Testing for Convergence in Carbon Dioxide Emissions Using a Century of Panel Data

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Abstract

This paper tests the convergence in per-capita carbon dioxide emissions for a collection of developed and developing countries using data spanning the period 1870 to 2002. For this purpose, three recently developed panel unit root tests that permit for dependence among the individual countries are employed. The results lend strong support in favor of convergence for the panel as a whole. Estimates of the speed of this convergence is also provided.

JEL Classification: C32; C33; Q28; Q54

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1 Introduction

We address two main issues in this paper. First, and most importantly, we investigate whether the per-capita carbon dioxide (CO_2) emissions in major developed countries share a common trend, and if so, have these countries experienced convergence in the CO_2 emissions? This analysis bears on the growing empirical literature on CO_2 convergence across developed and developing countries, see Aldy (2006) for a recent illustration. The second main issue addressed in this paper is how quickly the emissions level revert to that common trend following a global shock to the CO_2 emissions? An issue that has not received much attention but may prove

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particularly relevant both for policy and for empirical work. To answer these questions, we explore the dynamics of CO_2 emissions for a set of developed and developing countries over the period 1870 to 2002. To study the extent of the convergence, we employ a battery of recently developed panel unit root tests.

Emissions convergence is a core concern for policymakers, particularly in developed countries that are working towards the long term goal of allocating emissions equally to all countries on a per-capita basis. For this to happen evidence of convergence is a must, while lack of emissions convergence may protract the process of emissions allocation to materialize. To investigate the magnitude of emissions convergence empirically, recently researchers have relied on unit root tests to assess if shocks to CO_2 emissions are permanent, a feature that is argued to be evidence against convergence. Using annual data for 21 OECD nations between 1960 and 1997, Strazicich and List (2003) found significant evidence of convergence in per-capita CO_2 emissions. By contrast, Aldy (2006) reports no evidence of convergence for his global sample comprising 88 countries during the period 1960 to 2000, although some evidence of convergence was found for a subsample of 23 OECD countries.

Although these are encouraging results and deserve merit, no previous study has yet examined the per-capita CO_2 emissions from a factor structure perspective that may well characterize the data. In particular, our research is primarily directed at obtaining a better understanding of the sources behind the persistence of CO_2 emissions, both over time as well as across countries. For this purpose, a factor model is employed that allows us to distinguish between two different stochastic components of the data, an idiosyncratic component and an common component. This decomposition is appropriate because CO_2 emissions usually exhibit both high variability within each county over time as well as strong comovements across countries. For example, European countries often coordinate many of their economic and environmental policies, which make the CO_2 emissions correlated across countries.[1] The idea is to first remove the common component, and then to test for convergence in the idiosyncratic component.

This paper examines the extent of CO_2 convergence, and is therefore closely related to the work of Strazicich and List (2003) and Aldy (2006). Our approach, however, differs significantly from these two studies in at least four respects.

First, Strazicich and List (2003) examine the CO_2 convergence using the Im et al. (2003) panel unit root test, which is critically dependent on the assumption that the individual countries are independent. As explained above, this assumption is very unlikely to hold in the CO_2 data.[2]

[1]For instance, the 1979 convention on Long-range Transboundary Air Pollution was held in Geneva aiming to deal with problems of air pollution on a broad regional basis, see UNECE (1995) for further information.

[2]Banerjee et al. (2004) show that panel data unit root statistics tend to conclude in favor of stationarity, or convergence, when cross-section dependence is not considered.

Another drawback of this test is that a rejection might be caused by a single converging country, which is not very interesting. In this study, we employ three recently developed panel unit root tests that allow for cross-sectional dependence, and that differ in the formulation of alternative hypothesis, which simplifies the interpretation of the test outcome.

A second major difference is the sample size. Both Strazicich and List (2003) and Aldy (2006) use a relatively short span of data, which dates back to 1960, whereas our data stretches all the way back to 1870 and contains more recent observations. In addition, Aldy (2006) relies upon the conventional time series unit root testing approach, which is known to suffer from low power. Our approach is based on combining the information obtained from the time series dimension with that obtained from the cross-sectional dimension, and is therefore expected to produce more precise tests. In order to robustify our results with respect to the choice of countries, we consider two different samples, one developed and one global sample that includes both developed and developing countries.

Third, both Strazicich and List (2003) and Aldy (2006) adopt the Carlino and Mills (1993) notion of stochastic convergence, which states that a pair of countries converges if their CO_2 differential is stationary. However, as argued by Ericsson and Halket (2002), this form of convergence is relatively weak since the emissions of two countries could be diverging deterministically. To circumvent this problem, we employ an alternative definition introduced by Evans (1998), which translates the concept of pair-wise convergence into a single criterion that should apply to the panel as a whole.

Finally, we extend our analysis to measure the speed of convergence in the CO_2 emissions by calculating the half-lives of a CO_2 shock to each country.[3] In doing so, we employ several newly devised estimators that are unbiased and that allow for the possibility of cross-section dependence. To the best of our knowledge, no previous study has examined this issue in a panel data framework.

Our analysis is related to Lanne and Liski (2004), who tested CO_2 convergence among 15 developed countries between 1870 and 1998, while allowing for the possibility of structural breaks.[4] The authors find that per-capita CO_2 emissions did not converge after the oil-price shock of the 1970s, and that structural breaks cannot explain the declining trend in CO_2 emissions. In this paper, we argue that this weak empirical finding can in part be explained by the low power inherent in the time series methodology used by the authors, and that panel methods should

[3] The half-life is a popular measure for speed of convergence and is routinely used in the empirical literatures of growth theory and purchasing power parity.

[4] The 15 developed countries analyzed in Lanne and Liski (2004) is similar to our D16 sample which includes 16 developed countries. The marginal difference between our and their data set is that we included Spain in the analysis and our data ends at 2002.

be able to produce more accurate results.

Our two main results may be summarized as follows. Firstly, by using our panel approach, we are able to reject the presence of a unit root in the data, which leads us to the conclusion that the per-capita CO_2 emissions appear to be converging toward a common trend or mean value. Secondly, our estimates of the speed of convergence suggest that it takes about five years for a CO_2 shock to reduce by half. These results appear to be quite robust, and do not depend on whether or not there are developing countries in the sample. Thus, in contrast to Aldy (2006), we find evidence of convergence not only for our developed but also for our global sample.

The rest of the paper is organized as follows. Section 2 describes the criteria for testing convergence of per-capita CO_2 emissions followed by a brief account of the panel approach taken in this paper. Section 3 presents the data set that is used and reports the results of the analysis. Section 4 provides some concluding remarks.

2 Panel convergence tests

We root our methodology in the work of Evans (1998), who introduced a particular notion of convergence, which implies that the long-run CO_2 gap between any two country must be stationary. To formalize the idea empirically, suppose that y_{it}, the log CO_2 emissions for country $i = 1, ..., N$ at time $t = 1, ..., T$, is nonstationary, and thus exhibit a unit root. Then a pair-wise convergence is said to occur if, for any pair of countries i and j, the difference $y_{it} - y_{jt}$ is stationary so that y_{it} and y_{jt} are cointegrated. Specifically, this notion of pair-wise convergence is equivalent to the condition that the difference between the individual series and their mean value at each point in time is stationary.

This hypothesis can be tested using the following regression

$$\widetilde{y}_{it} = \alpha_i + \tau_i t + \phi_i \widetilde{y}_{it-1} + e_{it}, \tag{1}$$

where $\widetilde{y}_{it} = y_{it} - \frac{1}{N}\sum_{j=1}^{N} y_{jt}$, α_i and τ_i are country specific intercept and trend terms, and e_{it} is a disturbance term that may by correlated across both i and t. The key parameters in (1) is ϕ_i, which measure the degree of the convergence. If $\phi_i = 1$, then country i has a unit root and is thus nonconvergent, whereas, if $\phi_i < 1$, then country i is convergent. The exact hypothesis to be tested is given as follows

$$H_0 : \phi_i = 1 \text{ for all } i \text{ versus } H_1 : \phi_i < 1 \text{ for some } i.$$

A rejection of the null should therefore be taken as evidence in favor of convergence for at least one country, whereas a non-rejection should be taken as evidence of non-convergence for the whole panel. Interestingly, if we instead assume a common value, ϕ say, for the individual autoregressive parameters, then we still have the same null hypothesis but the alternative can be reformulated as

$$H_1 : \phi_i < 1 \text{ for all } i.$$

Thus, in this case, we are in fact testing the null of non-convergence against the alternative of convergence for the whole panel, which is different from the case when ϕ_i was allowed to differ.

To test these hypotheses, we employ three recently developed panel unit root tests that allow for cross-sectional dependence by assuming that (1) admits to the common factor representation

$$e_{it} = \lambda_i' f_t + u_{it}, \tag{2}$$

where f_t is a vector containing the unobserved common factors, which could represent oil-price shocks or any other feature affecting CO_2 emissions that is common for all countries. The disturbance u_{it} is assumed to be mean zero and uncorrelated across i but potentially correlated over time. The factors in (2) are introduced to model the cross-sectional dependence in e_{it}. The extent of this dependence is determined by λ_i, which is a vector of loading parameters that measure the effect of the common factors. This is easily seen by writing

$$E(e_{it}e_{jt}) = \lambda_i' E(f_t f_t')\lambda_i \text{ for } i \neq j.$$

Thus, if λ_i is zero, then there is no correlation, whereas, if λ_i is nonzero, then e_{it} is cross-sectionally correlated. The tests that we use are all based on first estimating the unobserved common factors and their loadings, and then running (1) on the de-factored series, $\widetilde{y}_{it} - \widehat{\lambda}_i' \widehat{f}_t$ say, which should be asymptotically cross-sectionally uncorrelated. We now provide a brief description of each test employed in this study.

Phillips and Sul (2003) assume that there is a single factor, which can be estimated using the method of moments. The three statistics used in this paper are defined as follows

$$G_{ols}^{++} = \frac{1}{\sqrt{N}\sigma_\xi} \sum_{i=1}^{N} \left(\frac{\widehat{\phi}_i^+ - 1}{\widehat{\sigma}_\phi^+} - \mu_\xi \right), \quad Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1}(p_i),$$

$$P_m = -\frac{1}{\sqrt{N}} \sum_{i=1}^{N} (\ln(p_i) + 1).$$

The first statistic is simply an average of N individual unit root tests, where $\widehat{\phi}_i^+$ is an estimate of ϕ_i based on the de-factored data and $\widehat{\sigma}_\phi^+$ is the associated standard error. The adjustments μ_ξ and σ_ξ give the statistic zero mean and unit variance. By contrast, Z and P_m are based on combining the p-values of the individual unit root t-statistics obtained from (1). These p-values are denoted by p_i, and we use $\Phi^{-1}(p_i)$ to denote the inverse normal cumulative distribution function. All three tests have a limiting normal distribution.

Phillips and Sul (2003) allow the individual autoregressive parameters ϕ_i to differ, which implies that a rejection of the null should be interpreted as evidence of convergence for at least some countries. By contrast, Moon and Perron (2004) take the alternative approach and assume a common autoregressive parameter ϕ for all countries, so that a rejection should be interpreted as evidence of convergence for the panel as a whole. This difference in interpretation makes both approaches interesting.

Moon and Perron (2004) develop two t-statistics, which are based on a pooled estimate of ϕ using the de-factored series. Contrary to Phillips and Sul (2003), the authors permit for an arbitrary, and potentially unknown, number of factors, which are estimated using the method of principal components. Specifically, if we let $\widehat{\phi}^{+}_{pool}$ denote the pooled least squares estimate of ϕ using the de-factored data, Moon and Perron (2004) suggest that the following two statistics can be used

$$t_a = \frac{\sqrt{N}T(\widehat{\phi}^{+}_{pool}-1)}{\sqrt{2\widehat{\lambda}^4_u/\widehat{\omega}^4_u}} \quad \text{and} \quad t_b = \frac{\sqrt{N}T(\widehat{\phi}^{+}_{pool}-1)}{\sqrt{\widehat{\lambda}^4_u/\widehat{\sigma}^2_u\widehat{\omega}^2_u}},$$

where $\widehat{\omega}^2_u$ is an estimate of ω^2_u, the cross-sectional average of the individual long-run variances of u_{it}, and $\widehat{\lambda}^4_u$ is an estimate of λ^4_u, the cross-sectional average of the square of these long-run variances. Note that, since $\widehat{\sigma}^2_u$ is an estimate of $\omega^2_u/2$, the limit of the numerators of t_a and t_b as N and T grows are equal, which means that the two statistics are asymptotically equivalent. However, as shown by Moon and Perron (2004), their small-sample performance may be quite different, and we therefore consider both statistics.

In contrast to Phillips and Sul (2003) and Moon and Perron (2004), Bai and Ng (2004) permit the nonstationarity to come either from the common factors or from the idiosyncratic errors, or from both. Consequently, Bai and Ng (2004) face the problem of having to estimate the factors when it is not known whether they are stationary or not. The authors suggest first using the principal components method on the first differenced data to estimate the factors and then to test the de-factored and recumulated series for a unit root. Similar to Phillips and Sul (2003), Bai and Ng (2004) propose a combination of p-value type statistic, which has the same form as the P_m statistic described earlier, namely

$$P^c_e = -\frac{1}{\sqrt{N}}\sum_{i=1}^{N}(\ln(p_i)+1),$$

where p_i is now the p-value of the individual unit root t-statistic in (1) based on the de-factored and recumulated series. As with G^{++}_{ols}, Z and P_m, the statistics of Moon and Perron (2004) and Bai and Ng (2004) are normally distributed under the null hypothesis of a unit root.

3 Empirical Results

3.1 Data

We use the total fossil fuel CO_2 emission data from Marland et al. (2006). The population data were extracted from Maddison (2006). All statistical analysis were conducted using log of per-capita CO_2 emissions and balanced samples.

Our analysis is based on two different samples. The first sample consists of per-capita CO_2 data for 16 developed countries, namely Australia, Austria, Belgium, Canada, Denmark, France, Finland, Germany, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, United Kingdom and United States. This will henceforth be referred to as the D16, or developed sample. The data are annual and cover the period 1870 to 2002.

To complement our analysis to existing studies, for instance, Aldy (2006), we have proceeded to construct an extended sample which includes the D16 sample mentioned above and as well as 12 developing countries, which are Argentina, Brazil, Chile, China, Greece, India, Indonesia, Mexico, New Zealand, Peru, Portugal and Taiwan. This will henceforth be referred to as the G28, or global sample. However, the data span is relatively shorter and cover the period 1901 to 2002.[5]

3.2 Graphical analysis

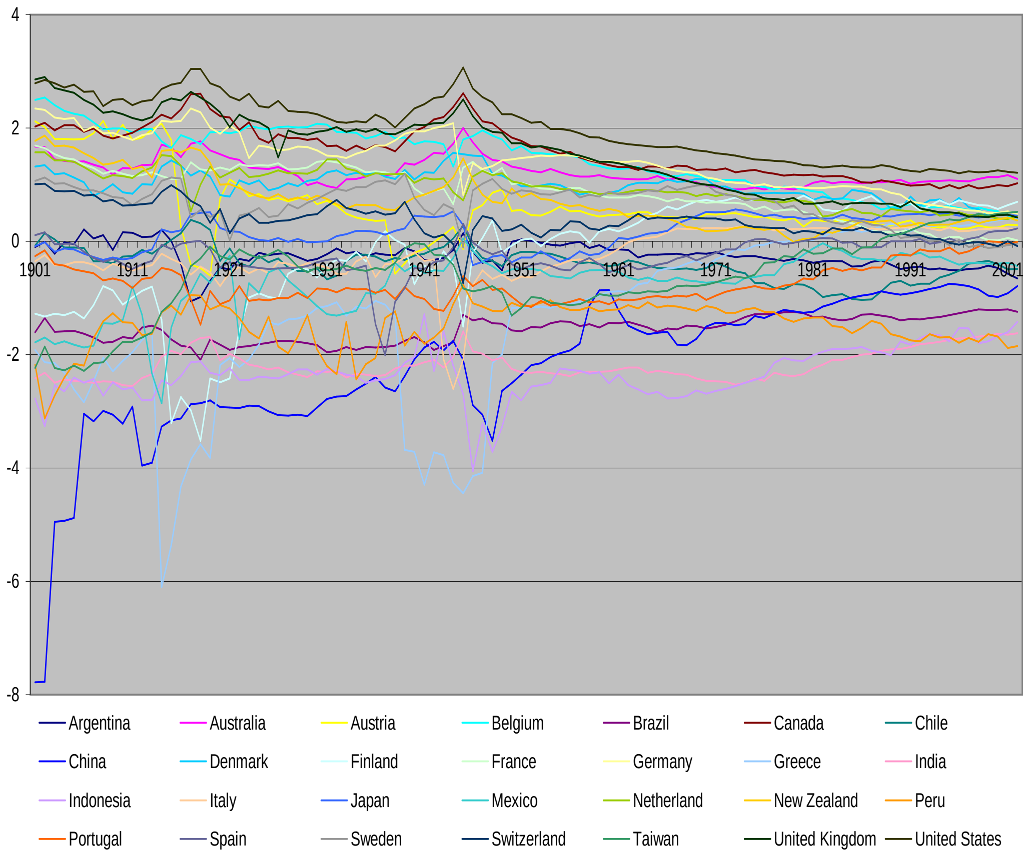
In order to get a feeling of the convergence in the per-capita CO_2 emissions, we begin with a graphical inspection of the data for the G28 panel. To foreshadow the more formal treatment in the next section, Figure 1 plots the log of per-capita CO_2 emissions relative to their cross-sectional mean, which, as mentioned in the introduction, are the series that form the basis of our convergence test. The figure clearly illustrates that while initially very dispersed, the series tend to converge towards a common mean value. Thus, if convergence is to be interpreted as a narrowing of cross-country emissions level, it appears that there is strong indication of convergence among the countries.

We also see that there is a strong tendency for the series to move together, which supports our claim that the assumption of cross-sectional independence is likely to be violated in the CO_2 data. Another interesting observation is that the speed of convergence appears to be quite similar across countries. It also appears to be very slow.

Although useful for developing a feeling of the extent of the convergence, graphical evidence

[5] Due to missing observations, New Zealand is excluded from D16 but included in the G28 sample. For China, 1901 CO_2 emission data is missing, we proxy it by the 1899 data. For Greece, 1912 CO_2 emission data is missing, we proxy the missing value by taking the average CO_2 emissions of the preceding and adjacent years.

Figure 1: Cross-sectionally demeaned CO_2 emissions for the G28 panel.



of this sort does not provide any formal evidence of whether the CO_2 emissions are actually converging or not. Therefore, in the next section, we employ the panel unit root tests described in Section 2, which will allow us to statistically test the significance of the convergence.

3.3 Convergence tests

The results are reported in Tables 1 and 2. As noted above, tests that rely on the assumption of cross-sectional independence can lead to erroneous conclusions when the countries are correlated. To get a feeling of the size of the cross-sectional dependence problem in the CO_2 data, we computed all pair-wise cross-correlations among the least squares residuals obtained from (1). The results are summarized in Table 1. It is seen that the country specific averages all lie between 0.115 and 0.303, with an overall average of 0.216 for the D16 panel and 0.2 for the G28 panel, which indicate that cross-correlation is present amongst the countries of the panel, so that the factor model discussed in Section 2 can capture the cross-section dependence in a better way.

Therefore, since the data appear to be cross-sectionally correlated, we proceed by testing for a unit root using the tests described in the previous section. To implement the Moon and Perron (2004) and Bai and Ng (2004) tests, we need to obtain an estimate of the true number of factors. For this reason, we employ the IC_1 information criterion recommended by Bai and Ng (2004). The maximum number of factors is set to five, but the estimation procedure suggests that three factors should be enough to capture the common movements in the CO_2 emissions. The three factors are then estimated together with their loadings as explained in Section 2, using either method of moments or principal components, depending on the test.

The results from the unit root tests are summarized in Table 2. As in equation (1), the test regression is fitted with both country specific intercept and trend terms.[6] The number of lagged differences of $\widetilde{y}_{it}$ to use for each country in order to eliminate the effects of serial correlation in the regression is determined using the Akaike information criterion, while all long-run variances are estimated using the Newey and West (1994) estimator. It is seen that all test values are far from zero, which is the expected value under the unit root null. This suggests that we should be able to reject the null hypothesis of a unit root. Indeed, based on the p-values from the asymptotic normal distribution, we can safely reject the null hypothesis of unit root at conventional levels of significance.

For the Phillips and Sul (2003) and Bai and Ng (2004) tests, the correct interpretation of this result is that the CO_2 emissions of at least some of the countries are converging. However, it is interesting to see that the Moon and Perron (2004) tests also result in a rejection of the null. This suggests that there is evidence of convergence not only for a few countries, but for the entire panel, which is a strong result. Furthermore, since all tests lead to the same outcome, we can be quite sure that the rejection by the Moon and Perron (2004) tests is not due to an invalid assumption of a common autoregressive parameter. On the contrary, as pointed out earlier in this section, the graphical evidence indicates that the speed of convergence actually seems to be very similar across countries.

We also tested the persistence of estimated common factors and found that the null of a unit root could be rejected at the 5% level of significance, which of course strengthens our earlier conclusion. Indeed, since neither the idiosyncratic nor the common component is nonstationary, the CO_2 emissions must be converging. To further infer the importance of the common component, we computed the proportion of the total variation of the CO_2 data that can be explained by each of the three estimated factors. The results for the D16 and G28 panels are

[6]Unreported results show that the unit root null can be rejected both when the trend is included and when it is not. Therefore, since the CO_2 emissions are stationary in both cases, we can test the significance of the trend in the usual way using its t-ratio. The results indicate that it is probably best to keep the trend in the model.

very similar, and suggest that the first factor explains about 50% of the total variation, while the second and third factors explain about 20% and 10%, respectively. Thus, in agreement with the high correlations reported in Table 1, we see that the common components are responsible for significant variations in the CO_2 data.

These findings suggest that the results reported by Lanne and Liski (2004) may not reflect the true underlying process generating the CO_2 data, but rather the poor power of their time series tests. This seems very reasonable because, if conventional unit root tests have low power, the tests used by Lanne and Liski (2004) with structural breaks have even lower power. In this regard, our panel approach seems more appropriate. On the other hand, one could of course argue that our results are spurious too, as we have ignored the possibility of structural breaks. However, this is very unlikely to be the case since this type of misspecification will tend to make the tests biased towards accepting the unit root null.

Nevertheless, to examine the possibility of breaks, we implemented a break estimation procedure very similar to the one used by Lanne and Liski (2004), who propose a sequential search scheme based on the t-ratios of the individual breaks for each country.[7] As in Lanne and Liski (2004), we focus our attention to the case when there is a shift in the trend slope only. The results suggest that, given a maximum of three breaks for each country, there are only three marginally significant breaks at the 1% level of significance, two for India and one for Sweden. Moreover, since the magnitude of the estimated parameters of these breaks are very small, 0.007, -0.002 and -0.01, respectively, it seem safe to proceed as if there are no breaks at all.

3.4 Speed of convergence

The above results indicate that the per-capita CO_2 emissions are in fact converging towards some common mean. In this section, we extend the analysis further, and ask how quickly CO_2 emissions revert back to that mean following a global CO_2 shock.

The speed of CO_2 convergence is measured in terms of the half-life for closing the gap between the CO_2 emissions for each country and the overall cross-sectional mean. The half-life is usually defined as the number of time periods required for a unit impulse to dissipate by one half. That is, the number of years it would take for half of the gap in emissions level between the cross-sectional average and the country i to be eliminated. This measure of convergence is

[7]The sequential search of breakpoints can essentially be performed in two ways. Lanne and Liski (2004) take the first approach, which involves first including the breaks one by one using dummy variables, and then estimating each of them using the entire time series dimension of the panel. The second approach involves splitting the sample after each estimated breakpoint, and then estimating subsequent breakpoints based on the resulting sub-samples. Although asymptotically indistinguishable, unreported simulation results suggest that the second approach is superior in terms of estimation accuracy, and it has therefore been employed in this paper. For further details on the break estimation procedure, we make reference to Lanne and Liski (2004).

well-known in the literature, and has been used extensively to study, for example, price index and income convergence. To the best of our knowledge, no previous study has examined this issue in this context while simultaneously considering the source of cross-sectional dependence.

The conventional way to obtain an estimate of the half-life is to fit (1) using least squares for each country. The estimated half-life can then be readily computed as $\log(0.5)/\log(\widehat{\phi}_i)$. Unfortunately, as shown by Nickell (1981), least squares estimation of the parameters in univariate dynamic models is generally biased, which in turn induces a bias in the estimated half-life. In panels, these individual bias effects have a tendency to accumulate, and to become quite serious as the cross-sectional dimension increases.

To account for this, we estimate ϕ_i using the median-unbiased method of Phillips and Sul (2003), who generalize the work of Andrews (1993) to panel data. Although this method can be implemented in many ways, in this section we focus our attention on their seemingly unrelated median-unbiased estimator, which can be used to obtain an estimated half-life for each country as well as for the whole panel. The advantage of using this particular estimator is that it permits for cross-sectional dependence while simultaneously correcting for the least squares bias.

Formally, idea behind the concept of median-unbiasedness can be explained as follows. Let $m(\phi_i)$ denote the median function of an arbitrary estimator, $\widehat{\phi}_i$ say, of ϕ_i. This function is defined by $P(\widehat{\phi}_i < m(\phi_i)) = 0.5$, which can be inverted to obtain another estimator $m^{-1}(\widehat{\phi}_i)$ of ϕ_i. By construction, this estimator satisfies $P(m^{-1}(\widehat{\phi}_i) < \phi_i) = 0.5$ so the probability of underestimation is equal to the probability of overestimation. An estimator that has this property is said to be median-unbiased. In the case of the seemingly unrelated median-unbiased estimator, $\widehat{\phi}_i$ is simply the seemingly unrelated regressions estimator of ϕ_i.

Table 3 reports results from the least squares, seemingly unrelated regressions and seemingly unrelated median-unbiased estimators. It is seen that the results differ markedly depending on whether the median-unbiased estimator has been used or not. The median-unbiased half-life estimates are generally largest, and are in fact equal to infinity on two occasions, for India and Taiwan. Thus, for these countries, convergence is practically nonexistent. For most of the countries, however, the estimated half-life is much more reasonable. This is clearly visible form the pooled estimates, which suggest a half-life of about five years.

It is interesting to note that the estimated speed of convergence is actually slower for the D16 panel than for the G28 panel. Although somewhat counterintuitive at first, there is a perfectly logical explanation for this, namely that the D16 sample is longer. In particular, while both samples end in 2002, the D16 starts 30 years earlier than the G28 sample, in 1870. The effect of extending the sample backwards in this way is clearly visible in Figure 1, which shows that the evidence of convergence is weaker as we move back in time. Thus, one conclusion that comes out of this is that the convergence has been faster in recent years.

4 Concluding remarks

In this paper we try to bring some light on per-capita CO_2 emissions convergence by using recently developed panel unit root tests. Previous studies have either used univariate methods with low power, or panel methods without proper adjustment for cross-sectional dependence, which we believe to be a key feature of the CO_2 emissions data. By contrast, this paper employs a factor model, in which the observed data is decomposed into a common and an idiosyncratic component. The idea is to first estimate and subtract the common component from the data and then to test for convergence in the remaining idiosyncratic component. In so doing, we employ the Evans (1998) notion of convergence, which exploits the panel structure of the data, and is more suitable for our purpose than the time series approach of Carlino and Mills (1993).

Using over a century of data across 28 developed and developing countries, we obtain overwhelming support in favor of convergence at the international level, as evident by the rejection of a unit root in cross-sectionally demeaned data. As a by-product, we also report half-life measures of the speed of convergence, which, to the best of our knowledge, has not been done before in the CO_2 emissions convergence literature. The results suggest an overall half-life of about five years, irrespectively of the sample used.

Several policy implications of these results come to mind. For example, evidence of convergence in the developed world is likely to make it easier for developing countries to agree to emissions abatement obligations. Moreover, for meaningful implementation of multilateral climate change agreements such as the Kyoto Protocol, a necessary condition is that the developed countries fulfill certain emission goals and commitments, which are unlikely to be fulfilled in a world of diverging emissions.[8]

Another implication follows from the fact that convergence is generally regarded as a key ingredient for long-run projections of CO_2 emissions. Take for example the special report on emissions scenarios published in 2000 by the Intergovernmental Panel on Climate Change. The CO_2 projections of this report is based on the assumption of convergence, which makes our results highly interesting, as a source of motivation.[9]

[8] See Aldy (2006) for further discussion.

[9] See Stegman and McKibbin (2005) for a detailed analysis of convergence in per-capita CO_2 emissions and its implications for undertaking projections of future emissions. See also McKitrick and Strazicich (2005).

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Table 1: Average absolute cross-correlations.

Country	Value	Country	Value
Argentina	0.122	Indonesia	0.127
Australia	0.271	Italy	0.139
Austria	0.180	Japan	0.251
Belgium	0.163	Mexico	0.151
Brazil	0.200	Netherland	0.211
Canada	0.250	New Zealand	0.285
Chile	0.229	Peru	0.115
China	0.123	Portugal	0.176
Denmark	0.154	Spain	0.186
Finland	0.229	Sweden	0.287
France	0.163	Switzerland	0.269
Germany	0.212	Taiwan	0.135
Greece	0.214	United Kingdom	0.197
India	0.303	United States	0.261
D16 panel[a]	0.216	G28 panel[a]	0.200

Notes: The values in the table are the cross-sectional averages of the absolute value of the estimated cross-correlations from the residuals in equation (1).

[a]The values represent the overall panel averages.

Table 2: Panel unit root tests.

		D16 panel		G28 panel	
Study	Test	Value	p-value	Value	p-value
Bai and Ng (2004)	P_e^c	5.424	0.000	6.722	0.000
Phillips and Sul (2003)	G_{ols}^{++}	−8.804	0.000	−8.069	0.000
	Z	−6.310	0.000	−7.562	0.000
	P_m	9.310	0.000	12.418	0.000
Moon and Perron (2004)	t_a	−4.394	0.000	−4.854	0.000
	t_b	−5.904	0.000	−5.457	0.000

Notes: All tests have been constructed using the Newey and West (1994) variance estimator. All lag lengths have been selected using the Akaike information criterion and the number of common has been selected using the CI_1 information criterion of Bai and Ng (2004).

Table 3: Estimated half-lives.

Country	OLS	SUR	SMU	Country	OLS	SUR	SMU
Argentina	2.499	2.510	3.225	Indonesia	2.234	1.633	1.914
Australia	5.261	5.077	9.804	Italy	3.033	2.840	3.783
Austria	4.072	4.104	6.559	Japan	6.344	4.236	6.996
Belgium	3.621	2.868	3.816	Mexico	1.809	1.737	2.053
Brazil	2.939	3.157	4.369	Netherland	1.082	1.071	1.205
Canada	6.636	6.297	18.024	New Zealand	5.727	5.523	12.183
Chile	4.217	4.155	6.714	Peru	2.722	2.778	3.679
China	1.786	1.718	2.031	Portugal	6.005	5.570	12.162
Denmark	4.110	4.032	6.336	Spain	3.045	3.339	4.737
Finland	3.438	3.678	5.441	Sweden	3.342	3.476	5.053
France	3.263	3.052	4.209	Switzerland	1.633	1.847	2.212
Germany	1.394	1.315	1.510	Taiwan	15.704	13.480	∞
Greece	3.216	2.670	3.500	United Kingdom	4.176	4.242	6.900
India	7.873	8.164	∞	United States	5.938	6.859	28.319
D16 panel[a]	4.219	4.375	6.241	G28 panel[a]	3.113	3.925	6.146

Notes: The abbreviations OLS, SUR and SMU refer the least squares, seemingly unrelated regressions and seemingly unrelated median-unbiased half-life estimates, respectively. Infinity represents slope estimates that are close to unity.

[a]The values represent the estimated pooled half-lifes.