Club Convergence and Clustering of U.S. Energy-Related CO_2 Emissions

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Abstract

This study examines the convergence of energy-related carbon dioxide emissions among a panel of U.S. states between the period 1960-2009. This examination is carried out by means of a two-stage procedure. In the first stage, we conduct a novel regression-based convergence test. Unlike previous studies, this methodology endogenously identifies groups of states with emissions that are converging to a similar steady state growth path over time. In the second stage, we evaluate the rate of convergence (beta-convergence) for the whole sample and for each club based on a panel data, fixed effects model which controls for unobserved, time-invariant heterogeneous effects. More specifically, we examine how structural and non-structural variables affect the rates of convergence. Results from stage one and stage two suggest that two groups of states are converging to similar, relative growth paths: a high-emitting group and a medium-emitting group. Finally, we discuss a differentiated policy approach to mitigating carbon dioxide emissions based on the club convergence hypothesis.

Keywords: Carbon dioxide emissions, Club convergence, Mitigation policies

JEL Codes: C23, Q47, Q48, Q54

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1 Introduction

Understanding the distribution of carbon dioxide emissions (CO_2) through time and space can help policy makers in designing policies to combat climate change. The geographic distribution of CO_2 emissions does not affect the global climatic impact, but it does affect the political economy of negotiating multilateral agreements (Aldy, 2006). If the United States were to formulate a national climate change policy or agree to ratify an international agreement such as the Kyoto protocol then it must begin to look inward to determine the sources and distribution of emissions. With this look inward, policy makers may be interested in determining how the distribution of state-level emissions are changing over time. That is, do interregional differences in emission levels tend to disappear or increase over time? If the differences diminish over time (and we observe a decrease in the overall growth rate compared to some base year), then legislators may be less worried about such a mitigation scheme. If, on the other hand, the differences tend to perpetuate over time (i.e., high emitting states remain high emitters now and in the future) then legislators may want to enact policies to reduce emissions.

One of the reasons perhaps that the U.S. has been slow to adopt a national mitigation scheme is due to uncertainty in state-level abatement costs. For example, if a state is currently a high emitter then arguably its marginal cost of reducing a unit of CO_2 should be relatively low, whereas a low-emitting state arguably would have higher relative marginal costs for reducing another unit. Current policy regimes often ignore location and dispersion characteristics of the sources of emissions, and emissions are penalized at a single permit price (Fowlie & Muller, 2013). Fowlie & Muller (2013) argue that in the presence of uncertainty in abatement costs, differentiated policies may improve welfare. We will explore these differentiated policies in the context of clubs of states whose emissions are converging through time.

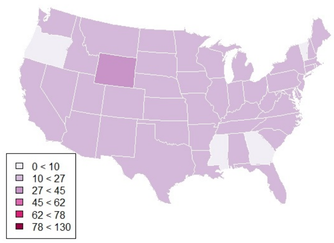
Global climate change is an international problem in scope, yet domestic or regional policies can be implemented to mitigate CO_2 emissions. In the U.S., the federal government has not been able to successfully formulate a national climate change policy that includes some mechanism to reduce CO_2 emissions, but various states have implemented programs. Renewable Portfolio Standards (RPSs), for example, have been adopted by thirty-three states and the District of Columbia as of 2009 (US Environmental Protection Agency, 2009). RPSs are goals or requirements for electric utilities or other retail electric providers to supply a specified minimum percentage of customer base load with electricity from various renewable energy sources. The goal of such programs is to not only develop sustainable forms of energy but also to reduce harmful greenhouse gases (GHGs) including CO_2. Additionally, some groups of states have adopted regional programs such as the Regional Greenhouse Gas Initiative (RGGI).[1] According to Regional Greenhouse Gas Initiative (2012), it is the first market-based regulatory program in the U.S. to reduce GHG emissions with the explicit goal of reducing regional CO_2 emissions from the power sector by ten percent by 2018. An understanding of the distribution of emissions can aid further states and regional initiatives in setting emission reduction goals and renegotiating emission obligations.

This study contributes to the literature in three ways. The first contribution is by offering a rigorous analysis of the convergence of energy-related emissions through time and space by observing U.S. state-level emissions for the period 1960-2009. This analysis differs from past studies by using a novel regression-based test on the state-level emissions, and it differs from other convergence test studies by examining sub-national data instead of comparing emissions across nations (e.g., Panopoulou & Pantelidis (2009)). This research is particularly interesting because it examines carbon dioxide emissions within an advanced economy in which no national climate policy exists. Examining sub-national emissions is consistent with the insights of Barro & Sala-i-Martin (1991), who posited that convergence is more likely among regions within a country than across different countries. To examine the convergence of state-level emissions, this analysis uses a nonparametric regression-based convergence test to examine convergence of emissions among different clubs of U.S. states. In other words, we seek to identify groups of states (clubs) with emissions that are converging to a similar steady state growth path over time. The second contribution is by offering additional years (i.e., extending the data to 2009) of state-level CO_2 emissions in comparison to past studies of U.S. state-level analysis (e.g., Aldy (2007)). The third contribution is by combining the club convergence analysis with a beta convergence analysis to determine the structural characters that are responsible for the club outcomes. In this regard, the approach is similar in nature to that of Durlauf & Johnson (1995), but the club convergence test endogenizes groupings as opposed to choosing clubs a priori and then testing the rate of convergence within clubs.

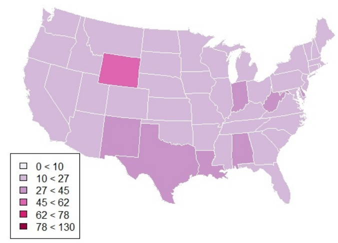
It is difficult to compare total carbon dioxide emissions across States because of the variation in their sizes, so we analyze state-level, per-capita emissions. Per-capita measures normalize emissions across States to offer a more compatible apples-to-apples comparison. Further, per-capita emissions offer a truer picture of how wasteful regions are. For example, China is the largest aggregate emitter of CO_2 emissions but

[1]The state participants in RGGI include Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont.

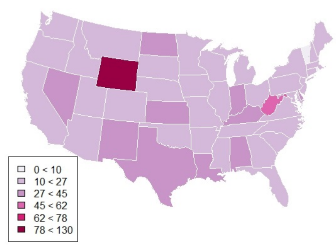
Figure 1: U.S. Energy-related CO_2 Emissions (metric tons per person), 1960-1980



(a) 1960



(b) 1970



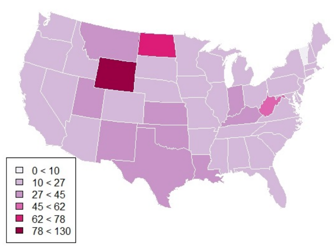
(c) 1980

the U.S. is the largest emitter per capita (International Energy Agency, 2011). From a policy sense, an analysis of per-capita emissions offers a more equitable measure for negotiating multilateral agreements. The structural and non-structural factors we examine are climate, population density, income per capita, the percentage of electricity from coal, and the percentage of electricity used in the industrial sector.

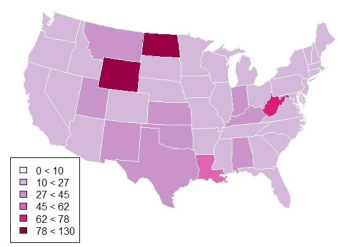
Chloropleth maps of state-level (aggregate) emissions for 1960-2009 (by decade) are offered in Figures 1 and 2. Each map's scale is based on the bins of per-capita emissions in the year 2009. These maps show a general increase in per-capita, state-level emissions, but a gradual easing of intensities in some states starting after 2000.

Looking ahead, the club convergence test reveals that there are two clubs of states whose emissions are converging to two unique steady state levels. Corroborating the findings within the first stage, the beta-convergence regression results imply that the rates of convergence are higher for states within the two separate clubs than with the entire sample – this suggests multiple regimes in emission convergence rates. Finally, we discuss how a multi-stage mitigation approach could potentially improve welfare in a national

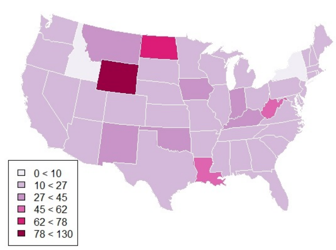
Figure 2: U.S. Energy-related CO_2 Emissions (metric tons per person), 1990-2009



(a) 1990



(b) 2000



(c) 2009

GHG mitigation scheme.

This paper is organized as follows. In the next two sections will examine the existing literature and discuss the various methodological approaches to test for convergence. In section four we will briefly explore the data. In the final two sections we examine the club convergence and beta convergence results, and then discuss potential mitigation policies.

2 Background

2.1 Climate Mitigation Commitment Regimes

Before discussing the economics literature on convergence it will be informative to first identify the different types of climate mitigation commitment regimes. A commitment regime can be loosely defined as multi-lateral or collective set of rules that a group of regions (e.g., countries) adopts to mitigate greenhouse gas (GHS) emissions including carbon dioxide. The most popular of these multi-lateral commitments is the Kyoto Protocol, which is based on the United Nations Framework Convention on Climate Change (UNFCCC). This protocol commits its signing parties to set internationally binding emission reduction targets. Countries that commit to the Kyoto Protocol meet their targets through market-based "flexible mechanisms," such as an emission trading scheme, clean development mechanism, and joint implementation (U.N. Framework Convention on Climate Change, 2012). In addition to the Kyoto Protocol, Höhne *et al.* (2003) analyze seven other types of regimes, which are sometimes called post-Kyoto regimes (Bows *et al.* , 2006). The analysis by Höhne *et al.* (2003) included the following regimes:

- *Intensity targets.* All regions reduce their greenhouse gas intensity (i.e., GHGs per unit of GDP) at the same rate.
- *Contraction and convergence.* Contract GHG emissions in each country so that all per-capita emissions are converging to the same level.
- *Global triptych approach.* Derive national targets from bottom-up sectoral targets (such as CO_2 from energy only).
- *Multi-sector convergence approach.* Derive national targets from converging per-capita sectoral targets.

- *Multi-stage approach.* Regions participate in the commitment regime in four stages, "graduating" from one to the next.

- *Equal mitigation cost.* Targets are set to distribute economic burden equally over all countries.

- *Coordinated policies and measures.* Regions are obligated to implement certain coordinated policies and measures.

Höhne *et al.* (2003) argue that the multi-stage approach is the "future of the climate regime" as it allows for flexibility in different groups of regions setting reduction targets. Such an approach could be especially beneficial to the different groups of U.S. states which have different aggregate GHG emissions, emissions per capita, GDP per capita, population growth rates, etc. There are other important implications about strategic behavior between states to reduce emissions, but we abstract away from such issues in the current study.

2.2 Economics Literature

2.2.1 Background of Convergence Hypothesis

The convergence hypothesis has received considerable attention over the past few decades. This concept is split into three competing hypotheses: (i) absolute convergence, (ii) conditional convergence, and (iii) club convergence (Galor, 1996). The first hypothesis implies that incomes across regions converge to one another in the long run independent of their initial conditions. The second hypothesis, like the first, implies convergence but conditional on the converging regions having similar structural characteristics; and, as in the first hypothesis, this convergence is independent of the region's initial conditions. Barro & Sala-i-Martin (2004) point out that is important not to confuse conditional convergence with absolute convergence. In the words of the authors, absolute convergence applies when economies with lower initial rates of per-capita emissions have a tendency for their emissions to grow faster than economies with higher initial rates of emissions – i.e., low-emitting states tend to "catch up" with higher emitting states. Conditional convergence applies when the growth rate of emissions declines as it approaches its own steady state. The two concepts are identical if a group of economies tend to converge to the same steady state (Barro & Sala-i-Martin, 2004).

The third hypothesis implies convergence if the regions have similar structural characteristics, as in the second hypothesis (conditional convergence), but the region's initial conditions are similar as well. Galor (1996) offered that theoretical models of club convergence are characterised by multiply steady state equilibria – that is, regions that are similar in their structural characteristics (e.g., preferences, technologies, population growth, government policies, etc.) converge to the same steady state equilibrium if their initial conditions are similar. The difference, therefore, between conditional versus club convergence is that the former may imply a globally stable, steady state equilibrium rather than multiple, locally stable steady state equilibria.[2]

Empirically, the convergence tests have been carried out by three principal methods: σ-convergence (sigma), β-convergence (beta), and club convergence. The first, σ-convergence refers to a decline in the dispersion of the variable of interest across a group of economies over time (Barro & Sala-i-Martin, 2004; Sala-i-Martin, 1996). This type of convergence then refers to the decline in cross-region inequality in the variable of interest. The second, β-convergence implies a negative relationship between the growth rate of emissions and the initial level of emissions – this is sometimes called "mean reversion." Borrowing the parlance of Sala-i-Martin (1996), both types of convergence are important because σ-convergence studies whether state-level emissions are becoming more similar over time whereas β-convergence applies to a state's efforts (or lack thereof) to reduce emissions within the same distribution. It is worth noting, that there are two different types of β-convergence. If the β-convergence model is regressed on the lagged values of the dependent variable alone then it is an "unconditional" model, whereas if it is regressed on other independent variables – that is, proxies for the steady-state level of emissions (Barro & Sala-i-Martin, 2004, p. 467)– then it is a "conditional" β-convergence model. The third method, club convergence was initially tested using the β-convergence method within subsamples of regions and tested against convergence rates in the overall sample (see for example, Durlauf & Johnson (1995)). The problem with using β-convergence to test for club convergence is that the groups of regions have to be determined a priori in the analysis. Durlauf & Johnson (1995) determined group membership through a regression tree analysis. A criticism of this approach is that the a priori selection of clubs can be somewhat arbitrary (Bartkowska & Riedl, 2012). More recent developments in club convergence tests identify clubs by endogenized groupings, leaving other factors unspecified that may have led to multiple steady states (Phillips & Sul, 2007). The latter methods focus on the cross-sectional distribution of the variable which is more akin to the concept of σ-convergence

[2]The (economic) growth rate of neoclassical economies with similar tastes and technologies, such as regions within a country, tend to converge to the same steady state Barro & Sala-i-Martin (2004).

(Bartkowska & Riedl, 2012).

The difficulty with the club convergence hypothesis, is that the endogenous groupings tests can identify convergence clubs, but these tests cannot confirm the club convergence hypothesis. Since the endogenous groupings tests leaves other factor unspecified, it is not possible to determine which factors led to multiple steady states. If only the structural characteristics are responsible for the club outcome, the outcome may be misinterpreted wrongly as club convergence where conditional convergence applies (Bartkowska & Riedl, 2012). Thus, it is empirically difficult to distinguish club convergence from conditional convergence. Nevertheless, we will proceed in two stage by first determining club convergence through the endogenous groupings test and second by conducting conditional β-convergence tests to see if the data provides a consistent story about the formulation of clubs.

2.2.2 Literature on Convergence of CO_2 Emissions

The analysis of the convergence of CO_2 emissions seeks to determine mechanisms to foster the adoption of multilateral carbon reduction agreements. Such studies have been regional and international in scope. Empirical studies implement a variety of econometric methodologies to investigate the cross-region convergence in carbon dioxide emissions. Each methodology examines the existence of a different type of convergence (Strazicich & List, 2003; Westerlund & Basher, 2008; Nguyen-Van, 2005; Ezcurra, 2007; Romero-Avila, 2008; Stegman, 2005).

For example, drawing from the economic growth literature, Strazicich & List (2003) were some of the first authors to examine the phenomena of convergence of CO_2 emissions. They examined emissions in twenty-one industrialized countries for the period 1960-1997. Using panel unit root tests and cross-section regressions, the authors found significant evidence for convergence in their estimated sample. A complementary study by Romero-Avila (2008) examined the existence of stochastic and deterministic convergence of CO_2 emissions in a panel of twenty-three countries over the period 1960-2002. Using recently developed unit root testing procedures (and further tests for panel stationarity), the author found strong evidence to support stochastic and deterministic convergence in CO_2 emissions.

Aldy (2006) evaluated the historic and future distributions of CO_2 emissions in a panel of over 100 countries (1960-2000) to determine if emissions are converging or will convergence in the future. He used σ-convergence (sigma) tests and found convergence among twenty-three member countries within the OECD but divergence among a 88 country global sample. His forecasted emissions provided little evidence of convergence and implied divergence in the near term over a large swath of the global sample. In a follow-up study, Aldy (2007), using cross-sectional and stochastic convergence tests, conducted an analysis of the convergence of U.S. state-level, per-capita CO_2 emissions for the period of 1960-1990. Specifically, he sought to determine, akin to the environmental Kuznets curve literature, whether state-level income convergence is a sufficient driver of state-level emissions convergence. Using both historical and forecasted data, he found convergence in incomes but stark divergence in CO_2 per capita.

An analysis by Panopoulou & Pantelidis (2009) used a similar methodology as this study to examine club convergence in CO_2 emissions among 128 international countries for the period 1960-2003. Their analysis suggested convergence in two separate clubs, one containing high per-capita emissions and another containing low per-capita emissions, in which the emissions converge to two separate steady states. Furthermore, they found evidence of transitioning between the two clubs suggesting perhaps slow convergence between the two clubs.

A recent study by Criado & Grether (2011) investigated the convergence of per-capita emissions for a panel of 166 world areas for the period 1960-2002. The authors analyzed the evolution of spatial distributions of emissions through time. They assessed emissions in levels and in proportional deviations. The proportional deviation measures indicated slight differences in the 1960s followed by stronger divergence and then stabilization in the 1990s. Whereas the unscaled measures indicated strong divergence before the oil shocks in the 1970s followed later by stabilization.

3 Methodological Approach

3.1 Club Convergence Approach

This econometric methodology in this study was introduced by Phillips & Sul (2007, 2009) (hereafter P&S). This methodology, which the authors call the "log t test," allows one to classify states into convergence groups or clubs. The methodology has numerous advantages over other existing measures of convergence including the fact that it is based on a general nonlinear time-varying factor model that incorporates the possibility of transitional heterogeneity (Panopoulou & Pantelidis, 2009). Given heterogeneity within the panel data, standard unit root and cointegration tests are not suitable for testing for convergence (Phillips & Sul, 2007). This methodology is robust to heterogeneity and the stationarity properties of the series. According to Panopoulou & Pantelidis (2009), this methodology can be interpreted as an asymptotic cointegration test that does not suffer from the small sample properties of traditional unit root and cointegration tests.

3.1.1 The log *t* Test

For this particular study we have a panel data set for state-level CO_2 emissions which we represent by the variable X_{it}, $i = 1, \dots, N$, $t = 1, \dots, T$, where N and T denote the number of states and the time periods respectively. P&S illustrated the series as a single factor model

$$X_{it} = \delta_i \mu_{it} + \epsilon_{it}, \tag{1}$$

where δ_i denotes a measure of the idiosyncratic distance between a common factor μ_t and the systematic part of X_{it}; ϵ_{it} denotes a noise term. Thus, the model seeks to examine the evolution of the individual X_{it} in relation to the common factor, by means of two idiosyncratic elements: the systematic element (δ_i) and the error (ϵ_{it}). P&S extended the model to allow the systematic element to have a random component which subsumes ϵ_{it} in (1) and allow for convergence of the random systematic element in relation to the common factor. The extension is represented as follows

$$X_{it} = \delta_{it} \mu_{it}, \tag{2}$$

where now both components δ_{it} and μ_t are time varying. The authors model the time varying behavior of δ_{it} in semi-parametric form as

$$\delta_{it} = \delta_i + \sigma_i \cdot \xi_{it} \cdot L(t)^{-1} \cdot t^{-\alpha}, \tag{3}$$

where δ_i is fixed, ξ_{it} is iid(0,1) across i and weakly dependent over t, and $L(t)$ is a slowly varying function (such as the log t) for which $L(t) \to \infty$ as $t \to \infty$. This formulation ensures that δ_{it} converges to δ_i for all $\alpha \geq 0$ and forms the null hypothesis of interest. The model allows for transitional heterogeneity and transitional divergence across the sample.

The sample counterpart of (2) can be represented by

$$X_{it} = g_{it} + a_{it}, \tag{4}$$

where g_{it} denotes the systematic component and a_{it} represents the transitory component. Rewriting (4) yields

$$X_{it} = \left(\frac{g_{it} + a_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t \text{ for all } i \text{ and } t, \quad (5)$$

where X_{it} is now decomposed into the two components as outlined in (2) above. An interpretation of (5) is that μ_t represents a common trend component in the panel and δ_{it} measures the relative share of μ_t contributed by region i at time t.

Due to the incidental parameters problem, it is not possible to estimate (5) without imposing *ex ante* restrictions on δ_{it} and μ_t. P&S devised a creative estimation scheme in which they eliminate the common factor, μ_t (since it is common to all the regions), by transforming the data to consider the relative loading coefficient of region i to the panel average at time t. This is formulated as

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N}\delta_{it}}. \quad (6)$$

In this particular paper, the loading coefficient is interpreted as the measure of the transition path of carbon dioxide emissions of state i relative to the panel average at time t. h_{it} is therefore called the *relative transition parameter*. By construction, the cross-sectional mean of h_{it} is unity; and if the factor loading coefficients δ_{it} converge to δ, then the relative transition parameters h_{it} converge to unity (Phillips & Sul, 2007). Hence, in the long run the cross-sectional variance of h_{it} converges to zero as follows

$$\sigma_t^2 = N^{-1}\sum_{i=1}^{N}(h_{it} - 1)^2 \rightarrow 0 \; as \; t \rightarrow \infty. \quad (7)$$

The property of (7) allows the test of the null hypothesis of convergence and to group regions into convergence clusters. The null hypothesis is formulated as

$$H_0 : \; \delta_i = \delta \text{ and } \alpha \geq 0$$

against the alternative

$$H_A : \; \delta_i \neq \delta \text{ for some } i \text{ and/or } \alpha < 0.$$

The null hypothesis implies convergence for all regions, while the alternative implies no convergence for some regions. The alternative can accommodate both overall divergence or club convergence; i.e., one or more subsets of the group of regions form convergent groups at different factor loadings (Panopoulou & Pantelidis, 2009).

To test the null hypothesis, P&S constructed a ratio of cross-sectional variation, H_1/H_t, where H_t is defined as

$$H_t = N^{-1} \sum_{i=1}^{N} (h_{it} - 1)^2 . \tag{8}$$

H_1 represents the variation at the beginning of the sample (i.e., $t = 1$), whereas H_t represents the variation for every point in time (i.e., $t = 1, \ldots, T$). The authors take the log of the ratio of H_1 to H_t to measure the distance of the panel from the common limit. The null hypothesis is tested in context of the following non-parametric regression

$$\log(H_1/H_t) - 2 \cdot \log\, L(t) = \hat{a} + \hat{b}\, \log\, t + \hat{u},$$
$$\text{for } t = [rT], [rT] + 1, \ldots, T \;\; \text{with} \;\; r > 0,$$

where $L(t) = \log(t)$ and r denotes a fraction of the initial sample that is removed prior to running the regression. This equation is what the authors define as the "log t" test. Following the advice P&S (based upon their Monte Carlo simulations), we set r equal to 0.3, which implies that the first third of the time series observations of the panel are omitted. Removing these observations helps alleviate against test results which are sensitive to initial conditions. The fitted coefficient on log t is $\hat{b} = 2 \cdot \hat{\alpha}$, where $\hat{\alpha}$ is the estimate of α (the speed of convergence) in H_0. To test the null hypothesis of convergence we determine if $\alpha \geq 0$ by using $\hat{b}$, and reject the null hypothesis of a one-sided t test if $t_{\hat{b}} < -1.65$ (i.e., the five percent significance level). Additionally, we employ heteroskedastic and autocorrelation (HAC) robust standard errors. More specifically, we used regressions with Newey-West standard errors. These robust regressions were conducted using Matlab code provided by James LeSages' Econ Toolbox.

This study's primary interest lies in the sign of the estimated coefficient $\hat{b}$ because it provides us with the test of convergence. If the t test suggests that $\hat{b}$ is either positive or equal to zero, then we fail to reject the null hypothesis of convergence. On the other hand, if $\hat{b}$ is negative, we reject the null. This form of panel convergence is analogous to conditional sigma convergence (Phillips & Sul, 2007).

3.1.2 Club Convergence Algorithm

In order to examine convergence within subgroups of regions (states) under scrutiny, this study employs the empirical algorithm suggested by P&S to determine subgroups of states that converge. The algorithm is as follows, which is repeated here in abridged form:

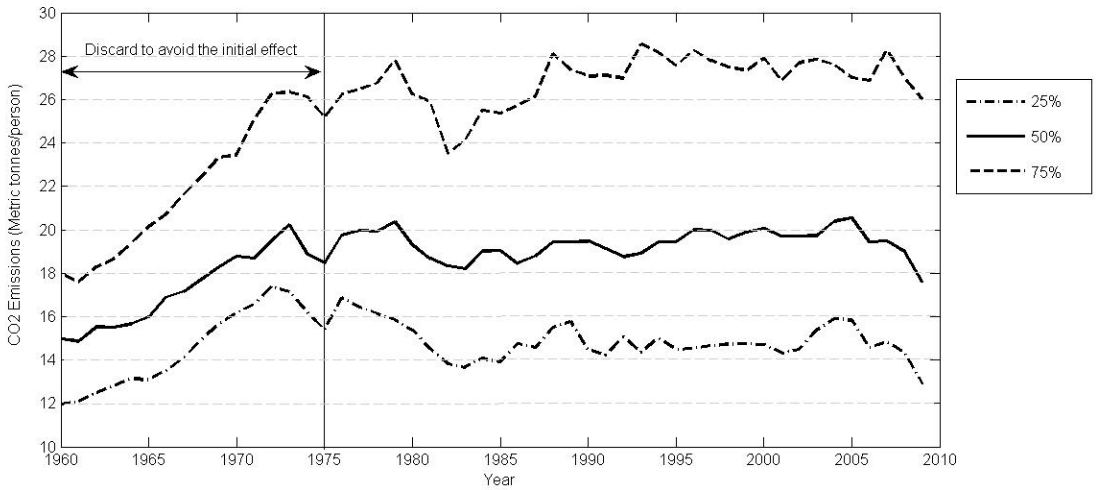
1. *Last Observation Ordering*. The observations within the panel are ordered according to the last observation. In other words, the panel is arranged in descending order according to the state with the highest level of CO_2 emissions in the last period of observation. The data is ordered in this manner as convergence behavior will generally be more apparent in recent years.

2. *Core Group Formation*. Identify a core group of states that converge by selecting the k highest states in the panel to form the subgroup G_k for $N > k \geq 2$. Run the log t regression and calculate the convergence test statistic $t_k = t(G_k)$ for the subgroup. Choose the core group size k^* by maximizing t_k over k; i.e., keep adding states into the core group until the null hypothesis of the log t test is rejected. If there is a single convergence club with all states included then the size of the convergence club is N. If the condition $t(G_k) < -1.65$ does not hold for the $k = 2$ states then the highest state in G_k can be dropped from the subgroup. Continue identifying addition subgroups within the entire panel.

3. *Sieve Individuals for Club Membership*. Let G^c_{k*} be a complementary set to the core group G_{k^*}. Add one individual at a time from G^c_{k*} to the k^* core members of G_{k^*} and run the log t test. If $t_{\hat{b}} > -1.65$ then the addition of these members forms new subconvergence group.

4. *Stopping Rule*. Once the log t test results suggest rejection of the null, stop forming additional subgroups. From the existing groups, test to see if there are smaller subgroups of convergent states within the panel. If there is no k in Step 2 from which $t_k > -1.65$ then we assume that the remaining states diverge.

Figure 3: Quartiles of Per-Capita CO_2 Emissions in the U.S. (1960-2009)



4 Data

The energy-related carbon dioxide data for this analysis were obtained from the Carbon Dioxide Information Analysis Center (CDIAC) within the U.S. Department of Energy (Blasing *et al.* , 2004; US Energy Information Administration, 2012). CDIAC estimates the emissions by multiplying state-level coal, petroleum, and natural gas consumption by their respective thermal conversion factors. Therefore, the data is based on estimates of CO_2 emissions and not actual atmospheric emissions. Despite this deficiency, this measure of emissions is one of the more common used in the literature as it is difficult to measure atmospheric emissions of carbon dioxide. The energy emission estimates are extended by using more recent calculations of energy-related carbon dioxide emission (2000-2009) offered by the US Energy Information Administration (2012). The U.S. Energy Information Administration (EIA) calculates emissions identically to the CDIAC, however, we visually inspected the data to ensure that new emission estimates are consistent with the previous estimates. The estimates are offered in units of a million metric tonnes for the forty-eight contiguous states excluding the District of Columbia. A plot of the quartiles of aggregate U.S. CO_2 emissions for the period 1960-2009 is offered in Figure 3. Following the advise of Phillips & Sul (2007), we omit the initial one-third of time series variables for the log t test which reduces the period of analysis to 1975-2009.

Itkonen (2012) offers the following simple explanation of how the energy emissions are estimated. The CDIAC and EIA define carbon dioxide emissions as a linear function of fossil fuel combustion and cement manufacturing. The amount of CO_2 emissions is determined by the chemical composition of the fuel source.

Emission estimates are calculated by multiplying the amount of fuel usage by a constant thermal conversion factor as determined by the chemical properties of the fuel. Therefore, CO_2 emissions are a linear combination of the usage of oil, E_t^{oil}, solid fuels such as coal, E_t^{coal}, natural gas, E_t^{gas}, and emissions from cement manufacturing, S_t. Formally, this is expressed as

$$CO_{2,t} \equiv \alpha_{oil} \cdot E_t^{oil} + \alpha_{coal} \cdot E_t^{coal} + \alpha_{gas} \cdot E_t^{gas} + \alpha_{flare} \cdot E_t^{flare} + S_t, \tag{9}$$

where $\alpha_{oil}, \alpha_{coal}, \alpha_{gas}, \alpha_{flare} > 0$ are the related thermal conversion factors.

The data on the percentage of electricity used in electricity consumption and the percentage of electricity consumed in

The state-level income data were obtained from the Bureau of Economic Analysis (BEA) within the U.S. Department of Commerce (US Bureau of Economic Analysis, 2012). The BEA offers annual state-level income estimates from 1960 to the near present. The estimates are based on aggregate income by state. The estimates were converted to real dollars by using the BEA's implicit price deflater for GDP.

To model climatic influences on energy demand we use Cooling Degree Days (CDD) and Heating Degree Days (HDD), which were obtained from the National Climate Data Center within the National Oceanic and Atmospheric Administration (US Nat'l Climate Data Center, 2010). CDD (or HDD) is a unit of measure to relate the day's temperature to the energy demand of cooling (or heating) at a residence or place of business – it is calculated by subtracting 65 degrees Fahrenheit from the day's average temperature (Swanson, 2010). Residential energy consumption has been found to be highly correlated with CDD and HDD (Diaz & Quayle, 1980). Since the CO_2 emissions are estimated from energy consumption, the CDD and HDD data as quantitative indices should capture much of the year-to-year variation in energy consumption. CDD and HDD are expected to be positively related to CO_2 emissions as cooler (or hotter) days would induce households or businesses to demand higher amounts of energy for heating (or cooling) a residence or place of business.

Annual state population data were obtained from the US Census Bureau (2010). These population estimates represent the total number of people of all ages (including military personnel) within a particular state.

5 Empirical Results

In this section we carry out the two separate analyses as outlined in the Introduction. In the first analysis we employ the Phillips & Sul (2007) algorithm to determine the subgroup convergence and clustering of state-level carbon dioxide emissions. In the second part we conduct the beta convergence analysis of the full sample and each individual club – which are determined in the first step. The second stage helps to determine if structural characteristics and the initial value of emissions play a role in convergence. If so, then the results will help validate the club convergence hypothesis.

5.1 Empirical Results for the log t test

The first step of the club convergence algorithm begins with sorting the emissions in descending order according to the largest state emitter in the last period of observation (2009). The ordering for the states is given in the first two columns of Table 2. As can be ascertained from the Table 2, Wyoming was the largest per-capita emitter and New York the lowest in 2009. Next, the relative transition paths were calculated for each state and then the log ratio variation was constructed to estimate the log t test. As outlined in Sections 3.1.1 and 3.1.2, the testing procedure begins by consecutively testing subgroups of states. We began by testing club convergence for all the 48 states in our sample – the tests results indicated a rejection ($t_{\hat{b}}$ = -11.0981) of the null of convergence, so we proceeded by testing states consecutively based on the last T ordering. The log t testing procedure implies that the first subgroup (i.e., group of states in which per-capita CO_2 emissions are converging over time) constitutes Nebraska and Texas. In other words, the log t tests indicated a rejection of the null hypothesis of convergence for the first eleven states, which implies the growth paths of emissions are diverging for these states. Figure 5(a) illustrates the relative transition paths of emissions for the first eleven states. The relative transition paths for the first (convergence) club are displayed in Figure 4(a). As displayed in the left-most cell of Table 1, the coefficient on log t ($t_{\hat{b}}$) for this first club is negative but statistically insignificant, implying that we fail to reject the null hypothesis of convergence for Nebraska and Texas.

The initial classifications for the rest of the U.S. state clubs, based upon the log t algorithm, are listed in the left-most cell of Table 1. The members of each corresponding club are listed in Table 2. Under this initial classification, the coefficients on the log t terms for Club Two is positive which is consistent with the null hypothesis. The log t coefficient for Club Three is negative which seems to violate the null condition

Table 1: Club Convergence Classification for Aggregate Emissions, 1960-2009

Initial classification		Test of club merger		Test of club merger	
Club One (2)				Club One-Three (3)	
log t	t-stat	Clubs One-Two (16)		log t	t-stat
-0.0346	-0.0189	log t	t-stat	-0.2766	-2.2123*
		-0.3219	-4.2064*		
Club Two (14)					
log t	t-stat	Clubs Two-Three (21)			
0.1858	1.6614	log t	t-stat		
		-0.1055	-0.6232		
Club Three (7)					
log t	t-stat				
-0.2141	-1.0173				

Note: * Rejection of the null hypothesis of convergence at the 5% level.
Numbers in parenthesis represent the number of states in the club.

that $\hat{\alpha} \geq 0$, but the t-stat is not significantly different from zero so we fail to reject the null. The log t results suggest that any state that does not appear within a club (in Table 2) has diverging CO_2 emissions. The diverging states are listed in the "Notes" section under Table 2.

Based upon Step 3 of the algorithm, we sieved the club members to determine if there were any club mergers. Within this step we tested for convergence among Clubs One and Two and then tested for convergence among Clubs Two and Three. The results of this step indicated a failure to reject the null of convergence for the second and third club, which implies a larger subgroup of the combined clubs. Otherwise, additional club mergers were rejected according to the log t tests. The final classification therefore consisted of testing for a club merger for among all the clubs in the initial classification – this test indicated a rejection of the null hypothesis, which implies that the three separate clubs in the initial classification are not converging. The members of each club are listed in Table 2, and graphics displaying the relative transition paths of each member within the clubs (initial classification) are offered in Figures 4. The sieving steps indicated two final clubs: Club One which consists of two states and Clubs Two-Three which consist of twenty-one states.

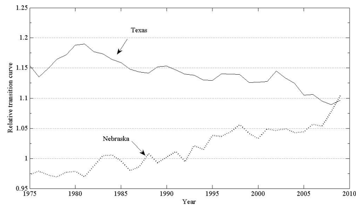
Finally, the relative transition paths of the final convergence clubs, based upon the club averages, is displayed in Figure 6. These average relative transition paths demonstrate the two different club types: high and medium. These averages suggest that the relative transition paths (note these are *relative* paths not absolute paths) of emissions is slightly increasing for the high emitting club and slightly decreasing for the medium emitting clubs. Note that there seems to be more volatility in the relative path of Club One – this is

Table 2: Club Convergence of Per-Capita CO_2 Emissions among U.S. States based upon Initial Classification

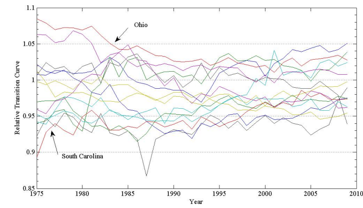
All States Last T Ordering		First Convergent Club	Second Convergent Club	Third Convergent Club
Wyoming	S. Carolina	Nebraska	Missouri	Arizona
N. Dakota	Wisconsin	Texas	Arkansas	Nevada
W. Virginia	Georgia		Ohio	N. Carolina
Louisiana	Michigan		Mississippi	Maine
Kentucky	Tennessee		Pennsylvania	Virginia
Montana	Arizona		Colorado	Delaware
Indiana	Nevada		S. Dakota	N. Hampshire
N. Mexico	N. Carolina		Illinois	
Oklahoma	Maine		Minnesota	
Iowa	Virginia		S. Carolina	
Kansas	Delaware		Wisconsin	
Nebraska	N. Hampshire		Georgia	
Texas	N. Jersey		Michigan	
Alabama	Maryland		Tennessee	
Utah	Florida			
Missouri	Washington			
Arkansas	Massachusetts			
Ohio	Oregon			
Mississippi	R. Island			
Pennsylvania	Connecticut			
Colorado	California			
S. Dakota	Vermont			
Illinois	Idaho			
Minnesota	New York			

Notes: The diverging states are Wyoming, N. Dakota, W. Virginia, Louisiana, Kentucky, Montana, Indiana, N. Mexico, Oklahoma, Iowa, Kansas, Alabama, Utah, N. Jersey, Maryland, Florida, Washington, Massachusetts, Oregon, R. Island, Connecticut, California,Vermont, Idaho, and N. York.

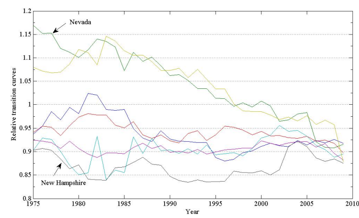
Figure 4: Relative Transition Paths (1975-2009)



(a) Club One



(b) Club Two



(c) Club Three

because the average relative path is averaged only over two states in Club One whereas it is averaged over twenty-one states in Club Two-Three. The averaging over more states smooths out the differences in relative emissions among member states in Club Two-Three making it appear less volatile.

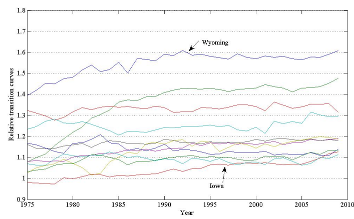
5.2 Beta-Convergence Tests

In the second stage of our empirical analysis we now estimate β-convergence regressions to ascertain if state-level structural and non-structural factors help determine the growth rate of emissions. If so, then such findings will help support the club convergence hypothesis in the first stage.

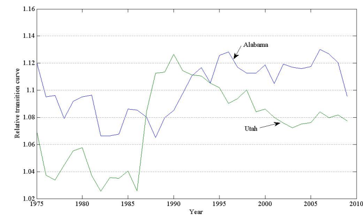
According to the US Energy Information Administration (2012), state-level, per-capita emissions are driven by the structure of the State economy, population density, energy sources, building standards and explicit State policies to reduce emissions.[3] To account for these factors we hypothesize that certain structural and non-structural factors will have an effect on the growth rate of state-level carbon dioxide emissions. The structural factors consist of state-level, per-capita income, population density, percentage of coal used for electricity production, and the percentage of electricity consumed by the industrial sector in the state economy. It is predicted a priori that each of these factors will have a positive effect on the growth rate of emissions. The exogenous, non-structural factors, which account for climatic impacts on the growth rate

[3] In this study we do not attempt to assess the impact of individual State policies on carbon dioxide emissions to we exclude building standards and explicit state policies.

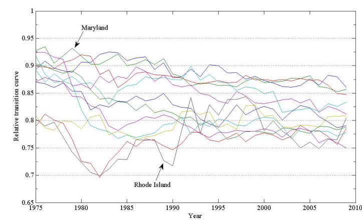
Figure 5: Relative Transition Paths of Diverging States (1975-2009)



(a) First set of diverging states

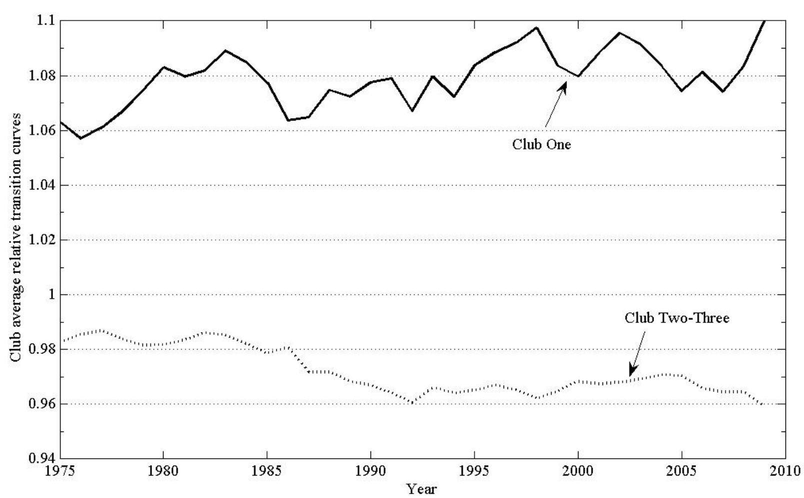


(b) Second set of diverging states



(c) Third set of diverging states

Figure 6: Average Relative Transition Paths of the Final Convergence Clubs (1975-2009)



of emissions, consist of state-level heating and cooling degree days. To test these hypotheses we specify a panel-data, β-convergence regression.

According to (Barro & Sala-i-Martin, 2004), one advantage of panel data over cross sections is that one does not need to hold constant the steady steady growth level because it is implicitly estimated using fixed effects – i.e., by including a term (or controlling for) a time invariant, state-level heterogenous effect. One potential problem with estimating beta convergence models using panel data is that one needs a sufficiently large amount of time series observations in order to overcome dynamic panel data bias (Nickell, 1981; Judson & Owen, 1999). Dynamic panel data bias occurs when a lagged dependent variable is specified on the right hand side of the regression and the panel does not contain enough time series observations. Another supposed drawback to estimating beta convergence with panel data is that such analyses tend to have larger estimates of the speed of convergence than do cross-sectional analyses. However as Shioji (1997) demonstrated, the estimated speed of convergence decreases as one examines greater time intervals between observations. That is, the estimated speed of convergence was less for intervals of five and ten years than with annual observations. Islam (1995) too identified that using annual observations may prove to be problematic with convergence analysis because short-term disturbances (e.g., the natural business cycle) loom large in brief time intervals, so the author choose a interval of five years between observations. We experimented with difference beta-convergence regressions with annual data and data in five year intervals. Our results (not included but available upon request), unlike convergence tests of economic growth as the dependent variable, indicated lower rates of convergence for annual observations than with the observations spaced over five year intervals. This is opposite of the findings of Islam (1995) and Shioji (1997), but this is perhaps because we are examining state-level CO_2 emissions rather than state-level GDP (indicator of economic growth). The former is also arguably less affected by natural economic cycles. Therefore, we eschew the prescription of Islam (1995) and analyze state-level carbon dioxide emissions in annual observations.

For consistent estimates of the speed of convergence, one needs many time series observations to avoid dynamic panel data bias. To help ensure that we getting efficient estimates of the speed of convergence we compare fixed effects models with a bias-corrected least squares dummy variable (LSDVC) model. Judson & Owen (1999) showed that the LSDVC model often performed best in Monte Carlo experiments with panel data. In other words, the LSDVC model provided the least biased (versus standard least squares dummy variable and general method of moment estimators) estimates of the coefficient on the lagged dependent variable.

Therefore, we proceed by estimating the β-convergence model using the LSDVC method, which we compare to ordinary least squares (OLS), fixed effects (FE), and general method of moments (GMM) estimates for a sensitivity analysis. To evaluate the LSDVC model we used the Stata procedure 'xtlsdvc' (Bruno, 2005). To evaluate the OLS and FE models we used the Stata procedures 'reg' and 'xtreg,' respectively. Finally, to evaluate the GMM model we used the Stata procedure 'xtabond,' which estimates a difference GMM (Arellano & Bond, 1991).

Following the notation of Islam (1995), the general econometric specification is expressed in discrete time (annual observations) as follows

$$\log(y_{it}) = \gamma \log(y_{i,t-1}) + X_{it}\beta + \eta_t + \mu_i + \varepsilon_{it}, \tag{10}$$

where γ denotes a scalar parameter on the lag of the dependent variable, X_{it} denotes a $(N \cdot T \times k)$ matrix of explanatory variables, the parameter β denotes a $(k \times 1)$ matrix of coefficients on the explanatory variables (also specified in natural logarithms), μ_i denotes the unobserved, time-invariant heterogeneous effect, η_t denotes time-level fixed effects, and ε_{it} denotes a disturbance term. The time-level fixed effects capture time-related shocks that affect all states within the given time period; such shocks may represent the passage of the Clean Air Act or economic recessions. The coefficient on the lagged dependent variable is implicitly equal to

$$\gamma = e^{-\lambda \cdot \tau}, \tag{11}$$

where λ is the speed of convergence, and τ is the time interval in between observations.[4] We presuppose the condition that $\gamma > 0$, which implies β-convergence because otherwise λ is negative which implies divergence. Based on equation (11), the implied speed of convergence is given by

$$-\lambda = \frac{1}{\tau} \cdot \ln(\gamma), \tag{12}$$

which shows that a higher estimated value of $\hat{\gamma}$ leads to a lower value of $\hat{\lambda}$. The disturbance term in equa-

[4] In the convergence literature the convergence model is often specified with the parameter "β" instead of "λ" to denote the speed of convergence and hence the name "beta convergence." Our econometric approach is no different, only the notation differs slightly.

Table 3: Descriptive Statistics for the Entire Sample and for Each Club

Variable	Mean	Std. Dev.	Min	Max
Entire Sample				
CO_2 per capita	22.5088	0.3091	7.7065	131.1058
Income per capita	15,567.4325	243.4665	1229.4849	56,959.4148
Population density	157.1694	4.4319	2.5776	1123.9540
Percent coal	0.4820	0.0070	0.0000	0.9934
Percent industrial	0.3626	0.0024	0.0753	0.8456
CDD	1072.7204	15.7581	80.0000	3875.0000
HDD	5273.9771	41.7241	400.0000	10,745.0000
Club One				
CO_2 per capita	25.5794	0.6489	12.9491	36.4247
Income per capita	15,335.1852	1151.3805	1964.7790	40,396.0208
Population density	40.4095	2.3285	18.2396	92.9344
Percent coal	0.3671	0.0218	0.0000	0.6882
Percent industrial	0.3200	0.0073	0.1962	0.4556
CDD	1572.81	114.6288	181.0000	3218.0000
HDD	4595.45	267.8317	1512.0000	8074.0000
Club Two				
CO_2 per capita	18.7636	0.1187	8.7973	34.9315
Income per capita	15,385.5582	358.7401	1229.4849	44,691.4788
Population density	111.2478	2.7296	2.5776	440.1431
Percent coal	0.5521	0.0081	0.0000	0.9934
Percent industrial	0.3647	0.0032	0.0899	0.7056
CDD	1111.7610	20.6811	118.0000	3364.0000
HDD	5227.7191	59.0399	1685.0000	9594.0000

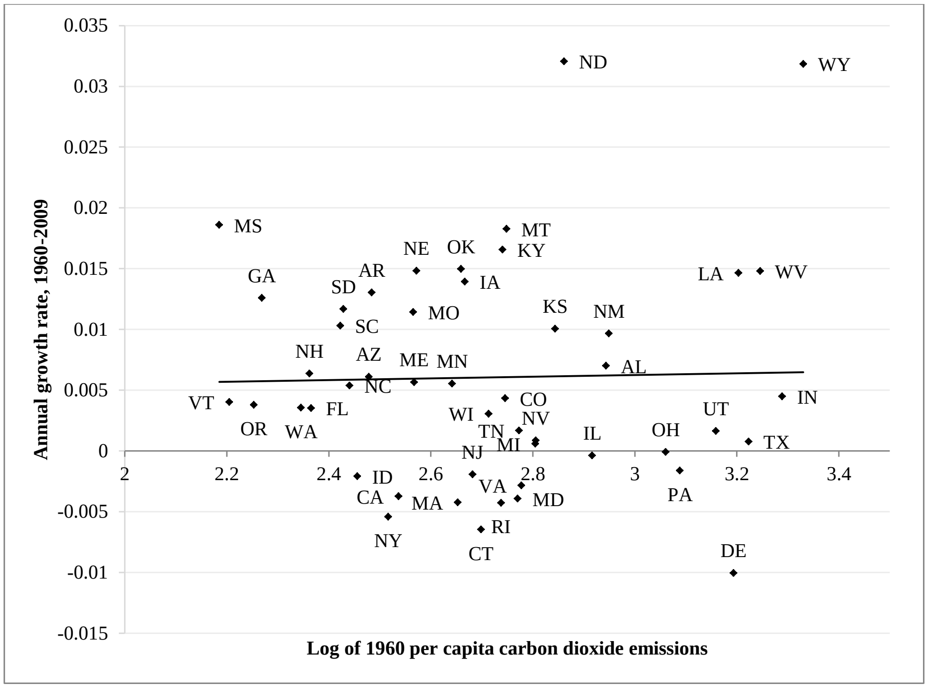
Note: Income is measured in millions of U.S. dollars and population is measured in thousands of people.

tion (10) captures temporary shocks to energy consumption, income, population growth, etc. The descriptive statistics for the entire sample and for each of the clubs is listed in Table 3.

In principle, equation (10) can be estimated by two models: least-squares dummy variable (LSDV) or fixed effects (FE) estimator. The former utilizes dummy variables for the unobserved, time-invariant effects. The fixed effects estimator is conducted by transforming the data to deviations from means within each cross-section. Essentially, this filters out the fixed effects from the data, but omits the estimated coefficient on the unobserved, time-invariant fixed effects. Asymptotically, the estimators should yield the same estimated coefficients in a maximum likelihood estimation context, although the LSDV model can lead to an incidental parameter problem if there is large number of cross-sections.

To test the hypothesis of absolute β-convergence we begin by plotting the average annual growth rates of state-level, per-capita emissions against the log of per-capita emissions in the first year of observation, 1960.

Figure 7: Convergence of per-capita emissions across U.S. states: 1960 emissions and 1960-2009 emissions growth



This plot is provided in Figure 7. A negative relationship between the average annual growth of emissions and emissions in the first year of observation would imply absolute convergence. However as illustrated in 7, the average growth rate of state per-capita emissions for 1960-2009, shown on the vertical axis, is not negatively related (in fact, the figure depicts a positive relationship) to the log of per-capita emissions in 1960, shown on the horizontal axis. Thus, absolute β-convergence does not appear to exit for the U.S. states.

For a sensitivity analysis we compare the regression results of the LSDVC to pooled OLS, FE, and GMM. The regression results for the full sample are offered in Table 4. The second set of results in Table 5 provide the estimates of the panel data models for the two clubs. To prevent simultaneity bias (i.e., a contemporaneous relationship between the independent and dependent variable) we treat the explanatory variables as predetermined, and therefore offer a distributed lag of the structural variables. The estimated coefficients for the annual indicator variables (the yearly fixed effects) have been omitted for the sake of

Table 4: Panel Data Convergence Estimates for the Full Sample (U.S., 1960-2009)

Regressors	Pooled OLS	Fixed Effects	LSDVC	GMM
γ	0.9922***	0.9126***	0.9283***	0.9032***
	(0.0033)	(0.0176)	(0.0428)	(0.0108)
Implied λ	0.0078	0.0915	0.0744	0.1018
Structural Factors				
Income per cap	-0.01364	0.0255	0.0222	-0.0024
	(0.0087)	(0.0181)	(0.0407)	(0.0247)
Pop density	-0.0045***	-0.0471***	-0.0328	-0.0525***
	(0.0011)	(0.0079)	(0.0538)	(0.0120)
Percent coal	0.0135***	0.0583***	0.0393**	-0.0114
	(0.0040)	(0.0127)	(0.0195)	(0.0124)
Percent ind	0.0084	0.0122*	0.0124	-0.0026
	(0.0079)	(0.0065)	(0.0105)	(0.0085)
Non-Structural Factors				
CDD	0.0015	0.0127**	0.0121*	0.0181***
	(0.0022)	(0.0060)	(0.0070)	(0.0064)
HDD	-0.00047	0.0114	0.0087	0.0558***
	(0.0022)	(0.0132)	(0.0145)	(0.0147)
Constant	0.1284	0.0190	–	–
	(0.0784)	(0.1750)	–	–
Number of obs	2352	2352	2352	2304
Number of groups	48	48	48	48
R^2	0.9910	0.9466	–	–

Note: The terms "***," "**," and "*," denote a statistical significance level of one percent, five percent, and ten percent, respectively.

brevity but are available upon request.

Looking at Table 4 first, the differences between the estimated coefficient on the lagged dependent variable does not vary tremendously across the different models. Based on Monte Carlo analysis, Judson & Owen (1999, Table 2, p. 14) showed the following general biasedness of the lagged dependent variable, γ: OLS is upward biased, FE/LSDV is downward biased, LSDVC is slightly downward biased, GMM (Arellano and Bond) is downward biased. Following Judson & Owen (1999) as a rough guide, our estimated results would imply that OLS is upward biased, FE is downward biased, and GMM is downward biased. Therefore, we posit that the LSDVC model provides the most accurate estimate of the speed of convergence which is approximately seven percent a year.[5]

Based on the estimated results in Table 4, we found that population density, the percentage of coal

[5]Note that the implied speed of convergence is larger than what is normally found in the economic growth convergence literature, which is generally around two percent (Barro & Sala-i-Martin, 2004). However, one must recall that we are examining the convergence of carbon dioxide emissions not economic growth across states.

Table 5: Panel Data Convergence Estimates for the Two Clubs (U.S., 1960-2009)

	Club One			Club Two		
Regressors	FE	LSDVC	GMM	FE	LSDVC	GMM
γ	0.6338***	0.6338***	0.7812***	0.8403	0.8793***	0.8643***
	(0.1356)	(0.1674)	(0.1457)	(0.0458)	(0.0756)	(0.0194)
Implied λ	0.4560	0.4560	0.2469	0.1740	0.1286	0.1458
Structural Factors						
Income per cap	0.0868	0.0799	0.0495	0.1264***	0.0118	0.1510***
	(0.1936)	(0.8809)	(0.1926)	(0.0278)	(0.0164)	(0.0349)
Pop density	-0.2015	-0.1943	-0.1225	-0.0496***	-0.0336	-0.0624***
	(0.1266)	(0.7372)	(0.1277)	(0.0120)	(0.0602)	(0.0124)
Percent coal	0.1529	0.1547	-0.0790	0.0841**	0.0571	0.0013
	(0.1281)	(0.6240)	(0.1380)	(0.0402)	(0.0348)	(0.0147)
Percent ind	0.3796	0.4029	0.3042	0.0416	0.0343	0.1074***
	(0.3292)	(2.2721)	(0.3253)	(0.0401)	(0.0852)	(0.0358)
Non-Structural Factors						
CDD	0.0313	0.0305	0.0335	-0.0114	-0.0121	-0.0023
	(0.0193)	(0.1022)	(0.0206)	(0.0082)	(0.0128)	(0.0100)
HDD	0.0067	0.0038	0.0489	-0.0133	-0.0185	0.0008
	(0.0757)	(0.3229)	(0.0823)	(0.0169)	(0.0419)	(0.0207)
Number of obs	98	98	96	1029	1029	1008
Number of groups	2	2	2	21	21	21
Observations per group	49	49	48	49	49	48
R^2	0.9832	–	–	0.9224	–	–

Note: The terms "***," "**," and "*," denote a statistical significance level of one percent, five percent, and ten percent, respectively.

used in electricity consumption, and cooling degree days are more or less consistently significant across the different models. Using the results from the LSDVC model, the estimated coefficient on population density implies that a one percent increase in the population size per square mile leads to an approximate five percent decrease in per capita emissions, but this estimate is not statistically significant. Interestingly, the estimated coefficient on the percentage of coal implies that a one percentage increase in coal used for electricity consumption leads to an approximate four percent increase in per capita emissions. Lastly, the coefficient on cooling degree days implies that a one percent increase in CDD leads to an approximate one percent increase in per capita emissions. The negative relationship between emissions and population density could possibly be explained by agglomeration effects in densely populated urban areas. Masayuki (2012) found that the efficiency of energy consumption is much higher for the service sector in densely populated cities. If such agglomeration effects are present then the efficiency of energy consumption would reduce carbon dioxide emissions.

Next we use the bias-corrected LSDV model to compare the speed of convergence across the two clubs (based on the results of the "log t" tests in previous section). As outlined in the Background section, if the speed of convergence is higher for the two clubs then it could perhaps suggest multiple equilibria of convergence which may perhaps corroborate the findings of club convergence with the log t tests.

The results of the LSDV estimates for the clubs are presented in Table 5. Again for a sensitivity analysis, we also include estimates of the fixed effects and the general method of moments models. The estimated coefficients on the lag dependent variable does not vary too much within the two clubs. Based upon the estimation results of the first club, the fixed effects and bias-corrected least squares dummy variable models provide remarkable similar estimates of the speed of convergence with an implied rate of approximately forty-five percent. For club one, the estimated coefficients on the structural and non-structural variables are very similar across all three models, but none of the variables are statistically significant. This could be perhaps due to the fact that the first club is only constituted by two cross-sections (or two states). For club two, the estimated rate of convergence again is remarkably similar. The results for the bias-corrected least squares dummy variable model indicates an implied speed of approximately thirteen percent – slightly less than the results of the fixed effects and general method of moments estimators. The LSDVC model yields statistically insignificant results for all the structural and non-structural variables, but the other two estimators indicate that per-capita income and population density have an effect on per-capita emissions. The fixed effects model suggests that a one percent increase in per-capita income increases per-capita emissions by approximately thirteen percent, whereas a one percent increase in population density leads to an approximate five percent decrease in emissions.

The main thing to note is that the estimated speed of convergence is higher for the two clubs than for the full sample. This may suggest, as with the club convergence (log-t) analysis, that certain groups (clubs) of states are converging to different equilibria. Based upon the estimation results, club one appears to be converging faster than club two, and both clubs are converging more quickly than the entire sample.

6 Conclusion

In this study we used a two-stage procedure to examine the convergence of state-level carbon dioxide emissions in the U.S. The results of the club-convergence test in the first stage imply that there are two clubs of states whose emissions are converging to unique steady states levels through time. Despite the nice statistical properties of the the club-convergence test, it endogenously groups states according to converging emissions but omits factors that may lead to club formation. To overcome this problem we conducted conditional, beta-convergence tests in the second stage in which we tested for beta-convergence across the entire sample and among clubs identified in the first stage – in this regard it is relatively similar to the approach offered by Durlauf & Johnson (1995). The beta-convergence tests allowed us to condition the growth rates of emissions on certain structural and non-structural factors that are important determinants of state-level energy consumption which in turn create CO_2 emissions. The beta-convergence tests imply that emissions are converging across the entire sample and among the clubs. Further, convergence rates are higher for the individual clubs than for the entire sample which implies multiple regimes of convergence and corroborates the findings within the first stage. The structural factors were found to be important determinants for the growth rate of emissions in some cases, but the structural factors alone were not responsible for convergence – i.e., we found robust evidence of convergence through the coefficients on the lagged dependent variable. According to Bartkowska & Riedl (2012), this may suggest that we can correctly interpret our findings as club convergence as opposed to conditional convergence. However, as clubs are identified endogenously in the first stage it is still difficult empirically to distinguish between these two different types of convergence.

As pointed out by Fowlie & Muller (2013), if there is uncertainty with state-level abatement costs, then differentiated policies to mitigate emissions may improve welfare. Current regulated pollution emissions are often penalized at a single permit price. Understanding different clubs of states whose emissions are converging to similar levels will help policy makers to develop differentiated policies. For example, if the marginal costs of reducing emissions in high emitting states exceeds that of low emitting states (as implied by club convergence in which we observed higher convergence rates in the higher emitting club), then perhaps different abatement costs could be applied to different sets of states.

This notion of a differentiated policy is consistent with the "multistage approach" policy discussed by Höhne *et al.* (2003) and originally developed by den Elzen *et al.* (1999, 2001). In this particular regime regions commit the mitigation policy in the following stages: (1) no commitment, (2) decarbonization, (3) stabilization, and (4) reduction. In the first stage the region (state) is free to continue with business as usual. In the second stage the region receives GHG intensity targets differentiated by per-capita GDP levels. In the third stage regions are required to stabilize emissions, and in the final stage regions are required to reduce emissions. Regions graduate into each stage if they exceed a certain threshold, e.g., state-level GDP per capita grows beyond a certain level. According to this scheme each region is reviewed and re-evaluated every five years, and if the region exceeds a certain threshold then it graduates into the next stage. This notion could be consistent with the club convergence hypothesis. That is, if states have different marginal costs of abatement (and the costs are uncertain and unobservable by other states) then a graduated program may be more equitable than a "one size fits all" policy in which all states are penalized at a single permit price. The club convergence hypothesis is amenable to equity and this differentiated policy as our test results indicate that state-level emissions are converging to unique steady state levels through time.

This study suffered from some limitations given data constraints. For example, Bartkowska & Riedl (2012) did a similar analysis of club convergence but tested convergence in a second stage by regressing club membership on the initial level of the dependent variable and other structural factors (specifically, the authors used a multinomial logit model to test for convergence). The authors had access to panel data with large observations within each cross-section (i.e., N was large) which allowed them to test for convergence in a logit model context. Unfortunately, as we only have forty eight observations within each cross-section, we simply lacked the data to follow a similar approach. We were somewhat able to circumvent this problem by estimating fixed effects (least squares dummy variable) models, which according to Barro & Sala-i-Martin (2004) implicitly control for the constant steady state. Future research should consider both the second stage approach adopted in this study (conditional beta-convergence) as well as the innovative approach offered by Bartkowska & Riedl (2012).

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