2024

# Performance and Policy Indexes in Carbon Pricing Efficacy: A Cross-country Analysis of Policy Impact (2012-2020)

Ke (Zoky) Zhou
*Colby College*

# Performance and Policy Indexes in Carbon Pricing Efficacy:

# A Cross-country Analysis of Policy Impact (2012-2020)

Zoky Zhou'24

Thesis Advisor: Michael Donihue

Colby College Department of Economics

**Abstract**

Climate change poses a significant threat to global ecosystems and human societies, driven largely by $CO_2$ emissions from various economic activities. This macroeconomic cross-country study empirically assesses the effectiveness of carbon pricing in reducing $CO_2$ emissions across three periods: 2012-2017, 2015-2019, and 2015-2020. Building on the foundational research by Best et al. (2020), the analysis extends to more recent data, capturing the evolving impacts of carbon pricing amid changing global economic and policy landscapes. A key advancement in this research is the creation and integration of two comprehensive indexes—a performance index and a policy index—constructed from 14 environmental performance or policy variables. These indexes control for a broader set of environmental and economic factors, thereby addressing omitted variable bias and enhancing the robustness of the analysis. The results strongly support carbon pricing as an effective tool for reducing $CO_2$ emissions. However, the direct impact of carbon pricing is less significant when the performance and policy indexes are included, indicating that its effectiveness is intertwined with other environmental policies. This study emphasizes the importance of maintaining carbon pricing, adopting comprehensive policy frameworks, tailoring approaches to local contexts, and improving data collection standards. This research also offers a holistic view of policy impacts and sets the stage for future studies on the complexities of environmental policies in mitigating climate change.

**Keywords**

Climate change, carbon pricing, environmental policy, policy performance, index, $CO_2$ emission reduction, environmental economics, cross-country analysis

**Acknowledgment**

Reflecting on the past four years at Colby, I am filled with gratitude and a sense of accomplishment. The journey has been marked by significant growth, both personally and academically. From a girl intimidated by public speaking to confidently presenting my work to large audiences without a script, my transformation is a testament to the courses and prestigious education I received at Colby, which have been instrumental in my personal growth.

First and foremost, I'd like to express my deepest gratitude to Prof. Michael Donihue for his unwavering support over the past year as my thesis advisor. His guidance has been invaluable, from helping me navigate the initial uncertainty of choosing a topic to now, as I graduate with a future closely aligned with my thesis work. Prof. Donihue's mentorship has not only enriched my academic journey but also shaped my professional aspirations. I am also immensely thankful to my second reader, Prof. Jennifer Meredith, for her insightful comments and constructive feedback, which greatly improved my work. Her willingness to take time out of her busy schedule to assist me is deeply appreciated. Working together at the Colby Laboratory for Economic Studies (CL4ES) was particularly transformative, where I was introduced to the intricate process of working with and constructing indexes—a critical skill set that became the foundation and inspiration for this project.

I would also like to extend my heartfelt thanks to all the professors who have supported me along the way. Special thanks to Prof. Sanval Nasim for introducing me to Natural Resources Economics. Without his guidance and the insights gained from his class, I wouldn't have been so determined to pursue an Economics major focused on Environmental Economics. His teachings inspired me to reflect deeply on the role of economics in combating climate change and solidified my commitment to this field. I am also profoundly grateful to Prof. Tim Hubbard, the

Economics department chair, for his unwavering support and guidance. His dedication to ensuring all honors thesis students stayed on track was invaluable.

Additionally, I am thankful to every professor I’ve had the privilege of learning from during my time at Colby. Each one of you has contributed to my academic journey in unique ways, helping me grow and develop the skills and knowledge that have brought me to where I am today. I truly could not imagine reaching this point without your collective wisdom and support.

A special thank you goes to the Office of the Provost and the Students' Special Projects Fund for their generous financial support. Their funding enabled me to work with invaluable datasets critical to my thesis project's success. Their support allowed for a level of analysis that would not have been possible otherwise.

I would like to thank my friends and family for their unwavering love and support throughout my time at Colby and during this thesis project. I will always cherish the memories of working with my roommates at Alfond Commons 513, stress-eating together, and pushing each other to excel. To my fellow thesis students, your encouragement has been invaluable.

As I prepare to graduate from Colby, I am excited to carry my work to Harvard Kennedy School, where I will deepen my understanding of carbon policy, clean energy transitions, sustainable resource management, and international cooperation in combating climate change. My commitment to making a difference, nurtured at Colby, will drive me throughout my career.

To everyone who has been part of this incredible journey, thank you from the bottom of my heart!

# Table of Contents

## 1. Introduction

Climate change due to greenhouse gas (GHG) emissions can bring irreversible changes to the ocean, ice sheets and global sea level, and pose threats to the longevity of global ecological balance (Wang, 2023; IPCC, 2021). At the same time 2022 was officially ranked by NOAA the sixth-warmest year on record since 1880, regions across the globe are already experiencing temperature increases exceeding the global average (NOAA, 2022; Allen et al., 2018). Human activities over the last 150 years are one of the main drivers of the increase in GHG in the atmosphere, therefore being identified as the dominant cause of global warming (EPA, 2020; Allen et al., 2018). By economic sector in the US in 2021, the transportation sector, with a share of 28% of total GHG emissions, is the most prominent source of GHG emissions, followed by the electricity production (25%) and the industry sectors (23%). Notably, GHG emissions from the three sectors are predominantly driven by fossil fuel combustion for vehicles and energy, which includes sources such as gasoline, diesel, coal, and natural gas (EPA, 2020). The escalating intensity of global warming and shifting climate patterns necessitate an urgent and decisive action to reduce GHG emissions.

Carbon pricing has emerged as a constructive tool that could achieve emission reduction goals while leaving flexibility for private agents, households, and companies on choices of implementation and amount of reduction (Bureau et al., 2019; Mankiw, 2008). A carbon tax incentivizes households and businesses to reduce emissions, particularly from fossil fuel combustion, by leveraging their private information on marginal costs. This market-based mechanism is flexible and effective even when public authorities provide limited information about the costs of reducing emissions, in contrast to command-and-control measures like standards that require more detailed information to implement efficiently. This tax also helps guide equipment choice and use, contrary to subsidies which often lead to the overuse of efficient equipment and reduce their effectiveness in emission reduction (Bureau et al., 2019). Moreover, a carbon tax has been shown to stimulate green innovation, particularly in renewable energy sources. This approach maintains maximum energy-use efficiency and offers benefits similar to those provided by subsidies but without the accompanying government costs. Additionally, the revenue generated from the carbon tax can be flexibly allocated to support various environmental and social programs, further enhancing its positive impact (Wang et al., 2019; Wang et al. 2022).

Despite the benefits of carbon pricing policies, their quantifiable effectiveness remains a topic of ongoing empirical investigation. The evolving literature in environmental economics provides an intricate perspective on the efficacy of carbon pricing mechanisms. A significant challenge lies in the lack of consensus regarding which policies should be recognized as implicitly pricing carbon (i.e. fuel taxes, removal of fossil fuel subsidies, etc.), complicating efforts to evaluate the effectiveness of carbon pricing mechanisms accurately (World Bank Group, 2019; Dominioni, 2022). Although carbon pricing is a central topic in global climate policy debates, empirical assessments of its true effects on emissions are both limited and inconsistent (Green, 2021). This complexity is further exacerbated by the absence of comprehensive cross-country empirical studies, highlighting the need for econometric models that consider both policy differences and other structural factors influencing the effectiveness of carbon pricing on CO2 emissions (Best et al., 2020).

Additionally, methodological limitations in current studies, such as a focus on predictive rather than evaluative analyses and challenges in establishing clear causal relationships, underscore the necessity for methodologically robust research (Vrolijk, 2023). Specifically, addressing omitted variable bias (OVB) in policy evaluation is crucial. OVB occurs when a model fails to include one or more relevant variables, potentially leading to biased results that inaccurately attribute changes in emissions to carbon pricing alone. For instance, ignoring variables such as technological advancements or international trade impacts in the analysis could skew results, either overstating or understating the policy's effectiveness. To overcome these challenges, researchers must strive for a more comprehensive approach, incorporating a broader array of variables that influence emissions. This approach enhances the accuracy and reliability of findings, thereby providing policymakers with a clearer understanding of the true impact of carbon pricing policies. Conducting macroeconomic cross-country comparisons is particularly valuable because it demonstrates the wide applicability of the results across different national contexts. While much of the existing literature focuses on within-country natural experiments due to concerns about causality, this study's broad, comparative perspective offers a unique contribution by capturing diverse economic and policy environments. Such rigorous research is essential not only for refining policy designs but also for ensuring that these policies effectively contribute to global climate goals.

The first part of this study aims to contribute to the empirical assessment of carbon pricing efficacy by building upon an existing cross-country study that evaluated the impact of carbon pricing– research by Best et al. (2020) employed a regression analysis to explore the relationship between carbon price and changes in carbon emissions over the period from 2012 to 2017. Recognizing the dynamic nature of environmental policies and economic conditions, I seek to update this analysis by extending the dataset to include the most recent five-year period, from 2017 to 2022. This would allow conducting a comparative analysis of three five-year periods, which in turn has the potential to shed light on how the impact of carbon pricing has evolved over recent years, taking into account diverse national contexts and emerging trends in global emissions.

To overcome the challenge of dissecting the impact of carbon pricing on emissions from other environmental and economic factors, the second part of the study introduces two indexes: the performance index and the policy index. These indexes are constructed from 14 environmental policy variables, thereby addressing omitted variable bias and improving the robustness of assessing the relationship between carbon pricing and emission changes. By integrating a range of environmental performance and policy variables within categories such as carbon emission reduction, fossil fuel, renewable energy, and deforestation, these indexes control for implicit policy outcomes that potentially drive carbon emissions. This promises a more nuanced and precise understanding of the interplay between carbon pricing instruments and their impact on emissions.

This study conclusively establishes the effectiveness of carbon pricing in reducing CO2 emissions across various national contexts, underscoring the robust nature of carbon pricing as a critical tool for climate change mitigation. This research significantly contributes to the field of environmental economics by introducing comprehensive performance and policy indexes that measure the collective impact of various environmental policies, including carbon pricing. By quantifying the interactions and cumulative effects of multiple policies, these indexes enhance the precision of policy evaluations. Unlike analyzing the interaction between specific policies, which can be fragmented and limited, the indexes provide a holistic view that captures the broad spectrum of policy influences, offering a more integrated and robust assessment of their overall effectiveness. Furthermore, the insights gained pave the way for future research to explore how these policies complement each other. This research also serves as a foundational model for evaluating the effectiveness of policy mixes across diverse economic and environmental contexts. This approach not only helps policymakers but also sets the stage for more effective climate change mitigation strategies globally.

## 2. Literature Review

### *2.1 Carbon Pricing Research Background*

According to Black et al. (2022), as of 2022, 46 countries have implemented carbon pricing mechanisms through either carbon taxes or emissions trading schemes (ETS). Collectively, these schemes cover about 30% of global emissions, with prices of carbon in some regions, like the European Union, rising as high as $90 per ton. For the breakdown between carbon taxes and ETS, in 2021, around 6% of global emissions were in countries or sectors with a carbon tax, and 20% were covered by an ETS, totaling 26% of global emissions under some form of carbon pricing (Ritchie & Rosado, 2022). More than 60 carbon tax and emissions trading programs exist at regional, national, and subnational levels. Recent significant initiatives include those launched in China and

Germany, along with the European Union's emissions price rising above €50 a ton, and Canada's announcement of its emissions price rising to CAN$170 a ton by 2030 (Parry, 2020).

The research on how carbon emissions respond to carbon pricing is broadly categorized into forward-looking ex-ante projections and retrospective ex-post evaluations, each offering unique insights. Theoretical models like input-output, computable general equilibrium (CGE), and integrated assessment models (IAMs) are used for ex-ante projections and provide quite varied policy response estimates. These are a priori-assumption-based models, and thus the application in real life is quite limited. For example, Cullen and Mansur (2017) focus on the electricity industry and estimate the effects of carbon pricing against the shale revolution. They find that both carbon pricing and lower natural gas prices reduce the cost advantage of coal-fired power plants and, hence, cause a shift in the location of natural gas-fired plants. At the same time, Cullen and Mansur (2017) show that a carbon tax of $10–$60 per ton could reduce emissions from 4% to 10%, respectively, with a better effectiveness profile at low natural gas prices.

As for ex-post evaluations, which use observational data, Haites (2018) offers a critical look at the effectiveness of carbon price mechanisms, specifically carbon taxes and ETSs, from 2005 to 2015. He observes that these mechanisms were associated with reduced fuel consumption and greenhouse gas emissions. However, he warns that attributing these reductions directly to carbon pricing alone is challenging due to potential impacts from other policies and economic developments. Similarly, Wilson and Staffell (2018) scrutinize that the reduction of Britain's carbon emissions in 2016 was due to switching from coal to natural gas generation, which has been promoted by strong carbon pricing and liberalization of the market.

Rafaty et al. (2020) further extend the outreach with the study of the impact of carbon pricing on five industries of 39 countries across the years 1990-2016. Their novel approach and findings have suggested that carbon pricing has led to a modest reduction in the growth of CO2 emissions, particularly in the electricity and heat sectors. Gugler et al. (2020) then compare the effectiveness of Germany and Britain in reducing the CO2 intensity of the power sector by looking into Britain's carbon pricing and Germany's renewable energy subsidies. They, however, conclude that the higher carbon price in Britain, supported by the Carbon Price Support (CPS), has been more effective in emissions reduction than the German approach.

In a more focused study, Arbell et al. (2021) evaluate the UK's CPS using a unique ex-post approach that combines economic theory with machine learning. Their analysis reveals a 6.2% reduction in emissions, hence underscoring the variability of emissions abatement impacted by fuel prices rather than the carbon tax rate itself. Finally, Vrolijk and Sato (2023) review quasi-experimental evidence on carbon pricing, examining 47 studies from 2012-2022. They find that carbon taxation is effective in reducing emissions with minimal economic impact, particularly in the transportation and power sectors.

Many of these articles also point to several risks and challenges facing carbon pricing research. A primary concern many of the ex-ante projections are founded on theoretical models developed upon a priori assumptions and quite often, therefore, limit their real-world applicability. However, based on observed data, ex-post evaluations have difficulty attributing direct emissions reductions to carbon pricing since some external factors like fuel prices, economic activities, and other policies exist. Further, the study by Vrolijk and Sato (2023) identifies the leading methodological challenges like inappropriate choice of methods, incorrect implementation of empirical analysis, and limitations in available data. Additionally, there is a noted variability in the effectiveness of carbon pricing across different sectors and geographic regions, indicating a need for more fine-tuned, sector-specific, and regional studies. The research also reveals a gap in understanding the optimal levels of carbon pricing necessary to balance emission reduction goals with economic feasibility. While my study provides a broad, cross-country perspective, highlighting general trends and outcomes, it underscores the need for further context-specific research to fully optimize carbon pricing effectiveness. This dual approach ensures that both wide applicability and detailed, localized insights contribute to more effective carbon emission reduction strategies.

### *2.2 Policy Index Background*

Studies have sought to address the evident remaining challenges in the analysis of environmental policies, such as the lack of standard and consistent measures for assessing the stringency of environmental, climate, and energy policies, the multi-dimensional nature of environmental policies, and issues like sample self-selection. In the face of the underutilization of composite indicators in environmental policy stringency measurements, for example, Botta and Kózluk (2014) propose a composite policy index approach, particularly in the context of cross-country economic analyses, which aggregates individual indicators into a unified measure. This methodology involves carefully selecting and scoring various policy instruments, followed by an aggregation process aimed at creating the Environmental Policy Stringency (EPS) index. Looking at different ways of constructing a policy index, Rogge (2012) presents the assessment of the Data Envelopment Analysis (DEA) approach, in particular, the Benefit of the Doubt (BoD) model. In particular, Rogge sees a potential application of the DEA in the development of composite indicators like the Environmental Performance Index (EPI). The flexibility of the BoD model allows countries to establish their desirable weights of the various indicators of performance. This may, however, be the downside of undesirable specialization, whereby a country gets to appear as a better performer through overemphasis on certain indicators. This flexibility in choosing, while perhaps beneficial in some ways, raises serious validity and reliability questions for global measures of performance.

Factor Analysis is a statistical method that is primarily used to explore and identify the underlying relationships between measured variables, especially when there are latent variables that are not directly observable but can influence the observed variables. This method is powerful as it reduces a large set of variables into a small and interpretable set of factors without much information loss (Costello & Osborne, 2005). One of the major strengths of factor analysis is its ability to identify and describe what the underlying dimensions or constructs are—that is to say, those dimensions or constructs that are abstractly possessed but not directly visible (Fabrigar et al., 1999). This makes the factor analysis method, in particular, an ideal method for index construction, since it can condense many variables into one coherent index that will represent a good reflection of the conceptual domain area. The fact is, however, that the quality of the results is highly dependent on the size and quality of the dataset. It also demands sample sizes so large as to be able to give reliable and valid results, considering the method of interpretation of the factors is quite subjective in this method. Furthermore, the method makes several assumptions, such as the linearity and normal distribution of variables, which may not always be met in practical scenarios. Nevertheless, factor analysis remains a popular and effective tool for the construction of indexes. Its ability to reduce data complexity and enhance interpretability makes it particularly useful in situations where researchers have a large number of interrelated variables and need to distill them into a more manageable form for analysis (Tabachnick & Fidell, 2007).

As for factors that could potentially impact carbon emissions in a region, Qin et al. (2021) examine the roles of environmental policy, green innovation, and a composite risk index in G7 countries. Unifying in it are environmental-related taxes, political, financial, and economic risks, alongside renewable energy research and development to assess their collective impact on CO2 emissions. By constructing several models incorporating various variables, they found that for G7 countries to achieve real carbon neutrality, a comprehensive focus on improving GDP, environmental-related taxes, green innovation, and renewable energy research & development is essential. While Qin et al.'s analysis is comprehensive and provides valuable insights into the dynamics of carbon neutrality in G7 economies, my study expands on their approach by developing two distinct indexes: a performance index and a policy index. These indexes not only include a broader range of environmental policy variables but also extend the analysis to include countries beyond the G7. Unlike Qin et al.'s composite risk index, my indexes also separately measure the collective impact of various environmental policies and their outcomes, thereby offering a more nuanced understanding of the effectiveness of specific policy measures across diverse national contexts.

## 3. Data

### *3.1 Temporal Trend in Carbon Pricing Efficacy*

In this analysis, I adopt the foundational data framework established by Best et al. (2020), while extending the dataset to include more recent years. The study primarily relies on CO2 emissions data sourced from the International Energy Agency (IEA), now including editions up to 2022. It is important to note that, similar to the original study, the number of countries included in specific regression models may vary due to the availability of certain variables. The extended dataset encompasses 143 countries, capturing all significant global emitters including China, the United States, and the nations that make up the European Union. The dataset, while comprehensive, excludes certain smaller emitting countries, consistent with the criteria used by Best et al (2020).

The data related to carbon pricing mechanisms were derived from multiple sources and constructed into several variables. Firstly, the binary carbon price variable was sourced from the World Bank. This dummy variable indicates whether a country has implemented carbon pricing instruments within a particular year. In 2015, 42 countries had implemented carbon pricing instruments, which include measures at both national and subnational levels (e.g., in the US and Japan). Notably, this variable specifically excludes other types of taxes like fuel excise taxes and does not consider voluntary or internal carbon pricing initiatives by firms or other entities. Additionally, the study introduces a duration-adjusted carbon price variable, calculated by multiplying the annual binary carbon price by the proportion of the 5-year analysis period during which a carbon price was operational. This adjustment allows for a more nuanced understanding of the temporal presence of carbon pricing within the study period. Lastly, the Carbon Price Score (CPS) was employed to measure the extent to which countries have achieved the pricing of all energy-related carbon emissions at specified benchmark values. Initially relying on data from RISE in Best et al. (2020), the study had to pivot to data from the OECD due to a lack of updates from the former. The OECD dataset also provides a detailed account of progress towards carbon pricing benchmarks. For example, a CPS of 100% against a benchmark of EUR 30 per ton of CO2 indicates that a country prices all its carbon emissions from energy at EUR 30 or above. Conversely, a CPS of 0% signifies no carbon pricing on emissions, with intermediate values indicating partial pricing adherence (OECD, 2021).

**Table 1. Descriptive Statistics**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Carbon price, binary | 143 | .28 | .45 | 0 | 1 |
| Carbon price, binary, duration adjusted | 143 | .29 | .45 | 0 | 1 |
| Carbon Price Score (30B) | 224 | 6.82 | 16.53 | 0 | 72.85 |
| Carbon Price Score (60B) | 224 | 5.65 | 13.85 | 0 | 69.91 |
| Carbon Price Score (120B) | 224 | 4.68 | 11.58 | 0 | 65.15 |
| CO2 emission from fuel combustion (tonnes) | 150 | 207417.11 | 870943.68 | 493.4 | 9134984 |
| CO2 growth rate per year over 5 years | 149 | .02 | .06 | -.18 | .23 |
| Population | 210 | 35149965 | 1.366e+08 | 10877 | 1.380e+09 |
| Population growth rate per year over 5 years | 210 | .01 | .01 | -.03 | .07 |
| GDP per capita (PPP constant 2017 international $) | 192 | 20713.93 | 21760.22 | 781.58 | 116855.53 |
| GDP per capita growth per year over 5 years | 190 | .02 | .02 | -.1 | .08 |
| Coal share | 143 | .13 | .18 | 0 | .71 |
| Oil share | 143 | .37 | .21 | .01 | 1 |
| Gas share | 143 | .21 | .23 | 0 | .99 |
| Transition economy, binary | 143 | .2 | .4 | 0 | 1 |
| Energy Intensity (MJ/$2011 PPP GDP) | 197 | 4.9 | 3.15 | .47 | 24.81 |

While the full dataset includes multiple years expanding to 2020, **Table 1** only shows data from 2015 the initial year of the updated study period, with the CO2 emissions from fuel combustion data reported for 150 countries. This choice was made because presenting the entire dataset in one table would be overwhelming and potentially confusing. By focusing on a single year, I aim to illustrate key patterns and relationships more clearly. The mean CO2 emissions amount to approximately 207,417 tonnes, accompanied by a high standard deviation of 870,943.68 tonnes, reflecting extensive variability in emissions among the countries. This variable ranges from 493.4 to 9,134,984 tonnes, demonstrating the broad spectrum of emission levels across the sample. Both the binary carbon price variable and the duration-adjusted carbon price variable were sampled across 143 countries. The binary carbon price variable indicates an average implementation rate of 28%, with a standard deviation of 0.45, highlighting considerable variance in the adoption of carbon pricing policies. The duration-adjusted carbon price exhibits a similar distribution but with a marginally higher average of 29%, suggesting some temporal stability in pricing policies. Moreover, the study incorporates the CPS at three benchmarks: 30B, 60B, and 120B. The mean CPS values for these benchmarks are 6.82%, 5.65%, and 4.68% respectively, with standard deviations of 16.53%, 13.85%, and 11.58%. These statistics underscore significant disparities in how different nations price carbon emissions relative to predefined benchmarks, illustrating the varied commitment levels towards carbon pricing.

Additionally, economic and demographic indicators such as population, GDP per capita, and their respective growth rates over five years are also included. These variables provide a backdrop against which carbon emission levels and carbon pricing mechanisms can be analyzed, offering insights into the economic conditions and demographic factors that may influence or correlate with carbon management strategies. The inclusion of energy composition variables—coal, oil, and gas shares—in national energy consumption, and energy intensity (measured as MJ per dollar of GDP) is essential to replicate the regression model constructed by Best et al. (2020). By including all of these controls, the analysis can more accurately isolate the impact of carbon pricing mechanisms on emissions, taking into account the underlying economic conditions and energy usage patterns. This comprehensive approach helps to ensure that the observed effects are not confounded by these critical factors, thereby providing more reliable insights into the effectiveness of carbon pricing.

### *3.2 Performance and Policy Indexes*

**Table 2. Descriptive Statistics for Index Variables**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Environmental Taxes | 125 | 1.42 | 1.09 | 0 | 4.15 |
| Fossil Fuel Subsidies | 168 | 5.4 | 6.42 | 0 | 48.51 |
| Electricity Generation from Renewables | 247 | 136414.63 | 576809.15 | 0 | 5516255 |
| Electricity Generation from Non-renewables | 248 | 468927.13 | 2016529.9 | 0 | 18812718 |
| Trade in Low Carbon Tech Products | 167 | 1.687e+10 | 1.120e+11 | 2132309.5 | 1.410e+12 |
| Green Bonds | 80 | 2.88 | 21.26 | 0 | 190.15 |
| Terrestrial Biome Protection | 220 | 10.07 | 6.17 | 0 | 17 |
| Protected Areas Representativeness Index | 217 | .12 | .06 | .03 | .31 |
| PM2.5 exposure, Adjusted | 198 | 1171.94 | 802.39 | 77.27 | 4388.48 |
| Solid Fuels Pollution, Adjusted | 198 | 1626.14 | 2301.26 | .18 | 11677.11 |
| Recycling | 219 | .8 | .12 | .33 | .99 |
| Emissions Growth for Methane, Adjusted | 190 | .01 | .03 | -.1 | .09 |
| Emissions Growth for Black Carbon, Adjusted | 202 | 0 | .04 | -.14 | .22 |
| Projected GHG Emissions in 2050 | 190 | 394006.63 | 2153176.3 | 0 | 28236142 |

To further enhance the robustness of the regression analysis exploring the relationship between carbon pricing and carbon emission levels, a performance index and a policy index will be developed to serve as control variables. These indexes are constructed from 14 variables presented in **Table 2**, sourced from the Environmental Performance Index (EPI) and the International Monetary Fund (IMF). Each variable is selected for its potential to influence or illustrate the effectiveness of environmental policies and economic practices across countries.

From the IMF, the selection includes fiscal measures such as Environmental Taxes (% of GDP) and Fossil Fuel Subsidies (% of GDP). Environmental taxes are used to evaluate the stringency of a country's policies aimed at reducing pollution and promoting efficient resource use. In contrast, fossil fuel subsidies represent a financial commitment to energy sources that can undermine environmental sustainability efforts by making high-emission fuels artificially cheap. Additionally, Electricity Generation from Renewables and Non-renewables (GWh) is included to delineate the energy profile of a nation, illustrating the balance between renewable and non-renewable energy sources, which has direct implications for carbon emissions. The economic engagement with environmental sustainability is further assessed through variables like Trade in Low Carbon Technology Products (USD) and Green Bonds (Billion USD), which gauge the market's orientation towards low-carbon technologies and green financing.

From the Environmental Performance Index (EPI), variables such as Terrestrial Biome Protection (% National Weights) and the Protected Areas Representativeness Index are included to measure the effectiveness of a country's efforts in conserving biodiversity and protecting natural habitats, critical for carbon sequestration. Pollution-related health impacts, indicated by PM2.5 exposure and Solid Fuels Pollution using the number of age-standardized disability-adjusted life-years lost per 100,000 persons (DALY rate), provide insight into the environmental quality and its effects on public health. These are complemented by the Recycling measured in proportions, which reflects the efficiency of national recycling and waste management practices. Pollution control is further represented through variables measuring the Adjusted Emissions Growth for Methane and Black Carbon in proportions, highlighting efforts to manage pollutants that significantly affect climate change and air quality. Finally, projections and assessments of greenhouse gas emissions, including Projected Greenhouse Gas Emissions in 2050 (Gg CO2-eq.), offer insights into the long-term environmental impact and current emission levels of each country.

## 4. Methodology

### *4.1 Roadmap*

The methodology section of this study is designed to build upon and extend the methodological framework established by Best et al. (2020), with a focus on assessing the efficacy of carbon pricing mechanisms. Unlike the original study, which analyzed data spanning from 2012 to 2017, this research extends the observational period to 2015-2020. This extension is pivotal for capturing recent trends and the impacts of evolving policies in the field of carbon pricing, reflecting significant developments in this dynamic area of study.

To maintain methodological consistency with Best et al. (2020) and facilitate comparative analysis, this study replicates the primary econometric models used in the referenced research. The models are predominantly cross-sectional growth-rate regressions, chosen for their relevance in analyzing the impact of policy over time. This replication ensures that any variations in findings can be attributed to changes in data or policy effectiveness rather than differences in analytical approach.

A significant advancement in this study is the creation and integration of novel performance and policy indexes, as detailed in **Section 4.3**. The policy index is meticulously designed to control for a variety of environmental policy variables alongside other factors that may influence the reduction of carbon emissions. The performance index, on the other hand, captures the overall effectiveness and outcomes of these policies in practice. Incorporating these indexes as additional control variables in the econometric models is intended to enhance the robustness and explanatory power of the analysis, providing a more nuanced understanding of the factors that impact carbon pricing efficacy.

Central to the methodology is a comparative analysis between the findings derived from the extended data period (2015-2020) and the results reported by Best et al. (2020). This comparison aims to identify any temporal shifts in the effectiveness of carbon pricing policies over the newer timeframe. Furthermore, the study rigorously evaluates the effectiveness of the newly developed indexes by conducting regression analyses both with and without their inclusion. This step is crucial in assessing the indexes' ability to account for unobservable variables that might otherwise confound the observed relationships between carbon pricing and emission reductions.

*4.2 Cross-Sectional Growth-Rate Regressions over Three Time Periods*

In their foundational study, Best et al. (2020) utilized cross-sectional growth-rate regression analysis to evaluate the immediate impacts of carbon pricing policies on the growth rates of CO2 emissions across a diverse set of nations. This methodological approach involves examining the correlation between the average annual growth rates of CO2 emissions and a range of policy measures, notably including carbon pricing. The primary rationale behind this approach is to discern the direct and immediate effects of policy implementations on emission trends, providing insights into the efficacy of these policies shortly after their introduction.

Building upon this foundation, my research replicates and extends this method by analyzing the growth rates of CO2 emissions over the period from 2015 to 2020, incorporating an additional analysis for the four-year period from 2015 to 2019 to control for the anomalous impacts of the COVID-19 pandemic. This study employs a similar set of variables to those used by Best et al., with an updated focus on how recent implementations of carbon pricing policies—including both taxes and ETS—along with other environmental policies, have influenced CO2 emission growth rates in various countries.

This regression analysis is designed to shed light on the short-term effectiveness of these policies in mitigating emissions. In this regression model, $E_c$ is CO2 emissions from fuel combustion, $CP_c$ is Carbon Price Variable (Binary, Duration-adjusted, or Score), and $X_c$ encompasses the economic, demographic, and energy-related control variables. The anticipated sign for the coefficient $\beta$ is negative, which indicates that carbon pricing is effective in reducing the average annual CO2 growth rate.

$$(ln\, E_c^{2017} - ln\, E_c^{2012})/5 = \alpha + \beta \cdot CP_c + \theta \cdot \triangle ln\, E_c^{2007-2012}/5 + \gamma \cdot X_c + \varepsilon$$

$$(ln\, E_c^{2019} - ln\, E_c^{2015})/4 = \alpha + \beta \cdot CP_c + \theta \cdot \triangle ln\, E_c^{2010-2015}/5 + \gamma \cdot X_c + \varepsilon$$

$$(ln\, E_c^{2020} - ln\, E_c^{2015})/5 = \alpha + \beta \cdot CP_c + \theta \cdot \triangle ln\, E_c^{2010-2015}/5 + \gamma \cdot X_c + \varepsilon$$

*4.3 Performance and Policy Indexes*

*4.3.1 Construction*

I will introduce factor analysis to efficiently consolidate the 7 environmental policy variables and 7 environmental performance variables chosen into two coherent indexes. This statistical technique is particularly suited for my objective, as it allows for the reduction of dimensionality in the dataset while preserving as much of the original information as possible.

As previously mentioned in the data section, the 7 environmental policy variables include Environmental Taxes, which penalize environmentally harmful activities. Fossil

Fuel Subsidies assess government financial support for fossil fuel consumption. Trade in Low Carbon Tech Products measures the market for environmentally friendly technologies, and Green Bonds reflect national investments in green projects. Also included are Terrestrial Biome Protection and the Protected Areas Representativeness Index, both of which gauge conservation efforts. And lastly, recycling evaluates waste management efficiency.

The 7 environmental performance variables include Electricity Generation from Renewables and Non-renewables indicates the balance between sustainable and traditional energy sources. PM2.5 Exposure and Solid Fuels Pollution provide indicators of air quality and pollution impacts. Emissions Growth for Methane and Black Carbon track the output of specific pollutants. Finally, Projected GHG Emissions in 2050 forecasts overall future greenhouse gas emissions.

The application of factor analysis begins with the assessment of the correlation matrix of each set of the 7 variables to evaluate the suitability of the data for this analysis. Key to this evaluation is the Kaiser-Meyer-Olkin (KMO) test for sampling adequacy and Bartlett's test of sphericity, which together confirm the appropriateness of the data for extracting meaningful factors. Confirming that my data meets these preliminary criteria with a KMO value of 0.71 from the set of performance variables and 0.55 from the policy variables, the exploratory factor analysis is conducted to identify latent factors that explain the correlations among variables within each set. The number of factors retained is determined based on eigenvalues greater than 1.0—a commonly accepted criterion known as Kaiser's criterion—and supported by the scree plots to ensure that each factor explains a significant portion of the variance within the dataset (**Figure 1**).

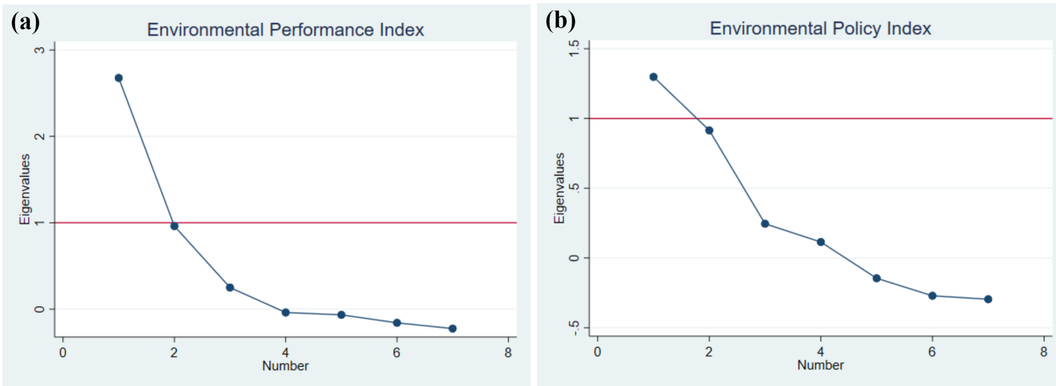



**Figure 1**. **Scree plots of eigenvalues plotted against number of factors using measurement variables retained from the initial exploratory factor analysis.** (a) Scree plot for the Environmental Performance variables; (b) Scree plot for the Environmental Policy variables

To improve the clarity of the factors identified before calculating the index scores, a varimax rotation—an orthogonal rotation technique—is applied. This method facilitates the interpretation of the factors by maximizing the variance of squared loadings of variables on factors, thus producing factors that are as distinct as possible. The resulting factor loadings are used to compute scores for each factor for each observation, which are then aggregated to form a composite index by averaging these scores.

The rationale for employing factor analysis in this research lies in its ability to distill a wide array of complex variables into a smaller, more interpretable set of factors without significant loss of information. This approach not only aids in handling the inherent complexities of environmental performance and policy analysis but also helps mitigate potential issues of multicollinearity in regression models. By capturing the latent structures within the dataset, the resulting two indexes serve as a pivotal explanatory variable in subsequent econometric analyses, thus enhancing our ability to assess the effectiveness of carbon pricing and other environmental policies.

*4.3.2 Integration to the Regression Model*

With the comprehensive environmental performance and policy indexes constructed through factor analysis, the study proceeds to integrate the two indexes into the original regression model established by Best et al. (2020) but with the most recent data (2015-2020). The updated regression model now incorporates the indexes ($I_c$) to enhance the robustness of the analysis and to capture the multidimensional nature of environmental policies beyond carbon pricing alone. The coefficient β will elucidate the direct influence of carbon pricing on emission growth rates, while μ will illuminate the isolated impact of the indexes. Similar to the first set of regressions, a negative coefficient for β would indicate the effectiveness of carbon pricing in reducing the average annual CO2 growth rate.

$$(ln\, E_c^{2020} - ln\, E_c^{2015})/5 = \alpha + \beta \cdot CP_c + \mu \cdot I_c + \theta \cdot \triangle ln\, E_c^{2010-2015}/5 + \gamma \cdot X_c + \varepsilon$$

# 5. Results

## *5.1 Cross-Sectional Growth-Rate Regressions over Three Time Periods*

**Table 3. Cross-Sectional Growth-Rate Regressions Results**

| Dependent variable: Avg. annual CO2 growth rate | 2012-2017 | | | 2015-2020 | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Carbon price score | -0.0006*** | | | -0.0005*** | | |
| | (0.0002) | | | (0.0002) | | |
| Carbon price, binary | | -0.043*** | | | -0.032*** | |
| | | (0.013) | | | (0.010) | |
| Duration-adjusted carbon price | | | -0.048*** | | | -0.030*** |
| | | | (0.014) | | | (0.010) |
| Initial log CO2 | -0.022 | -0.020 | -0.020 | 0.011 | 0.011 | 0.010 |
| | (0.022) | (0.021) | (0.021) | (0.017) | (0.017) | (0.017) |
| Initial log GDP per capita | 0.020 | 0.024 | 0.026 | -0.020 | -0.016 | -0.016 |
| | (0.020) | (0.019) | (0.019) | (0.017) | (0.017) | (0.017) |
| Initial log population | 0.024 | 0.023 | 0.024 | -0.010 | -0.009 | -0.008 |
| | (0.022) | (0.020) | (0.020) | (0.017) | (0.017) | (0.017) |
| Initial log energy intensity | -0.006 | -0.006 | -0.004 | -0.030* | -0.027 | -0.027 |
| | (0.017) | (0.016) | (0.016) | (0.017) | (0.016) | (0.017) |
| Initial coal share | -0.003 | -0.022 | -0.021 | -0.059 | -0.066 | -0.063 |
| | (0.059) | (0.059) | (0.058) | (0.050) | (0.051) | (0.051) |
| Initial oil share | -0.040 | -0.050 | -0.050 | -0.058 | -0.055 | -0.054 |
| | (0.047) | (0.047) | (0.045) | (0.038) | (0.037) | (0.037) |
| Initial natural gas share | -0.003 | -0.024 | -0.031 | 0.004 | -0.008 | -0.006 |
| | (0.038) | (0.039) | (0.039) | (0.031) | (0.033) | (0.033) |
| Transition, binary | -0.002 | 0.008 | 0.012 | -0.005 | 0.004 | 0.004 |
| | (0.009) | (0.009) | (0.009) | (0.010) | (0.010) | (0.010) |
| CO2 growth | 0.026 | -0.061 | -0.061 | 0.044 | -0.001 | 0.005 |
| | (0.135) | (0.137) | (0.132) | (0.101) | (0.099) | (0.100) |
| GDP per capita growth | 0.610** | 0.635*** | 0.656*** | 0.844*** | 0.904*** | 0.887*** |
| | (0.251) | (0.229) | (0.223) | (0.189) | (0.206) | (0.203) |
| Population growth | 0.692** | 0.636** | 0.639** | 0.673* | 0.691* | 0.699* |
| | (0.323) | (0.314) | (0.312) | (0.383) | (0.389) | (0.388) |
| Constant | -0.479 | -0.484 | -0.526 | 0.380 | 0.319 | 0.314 |
| | (0.501) | (0.474) | (0.472) | (0.412) | (0.410) | (0.413) |
| Observations | 134 | 134 | 134 | 133 | 133 | 133 |
| R-squared | 0.443 | 0.479 | 0.493 | 0.485 | 0.496 | 0.493 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05,
* p<0.1

An integral part of this study was to examine the efficacy of carbon pricing in reducing carbon emissions over three distinct time frames. Utilizing a cross-sectional growth-rate regression model, the estimated effects of carbon pricing were observed for the periods 2012-2017 (replicated regression, regression results in **Table 3/Appendix 1a**), 2015-2019 (a 4-year period regression to control for pandemic impacts, regression results in the **Appendix 1b**), and 2015-2020 (regression with most recent data, regression results in **Table 3/Appendix 1c**). To determine the consistency of carbon pricing's effectiveness across these periods, a series of statistical comparisons through Wald Chi-Squared tests were conducted on the null hypothesis that the coefficients associated with carbon pricing would be equivalent across the specified periods, indicating no significant temporal variation in carbon pricing effectiveness.

The first Wald test scrutinized the coefficients of the carbon price score variable from 2012 and 2015. The analysis yielded a chi-squared value of 0.62 and a p-value of 0.7320. This high p-value suggests that the coefficients for the carbon price score from 2012 to 2015 are not statistically distinguishable from each other, thus failing to reject the null hypothesis for this pair of time periods. Analogously, a subsequent test examined the binary carbon pricing variable over the three time periods. The resulting chi-squared statistic of 1.47 and the p-value of 0.4793 corroborated the initial test's outcome, indicating no significant difference in the impact of the binary carbon pricing variable across the compared periods. Finally, the comparison of the duration-adjusted binary carbon pricing variable across the full dataset span rendered a chi-squared statistic of 2.33 with a p-value of 0.3112. This non-significant result further substantiates the prior findings, leading to a retention of the null hypothesis across all three comparisons.

Overall, the statistical evidence indicates a consistent efficacy of carbon pricing on $CO_2$ emissions reduction over the periods of 2012-2017, 2015-2019, and 2015-2020. Given the statistical tests' outcomes, the null hypothesis—that the coefficients representing the effect of carbon pricing remain uniform across the specified time frames—cannot be rejected. The results, therefore, support the assertion that the effectiveness of carbon pricing as a policy instrument has not undergone significant changes over the studied periods. This temporal invariance justifies the utilization of the most recent dataset, encompassing the years 2015 to 2020, for the advancing phase of this research. With the validation of carbon pricing's steady impact over time, I will confidently integrate the policy index into the regression models using up-to-date data to evaluate the current and prospective influence of carbon pricing within the wider ambit of environmental policy mechanisms.

Delving deeper into the specifics of the regression results, data from Table 3 reveal that carbon pricing—represented by the carbon price score, the binary carbon pricing variable, and the duration-adjusted binary variable—displays a consistent and statistically significant negative association with $CO_2$ emission growth rates across all investigated time periods. For the most recent span of 2015-2020 (as shown in **Columns 4, Table 3**), the carbon price score exhibits a coefficient of -0.0005, which is significant at the 1% level. This relationship indicates that an elevation in the carbon pricing score corresponds with a decrease in the rate of growth for $CO_2$ emissions, reinforcing the policy's intended effect.

The binary carbon price variable also shows a consistently negative effect on emissions growth throughout the periods examined. However, it is noteworthy that there is a slight, though non-significant, attenuation in this effect, diminishing from -0.043 in the earlier period (2012-2017, as depicted in **Columns 2, Table 3**) to -0.032 in the 2015-2020 timeframe (as presented in **Columns 5, Table 3**). This trend suggests a marginally decreased impact of the binary carbon pricing mechanism over time, yet the change is not statistically significant, indicating that the efficacy of carbon pricing remains robust. Moreover, the duration-adjusted carbon price variable continues to exert a negative influence on emission growth rates across different model specifications, persistent through all periods. Such findings substantiate the role of carbon pricing—irrespective of its specific operationalization—as a crucial tool in the effort to curb CO2 emissions growth.

Control variables in the study show mixed effects on emissions growth: the initial log CO2, while intuitively expected to be a predictor of future emissions growth due to historical emission levels, does not exhibit a statistically significant relationship in any model iteration. This lack of significance might suggest that past CO2 emission levels are not deterministic of future trends, possibly due to changes in national energy policies, technological advancements in emissions control, or shifts in industrial activities that decouple historical emission baselines from future emissions trajectories. Conversely, the initial log energy intensity shows a negative and statistically significant correlation with CO2 growth rates in several models, including in **Appendix 1b**. This relationship indicates that countries starting with higher energy efficiency—meaning lower energy use per unit of GDP—tend to experience slower rates of emissions growth. This finding could be interpreted as evidence that investments in energy efficiency technologies and practices yield tangible reductions in emissions growth, reinforcing the importance of energy efficiency measures in climate policy.

Furthermore, economic growth, captured by GDP per capita growth and population growth rates, shows positive and significant coefficients. These relationships suggest that economic and demographic expansion are linked to increased CO2 emissions. Specifically, as economies grow and populations increase, the demand for energy typically rises, often resulting in higher emissions unless offset by significant improvements in energy efficiency or a shift towards cleaner energy sources. It implies that without proactive and stringent environmental policies, the effects of economic and population growth may exacerbate the challenge of reducing emissions, particularly in rapidly developing regions where economic growth and urbanization are most intense.

The R-squared values for the 2015-2020 period models suggest a strong model fit, explaining approximately 43.5% to 49.3% of the variance in CO2 growth rates. This substantial explanatory power indicates that the variables selected for inclusion in the model capture a significant portion of the factors influencing emissions growth.

### *5.2 Performance and Policy Indexes*

#### *5.2.1 Construction*

Exploratory factor analysis was conducted on two datasets incorporating 7 environmental performance variables and 7 environmental policy variables, resulting in the extraction of one distinct factor from each dataset. These factors were deduced by analyzing the extent to which each performance or policy variable correlates with and contributes to underlying policy dimensions (**Figure 2**).

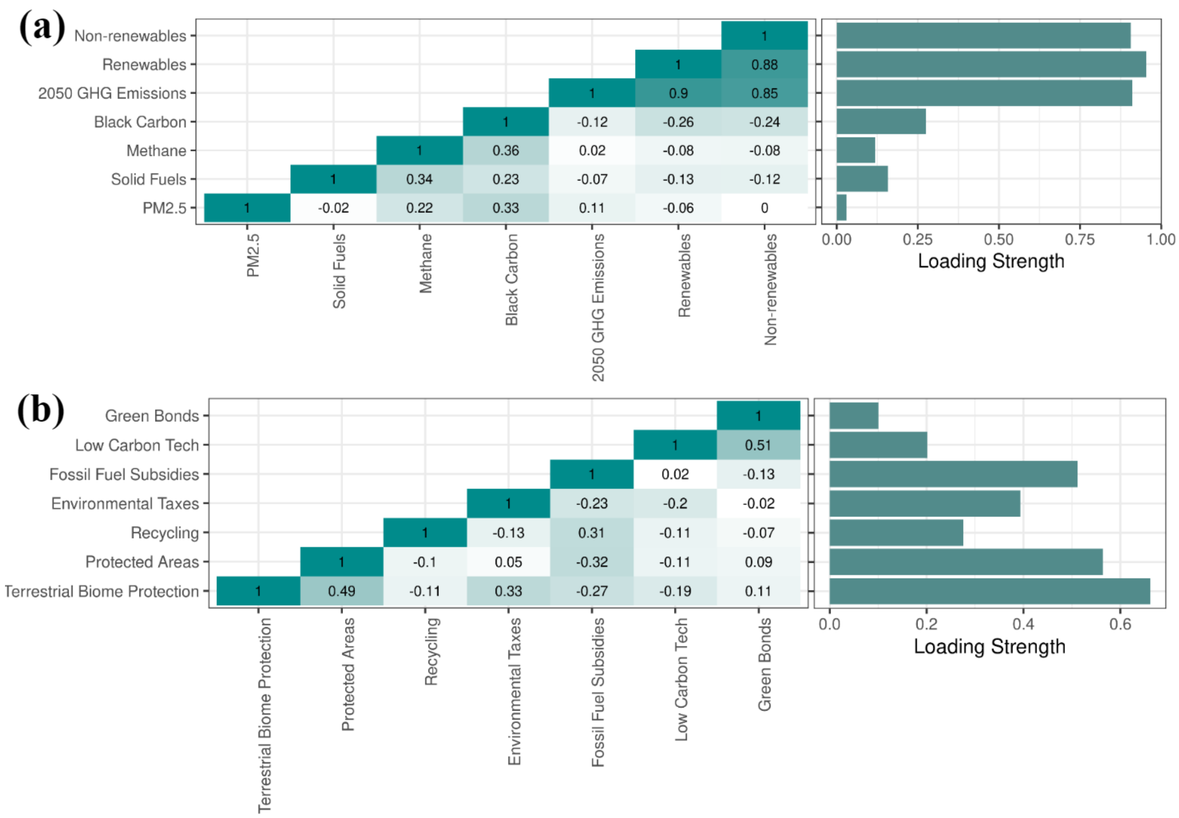
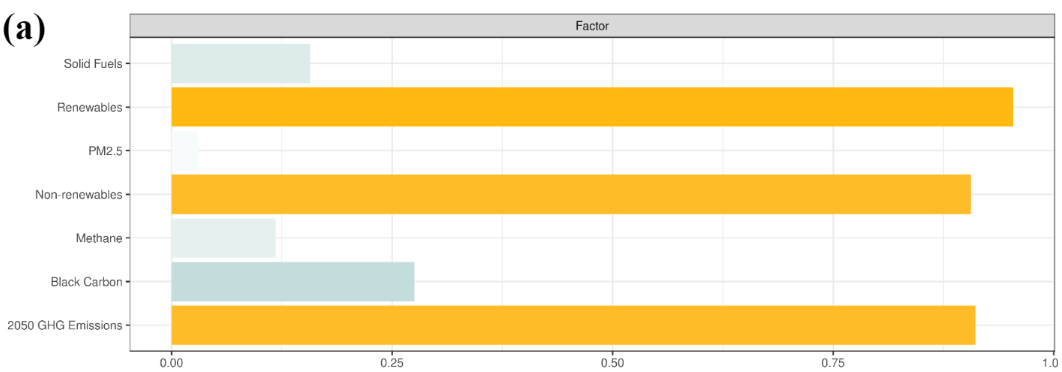



**Figure 2. Correlation Matrix and Factor Loading Strength of the Two Sets of Variables**
(a) Environmental Performance variables; (b) Environmental Policy variables. The heatmap on the left visualizes the pairwise correlations among the environmental policy variables. The bar chart on the right represents the absolute factor loadings. The loading strength is a metric of how strongly each variable is associated with the factor, and the length of the bars in the chart corresponds to the magnitude of these loadings. The variables with the most extended bars on a particular factor are considered the most influential for that factor.

In **Figure 2 (a)**, the correlation matrix from the performance variables uncovers significant positive correlations between variables such as 'Electricity Generation from Non-renewables', 'Electricity Generation from Renewables' and 'Projected GHG Emissions in 2050'. These associations, all above 0.85, imply that nations with higher electricity output from both non-renewable and renewable sources tend to exhibit elevated GHG emissions. Additionally, a moderate positive correlation the pollution indicators like 'PM2.5 Exposure', 'Solid Fuels Pollution', and emissions of pollutants such as 'Black Carbon' and 'Methane' suggests that these pollution indicators are interrelated and potentially influenced by similar factors. For instance, the use of solid fuels can contribute to both PM2.5 and methane emissions, while black carbon is a common byproduct of incomplete combustion processes. On the other hand, there are a few notable negative correlations. For instance, the moderate negative correlation between black carbon and renewables (-0.26) indicates that increasing the use of renewable energy sources leads to a decrease in black carbon emissions. This is because renewables, like wind and solar, do not produce black carbon, which is a byproduct of burning fossil fuels and biomass. Thus, more renewables mean less combustion and fewer emissions. Similarly, the negative correlation between black carbon and non-renewables (-0.24) could reflect the ongoing shift from high-emission fossil fuels to cleaner energy sources. As regulations and policies push for reduced greenhouse gas emissions, the use of coal and oil decreases, leading to lower black carbon emissions.

As for the correlation matrix from the policy variables, there is a strong positive correlation (0.51) between green bonds and the trade in low carbon technology. This relationship suggests that the issuance of green bonds can potentially promote trade in low carbon technologies and can be leveraged to support technological advancements. There is also a strong positive correlation (0.49) between terrestrial biome protection and protected areas, indicating that efforts to protect terrestrial biomes are closely linked to the establishment and maintenance of protected areas. Recycling shows a moderate positive correlation (0.31) with fossil fuel subsidies. This somewhat unexpected relationship may indicate that regions or sectors with higher fossil fuel subsidies also invest in recycling initiatives, possibly as a way to mitigate some of the environmental impacts of fossil fuel use. There are also significant negative correlations highlighting that certain policies or practices might conflict. For instance, there is a moderate negative correlation (-0.32) between protected areas and fossil fuel subsidies. This suggests that subsidies for fossil fuels could undermine efforts to expand protected areas, as financial support for fossil fuels may lead to increased exploitation of natural resources and habitat degradation, counteracting conservation efforts. Similarly, there is a moderate negative correlation (-0.27) between terrestrial biome protection and fossil fuel subsidies. This indicates that higher fossil fuel subsidies are associated with lower efforts to protect terrestrial biomes, reinforcing the notion that financial incentives for fossil fuels can be detrimental to environmental conservation. Additionally, there is a slight negative correlation (-0.20) between environmental taxes and the trade in low carbon technology. This relationship suggests that higher environmental taxes may not necessarily coincide with increased trade in low carbon technologies, possibly due to varying policy focuses or implementation challenges.

**(a)**



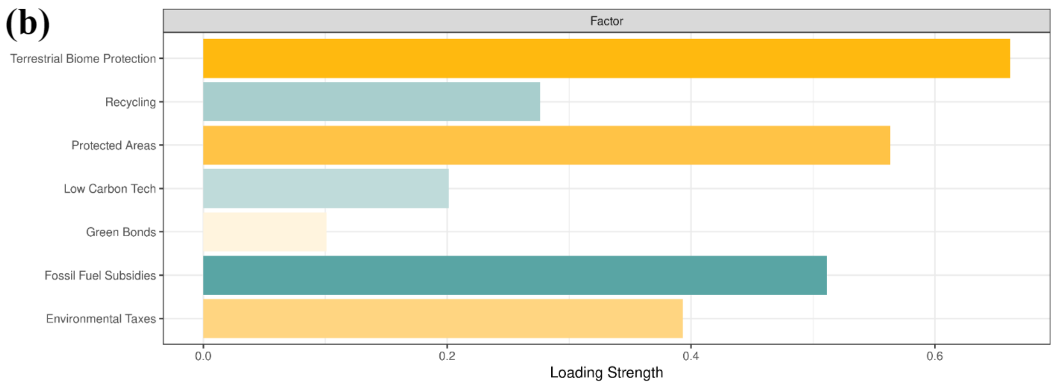



**Figure 3. Specific loadings of the 15 variables on each factor**
The factor loading strengths of 15 environmental policy variables on two distinct factors are depicted by the varying shades where yellow signifies positive loadings and teal indicates negative loadings. The darker the color, the stronger the loading of that specific variable. Figure created using data from **Appendix 2**.

Since there is a mix of two directions of each performance variable's contribution to the factor, I assume the performance index is positively oriented, meaning the higher the score is for a country, the better its environmental performance is. This assumption is based on the overall nature and implications of the factor loadings observed in **Figure 2 (a)** and **Figure 3 (a)**. The positive loadings on variables such as 'Renewables' (0.95), 'Non-renewables' (0.91), and '2050 GHG Emissions' (0.91) suggest that higher scores in these areas are associated with better environmental performance. Specifically, a high loading on 'Renewables' indicates that increased use of renewable energy sources contributes significantly to a positive environmental outcome, reducing dependence on fossil fuels and decreasing greenhouse gas emissions. Similarly, the positive loading on 'Non-renewables' might reflect the transition and management efforts towards reducing the environmental impact of these energy sources, likely through efficiency improvements or cleaner technologies.

Conversely, the negative loadings on variables such as 'Black Carbon' (-0.28), 'Solid Fuels' (-0.16), and 'Methane' (-0.12) indicate that higher levels of these pollutants detract from environmental performance. The very weak negative loading on 'PM2.5' (-0.03) further supports the assumption. While PM2.5 is a critical air pollutant, its minimal loading implies that its influence on the overall index is less significant compared to other factors. This may be because PM2.5 levels can be influenced by a variety of sources and mitigation efforts that are not as directly tied to the primary energy and emissions factors in this analysis. Given these loadings, it is reasonable to infer that the performance index rewards countries for positive environmental actions and outcomes, such as increasing renewable energy use and reducing harmful emissions. A higher score on the index likely indicates that a country is effectively managing its energy resources and minimizing its environmental footprint, thereby achieving better overall environmental performance.

The policy index could also be positively oriented, meaning that higher scores on this index indicate more stringent or better-developed environmental policies in a country. This orientation is based on the interpretation of the factor loadings in **Figure 2 (b)** and **Figure 3 (b)**, which reflect the direction and magnitude of each variable's contribution to the overall index. Specifically, 'Terrestrial Biome Protection' has a loading of 0.66, 'Protected Areas' a loading of 0.56, and 'Environmental Taxes' a loading of 0.39, which are then identified as having the most significant positive contributions to the policy index. Conversely, 'Fossil Fuel Subsidies' shows a strong negative loading (-0.51), suggesting that financial support for fossil fuels undermines environmental policy effectiveness by promoting activities that contribute to pollution and greenhouse gas emissions. Similarly, 'Recycling' has a negative loading (-0.28), which might seem counterintuitive but could indicate that regions with lower recycling rates have more strict overall environmental policies due to other effective policies or practices. 'Low

Carbon Tech' also shows a negative loading (-0.20), which may reflect the current challenges and slow pace of adopting low carbon technologies despite their potential benefits. Lastly, 'Green Bonds' has a positive but relatively weak loading (0.10), indicating a modest contribution to the policy index. While green bonds are crucial for funding environmentally friendly projects, their impact might be less pronounced in comparison to other variables such as protected areas and terrestrial biome protection.

Each index is then standardized on a scale of 0-100, offering a composite measure of a country's environmental policy and performance landscape. This standardization facilitates comparison across countries and provides a clear and consistent metric for evaluating environmental policy effectiveness.

**Table 4. Descriptive Statistics for Index Variables after Factor Analysis**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| PM2.5 exposure, Adjusted | 61 | 826.66 | 781.99 | 77.27 | 4388.48 |
| Solid Fuels Pollution, Adjusted | 61 | 356.6 | 871.71 | .27 | 4201.53 |
| Emissions Growth for Methane, Adjusted | 61 | 0 | .02 | -.08 | .05 |
| Emissions Growth for Black Carbon, Adjusted | 61 | -.02 | .04 | -.14 | .06 |
| Projected GHG Emissions in 2050 | 61 | 823000.56 | 3631003.1 | 0 | 28236142 |
| Electricity Generation from Renewables | 61 | 76348.1 | 199801.56 | 399.52 | 1381355.2 |
| Electricity Generation from Non-renewables | 61 | 238057.65 | 735200.98 | 4 | 4434057.7 |
| Environmental Taxes | 61 | 1.78 | 1.05 | .02 | 4.12 |
| Fossil Fuel Subsidies | 61 | 4.57 | 5.11 | .06 | 33.3 |
| Terrestrial Biome Protection | 61 | 12.72 | 4.68 | .19 | 17 |
| Protected Areas Representativeness Index | 61 | .13 | .05 | .04 | .25 |
| Green Bonds | 61 | .64 | 1.83 | 0 | 8.65 |
| Trade in Low Carbon Tech Products | 61 | 2.023e+10 | 4.206e+10 | 92797177 | 2.510e+11 |
| Recycling | 61 | .73 | .15 | .33 | .99 |

Before synthesizing these findings into the regression model, it is important to note that there is a decreased sample size after applying factor analysis. **Table 4** provides a detailed summary of the index variables for the final 61 countries included in this study. These variables were essential in calculating the two index scores—environmental performance and policy indexes—used in the final stage of the analysis. These 61 countries have a mean CO2 emission from fuel combustion of 379,552 tonnes, a mean population of 70 million, and a mean GDP per capita of 34,359.5 dollars in 2020. This reduction is due to the requirements of the factor analysis technique, which demands complete data for all variables included in the analysis. Missing values in any of the variables result in the exclusion of those observations from the factor analysis, leading to a smaller sample size. Consequently, while the resulting indexes provide a more streamlined and interpretable set of factors, the reduced sample size might limit the comparability and generalizability of the findings.

### *5.2.2 Integration to the Regression Model*

**Table 5. Cross-Sectional Growth-Rate Regressions 2015-2020**

| | 2015-2020 | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Carbon price score | 0.00003 | | |
| | (0.0002) | | |
| Carbon price, binary | | -0.0223* | |
| | | (0.0121) | |
| Duration-adjusted carbon price | | | -0.0179 |
| | | | (0.0113) |
| Performance Index Score | -0.0009*** | -0.0007** | -0.0008*** |
| | (0.0003) | (0.0003) | (0.0003) |
| Policy Index Score | -0.0005** | -0.0004** | -0.0004** |
| | (0.0002) | (0.0002) | (0.0002) |
| Initial log CO2 | 0.0713*** | 0.0716*** | 0.0717*** |
| | (0.0233) | (0.0212) | (0.0221) |
| Initial log GDP per capita | -0.0595*** | -0.0553*** | -0.0559*** |
| | (0.0195) | (0.0155) | (0.0161) |
| Initial log population | -0.0626*** | -0.0619*** | -0.0622*** |
| | (0.0213) | (0.0190) | (0.0199) |
| Initial log energy intensity | -0.0550*** | -0.0512*** | -0.0531*** |
| | (0.0161) | (0.0148) | (0.0151) |
| Initial coal share | -0.2111*** | -0.2267*** | -0.2231*** |
| | (0.0782) | (0.0786) | (0.0800) |
| Initial oil share | -0.0670* | -0.0733** | -0.0737** |
| | (0.0343) | (0.0312) | (0.0324) |
| Initial natural gas share | -0.1878*** | -0.1910*** | -0.1916*** |
| | (0.0553) | (0.0534) | (0.0548) |
| Transition, binary | 0.0153 | 0.0189** | 0.0187** |
| | (0.0093) | (0.0081) | (0.0083) |
| CO2 growth | 0.4404*** | 0.3148*** | 0.3497*** |
| | (0.1325) | (0.1153) | (0.1161) |
| GDP per capita growth | 0.9423*** | 1.0070*** | 0.9720*** |
| | (0.1855) | (0.1778) | (0.1753) |
| Population growth | 0.4539 | 0.2911 | 0.3540 |
| | (0.5215) | (0.5149) | (0.5074) |
| Constant | 1.5182*** | 1.4645*** | 1.4780*** |
| | (0.5040) | (0.4343) | (0.4530) |
| | | | |
| Observations | 61 | 61 | 61 |
| R-squared | 0.6936 | 0.7177 | 0.7114 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the last stage of our regression analysis, as shown in **Table 5**, the integration of the constructed performance and policy indexes profoundly influences the relationship between carbon pricing and $CO_2$ growth rates. This addition offers a multifaceted view of environmental policy effectiveness beyond carbon pricing alone.

When the performance and policy indexes are included, the carbon price score's impact on $CO_2$ growth rates diminishes from -0.0005 ($p<0.01$) to an insignificant coefficient of 0.00003 in Model 1 with the indexes. The positive yet not significant relationship observed between carbon pricing and average annual $CO_2$ emission growth when the indexes are included indicates that carbon pricing might interact with other policies in complex ways. For instance, countries with aggressive carbon pricing mechanisms may also have robust renewable energy policies, energy efficiency programs, and other measures that collectively contribute to emission reductions. These complementary policies may absorb some of the effects that would otherwise be attributed to carbon pricing alone, thereby diluting its isolated impact in the statistical model. Additionally, the performance index measures the overall effectiveness of a country's environmental policies, while the policy index accounts for the specific regulatory framework. These indexes likely capture the synergies between various policy instruments that drive emission reductions. As a result, the direct impact of carbon pricing appears less significant when the broader policy context is taken into account.

Similarly, the binary carbon price variable shows a reduction in its negative effect, moving from -0.032 ($p<0.01$) to -0.0223 ($p<0.10$, Model 2). The duration-adjusted carbon price also sees a decrease in its negative coefficient, from -0.030 ($p<0.01$) to -0.0179 ($p>0.10$, Model 3), highlighting the relative impact of comprehensive policy frameworks on $CO_2$ emissions. The persistence of negative coefficients, although reduced, indicates that carbon pricing remains an influential tool. It suggests that while carbon pricing alone might not be sufficient, it contributes to emission reductions when used alongside a suite of supportive environmental policies. This continued negative association, even if attenuated, underscores the importance of maintaining and possibly enhancing carbon pricing mechanisms as part of a broader, integrated climate strategy.

The performance index itself presents a significant negative coefficient (ranging from -0.0009 to -0.0007, $p<0.01$), emphasizing the effectiveness of broad-based environmental strategies in curbing $CO_2$ growth. This negative coefficient indicates that higher scores on the performance index, which reflect the overall success and impact of a country's environmental policies, are associated with lower $CO_2$ growth rates. This finding suggests that when countries implement a wide array of effective environmental measures—such as increasing energy efficiency, promoting renewable energy, and reducing deforestation—these actions collectively contribute to significant reductions in carbon emissions.

Similarly, the policy index shows significant negative coefficients (-0.0005 to -0.0004, $p<0.05$), affirming the overall efficacy of an aggregated environmental policy approach. The policy index captures the presence and intensity of various environmental regulations and initiatives. The significant negative coefficients imply that countries with more comprehensive and stringent environmental policies experience greater reductions in $CO_2$ growth rates. This result underscores the importance of not just isolated policy measures but also a cohesive and integrated policy framework that addresses multiple aspects of environmental management simultaneously.

The coefficients for control variables also shift in the presence of the performance and policy indexes. The initial log CO2 variable becomes significantly positive in the models with indexes (0.0713, $p<0.01$ in Model 1), suggesting that higher initial CO2 levels are associated with increased CO2 growth rates when environmental policies are accounted for. The initial log GDP per capita becomes significantly negative in the models with indexes, ranging from -0.0595 to -0.0553 ($p<0.01$), indicating that more developed economies may experience lower CO2 growth rates with a broader suite of environmental policies. Similarly, initial log population coefficients become significantly negative (ranging from -0.0626 to -0.0619, $p<0.01$ in Model 2), underscoring that larger populations are associated with decreased CO2 growth rates within a strong policy environment.

Moreover, the initial log energy intensity, along with initial shares of coal, oil, and natural gas, shows increasingly negative coefficients in the models with indexes. This pattern suggests that higher initial energy efficiency and a lower reliance on fossil fuels, coupled with comprehensive environmental policies, contribute to slower CO2 emissions growth.

The emergence of significance in control variables upon the addition of the performance and policy indexes suggests that these indexes capture a broader spectrum of environmental policy influences that were previously unaccounted for. The indexes likely embody interactions and cumulative effects of various environmental policies extending beyond the scope of carbon pricing alone. By encompassing a wider range of policy instruments, the indexes may clarify the underlying dynamics between economic, demographic, and energy-related factors and CO2 emissions growth. This integrative approach potentially highlights the indirect effects and synergies of comprehensive policy frameworks that could be overshadowed when examining isolated policy measures. Another explanation is that adding the performance and policy indexes reduced the total number of observations in the regression model. Hence, variables such as initial GDP, population, and energy intensity, which seemed inconsequential in isolation, are now revealed as significant factors within the context of a systemic policy environment.

It is important to note that the reduction in the sample size to 61 countries after the index construction poses a limitation in the comparability of these models to previous ones. The decreased sample size means that the models with the performance and policy indexes might not fully capture the broader trends observed in the larger dataset used in earlier stages of the analysis. While the inclusion of these indexes provides a more nuanced understanding of environmental policy effectiveness, they should be interpreted with caution, considering the constraints posed by the reduced number of observations.

Overall, the R-squared values in the Models with indexes are significantly higher (0.694 to 0.718) than in the ones without, demonstrating that the inclusion of the performance and policy indexes offers superior explanatory power in the regression models. The stronger model fit indicates that these indexes capture additional variation in $CO_2$ growth rates that is not explained by carbon pricing and other controls alone.

**6. Discussion and Conclusion**

The primary purpose of this research is to assess the efficiency of carbon pricing mechanisms from 2012 to 2020. Building on the foundational study by Best et al. (2020), this research aimed to update and extend the analysis to include more recent data, thereby capturing the evolving impacts of carbon pricing amid changing global economic and policy landscapes. By adding two comprehensive indexes—a performance index and a policy index—that act as controls for a wider set of both environmental and economic factors, I sought to enhance the robustness of this analysis. This dual approach not only aimed to validate the ongoing relevance of carbon pricing as a critical tool in climate policy but also to provide a deeper understanding of how integrated policy frameworks influence CO2 emissions. Overall, the goal was to offer actionable insights that could guide more effective and nuanced policy-making in the realm of climate change mitigation.

From the results, my investigation of the interaction between carbon pricing, environmental policies, and CO2 emissions from 2012 to 2020 has provided strong support for the notion that carbon pricing is an effective mechanism to inhibit CO2 emission growth. The fact that this observation holds true across significantly different countries—varying both economically and demographically—and despite recently shifted patterns of global emissions, suggests that carbon pricing maintains a solid position as one of the principal climate mitigation strategies. This robustness across diverse contexts underscores the universal applicability of carbon pricing as a tool to drive emission reductions.

Nonetheless, the addition of comprehensive performance and policy indexes has added an extra dimension to this relationship. The results show that the direct impact of carbon pricing as an isolated policy on emissions decline appears less significant when these indexes are included. This suggests that while carbon pricing is an important tool, its effectiveness cannot be fully understood without considering the broader policy environment. The indexes capture the overall policy landscape, indicating that carbon pricing's impact on reducing emissions is intertwined with other environmental measures and policies in place.

Moreover, the indexes have illuminated the dynamics of policy interactions within the framework. They have revived non-significant control variables, indicating that these variables are interconnected with other policies, thus making them meaningful indicators. This reveals that the indexes successfully capture the complex interplay and cumulative effects of various complementary policies. By doing so, they allow for a more comprehensive understanding of the forces behind emission trends. The performance index, by measuring the overall impact of environmental policies, and the policy index, by detailing the presence of specific regulations, together provide a nuanced picture of how different policies interact to influence CO2 emissions.

Based on those results, here are some policy recommendations and implications emerging from this study:

1. **Enduring Effectiveness of Carbon Pricing**: The demonstrated effectiveness of carbon pricing across multiple time periods reinforces its viability as a central instrument in climate policy. Governments should continue to

implement and refine carbon pricing mechanisms, ensuring they are adequately stringent to incentivize significant reductions in carbon emissions.

2. **Comprehensive Policy Frameworks**: The introduction of the performance and policy indexes in this study highlights the importance of comprehensive policy frameworks that include not only carbon pricing but also measures related to energy efficiency, renewable energy adoption, and pollution control. The significant role of these integrated policies suggests that governments should adopt a holistic approach to policy design, encompassing a range of strategies to address various aspects of emissions and environmental degradation. This could involve strengthening regulations on industrial emissions, providing incentives for renewable energy development, and implementing stricter fuel efficiency standards, among other measures.
3. **Tailored Approaches to Policy Implementation**: The findings suggest that policymakers need to pay close attention to the socio-economic contexts within which these policies are implemented. The variability in the effectiveness of carbon pricing and other policies across different demographic and economic contexts underscores the need for tailored approaches that consider local economic conditions, cultural norms, and existing technological capacities. For example, developing countries might require more support and international collaboration to implement effective carbon pricing mechanisms that do not stifle economic growth.
4. **Improved Data Collection and Reporting Standards**: The complexities and challenges identified in isolating the impact of carbon pricing from other

concurrent policies point to the need for improved data collection and reporting standards. Enhanced transparency and consistency in environmental data reporting by countries can greatly facilitate more accurate policy assessments and enable more informed policy decisions. International bodies and agreements could play a crucial role in setting these standards and providing frameworks for cooperation and data sharing among nations.

My research also faced certain limitations. The most prominent one was the variable nature of environmental policies across countries, making it difficult to extract and combine a broadly comparable policy index. Another challenge was the quality and consistency of data, which is not always reported with integrity and regularity by all countries. Finally, many environmental policies are also intertwined with socio-economic aspects, which sometimes introduces an additional level of complexity and complicates establishing causal pathways.

To further polish the evaluation, future research might consider decomposing the performance and policy indexes of evaluating the impact of individual policies. Expanding the dataset past 2020 could add the possibility to evaluate the long-term effects of policies, especially given the drastic shifts following the COVID-19 pandemic. Studies should also consider factors such as the enforcement of environmental policies, as some countries with carbon pricing might experience tax avoidance or non-compliance. Additionally, qualitative research could complement the quantitative data, offering insights into the implementation challenges.

All in all, my study sheds light on the topic of CO2 emissions using the multiple dimensions approach, highlighting the necessity of the complex of interconnected policy mechanisms. My study also highlights the important place of indexes as a useful tool of analysis, offering new insights into the varieties of climate policy efficacy. Looking forward, my research creates a solid basis for further study of the interaction complexities of environmental policies and remains an area of high relevance for creating a sustainable future.

**7. Works Cited**

EPA (2020). Sources of greenhouse gas emissions. Environmental Protection Agency. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

NOAA (2022). 2022 was world's 6th-warmest year on record. Antarctic sea ice coverage melted to near-record lows. National Oceanic and Atmospheric Administration. https://www.noaa.gov/news/2022-was-worlds-6th-warmest-year-on-record#:~:text=Antarctic%20sea%20ice%20coverage%20melted%20to%20near%2Drecord%20lows&text=The%20planet%20continued%20its%20warming,for%20Environmental%20Information%20(NCEI).

Allen, M.R., O.P. Dube, W. Solecki, F. Aragón-Durand, W. Cramer, S. Humphreys, M. Kainuma, J. Kala, N. Mahowald, Y. Mulugetta, R. Perez, M. Wairiu, and K. Zickfeld (2018). Framing and Context. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)].

Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 49-92, doi:10.1017/9781009157940.003.

IPCC (2021). Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 3−32, doi:10.1017/9781009157896.001.

Bureau, D., Henriet, F., & Schubert, K. (2019). A proposal for the climate: Taxing carbon not people. Notes du conseil danalyse economique, 50(2), 1–12.

Wang, R., Saunders, H., Moreno-Cruz, J., & Caldeira, K. (2019). Induced Energy-Saving Efficiency Improvements Amplify Effectiveness of Climate Change Mitigation. Joule, 3(9), 2103–2119. https://doi.org/10.1016/j.joule.2019.07.024

Wang, C., Chen, P., Hao, Y., & Dagestani, A. A. (2022). Tax incentives and green innovation—The mediating role of financing constraints and the moderating role of subsidies. Frontiers in Environmental Science, 10. https://www.frontiersin.org/articles/10.3389/fenvs.2022.1067534

Mankiw, N. G. (2008). Smart Taxes: An Open Invitation to Join the Pigou Club (SSRN Scholarly Paper 1268325). https://doi.org/10.2139/ssrn.1268325

World Bank Group. (2019). State and Trends of Carbon Pricing 2019. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1435-8

Best, R., Burke, P. J., & Jotzo, F. (2020). Carbon Pricing Efficacy: Cross-Country Evidence.

Environmental and Resource Economics, 77(1), 69–94. https://doi.org/10.1007/s10640-020-00436-x

Dominioni, G. (2022). Pricing carbon effectively: A pathway for higher climate change ambition. Climate Policy, 22(7), 897–905. https://doi.org/10.1080/14693062.2022.2042177

Green, J. F. (2021). Does carbon pricing reduce emissions? A review of ex-post analyses. Environmental Research Letters, 16(4), 043004. https://doi.org/10.1088/1748-9326/abdae9

Vrolijk, K., & Sato, M. (2023). Quasi-Experimental Evidence on Carbon Pricing. The World Bank Research Observer, 38(2), 213–248. https://doi.org/10.1093/wbro/lkad001

Black, S., Parry, I., & Zhunussova, K.. (2022). More Countries Are Pricing Carbon, but Emissions Are Still Too Cheap. https://www.imf.org/en/Blogs/Articles/2022/07/21/blog-more-countries-are-pricing-carbon-but-emissions-are-still-too-cheap

Ritchie, H. & Rosado, P.. (2022). Which countries have put a price on carbon? https://ourworldindata.org/carbon-pricing

Parry, I.. (2022). Five Things to Know about Carbon Pricing. https://www.imf.org/en/Publications/fandd/issues/2021/09/five-things-to-know-about-carbon-pricing-parry

Haites, E., Maosheng, D., Gallagher, K. S., Mascher, S., Narassimhan, E., Richards, K. R., & Wakabayashi, M. (2018). Experience with Carbon Taxes and Greenhouse Gas Emissions Trading Systems. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3119241

Haites, E. (2018). Carbon taxes and greenhouse gas emissions trading systems: What have we learned? Climate Policy, 18(8), 955–966. https://doi.org/10.1080/14693062.2018.1492897

Vrolijk, K., & Sato, M. (2023). Quasi-Experimental Evidence on Carbon Pricing. The World Bank Research Observer, 38(2), 213–248. https://doi.org/10.1093/wbro/lkad001

Rafaty, R., Dolphin, G., & Pretis, F. (2020). CAMBRIDGE WORKING PAPERS IN ECONOMICS Carbon pricing and the elasticity of CO2 emissions. https://www.econ.cam.ac.uk/research-files/repec/cam/pdf/cwpe20116.pdf

Cullen, J. A., & Mansur, E. T. (2017). Inferring Carbon Abatement Costs in Electricity Markets: A Revealed Preference Approach Using the Shale Revolution. American Economic Journal: Economic Policy, 9(3), 106–133. https://doi.org/10.1257/pol.20150388

Wilson, I. A. G., & Staffell, I. (2018). Rapid fuel switching from coal to natural gas through effective carbon pricing. Nature Energy, 3(5), Article 5. https://doi.org/10.1038/s41560-018-0109-0

Abrell, J., Kosch, M., & Rausch, S. (2021). How Effective is Carbon Pricing? – A Machine Learning Approach to Policy Evaluation (SSRN Scholarly Paper 3839268). https://doi.org/10.2139/ssrn.3839268

Gugler, K., Haxhimusa, A., & Liebensteiner, M. (2021). Effectiveness of climate policies: Carbon pricing vs. subsidizing renewables. Journal of Environmental Economics and Management, 106, 102405. https://doi.org/10.1016/j.jeem.2020.102405

Rogge, N. (2012). Undesirable specialization in the construction of composite policy indicators: The Environmental Performance Index. Ecological Indicators, 23, 143–154. https://doi.org/10.1016/j.ecolind.2012.03.020

Qin, L., Kirikkaleli, D., Hou, Y., Miao, X., & Tufail, M. (2021). Carbon neutrality target for G7 economies: Examining the role of environmental policy, green innovation and composite risk index. Journal of Environmental Management, 295, 113119. https://doi.org/10.1016/j.jenvman.2021.113119

Costello, A. B., & Osborne, J. (n.d.). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. https://doi.org/10.7275/JYJ1-4868

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. Psychological Methods, 4(3), 272–299. https://doi.org/10.1037/1082-989X.4.3.272

Tabachnick, B. G., & Fidell, L. S. (2007). Using Multivariate Statistics (5th ed.). Boston, MA: Pearson Education, Inc.

OECD (2021), Effective Carbon Rates 2021: Pricing Carbon Emissions through Taxes and Emissions Trading. OECD Series on Carbon Pricing and Energy Taxation, OECD Publishing, Paris, https://doi.org/10.1787/0e8e24f5-en.

## 8. Appendix

**Appendix 1a**. Average Annual CO2 Growth Rate Regression 2012-2017 (Replication)

Dependent variable: Average annual CO2 growth rate

| | 2012-2017 | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Carbon price score | -0.0006*** | | |
| | (0.0002) | | |
| Carbon price, binary | | -0.043*** | |
| | | (0.013) | |
| Duration-adjusted carbon price | | | -0.048*** |
| | | | (0.014) |
| Initial log CO2 | -0.022 | -0.020 | -0.020 |
| | (0.022) | (0.021) | (0.021) |
| Initial log GDP per capita | 0.020 | 0.024 | 0.026 |
| | (0.020) | (0.019) | (0.019) |
| Initial log population | 0.024 | 0.023 | 0.024 |
| | (0.022) | (0.020) | (0.020) |
| Initial log energy intensity | -0.006 | -0.006 | -0.004 |
| | (0.017) | (0.016) | (0.016) |
| Initial coal share | -0.003 | -0.022 | -0.021 |
| | (0.059) | (0.059) | (0.058) |
| Initial oil share | -0.040 | -0.050 | -0.050 |
| | (0.047) | (0.047) | (0.045) |
| Initial natural gas share | -0.003 | -0.024 | -0.031 |
| | (0.038) | (0.039) | (0.039) |
| Transition, binary | -0.002 | 0.008 | 0.012 |
| | (0.009) | (0.009) | (0.009) |
| CO2 growth, binary | 0.026 | -0.061 | -0.061 |
| | (0.135) | (0.137) | (0.132) |
| GDP per capita growth | 0.610** | 0.635*** | 0.656*** |
| | (0.251) | (0.229) | (0.223) |
| Population growth | 0.692** | 0.636** | 0.639** |
| | (0.323) | (0.314) | (0.312) |
| Constant | -0.479 | -0.484 | -0.526 |
| | (0.501) | (0.474) | (0.472) |
| Observations | 134 | 134 | 134 |
| R-squared | 0.443 | 0.479 | 0.493 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Appendix 1b**. Average Annual CO2 Growth Rate Regression 2015-2019 (Pre-Pandemic)

Dependent variable: Average annual CO2 growth rate

| | 2015-2019 | | |
|---|---|---|---|
| | (4) | (5) | (6) |
| Carbon price score | -0.0004** | | |
| | (0.0002) | | |
| Carbon price, binary | | -0.024*** | |
| | | (0.009) | |
| Duration-adjusted carbon price | | | -0.025*** |
| | | | (0.009) |
| Initial log CO2 | 0.018 | 0.018 | 0.018 |
| | (0.018) | (0.018) | (0.018) |
| Initial log GDP per capita | -0.027 | -0.024 | -0.023 |
| | (0.017) | (0.017) | (0.017) |
| Initial log population | -0.016 | -0.015 | -0.015 |
| | (0.018) | (0.018) | (0.018) |
| Initial log energy intensity | -0.044** | -0.041** | -0.042** |
| | (0.018) | (0.018) | (0.018) |
| Initial coal share | -0.057 | -0.064 | -0.064 |
| | (0.050) | (0.051) | (0.051) |
| Initial oil share | -0.066 | -0.066 | -0.066 |
| | (0.043) | (0.042) | (0.042) |
| Initial natural gas share | -0.016 | -0.026 | -0.027 |
| | (0.032) | (0.034) | (0.034) |
| Transition, binary | 0.002 | 0.009 | 0.009 |
| | (0.009) | (0.009) | (0.009) |
| CO2 growth, binary | 0.141 | 0.104 | 0.104 |
| | (0.085) | (0.085) | (0.085) |
| GDP per capita growth | 0.647*** | 0.701*** | 0.695*** |
| | (0.152) | (0.169) | (0.168) |
| Population growth | 0.747** | 0.783** | 0.789** |
| | (0.365) | (0.362) | (0.362) |
| Constant | 0.558 | 0.507 | 0.502 |
| | (0.437) | (0.440) | (0.440) |
| | | | |
| Observations | 133 | 133 | 133 |
| R-squared | 0.505 | 0.513 | 0.514 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Appendix 1c**. Average Annual CO2 Growth Rate Regression 2015-2020 (Most Recent)

| Dependent variable: Average annual CO2 growth rate | | | |
|---|---|---|---|
| | 2015-2020 | | |
| | (7) | (8) | (9) |
| Carbon price score | -0.0005*** | | |
| | (0.0002) | | |
| Carbon price, binary | | -0.032*** | |
| | | (0.010) | |
| Duration-adjusted carbon price | | | -0.030*** |
| | | | (0.010) |
| Initial log CO2 | 0.011 | 0.011 | 0.010 |
| | (0.017) | (0.017) | (0.017) |
| Initial log GDP per capita | -0.020 | -0.016 | -0.016 |
| | (0.017) | (0.017) | (0.017) |
| Initial log population | -0.010 | -0.009 | -0.008 |
| | (0.017) | (0.017) | (0.017) |
| Initial log energy intensity | -0.030* | -0.027 | -0.027 |
| | (0.017) | (0.016) | (0.017) |
| Initial coal share | -0.059 | -0.066 | -0.063 |
| | (0.050) | (0.051) | (0.051) |
| Initial oil share | -0.058 | -0.055 | -0.054 |
| | (0.038) | (0.037) | (0.037) |
| Initial natural gas share | 0.004 | -0.008 | -0.006 |
| | (0.031) | (0.033) | (0.033) |
| Transition, binary | -0.005 | 0.004 | 0.004 |
| | (0.010) | (0.010) | (0.010) |
| CO2 growth, binary | 0.044 | -0.001 | 0.005 |
| | (0.101) | (0.099) | (0.100) |
| GDP per capita growth | 0.844*** | 0.904*** | 0.887*** |
| | (0.189) | (0.206) | (0.203) |
| Population growth | 0.673* | 0.691* | 0.699* |
| | (0.383) | (0.389) | (0.388) |
| Constant | 0.380 | 0.319 | 0.314 |
| | (0.412) | (0.410) | (0.413) |
| Observations | 133 | 133 | 133 |
| R-squared | 0.485 | 0.496 | 0.493 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Appendix 2a.** Factor Loadings of the 7 Environmental Performance Variables

| Variable | Factor Loading |
|---|---|
| PM2.5 | -0.030424268 |
| Solid Fuels | -0.15698873 |
| Methane | -0.117848423 |
| Black Carbon | -0.275275719 |
| 2050 GHG Emissions | 0.911129198 |
| Renewables | 0.954050424 |
| Non-renewables | 0.906241037 |

**Appendix 2b.** Factor Loadings of the 7 Environmental Policy Variables

| Variable | Factor Loading |
|---|---|
| Environmental Taxes | 0.393282845 |
| Fossil Fuel Subsidies | -0.511448319 |
| Terrestrial Biome Protection | 0.661728896 |
| Protected Areas | 0.563368746 |
| Green Bonds | 0.101043018 |
| Low Carbon Tech | -0.201161453 |
| Recycling | -0.27622665 |

## **Appendix 3.** STATA Codes

### Appendix 3a. Phase 1: Replication, Expansion, and Comparison

```
//Phase 1
//Last Editted: 2/13/2024
ssc install outreg2
clear
import delimited "C:\Users\Student\Desktop\Thesis\Dataset construction\P1v1_wdacpbin.csv"

*Initial GDPpc
//preserve
//keep if year == 2015
//keep country gdppercapitapppconstant2017inter
//rename gdppercapitapppconstant2017inter gdppc15
//tempfile gdp2015
//save gdp2015
//restore

//preserve
//keep if year == 2014
//keep country gdppercapitapppconstant2017inter
//rename gdppercapitapppconstant2017inter gdppc14
//tempfile gdp2014
//save gdp2014
//restore

//merge m:m country using gdp2015, nogen
//merge m:m country using gdp2014, nogen
//save P1V2

clear
ssc install outreg2
use P1V2
*Adding subsectors
    *primary energy supply
       gen coal               = coalcp+peat+oilshale
       gen oil                = crude+oilp

       label variable coal      "Sum of coal/products, peat, oilshale from IEA World Energy
Balances, ktoe"
    label variable oil           "Sum of oil/products, crude from IEA World energy balances,
ktoe"

*Shares
       gen coal_share         = coal     /totaltpes
       gen oil_share          = oil      /totaltpes
       gen gas_share          = gas      /totaltpes

       label variable coal_share            "Coal share of energy"
       label variable oil_share             "Oil share of energy"
       label variable gas_share             "Natural gas share of energy"

*still need pretaxsub15, ee15, re15
*gen presub_pue = 1000*pretaxsub/(coal[_n-4] + oil[_n-4] + gas[_n-4])

*rename
rename gdppercapitapppconstant2017inter gdppc17
rename energyintensitylevelofprimaryene en_inten
rename populationtotalsppoptotl pop
rename ghgfromfuelcombustion co2
rename gdppc14 gdppcc14
rename gdppc15 gdppcc15


*clean
** CPS fron RISE is missiong, so I used the ones from OECD instead
keep country year gdppc17 gdppc11 gdppcc14 gdppcc15 en_inten pop co2 coal_share oil_share
gas_share transition cpbin cpbin_12to17p cpbin_15to19p cpbin_15to20p ross value120ball2012
```

```
value120ball2015 value30ball2012 value30ball2015 value60ball2012 value60ball2015 cpbin_tax
cpbin_ets

*logs
       gen lngdppc17          = ln(gdppc17)
       gen lngdppc11          = ln(gdppc11)
       gen lngdppcc14         = ln(gdppcc14)
       gen lngdppcc15         = ln(gdppcc15)
       gen ln_en_in           = ln(en_inten)
       gen ln_co2             = ln(co2/1000)
       gen ln_pop             = ln(pop)

       label variable lngdppc17             "Log GDP per capita (PPP, constant 2017
international dollars)"
       label variable lngdppc11             "Log GDP per capita (PPP, constant 2011
international dollars)"
       label variable lngdppcc14            "Log GDP per capita consistent 2014(PPP, constant
2017 international dollars)"
       label variable lngdppcc15            "Log GDP per capita consistent 2015(PPP, constant
2017 international dollars)"
       label variable ln_en_in              "Log energy intensity, level of primary energy
(MJ/$2011 PPP GDP)"
       label variable ln_co2                "Log fossil fuel combustion CO2 emissions"
       label variable ln_pop                "Log population"


*lags: 4 years
       gen lag4_lngdppc17     = lngdppc17[_n-4]
       gen lag4_lngdppc11     = lngdppc11[_n-4]
       gen lag4_lnco2         = ln_co2[_n-4]
       gen lag4_ln_enin       = ln_en_in[_n-4]
       gen lag4_cpbin         = cpbin[_n-4]
       gen lag4_cpbin_tax     = cpbin_tax[_n-4]
       gen lag4_cpbin_ets     = cpbin_ets[_n-4]
       gen lag4_cpbin_sn      = lag4_cpbin
replace lag4_cpbin_sn      = 0 if country=="Japan"|country=="United States"|country=="Canada"
       gen lag4_ross          = ross_y[_n-4]
    gen lag4_lnpop         = ln_pop[_n-4]
       gen lag4_co2           = co2[_n-4]/1000
       gen lag4_gdppc11       = gdppc17[_n-4]
       gen lag4_en_inten      = en_inten[_n-4]
       gen lag4_pop           = pop[_n-4]
       gen coal_share_lag4    = coal_share[_n-4]
       gen oil_share_lag4     = oil_share[_n-4]
       gen gas_share_lag4     = gas_share[_n-4]

       label variable lag4_lngdppc11       "Log of GDP per capita 2011 international dollars
PPP, lag 4"
       label variable lag4_lngdppc17       "Log of GDP per capita 2017 international dollars
PPP, lag 4"
    label variable lag4_lnco2           "Log fossil fuel combustion CO2 emissions , lag 4"
       label variable lag4_ln_enin         "Log energy intensity, level of primary energy
(MJ/$2011 PPP GDP), lag 4"
       label variable lag4_cpbin           "Carbon pricing instruments implemented, lag 4,
binary variable"
       label variable lag4_cpbin_tax       "Carbon pricing instruments implemented (tax), lag 4,
binary variable"
       label variable lag4_cpbin_ets       "Carbon pricing instruments implemented (ETS), lag 4,
binary variable"
    label variable lag4_ross            "Net gasoline tax (subsidy) using price gap of retail
price and global benchmark (const 2015 USD per liter), lag 4"
       label variable lag4_lnpop           "Log population, lag 4"
    label variable lag4_co2             "Lag 4, fossil fuel combustion CO2 emissions"
    label variable lag4_gdppc11         "Lag 4, GDP per capita"
    label variable lag4_en_inten        "Lag 4, energy intensity"
    label variable lag4_pop             "Lag 4, population"
       label variable lag4_cpbin_sn        "Lag 4, carbon pricing, excluding subnational
schemes, binary variable"
       label variable coal_share_lag4      "Lag 4, Coal share of energy"
       label variable oil_share_lag4       "Lag 4, Oil share of energy"
       label variable gas_share_lag4       "Lag 4, natural gas share of energy"
```

```
*4 year growth
       gen ch4_lngdppc11      = (lngdppc11-lngdppc11[_n-4])/4
       gen ch4_lngdppc17      = (lngdppc17-lngdppc17[_n-4])/4
       gen ch4_lnco2          = (ln_co2-ln_co2[_n-4])/4
       gen ch4_pop            = (ln_pop-ln_pop[_n-4])/4

       label variable ch4_lngdppc11        "Ann. avg. growth over 4yrs, GDP per capita 2011
(PPP, constant 2011 international dollars)"
       label variable ch4_lngdppc17        "Ann. avg. growth over 4yrs, GDP per capita 2017
(PPP, constant 2011 international dollars)"
       label variable ch4_lnco2            "Ann. avg. growth over 4yrs, fossil fuel combustion
CO2 emissions"
       label variable ch4_pop              "Ann. avg. growth over 4yrs, population"

*Previous
       gen ch4_lnco2_lag4         = ch4_lnco2[_n-4]
       label variable ch4_lnco2            " Previous Ann. avg. growth over 4yrs, fossil fuel
combustion CO2 emissions"

*lags: 5 years
       gen lag5_lngdppc17     = lngdppc17[_n-5]
       gen lag5_lngdppc11     = lngdppc11[_n-5]
       gen lag5_lnco2         = ln_co2[_n-5]
       gen lag5_ln_enin       = ln_en_in[_n-5]
       gen lag5_cpbin         = cpbin[_n-5]
       gen lag5_cpbin_tax     = cpbin_tax[_n-5]
       gen lag5_cpbin_ets     = cpbin_ets[_n-5]
       gen lag5_cpbin_sn      = lag5_cpbin
replace lag5_cpbin_sn      = 0 if country=="Japan"|country=="United States"|country=="Canada"
       gen lag5_ross          = ross_y[_n-5]
    gen lag5_lnpop         = ln_pop[_n-5]
       gen lag5_co2           = co2[_n-5]/1000
       gen lag5_gdppc11       = gdppc17[_n-5]
       gen lag5_en_inten      = en_inten[_n-5]
       gen lag5_pop           = pop[_n-5]
       gen coal_share_lag5    = coal_share[_n-5]
       gen oil_share_lag5     = oil_share[_n-5]
       gen gas_share_lag5     = gas_share[_n-5]

       label variable lag5_lngdppc11       "Log of GDP per capita 2011 international dollars
PPP, lag 5"
       label variable lag5_lngdppc17       "Log of GDP per capita 2017 international dollars
PPP, lag 5"
    label variable lag5_lnco2           "Log fossil fuel combustion CO2 emissions , lag 5"
       label variable lag5_ln_enin         "Log energy intensity, level of primary energy
(MJ/$2011 PPP GDP), lag 5"
       label variable lag5_cpbin           "Carbon pricing instruments implemented, lag 5,
binary variable"
       label variable lag5_cpbin_tax       "Carbon pricing instruments implemented (tax), lag 5,
binary variable"
       label variable lag5_cpbin_ets       "Carbon pricing instruments implemented (ETS), lag 5,
binary variable"
    label variable lag5_ross            "Net gasoline tax (subsidy) using price gap of retail
price and global benchmark (const 2015 USD per liter), lag 5"
       label variable lag5_lnpop           "Log population, lag 5"
    label variable lag5_co2             "Lag 5, fossil fuel combustion CO2 emissions"
    label variable lag5_gdppc11         "Lag 5, GDP per capita"
    label variable lag5_en_inten        "Lag 5, energy intensity"
    label variable lag5_pop             "Lag 5, population"
       label variable lag5_cpbin_sn        "Lag 5, carbon pricing, excluding subnational
schemes, binary variable"
       label variable coal_share_lag5       "Lag 5, Coal share of energy"
       label variable oil_share_lag5        "Lag 5, Oil share of energy"
       label variable gas_share_lag5        "Lag 5, natural gas share of energy"

*5 year growth
       gen ch5_lngdppc11      = (lngdppc11-lngdppc11[_n-5])/5
       gen ch5_lngdppc17      = (lngdppc17-lngdppc17[_n-5])/5
       gen ch5_lnco2          = (ln_co2-ln_co2[_n-5])/5
       gen ch5_pop            = (ln_pop-ln_pop[_n-5])/5
```

```
	label variable ch5_lngdppc11		"Ann. avg. growth over 5yrs, GDP per capita 2011 
(PPP, constant 2011 international dollars)"
	label variable ch5_lngdppc17		"Ann. avg. growth over 5yrs, GDP per capita 2017 
(PPP, constant 2011 international dollars)"
	label variable ch5_lnco2		"Ann. avg. growth over 5yrs, fossil fuel combustion 
CO2 emissions"
	label variable ch5_pop			"Ann. avg. growth over 5yrs, population"

*Previous
	gen ch5_lnco2_lag5		= ch5_lnco2[_n-5]
	label variable ch5_lnco2		" Previous Ann. avg. growth over 5yrs, fossil fuel 
combustion CO2 emissions"

*CPS
	replace value30ball2012=0 if value30ball2012==.
	replace value60ball2012=0 if value60ball2012==.
	replace value120ball2012=0 if value120ball2012==.
	replace value30ball2015=0 if value30ball2015==.
	replace value60ball2015=0 if value60ball2015==.
	replace value120ball2015=0 if value120ball2015==.


ssc install asdoc
asdoc sum if year==2015, replace dec(2)

//Replication
*Table 4, 5 years to 2017, not per capita
	reg ch5_lnco2 lag5_lnco2 lag5_lngdppc11 lag5_lnpop lag5_ln_enin coal_share_lag5 
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc11 ch5_pop value30ball2012 
if year==2017 , r
		outreg2 using p1.xls, dec(3)
	reg ch5_lnco2 lag5_lnco2 lag5_lngdppc11 lag5_lnpop lag5_ln_enin coal_share_lag5 
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc11 ch5_pop lag5_cpbin 
if year==2017 , r
		outreg2 using p1.xls, dec(3)
	reg ch5_lnco2 lag5_lnco2 lag5_lngdppc11 lag5_lnpop lag5_ln_enin coal_share_lag5 
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc11 ch5_pop cpbin_12to17p 
if year==2017 , r
		outreg2 using p1.xls, dec(3)
	*reg ch5_lnco2 lag5_lnco2 lag5_lngdppc11 lag5_lnpop lag5_ln_enin coal_share_lag5 
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc ch5_pop c12price100 
lag5_ross presub_pue ee12_xcp100 re12_xcp100	if year==2017 , r
		*estimates store res4
	*reg ch5_lnco2 lag5_lnco2 lag5_lngdppc11 lag5_lnpop lag5_ln_enin coal_share_lag5 
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc ch5_pop lag5_cpbin 
lag5_ross presub_pue ee12_xcp100 re12_xcp100	if year==2017 , r
		*estimates store res5
	*reg ch5_lnco2 lag5_lnco2 lag5_lngdppc11 lag5_lnpop lag5_ln_enin coal_share_lag5 
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc ch5_pop cpbin_12to17p 
lag5_ross presub_pue ee12_xcp100 re12_xcp100	if year==2017 , r
		*estimates store res6
	*xml_tab res1 res2 res3 res4 res5 res6 , stats(N r2) below sheet("T4") format(nTLR3) 
append save(results_cpecce)

//15to19
	reg ch4_lnco2 lag4_lnco2 lag4_lngdppc17 lag4_lnpop lag4_ln_enin coal_share_lag4 
oil_share_lag4 gas_share_lag4 transition ch4_lnco2_lag4 ch4_lngdppc17 ch4_pop value30ball2015 
if year==2019 , r
		outreg2 using p1.xls, dec(3)
	reg ch4_lnco2 lag4_lnco2 lag4_lngdppc17 lag4_lnpop lag4_ln_enin coal_share_lag4 
oil_share_lag4 gas_share_lag4 transition ch4_lnco2_lag4 ch4_lngdppc17 ch4_pop lag4_cpbin 
if year==2019 , r
		outreg2 using p1.xls, dec(3)
	reg ch4_lnco2 lag4_lnco2 lag4_lngdppc17 lag4_lnpop lag4_ln_enin coal_share_lag4 
oil_share_lag4 gas_share_lag4 transition ch4_lnco2_lag4 ch4_lngdppc17 ch4_pop cpbin_15to19p 
if year==2019 , r
		outreg2 using p1.xls, dec(3)

//15to20
```

```
        reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop value30ball2015
if year==2020 , r
               outreg2 using p1.xls, dec(3)
        reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop lag5_cpbin
if year==2020 , r
               outreg2 using p1.xls, dec(3)
        reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop cpbin_15to20p
if year==2020 , r
               outreg2 using p1.xls, dec(3)


//ttest
*Table 4, 5 years to 2017, not per capita
        reg ch5_lnco2 lag5_lnco2 lag5_lngdppc11 lag5_lnpop lag5_ln_enin coal_share_lag5
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc11 ch5_pop value30ball2012
if year==2017
               estimates store model1_1
        reg ch5_lnco2 lag5_lnco2 lag5_lngdppc11 lag5_lnpop lag5_ln_enin coal_share_lag5
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc11 ch5_pop lag5_cpbin
if year==2017
               estimates store model1_2
        reg ch5_lnco2 lag5_lnco2 lag5_lngdppc11 lag5_lnpop lag5_ln_enin coal_share_lag5
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc11 ch5_pop cpbin_12to17p
if year==2017
               estimates store model1_3

//15to19
        reg ch4_lnco2 lag4_lnco2 lag4_lngdppc17 lag4_lnpop lag4_ln_enin coal_share_lag4
oil_share_lag4 gas_share_lag4 transition ch4_lnco2_lag4 ch4_lngdppc17 ch4_pop value30ball2015
if year==2019
               estimates store model2_1
        reg ch4_lnco2 lag4_lnco2 lag4_lngdppc17 lag4_lnpop lag4_ln_enin coal_share_lag4
oil_share_lag4 gas_share_lag4 transition ch4_lnco2_lag4 ch4_lngdppc17 ch4_pop lag4_cpbin
if year==2019
               estimates store model2_2
        reg ch4_lnco2 lag4_lnco2 lag4_lngdppc17 lag4_lnpop lag4_ln_enin coal_share_lag4
oil_share_lag4 gas_share_lag4 transition ch4_lnco2_lag4 ch4_lngdppc17 ch4_pop cpbin_15to19p
if year==2019
               estimates store model2_3

//15to20
        reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop value30ball2015
if year==2020
               estimates store model3_1
        reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop lag5_cpbin
if year==2020
               estimates store model3_2
        reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5
oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop cpbin_15to20p
if year==2020
               estimates store model3_3

suest model1_1 model1_2 model1_3 model2_1 model2_2 model2_3 model3_1 model3_2 model3_3
test [model1_1_mean]value30ball2012 = [model2_1_mean]value30ball2015 =
[model3_1_mean]value30ball2015
test [model1_2_mean]lag5_cpbin = [model2_2_mean]lag4_cpbin = [model3_2_mean]lag5_cpbin
test [model1_3_mean]cpbin_12to17p = [model2_3_mean]cpbin_15to19p = [model3_3_mean]cpbin_15to20p
```

**Appendix 3b**. Factor Analysis & Index Construction

```
//FA based on EPI+IMF Raw data
//Last Editted: 5/15/2024
clear
ssc install factortest

//cleaning
use imf2
replace iso = "LIE" if country == "Liechtenstein"
replace iso = "MAC" if country == "China, P.R.: Macao"
replace iso = "BMU" if country == "Bermuda"
replace iso = "SMR" if country == "San Marino, Rep. of"
replace iso = "JEY" if country == "Jersey"
replace iso = "GGY" if country == "Guernsey"
save imf20152


clear
import excel "C:\Users\Student\Desktop\Thesis\Policy Index\FA\Raw2015.xlsx", sheet("Sheet1")
firstrow case(lower) clear

foreach var in tbn tbg par tcl grl wtl pmd had ozd noe soe coe voe rec cha fga nda bca ghn gib
ghp {
		replace `var'=. if `var'==-7777
		replace `var'=. if `var'==-8888
		replace `var'=. if `var'==-9999
		replace `var'=. if `var'==-4444
}


//merge with IMF data
merge m:m iso using imf20152
sort _merge
drop _merge

rename ET et
rename FFS ffs
rename TRE tre
rename NRE nre
rename TLC tlc
rename GB gb
rename EPA epa
rename EPE epe

//performance index
//global xlist tbn par tcl grl wtl pmd had ozd noe soe coe voe rec cha fga nda bca ghn gib ghp et
ffs tre nre tlc gb
global xlist pmd had cha bca ghn tre nre
global id country
global ncomp 2

describe $xlist
summarize $xlist
corr $xlist

//factor analysis
factor $xlist, factors(2)
screeplot, yline(1) title("Environmental Performance Index")

factor $xlist, mineigen(1) blanks(.3)
rotate, varimax
estat kmo

*export factor loadings
matrix M = e(r_L)
local rmax = rowsof(M)
local cmax = colsof(M)
putexcel set "Factor Loadings Table_perf.xlsx", sheet("Factor Loadings")
putexcel A1 = (e(Factors)) B2 = matrix(M), rownames
```

```
*score
predict f1
*egen score = rowmean (f2 f1)
*gen i_score = -1* f1

rename f1 i_score

//standard 1-100
egen i_score_min = min(i_score)
egen i_score_max = max(i_score)
gen perf_score = (i_score - i_score_min) / (i_score_max - i_score_min) * 100
drop i_score i_score_min i_score_max



*policy index
factor et ffs tbn par gb tlc rec
screeplot, yline(1) title("Environmental Policy Index")

factor et ffs tbn par gb tlc rec , mineigen(1) blanks(.3)
rotate, varimax blanks(.3)
estat kmo

*export factor loadings
matrix M = e(r_L)
local rmax = rowsof(M)
local cmax = colsof(M)
putexcel set "Factor Loadings Table_pol.xlsx", sheet("Factor Loadings")
putexcel A1 = (e(Factors)) B2 = matrix(M), rownames

*score
predict f1
rename f1 i_score


//standardize 1-100
egen i_score_min = min(i_score)
egen i_score_max = max(i_score)
gen pol_score = (i_score - i_score_min) / (i_score_max - i_score_min) * 100
drop i_score i_score_min i_score_max


save standardized_scoresv2_test
```

**Appendix 3b**. Phase 2: Indexes Integration

```
//P2 Policy Index Integration
//Last Updated: 05/15/2024

clear
use standardized_scoresv2_test
sum

*ssc install asdoc
*asdoc sum , replace dec(2)

replace iso = "KSV" if country == "Kosovo"
rename iso countrycode
merge m:m countrycode using P1V2
sort _merge
drop if _merge == 1
drop _merge
*Adding subsectors
    *primary energy supply
       gen coal              = coalcp+peat+oilshale
       gen oil               = crude+oilp

       label variable coal                 "Sum of coal/products, peat, oilshale from IEA World
Energy Balances, ktoe"
    label variable oil                  "Sum of oil/products, crude from IEA World energy
balances, ktoe"

*Shares
       gen coal_share        = coal     /totaltpes
       gen oil_share         = oil      /totaltpes
       gen gas_share         = gas      /totaltpes

       label variable coal_share           "Coal share of energy"
       label variable oil_share            "Oil share of energy"
       label variable gas_share            "Natural gas share of energy"

*rename
ssc install asdoc
asdoc sum , replace dec(2)
rename gdppercapitapppconstant2017inter gdppc17
rename energyintensitylevelofprimaryene en_inten
rename populationtotalsppoptotl pop
rename ghgfromfuelcombustion co2
rename gdppc14 gdppcc14
rename gdppc15 gdppcc15


*clean
** CPS fron RISE is missiong, so I used the ones from OECD instead
*keep country countrycode year gdppc17 gdppc11 gdppcc14 gdppcc15 en_inten pop co2 coal_share
oil_share gas_share transition cpbin cpbin_12to17p cpbin_15to19p cpbin_15to20p ross
value120ball2012 value120ball2015 value30ball2012 value30ball2015 value60ball2012 value60ball2015
cpbin_tax cpbin_ets  perf_score pol_score

replace country = "Anguilla" if country =="ANGUILLA"

merge m:m country using epi1416
sort _merge
drop _merge
*save P2epifa
save P2_v2

//Main
clear
*use P2epifa
use P2_v2
sort country year

*still need pretaxsub15, ee15, re15
```

```
*gen presub_pue = 1000*pretaxsub/(coal[_n-4] + oil[_n-4] + gas[_n-4])

*logs
       gen lngdppc17          = ln(gdppc17)
       gen lngdppc11          = ln(gdppc11)
       gen lngdppcc14         = ln(gdppcc14)
       gen lngdppcc15         = ln(gdppcc15)
       gen ln_en_in           = ln(en_inten)
       gen ln_co2             = ln(co2/1000)
       gen ln_pop             = ln(pop)

       label variable lngdppc17             "Log GDP per capita (PPP, constant 2017
international dollars)"
       label variable lngdppc11             "Log GDP per capita (PPP, constant 2011
international dollars)"
       label variable lngdppcc14            "Log GDP per capita consistent 2014(PPP, constant
2017 international dollars)"
       label variable lngdppcc15            "Log GDP per capita consistent 2015(PPP, constant
2017 international dollars)"
       label variable ln_en_in              "Log energy intensity, level of primary energy
(MJ/$2011 PPP GDP)"
       label variable ln_co2                "Log fossil fuel combustion CO2 emissions"
       label variable ln_pop                "Log population"


*lags: 4 years
       gen lag4_lngdppc17     = lngdppc17[_n-4]
       gen lag4_lngdppc11     = lngdppc11[_n-4]
       gen lag4_lnco2         = ln_co2[_n-4]
       gen lag4_ln_enin       = ln_en_in[_n-4]
       gen lag4_cpbin         = cpbin[_n-4]
       gen lag4_cpbin_tax     = cpbin_tax[_n-4]
       gen lag4_cpbin_ets     = cpbin_ets[_n-4]
       gen lag4_cpbin_sn      = lag4_cpbin
replace lag4_cpbin_sn      = 0 if country=="Japan"|country=="United States"|country=="Canada"
       gen lag4_ross          = ross_y[_n-4]
    gen lag4_lnpop         = ln_pop[_n-4]
       gen lag4_co2           = co2[_n-4]/1000
       gen lag4_gdppc11       = gdppc17[_n-4]
       gen lag4_en_inten      = en_inten[_n-4]
       gen lag4_pop           = pop[_n-4]
       gen coal_share_lag4    = coal_share[_n-4]
       gen oil_share_lag4     = oil_share[_n-4]
       gen gas_share_lag4     = gas_share[_n-4]

       label variable lag4_lngdppc11       "Log of GDP per capita 2011 international dollars
PPP, lag 4"
       label variable lag4_lngdppc17       "Log of GDP per capita 2017 international dollars
PPP, lag 4"
    label variable lag4_lnco2           "Log fossil fuel combustion CO2 emissions , lag 4"
       label variable lag4_ln_enin         "Log energy intensity, level of primary energy
(MJ/$2011 PPP GDP), lag 4"
       label variable lag4_cpbin           "Carbon pricing instruments implemented, lag 4,
binary variable"
       label variable lag4_cpbin_tax       "Carbon pricing instruments implemented (tax), lag 4,
binary variable"
       label variable lag4_cpbin_ets       "Carbon pricing instruments implemented (ETS), lag 4,
binary variable"
    label variable lag4_ross            "Net gasoline tax (subsidy) using price gap of retail
price and global benchmark (const 2015 USD per liter), lag 4"
       label variable lag4_lnpop           "Log population, lag 4"
    label variable lag4_co2             "Lag 4, fossil fuel combustion CO2 emissions"
    label variable lag4_gdppc11         "Lag 4, GDP per capita"
    label variable lag4_en_inten        "Lag 4, energy intensity"
    label variable lag4_pop             "Lag 4, population"
       label variable lag4_cpbin_sn        "Lag 4, carbon pricing, excluding subnational
schemes, binary variable"
       label variable coal_share_lag4      "Lag 4, Coal share of energy"
       label variable oil_share_lag4       "Lag 4, Oil share of energy"
       label variable gas_share_lag4       "Lag 4, natural gas share of energy"
```

```
*4 year growth
       gen ch4_lngdppc11      = (lngdppc11-lngdppc11[_n-4])/4
       gen ch4_lngdppc17      = (lngdppc17-lngdppc17[_n-4])/4
       gen ch4_lnco2          = (ln_co2-ln_co2[_n-4])/4
       gen ch4_pop            = (ln_pop-ln_pop[_n-4])/4

       label variable ch4_lngdppc11        "Ann. avg. growth over 4yrs, GDP per capita 2011
(PPP, constant 2011 international dollars)"
       label variable ch4_lngdppc17        "Ann. avg. growth over 4yrs, GDP per capita 2017
(PPP, constant 2011 international dollars)"
       label variable ch4_lnco2            "Ann. avg. growth over 4yrs, fossil fuel combustion
CO2 emissions"
       label variable ch4_pop              "Ann. avg. growth over 4yrs, population"

*Previous
       gen ch4_lnco2_lag4         = ch4_lnco2[_n-4]
       label variable ch4_lnco2            " Previous Ann. avg. growth over 4yrs, fossil fuel
combustion CO2 emissions"




*lags: 5 years
       gen lag5_lngdppc17     = lngdppc17[_n-5]
       gen lag5_lngdppc11     = lngdppc11[_n-5]
       gen lag5_lnco2         = ln_co2[_n-5]
       gen lag5_ln_enin       = ln_en_in[_n-5]
       gen lag5_cpbin         = cpbin[_n-5]
       gen lag5_cpbin_tax     = cpbin_tax[_n-5]
       gen lag5_cpbin_ets     = cpbin_ets[_n-5]
       gen lag5_cpbin_sn      = lag5_cpbin
replace lag5_cpbin_sn      = 0 if country=="Japan"|country=="United States"|country=="Canada"
       gen lag5_ross          = ross_y[_n-5]
    gen lag5_lnpop         = ln_pop[_n-5]
       gen lag5_co2           = co2[_n-5]/1000
       gen lag5_gdppc11       = gdppc17[_n-5]
       gen lag5_en_inten      = en_inten[_n-5]
       gen lag5_pop           = pop[_n-5]
       gen coal_share_lag5    = coal_share[_n-5]
       gen oil_share_lag5     = oil_share[_n-5]
       gen gas_share_lag5     = gas_share[_n-5]

       label variable lag5_lngdppc11       "Log of GDP per capita 2011 international dollars
PPP, lag 5"
       label variable lag5_lngdppc17       "Log of GDP per capita 2017 international dollars
PPP, lag 5"
    label variable lag5_lnco2           "Log fossil fuel combustion CO2 emissions , lag 5"
       label variable lag5_ln_enin         "Log energy intensity, level of primary energy
(MJ/$2011 PPP GDP), lag 5"
       label variable lag5_cpbin           "Carbon pricing instruments implemented, lag 5,
binary variable"
       label variable lag5_cpbin_tax       "Carbon pricing instruments implemented (tax), lag 5,
binary variable"
       label variable lag5_cpbin_ets       "Carbon pricing instruments implemented (ETS), lag 5,
binary variable"
    label variable lag5_ross            "Net gasoline tax (subsidy) using price gap of retail
price and global benchmark (const 2015 USD per liter), lag 5"
       label variable lag5_lnpop           "Log population, lag 5"
    label variable lag5_co2             "Lag 5, fossil fuel combustion CO2 emissions"
    label variable lag5_gdppc11         "Lag 5, GDP per capita"
    label variable lag5_en_inten        "Lag 5, energy intensity"
    label variable lag5_pop             "Lag 5, population"
       label variable lag5_cpbin_sn        "Lag 5, carbon pricing, excluding subnational
schemes, binary variable"
       label variable coal_share_lag5       "Lag 5, Coal share of energy"
       label variable oil_share_lag5        "Lag 5, Oil share of energy"
       label variable gas_share_lag5        "Lag 5, natural gas share of energy"

*5 year growth
       gen ch5_lngdppc11      = (lngdppc11-lngdppc11[_n-5])/5
       gen ch5_lngdppc17      = (lngdppc17-lngdppc17[_n-5])/5
```

```
	gen ch5_lnco2		= (ln_co2-ln_co2[_n-5])/5
	gen ch5_pop		= (ln_pop-ln_pop[_n-5])/5

	label variable ch5_lngdppc11	"Ann. avg. growth over 5yrs, GDP per capita 2011 (PPP, constant 2011 international dollars)"
	label variable ch5_lngdppc17	"Ann. avg. growth over 5yrs, GDP per capita 2017 (PPP, constant 2011 international dollars)"
	label variable ch5_lnco2		"Ann. avg. growth over 5yrs, fossil fuel combustion CO2 emissions"
	label variable ch5_pop		"Ann. avg. growth over 5yrs, population"

*Previous
	gen ch5_lnco2_lag5		= ch5_lnco2[_n-5]
	label variable ch5_lnco2		" Previous Ann. avg. growth over 5yrs, fossil fuel combustion CO2 emissions"

*CPS Clean
	replace value30ball2012=0 if value30ball2012==.
	replace value60ball2012=0 if value60ball2012==.
	replace value120ball2012=0 if value120ball2012==.
	replace value30ball2015=0 if value30ball2015==.
	replace value60ball2015=0 if value60ball2015==.
	replace value120ball2015=0 if value120ball2015==.

//15to20
	reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5 oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop value30ball2015 if year==2020 , r
		outreg2 using p2_v2t.xls, dec(4)
	reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5 oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop lag5_cpbin if year==2020 , r
		outreg2 using p2_v2t.xls, dec(4)
	reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5 oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop cpbin_15to20p if year==2020 , r
		outreg2 using p2_v2t.xls, dec(4)

//With Indexes
	reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5 oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop value30ball2015 perf_score pol_score						if year==2020 , r
		outreg2 using p2_v2t.xls, dec(4)
	reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5 oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop lag5_cpbin perf_score pol_score					if year==2020 , r
		outreg2 using p2_v2t.xls, dec(4)
	reg ch5_lnco2 lag5_lnco2 lag5_lngdppc17 lag5_lnpop lag5_ln_enin coal_share_lag5 oil_share_lag5 gas_share_lag5 transition ch5_lnco2_lag5 ch5_lngdppc17 ch5_pop cpbin_15to20p perf_score pol_score					if year==2020 , r
		outreg2 using p2_v2t.xls, dec(4)

*sum stats of the 61 countries
	estat e(sample)
	sum pmd had cha bca ghn tre nre et ffs tbn par gb tlc rec if e(sample)
	ssc install asdoc
	asdoc sum pmd had cha bca ghn tre nre et ffs tbn par gb tlc rec if e(sample), replace dec(2)
	sum year co2 gdppc17 pop if e(sample)
```