Baran Doda

Evidence on business cycles and CO2 emissions

Article (Accepted version) (Refereed)

Original citation:
Doda, Baran (2014) *Evidence on business cycles and CO2 emissions.* Journal of Macroeconomics, 40. pp. 214-227. ISSN 0164-0704

DOI: 10.1016/j.jmacro.2014.01.003

Evidence on Business Cycles and CO2 Emissions

Baran Doda[1,*]

Grantham Research Institute on Climate Change and the Environment
London School of Economics and Political Science
Houghton Street, London WC2A 2AE, United Kingdom
Email: L.B.Doda@lse.ac.uk

Abstract

CO_2 emissions and GDP move together over the business cycle. Most climate change researchers would agree with this statement despite the absence of a study that formally analyzes the relationship between emissions and GDP at business cycle frequencies. The paper provides a rigorous empirical analysis of this relationship in a comprehensive cross-country panel by decomposing the emissions and GDP series into their growth and cyclical components using the HP filter. Focusing on the cyclical components, four robust facts emerge: 1) Emissions are procyclical; 2) Procyclicality of emissions is positively correlated with GDP per capita; 3) Emissions are cyclically more volatile than GDP; and 4) Cyclical volatility of emissions is negatively correlated with GDP per capita. These facts are potentially important for the calibration of theoretical models used to evaluate climate change mitigation policies.

Keywords: business cycle fluctuations, climate change, CO_2 emissions

1. Introduction

Most climate change researchers have the intuition that CO_2 emissions and GDP move together as economic activity expands and contracts. While this intuition is confirmed in a few studies of individual OECD members, to the best of my knowledge there exists no paper which systematically studies the cyclical properties of emissions in a comprehensive panel of countries. A key benefit of a deeper understanding of the relationship between emissions and GDP at business cycle frequencies is that it allows us to think about climate change mitigation policies in a broader macroeconomic context.

Motivated by the gap in the literature, this paper provides a simple, rigorous and consistent analysis of the cyclical properties of emissions in a cross-country panel. Specifically, I decompose the observed emissions and GDP series into growth and cyclical components using the Hodrick-Presscott (HP) filter, and focus on the filtered series. Four facts emerge from this analysis:

* Corresponding author

[1] I have benefitted from comments by Alex Bowen, Antoine Dechezleprêtre, Sam Fankhauser, Hoseok Kim, Aiden Selsick and an anonymous referee. The usual disclaimer applies. Financial support from the Global Green Growth Institute, the Grantham Foundation for the Protection of the Environment, as well as the Centre for Climate Change Economics and Policy is gratefully acknowledged.

1. Emissions are procyclical in a typical country.
2. Procyclicality of emissions is positively correlated with GDP per capita across countries.
3. Emissions are cyclically more volatile than GDP in a typical country.
4. Cyclical volatility of emissions is negatively correlated with GDP per capita across countries.

Fact 1 confirms the intuition of most climate change economists that emissions are procyclical. Making use of the terminology from the real business cycle literature, emissions are said to be procyclical in this context if there is a positive correlation between the cyclical components of emissions and GDP, i.e. $\rho_{ey} > 0$. In other words, procyclicality implies that emissions are above trend during booms and below it during recessions. While fact 1 is about *the sign of* ρ_{ey} in a given country, fact 2 focuses on how *the magnitude of* ρ_{ey} varies with GDP per capita across countries. Specifically, fact 2 establishes that the cross-country correlation between ρ_{ey} and $GDPpc_{2009}$ is positive. Put differently, emissions and GDP are more tightly coupled at business cycle frequencies in countries which have a higher GDP per capita in 2009.

Facts 3 and 4 concern the cyclical volatility of emissions measured by the standard deviation of the series. In fact 3, I show that the cyclical volatility of emissions is greater than that of GDP in most countries, i.e. $\sigma_e > \sigma_y$. It is relatively well established and understood that economies become more stable as they become richer. Fact 4 demonstrates that the phenomenon is valid in the case of emissions as well by establishing that cyclical volatility of emissions and GDP per capita in 2009 are inversely related. Taken together these facts have potentially important implications for the calibration of theoretical models as well as the volatility of prices and allocations in emissions trading schemes around the world.

This is an empirical paper, and a theory of emissions determination over the business cycle is beyond its scope. However, it does have potentially significant implications for the theoretical analysis of the emissions-GDP relationship in environments featuring business cycle fluctuations.[2] Two recent theoretical papers push the research frontier precisely along this dimension. The main focus of Heutel [16] is how optimal abatement policies respond to business cycle fluctuations induced by shocks to total factor productivity. After demonstrating the higher volatility and procyclicality of emissions in the US, the author studies the optimal emissions mitigation policy in a calibrated dynamic stochastic general equilibrium (DSGE) model. His model implies that optimal policy dampens the procyclicality of emissions.[3]

A number of similarities and differences in the empirical sections of Heutel [16] and the current paper are noteworthy. Heutel [16] also uses the HP filter and finds that US emissions are procyclical. However, he stops short of extending the analysis beyond the US. Moreover, his results are sensitive to the elasticity of emissions with respect to output, a parameter closely related to the procyclicality and relative volatility of emissions studied in this paper. As I argue below, the variation in the calibration target for this parameter makes it hard to contemplate what his model would prescribe for policy in countries other than the US.

[2]See Fischer and Heutel [14] for a review.

[3]For a similar model which includes environmental shocks in addition to productivity shocks, see Angelopoulos et al. [3].

Whereas the focus is on optimal mitigation policy in Heutel [16], Fischer and Springborn [15] study the implications of alternative policy instruments (i.e. a cap, a tax or an intensity target) on levels and volatilities of macroeconomic variables in a real business cycle environment. The authors find that all policies imply a reduction in the levels of consumption and output for a given emissions reduction target but that the extent of the decline is the smallest under the intensity target.[4] While the intensity target achieves a given emissions reduction at minimum welfare cost, it also implies greater volatility for consumption, emissions and output than the cap. Indeed, the volatilities of all variables are lower under the cap relative to no policy, tax or intensity target. I come back to this matter in section 5.

There exists a large and related literature on the environmental Kuznets curve relationship as applied to the case of CO_2 emissions. The central theme in this literature is to confirm or contradict the existence of an inverse-U relationship between per capita emissions and GDP. Early results, e.g. Holtz-Eakin and Selden [18] and Schmalensee et al. [26] find evidence in favor of a carbon Kuznets curve while more recently Aldy [2] and Wagner [30], among others, present evidence to the contrary, and cast doubt on the validity of the econometric techniques previously used. The difference between the current paper and the literature on this topic is my explicit focus on the behavior of emissions and GDP over the business cycle. In other words, whereas the carbon Kuznets curve literature is concerned with the relationship between the *levels* of emissions and GDP *in the long run*, the current paper studies the relationship between the *cyclical components* of emissions and GDP *at business cycle frequencies*.

Similarly, Stefanski [27] studies the effect of structural transformation on a country's emissions and energy intensity profiles. His paper empirically establishes that in a typical country emissions intensity follows a hump-shaped pattern while energy intensity is broadly declining. He then uses a two sector general equilibrium model with endogenous fuel switching to account for these observations. Stefanski [27] also uses the HP filter to decompose the emissions and GDP series into their growth and cyclical components. Whereas his goal is to analyze and explain the relationship between the growth components of the series over long periods of time, the current paper studies the relationship between the cyclical components of the same series.

An older and large empirical literature dating back to Kraft and Kraft [21] and reviewed in Payne [24] studies the direction of the causal relationship between output and energy consumption. These studies employ various time series econometric techniques to identify the direction of causality between output and energy. The results are varied by geographical and temporal coverage of the samples, and the econometric methodology used.

While most papers in this literature have a long run focus, at least three studies which use monthly US data concentrate on the business cycle horizons. Erol and Yu [13] uses frequency domain techniques to find that energy consumption responds positively to industrial production. Similarly, Thoma [28] shows that changes in macroeconomic conditions cause significant changes in electricity consumption, particularly in the commercial and industrial sectors. Narayan et al. [23] uses a simple model in the Keynesian

[4] These reductions are not surprising because policy imposes a restriction on a productive input. Whether policy intervention is optimal or not cannot be evaluated in Fischer and Springborn [15] because damages from emissions are not modeled.

tradition to argue that permanent shocks explain most of the variation in energy consumption and output. All three papers are consistent with fact 1 of the current paper regarding the positive correlation between emissions and GDP. However, it should be noted that the link between energy and emissions can be far from clear because countries differ greatly in the share of fossil fuels in the total primary energy supply.

Kim and Loungani [19] also studies the relationship between output and energy, but does so using a real business cycle approach. The paper's strategy is to solve and simulate a DSGE model featuring total factor productivity and energy price shocks. The authors report that when the model is calibrated to the US, output and energy consumption are positively correlated and energy consumption is more volatile than output. These results are very similar to facts 1 and 3 of the current paper.

Bowen et al. [6] deals with a related but different matter: the emissions implications of the financial crisis of 2007-8 and the unusually large recession it triggered. It anticipates the central research question of the current paper by including a brief discussion of the relationship between the first-differenced GDP and CO_2 emissions series for the world and the US. The positive correlation the authors report is entirely consistent with fact 1. However, the geographic coverage of their sample is limited and their attention focuses on first-differenced series only.

The rest of this paper is organized as follows. In Section 2 I describe the data sources and the filter employed to decompose the raw data into growth and cyclical components. Section 3 establishes four facts about emissions. I undertake an extensive robustness analysis in Section 4 and present some corroborating evidence from long time series for a smaller set of countries. I discuss the implications of my results and conclude in Section 5.

2. Data and methods

CO_2 emissions, GDP and GDP per capita are the key variables of interest in this paper. Hereafter, their natural logarithms are denoted $EMIS_{it}$, GDP_{it} and $GDPpc_{it}$ where subscripts i and t indicate country and year respectively. $EMIS_{it}$ is from Boden et al. [5] at the Carbon Dioxide Information Analysis Center (CDIAC) of Oak Ridge National Laboratory in the US, which maintains one of the most reliable, comprehensive and current databases with long time series for CO_2 emissions for all countries of the world. While the main database contains observations up to and including 2009, preliminary estimates for several emitters are also available for 2010 and 2011. I include these in my sample. $EMIS_{it}$ is expressed in thousand metric tons of carbon. GDP_{it} and $GDPpc_{it}$ are drawn from the January 2013 version of the Conference Board [11] Total Economy Database, which provides data from 1950 onwards for most countries in the world. Both GDP_{it} and $GDPpc_{it}$ are in 1990 US$ which are converted using Geary-Khamis PPPs.

By combining information from these sources, I construct a core sample consisting of 122 countries for whom contiguous data on CO_2 emissions and GDP exist for all or some of the period covering 1950-2011. The result is an unbalanced panel of 81 countries with data for 60 years or more and 100 countries with data for 40 years or more. Those with less than 40 years of data are primarily ex-communist countries. Table 9 in the Appendix provides more detailed information about the countries in the core sample.

There are also other data sources for emissions such as the Climate Analysis Indicators Tool (CAIT) of the World Resources Institute [31] and the Emissions Database for Global

Atmospheric Research (EDGAR) of the European Commission and the Netherlands Environmental Assessment Agency, EC-JRC/PBL [12]. CAIT provides CO_2 emissions data for a large group of countries until 2008, whereas EDGAR has CO_2 emissions data for 1970-2008. I use data from these two sources to validate the results I obtain with CDIAC data. Furthermore, EDGAR also provides time series for greenhouse gases such as CH_4 and N_2O emissions. Moreover, it is possible to extend the time series coverage of the core data set at the cost of losing substantial international coverage. Specifically, longer time series on GDP for select countries are available from Maddison [22] so that for a group of 23 countries there is contiguous emissions and GDP data for more than 100 years. I use data obtained from these sources for the robustness checks in Section 4.

A relatively novel aspect of the current paper's approach to emissions is that I decompose the observed time series into growth and cyclical components using the HP filter. It should be noted that the use of the HP filter to identify business cycles is not without its critics. See in particular Canova [8] and a response to it in Burnside [7]. In the current paper, I give the HP filter default status because as Ravn and Uhlig [25] observes, the HP filter 'has become a standard method for removing trend movements in the business cycle literature' and also because 'it has withstood the test of time and the fire of discussion remarkably well.' This approach allows me to abstract from potentially different and time varying growth trends in emissions and GDP, and focus on the movements of these variables about their growth trend at business cycle frequencies. Clearly, the results may then be sensitive to the filter employed. To this end, I also report results from three other filters often used in the business cycle literature: first order differencing, the band pass filter and the random walk band pass filter. As shown in the Section 4 below, the central results are not different when alternative filters are used.

Table 1 provides the key for the variables and statistics that are used in establishing the stylized facts about emissions. The lower case variables $emis_{it}$ and gdp_{it} denote the cyclical components of emissions and GDP obtained using the HP filter. These two series enter into the computation of a number of summary statistics. Specifically, ρ^i_{ey} is the correlation coefficient between $emis_{it}$ and gdp_{it} in country i. Similarly, σ^i_e and σ^i_y are the standard deviations of the two time series, whereas σ^i_{rel} is the ratio of the two. With 122 countries in the sample, there are 122 of each of ρ^i_{ey}, σ^i_e, σ^i_y and σ^i_{rel}, i.e. one per country.

<Insert Table 1 around here.>

Two key conclusions of the current paper are about the association between these statistics and GDP per capita at a point in time. In particular, I identify broad patterns across countries by computing the correlation coefficient between $\{\rho^i_{ey}, \sigma^i_e, \sigma^i_{rel}\}$ and GDP per capita in 2009. For example, if the cross-country correlation of ρ_{ey} and $GDPpc_{2009}$ series is positive, i.e. $\rho(\rho_{ey}, GDPpc_{2009}) > 0$, then this paper's measure of cyclicality is greater in countries which have higher GDP per capita in 2009.

In order to illustrate the mechanics of the HP filter and to provide some intuition regarding the statistics discussed in the rest of this paper, I use the US as an example. The left panel of Figure 1 illustrates the natural logarithms of the emissions and GDP series, as well as the growth component extracted using the HP filter for each series.

Denoting the data to be filtered by y_t and its growth and cyclical components by g_t

and c_t, the HP filter solves the following optimization problem for each series:

$$min_{\{g_t\}} \left\{ \sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=1}^{T} \left[(g_t - g_{t-1}) - (g_{t-1} - g_{t-2}) \right]^2 \right\} \qquad subject\, to$$

$$\begin{gathered} y_t = g_t + c_t \\ y_t, \lambda\, given \end{gathered}$$

where λ is a penalty parameter as described in more detail in Hodrick and Prescott [17]. It is set to 6.25 as recommended for use with annual data by Ravn and Uhlig [25].

The right panel of Figure 1 illustrates the scatter plot of cyclical components of emissions and GDP, i.e. $c_t = y_t - g_t$ for each series. A positive correlation between the series is apparent in the figure. This observation is confirmed by the statistic $\rho_{ey}^{us} = \rho(emis, gdp) = 0.725$ with a p-value of the test that it is zero less than 1%. Since $\rho_{ey}^{us} > 0$ US emissions are said to be procyclical. The cyclical volatility of emissions is given by the standard deviations of *emis* and *gdp* which are $\sigma_e^{us} = 0.019$ and $\sigma_y^{us} = 0.014$. As a result, $\sigma_{rel}^{us} = 1.398$. In other words, the US emissions are cyclically more volatile than GDP.

I carry out identical calculations for other countries in the sample, which allows me to construct a cross-sectional data set summarizing the business cycle properties of emissions. I use the resulting cyclicality and volatility statistics to look for patterns across countries. Specifically, in the next section I report the linear association of these statistics with real GDP per capita in 2009.

Three final remarks are in order before a discussion of the empirical results. The first remark is about the data resolution along the time dimension. The business cycle statistics reported below are based on annual rather than quarterly data. It would have been preferable to undertake the analysis of this paper with quarterly data, however, emissions data at this frequency are not available.[5] An additional complication with quarterly data is that series need to be seasonally adjusted prior to filtering, adding a new layer of processing which is not necessarily innocuous for the results.

The second remark relates to the full and restricted samples for which I report results separately. The full sample is made up of the 122 countries whose emissions and GDP data are contiguous in the databases and includes OPEC countries, where emissions and GDP are particularly volatile, as well as ex-communist countries, where relatively few observations are available to compute business cycle statistics. Restricting the sample to non-OPEC countries which have more than 20 years of data reduces the sample size to 89.[6] Below I highlight the cases where the restriction has implications for the results.

Finally, where it does not lead to confusion, I suppress country and time indices in what follows to avoid clutter. In establishing facts 2 and 4, I use GDP per capita in 2009. As shown in Section 4 the choice of 2009 is innocuous.

[5] See van Rossum and Schenau [29] for a discussion of CO_2 emissions measurement at quarterly frequency in the Netherlands.

[6] For a list of countries which are not in the restricted sample, see Table 9 in the Appendix.

3. Four salient facts

Fact 1: Emissions are procyclical in a typical country.

Using the notation in Table 1 this fact can be formally stated as

$$\rho_{ey} = \rho(emis, gdp) > 0$$

The summary statistics for the distribution of the correlation coefficient between the cyclical components of emissions and GDP across countries is given in Table 2. The average values of ρ_{ey} are similar in the full (0.297) and restricted (0.260) samples. The fact that these values are much smaller than the US (0.725) suggests that there is heterogeneity across countries in this aspect of the emissions-GDP relationship. Indeed, ρ_{ey} can vary between -0.305 and 0.824 but is positive for 107 of the 122 countries in the sample. In those 15 countries where emissions are countercyclical, the negative correlation coefficient is statistically significant only in the case of Cameroon. In addition, none of the countries with $\rho_{ey} < 0$ is a major CO_2 emitter on a global scale, with Venezuela, whose emissions in 2011 were just under 0.6% of global total, being the largest.[7]

<Insert Table 2 around here.>

That ρ_{ey} is positive is in line with most economists' intuition that emissions and GDP move together as the economy experiences business cycle fluctuations. It is also consistent with the evidence put forward in the studies reviewed above. What is important about this fact is that the procyclicality of emissions is a phenomenon which applies much more generally than in a couple of advanced countries where it was previously shown.

Fact 2: Procyclicality of emissions is positively correlated with GDP per capita across countries.

Fact 2 is a novel result about the cross-country correlation between the cyclical components of emissions and GDP, ρ_{ey}, and the level of GDP per capita in 2009, $GDPpc_{2009}$. Formally, it can be expressed as

$$\rho(\rho_{ey}, GDPpc_{2009}) > 0$$

Table 3 shows that this statistic is positive and significant in both the full (0.327) and restricted (0.359) samples. Figure 2 visually summarizes the data. Since Figure 3 and others that follow share a number of features, I explain this figure in detail.

Each country in the sample is indicated by its three letter code in either blue or red. The color blue identifies countries that are in the restricted sample while red is used for countries in the full but not the restricted sample. Recall that countries are in the full but not the restricted sample if they are members of OPEC or have fewer than 20 years of data for calculating the business cycle statistics. The regression line in the figure is drawn for the full sample and is statistically indistinguishable from the one obtained (not shown) by using the restricted sample.

[7] The full list of countries with countercyclical emissions is: United Arab Emirates, Bangladesh, Cameroon, Ghana, Hong Kong, Saint Lucia, Morocco, Malta, Niger, Qatar, Sudan, Senegal, Syria, Venezuela and Viet Nam.

What exactly does the positive correlation between correlation coefficients ρ_{ey} and GDP per capita mean? $\rho(\rho_{ey}, GDPpc_{2009}) > 0$ suggests that in rich countries emissions and GDP are coupled relatively more tightly than in poor countries. In fact in the latter, emissions and GDP may be cyclically unrelated. This finding is not surprising when one considers observations from the relevant tails of the joint distribution of the two variables. The advanced management systems like just-in-time manufacturing and the sophisticated energy production and distribution systems in a country like Japan mean that the level of economic activity and energy demand are tightly linked. This stands in contrast to a country like Niger where value added in agricultural and mineral extraction sectors constitute a very large share of GDP and fluctuate significantly without necessarily having implications for energy demand.

Fact 3: Emissions are cyclically more volatile than GDP in a typical country.

Fact 3 is the analogue of fact 1 but focuses on the cyclical volatility of emissions. The main finding can be formally expressed as

$$\sigma_{rel} = \frac{\sigma_e}{\sigma_y} > 1$$

Table 4 provides the summary statistics for the distribution of cyclical volatilities of emissions and GDP as well as their ratio in the full and restricted samples. In both samples, the cyclical component of emissions is on average about 3 times as volatile as the cyclical component of GDP. Not surprisingly, these business cycle statistics show less variation in the restricted sample. That said, even in the restricted sample, the relative volatility of emissions can be as high as 15.

Although $\sigma_{rel} > 1$ for most countries, there are 5 countries for which the relative volatility of emissions is less than 1: Azerbaijan, Belarus, Croatia, Latvia and Russia. It is useful to point out that none of these countries are members of the restricted sample because they do not meet the criterion that the number of observations from which to calculate the business cycle statistics is greater than 20.

The fact that emissions are more volatile than GDP in a typical country can be consistent with a number of underlying mechanisms. For example, emissions-intensive sectors of the economy might be subject to exogenous shocks with a greater volatility than that of the shocks affecting the rest of the economy. Alternatively, this fact could emerge from the interaction of the decisions of economic agents in a way similar to how the consumption smoothing motive of standard real business cycle models generates an investment series which is substantially more volatile than output.

Finally, observe that $\bar{\sigma}_e = 0.068$ and $\bar{\sigma}_{rel} = 3.082$ in the restricted sample are much larger than their counterparts in the US, which are $\sigma_e^{us} = 0.019$ and $\sigma_{rel}^{us} = 1.398$. Moreover, the standard deviations computed from the sample distributions of these statistics indicate substantial cross-country heterogeneity. This observation motivates fact 4.

Fact 4: Cyclical volatility of emissions is negatively correlated with GDP per capita across countries.

Fact 4 is concerned with the systematic patterns in the relationship between the cyclical volatility of emissions and GDP per capita in 2009 across countries. In particular, it can be stated as

$$\rho(\sigma_e, GDPpc_{2009}) < 0 \quad \& \quad \rho(\sigma_{rel}, GDPpc_{2009}) < 0$$

In words, the richer a country, the less volatile its emissions tend to be both in absolute terms and relative to GDP. It is a well-established and studied fact that the amplitude of business cycles in richer economies are on average smaller.[8] Fact 4 demonstrates that this phenomenon is valid in the case of emissions as well. Moreover, fact 4 also provides evidence that the volatility of emissions declines more than the volatility of GDP as output per capita increases.

Table 5 and Figures 3 and 4 provide the data that support this fact. In particular, the top panel of Table 5 shows that the cross-country correlation between the cyclical volatility of emissions and GDP per capita in 2009 is negative and significant in both the full (-0.220) and restricted (-0.316) samples. While the statistic is negative in both cases, its magnitude is larger in the restricted sample, hinting that outliers might be driving the result. This is confirmed in Figure 3 where countries like the United Arab Emirates, Qatar, Cambodia, Iran and Cameroon exhibit extremely volatile emissions.

A natural question to ask in this context is whether σ_{rel} and $GDPpc_{2009}$ are negatively correlated as well. The answer is affirmative and the statistics to this end are provided in the lower panel of Table 5. The negative and significant coefficient in both the full (-0.203) and restricted (-0.235) samples suggest that the cyclical volatility of emissions declines more than that of GDP as GDP per capita rises. Figure 4 demonstrates how the relative volatility of emissions and GDP per capital are related. Notice that even among the countries in the restricted sample there are a few outliers that might be driving the results. However, excluding the top and bottom 5% of the distribution of σ_{rel} and computing the correlation coefficient produces similar results.

This fact is novel and interesting. It has direct implications for the calibration of theoretical models such as those in Heutel [16] and Fischer and Springborn [15]. It is crucially important for the volatility of prices and allocations in emissions trading schemes around the world, including those already in existence in Europe and North America, as well as those soon to be implemented in Korea, and China.

4. Robustness

In this section I perform a robustness analysis for the facts established above and report the results in Table 6. For ease of comparison, the facts of Section 3 are collected under the first column titled BM for benchmark. In columns (I)-(III), I investigate sensitivity with respect to alternative filters. The following three columns (IV)-(VI) report results by using data from alternative emissions data sources. Finally, in columns (VII) and (VIII) I compute the same statistics using $GDPpc_{2005}$ and $GDPpc_{1995}$, rather than $GDPpc_{2009}$ as in the benchmark. To avoid clutter I provide statistics for the full sample only. At the end of this section, I also offer some corroborating evidence from long times series (i.e. minimum of 100 years of emissions or GDP data) available for a smaller sample of 23 countries.

[8]See, for example, Acemoglu and Zilibotti [1], Koren and Tenreyro [20] and Carvalho and Gabaix [9].

<Insert Table 6 around here.>

The statistics reported in Columns (I), (II) and (III) show that the benchmark results are not driven by the choice of HP filter. To show this, I perform the same calculations on first order differenced (FOD) data, then on data filtered using the band pass filter (BP) recommended by Baxter and King [4] and finally the random walk band pass filter (RWBP) recommended by Christiano and Fitzgerald [10]. In the latter two cases the minimum and maximum period of oscillation retained in the time series is set to the conventional values of 2 and 8 years. The results are virtually the same as those obtained by using the HP filter. Consequently, when I perform further robustness tests I only report statistics obtained using the HP filter.

In column (IV), I turn my attention to emissions data from another prominent source: CAIT. The temporal coverage of emissions data from CDIAC and CAIT mostly overlap with the exception that CAIT data is not available beyond 2008. As a consequence, I have 5976 country-year observations with which to compute the business cycle statistics, relative to 6286 observations in the benchmark.

Defining *qualitatively identical* as the absence of statistically significant sign differences across columns of Table 6, it is clear that the statistics computed from CAIT data have this property. A point to highlight with CAIT data relates to the correlation coefficient between the relative volatility of emissions and GDP per capita in 2009, $\rho(\sigma_{rel}, GDPpc_{2009})$, which is no longer significant. Put differently, I would not have observed an important dimension of fact 4 had I been restricted to using CAIT data only.

As stated in Section 2, the data in EDGAR starts in 1970. In other words, in EDGAR I have about 23 fewer years of observations for most countries resulting in 4272 country-year observations to work with. The benefit of using data from this source is not only in validating the results from CDIAC but also in extending emissions coverage to CH_4 and N_2O.[9] The results are *qualitatively identical* and similar to CAIT, although with greenhouse gas (GHG) data from EDGAR, there is no evidence that $\rho(\sigma_{rel}, GDPpc_{2009})$ is significantly different from zero.

The final two columns of the table, (VII) and (VIII), report the results when the reference years for GDP per capita are 2005 and 1995, respectively. The results are *qualitatively identical* and similar in magnitude. This is not surprising since most countries' rankings in the cross-country distribution of GDP per capita are quite persistent.

The main message from Table 6 is that Facts 1-4 are not driven by the type of time series filter or the source of emissions data used to calculate them. The significance of the negative correlation coefficient between the relative volatility of emissions and GDP per capita disappears with data from CAIT and GHG data from EDGAR. However, the point estimate continues to be negative in both cases. Consequently, the loss of significance is likely due to the scarcity of data available to compute this statistic.

Another way to look at the relationship between emissions and GDP is to focus on the countries with long time series data on both emissions and GDP. Specifically, I study those 23 countries for which there exist at least 100 years of data and calculate ρ_{ey}, σ_e and σ_{rel}. The results for individual countries are provided in Table 7 of the appendix.

[9] The emissions data behind column (VI) is the total of CO_2, CH_4 and N_2O emissions expressed in tons of CO_2 equivalent.

For all countries other than India emissions are procyclical, and in the case of India the negative correlation coefficient is not statistically significant. With long time series, $\sigma_{rel} > 1$ for every country in the sample. The mean values for the cyclicality and relative volatility statistics are $\bar{\rho}_{ey} = 0.328$ and $\bar{\sigma}_{rel} = 3.090$, which are close to those in Tables 2 and 4. To the extent that emissions and GDP data are reliable when one goes back more than a century in history, these results suggest that Facts 1 and 3 are valid in long time series data.

It is not straightforward to replicate the analysis that results in Facts 2 and 4 with this sample of countries primarily because most of the countries with long time series data are currently rich countries and have undergone important structural transformation over the past 100+ years. Furthermore, unlike the post-1950 data in Section 3, the relative rankings of the countries over this long sample period change substantially.

There is, however, another way the long time series sample can be informative, especially for Facts 2 and 4. In particular, most of the countries undergo a process of sustained economic development over the sample period. Therefore, an individual country's experience earlier in its economic history compared with its experience more recently as a richer country can reveal pertinent information, while holding a host of country specific factors constant.

In order to undertake this analysis one must make somewhat arbitrary assumptions regarding two issues. First, one must identify a boundary period before which a country is deemed to be *poor*. Second, one must take a stand on how to deal with the two World Wars as well as the Great Depression, which have profound implications for GDP and emissions. I attempt to address both issues simultaneously by focusing on three periods: pre-1914, post-1960 and the period in between.

For a given country I consider pre-1914 data as the *poor* period. I further assume that by 1960 the most significant effects of the two World Wars and the Great Depression on GDP and emissions have died down. As a result, I take the post-1960 period to be the country's *rich* period. In order to make sure that data are not too scarce in the pre-1914 period, I only compute the statistics for countries that have a minimum of 20 years of pre-1914 data. The results for individual countries are presented in Table 8 of the appendix. Here it suffices to note that the results corroborate the aspects of the relationship between emissions and GDP highlighted in facts 1 through 4.

5. Discussion and conclusion

The findings of the current paper are essential to discipline the calibration of theoretical models similar to Heutel [16] and Fischer and Springborn [15]. In the case of Heutel [16], the elasticity of emissions with respect to output is a critical parameter of the DSGE model he calibrates to the US data. The sensitivity analysis conducted by the author varies this parameter in the range $[0.25, 1.20]$. He finds that the properties of the optimal abatement policy change substantially. As a result, it is crucial how this parameter is calibrated.

The author's strategy is to use the slope coefficient from the regression of the log of emissions on the log of GDP as the calibration target.[10] Denoting this slope coefficient

[10]For details refer to Section 1 in Heutel [16], in particular column (3) of Table 1.

with $\beta_{e|y}$, it is straightforward to show that $\beta_{e|y}$ is the product of two key summary statistics studied in this paper: the correlation coefficient between emissions and output and the relative volatility of emissions, i.e. $\beta_{e|y} = \rho_{ey}\sigma_{rel}$.

In the restricted sample defined above, $\beta_{e|y}$ varies between 0 and 1.80 which is larger than the range considered for sensitivity analysis in Heutel [16]. Moreover, important emitters are located close to the ends of this range, and outside that considered by Heutel. For example, in India, Japan and China, the point estimates (p-values) for $\beta_{e|y}$ are 0.02 (0.92), 1.60 (0.00) and 1.63 (0.00), respectively.[11] As a result, even if the model in Heutel [16] were a 'universal' model of emissions determination over the business cycle, it would potentially have different policy implications when calibrated to countries such as India, Japan and China, a result interesting in its own right.

Fischer and Springborn [15] studies the pros and cons of alternative climate change mitigation policy instruments. A key conclusion is that in a real business cycle framework, an emissions cap, a carbon tax and an intensity target offer different qualities. Given their model and calibration, an appropriately constrained intensity target outperforms the cap and the tax. However, their no-policy baseline model features emissions whose relative volatility is 1. As facts 3 and 4 of the current paper show, this is not the case in the data. Emissions are cyclically more volatile than GDP, and their volatility varies systematically with GDP per capita. It is conceivable that incorporating this aspect of the real world into the model is sufficient to tip the balance of welfare costs so that the least costly policy is in fact the cap, at least in some countries. The authors hypothesize but fail to find evidence for this in Section 3.5 of their paper.

These examples highlight the importance of having robust empirical targets when calibrating theoretical models. Once parametrized these models can serve as an ideal environment in which relative merits of alternative policies can be evaluated. Moreover, the general equilibrium nature of these models allows researchers to think about climate change mitigation policy in a broader macroeconomic context while avoiding the pitfalls of the Lucas critique.

A related dimension along which the current paper has potentially important implications is the price and allocation dynamics in emissions trading systems. In a world where the volatility of emissions differs across countries, identical emissions trading systems will deliver different price volatilities. Moreover, the dynamics of the price over the business cycle will in part be determined by the cyclicality of emissions. These observations are likely to be of particular concern to policy makers and emitting firms in countries where governments are currently in the process of setting up emissions trading systems (e.g. China and Korea). Against this backdrop, it would be informative to undertake an empirical study similar to the current paper using sectoral value added and emissions data because the sector coverage of the existing and proposed emissions trading systems is often limited to energy and manufacturing sectors.

The most important message of the paper is regarding the qualitative similarities and the quantitative differences across countries in the way emissions and GDP are related as the economy moves through business cycle fluctuations. Countries are qualitatively similar because emissions are procyclical and cyclically more volatile than GDP, as shown in facts 1 and 3. Countries are quantitatively different in that the degree of procyclicality

[11] The p-values are for the test of $H_0 : \beta_{e|y} = 0$ against $H_1 : \beta_{e|y} \neq 0$ using robust standard errors as in column (3) of Table 1 in Heutel [16].

and cyclical volatility vary in systematic ways, as illustrated with facts 2 and 4. One can exploit the similarities to construct theoretical models which can offer policy advice relevant for climate change mitigation. However, these models must account for the differences in order to make that policy advice sound and robust.

Tables

Table 1: Definitions of variables and statistics

Variable	**Definition**
$EMIS_{it}$	Log of CO_2 emissions in 1000s of metric tons of carbon
GDP_{it}	Log of GDP in millions of 1990 US$ (Geary-Khamis PPPs)
$GDPpc_{it}$	Log of GDP per capita in 1990 US$ (Geary-Khamis PPPs)
$emis_{it}$, gdp_{it}	Cyclical components of $EMIS_{it}$ and GDP_{it} obtained by HP filter ($\lambda = 6.25$)
Statistic	**Definition**
$\rho^i_{ey} = \rho(emis_i, gdp_i)$	Time series correlation of *emis* and *gdp* series
$\sigma^i_e = \sigma(emis_i)$	Standard deviation of *emis* series
$\sigma^i_y = \sigma(gdp_i)$	Standard deviation of *gdp* series
$\sigma^i_{rel} = \frac{\sigma^i_e}{\sigma^i_y}$	Relative volatility of emissions
$\rho(X, GDPpc_{it})$	Cross-country correlation of X and $GDPpc_{it}$ series where $X \in \{\rho^i_{ey}, \sigma^i_e, \sigma^i_{rel}\}$ and $t \in \{2009, 2005, 1995\}$

Table 2: Cyclicality of emissions

	Mean	**Std. Dev.**	**Min**	**Max**	**Sample**
$\bar{\rho}_{ey}$	0.297***	0.244	−0.305	0.824	Full (N=122)
$\bar{\rho}_{ey}$	0.260***	0.229	−0.305	0.725	Restricted (N=89)

Notes:

For definitions, see Table 1. A bar over a variable indicates a sample mean. The null hypothesis that $\bar{\rho}_{ey}$ is equal to zero tested against a two-sided alternative in each case, where * implies p<0.10, ** implies p<0.05, and *** implies p<0.01.

Table 3: Cyclicality of emissions across countries

	Value	**Sample**
$\rho(\rho_{ey}, GDPpc_{2009})$	0.327^{***}	Full (N=122)
$\rho(\rho_{ey}, GDPpc_{2009})$	0.359^{***}	Restricted (N=89)

Notes:
For definitions, see Table 1. The null hypothesis that $\rho(\rho_{ey}, GDPpc_{2009})$ is equal to zero tested against a two-sided alternative in each case. * implies p<0.10, ** implies p<0.05, and *** implies p<0.01.

Table 4: Volatility of emissions

	Mean	**Std. Dev.**	**Min**	**Max**	**Sample**
$\bar{\sigma}_e$	0.078	0.064	0.018	0.358	
$\bar{\sigma}_y$	0.029	0.018	0.006	0.109	Full (N=122)
$\bar{\sigma}_{rel}$	3.040^{***}	2.492	0.701	17.221	
$\bar{\sigma}_e$	0.068	0.051	0.018	0.285	
$\bar{\sigma}_y$	0.023	0.011	0.009	0.081	Restricted (N=89)
$\bar{\sigma}_{rel}$	3.082^{***}	2.197	1.019	15.258	

Notes:
For definitions, see Table 1. A bar over a variable indicates a sample mean. In the last row of each panel the null hypothesis that $\bar{\sigma}_{rel} = 1$ is tested against the alternative that $\bar{\sigma}_{rel} > 1$, where * implies p<0.10, ** implies p<0.05, and *** implies p<0.01.

Table 5: Volatility of emissions across countries

	Value	**Sample**
$\rho(\sigma_e, GDPpc_{2009})$	-0.220^{**}	Full (N=122)
$\rho(\sigma_e, GDPpc_{2009})$	-0.316^{***}	Restricted (N=89)
$\rho(\sigma_{rel}, GDPpc_{2009})$	-0.203^{**}	Full (N=122)
$\rho(\sigma_{rel}, GDPpc_{2009})$	-0.235^{**}	Restricted (N=89)

Notes:
For definitions, see Table 1. The null hypothesis that a given correlation coefficient is equal to zero is tested against a two-sided alternative in each case, where * implies p<0.10, ** implies p<0.05, and *** implies p<0.01.

Table 6: Robustness

	Benchmark	Other Filter			Other Emissions			Other Year		
		FOD	**BP**	**RWBP**	**CAIT**	**EDGAR**	**GHG**	**2005**	**1995**	**Fact**
	(BM)	**(I)**	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**	**(VII)**	**(VIII)**	
$\bar{\rho}_{ey}$	0.297^{***}	0.353^{***}	0.273^{***}	0.265^{***}	0.295^{***}	0.328^{***}	0.324^{***}			1
$\rho(\rho_{ey}, GDPpc_t)$	0.327^{***}	0.356^{***}	0.275^{***}	0.317^{***}	0.300^{***}	0.169^{*}	0.207^{**}	0.318^{***}	0.271^{***}	2
$\bar{\sigma}_e$	0.078	0.134	0.072	0.078	0.071	0.053	0.050			3
$\bar{\sigma}_{rel}$	3.040^{***}	2.847^{***}	3.129^{***}	3.216^{***}	2.801^{***}	2.178^{***}	2.071^{***}			3
$\rho(\sigma_e, GDPpc_t)$	-0.220^{**}	-0.223^{**}	-0.190^{**}	-0.229^{**}	-0.161^{*}	-0.229^{**}	-0.200^{**}	-0.225^{**}	-0.242^{***}	4
$\rho(\sigma_{rel}, GDPpc_t)$	-0.203^{**}	-0.195^{**}	-0.159^{*}	-0.202^{**}	-0.106	-0.163^{*}	-0.112	-0.188^{**}	-0.155^{*}	4

Notes:

For definitions, see Table 1. A bar over a variable indicates a sample mean. The null hypothesis that a given correlation coefficient or its mean is equal to zero is tested against a two-sided alternative. The null hypothesis that $\bar{\sigma}_{rel} = 1$ is tested against the alternative that $\bar{\sigma}_{rel} > 1$. In columns (BM) and (I)-(III), $t = 2009$ for $GDPpc_t$, while in columns (IV)-(VI), (VII) and (VIII), $t = 2008, 2005, 1995$, respectively. * implies p<0.10, ** implies p<0.05, and *** implies p<0.01.

Figures

Figure 1: Growth and cyclical components of GDP and emissions in the US

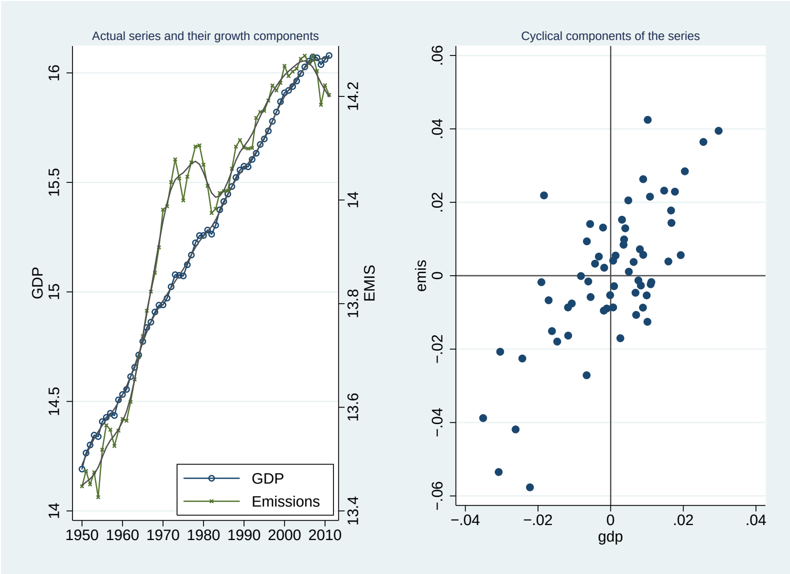


Figure 2: Procyclicality of emissions increases with GDP per capita (Fact 2)

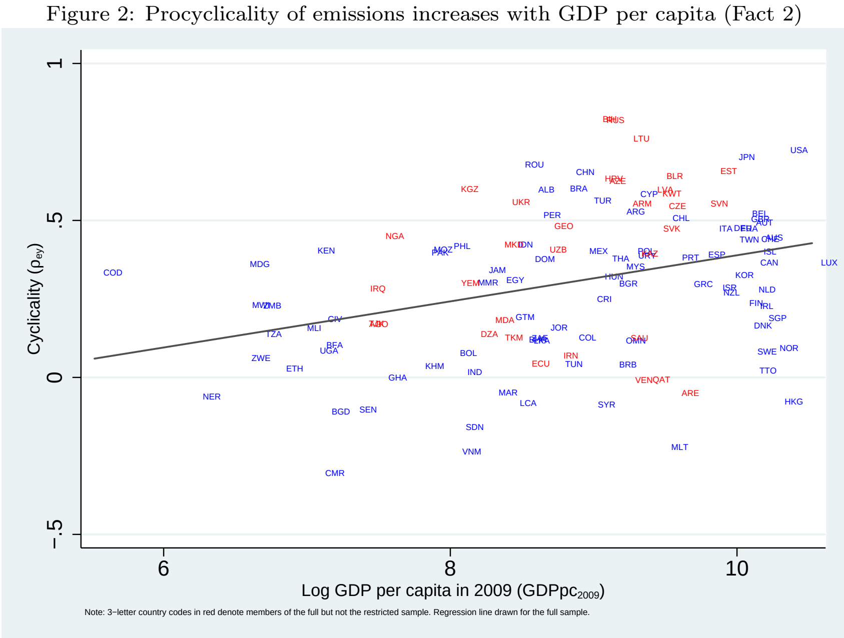


Figure 3: Volatility of emissions decreases with GDP per capita (Fact 4)

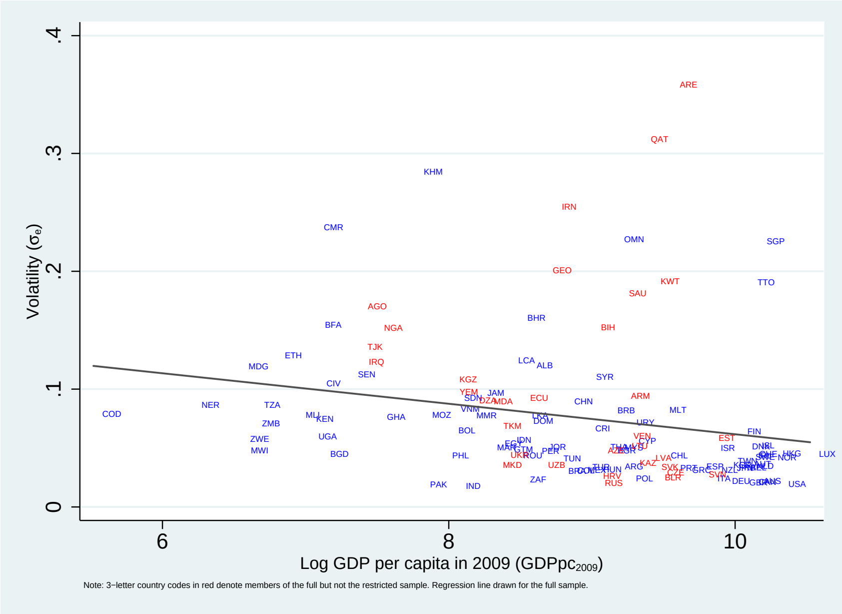
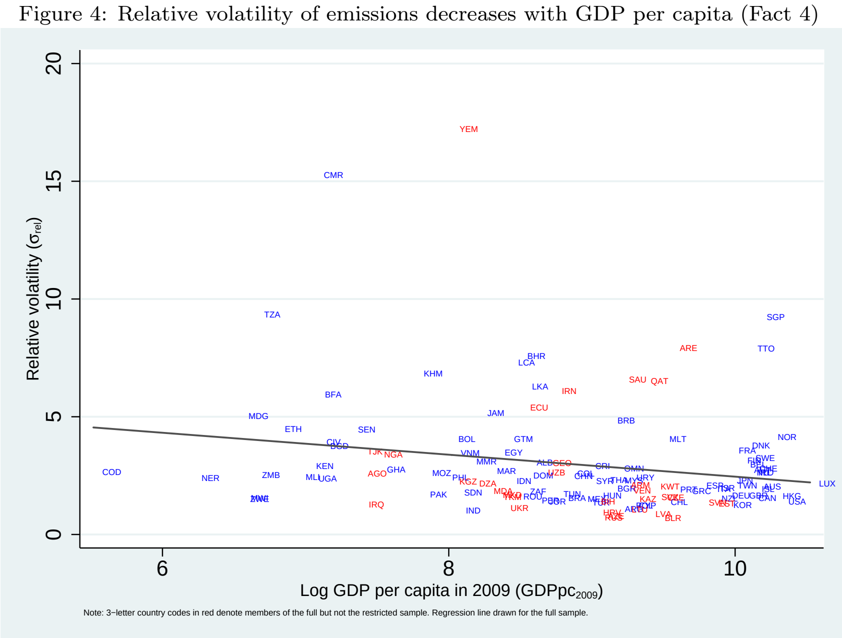


Figure 4: Relative volatility of emissions decreases with GDP per capita (Fact 4)



Appendix

Table 7 reports the values of the statistics ρ_{ey}, σ_e and σ_{rel} for those countries which have more than 100 years of GDP and emissions data.

Table 7: Long time series evidence on Facts 1 and 3

Country	Code	ρ_{ey}	σ_e	σ_{rel}	# of obs
France	FRA	0.514***	0.060	1.530	189
United Kingdom	GBR	0.429***	0.050	2.618	179
Norway	NOR	0.429***	0.102	4.650	174
Sweden	SWE	0.362***	0.127	5.842	170
Denmark	DNK	0.307***	0.077	3.393	166
Belgium	BEL	0.343***	0.068	2.863	163
Netherlands	NLD	0.547***	0.099	2.387	163
Germany	DEU	0.208***	0.104	1.885	159
Switzerland	CHE	0.026	0.114	3.673	151
Finland	FIN	0.390***	0.221	7.653	149
Australia	AUS	0.084	0.083	3.275	149
Italy	ITA	0.464***	0.169	4.736	148
Japan	JPN	0.291***	0.154	3.311	139
Canada	CAN	0.383***	0.068	2.199	139
Austria	AUT	0.248***	0.189	3.266	139
United States	USA	0.576***	0.046	1.296	139
New Zealand	NZL	0.183**	0.043	1.384	131
India	IND	−0.143	0.035	1.273	125
Chile	CHL	0.404***	0.079	1.502	114
Peru	PER	0.213***	0.174	5.359	113
Argentina	ARG	0.289***	0.094	2.886	109
Taiwan	TWN	0.574***	0.082	1.405	108
Brazil	BRA	0.432***	0.066	2.785	108
AVERAGE		0.328	0.100	3.090	

Notes:

For definitions, see Table 1. The null hypothesis that ρ_{ey} is equal to zero tested against a two-sided alternative for each country. * implies $p<0.10$, ** implies $p<0.05$, and *** implies $p<0.01$.

Table 8 reports the individual country values of the statistics ρ_{ey}, σ_e and σ_{rel} for those countries which have more than 20 years of GDP and emissions data in each of the pre-194 and post-1960 eras. In order to get some intuition for the information provided in table 8 take the US as an example. Emissions become more procyclical post-1960 relative to pre-1914. Furthermore, the relative and absolute volatilities of emissions are lower post-1960. These results are in accordance with the four facts identified in this paper.

Some aspects of Table 8 pose a challenge to the facts established in the main text. For example, $\rho_{ey} < 0$ and is significant in India pre-1914; ρ_{ey} declines in Belgium and Canada as these countries become richer. In Switzerland, France and New Zealand, σ_{rel} is greater in the post-1960 period (i.e. partial evidence against fact 4). Finally, a large number of countries feature insignificant ρ_{ey}. However, this is more prevalent in the pre-1914 era. Given the facts identified in this paper, this is consistent with the idea that the poorer a country, the lower (statistically indistinguishable from zero) one expects ρ_{ey} to be.

Table 8: Long time series evidence on Facts 2 & 4

	ρ_{ey}		σ_e		σ_{rel}	
	Pre-1914	***Post-1960***	***Pre-1914***	***Post-1960***	***Pre-1914***	***Post-1960***
Australia	−0.019	0.410***	0.130	0.019	4.191	1.862
Austria	0.171	0.197	0.152	0.032	7.031	3.474
Belgium	0.513***	0.425***	0.047	0.031	4.766	3.180
Canada	0.259*	0.193	0.100	0.020	3.256	1.580
Switzerland	−0.147	0.233	0.062	0.033	1.617	2.270
Germany	0.047	0.328**	0.046	0.020	2.292	1.802
Denmark	0.151	0.300***	0.085	0.055	5.427	4.428
Finland	0.238***	0.111	0.199	0.059	8.196	3.166
France	0.182*	0.410***	0.051	0.032	1.861	4.010
UK	0.318***	0.408***	0.030	0.020	1.775	1.637
India	−0.366**	0.098	0.042	0.019	1.175	1.002
Italy	0.009	0.569***	0.079	0.019	3.560	1.491
Japan	0.133	0.705***	0.256	0.026	8.663	1.961
Netherlands	0.009	0.319**	0.076	0.037	4.709	3.442
Norway	0.070	−0.018	0.085	0.043	5.000	4.391
New Zealand	−0.026	0.322**	0.038	0.032	1.213	1.746
Sweden	0.091	−0.132	0.099	0.040	4.171	4.032
US	0.544***	0.719***	0.046	0.017	1.621	1.334

Notes:

For definitions, see Table 1.The null hypothesis that ρ_{ey} is equal to zero tested against a two-sided alternative for each country.* implies p<0.10, ** implies p<0.05, and *** implies p<0.01.

Table 9 summarizes the time series and geographical coverage of the sample.

Table 9: Coverage of the data set

Country	Code	Start year	End year	# of obs	In restricted sample?
Angola	AGO	1950	2009	60	No
Albania	ALB	1950	2009	60	
United Arab Emirates	ARE	1959	2009	51	No
Argentina	ARG	1950	2011	62	
Armenia	ARM	1992	2009	18	No
Australia	AUS	1950	2011	62	
Austria	AUT	1950	2011	62	
Azerbaijan	AZE	1992	2011	20	No
Belgium	BEL	1950	2009	60	
Burkina Faso	BFA	1958	2009	52	
Bangladesh	BGD	1972	2011	40	
Bulgaria	BGR	1950	2011	62	
Bahrain	BHR	1950	2009	60	
Bosnia & Herzegovina	BIH	1992	2009	18	No
Belarus	BLR	1992	2011	20	No
Bolivia	BOL	1950	2009	60	
Brazil	BRA	1950	2011	62	
Barbados	BRB	1950	2009	60	
Canada	CAN	1950	2011	62	
Switzerland	CHE	1950	2011	62	
Chile	CHL	1950	2011	62	
China	CHN	1950	2011	62	
Cote D'ivoire	CIV	1958	2009	52	
Cameroon	CMR	1950	2009	60	
Congo, DR	COD	1950	2009	60	
Colombia	COL	1950	2011	62	
Costa Rica	CRI	1950	2009	60	
Cyprus	CYP	1950	2009	60	
Czech Republic	CZE	1992	2011	20	No
Germany	DEU	1950	2011	62	
Denmark	DNK	1950	2011	62	
Dominican Republic	DOM	1950	2009	60	
Algeria	DZA	1950	2011	62	No
Ecuador	ECU	1950	2011	62	No
Egypt	EGY	1950	2011	62	
Spain	ESP	1950	2011	62	
Estonia	EST	1992	2009	18	No
Ethiopia	ETH	1950	2009	60	

Country	Code	Start year	End year	# of obs	In restricted sample?
Finland	FIN	1950	2011	62	
France	FRA	1950	2011	62	
United Kingdom	GBR	1950	2011	62	
Georgia	GEO	1992	2009	18	No
Ghana	GHA	1950	2009	60	
Greece	GRC	1950	2011	62	
Guatemala	GTM	1950	2009	60	
Hong Kong	HKG	1950	2011	62	
Croatia	HRV	1992	2009	18	No
Hungary	HUN	1950	2011	62	
Indonesia	IDN	1950	2011	62	
India	IND	1950	2011	62	
Ireland	IRL	1950	2011	62	
Iran	IRN	1951	2011	61	No
Iraq	IRQ	1950	2009	60	No
Iceland	ISL	1950	2009	60	
Israel	ISR	1950	2011	62	
Italy	ITA	1950	2011	62	
Jamaica	JAM	1950	2009	60	
Jordan	JOR	1950	2009	60	
Japan	JPN	1950	2011	62	
Kazakhstan	KAZ	1992	2011	20	No
Kenya	KEN	1950	2009	60	
Kyrgyzstan	KGZ	1992	2009	18	No
Cambodia	KHM	1955	2009	55	
Korea	KOR	1950	2011	62	
Kuwait	KWT	1954	2011	58	No
Saint Lucia	LCA	1950	2009	60	
Sri Lanka	LKA	1950	2009	60	
Lithuania	LTU	1992	2011	20	No
Luxembourg	LUX	1950	2009	60	
Latvia	LVA	1992	2009	18	No
Morocco	MAR	1950	2009	60	
Moldova	MDA	1992	2009	18	No
Madagascar	MDG	1950	2009	60	
Mexico	MEX	1950	2011	62	
Macedonia	MKD	1992	2009	18	No
Mali	MLI	1959	2009	51	
Malta	MLT	1950	2009	60	
Myanmar	MMR	1950	2009	60	
Mozambique	MOZ	1950	2009	60	
Malawi	MWI	1964	2009	46	

Country	Code	Start year	End year	# of obs	In restricted sample?
Malaysia	MYS	1970	2011	42	
Niger	NER	1958	2009	52	
Nigeria	NGA	1950	2009	60	No
Netherlands	NLD	1950	2011	62	
Norway	NOR	1950	2011	62	
New Zealand	NZL	1950	2011	62	
Oman	OMN	1964	2009	46	
Pakistan	PAK	1972	2011	40	
Peru	PER	1950	2011	62	
Philippines	PHL	1950	2011	62	
Poland	POL	1950	2011	62	
Portugal	PRT	1950	2011	62	
Qatar	QAT	1950	2011	62	No
Romania	ROU	1950	2011	62	
Russia	RUS	1992	2011	20	No
Saudi Arabia	SAU	1953	2011	59	No
Sudan	SDN	1950	2009	60	
Senegal	SEN	1969	2009	41	
Singapore	SGP	1957	2011	55	
Slovakia	SVK	1992	2011	20	No
Slovenia	SVN	1992	2009	18	No
Sweden	SWE	1950	2011	62	
Syria	SYR	1950	2009	60	
Thailand	THA	1950	2011	62	
Tajikistan	TJK	1992	2009	18	No
Turkmenistan	TKM	1992	2011	20	No
Trinidad And Tobago	TTO	1950	2011	62	
Tunisia	TUN	1950	2009	60	
Turkey	TUR	1950	2011	62	
Taiwan	TWN	1950	2011	62	
Tanzania	TZA	1970	2009	40	
Uganda	UGA	1950	2009	60	
Ukraine	UKR	1992	2011	20	No
Uruguay	URY	1950	2009	60	
United States	USA	1950	2011	62	
Uzbekistan	UZB	1992	2011	20	No
Venezuela	VEN	1950	2011	62	No
Viet Nam	VNM	1970	2011	42	
Yemen	YEM	1991	2009	19	No
South Africa	ZAF	1950	2011	62	
Zambia	ZMB	1964	2009	46	
Zimbabwe	ZWE	1964	2009	46	

[1] D. Acemoglu and F. Zilibotti. Was Prometheus unbound by chance? risk, diversification, and growth. *The Journal of Political Economy*, 105:709–751, 1997.

[2] J. E. Aldy. Per capita carbon dioxide emissions: Convergence or divergence? *Environmental and Resource Economics*, 33:533–555, 2006.

[3] K. Angelopoulos, G. Economides, and A. Philippopoulos. First-and second-best allocations under economic and environmental uncertainty. *International Tax and Public Finance*, forthcoming, 2013.

[4] M. Baxter and R. G. King. Measuring business cycles: Approximate band-pass filters for economic time series. *The Review of Economics and Statistics*, 81:575–593, 1999.

[5] T.A. Boden, G. Marland, and R.J. Andres. Global, regional, and national fossil-fuel CO2 emissions. Technical report, Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A., 2012. URL `http://cdiac.ornl.gov/`.

[6] A. Bowen, P. M. Forster, A. Gouldson, K. Hubacek, R. Martin, D. W. O'Neill, A. Rap, and J. Rydge. The implications of the economic slowdown for greenhouse gas emissions and targets. *Policy Paper by the Centre for Climate Change Economics and Policy*, 2009.

[7] C. Burnside. Detrending and business cycle facts: A comment. *Journal of Monetary Economics*, 41:513–532, 1998.

[8] F. Canova. Detrending and business cycle facts. *Journal of Monetary Economics*, 41:475–512, 1998.

[9] M. V. Carvalho and X Gabaix. The great diversification and its undoing. manuscript, 2011.

[10] L. J. Christiano and T. J. Fitzgerald. The band pass filter. *International Economic Review*, 44: 435–465, 2003.

[11] The Conference Board. The Conference Board Total Economy Database (January 2013). Technical report, 2013. URL `http://www.conference-board.org/data/economydatabase/`.

[12] EC-JRC/PBL. Emission database for global atmospheric research. Technical report, European Commission, Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL), 2011. URL `http://edgar.jrc.ec.europa.eu`.

[13] U. Erol and E. S. H. Yu. Spectral analysis of the relationship between energy consumption, employment and business cycles. *Resources and Energy*, 11:395–412, 1989.

[14] C. Fischer and G. Heutel. Environmental macroeconomics: Environmental policy, business cycles, and directed technical change. *NBER Working Paper*, No. 18794, 2013.

[15] C. Fischer and M. Springborn. Emissions targets and the real business cycle: Intensity targets versus caps or taxes. *Journal of Environmental Economics and Management*, 62:352–366, 2011.

[16] G. Heutel. How should environmental policy respond to business cycles? optimal policy under persistent productivity shocks. *Review of Economic Dynamics*, 15:244–264, 2012.

[17] R. J. Hodrick and E. C. Prescott. Postwar U.S. business cycles: An empirical investigation. *Journal of Money, Credit and Banking*, 29:1–16, 1997.

[18] D. Holtz-Eakin and T. M. Selden. Stoking the fires? CO2 emissions and economic growth. *Journal of Public Economics*, 57:85–101, 1995.

[19] I. M. Kim and P. Loungani. The role of energy in real business cycle models. *Journal of Monetary Economics*, 29:173–189, 1992.

[20] M. Koren and S. Tenreyro. Volatility and development. *The Quarterly Journal of Economics*, 122: 243–287, 2007.

[21] J. Kraft and A. Kraft. On the relationship between energy and GNP. *Journal of Energy and Development*, 3:401–403, 1978.

[22] A. Maddison. Statistics on world population, GDP and Per Capita GDP, 1-2008 AD. Technical report, The Groningen Growth and Development Centre, 2011. URL `http://www.ggdc.net/MADDISON/oriindex.htm`.

[23] P. K. Narayan, S. Narayan, and R. Smyth. Energy consumption at business cycle horizons: The case of the United States. *Energy Economics*, 33:161–167, 2011.

[24] J. E. Payne. Survey of the international evidence on the causal relationship between energy consumption and growth. *Journal of Economic Studies*, 37(1):53–95, 2010.

[25] O. M. Ravn and H. Uhlig. On adjusting the Hodrick-Prescott filter for the frequency of observations. *The Review of Economics and Statistics*, 84:371–376, 2002.

[26] R. Schmalensee, T. M. Stoker, and R. A. Judson. World carbon dioxide emissions: 1950-2050. *The Review of Economics and Statistics*, 80:15–27, 1998.

[27] R. Stefanski. Structural transformation and pollution. manuscript, 2012.

[28] M. Thoma. Electrical energy usage over the business cycle. *Energy Economics*, 26:365–385, 2004.

[29] M. van Rossum and S. Schenau. Co2 emissions on quarterly basis. Technical report, National Accounts Department, Statistics Netherlands, 2010.

[30] M. Wagner. The carbon kuznets curve: A cloudy picture emitted by bad econometrics? *Resource*

and Energy Economics, 30:388–408, 2008.

[31] The World Resources Institute. Climate analysis indicators tool (cait) version 9.0. Technical report, World Resources Institute, Washington, DC, 2012. URL `http://cait.wri.org/`.