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Evidence on CO_2 Emissions and Business Cycles

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Abstract

CO_2 emissions and GDP are positively correlated over the business cycle. Most climate change researchers would agree with the preceding intuitive statement despite the absence of a study that formally analyzes the relationship between emissions and GDP at business cycle frequencies. The current paper attempts to address this gap in the literature by providing a simple, rigorous and consistent analysis of the relationship in a comprehensive cross country panel. To this end, I decompose the aggregate emissions and GDP series into their growth and cyclical components using the HP filter and focus on the cyclical components. Four robust facts emerge from this analysis: i) Emissions are procyclical and cyclically more volatile than GDP in a typical country; ii) Cyclical volatility of emissions is negatively correlated with GDP per capita across countries; iii) Procyclicality of emissions is positively correlated with GDP per capita across countries; and iv) The composition of GDP is crucial for the business cycle properties of emissions but the relationship is complex. I undertake and report an extensive set of robustness checks which corroborate these findings. Finally, I propose some preliminary thoughts on the mechanisms that may be generating the data with these properties.

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[†]I have benefited substantially from comments by Alex Bowen, Antoine Dechezleprêtre and Sam Fankhauser. All remaining errors are mine.

1 Introduction

The primary motivation for this paper is to identify salient facts about the relationship between emissions and GDP at business cycle frequencies. Although most climate change researchers have an intuitive understanding of and indeed make passing references to this relationship, to the best of my knowledge there exists no paper that systematically studies it in a large sample of countries. Here I attempt to fill this gap in the literature by providing a simple, rigorous and consistent analysis of the cyclical properties of emissions in a comprehensive cross country panel. Specifically, I decompose the observed emissions and GDP series into growth and cyclical components using the Hodrick-Prescott (HP) Filter and focus on the filtered series. Four facts emerge as a result of this analysis:

1. Emissions are procyclical and cyclically more volatile than GDP in a typical country.

2. Cyclical volatility of emissions is negatively correlated with GDP per capita across countries.

3. Procyclicality of emissions is positively correlated with GDP per capita across countries.

4. The composition of GDP is crucial for the business cycle properties of emissions but the relationship is complex.

In part, fact 1 confirms the intuition of most climate change economists that emissions are procyclical. Making use of the terminology from the 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. In words, emissions tend to be above their trend during booms and below it during recessions. Furthermore, measuring cyclical volatility with the standard deviation of the filtered series I find that the cyclical volatility of emissions is greater than that of GDP in most countries.[1]

It is relatively well established and understood that economies become more stable as they become richer. Fact 2 demonstrates that the phenomenon is valid in the case of emissions as well by establishing that σ_e and GDP per capita are inversely related. Fact 3 states that the procyclicality of emissions is also systematically related to GDP per capita across countries. In particular, emissions and GDP are relatively relatively more tightly coupled (i.e. ρ_e is greater) in rich economies than in poor ones.

Fact 4 is about the relationship between the sectoral composition of GDP and the business cycle properties of emissions. I find that the greater the share of agriculture (services) in GDP, the greater (smaller) is the country's σ_e. The opposite is true for the procyclicality of emissions: the greater the share of agriculture (services) in GDP, the smaller (greater) is the country's ρ_e. These

[1]Hereafter I denote the correlation between the cyclical components of emissions and GDP by ρ_e. Similarly, I use σ_e and σ_y for the cyclical volatility of emissions and GDP. See Table 1 for details.

observations are consistent with facts 2 and 3 in that rich economies tend to have small agriculture and large services sectors.

The relationship between σ_e and ρ_e on the one hand and industry and manufacturing share of GDP on the other other is more nuanced.[2] Industry's share of GDP appears unrelated to the cyclical properties of emissions across countries. Manufacturing share of GDP, however, is negatively correlated with σ_e and positively correlated with ρ_e. Given the fact that manufacturing activities are a subset of industry and that the latter includes key carbon intensive sectors like mining and electricity/gas/water supply, a more detailed investigation of industrial composition and its effects on the properties of emissions will undoubtedly be informative.

This is an empirical paper and a theory of emissions determination over the business cycle is beyond its scope. However, taken together facts 1 through 4 provide several hints about the central components of such a theory. Specifically, interlinked factors such as the structure of the economy and its evolution as the country develops, the nature of sector specific shocks and the process of globalization are likely to be central. Against a backdrop of governments around the world adopting increasingly stringent climate change mitigation policies, both empirical and theoretical contributions regarding the cyclical properties of emissions are likely to be in demand.

While the current paper advances along the empirical dimension of this research agenda, Heutel [2012] makes a primarily theoretical contribution. After establishing the procyclicality of emissions in the US, the author studies the properties of the optimal emissions mitigation policy in a calibrated dynamic stochastic general equilibrium model. A number similarities and differences in the empirical sections of the two papers are noteworthy. Heutel [2012] also uses the HP filter to decompose emissions and GDP series into their components and finds that US emissions are procyclical. However, he stops short of extending the analysis to countries other than the US, to the cyclical volatility of emissions or to the relationship between cyclical properties of emissions on the one hand and the level of GDP per capita and the composition of output on the other.

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 [1995] and Schmalensee et al. [1998] find evidence in favor of a carbon Kuznets curve while more recently Aldy [2006] and Wagner [2008], among others, present evidence to the contrary, and cast doubt on the validity of the econometric techniques previously used. The difference of the current paper from 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

[2] I follow the World Bank's definition of industry and manufacturing. Specifically, industry corresponds to SIC divisions 10-45, and manufacturing to SIC divisions 15-37. In addition to manufacturing, industry includes mining, construction, electricity, water, and gas sectors..

GDP *at business cycle frequencies.*

Along similar lines, Stefanski [2012] studies the affect of structural transformation on a country's emission and energy intensity profiles. He 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 [2012] is related to the current paper in two ways. First, it underlines the importance of the composition of an economy's output for the long run trends in its emissions intensity, a point also pertinent in the context of the relationship between the cyclical components of emissions and GDP. Second, he 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, the current paper studies the relationship between the cyclical components of the same series.

Bowen et al. [2009] deal 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.[3] 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, GDP and their relationship as well as their interaction with the level of development across countries. I undertake an extensive robustness analysis in Section 4 and present some corroborating evidence from long time series for a smaller set of developed countries. I offer some preliminary thoughts on the key elements of a theory of emissions determination over the business cycle in Section 5. Finally, Section 6 contains some concluding remarks.

2 Data and methods

The main emissions variable used in the paper is drawn from Carbon Dioxide Information Analysis Center (CDIAC).[4] The CDIAC database has long annual time series for CO_2 emissions for all countries of the world and is one of the most reliable and current sources for emissions data. I use annual GDP and population data from Total Economy Database (TED) of The Conference Board.[5] Finally, data on the sectoral composition of GDP is obtained from the World Development Indicators of the World Bank.[6]

[3] See also footnote 17 and column (I) of Table 4.

[4] See Boden et al. [2011]. The database was accessed in December 2011.

[5] See Conference Board [2012]. The database was accessed in September 2011.

[6] See World Bank [2012]. The database was accessed January 2011.

By combining information from these sources, I construct a core data set of 122 countries for whom contiguous data on CO_2 emissions and GDP exist for all or some of the period covering 1950-2010. The result is an unbalanced panel of 81 countries with data for 60 years or more, 98 countries with data for 40 years or more. Those with less than 40 years of data are primarily ex-communist countries.

There are also other sources which provide data on emissions. World Resources Institute's Climate Analysis Indicators Tool (CAIT) provides CO_2 emissions data for a large group of countries until 2008.[7] The Emissions Database for Global Atmospheric Research (EDGAR) has CO_2 emissions data for 1970-2008.[8] 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.[9]

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 Angus Madison so that for a group of 23 countries there is contiguous emissions and GDP data for more than 100 years.[10]

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 [1998] and a response to it in Burnside [1998]. In the current paper, I give the HP filter default status because as Ravn and Uhlig [2002] states, 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 discussed in more detail in the section on robustness below, the central results are not sensitive to the particular filter employed in decomposing the series.

Table 1 summarizes the key variables and statistics I refer to in the rest of this paper. Note that for each of $\rho^i_e, \sigma^i_e, \sigma^i_y$ and σ^i_{rel} there is *one statistic per country.* These statistics are computed to summarize the relationship between emissions and GDP in a given country. The statistics $\rho(X^i, Z^i)$ are calculated to summarize broader tendencies *across countries*. For example, if $\rho(\rho^i_e, GDP^i_{pc}) > 0$, then the measure of cyclicality used in this study, ρ^i_e, is positively correlated with GDP per capita

[7]See World Resources Institute [2012]. The database was accessed in February 2012.
[8]See EC-JRC/PBL [2011]. The database was accessed in December 2011.
[9]For differences across these databases, see Winne [2009].
[10]See Maddison [2011]. The database was accessed on December 2011.

across countries.

Table 1: Key variables and statistics

Variable	**Definition**
$EMIS$	Log of CO_2 emissions (in thousands of metric tons of Carbon)
GDP	Log of total GDP (in millions of 1990 US$, Geary-Khamis PPPs)
$emis$, gdp	Cyclical components of $EMIS$ and GDP extracted by HP filter ($\lambda = 6.25$)
$TPOP$	Mid year population (in thousands of persons)
$GDPpc = log(\frac{exp(GDP)}{TPOP})$	Log of GDP per capita
shr_A, shr_I, shr_M,shr_S	Share of agriculture, industry, manufacturing and services in GDP

Statistic	**Definition**
$\rho_e^i = \rho(emis, gdp)$	Correlation of $emis$ and gdp series for country i
$\sigma_e^i = \sigma(emis)$	Standard deviation of $emis$ series for country i
$\sigma_y^i = \sigma(gdp)$	Standard deviation of gdp series for country i
$\sigma_{rel}^i = \frac{\sigma_e^i}{\sigma_y^i}$	Relative volatility of emissions for country i
$\rho(X^i, Z^i)$	Correlation of X^i and Z^i across countries, $X^i \in \{\rho_e^i, \sigma_e^i\}$, $Z^i \in \{GDP_{pc}^i, shr^i\}$

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. Figure 1 illustrates the natural logarithms of the raw data on emissions and GDP, i.e. $EMIS$ and GDP, 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:

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

$$y_t = g_t + c_t$$
$$y_t, \lambda \, given$$

where λ is a penalty parameter.[11] Figure 2 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 Figure 2. This observation is confirmed by the statistic $\rho_e^{us} = \rho(emis, gdp) = 0.731$ with a p-value less than 1%. Since $\rho_e^{us} > 0$ US emissions are said to be procyclical. The cyclical volatility of emissions are given by the standard deviations of $emis$ and gdp which are $\sigma_e^{us} = 0.020$

[11]See Hodrick and Prescott [1997] for details. The parameter λ is set to 6.25 as recommended for use with annual data by Ravn and Uhlig [2002].

and $\sigma_y^{us} = 0.014$. As a result, $\sigma_{rel}^{us} = 1.405$. In other words, the US emissions are cyclically more volatile than its GDP.

Calculations analogous to those for the US can be carried out for each country in the sample. The resulting cyclical correlation and volatility statistics allow me to look for patterns across countries. The first steps in this direction are taken in the next section by analyzing how business cycle properties of emissions correlate with GDP per capita and the composition of GDP across countries.

Two final remarks are in order before a detailed 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 ideal to undertake the analysis of this paper with quarterly data. However, emissions data at this frequency is not available.[12]

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 for a minimum of 19 years. The full sample also includes OPEC countries where emissions and GDP are particularly volatile. Restricting the sample to non-OPEC countries which have a minimum 20 years of data reduces the sample size to 90.[13] In what follows I highlight the cases where the restriction has important implications for the results.

3 Four salient facts

This section establishes the facts summarized above and provides additional detail about each of them.

FACT 1: Emissions are procyclical and cyclically more volatile than GDP in a typical country.

Using the notation in Table 1 this fact can be formally stated in two parts:

$$\rho_e^i = \rho(emis, gdp) > 0$$

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

[12]See van Rossum and Schenau [2010] for a discussion of CO_2 emissions measurement at quarterly frequency in the Netherlands. Such data are not readily available to be used in an analysis similar to that in this paper.

[13]The countries excluded under this restriction are Angola, United Arab Emirates, Armenia, Azerbaijan, Bosnia and Herzegowina, Belarus, Czech Republic, Algeria, Ecuador, Estonia, Georgia, Croatia, Iran, Iraq, Kazakhstan, Kyrgyzstan, Kuwait, Libya, Lithuania, Latvia, Moldova, Macedonia, Nigeria, Qatar, Russia, Saudi Arabia, Slovakia, Slovenia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan and Venezuela.

The summary statistics for the distribution of ρ_e^i and cyclical volatility statistics in the 122-country sample are given in upper panel of Table 2. The correlation between cyclical components of emissions and GDP is positive and statistically significant for a large majority of the countries in the sample with the exception of 15 where emissions are countercyclical. However, a negative correlation is statistically significant only in the case of Cameroon. Furthermore, none of the countries with $\rho_e^i < 0$ is a major CO_2 emitter on a global scale, with Venezuela, whose emissions in 2010 were just over 0.5% of global total, being the largest.[14]

Although $\sigma_{rel}^i > 1$ for most countries in the sample, there are 8 countries for which the cyclical volatility of emissions is less than the cyclical volatility of GDP. Furthermore, these countries include some big emitters such as India and Russia.[15] These important exceptions notwithstanding, there is support in this sample for the claim that emissions are procyclical and more volatile than GDP over the business cycle.

Table 2: Cyclicality and Volatility

Full sample					
	Mean	Std. Dev.	Min	Max	N
ρ	0.264	0.232	-0.304	0.731	122
σ_e	0.078	0.064	0.017	0.355	122
σ_y	0.029	0.018	0.007	0.107	122
σ_{rel}	2.986	2.371	0.645	15.287	122
Restricted sample (excl. OPEC and ex-communist)					
	Mean	Std. Dev.	Min	Max	N
ρ	0.260	0.230	-.0304	.731	90
σ_e	0.068	0.052	0.017	0.287	90
σ_y	0.023	0.011	0.007	0.084	90
σ_{rel}	3.175	2.483	0.959	15.287	90

Note: For definitions, see Table 1.

It is worth noting here that fact 1 holds true at the aggregate level as well. Specifically, using the same filtering technique and computing the relevant statistics from global emissions and GDP data for the 1950-2008 period, the correlation between cyclical components of emissions and GDP is 0.761 and the relative volatility of emissions is 1.99.[16,17]

[14] The full list of countries in this group are: Armenia, Cameroon, Ghana, Hong Kong, Malta, Morocco, Niger, Qatar, Saint Lucia, Senegal, Sudan, Syria, United Arab Emirates, Venezuela, Vietnam.

[15] The other countries are: Argentina, Azerbaijan, Belarus, and Croatia, Latvia and Ukraine. Note that 6 of the countries in this group belong to the ex-communist bloc with only 19 years of data to calculate the reported statistics.

[16] Not surprisingly, both emissions and GDP are much less volatile for global aggregate than the average of individual countries, with $\sigma_{emis}^{world} = 0.014$ and $\sigma_{gdp}^{world} = 0.007$.

[17] Alternatively, computing the correlation coefficient between the unfiltered but first differenced series results in $\rho(d.EMIS, d.GDP) = 0.810$.

FACT 2: Cyclical volatility of emissions is negatively correlated with GDP per capita across countries.

This fact is concerned with the systematic patterns in the relationship between the cyclical volatility of emissions and GDP per capita across countries. In particular, using GDP per capita in 2008 it can be stated as

Statistic	p-value	Sample (N)
$\rho(\sigma_e^i, GDP_{pc}^i) = -0.225$	0.013	Full (122)
$\rho(\sigma_e^i, GDP_{pc}^i) = -0.327$	0.002	Restricted (90)

Note: For definitions, see Table 1.

In words, the richer a country, the less volatile its emissions tend to be. It is a relatively well-established and studied fact that richer economies are on average more stable.[18] Fact 2 demonstrates that this phenomenon is valid for the case of emissions as well.

Figure 3 provides a visual representation of this fact for σ_e. Since Figure 3 and several others that follow share a number of features, I discuss this figure in detail. First, each country in the sample is indicated by its three letter code in either blue or yellow. The color blue identifies countries that are in the restricted sample while yellow is reserved for countries that are members of OPEC or countries that have fewer than 20 years of data for calculating the business cycle statistics. Second, there are two linear predictions in the figure. The green line provides a summary of the information in the full sample.[19] The blue line does the same for the 90 countries in the restricted sample. The slope coefficients in the two regressions are statistically indistinguishable from each other.

A natural question to ask in this context is whether σ_{rel} and GDP_{pc} are negatively correlated as well. The answer is a qualified no despite the fact that $\rho(\sigma_{rel}^i, GDP_{pc}^i)$ is -0.199 and -0.223 in the full and restricted samples, respectively. These statistics have p-values less that 5% in both cases. This evidence of a negative relationship aside, Figure 4 suggests that the result may be driven by a relatively few but quantitatively important outliers such as Cameroon, Yemen and Tanzania. Indeed, excluding the outliers, the negative and significant relationship disappears. Furthermore, the value of $\rho(\sigma_{rel}^i, GDP_{pc}^i)$ is sensitive with respect to other robustness checks considered in Section 4. Consequently, the data do not support the claim that $\rho(\sigma_{rel}^i, GDP_{pc}^i) < 0$ in a robust manner.

[18] See, for example,Acemoglu and Zilibotti [1997], Koren and Tenreyro [2007] and Carvalho and Gabaix [2011].

[19] It might be helpful to remember that adding yellow to blue produces the color green.

FACT 3: Procyclicality of emissions is positively correlated with GDP per capita across countries.

Fact 3 is about how the correlation between cyclical components of emissions and GDP relate to the level of GDP per capita. It can be formally stated as:

Statistic	p-value	Sample (N)
$\rho(\rho_e^i, GDP_{pc}^i) = 0.300$	0.001	Full (122)
$\rho(\rho_e^i, GDP_{pc}^i) = 0.367$	0.000	Restricted (90)

Note: For definitions, see Table 1.

where GDP per capita is again at its 2008 value. Figure 5 visually summarizes the data. As before, the linear predictions based on the full and restricted samples are given by the green and blue lines, respectively. Whereas facts 1 and 2 are relatively intuitive and have counterparts in business cycle literature, the positive association between procyclicality of emissions and GDP per capita is a novel result of this paper. Intuitively, $\rho(\rho^i, GDPpc^i) > 0$ suggests that in rich countries emissions and GDP are coupled relatively more tightly than in poor countries.

One of the most important dimensions along which rich and poor countries differ is the composition of GDP. Specifically, rich countries tend to have large service and small agriculture sectors as measured by the share of value added in a given sector. The opposite is true for poor countries. Fact 4 sheds light on the complex relationship between properties of emissions and the composition of GDP.

FACT 4: The composition of GDP is crucial for the business cycle properties of emissions but the relationship is complex.

In order to study the relationship between the sectoral composition of GDP and the business cycle properties of emissions, in Table 3 I report the correlation coefficients between σ_e and ρ_e on the one hand, and share of value added in agriculture, services, industry and manufacturing on the other. As above the results are reported for both the full and restricted samples. However, note that the sample sizes are somewhat smaller than before in both cases because share data are not as widely available. Finally, Figures 6 to 13 visually summarize the data. In all figures I follow the same color coding conventions adopted above.

Table 3: Cyclicality, Volatility and Composition of GDP

Sector	Statistic	p-value	Sample (N)	Reference
Agriculture	$\rho(\sigma_e^i, shr_A^i) = 0.239$	0.015	Full (104)	Fig.6
	$\rho(\sigma_e^i, shr_A^i) = 0.404$	0.000	Restricted (78)	
	$\rho(\rho_e^i, shr_A^i) = -0.237$	0.015	Full (104)	Fig. 7
	$\rho(\rho_e^i, shr_A^i) = -0.291$	0.010	Restricted (78)	
Services	$\rho(\sigma_e^i, shr_S{}^i) = -0.345$	0.000	Full (104)	Fig.8
	$\rho(\sigma_e^i, shr_S^i) = -0.341$	0.002	Restricted (78)	
	$\rho(\rho^i, shr_S^i) = 0.246$	0.012	Full (104)	Fig. 9
	$\rho(\rho^i, shr_S^i) = 0.281$	0.013	Restricted (78)	
Industry	$\rho(\sigma_e^i, shr_I^i) = 0.200$	0.041	Full (105)	Fig. 10
	$\rho(\sigma_e^i, shr_I^i) = 0.003$	0.980	Restricted (79)	
	$\rho(\rho_e^i, shr_I^i) = -0.082$	0.408	Full (105)	Fig. 11
	$\rho(\rho_e^i, shr_I^i) = -0.044$	0.700	Restricted (79)	
Manufacturing	$\rho(\sigma_e^i, shr_M^i) = -0.289$	0.034	Full (101)	Fig. 12
	$\rho(\sigma_e^i, shr_M^i) = -0.164$	0.158	Restricted (76)	
	$\rho(\rho_e^i, shr_M^i) = 0.377$	0.000	Full (101)	Fig. 13
	$\rho(\rho_e^i, shr_M^i) = 0.336$	0.003	Restricted (76)	

Note: For definitions, see Table 1.

First, focus on the top two panels of Table 3 corresponding to agriculture and services. I find that the greater the share of agriculture (services) in GDP, the greater (smaller) is the country's σ_e. The opposite is true for ρ_e: the greater the share of agriculture (services) in GDP, the smaller (greater) is the measure of emissions cyclicality in the country. These observations are consistent with facts 2 and 3 in that rich economies tend to have small agricultural and large services sectors. Furthermore, they hint at important differences in the cyclical properties of emissions across sectors. Intuitively, if emissions from agriculture are more volatile than, and less tightly coupled with, valued added in agriculture than in services, differences in the composition of GDP across countries would generate statistics with this pattern.

The relationship between σ_e and ρ_e on the one hand and industry and manufacturing share of GDP on the other other is more nuanced. Industry's share of GDP appears positively correlated related with σ_e across countries but this relationship disappears in the restricted sample where data are more reliable. There is no apparent relationship between ρ_e and the size of the industrial sector. Manufacturing share of GDP, however, is negatively correlated with σ_e but this relationship is is not significant in the restricted sample. There is a strong, positive and robust relationship between manufacturing value added and ρ_e across countries.

The main message that emerges from Table 3 is that the composition of GDP influences the properties of emissions in a complicated way. Two crucial indicators of development, i.e. size of agriculture and services in a country's GDP, suggest that the level of development is negatively correlated with σ_e and positively correlated with $\rho_{e.}$ This observation is consistent with Facts 2 and 3.

The relationship between industrial value added and business cycle properties of emissions is confounded by some important sectors such as mining and electricity/gas/water supply which are included in industry but crucially not in manufacturing. For example, countries in the right tail of industrial value added distribution include fossil fuel exporters (e.g. Azerbaijan, Trinidad and Tobago, Angola, etc.) and manufacturing hubs (e.g. China, Indonesia, Malaysia, etc.). In the left tail one finds extremely poor countries like Ethiopia and Malawi with large agriculture sectors and rich countries like Hong Kong and Luxembourg with large service sectors. Focusing solely on manufacturing share, an intuitive pattern similar to that for services emerges. Nevertheless, a more detailed investigation of industrial composition and its effects on the properties of emissions will undoubtedly be informative.

4 Robustness

In this section I perform a robustness analysis for the facts established above and report the results in Table 4. For ease of comparison, the facts of Section 3 are collected under the first column titled BM for benchmark. In columns (I) and (III), I investigate sensitivity with respect to alternative filters. The following three columns (IV)-(VI) report results by using data for alternative emissions data sources. Finally, in columns (VII) and (VIII) I compute the same statistics using GDP_{pc} and GDP composition data from 2000 and 1990, rather than 2008 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.

The statistics reported in Columns (I), (II) and (III) suggest that the benchmark results are not driven by the HP filter. To show this, I perform the same calculations on first order differenced (FOD) data as well as on data filtered using the band pass filter (BP) recommended by Baxter and King [1999] and the random walk band pass filter (RWBP) recommended by Christiano and

Table 4: Robustness

	Benchmark	Other Filter			Other Emissions			Other Year		
		FOD	BP	RWBP	CAIT	EDGAR	GHG	2000	1990	Fact
	(BM)	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	
ρ_e	**0.264**	0.344	0.248	0.223	0.291	0.317	0.312			1
σ_e	**0.078**	0.134	0.072	0.078	0.074	0.061	0.058			1
σ_{rel}	**2.986**	2.807	2.855	3.211	2.700	2.177	2.074			1
$\rho(\sigma_e^i, GDP_{pc}^i)$	**-0.225**	-0.227	-0.189	-0.233	*-0.163*	-0.217	-0.183	-0.235	-0.215	2
$\rho(\rho_e^i, GDP_{pc}^i)$	**0.300**	0.350	0.296	0.295	0.315	*0.120*	*0.163*	0.280	0.302	3
$\rho(\sigma_e^i, shr_A^i)$	**0.239**	0.233	0.230	0.249	0.202	0.306	0.249	0.256	*0.144*	4
$\rho(\rho_e^i, shr_A^i)$	**-0.237**	-0.268	-0.248	-0.249	-0.268	*-0.057*	*-0.152*	-0.282	-0.254	4
$\rho(\sigma_e^i, shr_S^i)$	**-0.345**	-0.345	-0.343	-0.350	-0.360	*-0.163*	*-0.154*	-0.422	-0.225	4
$\rho(\rho_e^i, shr_S^i)$	**0.246**	0.2748	*0.184*	0.225	0.357	*-0.032*	*0.023*	0.268	*0.104*	4
$\rho(\sigma_e^i, shr_I^i)$	**0.200**	0.205	0.205	0.198	0.243	*-0.067*	*-0.028*	0.218	*0.065*	4
$\rho(\rho_e^i, shr_I^i)$	*-0.082*	*-0.095*	*-0.004*	*-0.052*	*-0.182*	*0.071*	*0.089*	*-0.001*	0.199	4
$\rho(\sigma_e^i, shr_M^i)$	**-0.289**	-0.294	-0.279	-0.290	-0.252	-0.211	-0.230	-0.297	-0.414	4
$\rho(\rho_e^i, shr_M^i)$	**0.377**	0.317	0.327	0.332	0.287	0.254	0.281	0.232	0.332	4

Note: For definitions, see Table 1. *Italics* indicate p-value>0.05.

Fitzgerald [2003]. 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.[20] 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 at the time of writing. The results are qualitatively identical[21] and very similar in magnitude. This is reassuring particularly because there exists a number of statistics that are significant and similar in columns (BM) and (IV), but insignificant when using CO_2 and GHG emissions data from EDGAR, reported respectively, in columns (V) and (VI).

As stated in Section 2, the data in EDGAR starts in 1970. In other words, in EDGAR I have about 20 fewer years of observations for most countries. 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.[22] The results are qualitatively identical as above. However, $\rho(\rho_e^i, GDP_{pc})$ becomes insignificant implying that Fact 3 would not have been picked up using EDGAR data. Similarly, several results relating to the composition of GDP also lose significance. Put differently, if I was restricted to using EDGAR data only, I would not observe any patterns in the relationship between ρ_e and σ_e on the one hand and the composition of GDP on the other.

There are complementary reasons behind these differences. First, each emissions series differs in emission sectors and periods covered.[23] Furthermore, excluding the OPEC and ex-communist countries from the sample eliminates some instances of insignificance and renders the results very similar to those in column (BM). In any case, it is important to keep in mind that columns (V) and (VI) do not contradict the benchmark results or those in column (IV). They simply do not to provide supporting evidence along the dimensions highlighted above.

The final two columns of the table, (VII) and (VIII), report the results when the reference year for GDP per capita and output composition data is 2000 and 1990, respectively. The results are qualitatively identical and similar in magnitude, although a few statistics in 1990 are no longer significant. This is not surprising since most countries' ranking in the relevant cross country distribution of GDP per capita and value added share are rather persistent.

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. Here I study those countries for which there exist at least 100 years of data and construct the analogue of Table 2. The results are provided in

[20] The only exception is a significantly larger σ_e value under first order differencing. It is well-known that FOD amplifies high frequency fluctuations in the data.

[21] I define qualitatively identical as no statistically significant sign differences across columns of Table 4.

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

[23] See Winne [2009] for a detailed comparison of various data sources on emissions.

Table 5 where, unlike in Table 2, I focus on the experience of individual countries.

Table 5: Long time series evidence on Fact 1

Country	Code	ρ_e	σ_e	σ_{rel}	**Length**
FRANCE	FRA	0.514	0.060	1.530	189
UNITED KINGDOM	GBR	0.429	0.050	2.618	179
NORWAY	NOR	0.431	0.102	4.644	174
SWEDEN	SWE	0.362	0.127	5.846	170
DENMARK	DNK	0.306	0.077	3.394	166
NETHERLANDS	NLD	0.547	0.099	2.387	163
BELGIUM	BEL	0.343	0.068	2.864	163
GERMANY	DEU	0.208	0.104	1.885	159
SWITZERLAND	CHE	*0.026*	0.114	3.673	151
FINLAND	FIN	0.388	0.221	7.655	149
AUSTRALIA	AUS	*0.084*	0.083	3.275	149
ITALY	ITA	0.464	0.169	4.736	148
UNITED STATES	USA	0.576	0.046	1.296	139
AUSTRIA	AUT	0.248	0.189	3.268	139
CANADA	CAN	0.382	0.068	2.201	139
JAPAN	JPN	0.291	0.154	3.311	139
NEW ZEALAND	NZL	0.179	0.043	1.376	131
INDIA	IND	*-0.142*	0.034	1.270	125
CHILE	CHL	0.403	0.079	1.501	114
PERU	PER	0.212	0.174	5.360	113
ARGENTINA	ARG	0.276	0.094	2.866	109
BRAZIL	BRA	0.439	0.066	2.802	108
TAIWAN	TWN	0.574	0.082	1.405	108
MEAN		**0.328**	**0.035**	**0.100**	

Note: For definitions, see Table 1. *Italics* indicate p-value>0.05.

For all countries other than India, emissions are procyclical and in the case of India the correlation coefficient is not statistically significant. With long time series, σ_{rel} is greater than 1 for every country in the sample. The mean values for the statistics measuring cyclicality and volatility are similar to those given in Table 2. To the extent that emissions and GDP data are reliable when one goes back more than a century in history, these results suggest that Fact 1 is robust to the variations in sample period.

It is not straightforward to replicate the analysis that results in Facts 2 and 3 with this sample of countries primarily because most of the countries listed in Table 5 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 for Facts 2 and 3. Specifically, most of the countries in Table 5 undergo a process of sustained economic development over the sample period. Therefore, the comparison of an individual country's experience earlier in its economic history to its experience more recently as a rich 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 after which a country is deemed to be *poor* relative to before. Second, one must take a stand on how to deal with the two world wars which have profound implications for GDP and emissions. I address both issues simultaneously and treat all countries symmetrically, i.e. irrespective of the sample length, by considering 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 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.[24] The results are presented in Table 6.

Table 6: Long time series evidence on Facts 1, 2 & 3

	ρ_e		σ_e		σ_{rel}	
	Pre-1914	***Post-1960***	***Pre-1914***	***Post-1960***	***Pre-1914***	***Post-1960***
AUSTRALIA	*-0.019*	0.407	0.130	0.019	4.191	1.866
AUSTRIA	*0.171*	*0.208*	0.152	0.034	7.031	3.700
BELGIUM	0.513	0.426	0.047	0.031	4.766	3.185
CANADA	*0.259*	*0.186*	0.100	0.020	3.256	1.635
SWITZERLAND	*-0.147*	*0.233*	0.062	0.033	1.617	2.271
GERMANY	*0.047*	0.340	0.046	0.020	2.292	1.815
DENMARK	*0.151*	0.297	0.085	0.055	5.427	4.441
FINLAND	*0.238*	*0.070*	0.199	0.060	8.196	3.201
FRANCE	*0.182*	0.407	0.051	0.032	1.861	4.013
UNITED KINGDOM	0.318	0.410	0.030	0.020	1.775	1.640
INDIA	-0.366	0.116	0.042	0.018	1.175	0.980
ITALY	*0.009*	0.572	0.079	0.019	3.560	1.483
JAPAN	*0.133*	0.703	0.256	0.026	8.663	1.957
NETHERLANDS	*0.009*	0.320	0.076	0.037	4.709	3.445
NORWAY	*0.070*	*0.003*	0.085	0.042	5.000	4.259
NEW ZEALAND	*-0.026*	0.305	0.038	0.031	1.213	1.694
SWEDEN	*0.091*	*-0.131*	0.099	0.041	4.171	4.124
UNITED STATES	0.544	0.718	0.046	0.017	1.621	1.332

Note: For definitions, see Table 1. *Italics* indicate p-value>0.05.

[24]This means that I drop China, Peru, Argentina, Brazil, and Taiwan from the countries listed in Table 5.

In order get some intuition for the information provided in Table 6 take the US as an example. Emissions become more procyclical post-1960 relative to pre-1914. Furthermore, the volatility of emissions is lower post-1960. These results are in accordance with facts 2 and 3. Furthermore, in all periods the volatility and correlation statistics are consistent with fact 1. The experience of the US is typical for a large majority of countries, providing further reassurance that the aspects of the relationship between emissions and GDP highlighted in facts 1 through 3 are not mere coincidences.

The corroborating evidence aside, some aspects of Table 6 pose a challenge to the facts established in Section 3. Emissions are countercyclical and significant in India pre-1914 (i.e. partial evidence against fact 1). Procyclicality of emissions declines in Belgium, Canada, Norway and Sweden as these countries become richer (i.e. partial evidence against fact 3). Furthermore, a large number of countries feature insignificant correlation statistics. 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 and more agriculture dominated a country, the lower, i.e. statistically indistinguishable from zero, one expects ρ_e to be.

5 Speculations on the causal mechanisms

I readily acknowledge that these facts are based on simple summary statistics. Accordingly, it is not possible to make any claims regarding the mechanisms that generate the data with these properties. Indeed, the aim of the paper is to highlight the regularities in the data which can motivate research on the theory of emissions determination over the business cycle. It is, however, possible to speculate briefly about some key components of such a theory.

First, the observation that typically $\sigma^i_{rel} > 1$ suggests that the shocks affecting the emissions intensive sectors of the economy might be more volatile than the shocks affecting the aggregate economy. Putting structure on the production side of the economy can shed light on this matter. Second, the composition of an economy's GDP and its change through the process of development is likely to be important. By the process of development I mean countries shifting productive resources away from agriculture and towards industry first and services later. In this context, it would not be surprising to find that the cyclicality and relative volatility of emissions vary significantly across sectors due to the inherent properties of the production technology and shocks in these sectors. Consequently, even if the countries are subject to shocks drawn from the same sector specific distributions and use the same technologies, the relationship between aggregate emissions and GDP will vary across countries based on the composition of a country's GDP. Papers that can provide guidance along these lines, albeit without reference to emissions, include Da-Rocha and Restuccia [2006] and Moro [2012].

Third, globalization is likely to be another pertinent mechanism which in part generates these facts. This may happen directly or through interaction with the process of development. By reducing the inefficiencies associated with self sufficiency in an autarkic world, globalization may influence the cyclicality and relative volatility of emissions directly. Consider, for example, how the primary and secondary energy supply mix of a country might be different under autarky versus international trade and investment flows. In addition, by accelerating or impeding the structural change associated with development, globalization may have an indirect effect. The recent experiences of East Asian countries and China are good examples of globalization accelerating structural change. Conversely, countries can be locked into producing commodities under globalization as specialization may be efficient from a global perspective.

Finally, the emissions reduction policies of governments can alter the behavior of agents which in turn affects the relationship between emissions and GDP. See, for example, Heutel [2012] for a theoretical contribution on this topic. Alternatively, policies aiming to decarbonize a country's power, industrial and transportation sectors can weaken the procyclicality of emissions and reduce their relative volatility. To see this, compare country A where the only emissions in the country originate from fossil fueled power stations to an otherwise identical country B which has a carbon free power sector.[25] In this highly idealized example, $\rho^A > \rho^B = 0$ and $\sigma_e^A > \sigma_e^B = 0$ trivially because emissions are zero and unrelated to the level economic activity in country B for structural reasons. If the government of A uses policies to make A's power sector more like B's, one would expect to see a reduction in ρ^A and σ_e^A.

It is probably too early to empirically test whether existing emissions reduction policies are having effects like this on the business cycle properties of emissions because these policies are either relatively young or completely absent even among developed countries. The most comprehensive, well-known and oldest example of such a policy is the Emission Trading System of the European Union which came into effect in 2005. Even if this policy worked effectively and the business cycles since 2005 were typical, a researcher would have a maximum of 6 data points per EU member country to infer the policy's affect on the relationship between emissions and GDP. That said, exploiting the variation in policies and outcomes across US states, or seeking to identify structural breaks in countries which adopted climate change mitigation policies earlier (e.g. carbon taxes in Scandinavia, climate change levy in the UK, etc.) are promising avenues of research.

[25] Suppose, for simplicity, the rest of the economies of A and B do not have any direct emissions, e.g. transportation, industry, residential and commercial sectors use electricity as their only source of energy.

6 Conclusion

The paper provides a rigorous analysis of the business cycle properties of CO_2 emissions within and across countries and proposes four salient facts regarding their cyclicality and volatility. A key innovation is the paper's focus on the cyclical components of emissions and GDP which are obtained using the HP filter. The results of the analysis are subjected to and survive a battery of robustness tests.

Although a theory of emissions determination over the business cycle is beyond the scope of the paper, I propose a number of mechanisms that are likely to be important. Against the backdrop of the empirical facts and theoretical considerations outlined above, two questions are of immediate interest. First, which growth models are consistent with these facts, and in particular, are multi-sector neoclassical growth models able to explain these facts? Second, what are the likely effects of climate change mitigation policies on the properties of emissions over the business cycle? These topics are left for future research and the current author's efforts on both fronts is ongoing.

Figures

Figure 1: GDP and Emissions in the US

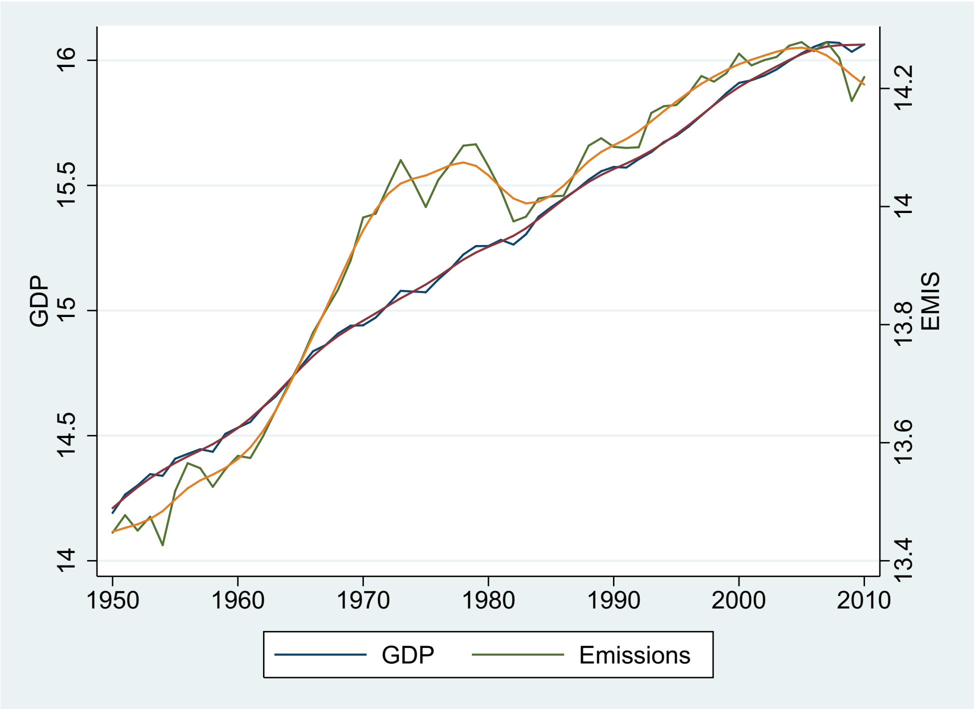

Figure 2: Cyclical Components of Emissions versus GDP in the US

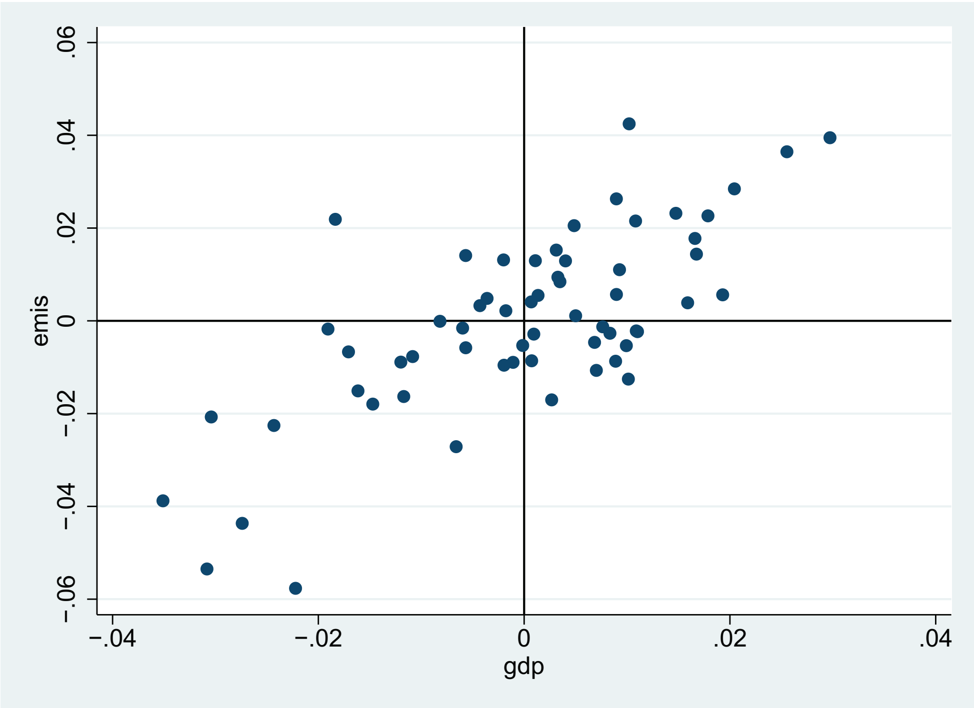

Figure 3: Volatility of Emissions versus GDP per capita

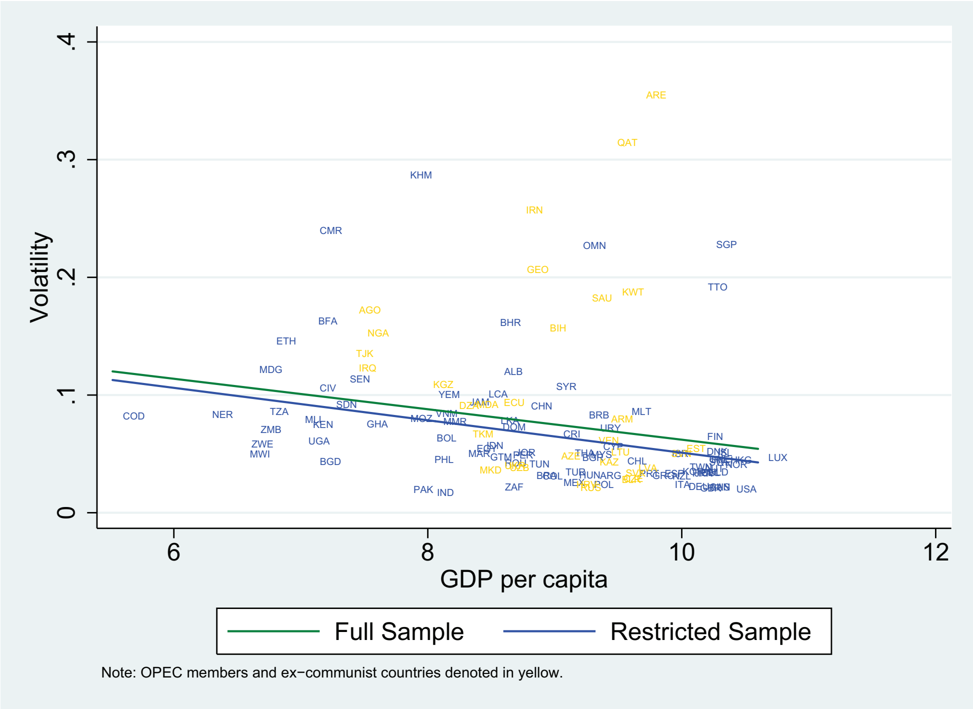

Figure 4: Relative Volatility of Emissions versus GDP per capita

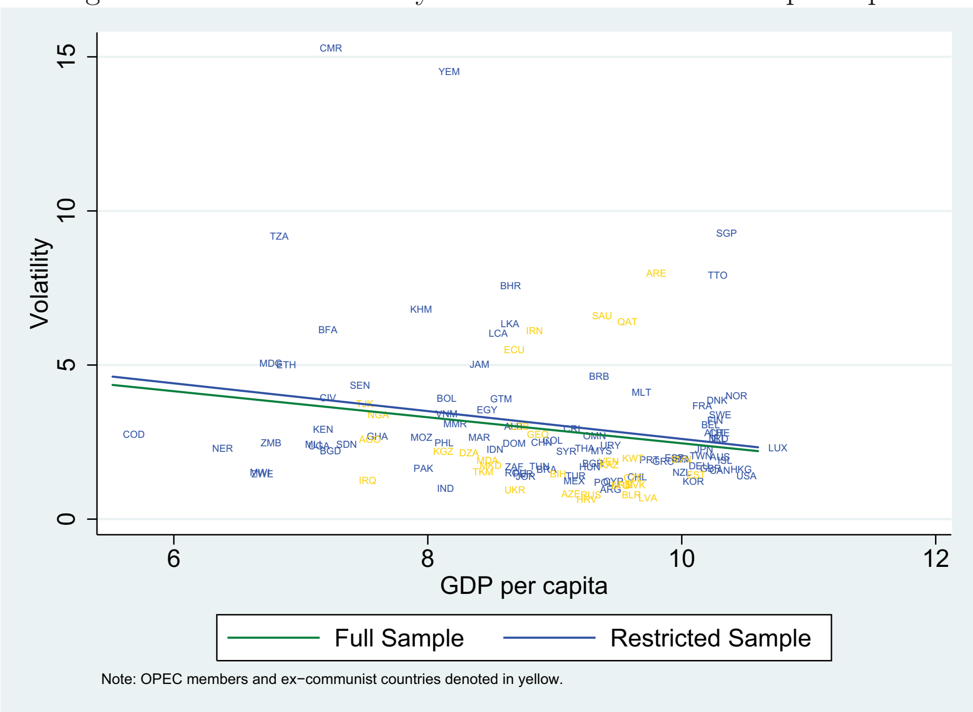

Figure 5: Cyclicality of Emissions versus GDP per capita

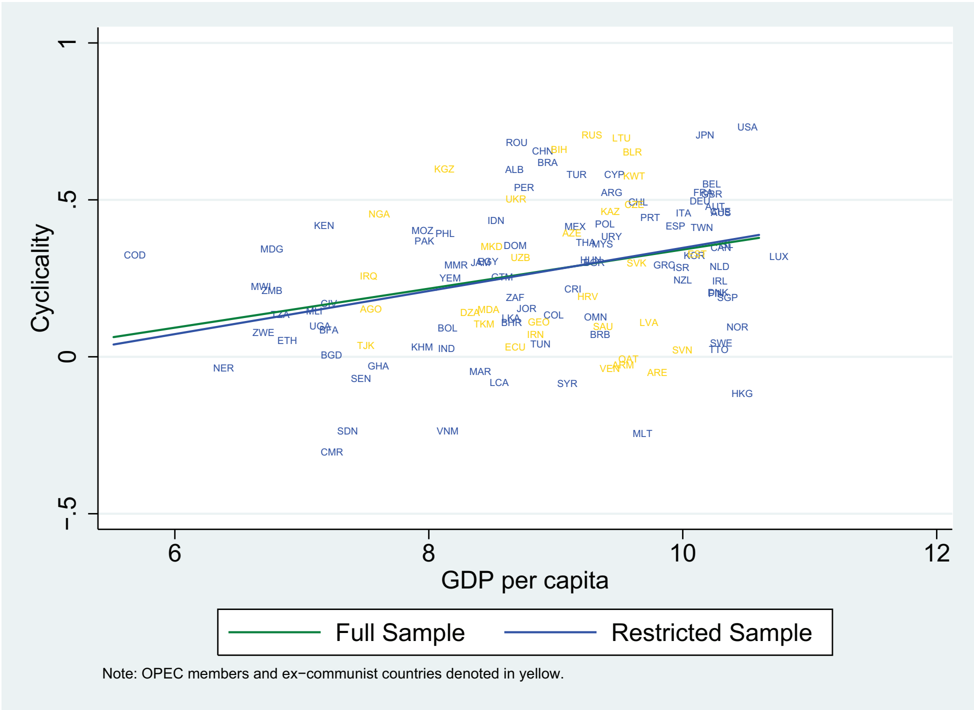

Figure 6: Volatility of Emissions versus Share of Agriculture in GDP

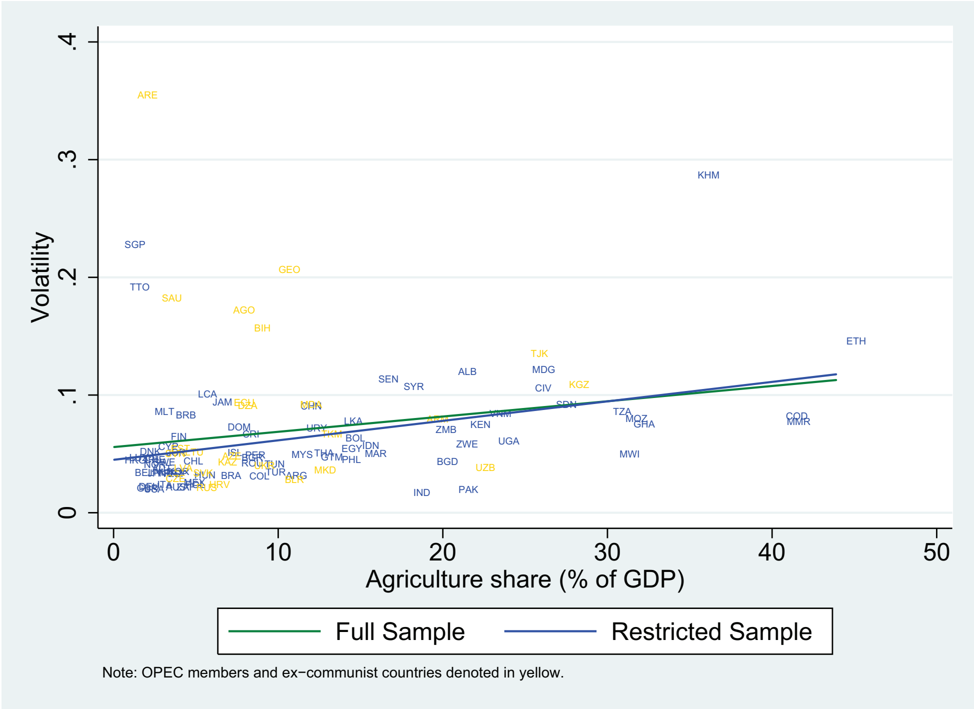

Figure 7: Cyclicality of Emissions versus Share of Agriculture in GDP

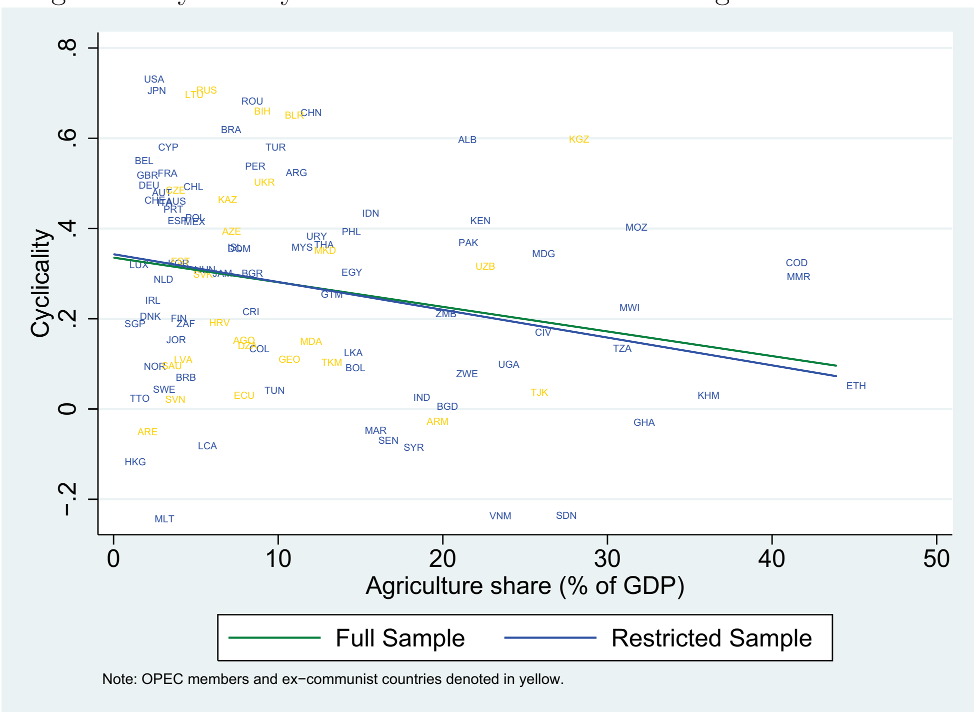

Figure 8: Volatility of Emissions versus Share of Services in GDP

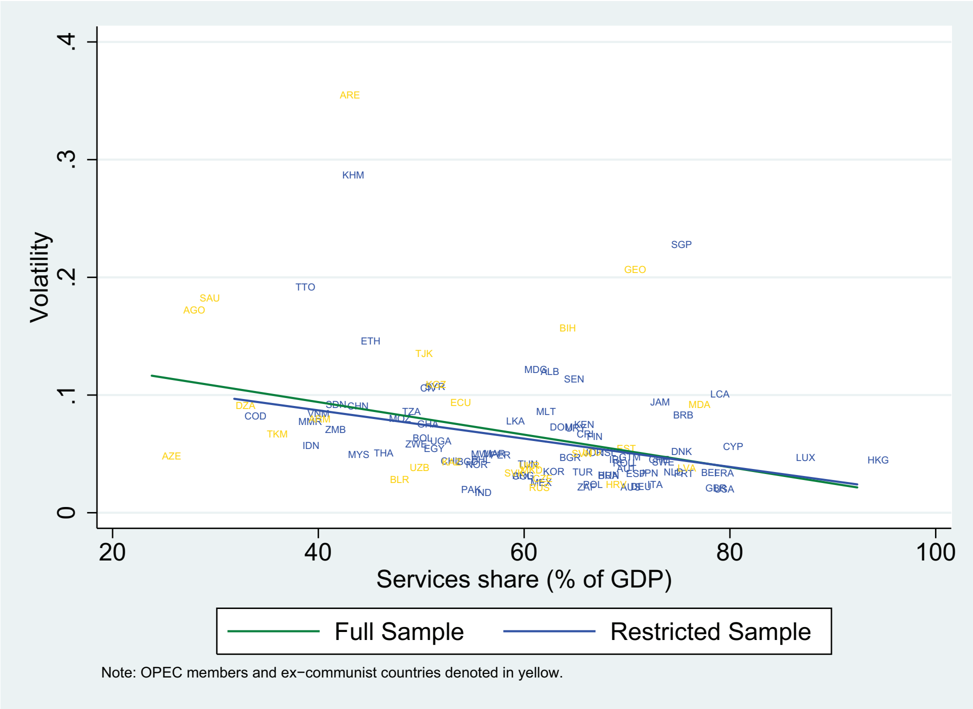

Figure 9: Cyclicality of Emissions versus Share of Services in GDP

Figure 10: Volatility of Emissions versus Share of Industry in GDP

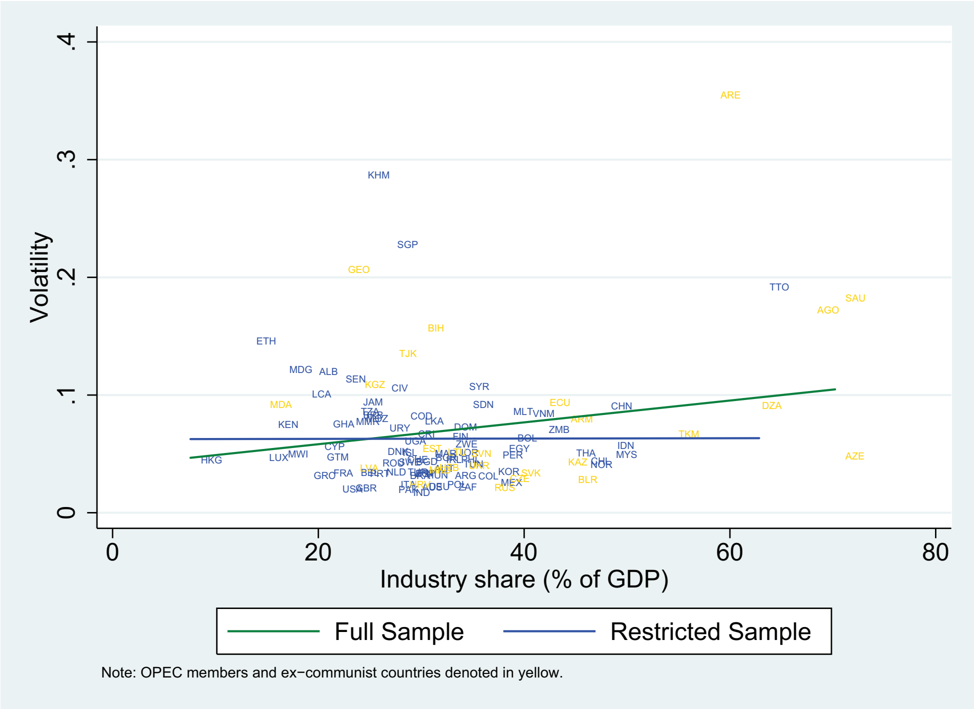

Figure 11: Cyclicality of Emissions versus Share of Industry in GDP

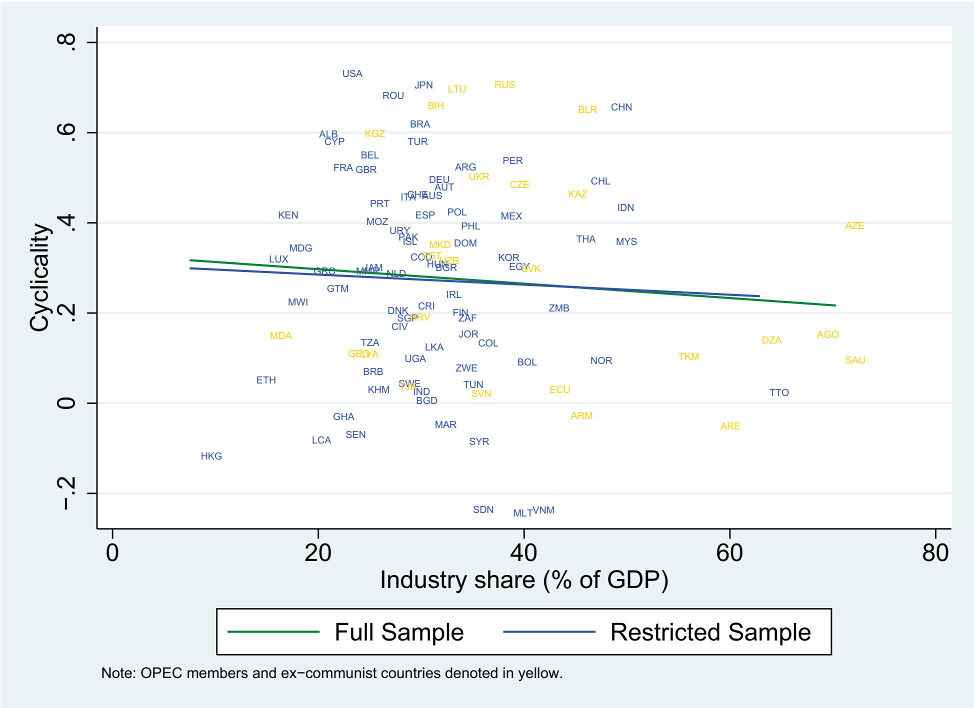

Figure 12: Volatility of Emissions versus Share of Manufacturing in GDP

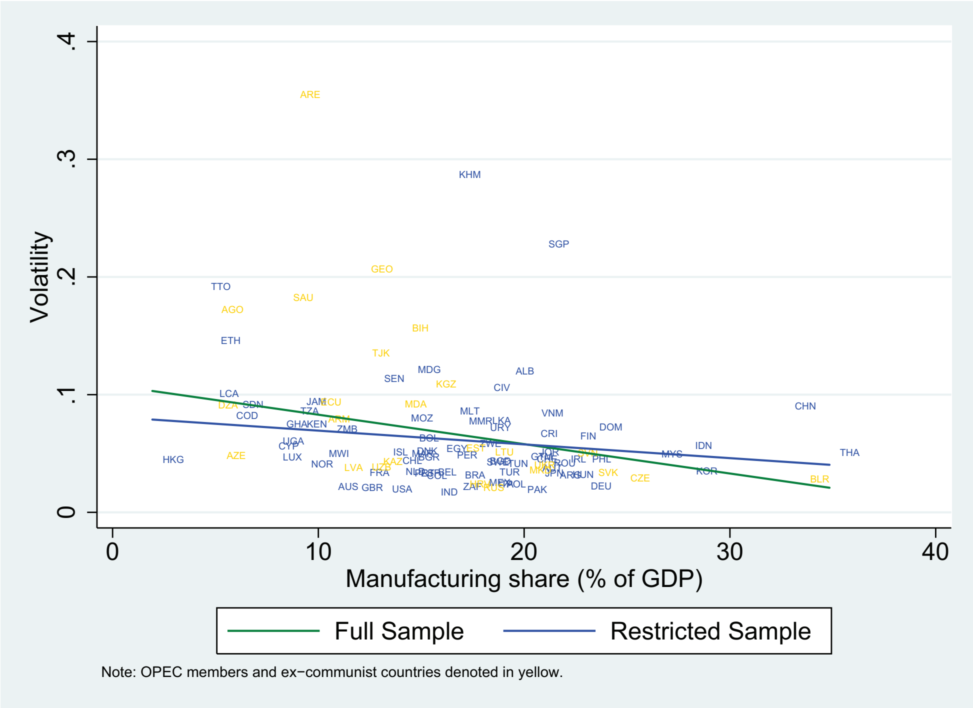

Figure 13: Cyclicality of Emissions versus Share of Manufacturing in GDP

References

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

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

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.

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., 2011. URL `http://cdiac.ornl.gov/`.

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.

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

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

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

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

The Conference Board. The conference board total economy database. Technical report, 2012. URL `http://www.conference-board.org/data/economydatabase/`.

J. M. Da-Rocha and D. Restuccia. The role of agriculture in aggregate business cycles. *Review of Economic Dynamics*, 9:455–482, 2006.

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`.

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

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.

D. Holtz-Eakin and T. M. Selden. Stoking the fires? co2 emissions and economic growth. *Journal of Public Economics*, 57:85–101, 1995.

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

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`.

A. Moro. The structural transformation between manufacturing and services and the decline in the us gdp volatility. *Review of Economic Dynamics*, forthcoming, 2012.

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.

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.

R. Stefanski. Structural transformation and pollution. manuscript, 2012.

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

M. Wagner. The carbon kuznets curve: A cloudy picture emitted by bad econometrics? *Resource and Energy Economics*, 30:388–408, 2008.

S. Winne. Global greenhouse gases emissions review. Technical report, Work stream 2, Report 1 of the AVOID programme (AV/WS2/D1/R01), 2009.

The World Bank. World development indicators. Technical report, 2012. URL `http://data.worldbank.org/data-catalog/world-development-indicators`.

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/`.