Trends and Cycles in CO_2 Emissions and Incomes: Cross-Country Evidence on Decoupling[1]

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Abstract

This paper provides cross-country evidence on the relationship between growth in CO_2 emissions and real GDP growth from 1960 to 2018. The focus is on distinguishing longer-run trends in this relationship from short-run cyclical fluctuations, and on documenting changes in these relationships over time. Using two filtering techniques for separating trend and cycle, we find that long-run trends show evidence of decoupling in richer nations—particularly in European countries—but not yet in developing economies, and that there is stronger evidence of decoupling over the 1990 to 2018 sub-period than over the earlier 1960 to 1989 sub-period. There is also a strong cyclical relationship between emissions and real GDP growth in both advanced and developing economies, and the strength of this relationship has not weakened much over time. The cyclical relationship is largely symmetric: emissions fall about as much during recessions as they rise during booms. The transition to a low-carbon economy will thus require continued progress not only in bringing down trend emissions, particularly in developing economies, but also in taming the increase in emissions that occurs during the boom phase of the business cycle.

Keywords: climate change; emissions; decoupling; filtering
JEL Classifications: E32, O44, Q43, Q54, Q56.

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1. Introduction

The steady rise in global average surface temperature and the severity of climate shocks—ranging from heatwaves and droughts to hurricanes and coastal flooding—have raised the urgency of national and international policy actions to accelerate the transition to a low-carbon economy (IPCC, 2018; OECD/IEA, 2018). Encouragingly, 196 countries signed the Paris Agreement in 2016 committing to domestic policy actions to limit the increase in global average temperature to 2º Celsius within this century (Peters et al., 2017). The United Nations 2030 Agenda for Sustainable Development also sets out several ambitious goals for environmental sustainability (TWI2050, 2018).

A key indicator of progress toward these goals is the extent of decoupling between the growth in greenhouse gas (GHG) or CO_2 emissions and growth in economic activity, typically measured by real GDP growth. This decoupling can be relative or absolute: "GDP growth coinciding with absolute reductions in emissions or resource use is denoted as "absolute decoupling", as opposed to "relative decoupling", where resource use or emissions increase less so than does GDP" (Haberl et al., 2020; UNEP, 2011).

This paper provides estimates of the extent of decoupling between CO_2 emissions and real GDP for a large group of countries—178 countries spanning the advanced, emerging market economies, and low-income country groups—for the period 1960-2018. The novelty of our work is to distinguish between trend and cyclical fluctuations in both emissions and output and to use this distinction to (i) provide estimates of both trend (or longer-run) decoupling and cyclical (or shorter-run) decoupling; and (ii) provide evidence on how this relationship has changed over time.

Our paper has two important sets of findings. First, the underlying trends reveal relative decoupling between emissions and real GDP for some of the richer nations, particularly in Europe, but not yet in developing countries; in a few countries, we encouragingly find evidence of absolute decoupling. Among the twenty major emitting countries in the world, there is an increase in the extent of relative decoupling in all but two cases.

At the same time, the cyclical relationship between emissions and real GDP is very strong for most countries across all income groups. The cyclical relationship is also symmetric: almost everywhere, emissions rise as much during booms as they fall during busts. Moreover, in contrast to the evidence on trend decoupling, the cyclical relationship has become weaker in only half the cases among the twenty major emitters.

These results are robust to two ways of decomposing trend and cycle, the popular HP filter (Hodrick and Prescott, 1981) as well as the newer filter suggested by Hamilton (2018). The results also hold up for a longer period starting in 1948; specifically, when comparing the post-WWII period (1948-1982) with the post-1983 period, we find that the trend elasticity has halved while the cyclical elasticity has nearly doubled (these results are available upon request from the authors). Progress towards a low-carbon economy thus requires progress on both further lowering the trend elasticity of emissions and taming the cyclical elasticity of emissions during booms.

Section 2 presents a review of the literature on decoupling and delineates the contribution of our paper. Section 3 lays out our econometric framework and describes the data sources used. Section 4 presents baseline estimates of both the trend and cyclical elasticities, using alternatively the top 20 emitting countries and selected countries from the "Global South" to illustrate the results and to show that they are robust to several checks. Section 5 summarizes the evidence on trend and cyclical elasticities for 178 countries, focusing on differences across country groups and also presents evidence on how these elasticities differ between booms and busts. The last section draws out the policy implications of our findings. An annex presents detailed country-by-country results.

2. Literature Review

Our review takes advantage of a recent comprehensive two-part survey of the literature on the extent of decoupling based on "analyzing full texts of 835 empirical on the relationship" (Wiedenhofer et al. 2020 and Haberl et al., 2020). About 40% of the studies are based on analysis of CO_2 emissions and about half used data for more than one country. Our paper addresses three gaps in the literature identified by the survey.

First, the survey finds "a dominance of studies on industrial/OECD economies and China in terms of geographical coverage, while the global South is not covered well." As the survey notes, "better knowledge for the Global South is urgently required, as these countries are in the midst of industrialization processes and could still avoid resource and emission intensive lock-ins." Attainment of decoupling is also important for the health and welfare of the citizens of these often very populous nations. Hence, in addition to the advanced economies, our work provides evidence on decoupling for the full set of emerging markets and low-income countries for which there is data available. We present detailed country-by-country results for the twenty largest carbon emitters in the world; the need to achieve decoupling in these top emitters is critical to the achievement of global climate goals. This group includes several major emerging markets such as the BRICS (Brazil, Russia, India, China and South Africa) as well as Indonesia, Poland and Turkey. We also include a section focused on selected countries associated with the "Global South" to shed more light on their transition process. For the full set of 178 countries, in the main text of the paper we restrict attention to presenting results by income groupings and regions, while relegating the country-by-country results to an annex.

Second, the survey notes that a variety of sophisticated modeling and econometric methods have been used for the analysis of decoupling but it concludes that "the statistical complexity of the method of analysis does not automatically translate into more robust insights." Our attempt here is to provide a simple and transparent econometric framework for the analysis of decoupling—one that parallels the one commonly-used trend/cycle decomposition used in many other fields of applied economics—that yields new insights into the process. We distinguish trend from cyclical decoupling and show that progress is needed on both fronts to achieve climate goals.

Third, the survey finds that only a small number of analyses cover a long enough period to offer a perspective on how decoupling has changed over time with the process of industrialization. However, such long-term perspectives "are highly relevant as the majority of countries are still in the midst of the transition into fossil fueled industrialization." Our analysis uses yearly data from 1960 onwards to show how the extent of relative decoupling has increased over time.

In addition to relying on the comprehensive survey just discussed, we also conducted our own literature review. Relevant studies can be classified under a couple of headings; under each heading we summarize a few of the most recent ones and our contribution to the literature.

Cross-country studies of trend changes in emissions:

A number of studies are motivated by the conjecture that we should be seeing signs of absolute decoupling at least in some advanced economies given the structural transformation of these economies toward services and their attempts to foster renewables, whereas emerging markets are likely not at that point as yet. Specifically, Le Quéré et al. (2019) studied 18 advanced economies in which CO_2 emissions appear to have peaked and are now declining and compared them to a broader control group of countries. They identified the 18 countries based on the estimation of a linear trend in emissions data over the period 2005-15. Likewise, Kasperowicz (2015) uses an error-correction model to estimate decoupling in 18 EU countries during the 1992-2012 period. Moreover, like us, he probes the difference between the longer-run and the short-run relationship, concluding that even when the long-run relationship is negative for many countries, the short-run relationship is positive.

To investigate differences between advanced economies and emerging markets, Wang and Su (2020) estimated decoupling over the period 2000-14 for nine groups, consisting of five major individual emitters (China, the United States, India, Russia and Japan) and four country groups (European Union (EU); other developed countries; other developing countries; and least developed countries). They find the developed country groups moving toward "stable weak decoupling" while developing country groups "did not appear to have a significant decoupling process." Wang and Jiang (2020) study decoupling in the BRICS group of emerging market economies and concluded that extent to decoupling was greater in Russia and South Africa than in India, China and Brazil.

As noted earlier, our paper adds value to these studies by looking at the full spectrum of advanced and emerging market countries (in addition to low-income countries) and shows that there is considerable heterogeneity among each of these country groups. We also estimate trends over a longer period of time than the 10-15 years used in these studies—which could provide a more reliable estimate of the trend—and explore alternate ways of trend/cycle decomposition (which allow for the linear trend used in Le Quéré et al. (2019) as a special case).

Cyclical properties of changes in emissions:

Another set of papers studies the cyclical (short-run) properties of emissions. The most comprehensive attempt is by Doda (2014), who uses the HP filter to decompose emissions and GDP in trend and cycle components for 122 countries over the period 1950–2011. He established that emissions are procyclical and, moreover, that the degree of procyclicality was higher for richer countries.

A number of studies carry out more detailed and technical analyses for the United States. Klarl (2020) investigated the response of CO_2 emissions to the business cycle for the U.S. using four alternate filtering methods, two of which we also use in our own work. He found that emissions were much more responsive to GDP during recession times than during normal times. Sheldon (2017) also found that U.S. “emissions fall more sharply per unit decrease in GDP than they rise per unit increase in GDP.” Gozgor et al (2019) also found a similar asymmetric relationship such that the decline in U.S. CO_2 emissions during the contraction periods was higher than the increase in CO_2 emissions during the expansion periods.”[6]

In addition to extending Doda’s work to a larger set of countries and updating the analysis to 2018, we also look at changes over time in the trend and cyclical relationships as well as the asymmetry in the response of emissions to cyclical changes in GDP (between boom and bust phases of the business cycle). This is important because progress toward a low-carbon economy requires both greater trend decoupling and also progress in taming the rise in emissions during economic booms. Our results for the United States are similar to what the studies cited above found. However, we do not find the magnitude of the difference between elasticities during the boom and the bust to be large, either for the United States or more most other countries and country groups.

3. Data and Econometric Framework

3.1 Data

The emissions (CO_2) data in this paper are taken from the Carbon Dioxide Information and Analysis Center (CDIAC), the National Inventory Submissions to the United Nations Framework Convention on Climate Change (UNFCCC), the BP Statistical Review of World Energy, and Global Carbon Atlas.[7] The dataset captures territorial fossil fuel CO_2 emissions (measured in metric tons) for 178 countries—36 advanced, 87 emerging and 55 low-income—over the period 1960 to 2018.[8] Real GDP growth is taken from the IMFs World Economic Outlook (WEO)

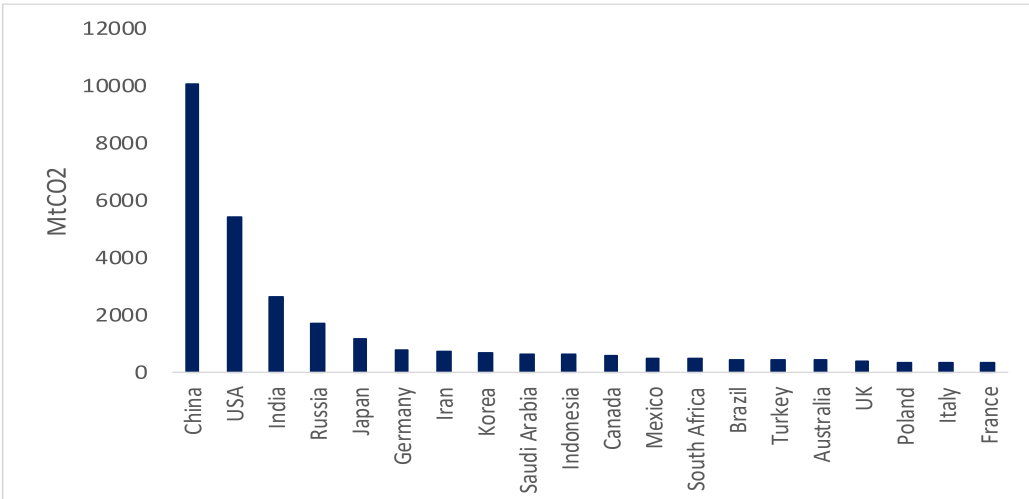
[6] York (2012) and Burke et al. (2015) seemingly find results at odds with this finding but as Sheldon (2017) notes these studies estimate the average emissions elasticity across a panel of countries and estimates for individual countries can be quite different.

[7] See also Gilfillan et al. (2019). CDIAC ceased operation in September 2017 but updates are available from Appalachian State University (https://energy.appstate.edu/research/work-areas/cdiac-appstate). Other series are available at the following links: National Inventory Submissions 2019 to the United Nations Framework Convention on Climate Change (UNFCCC): https://unfccc.int/process-and-meetings/transparency-and-reporting/reporting-and-review-under-the-convention/greenhouse-gas-inventories-annex-i-parties/national-inventory-submissions-2019.;BP Statistical Review of World Energy: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html.;Global Carbon Atlas can be accessed at: http://www.globalcarbonatlas.org/en/CO2-emissions.

[8] Country group classification follows the World Bank definition.

database. Both emissions and GDP data are on a yearly basis. In addition to evidence on decoupling for a large group of countries, we will provide detailed results for the twenty largest CO_2 emitters, shown in Figure 1 by annual amount of CO_2 released.

Figure 1: Top 20 world emitters, 2018



Source: Global Atlas Data.

3.2 Econometric Framework

We begin by considering, for each country, the following reduced-form time-series relationship between the growth of emissions and real GDP growth:

$$\Delta \ln e_t = \alpha + \omega \Delta \ln y_t + u_t \quad (1)$$

where e_t and y_t denote emissions and real GDP in year *t*, respectively. Δ and ln(.) denote a first-difference operator and the logarithm respectively. ω is an unknown parameter to be estimated. u_t is an i.i.d. error term satisfying standard assumptions of zero mean and constant variance.

An assessment of the extent of decoupling could be made based on estimates of the parameter ω in equation (1). However, this estimate conflates two forces. The first is the longer-run trend in carbon dependence that is the result of structural change (e.g. movement away from manufacturing industries) and impacts of policies (e.g. the support provided for renewables). The second is the purely cyclical fluctuations in emissions that occur over the course of the business cycle: it is likely that emissions fall when the economy is in a bust and rise when it is booming. Even an economy where emissions have been declining over the longer-term may experience an increase in emissions if the economy is in the midst of a strong boom.

To separate these two forces, we decompose emissions and real GDP into a trend and a cyclical component and look separately at decoupling at the trend and cyclical frequencies. To estimate the trend relationship, we regress (the log of) trend emissions, ${e^{\tau}}_t$ on (the log of) trend real GDP, ${y^{\tau}}_t$:

$$\ln {e^{\tau}}_t = \gamma + \beta^{\tau} \ln {y^{\tau}}_t + {\varepsilon^{\tau}}_t \tag{2}$$

where ${\varepsilon^{\tau}}_t$ is a disturbance term satisfying standard assumptions and the estimate of the parameter β^{τ} provides evidence on the long-run or trend decoupling between emissions and real GDP—we refer to this estimate as the *trend elasticity* of emissions with respect to GDP. The estimated equation includes an intercept (γ) as countries start out from relatively different initial conditions and are therefore likely to have different levels of emissions in the absence of growth. [9]

Likewise, we estimate the cyclical relationship between emissions and real GDP:

$$\ln {e^{c}}_t = \beta^{c} \ln {y^{c}}_t + {\varepsilon^{c}}_t \tag{3}$$

where ${e^{c}}_t$ and ${y^{c}}_t$ are the cyclical components of the (log of) emissions and (log of) real output, respectively, ${\varepsilon^{c}}_t$ is a disturbance term satisfying standard assumptions and β^{c} captures how responsive emissions are to economic activity over the course of the business cycle—we refer to this as the *cyclical elasticity* of emissions with respect to GDP.[10]

To obtain the trend and cyclical components of emissions and real GDP, we use the filter most commonly used for this purpose in applied econometrics, viz., the HP filter (see Hodrick and

[9] In results available on request, we have also studied the relationship between trend emissions and trend GDP in a cointegration framework. The results from that approach are fairly similar to the simpler approach presented here.
[10] Equation (3) is akin to the cyclical relationship between the unemployment rate and real GDP – the so-called Okun's Law, a "sturdy empirical regularity" in advanced economies (Ball et al., 2017) and in many emerging markets and low-income countries (Ball et al., 2019; An et al., 2019). Cohen et al. (2018) refer to the cyclical relationship between emissions and real GDP as Environmental Okun's Law.

Prescott, 1981). Using real GDP to illustrate the details of the filter (similar steps are followed for emissions), the HP filter extracts the trend component by minimizing the following function:

$$\min_{\tau_t}\{\sum_{t=1}^{T}(y_t - y_t^{\tau})^2 + \lambda \sum_{t=1}^{T}[(y_t^{\tau} - y_{t-1}^{\tau}) - (y_{t-1}^{\tau} - y_{t-2}^{\tau})]^2\} \tag{4}$$

where y_t^{τ} is the trend component and λ is a parameter that determines how smooth the trend component is relative to the raw series y_t. The greater the value of λ, the larger is the penalty on variations of the trend's growth rate (i.e. the sum of the squares of the trend's second differences) and hence the smoother the trend component. We use two values of this smoothness parameter: 100 for advanced economies—which is the one typically used for annual data—and 12 for developing countries as suggested by Rand and Tarp (2002).

Though the HP filter is the most commonly-used method for trend/cycle decomposition, it is not without its critics. Hamilton (2018) argues that the filter can introduce “spurious dynamic relations that have no basis in the underlying data-generating process” and the problem can be more acute for filtered values at the end of the sample period. He has proposed his own filter that does not suffer from these limitations, which we use to ensure that our results are not dependent on the use of the HP filter.[11]

Following Hamilton’s approach, we estimate:

$$y_{t+h} = \gamma_0 + \sum_{j=0}^{k} \gamma_j \, y_{t-j} + u_{t+h} \tag{5}$$

where y_t equals the sum of the trend and cyclical components, that is, $y_t = y_t^{\tau} + y_t^{c}$. The stationary part of the regression (5) provides the cyclical component:

$$y_t^{c} = \hat{u}_t \tag{6}$$

while the trend is given by

$$y_t^{\tau} = \hat{\gamma}_0 + \sum_{j=0}^{k} \hat{\gamma}_j \, y_{t-h-j} \tag{7}$$

[11] For more details on *pros* and *cons* of the filtering techniques discussed in this section see Hodrick (2020).

The choice of h and k should be such that the residuals from estimating equation (5) are stationary. Based on the dynamics of both emissions and GDP, we choose $h = 2$, which is in line with Hamilton's suggested value for annual data, and $k = 3$.[12]

Figure 2.a: Trends and cycles in selected advanced economies

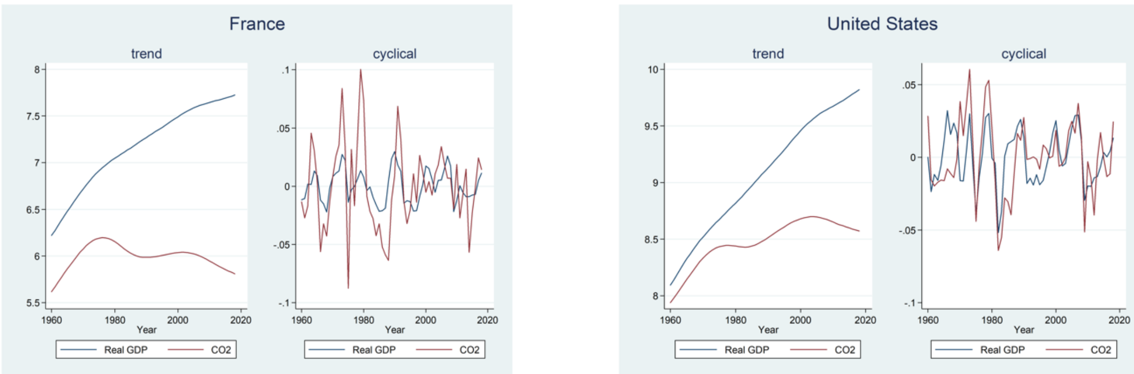


Figure 2.b: Trends and cycles in selected emerging market economies

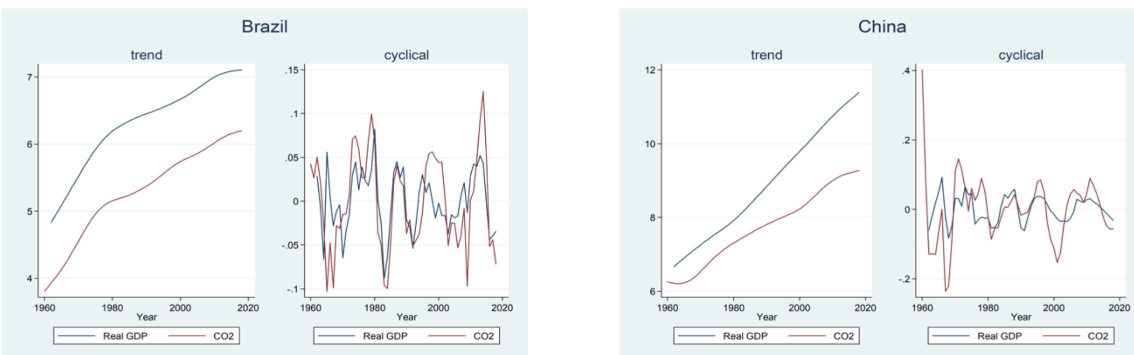
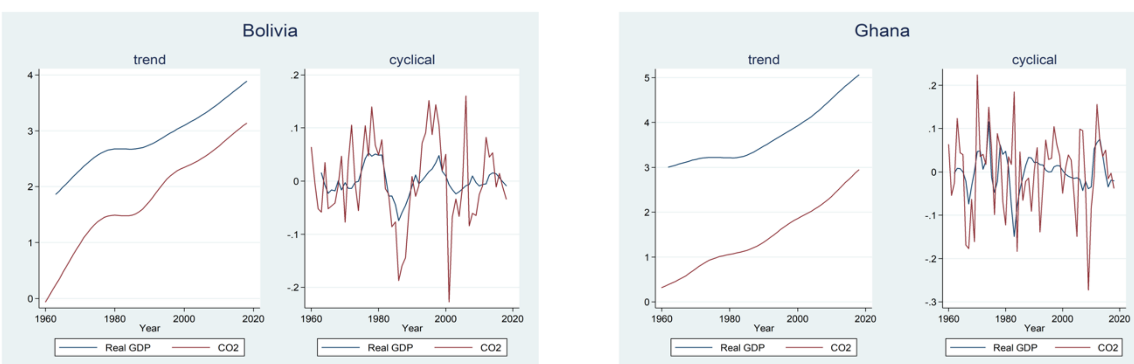


Figure 2.c: Trends and cycles in selected low-income countries



[12] We cross-checked our findings using alternative filtering methods, such as the Baxter-King and the Christiano-Fitzgerald random walk. Other methods exist such as the one explored in Chang et al. (2015), who develop a Bayesian reduced-rank method to decompose the series.

Equations (1), (2), and (3) are estimated using ordinary least squares (OLS) for each country in our dataset with at least 20 continuous observations for both real GDP and emissions. Before moving to detailed results, we illustrate our methods for a selected number of countries in Figure 2a, 2b and 2c covering advanced, emerging and low-income countries, respectively. The left-hand side of each panel shows the relationship between the trend components of emissions and real GDP (i.e. based on estimation equation (2)), while the right-hand side panel shows the cyclical relationship (based on equation (3)).

There is a sharp decoupling between trend emissions and trend real GDP for France and, in the later part of the sample, for the United States (Figure 2.a, left panel), while for emerging markets and low-income countries trend components still co-move— the exception being China in the more recent period (Figures 2.b and 2.c, left panels). In contrast, the right-hand panels show that for most countries, cyclical emissions track cyclical output closely across most countries, with peaks and troughs matching fairly well.

4. Separating Trends from Cycles

4.1 Baseline Results: Major Emitters

We begin by presenting estimates of the elasticity of emissions with respect to real GDP based on equation (1) discussed above. These estimates are reported in the first column of Table 1 for the twenty largest CO_2 emitters. With one exception (India), these estimates are all positive and range from 0.45 (Iran) to 1.7 (Italy).[13] Taken at face value, these estimates show only modest evidence of relative decoupling—over half of the elasticity estimates are close to or greater than one—and there is no evidence of absolute decoupling.

However, these estimates confound trend and cyclical movements as noted earlier. When we estimate equation (2), the evidence changes dramatically, as shown in column (2) of Table 1 and also displayed in Figure 3. Now, the estimates for the advanced economies and China are much lower than those in column (1) while the estimates for the emerging markets go up and sharply so in many cases. Moreover, a couple of advanced economies now show signs of absolute decoupling (Germany, UK) or close to it (France) and a few show signs of fairly strong relative

[13] There appear to be some issues with the emissions data for India for the initial years of the sample.

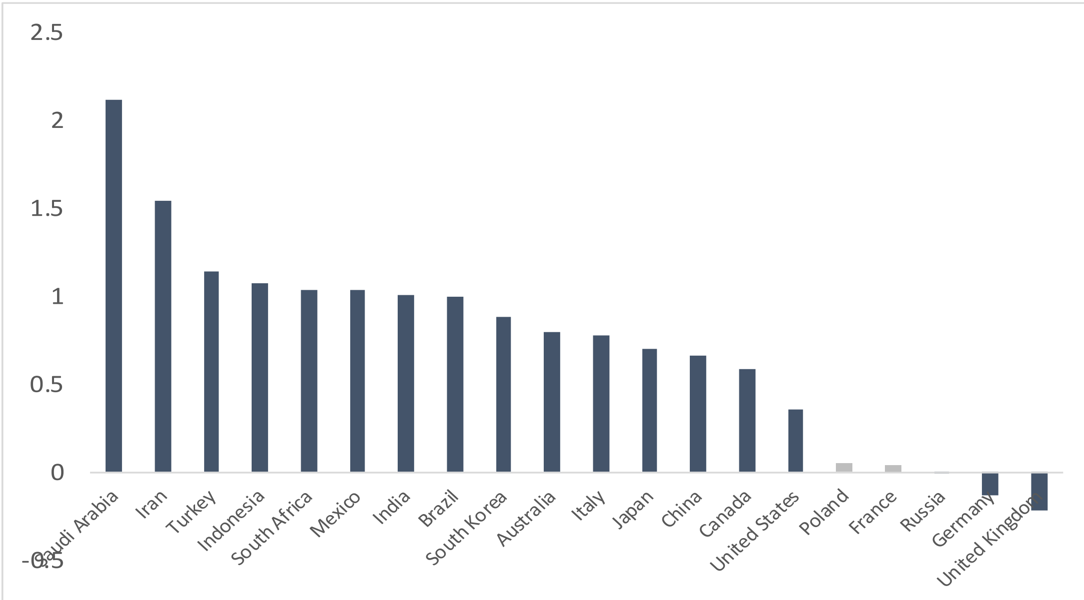
decoupling (e.g. the US coefficient is 0.35). This evidence largely bears out the evidence from the previous studies cited in the literature review of section 2.

Table 1: Trend and Cyclical Elasticities: Top 20 Emitters

	No. obs.	(1)	coef. >=1 (p-value)	(2)	coef. >=1 (p-value)	(3)	coef. >=1 (p-value)
Country		$\hat{\omega}$		$\hat{\beta}^{trend}$		$\hat{\beta}^{cyclical}$	
Australia	57	0.793***	0.124	0.795***	0.000	0.489***	0.001
		(0.177)		(0.020)		(0.156)	
Brazil	55	0.635***	0.004	0.997***	0.392	0.971***	0.429
		(0.132)		(0.012)		(0.162)	
Canada	57	0.964***	0.422	0.582***	0.000	0.661***	0.016
		(0.182)		(0.021)		(0.155)	
China	55	0.936***	0.384	0.658***	0.000	1.128***	0.697
		(0.216)		(0.012)		(0.247)	
France	57	1.586***	0.984	0.037	0.000	1.574***	0.979
		(0.266)		(0.039)		(0.275)	
Germany	57	0.893***	0.258	-0.134***	0.000	0.609***	0.006
		(0.163)		(0.030)		(0.150)	
India	57	-0.074	0.000	1.009***	0.701	0.194	0.000
		(0.138)		(0.017)		(0.166)	
Indonesia	57	0.782**	0.242	1.073***	1.000	0.875***	0.321
		(0.309)		(0.011)		(0.269)	
Iran	57	0.457***	0.000	1.541***	1.000	0.515***	0.000
		(0.102)		(0.072)		(0.079)	
Italy	57	1.664***	1.000	0.781***	0.000	1.297***	0.966
		(0.151)		(0.048)		(0.160)	
Japan	57	1.262***	0.976	0.700***	0.000	1.437***	0.994
		(0.129)		(0.023)		(0.170)	
Mexico	55	0.856***	0.201	1.033***	0.956	0.686***	0.015
		(0.171)		(0.019)		(0.140)	
Poland	54	0.496***	0.000	0.051	0.000	0.504***	0.000
		(0.128)		(0.045)		(0.091)	
Russia	27	0.648***	0.000	-0.006	0.000	0.730***	0.001
		(0.093)		(0.079)		(0.078)	
Saudi Arabia	55	0.548	0.134	2.121***	1.000	0.318	0.011
		(0.403)		(0.064)		(0.289)	
South Africa	55	0.642**	0.088	1.040***	0.874	0.922***	0.392
		(0.260)		(0.035)		(0.281)	
South Korea	57	0.837***	0.187	0.885***	0.000	0.535***	0.005
		(0.181)		(0.018)		(0.173)	
Turkey	57	0.761***	0.067	1.145***	1.000	0.810***	0.062
		(0.157)		(0.018)		(0.122)	
United Kingdom	57	0.900***	0.325	-0.217***	0.000	0.657***	0.018
		(0.219)		(0.025)		(0.161)	
United States	57	1.054***	0.645	0.352***	0.000	0.801***	0.083
		(0.146)		(0.020)		(0.142)	

Note: The table presents country-specific estimates. For further details refer to the main text. *, **, *** denote statistical significance at the 10, 5 and 1 percent levels, respectively; standard errors are in parentheses; p-values shown in the columns close to the point estimates refers to testing the null hypotheses H0: $\hat{\omega} \geq 1$, H0: $\hat{\beta}^{trend} \geq 1$, $H0$: $\hat{\beta}^{cyclical} \geq 1$, respectively.

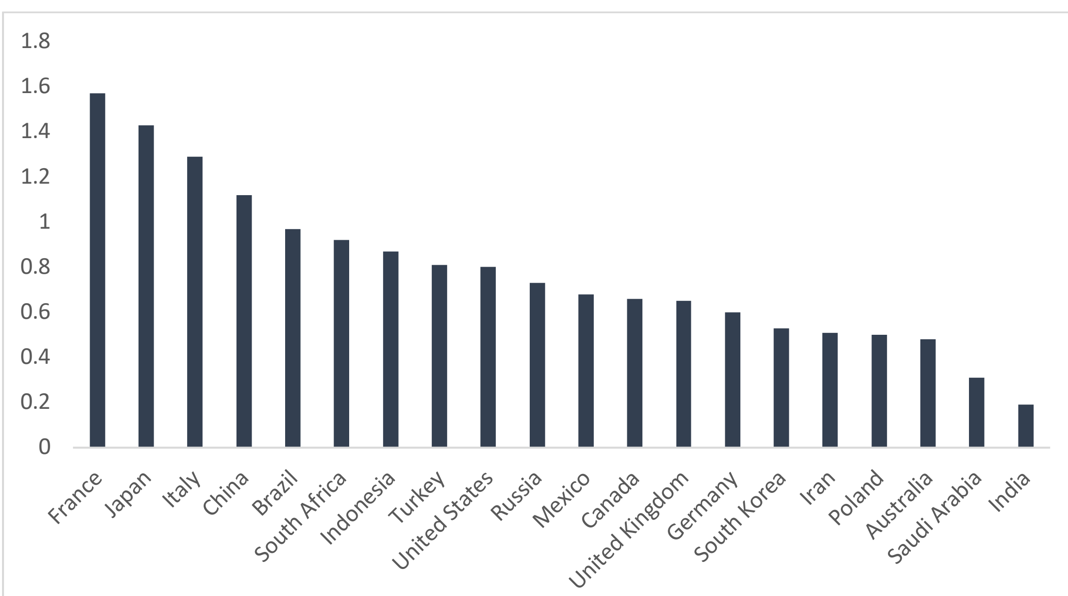
Figure 3: Trend elasticities of emissions with respect to real GDP



Note: Coefficients that are not statistically different from zero are shown in lighter color.

The results from estimating equation (3) are shown in column (3) of Table 1 and displayed in Figure 4. It is striking that these cyclical elasticities are all positive and fairly large in value. Moreover, the values for advanced economies tend to be just as large, on average, as for emerging markets, through there is a fair bit of heterogeneity within each income group.

Figure 4: Cyclical elasticities of emissions with respect to real GDP



4.2 Robustness and Sensitivity Exercises – Major Emitters

We carry out three robustness checks of the results just presented. First, we contrast the coefficients obtained from the more recent Hamilton (2018) filtering method with the baseline estimates obtained from using the HP filter. The first two columns of Table 2 show the estimates for the trend and cyclical elasticities for the top 20 emitters using Hamilton's method. Estimates are fairly similar between the two filtering methods for most countries in our sample—the correlation coefficients between the two sets of estimates are 0.94 and 0.79 for the trend and cyclical cases, respectively. Some notable differences between the HP and Hamilton filters are the trend estimates for Italy, Japan, and Russia.

Our second robustness check is to use an instrumental variable (IV) approach instead of OLS. Instrumental variable approach is usually adopted to address one of three problems: omitted variable bias (OVB), measurement error or reverse causality. In assessing the elasticities with respect to GDP we are most concerned about the first two aspects. First, our baseline specifications do not allow us to claim a full removal of OVB. Second, to some extent GDP and carbon emission data (especially) for lower income countries may be affected by measurement errors. In the best-case scenario, the measurement error does not correlate with the error term and OLS estimates are only imprecisely estimates with larger standard errors, making less likely to reject the null even when the effect is there.[14] But when the measurement error is correlated with the error term, this so-called attenuation bias creates endogeneity and can distort the coefficient itself. To address these potential issues, we use up to two lags of domestic real GDP growth and up to two lags of the growth rate of the main trading partners as instruments.[15] To check the validity of our instruments, we rely on the Kleibergen-Paap and Hansen statistics.[16] The estimates are given in the last two columns of Table 2. Estimates are fairly similar across the OLS and IV estimates—the correlation coefficients are 0.99 and 0.86 trend and cyclical case, respectively. Largest pairwise coefficient differences in the cyclical case can be found for Brazil and South Korea.

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[14] Especially in our case this is a minor issue since the effect is just to increase the unexplained (and unexplainable) part of the regression without affecting point estimates (it is worth mentioning that about 75% of our estimated coefficients are already significant at 95%).

[15] Data for the growth rate of main trading partners comes from the IMF´s World Economic Outlook.

[16] The Kleibergen-Paap rk Wald F statistic of weak exogeneity tests the validity of the instruments used. The null hypothesis of the Kleibergen-Paap test is that the structural equation is underidentified (i.e., the rank condition fails) and tests that the excluded instruments are "relevant". Stock-Yogo critical values were applied. The Hansen test is a test of overidentifying restrictions.

Table 2: Trend and Cyclical Elasticities-Robustness Checks: major emitters

	(Hamilton, OLS)				(HP, IV)			
	(1)		(2)		(3)		(4)	
Country	$\hat{\beta}^t$	**coef. >=1 (p-value)**	$\hat{\beta}^c$	**coef. >=1 (p-value)**	$\hat{\beta}^t$	**coef. >=1 (p-value)**	$\hat{\beta}^c$	**coef. >=1 (p-value)**
Australia	0.744***	0.000	0.430***	0.000	0.777***	0.000	0.598**	0.066
	(0.019)		(0.153)		(0.020)		(0.263)	
Brazil	1.032***	0.918	0.851***	0.155	1.008***	0.731	1.533***	0.934
	(0.023)		(0.145)		(0.013)		(0.349)	
Canada	0.488***	0.000	0.834***	0.140	0.548***	0.000	0.602**	0.048
	(0.020)		(0.153)		(0.020)		(0.235)	
China	0.635***	0.000	0.990***	0.482	0.653***	0.000	0.818**	0.304
	(0.017)		(0.226)		(0.012)		(0.353)	
France	-0.077**	0.000	1.322***	0.818	-0.030	0.000	1.312***	0.776
	(0.037)		(0.351)		(0.038)		(0.407)	
Germany	-0.201***	0.000	0.586***	0.006	-0.182***	0.000	0.191	0.001
	(0.032)		(0.159)		(0.029)		(0.256)	
India	0.980***	0.138	0.321*	0.000	0.998***	0.463	0.229	0.051
	(0.019)		(0.164)		(0.017)		(0.463)	
Indonesia	1.045***	0.996	0.830***	0.288	1.065***	1.000	0.824*	0.353
	(0.016)		(0.303)		(0.012)		(0.464)	
Iran	1.665***	1.000	0.482***	0.000	1.634***	1.000	0.599***	0.000
	(0.121)		(0.102)		(0.082)		(0.104)	
Italy	0.560***	0.000	1.341***	0.981	0.696***	0.000	1.016***	0.524
	(0.046)		(0.160)		(0.048)		(0.262)	
Japan	0.570***	0.000	1.251***	0.906	0.653***	0.000	1.689***	0.996
	(0.027)		(0.188)		(0.023)		(0.254)	
Mexico	1.012***	0.690	0.551***	0.003	1.025***	0.884	0.765***	0.153
	(0.024)		(0.155)		(0.021)		(0.227)	
Poland	-0.050	0.000	0.357***	0.000	-0.013	0.000	0.479***	0.000
	(0.043)		(0.120)		(0.044)		(0.107)	
Russia	0.148***	0.000	0.308**	0.000	0.008	0.000	0.429***	0.000
	(0.024)		(0.126)		(0.057)		(0.105)	
S. Arabia	1.744***	1.000	0.399	0.022	1.999***	1.000	0.066	0.009
	(0.098)		(0.292)		(0.061)		(0.384)	
S. Africa	1.015***	0.631	0.357	0.006	1.034***	0.810	1.254***	0.713
	(0.045)		(0.248)		(0.038)		(0.449)	
S. Korea	0.816***	0.000	0.594***	0.009	0.858***	0.000	1.221**	0.648
	(0.015)		(0.166)		(0.016)		(0.580)	
Turkey	1.090***	1.000	0.780***	0.036	1.122***	1.000	0.853***	0.260
	(0.016)		(0.120)		(0.017)		(0.227)	
UK	-0.236***	0.000	0.817***	0.169	-0.235***	0.000	0.533**	0.022
	(0.031)		(0.189)		(0.026)		(0.226)	
US	0.279***	0.000	0.970***	0.417	0.325***	0.000	0.815***	0.192
	(0.020)		(0.140)		(0.019)		(0.211)	

Note: The table presents country-specific estimates applying either the HP or Hamilton detrending methods and using either OLS or IV as estimating technique. For further details refer to the main text. *, **, *** denote statistical significance at the 10, 5 and 1 percent levels, respectively; standard errors are in parentheses; p-values shown in the columns close to the point estimates refers to testing the null hypotheses H0: $\hat{\beta}^{trend} \geq 1$, $H0$: $\hat{\beta}^{cyclical} \geq 1$, respectively.

A final useful sensitivity exercise to our baseline results is to check whether the estimates of the elasticities are stable over time. The evidence is presented in Table 3, which compares the elasticities for two sub-periods, 1960 to 1989 and 1990 to 2018. The trend elasticities are lower in the second sub-period in all but two cases; the exceptions are Brazil and Iran.[17] France, Germany and the UK show absolute decoupling over the second period, with the US also close to it. For resource-producing advanced economies (Australia, Canada) and many emerging markets the reduction in the trend elasticities is not only statistically significant but also economically relevant. In contrast, the cyclical elasticities are lower in only about half the cases, and they remain fairly high in several advanced and emerging economies.

Table 3: Trend and Cyclical Elasticities-Sub-sample stability: major emitters

	Trend Elasticities					**Cyclical Elasticities**				
	1960-89	**coef. >=1 (p-value)**	**1990-2018**	**coef. >=1 (p-value)**	**Direction of Change (if negative)**	**1960-89**	**coef. >=1 (p-value)**	**1990-2018**	**coef. >=1 (p-value)**	**Direction of Change (if negative)**
Country	$\widehat{\beta}^t$		$\widehat{\beta}^t$			$\widehat{\beta}^c$		$\widehat{\beta}^c$		
Australia	1.043***	1.000	0.487***	0.000	↓	0.457**	0.010	0.614***	0.044	
	(0.008)		(0.022)			(0.222)		(0.218)		
Brazil	0.892***	0.000	1.118***	1.000		0.870***	0.272	1.168***	0.736	
	(0.012)		(0.029)			(0.211)		(0.263)		
Canada	0.782***	0.000	0.334***	0.000	↓	0.556**	0.056	0.783***	0.060	
	(0.037)		(0.032)			(0.271)		(0.135)		
China	0.880***	0.000	0.640***	0.000	↓	1.009***	0.510	1.410***	0.889	
	(0.030)		(0.014)			(0.361)		(0.328)		
France	0.384***	0.000	-0.320***	0.000	↓	2.391***	0.999	0.779**	0.230	↓
	(0.069)		(0.075)			(0.420)		(0.294)		
Germany	0.218***	0.000	-0.643***	0.000	↓	0.811***	0.192	0.361*	0.002	↓
	(0.028)		(0.012)			(0.214)		(0.204)		
India	1.301***	1.000	0.777***	0.000	↓	-0.047	0.000	0.652**	0.132	
	(0.003)		(0.006)			(0.177)		(0.306)		
Indonesia	1.199***	1.000	0.946***	0.023	↓	0.873**	0.374	0.875**	0.372	
	(0.021)		(0.026)			(0.391)		(0.379)		
Iran	1.030***	0.655	1.419***	1.000		0.593***	0.000	0.055	0.000	↓
	(0.074)		(0.021)			(0.096)		(0.153)		
Italy	1.083***	0.899	-0.082	0.001	↓	1.117***	0.679	1.510***	0.994	
	(0.063)		(0.309)			(0.249)		(0.191)		
Japan	0.825***	0.000	0.347***	0.000	↓	1.624***	0.995	1.044***	0.566	↓
	(0.043)		(0.079)			(0.223)		(0.262)		
Mexico	1.204***	1.000	0.682***	0.000	↓	0.721***	0.107	0.612***	0.008	↓
	(0.014)		(0.031)			(0.220)		(0.153)		
Poland	0.780***	0.000	-0.159***	0.000	↓	0.513***	0.000	0.483**	0.004	↓
	(0.018)		(0.024)			(0.099)		(0.180)		

[17] For Russia, we do not have enough observations to estimate the elasticities for the first sub-period.

Russia			-0.006	0.000				0.730***	0.001	
			(0.079)					(0.078)		
S. Arabia	2.619***	1.000	1.284***	1.000	↓	0.204	0.032	1.039**	0.537	
	(0.090)		(0.025)			(0.412)		(0.410)		
S. Africa	1.268***	1.000	0.548***	0.000	↓	0.664*	0.181	1.212***	0.686	
	(0.054)		(0.019)			(0.363)		(0.433)		
S. Korea	1.096***	0.998	0.638***	0.000	↓	0.330	0.003	0.855***	0.296	↓
	(0.031)		(0.011)			(0.225)		(0.267)		
Turkey	1.313***	1.000	0.844***	0.000	↓	1.071***	0.633	0.636***	0.006	↓
	(0.021)		(0.018)			(0.208)		(0.136)		
United Kingdom	- 0.110***	0.000	- 0.592***	0.000	↓	0.834***	0.222	0.423*	0.012	↓
	(0.028)		(0.084)			(0.214)		(0.240)		
United States	0.519***	0.000	0.084*	0.000	↓	0.810***	0.199	0.785***	0.090	↓
	(0.042)		(0.046)			(0.222)		(0.156)		

Note: The table presents country-specific estimates by sub-period and indicates the direction of change with a downward facing arrow if negative. For further details refer to the main text. *, **, *** denote statistical significance at the 10, 5 and 1 percent levels, respectively; standard errors are in parentheses; p-values shown in the columns close to the point estimates refers to testing the null hypotheses H0: $\hat{\beta}^{trend} \geq 1$, $H0$: $\hat{\beta}^{cyclical} \geq 1$, respectively.

4.3 Additional evidence from the "Global South"

The previous analysis on top-emitters already includes a number of countries typically associated to the so-called "Global South" (for example, Brazil, China and India, among the others). There is no agreed list[18] but what is evident is that together with the Global North, the economic catching-up of the Global South has come at a high cost to the environment. Driven by its high energy intensity and the use of fossil fuels, the South has contributed a significant portion of global emissions during the last 30 years and is now contributing some 63 percent of today's total GHG emissions (including land-use change and forestry) (Fuhr, 2021). This sub-section focuses on this category of countries to shed light on how do emissions´ cyclical and trend components compare.[19]

Tables 4 and 5 show the results for the whole period of analysis and the two sub-periods previously identified for a group of 10 additional selected economies belonging to the "Global South", whose total emissions are above the median level observed in our sample. Several interesting findings emerge. First, trend elasticities are all positive and fairly large in value, with only five out of ten countries with statistically significant coefficients below unity (Chile, Colombia, Nigeria, Peru

[18] Terms such as "Global South" and "Global North" have been an integral part of a body of literature that has assessed economic, political, social and cultural inequalities at the global level. Ever since the Brandt Commission's Report in 1980 called for "a program of survival", the divisions between the wealthy North and the poor South have been widely known in policy circles. International organizations such as the World Bank, the International Monetary Fund and the UNDP have sought to classify countries according to their differing levels of economic and social development.

[19] We thank an anonymous referee for this suggestion.

and Vietnam). Again, this is a quite different picture with respect to that observed in previous sections for some advanced countries. More encouragingly, when looking at sub-periods estimates we observe some evidence of statistically significant relative decoupling in all but two cases (Thailand and Vietnam). Furthermore, four economies (Argentina, Dominican Republic, Philippines, and Thailand) that show trend elasticity above unity when considered over the whole sample period, are apparently moving towards relative decoupling since they show lower coefficients in the second sub-period than in the first one. Looking finally at cyclical elasticities, they are almost all positive and fairly large in value (exceptions are Venezuela and Vietnam). Also for the selected countries discussed in this section, the coefficients tend to be lower than the values observed in advanced economies, though with only minimal evidence of decrease over time.

Table 4: Trend and Cyclical Elasticities: ***Additional evidence from the Global South***

	No. obs.	**(1)**	**coef. >=1 (p-value)**	**(2)**	**coef. >=1 (p-value)**	**(3)**	**coef. >=1 (p-value)**
Country		$\hat{\omega}$		$\hat{\beta}^{trend}$		$\hat{\beta}^{cyclical}$	
Argentina	57	0.463***	0.000	0.990***	0.314	0.487***	0.000
		(0.078)		(0.021)		(0.075)	
Chile	59	0.848***	0.172	0.774***	0.000	0.800***	0.097
		(0.159)		(0.014)		(0.152)	
Colombia	57	0.762**	0.225	0.630***	0.000	0.788***	0.142
		(0.313)		(0.015)		(0.196)	
Dominican Republic	57	0.999***	0.498	1.071***	0.967	1.363***	0.903
		(0.334)		(0.038)		(0.276)	
Nigeria	29	0.979	0.491	0.836***	0.000	0.171	0.172
		(0.927)		(0.038)		(0.863)	
Peru	59	0.857***	0.282	0.893***	0.000	0.765***	0.111
		(0.246)		(0.014)		(0.190)	
Philippines	59	1.262***	0.837	1.012***	0.663	1.179***	0.814
		(0.264)		(0.028)		(0.199)	
Thailand	59	1.387***	0.899	1.255***	1.000	1.164***	0.810
		(0.300)		(0.017)		(0.185)	
Venezuela	57	0.075	0.000	1.072***	0.924	-0.050	0.000
		(0.170)		(0.050)		(0.139)	
Vietnam	56	-0.185	0.009	0.862***	0.000	-0.327	0.005
		(0.488)		(0.039)		(0.497)	

Note: The table presents country-specific estimates. For further details refer to the main text. *, **, *** denote statistical significance at the 10, 5 and 1 percent levels, respectively; standard errors are in parentheses; p-values shown in the columns close to the point estimates refers to testing the null hypotheses H0: $\hat{\omega} \geq 1$, H0: $\hat{\beta}^{trend} \geq 1$, $H0$: $\hat{\beta}^{cyclical} \geq 1$, respectively.

Table 5: Trend and Cyclical Elasticities-Sub-sample stability: ***Additional evidence from the Global South***

	Trend Elasticities					**Cyclical Elasticities**				
	1960-89	**coef. >=1 (p-value)**	**1990-2018**	**coef. >=1 (p-value)**	**Direction of Change**	**1960-89**	**coef. <=1 (p-value)**	**1990-2018**	**coef. <=1 (p-value)**	**Direction of Change**
Country	$\widehat{\boldsymbol{\beta}}^{t}$		$\widehat{\boldsymbol{\beta}}^{t}$		**(if negative)**	$\widehat{\boldsymbol{\beta}}^{c}$		$\widehat{\boldsymbol{\beta}}^{c}$		**(if negative)**
Argentina	1.336***	1.000	0.809***	0.000	↓	0.372***	0.000	0.561***	0.000	
	(0.025)		(0.008)			(0.128)		(0.089)		
Chile	0.638***	0.000	0.807***	0.000		0.743***	0.059	1.191**	0.668	
	(0.076)		(0.017)			(0.160)		(0.435)		
Colombia	0.805***	0.000	0.571***	0.000	↓	0.388*	0.005	0.999***	0.499	
	(0.007)		(0.044)			(0.221)		(0.297)		
Dominican Republic	1.434***	1.000	0.536***	0.000	↓	1.500***	0.870	1.109***	0.740	↓
	(0.050)		(0.042)			(0.435)		(0.301)		
Nigeria			0.836***	0.000				0.171	0.172	
			(0.038)					(0.863)		
Peru	1.089***	0.996	0.845***	0.000	↓	0.800***	0.110	0.724*	0.226	↓
	(0.030)		(0.010)			(0.159)		(0.362)		
Philippines	1.137***	0.963	0.763***	0.000	↓	1.258***	0.865	0.719	0.282	↓
	(0.074)		(0.033)			(0.230)		(0.481)		
Thailand	1.391***	1.000	1.027***	0.761	↓	1.581***	0.905	0.983***	0.442	↓
	(0.043)		(0.038)			(0.432)		(0.117)		
Venezuela	0.675***	0.000	0.825***	0.017		-0.327	0.000	0.021	0.000	
	(0.075)		(0.078)			(0.300)		(0.160)		
Vietnam	0.111	0.000	1.300***	1.000		-0.943	0.006	1.983***	0.973	
	(0.087)		(0.020)			(0.724)		(0.489)		

Note: The table presents country-specific estimates by sub-period and indicates the direction of change with a downward facing arrow if negative. For further details refer to the main text. *, **, *** denote statistical significance at the 10, 5 and 1 percent levels, respectively; standard errors are in parentheses; p-values shown in the columns close to the point estimates refers to testing the null hypotheses H0: $\hat{\beta}^{trend} \geq 1$, $H0$: $\hat{\beta}^{cyclical} \geq 1$, respectively.

5. Global Evidence on Decoupling

5.1 Trend and cyclical elasticities

This section presents estimates for our full set of 178 countries. In the main text of the paper, we restrict our attention to differences between the group of 36 advanced economies and the groups of 87 emerging market economies and 55 low-income countries (whose intersection we call also Emerging Market and Developing Economies – EMDE). The annex has detailed country-by-country estimates.

Table 6 presents summary statistics (the median, the inter-quartile range and the number of countries with elasticity<1 (and <0) at 90% confidence level) for the three country groups. Looking first at the trend elasticities, it is evident that these are quite different across the groups. The median trend elasticity in advanced economies is half of that in EMDE (EM and LIC show very similar coefficients).[20] Moreover, a quarter of the advanced economies shows evidence of absolute decoupling (with 10 out of 11 countries showing negative coefficients statistically significant at the 90%), whereas the first quartile elasticity for EMDE remains fairly high at 0.67 for EM and at 0.82 for LIC. At the other end as well, the third quartile value for advanced economies (0.80) is much lower than that for EM (1.29) and LIC (1.51). This results in only a third of EM and LIC showing statistically significant evidence of (at least) relative decoupling compared to almost all of AE (34 out of 36) having a trend elasticity significantly less than 1.

When looking at weighted means, as shown in Table A1 (note that as a weight, we used average emissions over time), trend elasticity coefficients are lower than their unweighted version in each country group. These findings seem to suggest that top emitters (regardless of country group) have a major role in decoupling (and this is true especially in EMDE where the coefficients go from 1 to about 0.7).

Table 6: Trend Elasticities—Summary Statistics for Country Groups

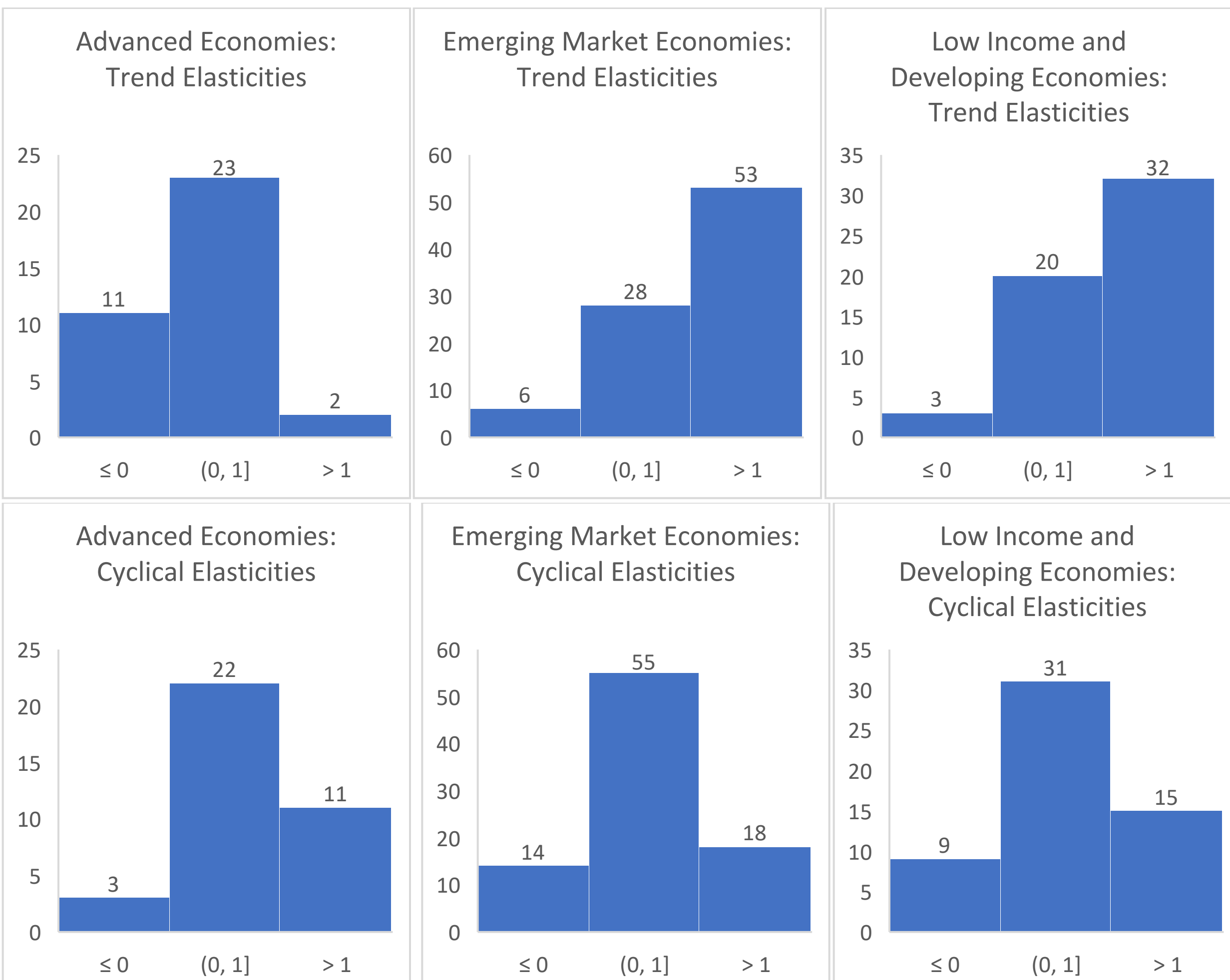
Country Group	**No. of countries**	**Q1**	**Median**	**Q3**	**No. of countries with elasticity<1 at 90% confidence level**	**No. of countries with elasticity<0 at 90% confidence level**
Trend Elasticities						
Advanced Economies	(36)	-0.101	0.481	0.795	34	10
Emerging market economies	(87)	0.667	1.072	1.293	32	3
Low Income and Developing Countries	(55)	0.820	1.134	1.512	21	2
Cyclical Elasticities						
Advanced Economies	(36)	0.499	0.659	1.188	21	1
Emerging market economies	(87)	0.182	0.644	0.959	42	7
Low Income and Developing Countries	(55)	0.170	0.532	1.032	26	1

Note: The table presents the first, second and third quartile of the respective trend and cyclical elasticities´ distributions by income group. The latest two columns indicate the number of countries with trend (cyclical) elasticity less than 1 (relative decoupling) or 0 (absolute decoupling) at 90% confidence level, respectively.

[20] The detailed results presented in the Annex confirm the findings of other studies that several European countries are in the forefront of decoupling and the energy transition. Lin and Li (2011) noted that Denmark, Finland, Sweden, Netherlands and Norway were the first adapters of carbon tax and demonstrated the carbon tax in Finland led to a significant and negative impact on the growth of CO2 per capita emissions. Andersson (2015) also found that the carbon tax was effective in reducing CO2 emissions in Sweden during 1990-2005. Urban and Nordensvard (2013) found out that the Nordic countries were the leaders in low carbon energy transitions.

Moving to the cyclical elasticities, these look far more similar between the three groups than the trend elasticities. The median elasticity is about the same (0.66 in AE vs. 0.64 in EM and 0.53 in LIC), and in this case it is actually the EMDE group that displays a more favorable inter-quartile range than the advanced economies: the first quartile value is lower in EMDE (0.18 in EM and 0.17 in LIC vs. 0.50 in advanced economies) as is the third quartile value (0.96 in EM and 1.03 in LIC vs. 1.19 in AE). Moreover, weighted means of cyclical elasticity coefficients are slightly higher than their unweighted version in each country group, with larger differences observed in EMDE (Table A2).

Figure 5: Frequency Distribution of Trend and Cyclical Elasticities, by Income Group



Note: Absolute frequency shown on vertical axes. The range of trend and cyclical elasticities are shown in the horizontal axes.

The plots of the frequency distributions, displayed in Figure 5, illustrate this difference clearly. The top panels show that the distribution of trend elasticities looks quite different in the two groups (AE vs EMDE). In advanced economies the distribution is right-skewed, with the majority of the economies with absolute (or close to absolute) decoupling and with relative (or close to relative) decoupling. The distribution for the EMDE group looks much more left-skewed, with a more than half of the economies for each sub-group clustered in the >1 range.

The distribution of cyclical elasticities looks much more similar between the three groups than was the case with the trend elasticities. Indeed, it appears quasi-symmetrical in all the groups with the majority of the countries clustered in the (0,1] range.

5.2 Asymmetries in cyclical elasticities

As the cyclical elasticity may not be symmetric between good and bad times, we take our analysis one step further and estimate the following reduced-form regression that explicitly differentiates the effect of output on emissions in boom versus bust periods:

$$\ln e^{c}{}_{t} = \beta^{c,boom} \ln y_t{}^{c,boom} + \beta^{c.bust} \ln y_t{}^{c,bust} + \varepsilon^{c}{}_{t} \qquad (8)$$

where $\ln y_t{}^{c,boom}$ is $\ln y_t{}^{c}$ from equation (3) when cyclical GDP is above trend (i.e. positive gap) and 0 otherwise; and $\ln y_t{}^{c,bust}$ is given by $\ln y_t{}^{c}$ when it is below trend (i.e. negative gap) and 0 otherwise.[21]

Figure 6a shows the effect for the top twenty largest emitters. Most countries (14 out of 20) experience sharper reductions in cyclical emissions when the economy is in a contractionary phase. Nevertheless, the quantitative difference between the elasticities in boom and bust periods is not very large. This result is in line with Burke et al. (2015), who found no significant differences in elasticities during expansions or contractions. For the US our finding is consistent with Sheldon´s (2017) who reports that for the U.S. the emissions-output elasticity is greater in recessions than in booms. If one splits the 178 countries by income groups, geographically the story is of greater

[21] We are aware that using higher frequency data could have led to more accurate results since yearly data can smooth over the important quarterly/monthly variation in recessions or busts. However, it is not possible to go higher frequency with such a heterogeneous panel of countries included in our analysis (especially for the numerous low-income economies).

emissions-output elasticity in recessions, on average, for countries in Latin America and Europe (Figure 6b).

Figure 6a: Cyclical elasticities in booms and busts

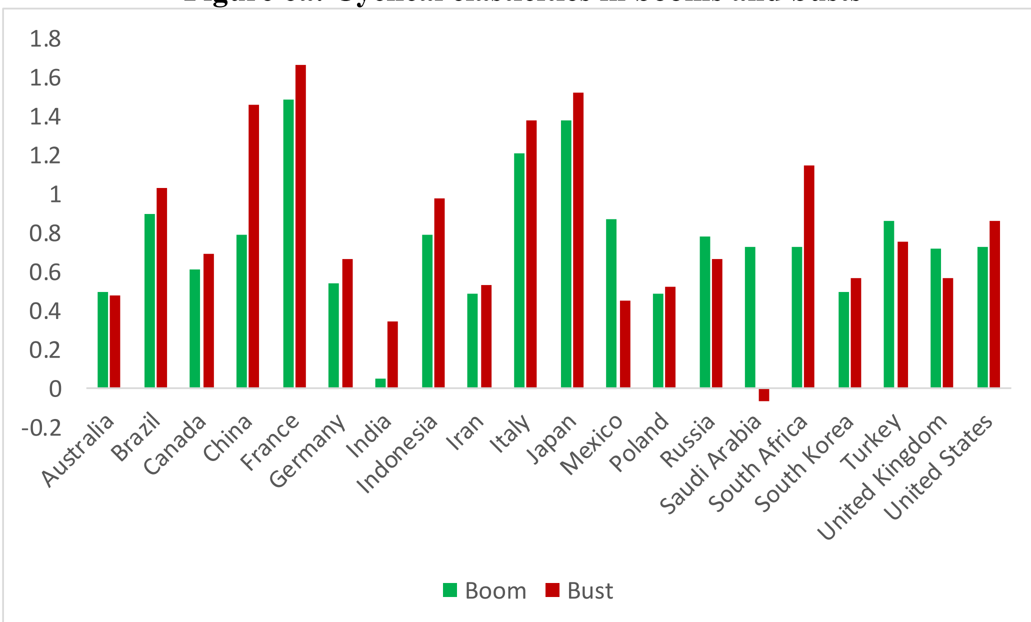
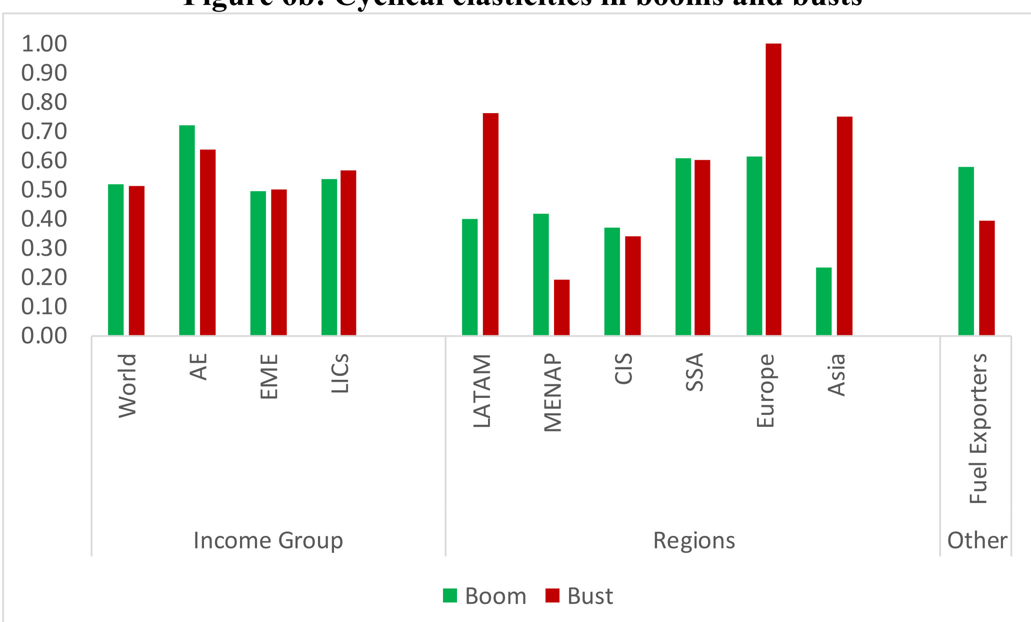


Figure 6b: Cyclical elasticities in booms and busts



Note: "Boom" and "Bust" denote positive and negative output gaps, respectively. See main text for details.

6. Conclusions

In this paper, we documented the changing relationship between emissions and real GDP for 178 countries over the last 60 years using a simple and transparent framework to separate trend movements from cyclical movements. The methods we use for the trend/cycle decomposition are similar to those used in empirical exercises in other fields of applied economics.

We find that the nature and the magnitude of the relationship between emissions and GDP has changed over time (Stavins, 2016). Estimates of the trend elasticities—the response to trend emissions to the change in trend GDP—show an absolute decoupling between emissions and GDP for some advanced economies but not yet for most emerging markets and developing economies (EMDEs). Among the top twenty emitting economies, the trend elasticity is lower over the 1990-2018 sub-period than over 1960-89 in virtually all cases.

Estimates of cyclical elasticities—the response of emissions to the business cycle—point to a strong relationship for the vast majority of countries. Unlike in the case of trend elasticities, cyclical elasticities are as high, on average, in advanced economies as in emerging markets and developing economies. Moreover, and again in contrast to the evidence for trend elasticities, cyclical elasticities are lower for only about half of the top twenty emitters in the post-1990 subperiod than over 1960-89. We also find little evidence of a strong asymmetry in cyclical elasticities: emissions go up about as much as booms as they decline in busts.

In ongoing work, we are attempting to identify the respective roles of (i) efficiency gains, (ii) change in the structure of production, and (iii) economic policies (e.g. policies to promote renewables) in explaining cross-country differences in the magnitude of trend and cyclical elasticities. Of course, these three factors are inter-related so a neat decomposition would be difficult. Nevertheless, it would be useful to get some sense of the extent to which progress of decoupling can be expected on the basis of the natural evolution of market economies toward the service sector and progress on cleaner technologies, and therefore of the extent of the push needed from government policies. There is a consensus that the extent of decoupling needed to achieve climate goals would be difficult in the absence of strong government interventions such as major increases in carbon taxes. However, there are questions about the political feasibility and distributive fairness of raising the tax to this level. Hence, it is worth considering if other complementary measures could be used to bring about the desired reduction in emissions. The forces driving the absolute decoupling in some advanced economies, particularly in Europe, can be instructive in offering a road map for other countries, particularly for the major emerging markets where progress on decoupling is essential to meeting climate goals.

ANNEX

The annex presents country-by-country results as well as results in which the EMDE group discussed in the main text is divided between an EM group of 87 countries and a LIC group of 55 countries.

Table A0: List of Countries and Income Group Classification: AE, EM and LIC

Country Group	Country	Period of analysis	Years with negative output gap ("busts")
AE	Australia	1960 - 2018	35
AE	Austria	1960 - 2018	33
AE	Belgium	1960 - 2018	31
AE	Canada	1960 - 2018	25
AE	Cyprus	1963 - 2018	27
AE	Czech Republic	1995 - 2018	12
AE	Denmark	1965 - 2018	28
AE	Estonia	1993 - 2018	15
AE	Finland	1960 - 2018	30
AE	France	1960 - 2018	29
AE	Germany	1960 - 2018	28
AE	Greece	1960 - 2018	34
AE	Hong Kong	1961 - 2018	30
AE	Iceland	1960 - 2018	25
AE	Ireland	1960 - 2018	28
AE	Israel	1961 - 2018	33
AE	Italy	1960 - 2018	32
AE	Japan	1960 - 2018	35
AE	Latvia	1992 - 2018	19
AE	Lithuania	1995 - 2018	14
AE	Luxembourg	1960 - 2018	29
AE	Malta	1979 - 2018	20
AE	Netherlands	1980 - 2018	22
AE	New Zealand	1965 - 2018	25
AE	Norway	1960 - 2018	31
AE	Portugal	1960 - 2018	29
AE	Singapore	1960 - 2018	29
AE	Slovak Republic	1993 - 2018	16
AE	Slovenia	1992 - 2018	20
AE	South Korea	1960 - 2018	31
AE	Spain	1960 - 2018	27
AE	Sweden	1960 - 2018	26
AE	Switzerland	1960 - 2018	34
AE	Province	1960 - 2018	29
AE	United Kingdom	1960 - 2018	33
AE	United States	1960 - 2018	28
EM	Albania	1960 - 2018	24
EM	Algeria	1963 - 2018	30
EM	Angola	1962 - 2018	29
EM	Antigua and Barbuda	1963 - 2018	28
EM	Argentina	1962 - 2018	26
EM	Armenia	1992 - 2018	19
EM	Aruba	1995 - 2018	12
EM	Azerbaijan	1992 - 2018	16
EM	Bahamas	1962 - 2018	26

EM	Bahrain	1962	-	2018	29
EM	Barbados	1963	-	2018	30
EM	Belarus	1981	-	2018	20
EM	Belize	1963	-	2018	29
EM	Bosnia and Herzegovina	1994	-	2018	14
EM	Botswana	1972	-	2018	30
EM	Brazil	1962	-	2018	29
EM	Brunei Darussalam	1985	-	2018	20
EM	Bulgaria	1960	-	2018	35
EM	Cape Verde	1963	-	2018	29
EM	Chile	1960	-	2018	29
EM	China	1962	-	2018	28
EM	Colombia	1962	-	2018	29
EM	Costa Rica	1960	-	2018	36
EM	Croatia	1992	-	2018	14
EM	Dominica	1963	-	2018	26
EM	Dominican Republic	1962	-	2018	25
EM	Ecuador	1969	-	2018	22
EM	Egypt	1962	-	2018	31
EM	El Salvador	1963	-	2018	29
EM	Equatorial Guinea	1963	-	2018	25
EM	Fiji	1963	-	2018	24
EM	Gabon	1963	-	2018	35
EM	Georgia	1990	-	2018	13
EM	Grenada	1963	-	2018	28
EM	Guatemala	1963	-	2018	30
EM	Guyana	1962	-	2018	27
EM	Hungary	1962	-	2018	30
EM	India	1960	-	2018	33
EM	Indonesia	1960	-	2018	28
EM	Iran	1960	-	2018	30
EM	Iraq	1998	-	2018	10
EM	Jamaica	1960	-	2018	31
EM	Jordan	1962	-	2018	27
EM	Kazakhstan	1992	-	2018	13
EM	Kuwait	1962	-	2018	27
EM	Lebanon	1962	-	2018	29
EM	Libya	1960	-	2018	32
EM	Malaysia	1962	-	2018	28
EM	Maldives	1971	-	2018	30
EM	Marshall Islands	1997	-	2018	9
EM	Mauritius	1960	-	2018	28
EM	Mexico	1962	-	2018	26
EM	Micronesia	1995	-	2018	11
EM	Morocco	1962	-	2018	26
EM	Namibia	1991	-	2018	19
EM	Oman	1964	-	2018	26
EM	Pakistan	1960	-	2018	30
EM	Panama	1960	-	2018	28
EM	Paraguay	1960	-	2018	36
EM	Peru	1960	-	2018	29
EM	Philippines	1960	-	2018	32
EM	Poland	1963	-	2018	30
EM	Qatar	1963	-	2018	27
EM	Romania	1962	-	2018	27
EM	Russia	1990	-	2018	15
EM	Samoa	1961	-	2018	32
EM	Saudi Arabia	1962	-	2018	25
EM	Serbia	1997	-	2018	12

EM	Seychelles	1963	-	2018	24
EM	South Africa	1962	-	2018	30
EM	Sri Lanka	1962	-	2018	29
EM	St. Kitts and Nevis	1981	-	2018	27
EM	St. Lucia	1962	-	2018	23
EM	St. Vincent and the Grenadines	1963	-	2018	29
EM	Suriname	1963	-	2018	26
EM	Syria	1960	-	2010	26
EM	Thailand	1960	-	2018	29
EM	Tonga	1976	-	2018	25
EM	Trinidad and Tobago	1963	-	2018	32
EM	Tunisia	1962	-	2018	26
EM	Turkey	1960	-	2018	31
EM	Turkmenistan	1992	-	2018	10
EM	Ukraine	1991	-	2018	15
EM	United Arab Emirates	1969	-	2018	22
EM	Uruguay	1962	-	2018	26
EM	Vanuatu	1963	-	2018	23
EM	Venezuela	1962	-	2018	27
LIC	Bangladesh	1962	-	2018	31
LIC	Benin	1962	-	2018	27
LIC	Bhutan	1970	-	2018	31
LIC	Bolivia	1963	-	2018	32
LIC	Burkina Faso	1962	-	2018	23
LIC	Burundi	1963	-	2018	29
LIC	Cambodia	1987	-	2018	21
LIC	Cameroon	1962	-	2018	26
LIC	Central African Republic	1963	-	2018	28
LIC	Chad	1963	-	2018	27
LIC	Comoros	1963	-	2018	27
LIC	Democratic Republic of the	1962	-	2018	30
LIC	Republic of Congo	1963	-	2018	32
LIC	Cote d'Ivoire	1962	-	2018	32
LIC	Djibouti	1990	-	2018	14
LIC	Eritrea	1994	-	2018	15
LIC	Ethiopia	1963	-	2018	27
LIC	Gambia	1963	-	2018	30
LIC	Ghana	1962	-	2018	28
LIC	Guinea	1963	-	2018	27
LIC	Guinea-Bissau	1980	-	2018	21
LIC	Haiti	1963	-	2018	28
LIC	Honduras	1963	-	2018	32
LIC	Kenya	1962	-	2018	26
LIC	Kiribati	1979	-	2018	22
LIC	Kyrgyz Republic	1992	-	2018	13
LIC	Lao P.D.R.	1963	-	2018	25
LIC	Lesotho	1990	-	2018	26
LIC	Madagascar	1960	-	2018	35
LIC	Malawi	1963	-	2018	30
LIC	Mali	1962	-	2018	24
LIC	Mauritania	1990	-	2018	17
LIC	Moldova	1990	-	2018	16
LIC	Mongolia	1960	-	2018	33
LIC	Mozambique	1963	-	2018	23
LIC	Myanmar	1998	-	2018	13
LIC	Nepal	1960	-	2018	28
LIC	Nicaragua	1963	-	2018	25
LIC	Niger	1962	-	2018	26
LIC	Nigeria	1990	-	2018	12

LIC	Papua New Guinea	1963 - 2018	32
LIC	Rwanda	1960 - 2018	24
LIC	Sao Tome and Principe	1963 - 2018	29
LIC	Sierra Leone	1963 - 2018	27
LIC	Solomon Islands	1963 - 2018	26
LIC	Sudan	1962 - 2018	27
LIC	Tajikistan	1992 - 2018	14
LIC	Tanzania	1962 - 2018	31
LIC	Togo	1962 - 2018	26
LIC	Uganda	1963 - 2018	29
LIC	Uzbekistan	1991 - 2018	13
LIC	Vietnam	1963 - 2018	27
LIC	Yemen	1990 - 2018	19
LIC	Zambia	1962 - 2018	32
LIC	Zimbabwe	1998 - 2018	11

Trend Relationship between Emissions and Real GDP

Advanced economies have the lowest mean trend elasticity (0.38)—Table A1—and are the only group of countries for which this elasticity is lower than the mean cyclical elasticity (0.78). There is nonetheless heterogeneity within the 36 advanced countries. Output in richer economies (e.g. UK, Germany, Sweden) tends to be correlated with a decrease in CO_2 emissions, while countries such as Greece, Portugal or Spain are at the other end of the spectrum with positive estimates above 0.9 (Greece has the highest trend estimate at 1.49). Looking at the weighted mean (note that as a weight, we used average emissions over time), the coefficients are lower than their unweighted version in each country group. Perhaps this means that top emitters (regardless of country group) have a major role in decoupling (and this is true especially in EMDE where the coefficients go from 1 to about 0.7).[22]

Table A1: Trend Elasticities—Summary Statistics for Country Groups

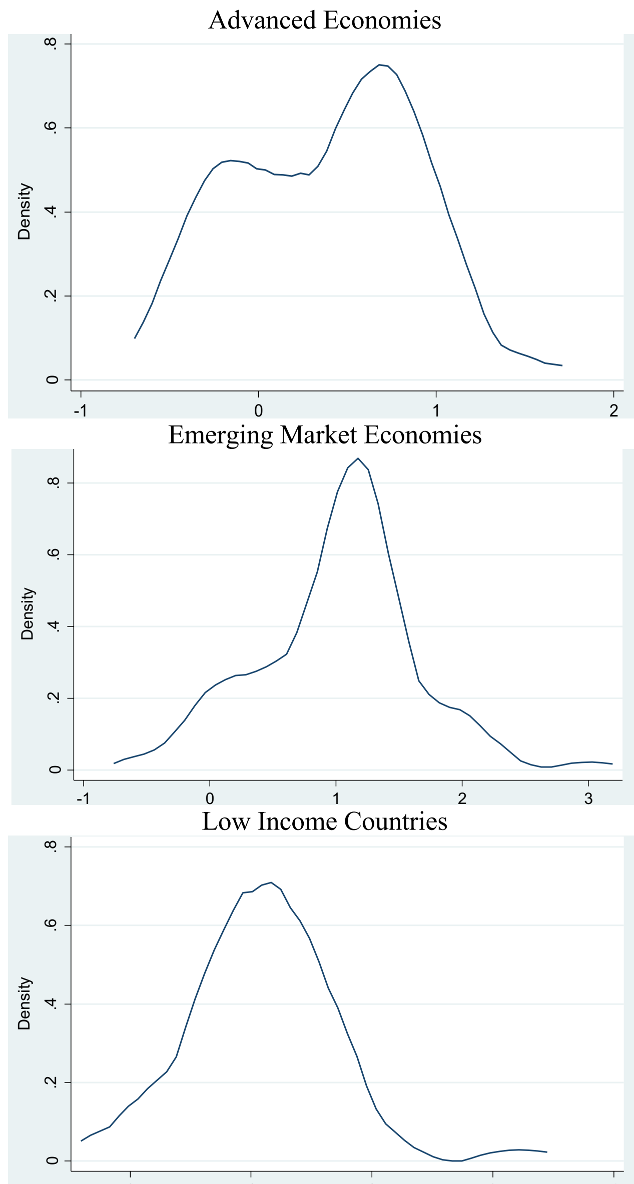
Country group	No. of countries	Mean	Standard deviation	Q1	Q3	Weighted Mean
Advanced Economies	(36)	0.383	0.499	-0.101	0.795	0.354
Emerging market economies	(87)	1.043	0.727	0.667	1.293	0.667
Low Income and Developing Countries	(55)	1.150	0.628	0.820	1.512	0.681

Note: The table presents each income group´s descriptive statistics. For weighted mean, we used average emissions over time as a weight.

[22] We thank an anonymous referee for this suggestion

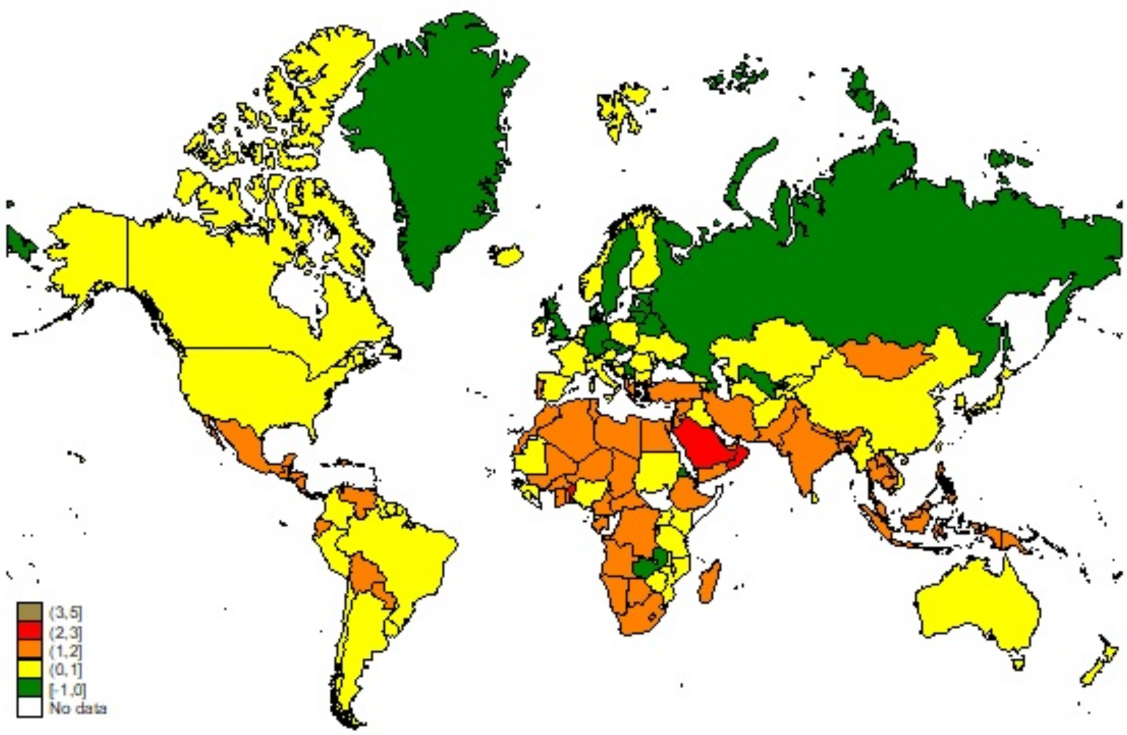
Figure A1 maps the trend elasticities for each country group in our sample. The mean trend coefficients for the entire sample is 1.01 (with the median trend at 1.04) and estimates tend be statistically significant for the vast majority of countries (152 out of 178). Figure A2 plots in a world-map format the trend elasticities for each country in our dataset with a color gradient such that greener means decoupling.

Figure A1: Differences in Trend Elasticities across Country Groups



Note: Epanechnikov Kernel densities with x-axis denoting the value of trend elasticities.

Figure A2: Trend Elasticities Around the World



Note: The world map plots the trend elasticities for each country irrespectively of their statistical significance.

Several emerging markets and low-income countries have trend above 1, in particular, oil producers (such as Libya, Oman, Iran, and Saudi Arabia) and small island states (such as Haiti, Kiribati, Seychelles, Tonga, Antigua and Barbuda, St. Kitts and Nevis, Maldives, and Mauritius). After power plants, oil and natural gas production is a major source of CO_2 emissions. The continued heavy reliance on these sectors leads to high trend estimates in oil producing countries. Among the highest emitters per capita, small island states tend to have energy markets that rely heavily on fossil fuels. This dependence helps explain the predominance of extreme trend coefficients. The mean of the statistically significant trend coefficients (78 emerging countries) is 1.12. The mean trend estimate for the 53 low-income countries for which it is statistically significant is 1.17, pushed by heavy outliers (Benin and Haiti with coefficients above 2) and several African countries with coefficients greater than unity (Burundi, Cote d´Ivoire, Ghana, Madagascar, Niger).

More than 76 percent of developing markets show a strong long-run correlation of CO_2 emissions and GDP (trend estimates above 0.5), while mostly eastern European countries (Estonia, Latvia, Lithuania, Slovak Republic) have a negative long-run emissions-output relationship.

All in all, several advanced economies have managed to transition to a low-carbon path with trend real GDP and trend emissions moving in opposite directions. For about half of the countries in our sample, trend elasticities are below 1. Interestingly, output in Belarus, Germany, Czech Republic, Latvia, Lithuania, Luxembourg, Macedonia, Slovakia, Sweden, the United Kingdom, Uzbekistan or Denmark tends to be correlated with a decrease in CO_2 emissions – hence some signs of "absolute decoupling". From a global perspective, the Nordic European countries achievements to date towards a carbon-neutral future are significant.

Cyclical Relationship between Emissions and Real GDP

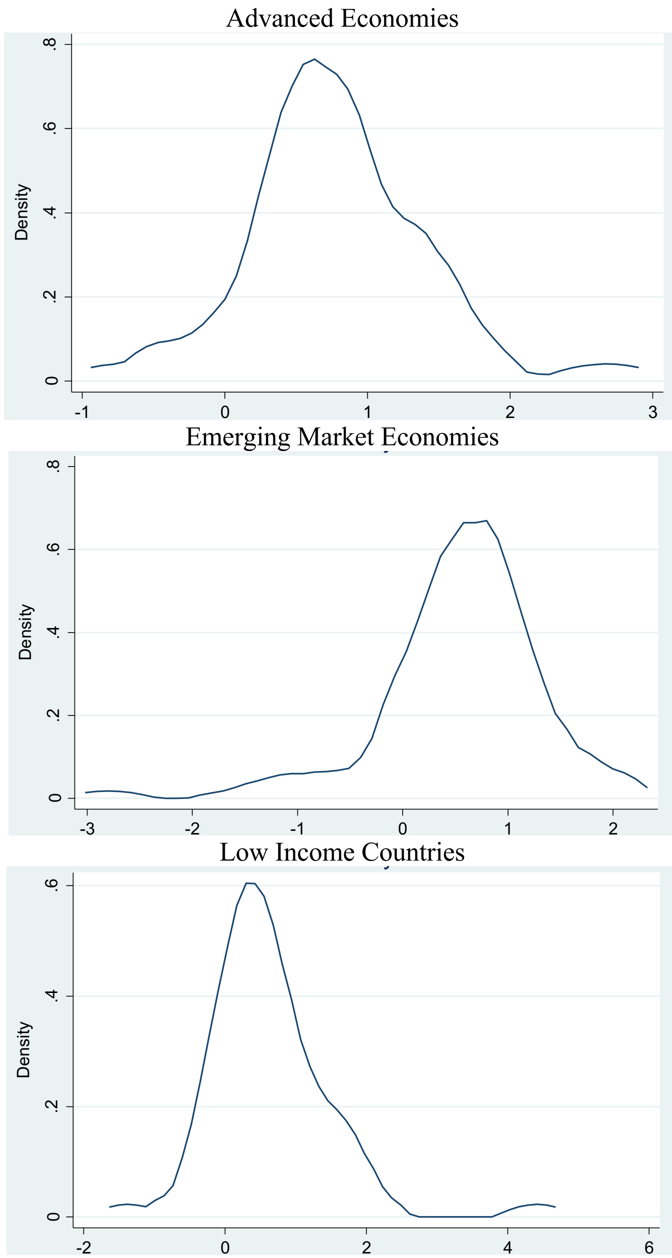
Table A2 shows that the differences among country groups in the cyclical elasticities, on average, are much smaller than the differences in trend elasticities. The distribution of elasticities is also more similar (Figure A3), though it is worth noting that some advanced countries show signs of decoupling even for cyclical elasticities—these cases would merit further study in future research. Looking at the weighted mean the coefficients are higher than their unweighted version in each country group with larger differences observed in EMDE.

Table A2: Cyclical Elasticities—Summary Statistics for Country Groups

Country group	No. of countries	Mean	Standard deviation	Q1	Q3	Weighted Mean
Advanced Economies	(36)	0.781	0.619	0.499	1.188	0.868
Emerging market economies	(87)	0.540	0.771	0.182	0.959	0.786
Low Income and Developing Countries	(55)	0.648	0.827	0.170	1.032	0.827

Note: The table presents each income group´s descriptive statistics. For weighted mean, we used average emissions over time as a weight.

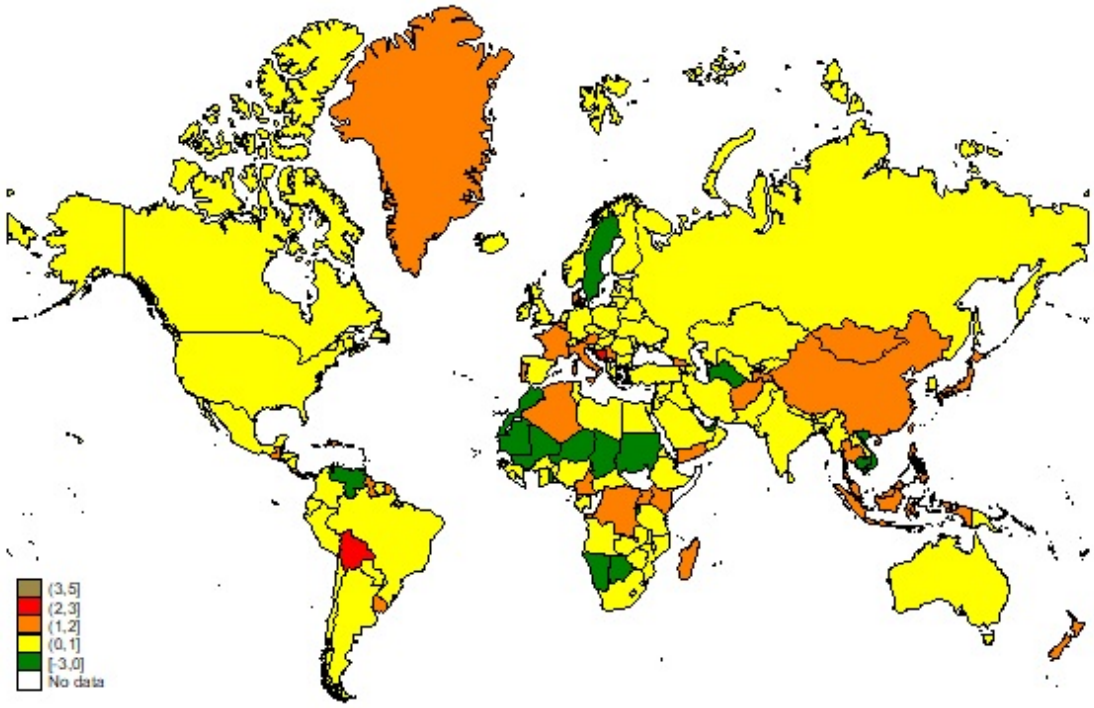
Figure A3: Differences in Cyclical Elasticities across Country Groups



Note: Epanechnikov Kernel densities with x-axis denoting the value of cyclical elasticities.

Figure A4 maps the (short-run) cyclical elasticities for each country in our sample. Elasticities are positive and statistically different from zero at the 10 percent level for 102 countries. In slightly more than 50 percent of the sample we obtained estimates above 0.5. Emissions are highly procyclical in countries such as Albania, Austria, Belgium, Bolivia, France, Japan or Singapore, but only countercyclical in Brunei, Maldives, Tonga and the United Arab Emirates.

Figure A4: Cyclical Elasticities around the World



Note: The world map plots the cyclical elasticities for each country irrespectively of their statistical significance.

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