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Structural Breaks in Carbon Emissions: A Machine Learning Analysis

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ABSTRACT: To reach the global net-zero goal, the level of carbon emissions has to fall substantially at speed rarely seen in history, highlighting the need to identify structural breaks in carbon emission patterns and understand forces that could bring about such breaks. In this paper, we identify and analyze structural breaks using machine learning methodologies. We find that downward trend shifts in carbon emissions since 1965 are rare, and most trend shifts are associated with non-climate structural factors (such as a change in the economic structure) rather than with climate policies. While we do not explicitly analyze the optimal mix between climate and non-climate policies, our findings highlight the importance of the non-climate policies in reducing carbon emissions. On the methodology front, our paper contributes to the climate toolbox by identifying country-specific structural breaks in emissions for top 20 emitters based on a user-friendly machine-learning tool and interpreting the results using a decomposition of carbon emission (Kaya Identity).

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Keywords:	Climate Policies, Carbon Emissions, Machine Learning, Structural Break, Kaya Identity

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Content

I. INTRODUCTION

The danger of climate change has been increasingly recognized across the world, with a growing number of countries pledging reduction of carbon emissions and implementing climate-related policies, such as sectoral standards, carbon taxes, and strategic planning. The gap, however, remains enormous between actions so far and what is needed to reach (global) net-zero emissions by 2050 and to limit the increase in global temperatures to 1.5 ℃.

It is well-understood that to reach the net-zero goal, the level of gross carbon emissions has to fall substantially at speed rarely seen in history.[2] [3] Identifying structural breaks in carbon emission patterns and understanding forces that could bring about such breaks are important goals. In this paper, we identify and analyze these structural breaks using machine learning methodologies and shed light on potential game-changing policies for mitigating emissions. Our analysis focuses on the top 20 carbon emitters, which account for 80 percent of cumulative global carbon dioxide emissions.

We take an agnostic approach to examine trend changes and structural breaks for each of the top 20 emitters. To this end, we apply a well-established machine learning-based method, developed by Oxford University's Climate Econometrics and Senior Research Fellow (Castle, Doornik, and Hendry, 2012; and Hendry, 2020). The approach has the advantages of imposing minimal prior restrictions on the data patterns (i.e., "Let the data speak") and being able to identify meaningful patterns in the presence of highly nonstationary data (a common feature of carbon emissions data). We surmise that most of the downward trend shifts (which are long-lasting rather than transitory changes) in carbon emissions are related to non-climate structural

[2] IPCC (2021) assesses that global surface temperature will continue to increase to above 1.5 ℃ by 2040 even in the best-case scenario.

[3] In theory, we also need to consider the carbon absorption by "carbon sinks", i.e., systems that absorb more carbon than they emit. These include natural sinks (the main ones being soil, forests, and oceans) and artificial sinks (developed through, e.g., the carbon capture and storage technologies). However, "according to estimates, natural sinks remove between 9.5 and 11 Gt of CO2 per year. Annual global CO2 emissions reached 38.0 Gt in 2019. To date, no artificial carbon sinks are able to remove carbon from the atmosphere on the necessary scale to fight global warming. The carbon stored in natural sinks such as forests is released into the atmosphere through forest fires, changes in land use or logging. This is why it is essential to reduce carbon emissions in order to reach climate neutrality." (European Parliament, June 24, 2021)

factors (such as changes in a country's economic structure following a major economic reform) rather than coincide with the announcement of climate policies, including the major global climate initiatives such as the Kyoto Protocol. We also conduct case studies for some prominent emitters and explore the potential contribution of climate policies to emission growth slowdowns.

We find that both the economic structural changes (such as Germany's shift away from heavy industries associated with its reunification in October 1990) and policy changes in response to a pollution shock (such as China's significant change in its evaluation system for government officials following a severe air pollution crisis in January 2013) have played a significant role. By taking a broad view and considering policies and factors affecting carbon emissions that are not directly related to climate policies, we hope to enrich discussions on carbon reduction strategies to include broader economic transitions rather than limiting strategies to traditional climate policies.

The paper's contribution is two-fold. First, our empirical analysis highlights that addressing climate change may need to not only involve policies that directly mitigate carbon emissions, but also policies that indirectly mitigate emissions by reshaping the economic structure. We have also presented an indicative cross-country panel data analysis in an appendix, which shows that the existing climate policies appear far from being sufficient for reducing the absolute level of carbon emissions.

Second, in terms of methodologies, the paper applies a user-friendly analytical framework to analyze empirical associations between the adoption of climate policies and changes in CO2 emission. We illustrate how to implement Oxford University's machine-learning approach for twenty countries using a readily available R package. Our algorithm can be applied to identify potential trend changes or structural breaks in each country's carbon emissions. We then interpret these results with a well-established, intuitive Kaya Identity, which can shed light on the driving forces of structural changes in emissions (the driving forces include population, GDP per capita, energy intensity per unit of GDP, and carbon intensity per unit of energy consumed). This analytical framework can also be used to build a web-based toolbox that facilitates the analysis of emission patterns and simulation of climate/economic policies for a broader set of countries (we are building such a toolbox in a follow-up project).

The rest of the paper is structured as follows. Section II reviews related literature; Section III discusses the machine-learning approach and findings; Section IV concludes and discusses some policy implications. The appendices report the complementary panel-data analysis and some other technical details.

II. Literature Review

The paper is related to several strands of literature. First, it is related to a vast literature on the importance of energy transition in climate change mitigation (Smil, 2010; Fouquet and Pearson, 2012). From a backward-looking perspective, Peralta-Alva, Tavares, and Xi (2017) find a hump-shape relation between energy intensity and income per capita across countries, highlighting the correlation between energy transition and economic development. Millot, Krook-Riekkola, and Maïzi (2020) compare the past energy transitions in France and Sweden, two countries that have significantly reduced their CO2 emissions and fossil fuel dependency; they emphasize that to reach carbon neutrality, energy policy has to be guided by a long-run perspective. From a forward-looking perspective, IEA (2021) outlines the key milestones in the pathway to net zero emissions by 2050, calling for unprecedented clean energy push and huge leaps in clean energy innovation.[4] This paper examines structural breaks in historical emissions, focusing on the dynamics of both unconditional emissions—which is ultimately relevant for mitigation—and emissions conditional on development, which encompasses energy intensity of an economy and carbon intensity of energy that are at the core of energy transition.

Second, this paper's finding highlights that transformative policies are needed to induce structural breaks in carbon emissions. One promising policy is carbon taxation, which has been shown to be effective in the literature (Lin and Li, 2011; Rivers and Schaufele, 2015; Haites, 2018; Best, Burke, and Jotzo, 2020; among others) and is favored by economists as a market mechanism to price emission externalities—dating back to Kneese (1971), Solow (1972), and including more recently IMF (2020) and a joint statement by a group of prominent economists made in 2019. Currently carbon tax rates are low among most of the top 20 emitters (see, for example, Table 1 in Metcalf and Stock, 2020). Moreover, the effectiveness of carbon taxation is

[4] Relatedly, Yao (2021) finds that the world's average temperature has surpassed the critical point for electricity consumption and further increase in temperatures means more electricity consumption.

currently compromised by severe political constraints, as pointed out by Nordhaus (2015), Gillingham and Stock (2018), and Pahle et al. (2018), although the impact of such constraints depends on policy designs and contexts, as pointed out by Furceri, Ganslmeier, and Ostry (2021). Our analysis of historical emissions of major emitters shows that many structural breaks in emissions are associated with economic crises or major politically-related events (such as the German reunification). Short of these crises or events, carbon tax remains one of the most important options to mitigate emissions by directly altering the economic incentives of firms and households.

Third, the paper's empirical results are consistent with the literature's finding that certain types of green finance appear to have limited impact on carbon emissions. For example, Ehlers, Mojon, and Packer (2020) find that green bond projects have not necessarily translated into comparatively low or falling carbon emissions at the firm level. Another example of green finance is the environmental, social, and governance (ESG) investing, as discussed by IMF (2019), Krueger, Sautner, and Starks (2020), Matos (2020), Starks (2020), Hong, Wang, and Yang (2021). However, Elmalt, Igan, and Kirti (2021) find limited scope for sustainable investing strategies conditioned solely on ESG indicators to meaningfully help mitigate climate change; accordingly, they highlight the need to continue to build consensus towards effective economy-wide policies to address climate change. In this regard, the green agri-food systems as proposed by Batini (2021) and others can be an important step forward.

Fourth, the paper is related to the econometric literature on climate *policy evaluation*. This can be done in several approaches, such as panel data regressions (as in Furceri, Ganslmeier, and Ostry, 2021) and machine learning-based nonparametric models (as in Hendry, Johansen, and Santos, 2008; Johansen and Nielsen, 2009; Castle, Doornik, and Hendry, 2012; and Hendry, 2020). As discussed subsequently, the machine learning approach has the advantage of imposing minimal prior assumptions and being able to identify patterns even when the data are nonstationary, which is a typical feature of most climate data. Our paper employs both the panel data regression and the machine-learning approach. In particular, Hendry (2020) applies the same machine-learning approach to identify the structural breaks in the United Kingdom's CO2 emissions and discusses the driving forces to these breaks; the second part of our paper is a natural extension of Hendry (2020) to other countries. One difference is that we investigate further the driving sources using the Kaya Identity, originally proposed by Kaya and Yokoburi (1997) and widely used by policymakers, scholars, and civil societies.[5]

III. Country-Specific Machine-Learning Analysis

A. Data and Methodology

The raw data used in this section include the gross CO2 emissions from the Global Carbon Project, PPP GDP per capita from the World Bank, and coal and oil consumption from BP's Statistical Review of World Energy (2020) compiled by *Our World in Data*.

Note that the CO2 emissions we use are highly correlated with the greenhouse gas (GHG) emissions. As CO2 data are available for more countries, particularly for emerging markets, we choose to focus on CO2. In addition, we use gross emissions instead of net emissions due to the lack of accurate estimation of the latter. Moreover, as noted in the introduction, neither natural nor artificial carbon sinks are able to remove carbon from the atmosphere on the necessary scale to fight global warming, and the carbon stored in natural sinks is released into the atmosphere again through forest fires, etc., highlighting the importance of reducing gross carbon emissions (European Parliament, June 24, 2021).

For all variables in levels, we use their logarithm in the analysis. Specifically, we take the annual data from 1965 to 2019 for countries that have ranked among the top 20 in terms of the cumulative carbon emissions as of 2019. These 20 countries are (from high to low emissions): USA, CHN, RUS, DEU, GBR, JPN, IND, FRA, CAN, UKR, POL, ITA, ZAF, MEX, IRN, AUS, KOR, BRA, SAU, and ESP.[6] In total, their cumulative emissions account for 80 percent of the world's total cumulative emissions as of 2019.

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[5] Many countries have expressed their climate policies based on the Kaya components. See the references in Section V..

[6] When using other criteria for selecting the top 20 emitters, the majority of countries are the same. Specifically: (a) When using the CO2 emissions during the single year of 2019 (instead of the cumulative CO2 emissions up to 2019), 18 out of the top 20 emitters remain the same, with IND and TUR entering the list (instead of UKR and ESP in our list). (b) When using all kinds of greenhouse gas emissions (beyond CO2) during the *single* year of *2018* (which is the criterion used to determine the top 20 emitters during the IMF's 2021 Comprehensive Surveillance Review), 17 out of the top 20 emitters remain the same, with IDN and TUR entering the list (instead of UKR, ESP, and FRA in our list). Given that our

Note that this section does not use the climate policy data because this section takes a data-driven approach to identify structural breaks in the carbon emissions (without considering climate policies *per se*) rather than a policy-evaluation approach. The climate policy data will be discussed in a subsequent section.

In terms of the methodology, we conduct a machine learning-based approach of indicator saturation to detect structural changes in carbon emissions. An important feature of this approach is that it allows us to remain agonistic *ex ante* about the dates of structural changes while letting the data speak about the shifts in the trends of carbon emissions. This then allows us to compare the identified periods of structural changes with major economic and policy events to determine the necessary conditions that lead to long-term carbon emission reductions. The same approach is used by, for example, Hendry (2020) to identify the structural breaks and their driving forces in the United Kingdom's CO2 emissions.

We consider a standard regression with a constant and a linear trend:

$$y_t = \alpha + \boldsymbol{\beta} \boldsymbol{z}_t + \varepsilon_t,$$

where y_t is carbon emissions of a country at time t; $\boldsymbol{z}_t$ is k-dimensional vector containing exogenous regressors as well as lagged values of y_t. Following the dummy saturation approach, originally proposed in Hendry, Johansen, and Santos (2008), Johansen and Nielsen (2009), and Castle, Doornik, and Hendry (2012), the regression can be saturated with dummies in the following general form:

$$y_t = \alpha + \boldsymbol{\beta} \boldsymbol{z}_t + \textstyle\sum_{i=1}^{T} (\gamma_i D_{i,t}^I + \psi_i D_{i,t}^S + \omega_i D_{i,t}^T) + \varepsilon_t,$$

where $D_{i,t}^I = \boldsymbol{I}_{t=i}$ is an impulse indicator, $D_{i,t}^S = \boldsymbol{I}_{t \geq i}$ is a step indicator, and $D_{i,t}^T = (t-i)\boldsymbol{I}_{t \geq i}$ is a trend indicator.

The impulse indicators capture outliers in carbon emissions, while the step and trend indicators capture structural changes. As the indicator dummies are colinear—for example, an impulse indicator is the same as the difference of two step indicators— and our primary interest is in structural changes, we drop impulse indicators and focus only on step and trend indicators. Because there are more explanatory variables than there are observations, we employ a machine learning-based block search algorithm to eliminate statistically insignificant indicators through a

paper analyzes the policy effectiveness starting as early as 1965 and that the emission patterns in some countries (such as UKR) have shifted dramatically since then, we analyze the cumulative (CO2) emissions instead of the emissions in one single year.

general-to-specific (GETS) approach.[7] The statistically significant indicators that are selected will then indicate periods when structural breaks occur, which is what we are after. Castle, Doornik, and Hendry (2012) show that under the null of no outliers or breaks, αT impulse indicators are retained on average at a level of significance α. More generally, the proportion of spuriously retained variables, also referred to as gauge in the GETS literature, is close to α (Pretis, Reade, and Sucarrat, 2018). Throughout, we choose α to be 0.05.[8] We conduct both *unconditional* analysis and *conditional* analysis. The unconditional analysis examines the pattern of carbon emissions without controlling for any contributing factors, whereas the conditional analysis controls for the major (non-policy) contributing factors, particularly GDP growth. This is to account for the extensive evidence that the economic development affects a country's carbon emissions, while allowing maximum flexibility for the model to identify other drivers of emissions.

Mathematically, the unconditional analysis attempts to detect any structural break in carbon emissions using a machine-learning model. The model only employs a combination of step indicator saturation (SIS) and trend indicator saturation (TIS), both of which are based on the raw carbon emission data instead of other controls. That is,

$$y_t = \alpha + \sum_{i=1}^{T}(\psi_i D_{i,t}^S + \omega_i D_{i,t}^T) + \varepsilon_t \tag{1}$$

By contrast, the conditional analysis attempts to detect any structural break in carbon emissions by controlling for some other contributing factors to emissions. That is, it adds to equation (1) a vector of control variables:

$$y_t = \alpha + \boldsymbol{\beta} \boldsymbol{z}_t + \sum_{i=1}^{T}(\psi_i D_{i,t}^S + \omega_i D_{i,t}^T) + \varepsilon_t \tag{2}$$

where the vector $\boldsymbol{z}_t$ could consist of contributing factors such as the GDP. Consequently, the "indicator coefficient path", $\sum_{i=1}^{T}(\psi_i D_{i,t}^S + \omega_i D_{i,t}^T)$, captures carbon emissions over and above those induced by the controlled factors. This term is essentially the residual term while regressing the carbon emissions y_t on a constant and the controls $\boldsymbol{z}_t$ (the real residual term in

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[7] This is conveniently implemented in *R* through the *gets* package, v0.27 (the latest publicly available version).

[8] We have experimented with lower significance levels, which typically result in fewer structural breaks selected. Since the purpose of this analysis is to examine the association between structural breaks in carbon emissions with climate policies, we choose to err on the side of generosity in our main results. At the end of this section, we also discuss the results with lower significance levels.

such a regression also includes the ε_t in the above equation). Therefore, for simplicity, we will refer to this "indicator coefficient path" as the "residual carbon emissions". As discussed later, we will focus on the specification that controls for GDP only, i.e., the vector $\boldsymbol{z}_t$ we consider is a degenerate vector with one element, the GDP variable.

In both unconditional and conditional analysis, our focus is on the number, timing, and magnitude of trend indicators and step indicators. A negative trend indicator indicates a decreasing pace of carbon emissions or an accelerating pace of carbon reductions, while a negative step indicator signals a downward level shift in carbon emissions. Since the models are agnostic about what brings about structural breaks, we place the timing of those structural breaks in the context of major economic, political, and environmental changes.

B. Unconditional Analysis: Results and Interpretation

The unconditional analysis is useful in identifying the changes in the *absolute* level of emissions, which is ultimately what matters for climate change mitigation. To reach net zero emissions, the absolute level has to decrease markedly for most countries over a sufficiently long period of time.

Figure 1 presents the CO2 emissions data (the red dotted line) and the structural breaks detected by our unconditional machine-learning model (the blue solid line), for six selected countries among the top 20 emitters. The six countries include three emerging markets (EMs) and three advanced economies (AEs). Appendix Figure 5 presents the results for the other 14 countries, including seven EMs and seven AEs. These two figures also make it clear that our model fits the data well.

Table 1 reports the years of structural breaks for the same six countries, and Appendix Table 11 reports those for the remaining 14 countries among the top 20 emitters. In the table, tis and sis represent a structural break in the trend and in the level, respectively; "1" and "-1" represent positive and negative signs, respectively. For example, the table indicates that the latest structural break in China's carbon emission trend occurred in 1972, where the trend experienced a notable *downward* shift.

A few remarks are in order on the findings of our unconditional analysis:

First, since the 1990s, downward trend shifts in carbon emissions have been rare-- only 16 downward trend shifts in total--for the top 20 emitters, a result consistent with that in the panel data analysis in Appendix 1. This pattern is clear for the three EMs in Figure 1—China, India, and South Africa, none of which has witnessed any structural breaks in trends, implying that the pace of emissions has remained relatively unchanged in the past decades. Meanwhile, all three EMs have experienced positive level shifts in emissions, indicating that their carbon emissions are permanently higher after those shifts.

For the three AEs—the United Kingdom, the United States, Germany—the rapid decline in their carbon emissions reflects downward shifts in levels, but the *pace* of the decline did *not* accelerate in the last two decades except right after the global financial crisis. As Table 1 makes it clear, since 2000, the only structural break in the *trend* took place in 2008 for both the United Kingdom and the United States, and in 2018 for Germany; all other structural breaks were in the level rather than in the trend. The other 14 countries display the same pattern, as shown in Appendix Table 11. Note that the emissions in some countries, especially in AEs, experienced downward trend shifts around 1980, likely reflecting the lower oil consumption amid the oil crisis during the late 1970s and early 1980s.

Second, for all the top emitters that do display some downward patterns, the reduction in the CO2 emission level has not been fast enough. For example, Germany has been making steady progress in reducing its CO2 emission level since 1980. However, over almost 40 years, its gross CO2 emission level has reduced from around 1.1 Gt (20.8 log tons) in 1980 to 0.7 Gt (20.4 log tons) in 2019, or a 33 percent reduction. While such a reduction is an impressive feat against the background of Germany's strong economic growth, the challenges of further reduction are non-trivial, particularly from a low base. Even maintaining the current rate of CO2 reduction, Germany would be able to reduce the gross CO2 emission to *half* of its 2019 level only by 2053[9] and to zero only by 2088. Although reaching the net-zero goal does not require the gross emission level to be zero due to, e.g., the absorption by natural sinks[10], these simple calculations still highlight the challenges for reaching the goal with the current rate of CO2 reduction, let alone it is harder to cut the emissions from a lower base.

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[9] The per-year reduction from 1980 to 2019 is 10,207,804 tons; based on this rate, it would take 34 years to reduce half (350,977,554 tons) of the 2019 emission level.

[10] The carbon stored in natural sinks will be released into the atmosphere again through forest fires, etc., so it is still important to focus on cutting the gross emissions, as discussed earlier.

Third, downward trend shifts do *not* seem to occur following major climate initiatives. For example, the Kyoto Protocol, which was adopted in December 1997 and entered into force in February 2005, was not followed by statistically significant downward trend shifts in carbon emissions.[11] Neither was the Paris Agreement, which was adopted in December 2015 and entered into force in November 2016. Of course, this is a simplifying observation because it takes time for countries to enact specific policy measures and for these measures to take effect. However, it is still noteworthy that these global major initiatives did not seem to have significantly arrested the trends of carbon emissions for the top emitters. The result is also consistent with IMF (2021, GFSR Chapter 3) that the major climate events such as the Paris Agreement are not associated with significant changes in the returns and flows of investment funds.

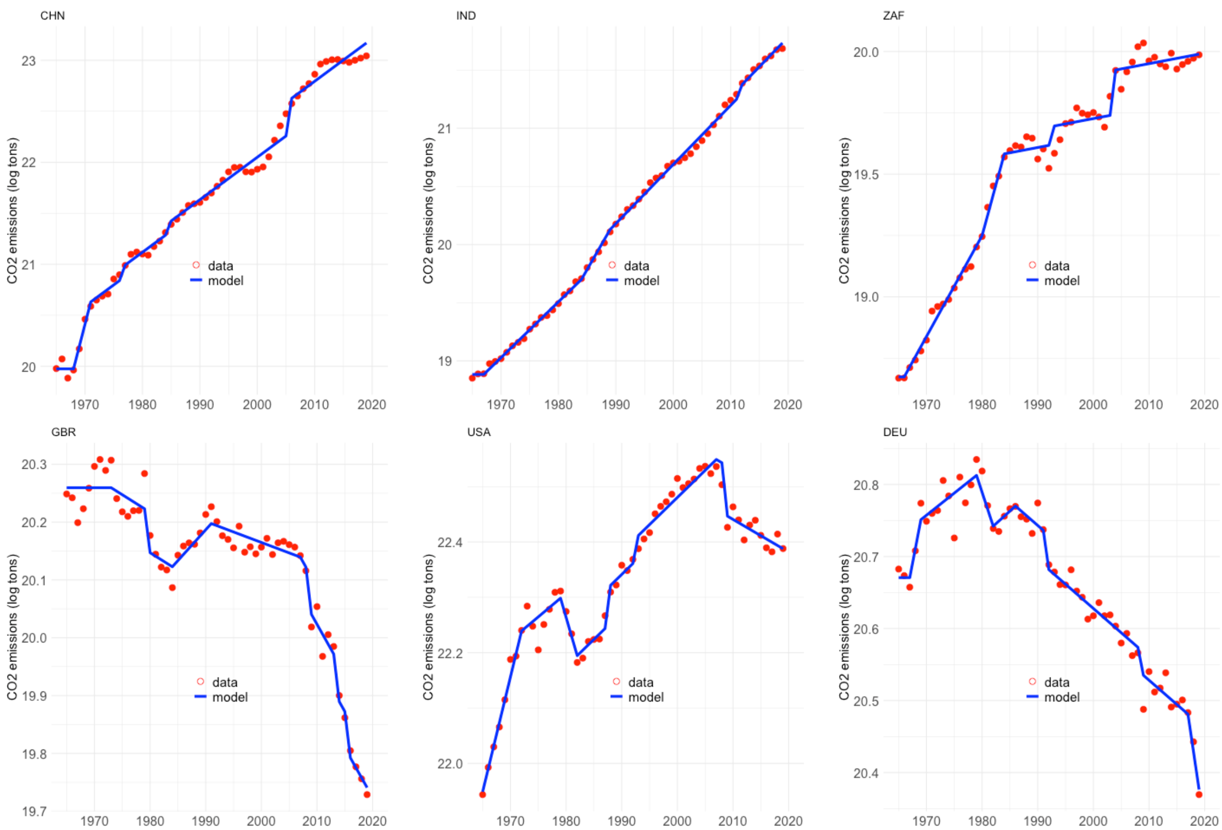
Fourth, as suggested by Figure 1 and Table 1, economic development significantly affects carbon emissions, and structural breaks in carbon emissions typically occurred around major economic crises. The same crisis, however, may have opposite impacts on different countries. For instance, Figure 1 and Table 1 show that while the 2008 global financial crisis was not associated with either level or trend shifts of carbon emissions for major EM emitters, it induced top AE emitters to fall on a declining emission path. One interpretation is that the dramatic economic developments and policy responses during major economic crises may have affected demand for energy and with the arrival of cheaper shale oil and gas, more expensive and higher carbon-generating inputs such as coal saw strong declines (see further below). In the case of EMs, economic rescue measures following the 2008 crisis, such as large infrastructure projects, may have led to more carbon emissions and offset the reduction of emissions associated with the crisis-era economic contractions. In the case of AEs, the rise in coal/oil prices and the decline in gas/solar energy prices after 2008 might have contributed to trend shifts in carbon emissions. However, many other factors are at play for structural breaks in carbon emissions. To examine factors beyond economic development, we will need to conduct conditional analysis controlling for GDP, as discussed in the subsequent section.

Finally, the effect of carbon taxes has yet to show up as major structural breaks in large emitters. Of the six emitters considered in Figure 1, only the United Kingdom implemented nationwide carbon taxes during the sample period, with an introduction of carbon price support

[11] The trend shifts in 2008 are driven by economic contraction, as analyzed subsequently.

in 2013. Table 1 identifies two level shifts for the United Kingdom in 2014 and 2016, respectively, providing some evidence that the United Kingdom carbon price support might be associated with structural breaks. Of the 14 other breaks among the top 20 emitters in the Appendix Table 11, only Ukraine displayed a level shift in 2014 after it introduced carbon tax in 2011. This is not to say that carbon taxes might not be useful; to the contrary, country case studies have shown that they are quite effective (Lin and Li, 2011; Rivers and Schaufele, 2015; Haites, 2018; Best, Burke, and Jotzo, 2020, among others). One reasons why effects are not detectable via large shifts in carbon emissions, is that higher taxes and wider implementation may be needed (Nordhaus , 2015; Gillingham and Stock, 2018; and Pahle et al, 2018).

Figure 1. Structural Breaks for Six Countries: Unconditional Analysis



Sources: Global Carbon Project; and Authors' calculations.

Table 1. Timing of Structural Breaks for Six Countries: Unconditional Analysis

	CHN		IND		ZAF		GBR		USA		DEU	
	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign
Trend Shift	tis1969	1	tis1968	1	tis1967	1	tis1974	-1	tis1966	1	tis1968	1
	tis1972	-1	tis1985	1	tis1981	1	tis1985	1	tis1973	-1	tis1970	-1
			tis1990	-1	tis1985	-1	tis1992	-1	tis1980	-1	tis1980	-1
							tis2008	-1	tis1983	1	tis1983	1
									tis2008	-1	tis1987	-1
											tis2018	-1
Level Shift	sis1977	1	sis2012	1	sis1993	1	sis1980	-1	sis1988	1	sis1992	-1
	sis1985	1			sis2004	1	sis2009	-1	sis1993	1	sis2009	-1
	sis2006	1					sis2014	-1	sis2009	-1		
							sis2016	-1				

Sources: Global Carbon Project; and Authors' calculations.

C. Kaya Identity

To gain more insights into various forces behind carbon emissions, we resort to the Kaya Identity, a conceptual framework that analyzes the drivers of CO2 emissions (Kaya and Yokoburi, 1997; Wang, Tukker, and Rodrigues, 2019). It is an accounting identity expressing the total CO2 emission as the product of four factors: population, GDP per capita, energy intensity (per unit of GDP), and carbon intensity (per unit of energy consumed):

$$CO2 = Population \times \frac{GDP}{Population} \times \frac{Energy}{GDP} \times \frac{CO2}{Energy}$$

The energy intensity term, $\frac{Energy}{GDP}$, is closely related the structure of an economy: If a country relies more on heavy industries, then its energy intensity tends to be higher. For example, Peralta-Alva, Tavares, and Xi (2017) find that sectoral composition is an important factor behind cross-country differences in energy intensity. The carbon intensity term, $\frac{CO2}{Energy}$, reflects energy structure: If a country uses more “dirty” energy sources, then its carbon intensity tends to be higher. It is widely believed that the coal has the highest carbon footprint, followed by oil, gas, and renewables.

Despite its simplicity, the Kaya Identity is powerful in identifying the driving forces for the CO2 level. It has been widely used by scholars and policymakers alike. It plays a central role in the development of future emissions scenarios in the *Special Report on Emissions Scenarios* by the Intergovernmental Panel on Climate Change (IPCC, 2000). Moreover, many countries have expressed their climate policies based on the Kaya components: Under the Paris Agreement, treaty parties set their nationally determined contribution (NDCs) plans based on the Kaya Identity with respect to various CO2 emission scenarios (Aye and Edoja, 2017; Tavakoli, 2018), and the parties of the UNFCCC extend the Kaya components into different sectors for designing detailed NDC goals (UNFCCC, 2015).

Figure 2 plots the Kaya decomposition for the aforementioned six countries, with carbon emissions normalized to zero at the beginning year of the sample; see Appendix Figure 4 for the remaining 14 countries. The first notable observation is that the sudden drop of the CO2 (black) in 2008 for the US coincides with the contraction of its GDP per capita (grey) and the shift of its carbon intensity (red) that started around the same time. Following the enaction of the Energy Independence and Security Act in December 2007, there was a dramatic increase in natural gas production from shale and a sharp decrease in natural gas price from $16.75 per gallon in June 2008 to $3.12 in August 2009[12], leading to a switch from coal/oil to gas and a reduction in CO2 emissions. Note that, as the name suggests, the *main* goal of the Energy Independence and Security Act was to move the United States toward greater energy independence and security (i.e., lower dependence on energy imports), as opposed to curbing CO2 emissions *per se* (although some clauses of the Act did aim at achieving that goal).[13]

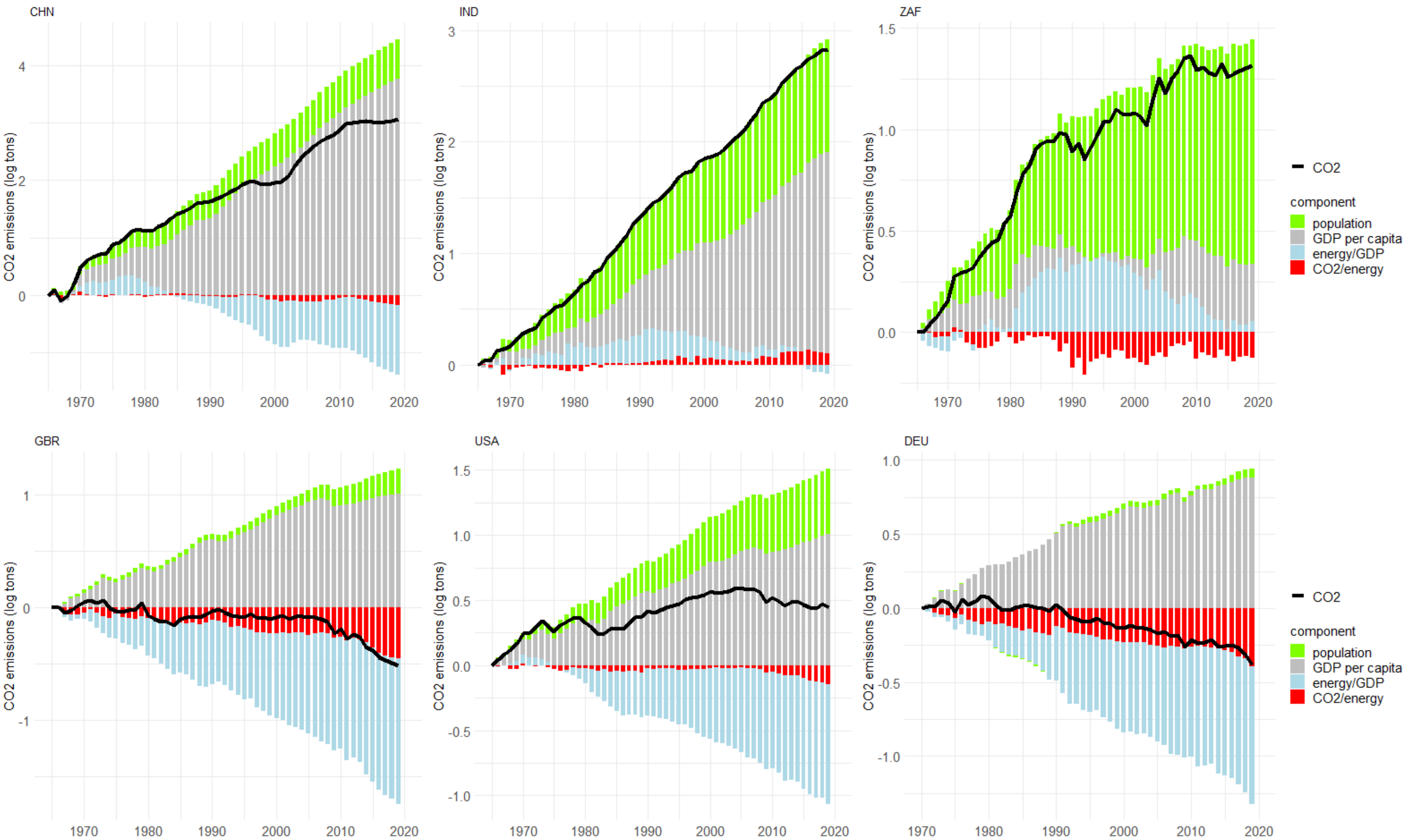
The second notable observation is that, for three of the six countries (the UK, the US, and Germany), the contribution of their energy intensity (blue) to CO2 emissions has been increasingly negative over time since 1965. This likely reflects the shift of their economic structures away from energy-intensive industries to less intensive industries.[14] China followed a similar pattern after the 1980s. For India and South Africa, however, the energy intensity contribution to CO2 emissions has remained broadly positive in the past decades (Figure 2). Such preliminary evidence points to the importance of changes in the economic structure.

[12] Data source: Macrotrends.

[13] More details are available from the EPA.

[14] More discussions of the US case are available from the Energy Information Administration.

Figure 2. Kaya Decomposition for Six Countries



Sources: Global Carbon Project; World Bank; Our World in Data; and Authors' calculations.

D. Conditional Analysis: Results and Interpretation

In this section, we combine the machine-learning analysis of structural breaks and the Kaya Identity-based analysis of driving forces. While the Kaya identity provides a useful accounting decomposition, it does not take into account the interlinkages between GDP, energy intensity, and carbon intensity. For example, as a country moves up the income ladder, the service sector typically takes up a larger share of the economy, which lowers energy intensity; meanwhile, better environmental regulations may restrict the use of dirty energies, which reduces carbon intensity. To examine the drivers of carbon emissions beyond GDP, we focus on the following equation:

$$Ln(CO2) = \alpha + \beta Ln(GDP)_t + \sum_{i=1}^{T} (\psi_i D_{i,t}^S + \omega_i D_{i,t}^T) + \varepsilon_t \quad (3)$$

As a comparison, the Kaya Identity can be rewritten in logarithms as the following, after merging the population with the GDP per capita:

$$Ln(CO2) = Ln(GDP) + Ln\left(\frac{Energy}{GDP}\right) + Ln(\frac{CO2}{Energy}) \quad (4)$$

In equation (3), by allowing the coefficient β before $Ln(GDP)_t$ to be different from 1, the structural break in carbon emissions we identify could capture the effect of climate polices on emissions independent of the impact of such policies on GDP. To see this, suppose a country is moving from an agriculture-based to manufacture-based economy. In this process, both the country's GDP and energy/GDP (i.e., energy intensity) would increase because of an increasing share of industrial output in the economy. From its pure accounting perspective, the Kaya Identity assumes the CO2 contribution of GDP and that of energy/GDP are independent from each other. However, these two contributions are in fact tightly linked because the increase in industrial output would increase both GDP and energy/GDP. What the conditional analysis does is that by projecting CO2 onto GDP, it strips out those factors that affect both GDP and energy/GDP. What is left in the "residual" can be considered as the part of energy/GDP that is unrelated to GDP. If a climate policy such as carbon taxation affects both GDP and energy/GDP, its partial impact on energy/GDP on top of its impact on GDP should be reflected in the "residual", especially the non-GDP components (i.e., the step and trend indicators) of the right-hand-side of Equation (3).

Figure 3 graphically presents the residual carbon emissions for the same six countries in Figure 1, and Appendix Figure 3 presents that for the remaining 14 countries among the top 20 emitters. Table 2 presents the years when the identified structural breaks occurred, and Appendix Table 12 reports those for the remaining 14 countries. Similar to the unconditional machine-learning analysis results, downward trend shifts have been rare for all the top 20 emitters, and they do *not* seem to occur following major climate initiatives such as the Kyoto Protocol. Besides these, we would like to highlight the following additional patterns revealed by our unconditional analysis.

The first notable pattern is that conditional emission patterns differ from unconditional emission patterns for several countries and time periods. For example, China and the United

States both exhibited broadly increasing emissions before 2008 (Figure 1), while emissions conditional on GDP have been declining for both countries (Figure 2). This suggests that mitigating forces have been at work outside the channel of economic development.

Second, some structural breaks in the unconditional analysis disappear and new structural breaks appear in the conditional analysis. This reflects the role of economic development in inducing large changes in carbon emissions and helps identify policies and non-economic forces (such as political events) that significantly affect carbon emissions.

For example, the structural breaks in 2008 for emission trend of the United Kingdom and the United States are no longer present once conditioning on GDP (comparing Table 2 with Table 1). This suggests that the structural breaks in the unconditional emission trend are driven by the GDP contraction during the Global Financial Crisis (which reduced the oil consumption and emissions) rather than by other factors including climate policies that had been enacted up to then. In particular, it suggests that even the sharp gas price decrease (from $16.75 per gallon in June 2008 to $3.12 in August 2009) did not seem to have led to a structural break in the conditional emission trend of the United States.

By contrast, Germany's conditional emission displays a downward trend shift in 1991 (even though the unconditional emission does not display a trend shift in the same year). This likely reflects the German reunification in October 1990 that brought about fundamental changes to its economic structure. Another example is the downward trend shift of China's conditional emission in 1978, the year when the country started implementing its economic reforms and opening-up strategy that dramatically reshaped its economic structure away from heavy industries.[15]

The third notable pattern is that country-specific policy responses to pollution crises may have played a significant role in driving some downward shifts of the emission trends. Consider the example of China again, given that the country's annual CO2 emission in 2019 accounted for

[15] Note that for South Africa's conditional analysis, 2012 emerges as a new structural break point for a downward level shift compared with its unconditional analysis (Table 1 and Table 10). This reflects the decarbonization progress made by the country, consistent with the decreased contributions of energy/GDP and CO2/energy to carbon emissions around 2012 shown in the Kaya decomposition result in Figure 4. However, this year is not identified as a break point for a downward trend shift in South Africa. This can also be seen in Figure 5, as the declining trend of South Africa's carbon emissions did not accelerate after 2012.

28 percent of the world's total CO_2 emission.[16] After controlling for GDP, China's emission trend had another downward shift in 2012. As documented by Finamore (2018), China went through a severe air pollution crisis in January 2013, which was widely regarded as a "turning point". In response, in September 2013, the central government announced the Air Pollution Prevention and Control Action Plan, a four-year plan to significantly improve the air quality of the entire country by end-2017. And in December 2013, the central government announced that GDP growth would no longer be the most important factor when evaluating an official's performance, a fundamental change to the long-standing GDP-oriented evaluation system that may have incentivized local officials to pursue high local GDPs at the cost of the environment.[17]

In sum, the major climate initiatives—such as Kyoto Protocol in 2005 and Paris Agreement in 2015-2016—and "traditional" climate policies do not seem to have reduced the trends of either unconditional or conditional carbon emissions. Instead, analysis of a few country cases shows that both the economic structural changes and policy changes in response to a pollution shock have played a significant role. Moreover, the comparison of structural breaks in the conditional analysis with those in the unconditional analysis helps us gain insights into what forces could induce changes in carbon emissions after accounting for the fact that carbon emissions may unavoidably increase as the economy expands (especially from a low level) and the country uses more energies.

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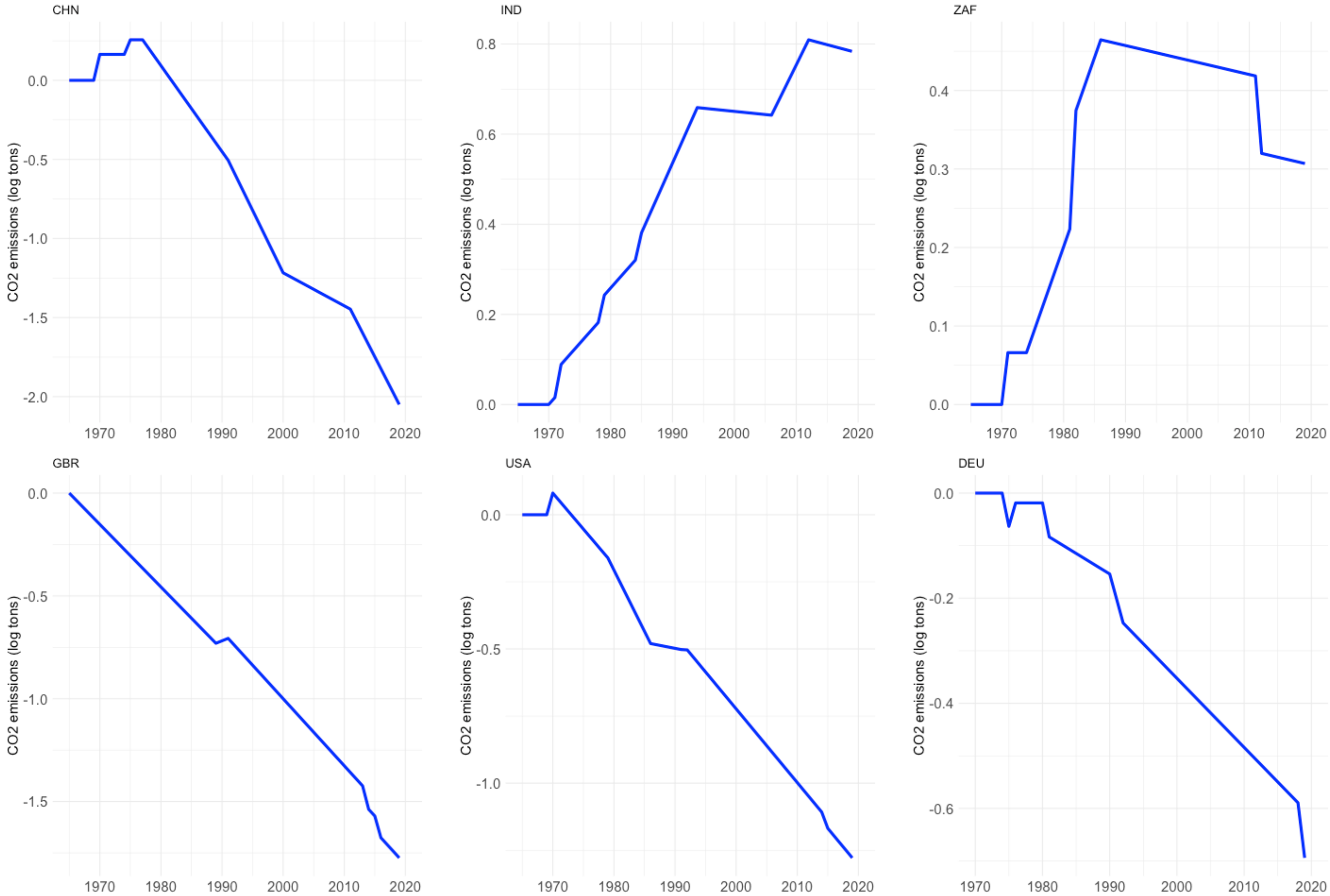
[16] Author calculation based on the emission data from Global Carbon Project.

[17] One caveat is that the year of policy change (2013) is ahead of the structural break point (2012). This is likely driven by the statistical errors associated with our machine-learning analysis. In addition, even though the central government only announced rather than implemented a four-year plan in 2013, the effect of this announcement on could be immediate and significant. This can be seen in some past episodes not related to climate issues, especially following announcements of central government policies that were accompanied with strong and clear top-down political will.

Figure 3. Structural Breaks for Six Countries: Conditional Analysis



Sources: Global Carbon Project; World Bank; and Authors' calculations.

Table 2. Timing of Structural Breaks for Six Countries: Conditional Analysis

	CHN		IND		ZAF		GBR		USA		DEU	
	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign
Trend Shift	tis1978	-1	tis1971	1	tis1975	1	tis1966	-1	tis1970	-1	tis1981	-1
	tis1992	-1	tis1985	1	tis1987	-1	tis1990	1	tis1980	-1	tis1991	-1
	tis2001	1	tis1995	-1			tis1992	-1	tis1987	1	tis1993	1
	tis2012	-1	tis2007	1					tis1992	-1		
			tis2013	-1								
Level Shift	sis1970	1	sis1972	1	sis1971	1	sis2014	-1	sis1970	1	sis1975	-1
	sis1975	1	sis1979	1	sis1982	1	sis2016	-1	sis1992	1	sis1976	1
			sis1985	1	sis2012	-1			sis2015	-1	sis1981	-1
											sis2019	-1

Sources: Global Carbon Project; World Bank; and Authors' calculations.

These results (both unconditional and conditional) are obtained using a 5 percent significance level. The results under a 1 percent significance level are presented in Appendix

Figure 6 for unconditional and Appendix Figure 7 for conditional. In both figures, the results for the ten EMs are presented first, followed by those for the ten AEs. These results are very similar to those under a 5 percent significance level. The major difference is that there are fewer structural breaks under the 1 percent significance level than under the 5 percent. This is intuitive because the criteria for determining structural breaks are more stringent under the 1 percent significance level.

IV. Conclusion and Policy Implications

We apply country-specific machine learning-based analysis to identify structural breaks in carbon emissions. We then discuss the driving forces for such breaks and draw lessons for future policy designs. Our paper also contributes to an emerging climate toolbox by introducing a user-friendly machine-learning algorithm to identify structural breaks in carbon emissions and applying a well-established Kaya Identity to interpret such breaks.

We find that the major climate initiatives (such as Kyoto Protocol in 2005 and Paris Agreement in 2015-2016) and “traditional” climate policies do not seem to have reduced trends in carbon emissions or emissions conditional on GDP. Case study analysis suggest that economic structural changes and strong political will appear to have played a factor in some of the breaks. These results are consistent with those from a complementary indicative cross-country study, which finds that the climate policies implemented in the top 20 emitters so far have been insufficient in reducing the absolute *level* of carbon emissions. These results are consistent with recent studies, such as the October 2021 GFSR by the IMF.

By taking a broad view and considering policies and factors affecting carbon emissions that are not directly related to climate policies, we hope to enrich discussions on carbon reduction strategies to include broader economic transitions rather than limiting strategies to traditional climate policies.

One limitation, which applies to the cross-country analysis in the appendix, is that the climate policy index does not sufficiently consider the specific features of different policies. The machine learning-based country-specific analysis used to obtain our main results addresses this limitation. Another limitation, which applies to both the country-specific and cross-country analyses, is that we cannot conduct causal analyses to evaluate climate and non-climate policies given data limitations. Instead, the interpretation of our machine-learning country-specific results is based on case studies for selected top emitters. As such, our results need to be interpreted with caution.

Despite the need for further work, hereby we still lay out some preliminary policy implications to stimulate more discussions. In particular, our findings suggest that, despite being effective in slowing down the growth of carbon emissions, the existing climate policies implemented so far do not seem to be sufficient. Thus, bolder, more transformative climate policies are urgently needed to arrest the rising trend of carbon emissions, reduce their absolute levels, and ultimately achieve the goal of carbon neutrality by 2050. For example, the green agri-food systems proposed by Batini (2021) and the international carbon price floor by Parry, Black, and Roaf (2021) could be policy areas worth exploring further. Our results also highlight the importance of non-climate policies: Effectively addressing climate change involves not only policies directly related to climate and carbon, but also broader policy areas that shape the economic structure.

APPENDICES

Appendix 1. Climate Policies and Carbon Emissions: A Panel Data Analysis

This appendix provides a complementary study to the one presented in the main text. It consists of description of the raw data, construction of the policy variable to be used in the panel regressions (Climate Policy Intensity Index), description of the cleaned data, results and interpretation, as well as robustness checks.

A. Description of Raw Data

The data sources we use for non-policy measures are almost the same as those presented in Section III.A of the main text. The only difference is that this Appendix also uses the data on public and private capital stocks, which are from the IMF investment and capital stock dataset.

The data source we use for policy measures is the *Climate Policy Database* maintained by NewClimate Institute with support from PBL Netherlands Environmental Assessment Agency and Wageningen University and Research.[18] The database covers national mitigation-related policies and is updated periodically. It mostly covers implemented rather than planned policies, with an exception of energy and emission targets announced as Intended Nationally Determined Contributions (INDCs) for the post-2020 period.

This is a new, yet comprehensive dataset used in a small number of recent environmental economics studies. It covers information from 1927 to 2021 with a total of 4,980 policy measure occurrences in the raw data, although the coverage in earlier years is sparse due to data availability. The fields reported in the dataset are comprehensive and include: Country/region name; geographic indicators (subnational region, state, city, or local); type of policy instrument; sector name; policy description; policy type; date of decision (i.e., when the policy was announced); estimated impact; policy objective; and some other indicators.

We first describe the types of climate policy measures covered by the raw dataset. Note that there are 1,458 distinctive policy types in total in the raw data (most of which only appear once or twice), so it is infeasible to provide the summary statistics for the full sample by the type of policy instruments. Hence, Appendix Table 1 provides the summary statistics for an incomplete sub-sample with the top 10 most frequent policy types, accounting for one quarter of

[18] The raw data are available here.

the full sample available in the Climate Policy Database. As shown in the table, countries have employed a wide range of different types of policies, with a low concentration on any particular type. The most frequent type of policy instrument is "strategic planning," accounting for 5.7 percent of the sample, followed by "grants and subsidies" and "tax relief," accounting for 4.1 and 2.8 percent, respectively.

To better understand the construction of the climate policy intensity index (CPII) discussed below, we then describe some other features of the raw data. Appendix Table 2 shows that about 93 percent of the observations are country-level policy measures, followed by the subnational region level (5.6 percent), the city level (0.9 percent), and the supranational region level (0.5 percent). About one fifth of the policies are applicable to all economic sectors, followed by renewables (14.5 percent) and electricity and heat (6.4 percent, Appendix Table 3). The dataset also identifies a small fraction of policy measures (5.7 percent, Appendix Table 4) as having a "high impact," which will help us construct the CPII.

Appendix Table 1. Summary Statistics by Type of Policy Instrument: Top 10 Most Frequent Types

Type of policy instrument	Freq.	Percent	Cum.
Strategic planning	267	5.7	5.7
Grants and subsidies	194	4.1	9.8
Tax relief	132	2.8	12.6
Policy support	93	2.0	14.6
Target, GHG reduction target, Political & non-binding GHG reduction target	93	2.0	16.6
Fiscal or financial incentives	84	1.8	18.4
Regulatory Instruments	84	1.8	20.1
Policy support, Strategic planning	77	1.6	21.8
Building codes and standards	75	1.6	23.4
Energy and other taxes	75	1.6	25.0
Sub-Total	1,174	25.0	

Sources: Climate Policy Database and Authors' calculations.

Appendix Table 2. Summary Statistics by Jurisdiction: Full Sample

Jurisdiction	Freq.	Percent	Cum.
Country	4,383	92.90	92.90
Subnational region	266	5.64	98.54
City	44	0.93	99.47
Supranational region 1/	25	0.53	100.00
Total	4,718	100.00	

Sources: Climate Policy Database and Authors' calculations.
Note: Supranational policy measures are used in the analysis. Because such measures apply to the entire country, they receive the same weight as the country-level measures, as detailed in the subsequent section.

Appendix Table 3. Summary Statistics by Sectors: Top 10 Most Frequent Types

Sector name	Freq.	Percent	Cum.
General 1/	1,001	21.3	21.3
Electricity and heat, Renewables	680	14.5	35.7
Electricity and heat	301	6.4	42.1
Transport	261	5.6	47.7
Buildings	207	4.4	52.1
Industry	165	3.5	55.6
Agriculture and forestry, Forestry	158	3.4	59.0
Buildings, Appliances	145	3.1	62.0
Transport, Low-emissions mobility	120	2.6	64.6
Transport, Light-duty vehicles	105	2.2	66.8
Sub-Total	3,143	66.8	

Sources: Climate Policy Database and Authors' calculations.
Note: 1/ refers to economy-wide measures.

Appendix Table 4. Summary Statistics by Recorded Policy Impact

Impact	Freq.	Percent	Cum.
Unknown	4,273	92.9	92.9
High	261	5.7	98.6
unclear	65	1.4	100.0
Total	4,599	100.0	

Sources: Climate Policy Database and Authors' calculations.
Notes: High: Policies identified by national experts to have high potential to reduce greenhouse emissions. Unclear: Policies with unclear impact due to lack of quantifiable indicators or policy stringency. Unknown: Policies which impact has not been analyzed.

B. Climate Policy Intensity Index (CPII)

To provide a summary statistic for an initial overview of a country's climate policies, we propose a simple index, Climate Policy Intensity Index (CPII), that effectively captures the frequency/intensity of climate policy measures. Although such an index does not sufficiently distinguish the different features for the specific policy measures, the large number of policy measures available in the Climate Policy Database suggests that the measures are so granular that different measures (in most cases) are unlikely to have dramatically different effects. Therefore, they are largely treated equally for the purpose of constructing a simple summary statistic. However, while constructing the CPII, we still account for the policy-specific features to the extent possible. Specifically, the following algorithm is used to generate the CPII:

- First, create a score for each occurrence of every policy instrument, and set the initial score to 1.

- Second, to account for different *geographic* scopes of different policies, set the score to 0.5 if the policy instrument applies to a jurisdiction of "Subnational region" or "City" *and* if it applies to "General" sectors. Note that supranational policy measures receive the same weight as the country-level measures because they also apply to the entire country.
- Third, to further account for different *sectoral* scopes, set the score to 0.25 if the policy instrument applies to a jurisdiction of "Subnational region" or "City" *and* if it applies to some specific sectors (e.g., the energy sector).
- Fourth, to account for different "intensities" of different policies, double the score if the "Impact" indicator available in the dataset reports a value of "High". One example of such "high-impact" policies is a country's five-year plan.[19] While the alternative categories of "unclear" and "unknown" (Appendix Table 4) policy impact do not preclude the possibility that such measures have a "high-impact", the authors assume that policies with "high impact" are likely assessed (hence not unknown) or would have available information available (hence not uncertain).
- Fifth, take the cumulative sum of the scores (i.e., the sum of the scores from 1965 to the current year). This is to capture the aggregate effect of policy measures while implicitly assuming that measures remain in place perpetually.

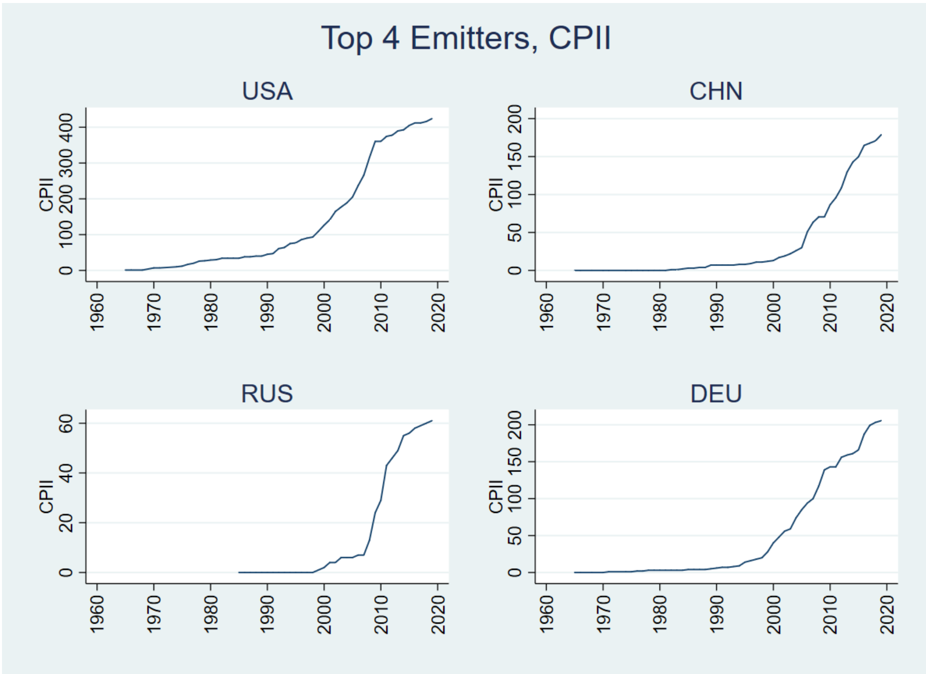
In addition, to ensure sufficient coverage and to be consistent with the coverage of other non-policy data (discussed in subsequent sections), we only use the climate policy data from s1965 to 2019, covering 193 countries/regions.

We would like to caution that the CPII constructed above mostly measures the quantity rather than the quality of climate policies. As such, it should be used only for a preliminary first-step analysis that is followed by more in-depth analyses. The result should also be considered illustrative as granular information is combined into an aggregate index and weight in the CPII are based on judgment. Note that the empirical approach presented in the main text—the machine learning-based approach—does not rely on the CPII index and thus is not affected by the construction of the index.

[19] Note that not all the five-year plans or other strategic plans are recorded to have "High" impact in the dataset.

In the final cleaned sample (with 18,335 observations), the constructed CPII has a mean of 3.2, essentially suggesting that an "average" or "typical" country in a typical year issues 3.2 climate-related policy measures. However, the CPII has a large standard deviation of 18.6, reflecting different policy intensities across different countries. Another clear patten across all the top 20 countries is that starting in mid-2000s, they dramatically accelerated the effort in issuing climate-related policies, as shown in Appendix Figure 1 (plotting the examples of the top 4 countries).

Appendix Figure 1. Climate Policy Intensity Index for Top Four Carbon Emitters



Sources: Climate Policy Database and Authors' calculations.

C. Summary of Cleaned Data and Methodology

The dependent variable used in the main results of the panel data analysis is the (annualized) three-year cumulative growth rate of carbon emissions.[20] We use the three-year cumulative carbon growth rate because it takes time for climate policies to meaningfully affect carbon

[20] We annualize these growth rates only for the convenience of understanding the magnitudes of the growth rates. Because both the dependent variable and all independent variables are annualized in exactly the same way (i.e., by dividing by 3 in this case), the regression coefficient of an annualized 3-year growth rate is the same as that of a 3-year cumulative growth rate.

emissions. In the robustness check section, we also present the results with one-year carbon growth rate (and one-year changes of all other variables), as well as with five-year growth rates.

Accordingly, the independent variables include the annualized three-year cumulative change in the CPII; the annualized three-year cumulative growth rates of GDP, coal consumption, oil consumption, general government capital stock, and private capital stock. All the variables except the CPII are used in Hendry (2020), among others; given our interest in the policy analysis, we have added the CPII as an additional variable. Appendix Table 5 provides the summary statistics for the full sample of the top 20 emitters used in the panel data analysis, where all growth rates/changes are the annualized three-year cumulative growth rates/changes. The average CO2 growth rate is 4.2 percent, higher than the corresponding GDP growth rate (3.8 percent). As for climate policy measures, there are significant variations across countries and over time. On average, there are 2.8 new measures issued per year per country.

To visualize the data used in the panel data analysis, Appendix Figure 2 plots some selected indicators for China, where all growth rates (changes) are also the annualized three-year cumulative growth rates (changes). Despite the decelerating trend of the country's CO2 growth since 1975, it accelerated again in early 2000s, before going down quickly in 2011 thanks to the government's renewed effort in curbing carbon emissions. The government's intensified effort can also be seen in the second chart in the figure, where the change of the CPII index spiked in 2013. Note that non-stationarity of the dependent and independent variables is a concern typically in a *dynamic* panel data model (Greene, 2012, Page 452), which is not the case here. Hence, a strict testing of stationarity is not needed in our case. Still, Appendix Figure 2 shows that the variables used in the panel regressions (all of which are growth rates) appear stationary across the sample period (except the change of CPII, which appears stationary since the 2000s).

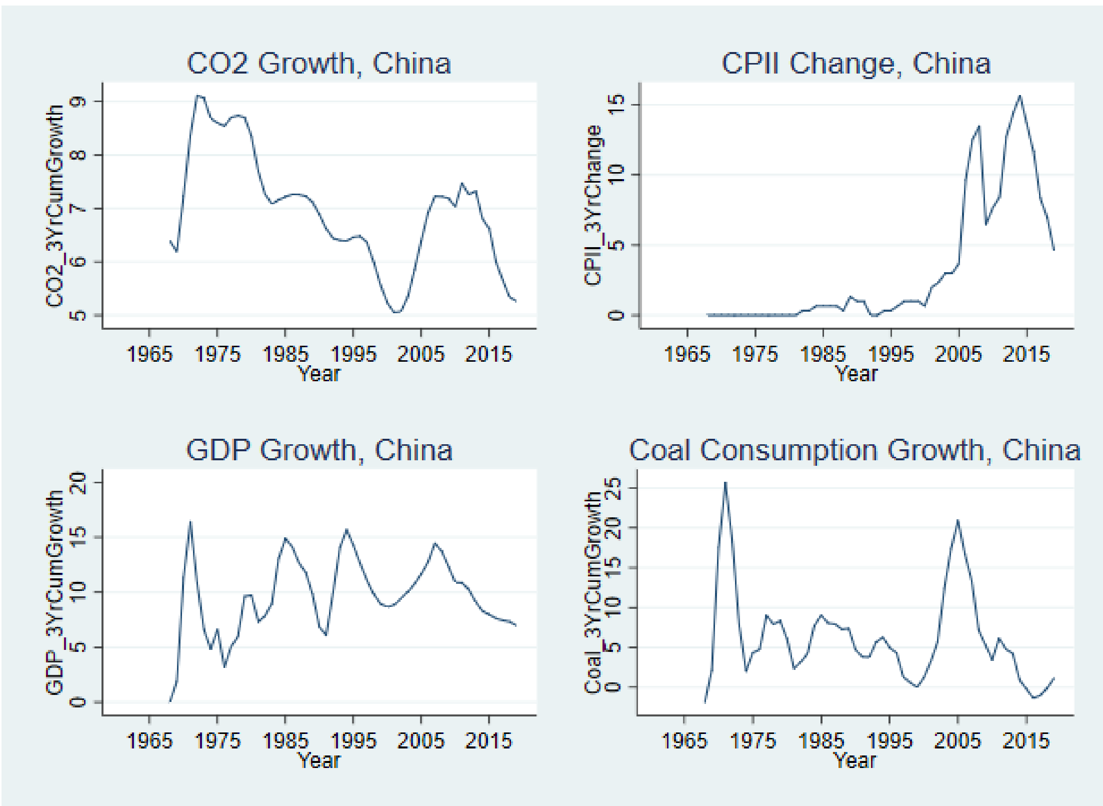
The specific methodology used in this Appendix is panel data regressions. As is standard in the literature, we conduct both the fixed-effect and random-effect models and then select the preferred model using the Hausman test. Note that we do not control for time dummies in our panel regressions for three reasons: First, given the global nature of the climate change challenge, many countries have coordinated and enacted their climate policy actions around similar times (e.g., following the Paris Agreement). Hence, controlling for time dummies would significantly weaken the identification of the true impact of the climate policies. Second, we have controlled for several major macroeconomic variables such as the GDP growth, which have accounted for most time-specific idiosyncratic shocks. Third, our data has a long time period, and adding time dummies would significantly decrease our models' degrees of freedom.

Appendix Table 5. Summary Statistics of the Full Sample for Top 20 Emitters

Variable	Obs	Mean	Std. Dev.	Min	Max
year	1,060	N.A.	N.A.	1965	2019
CO2 Growth	1000	4.2	3.1	0.5	24.3
CPII	1,060	35.4	64.3	0.0	424.0
CPII Change	1,000	2.8	4.5	0.0	41.2
Change of Unweighted Policy Count	1,000	2.8	4.6	0.0	41.0
GDP Growth	961	3.8	4.4	-14.8	45.0
Coal Growth	964	2.1	8.3	-23.3	97.9
Oil Growth	1000	3.0	7.2	-21.9	94.6
Government Capital Growth	910	3.6	3.3	-2.1	27.8
Private Capital Growth	910	4.2	4.2	-3.2	28.6

Sources: Climate Policy Database and Authors' calculations.

Appendix Figure 2. CO2 Growth and Other Key Indicators for China



Sources: Climate Policy Database; World Bank; and Authors' calculations.

D. Results and Interpretation

Appendix Table 6 presents the aggregate results, where the fixed-effect and random-effect results are both reported. All the variables have statistically significant and intuitive signs. In particular, the three-year cumulative change in CPII (effectively measuring the intensity or frequency of new climate policies in a given year) is *negatively* correlated with the three-year cumulative growth rate of carbon emissions. And the three-year cumulative growth rates of GDP, coal consumption, oil consumption, general government capital stock, and private capital stock are all positively correlated with the growth rate of carbon emissions, which is intuitive.[21] Moreover, as expected, the impact of climate policies monotonically decreases as we control for more and more factors that positively contribute to carbon emissions. The random-effect results are very similar to their fixed-effect counterparts (e.g., Column (8) vs. Column (7)). The last row of Appendix Table 6 presents the p-values of the Hausman test, suggesting that the fixed-effect model is the preferred model in three out of the four cases under a 5 percent significance level. Note that a lower-than-the-significance-level p-value of the Hausman test is in favor of the fixed-effect model; see Greene (2012, Page 380).

To further assess the *economic importance* of the climate policies, we estimate the implied minimum change of the CPII that is required to induce a decrease in the absolute *level* of carbon emissions, i.e., a negative growth rate of the carbon emissions. A simple estimate can be obtained based on Column (1) of Appendix Table 6: In the absence of any new climate policies (the change of CPII being equal to 0), carbon emissions would grow at 4.613 percent a year; given the estimated marginal impact of -0.134, an annualized change of 34.4 in CPII would be required to arrest the carbon emission growth. That is, roughly 34.4 new climate policies per year (without closely considering the weights of different policy measures) are needed to induce a decrease in the absolute *level* of carbon emissions. This minimum requirement of 34.4 is close to the maximum CPII change observed in the top 20 emitters (41.2, as in Appendix Table 5) and is much larger than the average observed CPII change (2.8).

The difference is even more significant if we conduct the estimation based on the more rigorous regression result in Column (7), which controls for more variables and is the preferred

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[21] Columns (7) and (8) have 19 countries instead of 20 because the capital stock data for Australia is not available.

model based on the Hausman test: For a "typical" country in a "typical" year among the top 20 emitters (i.e., if we evaluate the statistically significant non-policy variables at their sample means), roughly 53.7 new climate policies per year are needed to induce a decrease in the level of carbon emissions[22], much larger than the average observed CPII change of 2.8.

Appendix Table 6. Panel Regressions of Carbon Emission Growth on Climate Policies

	(1) FE	(2) RE	(3) FE with GDP	(4) RE with GDP	(5) FE with GDP Coal Oil	(6) RE with GDP Coal Oil	(7) FE with GDP Coal Oil Capital	(8) RE with GDP Coal Oil Capital
CPII_3YrChange	-0.134***	-0.135***	-0.106***	-0.107***	-0.088***	-0.087***	-0.080***	-0.079***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP_3YrCumGrowth			0.219***	0.224***	0.046***	0.050***	0.027*	0.028**
			(0.000)	(0.000)	(0.001)	(0.000)	(0.053)	(0.043)
Coal_3YrCumGrowth					0.017***	0.019***	0.011**	0.012**
					(0.001)	(0.000)	(0.041)	(0.023)
Oil_3YrCumGrowth					0.098***	0.099***	0.097***	0.099***
					(0.000)	(0.000)	(0.000)	(0.000)
kgov_3YrCumGrowth							0.115***	0.119***
							(0.000)	(0.000)
kpriv_3YrCumGrowth							0.062***	0.065***
							(0.000)	(0.000)
Constant	4.613***	4.521***	3.723***	3.561***	3.750***	3.612***	3.198***	3.044***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,000	1,000	961	961	928	928	838	838
R-squared	0.084		0.274		0.391		0.459	
Number of Countries	20	20	20	20	20	20	19	19
Hausman Test P-value	0.410		0.000		0.000		0.005	

Sources: Global Carbon Project; World Bank; IMF; Our World in Data; and Authors' calculations.
Notes:
(1) CPII_3YrChange is defined as the annualized 3-year difference in the CPII.
(2) 3YrCumGrowth is defined as the annualized 3-year cumulative growth rate.
(3) kgov = government capital; kpri = private capital.

[22] This is estimated as the constant plus the contributions of all other statistically significant regressors except the CPII_3YrChange (e.g., the coefficient of GDP_3YrCumGrowth multiplied by the mean GDP_3YrCumGrowth), divided by the absolute value of the coefficient of CPII_3YrChange. More rigorously, since Column (7) is estimated for 19 emitters due to the missing capital data for Australia, the minimum requirement for the policies is estimated for a typical country in a typical year among these 19 emitters. The same comment applies to the subsequent discussion that considers the policy types. Note that the sample means of the policy variables are very close between the top 20 emitters and the 19 emitters.

(4) FE = Fixed Effect, RE = Random Effect.
(5) pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

In sum, our results suggest that, on the one hand, the climate policies implemented in the top 20 emitters so far have been effective in slowing down the *growth* rate of carbon emissions. On the other hand, the existing policies appear far from being sufficient for reducing the absolute *level* of carbon emissions, a result that does not appear encouraging at first glance but does seem consistent with the ever-increasing carbon emissions across most top 20 emitters.

We would like to note an important caveat with the panel regression methodology. Because our CPII index does not fully account for the quality of each climate policy measure, the index may not have high comparability across countries, which tends to decrease the usefulness of the cross-country panel regression analysis. As such, the panel regression results need to be interpreted with caution. The country-specific analysis presented in the main text can mitigate this concern.

E. Robustness Checks

This section reports the results of several robustness checks. Firstly, we use the unweighted/raw count of the policy instruments instead of the weighted CPII. Appendix Table 7 presents the results, which are very similar to those presented above.

Secondly, we use the current-year growth rates and the five-year cumulative growth rates, instead of the three-year cumulative growth rates. The results using the current-year changes are presented in Appendix Table 8; and those using the five-year cumulative changes are presented in Appendix Table 9. All results are similar with those discussed earlier.

Notably, the magnitudes of all the policy impacts monotonically *increase* as we move from the current-year policy change to three-year cumulative policy change, and then to five-year cumulative policy change. For example, the aggregate effect of CPII on carbon emission growth (in absolute value) increases from the 0.059 using the current-year changes, to 0.080 using the three-year cumulative changes, and further to 0.092 using the five-year cumulative changes. This verifies our prior that climate policies take time to affect carbon emissions.

Thirdly, to capture the lagged effect of climate policies on carbon emissions in an alternative way, we use the lagged year-on-year policy changes instead of the contemporaneous three-year cumulative changes. Note that in this set of robustness checks, only the policy change variables take the lagged values and all other variables (including the carbon emission growth rate) take the contemporaneous values. The results using the three-year lagged policy changes are presented in Appendix Table 10.[23] All results are similar with those discussed earlier, including the signs of all coefficients and their magnitudes.

Appendix Table 7. Panel Regressions of Carbon Emission Growth on Climate Policies: Raw

	(1) FE	(2) RE	(3) FE with GDP	(4) RE with GDP	(5) FE with GDP Coal Oil	(6) RE with GDP Coal Oil	(7) FE with GDP Coal Oil Capital	(8) RE with GDP Coal Oil Capital
CumCount_3YrChange	-0.125***	-0.125***	-0.100***	-0.100***	-0.082***	-0.081***	-0.073***	-0.073***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP_3YrCumGrowth			0.221***	0.226***	0.048***	0.052***	0.028**	0.029**
			(0.000)	(0.000)	(0.001)	(0.000)	(0.043)	(0.034)
Coal_3YrCumGrowth					0.017***	0.019***	0.011**	0.012**
					(0.001)	(0.000)	(0.038)	(0.022)
Oil_3YrCumGrowth					0.099***	0.100***	0.098***	0.099***
					(0.000)	(0.000)	(0.000)	(0.000)
kgov_3YrCumGrowth							0.118***	0.122***
							(0.000)	(0.000)
kpriv_3YrCumGrowth							0.061***	0.064***
							(0.000)	(0.000)
Constant	4.585***	4.494***	3.694***	3.533***	3.721***	3.584***	3.166***	3.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,000	1,000	961	961	928	928	838	838
R-squared	0.075		0.268		0.384		0.453	
Number of Countries	20	20	20	20	20	20	19	19
Hausman Test P-value	0.354		0.000		0.000		0.006	

Sources: Global Carbon Project; World Bank; IMF; Our World in Data; and Authors' calculations.
Notes:
(1) CumCount_3YrChange is defined as the annualized 3-year difference in the unweighted climate policy counts.
(2) 3YrCumGrowth is defined as the annualized 3-year cumulative growth rate.
(3) kgov = government capital; kpri = private capital.
(4) FE = Fixed Effect, RE = Random Effect.
(5) pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

[23] Those using the five-year lagged policy changes are not reported for the sake of brevity, but they are available upon request.

Appendix Table 8. Panel Regressions of Carbon Emission Growth on Climate Policies: Current-Year

	(1) FE	(2) RE	(3) FE with GDP	(4) RE with GDP	(5) FE with GDP Coal Oil	(6) RE with GDP Coal Oil	(7) FE with GDP Coal Oil Capital	(8) RE with GDP Coal Oil Capital
CPII_Change	-0.089***	-0.089***	-0.077***	-0.077***	-0.065***	-0.065***	-0.059***	-0.059***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP_Growth			0.119***	0.122***	0.022**	0.024**	0.014	0.015
			(0.000)	(0.000)	(0.037)	(0.024)	(0.150)	(0.127)
Coal_Growth					0.006**	0.006**	0.003	0.003
					(0.038)	(0.023)	(0.240)	(0.188)
Oil_Growth					0.077***	0.079***	0.074***	0.075***
					(0.000)	(0.000)	(0.000)	(0.000)
kgov_Growth							0.119***	0.123***
							(0.000)	(0.000)
kpriv_Growth							0.077***	0.080***
							(0.000)	(0.000)
Constant	4.232***	4.155***	3.794***	3.648***	3.670***	3.561***	3.056***	2.929***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,040	1,040	1,001	1,001	968	968	876	876
R-squared	0.067		0.178		0.290		0.387	
Number of Countries	20	20	20	20	20	20	19	19
Hausman Test P-value	0.375		0.000		0.000		0.003	

Sources: Global Carbon Project; World Bank; IMF; Our World in Data; and Authors' calculations.
Notes:
(1) CPII_Change is defined as the 1-year difference in the CPII.
(2) Growth is defined as the year-on-year growth rate.
(3) kgov = government capital; kpri = private capital.
(4) FE = Fixed Effect, RE = Random Effect.
(5) pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 9. Panel Regressions of Carbon Emission Growth on Climate Policies: Five-Year

	(1) FE	(2) RE	(3) FE with GDP	(4) RE with GDP	(5) FE with GDP Coal Oil	(6) RE with GDP Coal Oil	(7) FE with GDP Coal Oil Capital	(8) RE with GDP Coal Oil Capital
CPII_5YrChange	-0.163***	-0.164***	-0.123***	-0.124***	-0.102***	-0.100***	-0.092***	-0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP_5YrCumGrowth			0.295***	0.300***	0.097***	0.103***	0.062***	0.064***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Coal_5YrCumGrowth					0.015**	0.018***	0.010	0.012*
					(0.013)	(0.004)	(0.112)	(0.067)
Oil_5YrCumGrowth					0.106***	0.107***	0.108***	0.110***
					(0.000)	(0.000)	(0.000)	(0.000)
kgov_5YrCumGrowth							0.116***	0.121***
							(0.000)	(0.000)
kpriv_5YrCumGrowth							0.044***	0.047***
							(0.002)	(0.001)
Constant	4.965***	4.858***	3.697***	3.515***	3.771***	3.607***	3.294***	3.105***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	960	960	921	921	888	888	800	800
R-squared	0.083		0.320		0.438		0.480	
Number of Countries	20	20	20	20	20	20	19	19
Hausman Test P-value	0.419		0.003		0.000		0.004	

Sources: Global Carbon Project; World Bank; IMF; Our World in Data; and Authors' calculations.
Notes:
(1) CPII_5YrChange is defined as the annualized 5-year difference in the CPII.
(2) 5YrCumGrowth is defined as the annualized 5-year cumulative growth rate.
(3) kgov = government capital; kpri = private capital.
(4) FE = Fixed Effect, RE = Random Effect.
(5) pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

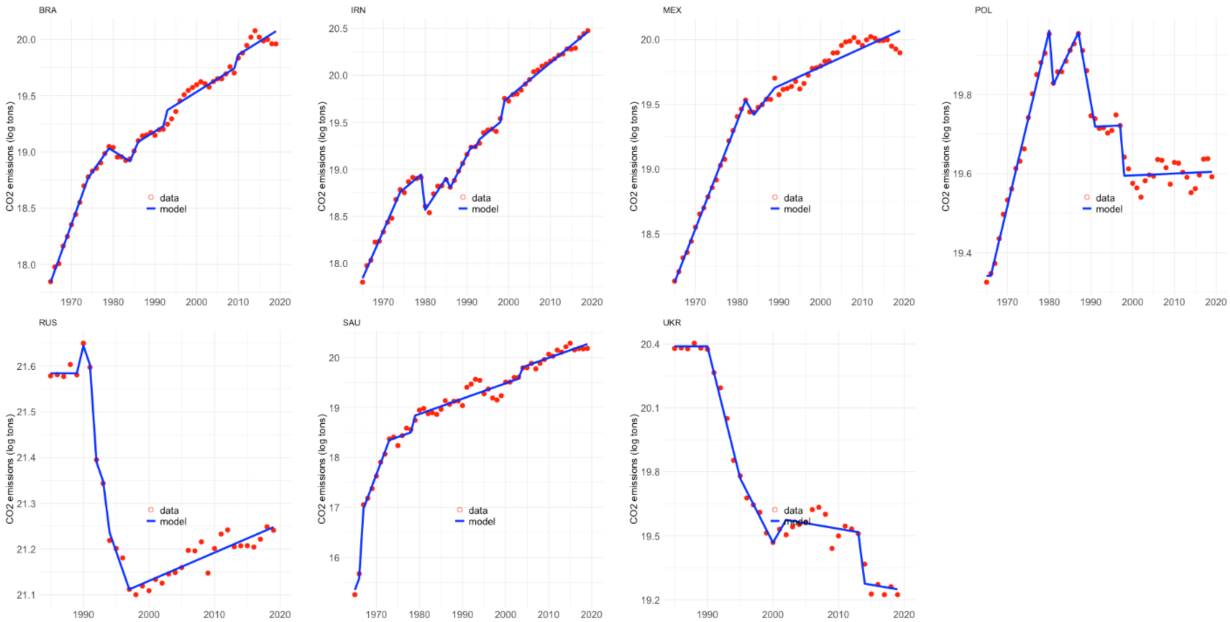
Appendix Table 10. Panel Regressions of Carbon Emission Growth on Climate Policies: Three-Year Lagged Policy Changes

	(1) FE	(2) RE	(3) FE with GDP	(4) RE with GDP	(5) FE with GDP Coal Oil	(6) RE with GDP Coal Oil	(7) FE with GDP Coal Oil Capital	(8) RE with GDP Coal Oil Capital
L3.CPII_Change	-0.089***	-0.090***	-0.080***	-0.081***	-0.072***	-0.072***	-0.062***	-0.062***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP_Growth			0.115***	0.118***	0.028**	0.030***	0.028***	0.029***
			(0.000)	(0.000)	(0.011)	(0.007)	(0.006)	(0.005)
Coal_Growth					0.005**	0.006**	0.003	0.003
					(0.045)	(0.030)	(0.213)	(0.167)
Oil_Growth					0.062***	0.063***	0.054***	0.055***
					(0.000)	(0.000)	(0.000)	(0.000)
kgov_Growth							0.138***	0.142***
							(0.000)	(0.000)
kpriv_Growth							0.068***	0.071***
							(0.000)	(0.000)
Constant	4.147***	4.060***	3.759***	3.617***	3.663***	3.566***	2.995***	2.878***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	980	980	955	955	922	922	833	833
R-squared	0.071		0.177		0.238		0.348	
Number of Countries	20	20	20	20	20	20	19	19
Hausman Test P-value	0.344		0.000		0.000		0.009	

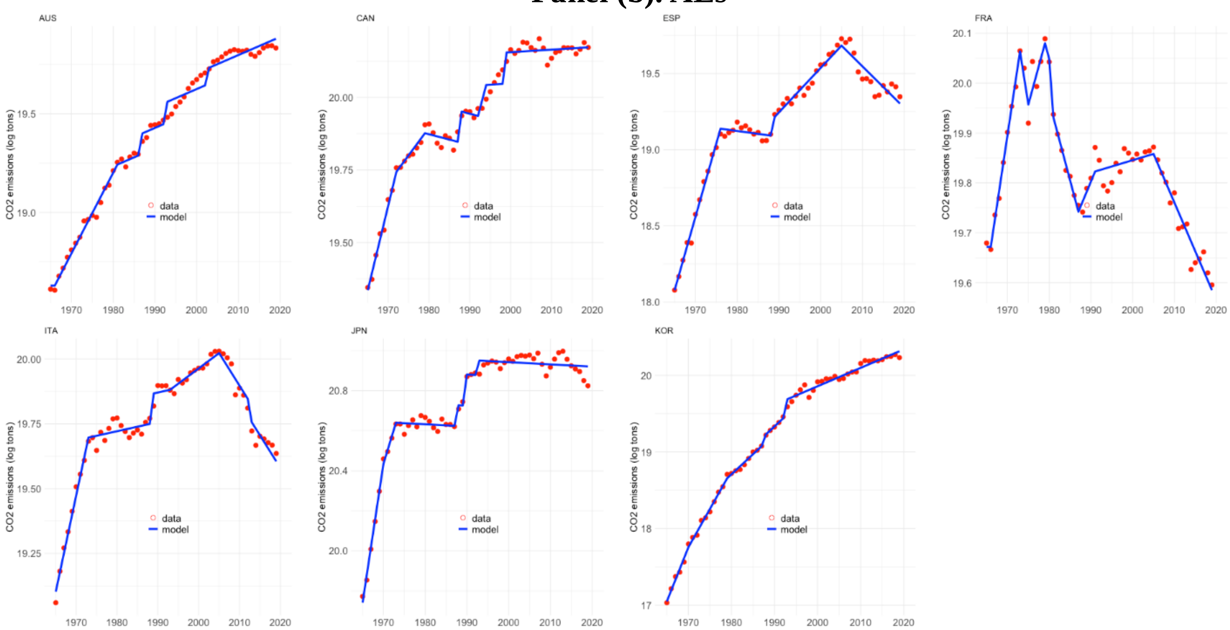
Sources: Global Carbon Project; World Bank; IMF; Our World in Data; and Authors' calculations.
Notes:
(1) L3.CPII_Change is defined as the 3-year lagged change in the CPII.
(2) Growth is defined as the year-on-year growth rate.
(3) kgov = government capital; kpri = private capital.
(4) FE = Fixed Effect, RE = Random Effect.
(5) pval in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Figure 3. Structural Breaks for 14 Countries: Unconditional Analysis

Panel (a). EMs



Panel (b). AEs



Sources: Global Carbon Project; and Authors' calculations.

Appendix Table 11. Timing of Structural Breaks for 14 Countries: Unconditional Analysis

Panel (a). EMs

	BRA		IRN		MEX		POL		RUS		SAU		UKR	
	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign
Trend Shift	tis1966	1	tis1966	1	tis1966	1	tis1967	1	tis1990	1	tis1966	1	tis1991	-1
	tis1975	-1	tis1975	-1	tis1983	-1	tis1981	-1	tis1991	-1	tis1974	-1	tis1996	1
	tis1980	-1	tis1980	-1	tis1985	1	tis1982	1	tis1998	1			tis2001	1
	tis1985	1	tis1981	1	tis1990	-1	tis1988	-1					tis2003	-1
	tis1987	-1	tis1986	-1			tis1992	1						
			tis1987	1										
			tis1994	-1										
Level Shift	sis1993	1	sis1992	-1			sis1998	-1	sis1992	-1	sis1967	1	sis2014	-1
	sis2010	1	sis1999	1	None	None			sis1994	-1	sis1979	1		
											sis2004	1		

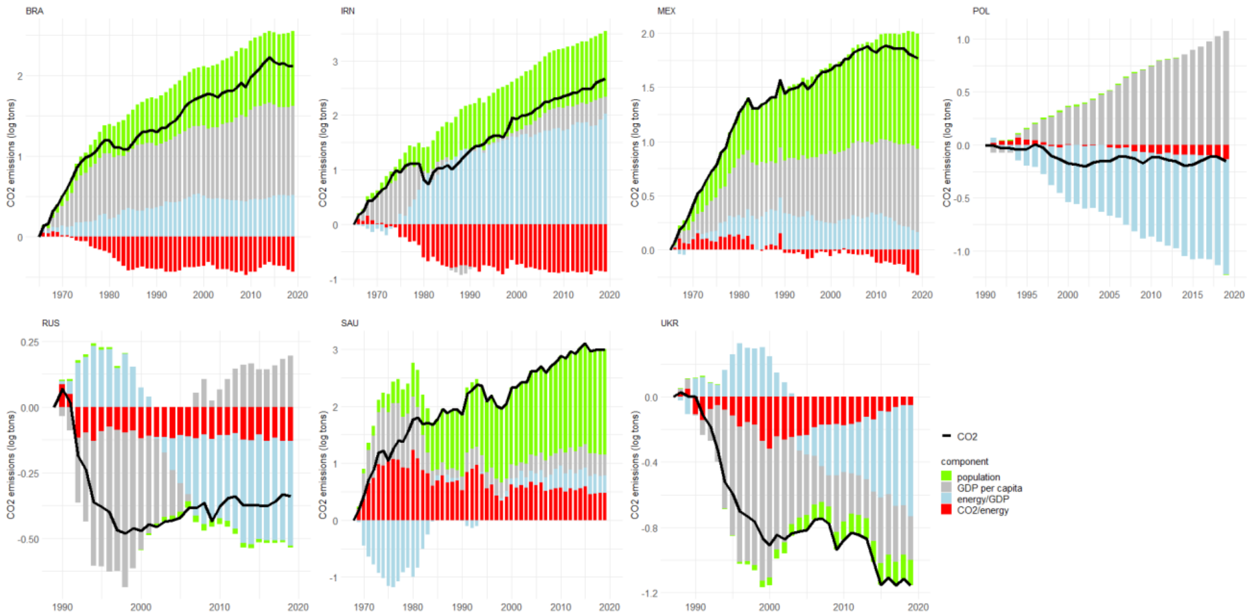
Panel (b). AEs

	AUS		CAN		ESP		FRA		ITA		JPN		KOR	
	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign
Trend Shift	tis1967	1	tis1966	1	tis1966	1	tis1967	1	tis1966	1	tis1966	1	tis1966	1
	tis1982	-1	tis1973	-1	tis1977	-1	tis1974	-1	tis1974	-1	tis1971	-1	tis1971	-1
			tis1980	-1	tis1989	1	tis1976	1	tis1994	1	tis1974	-1	tis1980	-1
			tis1993	1	tis2006	-1	tis1980	-1	tis2006	-1			tis1993	-1
			tis1995	-1			tis1988	1						
							tis1992	-1						
							tis2006	-1						
Level Shift	sis1987	1	sis1988	1	sis1989	1	sis1981	-1	sis1989	1	sis1988	1	sis1988	1
	sis1993	1	sis1999	1					sis2013	-1	sis1990	1	sis1993	1
	sis2003	1									sis1993	1		

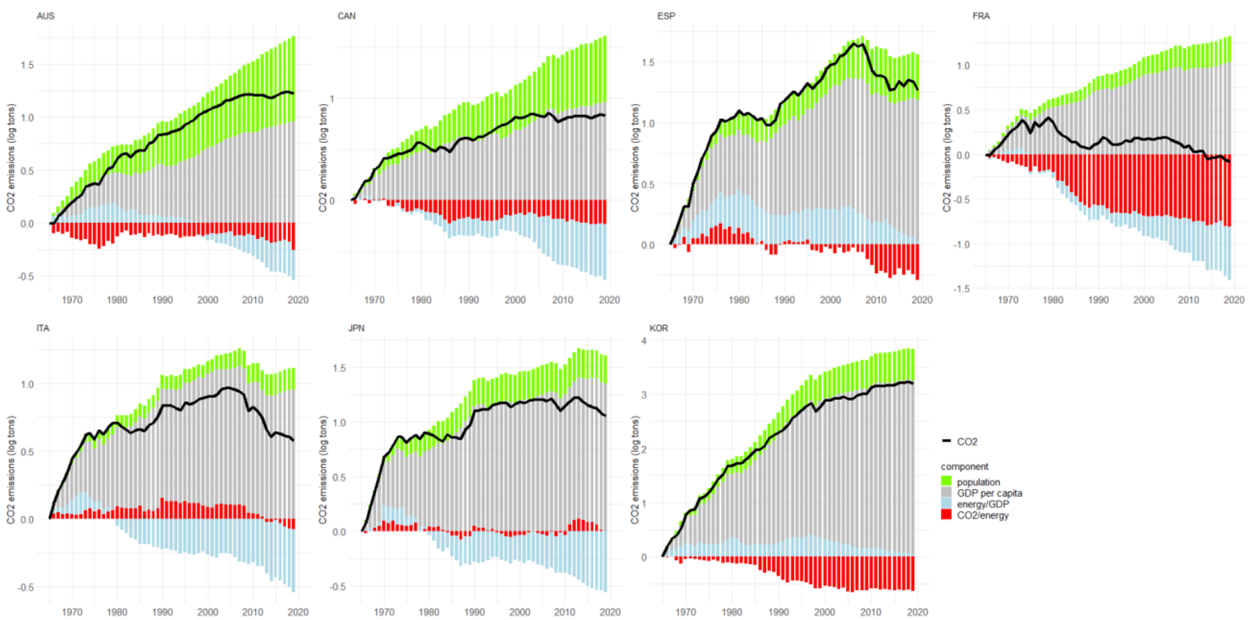
Sources: Global Carbon Project; and Authors' calculations.

Appendix Figure 4. Kaya Decomposition for 14 Countries

Panel (a). EMs



Panel (b). AEs

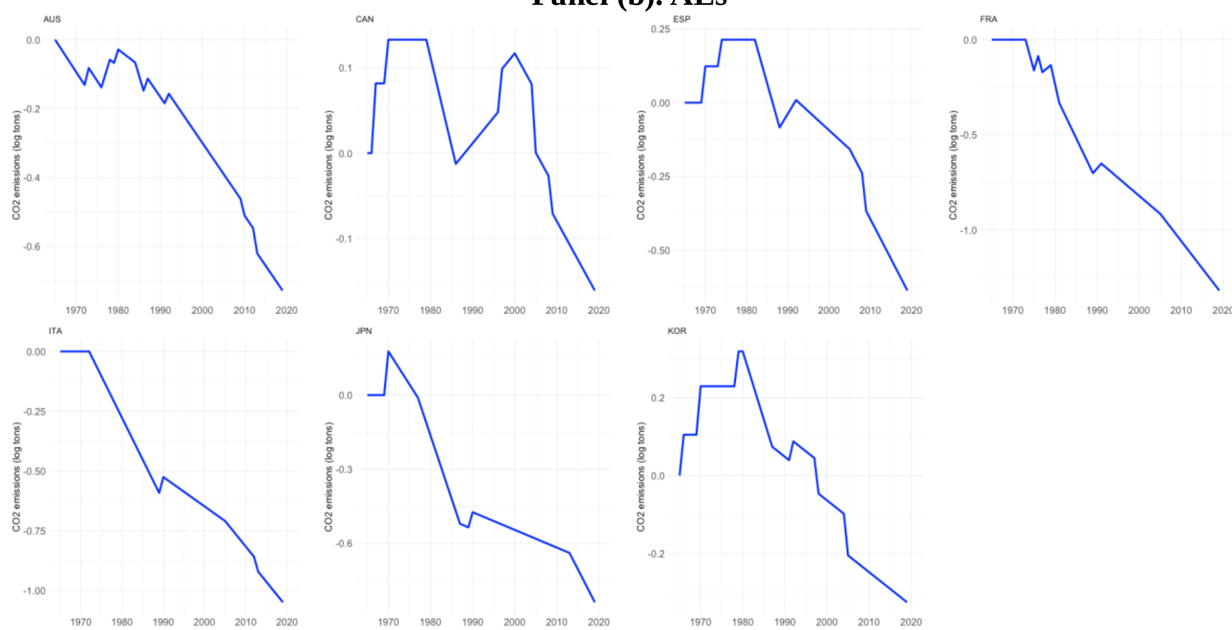


Sources: Global Carbon Project; World Bank; Our World in Data; and Authors' calculations.

Appendix Figure 5. Structural Breaks for 14 Countries: Conditional Analysis

Panel (a). EMs

Panel (b). AEs



Sources: Global Carbon Project; World Bank; and Authors' calculations.

Appendix Table 12. Timing of Structural Breaks for 14 Countries: Conditional Analysis

Panel (a). EMs

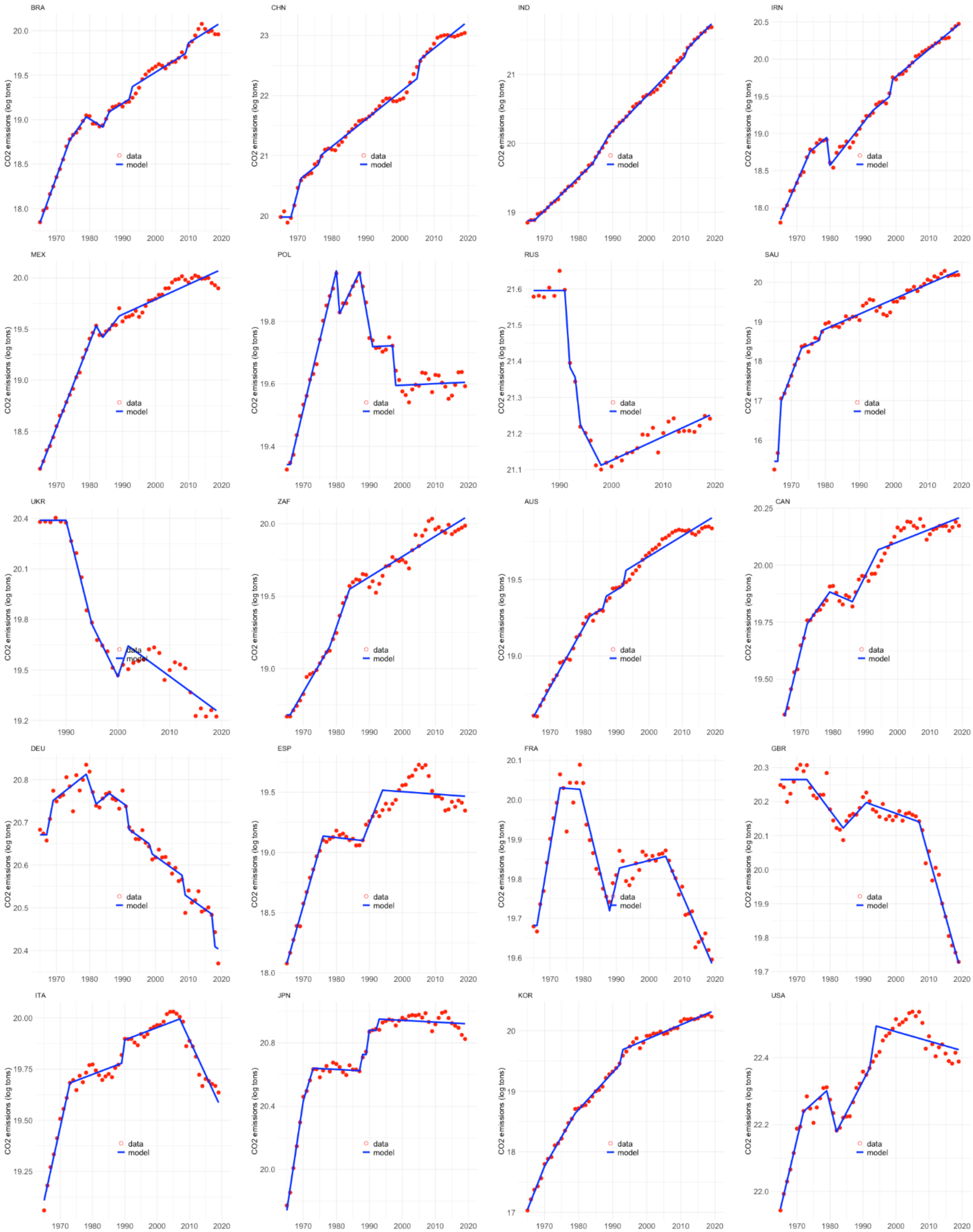
	BRA		IRN		MEX		POL		RUS		SAU		UKR	
	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign
Trend Shift	tis1966	1	tis1966	1	tis1989	1	tis1992	-1	tis1990	-1	tis1977	1	tis1998	-1
	tis1976	-1	tis1980	-1	tis1990	-1	tis1997	-1	tis1999	1	tis1986	-1	tis2005	1
	tis1985	1	tis1982	1	tis1991	1	tis2001	1			tis1999	1		
	tis1995	1	tis1994	-1	tis2001	1	tis2006	-1			tis2003	-1		
	tis2000	-1			tis2010	-1								
	tis2010	1												
	tis2015	-1												
Level Shift	sis1980	-1	sis1999	1	sis1970	1	sis2017	1	sis1990	1	None	None	sis2014	-1
					sis1976	1			sis1992	-1				
					sis1986	1			sis1994	-1				
					sis2017	-1								

Panel (b). AEs

	AUS		CAN		ESP		FRA		ITA		JPN		KOR	
	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign	Year	Sign
Trend Shift	tis1966	-1	tis1980	-1	tis1983	-1	tis1974	-1	tis1973	-1	tis1970	-1	tis1981	-1
	tis1977	1	tis1987	1	tis1989	1	tis1976	1	tis1990	1	tis1978	-1	tis1988	1
	tis1979	-1	tis2001	-1	tis1993	-1	tis1977	-1	tis1991	-1	tis1988	1		
	tis1985	-1			tis2006	-1	tis1978	1	tis2006	-1	tis2014	-1		
	tis1987	1					tis1980	-1						
							tis1982	1						
							tis1990	1						
							tis1992	-1						
							tis2006	-1						
Level Shift	sis1973	1	sis1967	1	sis1970	1	None	None	sis2013	-1	sis1970	1	sis1966	1
	sis1980	1	sis1970	1	sis1974	1					sis1990	1	sis1970	1
	sis1987	1	sis1997	1	sis2009	-1							sis1979	1
	sis1992	1	sis2005	-1									sis1992	1
	sis2010	-1	sis2009	-1									sis1998	-1
	sis2013	-1											sis2005	-1

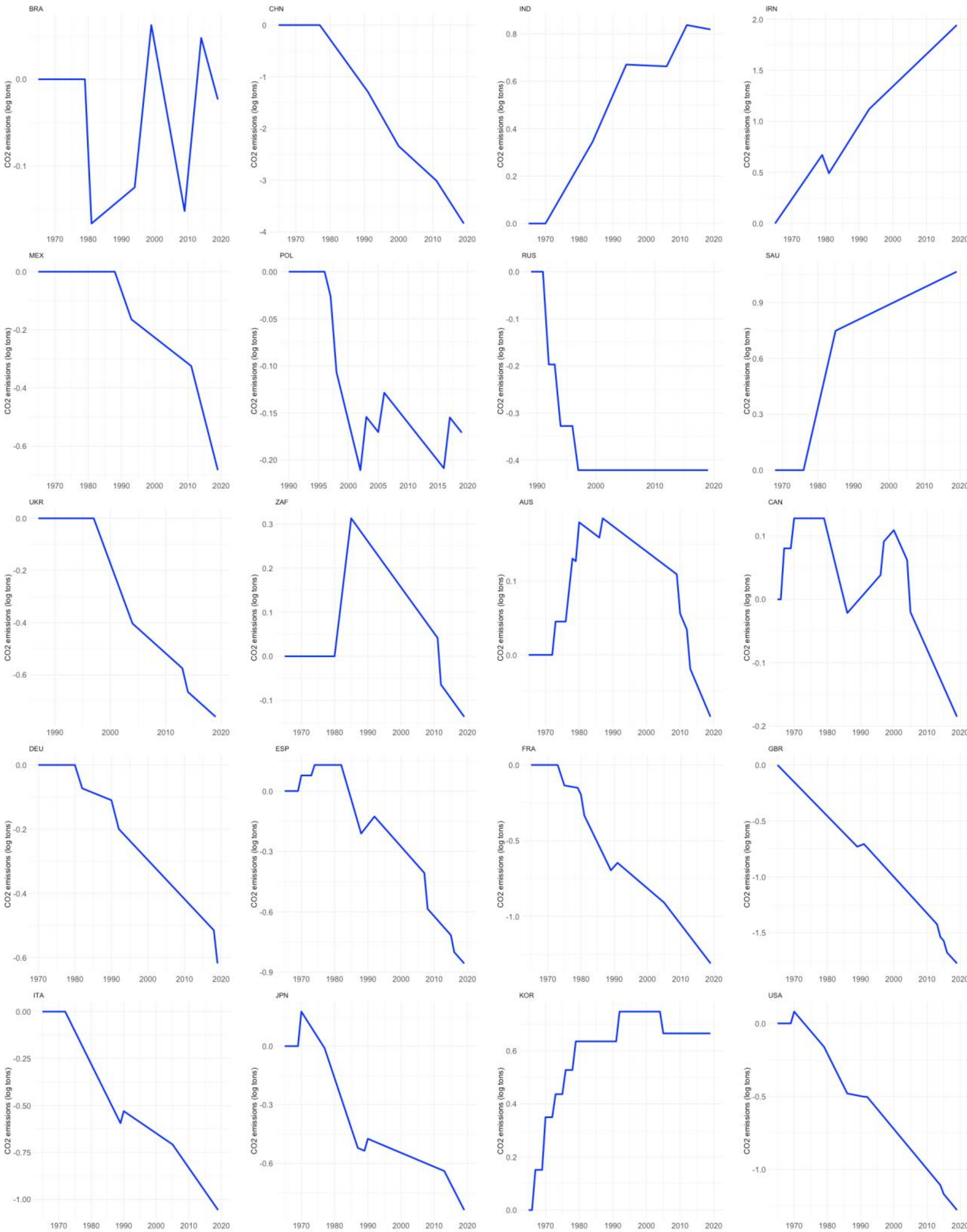
Sources: Global Carbon Project; World Bank; and Authors' calculations.

Appendix Figure 6. Structural Breaks for Top 20 Emitters: Unconditional Analysis (1 Percent)



Sources: Global Carbon Project; and Authors' calculations.

Appendix Figure 7. Structural Breaks for Top 20 Emitters: Conditional Analysis (1 Percent)



Sources: Global Carbon Project; World Bank; and Authors' calculations.

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