by contemporary policy changes.

The shift component captures global shocks in environmental policy, measured as the global average of EPS with a leave-one-out calculation to mitigate endogeneity. By excluding each country's EPS from the global mean calculation, we ensure that the instrument captures a global policy trend unaffected by national-level variation. This shock component, therefore, reflects exogenous global trends, varying over time but remaining independent of individual countries' policy decisions.

The Bartik instrument can be expressed as:

$$\text{Bartik\_instrument}_{cy} = S_c \times Z_y$$

where S_c represents each country's initial share of GDP from agriculture and forestry in 1990, and Z_y is the leave-one-out global mean of EPS in year y.

First-Stage Regression

In the first stage, we estimate the effect of the Bartik instrument on EPS while controlling for relevant covariates. The first-stage regression is specified as:

$$\text{EPS}_{cy} = \beta_0' + \beta_1' \mathbf{X_{cy}} + \beta_2' \text{Bartik\_instrument}_{cy} + \alpha_c' + \gamma_y' + \epsilon_{cy}'$$

Table B.8: First-Stage Regression Results: Predicting EPS Variables

	EPS_OCDE	EPS_BOD	EPS_GHG	EPS_GDP
Cov. Estimator	Clustered			
No. Observations	1138			
R^2 (Within)	-0.3101	-0.2515	-0.3213	-0.2716
R^2 (Overall)	-3.9036	-4.2507	-4.0557	-4.3738
Log-likelihood	-494.68	-894.23	-545.13	-614.78
F-statistic	72.235	68.214	72.554	53.961
F-statistic (robust)	61.711	91.671	64.389	48.206
const	73.037***	106.05***	75.052***	76.159***
	(12.834)	(14.837)	(12.514)	(12.645)
ln(GDP)	-6.4855***	-9.4083***	-7.2875***	-6.1004***
	(-12.278)	(-13.884)	(-12.949)	(-11.026)
$\ln(\text{GDP})^2$	0.2634***	0.3999***	0.2854***	0.2554***
	(11.201)	(13.188)	(11.592)	(10.160)
ln(POP)	-1.9321***	-2.9965***	-1.6671***	-2.3364***
	(-7.1209)	(-8.5049)	(-5.9727)	(-7.8395)
urban_growth	0.0328	0.0493	0.0442	0.0102
	(1.2541)	(1.3832)	(1.6179)	(0.3577)
Bartik_instrument	-0.0240***	-0.0250***	-0.0200***	-0.0229***
	(-8.2515)	(-8.8125)	(-6.0326)	(-6.8031)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

Second-Stage Regression

Using the predicted EPS $\widehat{\text{EPS}}_{cy}$, from the first stage, we estimate the causal effect on GHG emissions in the second stage:

$$\ln(\text{GHG})_{cy} = \beta_0'' + \beta_1''\mathbf{X_{cy}} + \beta_2''\widehat{\text{EPS}}_{cy} + \alpha_c'' + \gamma_y'' + \epsilon_{cy}''.$$

Table B.9: Second-Stage Regression Results: Predicting ln(GHG)with Predicted EPS Variables

	EPS_OCDE	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG)			
Cov. Estimator	Clustered			
No. Observations	1138			
R^2 (Within)	-1.5682	-1.5552	-1.5706	-1.5671
R^2 (Overall)	0.8787	0.8796	0.8782	0.8790
Log-likelihood	1217.4	1216.2	1217.6	1217.2
F-statistic	190.41	189.54	190.54	190.28
F-statistic (robust)	120.28	119.85	120.29	120.46
const	9.4561*	10.120*	12.861**	10.253**
	(2.5181)	(2.5518)	(2.7924)	(2.5832)
ln(GDP)	-1.1418**	-1.1934**	-1.5743***	-1.1002**
	(-3.1721)	(-3.1538)	(-3.3585)	(-3.1353)
$\ln(\text{GDP})^2$	0.0683***	0.0726***	0.0836***	0.0679***
	(4.8781)	(4.7536)	(4.6960)	(4.8672)
ln(POP)	0.3674***	0.3233**	0.3439***	0.2915*
	(3.7708)	(3.0110)	(3.3603)	(2.5513)
urban_growth	-0.0336***	-0.0332***	-0.0299***	-0.0372***
	(-4.7679)	(-4.6510)	(-3.9858)	(-5.5488)
pred_EPS	-0.1642***	-0.1186***	-0.2056***	-0.1675***
	(-3.7525)	(-3.6926)	(-3.7624)	(-3.7348)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

Robustness of the SSIV We first check the F-statistic and robust F-statistic of the first-stage regression, both of which exceed 30, indicating a strong instrument (see Appendix B.3.2). We employ the approximate correlation test from van Kippersluis and Rietveld (2018) to check for potential autocorrelation. These authors provide a way to approximate the deviation from the exclusion restriction by estimating the degree of correlation between the instrument and the error term in the structural equation. The test results in a p-value of lower than 0.001, rejecting the assumption of the instrument's exogeneity.

To further analyzing the robustness our IV strategy, we employ a shock-level decomposition following Borusyak et al. (2022). This approach allows us to test the robustness of our instrument by decomposing the study period into three intervals, each reflecting different levels of EPS intensity:

- **Period 1** (1991–2000): Low or stable EPS levels, serving as a baseline with minimal global environmental policy shocks.
- **Period 2** (2001–2010): Moderate increases and fluctuations in EPS, capturing initial global shifts toward environmental policy integration.
- **Period 3** (2011–2020): High EPS growth and large shocks, representing substantial changes in global environmental policies.

By examining the heterogeneity of treatment effects across these periods, we can evaluate whether the relationship between EPS and GHG emissions holds consistently under different levels of policy intensity. Borusyak et al. (2022) further suggest conducting a placebo test by applying the instrument in a period without significant policy changes; in our analysis, this placebo period yields no significant effects. This shock-level decomposition confirms what we find without the IV in the period decomposition that the instrument is temporally instable.

Table B.10: The Borusyak et al. (2022) Shock-Level Decomposition

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
	Period 1 (1991-2000) - 293 obs			
F-statistic	34.34	34.31	34.42	34.43
Robust F-statistic	25.98	25.98	26.06	26.07
predicted_EPS	0.055	0.029	0.051	0.051
	(0.53)	(0.47)	(0.65)	(0.67)
	Period 2 (2001-2010) - 416 obs			
F-statistic	54.58	54.62	54.60	54.58
Robust F-statistic	36.37	36.37	36.38	36.30
predicted_EPS	-0.105	-0.049	-0.117	-0.142
	(-0.95)	(-0.94)	(-0.97)	(-0.94)
	Period 3 (2011-2020) - 429 obs			
F-statistic	9.42	25.57	11.80	8.37
Robust F-statistic	9.44	21.95	11.19	8.52
predicted_EPS	0.131**	0.258***	0.163**	0.083*
	(2.41)	(5.61)	(3.11)	(1.94)
	Placebo - 1138 obs			
F-statistic	177.78	177.78	177.78	177.78
Robust F-statistic	102.52	102.50	102.52	102.52
Placebo	-0.102	-0.083	-0.291	-0.068
	(-0.39)	(-0.41)	(-0.39)	(-0.40)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

Note: Results come from a two-way fixed effects OLS with control variables, including ln(GDP), ln(GDP)^2, ln(POP) and urban growth.

The Borusyak's test reveals that while all indicators maintain a relationship with emissions over time, EPS_BOD shows greater variability This fluctuation may reflect EPS_BOD's broader design, which might be less adaptable to national policy differences. By contrast, EPS_OECD, EPS_GHG and EPS_GDP exhibit more stable values around -0.15 and -0.10 initially and stronger, consistent negative coefficients around -0.43 and -0.31 in the later period (2011–2020). The placebo test further confirms instrument reliability, showing no significant impacts.

However, if the SSIV is significant at the aggregate level, it is not for the sectoral decomposition, regardless on the type of EPS indicator.

B.4 EPS on GHG/cap

B.4.1 Total EPS effect on GHG

Table B.11: Total EPS Effects on GHG Emissions Per Capita

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG/cap)			
Cov. Est	Clustered			
No. Observations	1151			
R^2 (Within)	0.4197	0.1355	0.3421	0.4513
R^2 (Overall)	0.4117	0.3954	0.4128	0.4038
Log-likelihood	1226.8	1203.5	1218.8	1241.4
F-statistic	133.33	119.54	128.53	142.24
const	-3.6387***	-3.7585***	-3.7123***	-3.2774***
	(-11.225)	(-11.180)	(-11.240)	(-10.674)
ln(GDP/cap)	0.0470	-0.0046	0.0256	0.1952
	(0.3353)	(-0.0318)	(0.1790)	(1.4748)
$\ln(GDP/cap)^2$	-0.0458**	-0.0536***	-0.0477***	-0.0315*
	(-3.1355)	(-3.5300)	(-3.2031)	(-2.2710)
POP_growth	0.0647***	0.0702***	0.0635***	0.0550**
	(3.4993)	(3.8726)	(3.4601)	(3.0102)
urban_growth	-0.1025***	-0.1064***	-0.1016***	-0.0975***
	(-6.9974)	(-7.4850)	(-7.0315)	(-6.8056)
EPS	-0.0523***	-0.0234***	-0.0452***	-0.0572***
	(-7.2095)	(-4.1911)	(-5.9202)	(-8.7088)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

B.4.2 sectoral EPS on GHG

Table B.12: Sectoral EPS Effects on GHG Emissions Per Capita

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG/cap)			
Cov. Estimator	Clustered			
No. Observations	1118			
R^2 (Within)	0.4213	0.1505	0.4413	0.4826
R^2 (Overall)	0.4383	0.4256	0.4737	0.4422
Log-likelihood	1191.9	1183.2	1217.0	1212.9
F-statistic	83.639	80.354	93.418	91.823
const	-3.5464***	-3.6806***	-3.5744***	-3.4283***
	(-10.991)	(-11.501)	(-11.168)	(-9.7817)
ln(GDP/cap)	0.0954	0.0605	0.1039	0.1361
	(0.6808)	(0.4335)	(0.7430)	(0.9077)
ln(GDP/cap)_2	-0.0408**	-0.0445**	-0.0358*	-0.0363*
	(-2.7953)	(-3.0573)	(-2.4297)	(-2.3899)
POP_growth	0.0620***	0.0660***	0.0439*	0.0493**
	(3.3271)	(3.4444)	(2.4439)	(2.6801)
urban_growth	-0.1044***	-0.1101***	-0.0771***	-0.0926***
	(-7.1596)	(-7.5481)	(-5.5638)	(-6.3094)
EPS_building	0.0127	0.0726***	-0.1257***	-0.0958***
	(0.5384)	(3.9377)	(-7.4807)	(-5.3137)
EPS_elec	-0.0006	0.0085	-0.0078	0.0683**
	(-0.0246)	(0.4414)	(-0.6490)	(2.9698)
EPS_indus	-0.1190***	-0.1174***	-0.0015	-0.0509***
	(-7.1608)	(-7.3934)	(-0.1063)	(-6.1554)
EPS_transport	-0.0883***	-0.0493*	-0.1315***	-0.0736***
	(-3.6796)	(-2.5059)	(-7.9832)	(-5.2508)
Signif. codes	0.001 '***', 0.01 '**', 0.05 '*'			

B.4.3 Cross-country comparison

Table B.13: Total EPS Effects on GHG Emissions per capita (Developed vs Developing Countries)

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG/cap)			
Cov. Est	Clustered			
Developed countries (713 obs.)				
R^2 (Within)	0.4051	0.3557	0.3950	0.4287
R^2 (Overall)	-0.1746	-0.1785	0.0229	-0.2054
Robust F-statistic	64.861	48.240	47.918	79.883
EPS	-0.0756***	-0.0315***	-0.0330***	-0.0802***
	(-9.3346)	(-5.3005)	(-4.0183)	(-11.721)
Developing countries (438 obs.)				
R^2 (Within)	0.1997	0.2340	0.2270	0.2258
R^2 (Overall)	-0.0691	-0.0695	-0.0701	-0.0683
Robust F-statistic	22.311	20.735	21.127	28.815
EPS	-0.0290	-0.0081	-0.0205	-0.0612***
	(-1.7747)	(-0.6448)	(-1.2827)	(-4.7139)
Signif. codes	0.001 '***'	0.01 '**'	0.05 '*'	

Note: Results come from two-way fixed effects OLS with control variables, including ln(GDP/cap), $\ln(\mathrm{GDP/cap})^2$, ln(POP_growth) and urban growth.

B.4.4 Time period decomposition

Table B.14: Time-period Decomposition (GHG per capita)

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
	Period 1 (1991-2000) - 292 obs			
R^2 (Within)	-0.3143	-0.2324	-0.2914	-0.3272
F-statistic	12.85	13.12	12.88	12.87
EPS	-0.0041	-0.0175	-0.0012	-0.0079
	(-0.1528)	(-0.9902)	(-0.0419)	(-0.3549)
	Period 2 (2001-2010) - 416 obs			
R^2 (Within)	0.2627	0.2197	0.2766	0.2631
F-statistic	52.25	51.26	53.94	52.42
EPS	-0.0500***	-0.0305***	-0.0484***	-0.0520***
	(-5.1817)	(-4.7785)	(-5.3698)	(-5.8069)
	Period 3 (2011-2020) - 429 obs			
R^2 (Within)	0.1612	-0.2013	0.1746	-0.1097
F-statistic	14.18	15.61	14.41	14.19
EPS	0.0048	0.0201*	-0.0050	0.0108
	(0.4525)	(2.4934)	(-0.5019)	(1.1829)

Note: Results come from two-way fixed effects OLS with control variables, including ln(GDP/cap), $\ln(\text{GDP/cap})^2$, ln(POP_growth) and urban growth.

B.5 EPS on GHG/GDP

B.5.1 Total EPS on GHG/GDP

Table B.15: Total EPS Effects on GHG Emissions Per GDP

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG/GDP)			
Cov. Est	Clustered			
No. Observations	1130			
R^2 (Within)	0.1010	-0.0534	-0.0052	0.2479
R^2 (Overall)	-0.6326	-0.7116	-0.6936	-0.5069
Log-likelihood	1096.7	1092.1	1093.2	1107.1
F-statistic	46.103	44.037	44.553	50.872
const	-1.1259	-1.3368	-1.3036	-0.6938
	(-0.9422)	(-1.1309)	(-1.1070)	(-0.5700)
ln(POP)	0.4462***	0.4576***	0.4559***	0.4214***
	(6.1103)	(6.3273)	(6.3258)	(5.6752)
GDP_growth	-0.5435***	-0.5394***	-0.5469***	-0.5250***
	(-3.4618)	(-3.4178)	(-3.4590)	(-3.4072)
GDP_growth^2	-2.3536	-2.5310**	-2.4242	-1.9625
	(-1.8363)	(-1.9734)	(-1.8675)	(-1.5292)
urban_growth	-0.0592***	-0.0590***	-0.0592***	-0.0600***
	(-6.7360)	(-6.7416)	(-6.7380)	(-6.7903)
EPS	-0.0216**	-0.0065	-0.0128	-0.0340***
	(-2.8579)	(-1.2035)	(-1.6686)	(-4.3890)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

B.5.2 Sectoral EPS on GHG/GDP

Table B.16: Sectoral EPS Effects on GHG Emissions Per GDP

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG/GDP)			
Cov. Est	Clustered			
No. Observations	1098			
R^2 (Within)	0.1273	-0.0946	0.0516	0.1957
R^2 (Overall)	-0.6530	-0.9684	-0.8602	-0.3841
Log-likelihood	1062.2	1064.0	1073.3	1088.6
F-statistic	29.798	30.318	32.988	37.523
const	-0.5898	-1.6085	-1.4002	0.5041
	(-0.4604)	(-1.2795)	(-1.1613)	(0.3902)
ln(POP)	0.4124***	0.4721***	0.4628***	0.3458***
	(5.2565)	(6.1280)	(6.2567)	(4.3667)
GDP_growth	-0.5258***	-0.5712***	-0.5953***	-0.4450***
	(-3.3180)	(-3.5739)	(-3.7484)	(-2.8931)
GDP_growth^2	-2.2153	-2.0116	-2.2458	-1.8760
	(-1.7051)	(-1.5282)	(-1.7271)	(-1.4044)
urban_growth	-0.0622***	-0.0627***	-0.0500***	-0.0641***
	(-6.9907)	(-6.8016)	(-5.9292)	(-7.0083)
EPS_building	0.0254	0.0910***	-0.0492*	0.0328
	(1.0288)	(4.3883)	(-2.5472)	(1.7673)
EPS_elec	0.0413	-0.0201	0.0028	0.0577**
	(1.4750)	(-0.9609)	(0.2274)	(2.6499)
EPS_indus	-0.0803***	-0.0715***	0.0364*	-0.0550***
	(-3.9391)	(-3.8667)	(2.3785)	(-5.0019)
EPS_transport	-0.0575*	-0.0164	-0.0962***	-0.0483**
	(-2.2376)	(-0.7704)	(-5.6033)	(-2.8836)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

B.5.3 Cross-country comparison

Table B.17: Total EPS Effects on GHG per GDP Emissions (Developed vs Developing Countries)

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG/GDP)			
Cov. Est	Clustered			
Developed countries (701 obs.)				
R^2 (Within)	0.5044	0.2180	0.3304	0.6914
R^2 (Overall)	-0.5286	-0.2089	-0.3111	-0.9154
Robust F-statistic	9.6306	7.0084	7.4091	15.038
EPS	-0.0393***	-0.0111	-0.0238**	-0.0598***
	(-4.4347)	(-1.8832)	(-2.6957)	(-6.2303)
Developing countries (429 obs.)				
R^2 (Within)	0.2070	0.0722	0.1573	0.2489
R^2 (Overall)	-3.0046	-3.1131	-3.0202	-2.6443
Robust F-statistic	35.189	32.593	32.635	36.620
EPS	-0.0314*	-0.0113	-0.0263*	-0.0358**
	(-2.3853)	(-1.1353)	(-1.9677)	(-3.2150)
Signif. codes	0.001 '***'	0.01 '**'	0.05 '*'	

Note: Results come from two-way fixed effects OLS with control variables, including ln(GDP_growth), $\ln(\text{GDP\_growth})^2$, ln(POP_growth) and urban growth.

B.5.4 Time period decomposition

Table B.18: Time-period Decomposition (GHG per GDP)

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Period 1 (1991-2000) - 284 obs				
R^2 (Within)	0.0275	0.0949	-0.0165	0.0319
Robust F-statistic	3.37	3.60	3.34	3.38
EPS	-0.0093	-0.0190	0.0013	-0.0092
	(-0.3049)	(-1.0123)	(0.0411)	(-0.3675)
Period 2 (2001-2010) - 416 obs				
R^2 (Within)	0.3434	0.2924	0.3045	0.3613
Robust F-statistic	12.08	11.14	11.09	13.38
EPS	-0.0486***	-0.0282***	-0.0420***	-0.0524***
	(-4.4144)	(-3.8471)	(-4.2191)	(-5.3073)
Period 3 (2011-2020) - 429 obs				
R^2 (Within)	-0.0719	-0.1157	0.0177	-0.0245
Robust F-statistic	14.54	15.38	14.35	14.38
EPS	0.0118	0.0187*	-0.0020	0.0047
	(1.0359)	(2.1101)	(-0.1782)	(0.4577)

Note: Results come from two-way fixed effects OLS with control variables, including ln(GDP_growth), $\ln(\text{GDP\_growth})^2$, ln(POP_growth) and urban growth.

B.6 EPS on Sectoral emissions

B.6.1 Total EPS

Table B.19: Total Effect on sectoral Emissions

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Cov. Est	Clustered			
No. Observations	1124			
Dep. Variable	ln(GHG_building)			
R^2 (Within)	-0.0779	-0.1697	-0.3964	0.0356
F-statistic	42.317	41.889	39.763	45.134
EPS	-0.0524*	-0.0345*	-0.0240	-0.0643**
	(-2.5529)	(-2.3847)	(-1.1610)	(-3.3047)
Dep. Variable	ln(GHG_elec)			
R^2 (Within)	0.2832	0.0732	0.2871	0.2984
F-statistic	66.947	60.372	67.993	70.535
EPS	-0.0980***	-0.0410**	-0.0996***	-0.1028***
	(-5.5264)	(-2.9942)	(-5.6168)	(-6.7533)
Dep. Variable	ln(GHG_indus)			
R^2 (Within)	0.2994	0.0736	0.2431	0.2492
F-statistic	135.37	124.90	131.91	133.96
EPS	-0.0996***	-0.0528***	-0.0894***	-0.0875***
	(-7.8688)	(-6.0117)	(-6.8674)	(-7.3856)
Dep. Variable	ln(GHG_transport)			
R^2 (Within)	0.7012	0.7012	0.7135	0.6984
F-statistic	259.15	243.73	249.73	269.89
EPS	-0.0628***	-0.0333***	-0.0522***	-0.0646***
	(-8.4332)	(-5.8209)	(-6.6007)	(-8.8368)
signif. code	0.001 '***'	0.01 '**'	0.05 '*'	

B.6.2 Sectoral EPS

Table B.20: Sectoral EPS Effects on Building GHG Emissions

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable		ln(GHG_building)		
Cov. Estimator		Clustered		
No. Observations	1119	1119	1119	1119
R^2 (Within)	0.0038	-0.0551	-0.2648	-0.1026
R^2 (Overall)	0.8620	0.8617	0.8063	0.8621
Log-likelihood	369.86	363.96	420.33	371.68
F-statistic	31.963	30.268	47.204	32.488
const	-2.1472	-2.7675	-12.185	-1.7975
	(-0.5661)	(-0.6903)	(-2.8513)	(-0.4449)
ln(GDP)	-0.1641	-0.1229	0.7423**	-0.0494
	(-0.6407)	(-0.4589)	(2.7939)	(-0.1949)
$\ln(GDP)^2$	0.0275*	0.0263*	-0.0098	0.0269*
	(2.4814)	(2.2665)	(-0.8326)	(2.3428)
ln(POP)	0.5741**	0.5911**	0.8518***	0.4685*
	(2.7298)	(2.8508)	(3.7926)	(2.0422)
urban_growth	-0.0229	-0.0232	-0.0211	-0.0297
	(-1.4012)	(-1.3779)	(-1.3143)	(-1.7998)
EPS_building	0.0649	0.0894**	0.3560***	0.1134*
	(1.4916)	(2.7343)	(7.5294)	(2.4256)
EPS_elec	0.0026	-0.0519	0.0077	-0.0111
	(0.0518)	(-1.2431)	(0.3108)	(-0.2148)
EPS_indus	-0.0333	-0.0182	-0.0564**	-0.0775***
	(-0.8906)	(-0.5991)	(-2.9229)	(-5.4984)
EPS_transport	-0.3221***	-0.2075***	-0.2760***	-0.1506***
	(-5.5141)	(-4.4703)	(-5.4054)	(-4.1303)
Signif. codes	0.001 '***', 0.01 '**', 0.05 '*'			

Table B.21: Sectoral EPS Effects on Electricity GHG Emissions

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable		ln(GHG_elec)		
Cov. Estimator		Clustered		
No. Observations	1119	1119	1119	1119
R^2 (Within)	0.2907	0.1168	0.3236	0.3216
R^2 (Overall)	0.7107	0.6982	0.7586	0.7575
Log-likelihood	246.76	245.46	282.34	262.40
F-statistic	45.408	45.002	56.891	50.368
const	3.1081	0.0947	-0.6395	3.2188
	(0.6620)	(0.0203)	(-0.1434)	(0.6924)
ln(GDP)	-1.6870***	-1.3120***	-1.1871***	-1.3662***
	(-4.3854)	(-3.4317)	(-3.3673)	(-3.7774)
$\ln(GDP)^2$	0.0906***	0.0757***	0.0644***	0.0757***
	(5.7395)	(4.7647)	(4.4862)	(5.1174)
ln(POP)	0.8640***	0.9021***	0.9695***	0.7605***
	(4.7538)	(5.0143)	(5.6889)	(4.1373)
urban_growth	-0.0631***	-0.0669***	-0.0439***	-0.0653***
	(-4.3322)	(-4.4819)	(-3.3520)	(-4.6719)
EPS_building	0.1229**	0.2053***	-0.2913***	-0.2061***
	(2.5909)	(5.0527)	(-7.4959)	(-5.9450)
EPS_elec	-0.1122*	-0.0119	0.0294	0.2132***
	(-2.0593)	(-0.2914)	(1.1432)	(4.3014)
EPS_indus	-0.2215***	-0.1881***	-0.0246	-0.0948***
	(-6.3959)	(-5.7996)	(-0.9505)	(-5.0936)
EPS_transport	-0.1674***	-0.1789***	-0.2498***	-0.1182***
	(-3.5965)	(-4.2892)	(-5.6081)	(-3.7890)
Signif. codes	0.001 '***', 0.01 '**', 0.05 '*'			

Table B.22: Sectoral EPS Effects on Industrial GHG Emissions

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable		ln(GHG_indus)		
Cov. Estimator		Clustered		
No. Observations	1119	1119	1119	1119
R^2 (Within)	0.3224	0.0362	0.3566	0.3224
R^2 (Overall)	0.5482	0.4094	0.5474	0.5025
Log-likelihood	618.06	608.90	624.53	618.83
F-statistic	96.830	93.152	99.462	97.140
const	-17.488	-20.502	-18.247	-18.721
	(-5.2695)	(-6.2537)	(-5.7775)	(-5.5009)
ln(GDP)	0.7795**	1.0338***	0.8971***	0.9123***
	(2.7917)	(3.7216)	(3.4490)	(3.3123)
$\ln(\text{GDP})^2$	-0.0088	-0.0173	-0.0138	-0.0133
	(-0.7554)	(-1.4925)	(-1.2759)	(-1.1661)
ln(POP)	1.1870***	1.2542***	1.1932***	1.2053***
	(8.8232)	(9.4452)	(9.1742)	(8.7057)
urban_growth	-0.0346**	-0.0392***	-0.0214*	-0.0329**
	(-3.2377)	(-3.6279)	(-2.1122)	(-3.1808)
EPS_building	-0.0147	0.0609*	-0.1709***	-0.1264***
	(-0.4493)	(2.2588)	(-6.3851)	(-4.4954)
EPS_elec	-0.1809***	-0.1493***	-0.1414***	-0.2241***
	(-4.6071)	(-4.9049)	(-7.6882)	(-6.1748)
EPS_indus	-0.1583***	-0.1472***	0.0111	-0.0964***
	(-6.1476)	(-6.1657)	(0.5611)	(-7.6931)
EPS_transport	-0.0625	0.0331	-0.1480***	-0.0494*
	(-1.6580)	(1.0987)	(-5.2854)	(-1.8522)
Signif. codes	0.001 '***', 0.01 '**', 0.05 '*'			

Table B.23: Sectoral EPS Effects on Transport GHG Emissions

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG_transport)			
Cov. Estimator	Clustered			
No. Observations	1119	1119	1119	1119
R^2 (Within)	0.7024	0.7062	0.7139	0.6534
R^2 (Overall)	0.8777	0.8862	0.8955	0.8499
Log-likelihood	1154.4	1127.1	1131.8	1165.3
F-statistic	167.32	153.19	155.58	173.17
const	3.0847	1.7145	1.2325	2.5795
	(1.8414)	(1.0482)	(0.6763)	(1.5481)
ln(GDP)	0.5917***	0.7783***	0.7922***	0.7672***
	(3.8980)	(5.1796)	(4.7774)	(5.1867)
$\ln(GDP)^2$	0.0122*	0.0058	0.0035	0.0034
	(1.9446)	(0.9140)	(0.4982)	(0.5450)
ln(POP)	-0.1420*	-0.1411*	-0.0993	-0.1591*
	(-1.9877)	(-1.9500)	(-1.3420)	(-2.1123)
urban_growth	0.0029	-0.00002	0.0001	-0.0029
	(0.4726)	(-0.0026)	(0.0168)	(-0.4713)
ln_EPS_building	-0.0333	-0.0025	-0.0845***	-0.1286***
	(-1.4982)	(-0.1260)	(-3.3747)	(-6.9827)
EPS_elec	-0.1127***	-0.0632**	-0.0506***	0.0283
	(-4.6034)	(-3.2393)	(-4.3807)	(1.2304)
EPS_indus	-0.0091	-0.0063	-0.0220	-0.0509***
	(-0.4973)	(-0.3776)	(-1.6428)	(-4.3821)
EPS_transport	-0.1460***	-0.0819***	-0.0770***	-0.0790***
	(-6.2091)	(-4.2228)	(-3.9800)	(-5.1893)
Signif. codes	0.001 '***', 0.01 '**', 0.05 '*'			

B.7 EPS on GHG

B.7.1 Regional comparison of sectoral EPS

Table B.24: Sectoral EPS Effects on GHG Emissions (Developed vs Developing Countries)

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG)			
Cov. Est	Clustered			
Developed countries (709 obs.)				
R^2 (Within)	0.0955	-1.2084	0.0972	0.2891
R^2 (Overall)	0.9068	0.9064	0.9363	0.7898
Robust F-statistic	46.269	51.467	83.607	64.411
EPS_building	0.0528*	0.1526***	-0.1297***	-0.0182
	(2.0830)	(7.8518)	(-5.5334)	(-0.9194)
EPS_elec	-0.0749**	-0.0255	-0.0167	0.0224
	(-2.9018)	(-1.3604)	(-1.3098)	(1.3278)
EPS_indus	-0.1123***	-0.1120***	0.0285*	-0.0703***
	(-5.6858)	(-6.7414)	(2.0748)	(-7.0064)
EPS_transport	-0.0874***	-0.0570**	-0.1322***	-0.1074***
	(-3.3026)	(-2.5874)	(-7.6825)	(-6.2825)
Developing countries (410 obs.)				
R^2 (Within)	0.5676	0.4620	0.4864	0.5889
R^2 (Overall)	0.9430	0.9403	0.9389	0.9423
Robust F-statistic	73.682	67.456	65.322	80.022
EPS_building	0.0017	-0.0077	-0.1047*	-0.0442
	(0.0444)	(-0.2248)	(-2.6555)	(-1.1765)
EPS_elec	0.0570	0.0613	-0.0003	0.1248**
	(1.1737)	(1.6815)	(-0.0127)	(2.7227)
EPS_indus	-0.1100***	-0.1049***	-0.0621	-0.0908***
	(-3.7592)	(-3.4357)	(-1.8194)	(-5.7446)
EPS_transport	-0.0796	0.0013	0.0084	-0.0242
	(-1.7233)	(0.0325)	(0.2030)	(-1.0042)
Signif. codes	0.001 '***'	0.01 '**'	0.05 '*'	

Note: Results come from a two-way fixed effects OLS with control variables, including ln(GDP), $\ln(GDP)^2$, ln(POP) and urban growth.

B.7.2 Sectoral decomposition with interactions

Table B.25: VIF Comparison Across Sectoral Models with Interaction (Best Model)

Variable	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
ln(GDP)	24.13	24.76	25.20	22.67
$\ln(GDP)^2$	24.00	24.82	25.36	23.20
ln(POP)	1.24	1.25	1.22	1.25
urban_growth	1.09	1.10	1.13	1.08
EPS_indus	3.12	6.22	2.38	2.17
EPS(Elec*Indus)	6.56	10.33	4.33	5.24
EPS(Elec*Transport)	7.15	8.01	2.86	5.38
EPS(Building*Transport)	3.75	5.23	1.85	1.52

Table B.26: VIF Comparison Across Sectoral Models with Interaction (All Variables)

Variable	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
ln(GDP)	26.03	26.32	26.94	24.18
$\ln(GDP)^2$	25.96	26.07	27.16	24.44
ln(POP)	1.33	1.39	1.31	1.39
urban_growth	1.12	1.13	1.17	1.11
EPS_elec	12.74	10.54	3.99	11.55
EPS_indus	13.67	19.21	10.39	6.85
EPS_building	5.37	9.33	7.48	6.44
EPS_transport	4.32	6.62	3.62	2.61
EPS(Elec*Indus)	30.58	53.95	8.88	8.90
EPS(Elec*Transport)	30.99	67.36	11.16	13.61
EPS(Building*Transport)	32.83	65.42	11.92	11.44
EPS(transport*indus)	33.46	67.61	9.96	7.88
EPS(building*elec)	64.11	86.81	10.29	14.76
EPS(indus*building)	35.47	65.23	13.57	7.61

B.7.3 GHG Elasticities with respects to EPS

Table B.27: GHG Elasticities with Respect to Total EPS

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG)			
Cov. Estimator	Clustered			
No. Observations	1152			
R^2 (Within)	-0.2585	-0.6990	-0.4028	-0.1494
R^2 (Overall)	0.8905	0.8776	0.8863	0.8937
Log-likelihood	1208.5	1198.4	1204.9	1215.7
F-statistic	205.88	198.58	203.31	211.21
const	-1.4011	-2.2398	-1.6172	-1.1257
	(-0.9107)	(-1.4257)	(-1.0630)	(-0.7507)
ln(GDP)	0.0184	0.0689	0.0063	0.0130
	(0.1431)	(0.5209)	(0.0485)	(0.1009)
$\ln(GDP)^2$	0.0257***	0.0235***	0.0259***	0.0261***
	(4.6917)	(4.1780)	(4.6878)	(4.8156)
ln(POP)	0.5443***	0.5753***	0.5634***	0.5281***
	(7.9415)	(8.2339)	(8.3718)	(7.9629)
urban_growth	-0.0490***	-0.0510***	-0.0496***	-0.0491***
	(-6.9095)	(-7.0035)	(-6.8905)	(-7.0314)
ln(EPS+1)	-0.1061***	-0.0494*	-0.0853***	-0.1206***
	(-4.4039)	(-2.3714)	(-3.8485)	(-5.2014)
Signif. codes	0.001 '***', 0.01 '**', 0.05 '*'			

Table B.28: GHG Elasticities with Respect to Sector-Specific EPS

	EPS_OECD	EPS_BOD	EPS_GHG	EPS_GDP
Dep. Variable	ln(GHG)			
Cov. Estimator	Clustered			
No. Observations	1119	1119	1119	1119
R^2 (Within)	0.3061	-0.1304	0.3692	0.2761
R^2 (Overall)	0.9108	0.8919	0.9287	0.9194
Log-likelihood	1210.2	1199.7	1211.7	1206.7
F-statistic	144.72	139.61	145.46	143.01
const	1.1155	-0.8951	0.3640	1.1970
	(0.7278)	(-0.5515)	(0.2310)	(0.7978)
ln(GDP)	-0.3349**	-0.1749	-0.1489	-0.1787
	(-2.6603)	(-1.3255)	(-1.1490)	(-1.3703)
$\ln(GDP)^2$	0.0383***	0.0316***	0.0294***	0.0330***
	(7.1971)	(5.6562)	(5.3469)	(5.9272)
ln(POP)	0.5383***	0.6002***	0.5307***	0.4668***
	(7.8374)	(8.4693)	(7.6938)	(6.8552)
urban_growth	-0.0502***	-0.0556***	-0.0437***	-0.0535***
	(-7.1609)	(-7.4051)	(-6.5333)	(-7.7519)
ln_EPS_building	0.0705	0.1415***	-0.1823***	-0.0844**
	(1.8449)	(4.0828)	(-5.6716)	(-2.5244)
ln_EPS_elec	-0.1186**	-0.0260	-0.0388	0.0070
	(-3.1110)	(-0.8701)	(-1.7112)	(0.1651)
ln_EPS_indus	-0.2272***	-0.2433***	-0.0671**	-0.1669***
	(-8.6296)	(-8.9687)	(-2.8177)	(-9.1621)
ln_EPS_transport	-0.1116**	-0.0422	-0.1839***	-0.0696**
	(-2.9264)	(-1.1683)	(-5.4653)	(-2.4993)
Signif. codes	0.001 '***', 0.01 '**', 0.05 '*'			

Note: ln_EPS_{sector} variables correspond to ln(EPS_{sector} +1).

In the previous sections, we examined the effect of EPS on the logarithm of GHG, interpreting the results as partial elasticities. Here, we present the findings for total elasticities, as detailed in Tables B.27 and B.28. To assess these effects, we computed the logarithm of the EPS score plus one to account for cases where the score is zero.

The results reveal similar trends to those observed with partial elasticities, particularly under the Proxy and Effectiveness assumptions. However, there is a general decline in the significance of the overall model under these specifications, which led us to exclude it as the primary model.

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