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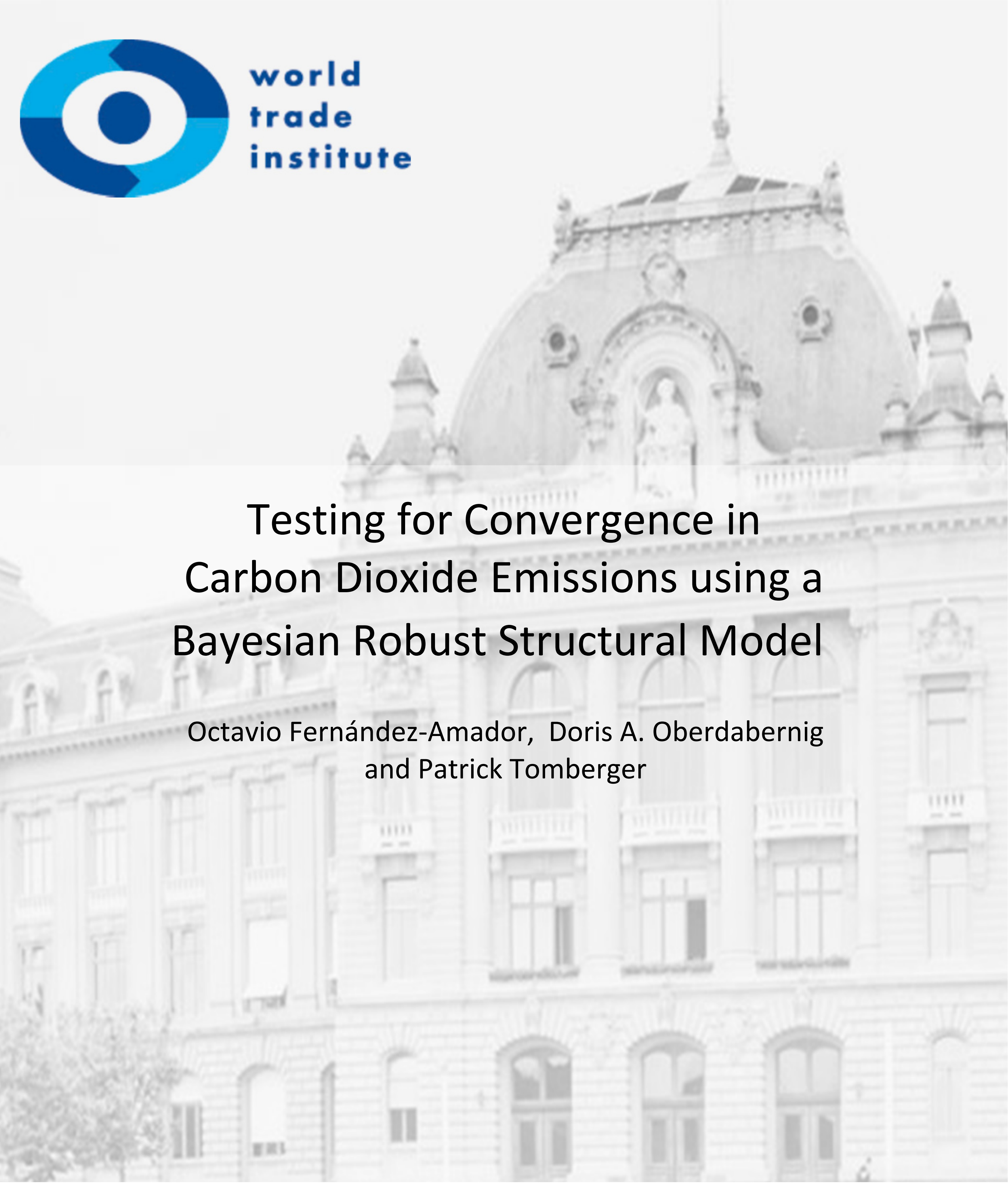

Testing for Convergence in Carbon Dioxide Emissions using a Bayesian Robust Structural Model

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Testing for Convergence in Carbon Dioxide Emissions using a Bayesian Robust Structural Model *

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Abstract

We address international convergence in Carbon Dioxide emissions per capita and per value added derived from emission inventories based on production and consumption patterns. We propose a Bayesian structural model that accounts for heteroscedasticity, endogeneity between emissions and economic growth, and tests for the existence of group-specific convergence via shrinkage priors. We find evidence for country-specific conditional convergence in all emission inventories, implying a half-life of 2.8–3.1 years for emissions per capita and 3.2–5 years for emission intensities. When testing for global convergence without allowing for individual-specific convergence paths, the half-life of CO_2 intensities increases to 20–24 years, whereas emissions per capita do not show convergence towards global steady states. Our results highlight the current incompatibility between emission targets and economic growth and the need for greener technologies. Moreover, there is no evidence for specific convergence dynamics in the European Union, the OECD, or the countries that ratified the Kyoto Protocol. The institutional frameworks implemented in industrialized countries did not induce faster convergence among developed economies.

Keywords: CO_2 emissions, production-based inventories, carbon footprint, convergence test, half-life.

JEL-codes: F18, F64, O44, Q54, Q56.

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1 Introduction

Global warming and its consequences are at the center of current policy debate on the sustainability of economic development. The Paris Agreement stipulates holding the global average temperature below 2°C above pre-industrial levels to bring climate change under control;[1] for this to happen, the 194 countries that signed the agreement are compelled to reach the global peak of greenhouse gas (GHG) emissions as soon as possible (Paris Agreement, Art. 2 and 4). The underlying question is how to make economic growth compatible with limited or decreased pollution, particularly GHG emissions.

The Environmental Kuznets Curve (EKC) predicts that pollution increases with rising per capita income and falls with rising income after a peak in emissions has been reached. However, the existence of a turning point in GHG emissions after which emissions start to decrease with economic growth has not been unanimously confirmed by empirical research. Especially for Carbon Dioxide (CO_2) emissions the existence of such peak has often been rejected.[2] Against this background, it is important to know whether global carbon emissions will eventually reach a limit; only then the growth rate of atmospheric concentrations of CO_2 will stabilize.

The patterns of convergence of CO_2 emissions per capita towards a certain emission level and the height of this level have important implications for the design of the international regulatory framework. Reliable information on whether the steady state of emissions is global or country-specific and on how long it will take for countries to reach this steady state can strengthen the ongoing policy debate. Related to this, the convergence dynamics of carbon emissions derived from both national production and consumption activities should be better understood when revising environmental responsibility, as they characterize the path of emissions associated with further economic development in a globalized context. Increasingly fragmented value chains allow the geographical location of production stages to differ from the place of final consumption. A mere focus on territorial-based emissions neglects the importance of trade in intermediates and carbon leakage, i.e. the shift of highly pollutant industries from countries with stringent environmental regulation to countries with less strict regulation (e.g. Aichele and Felbermayr, 2015; Babiker, 2005; Fernández-Amador et al., 2016).

[1] See Knutti and Fischer (2015) for a critical analysis of the 2°C target.

[2] Empirical studies that investigate the existence of an EKC in CO_2 emissions usually fail to find such a relationship in samples covering a large group of countries (see e.g. Stern, 2004, and Stern, 2017, for exhaustive surveys or Fernández-Amador et al., 2017, for a survey on empirical applications). Aslanidis and Iranzo (2009) and Fernández-Amador et al. (2017) provide evidence that the income elasticity of CO_2 emissions decreases as income per capita rises above a threshold level though emissions continue growing, challenging sustainability.

In addition, it is relevant to understand to what extent the dynamics of international convergence of emissions per capita is driven by convergence in carbon efficiency worldwide. The adoption of more environmentally friendly technologies will lower carbon intensities, which is particularly relevant for developing countries, as they need to combine remarkable economic growth targets with emission reduction goals.[3] If international technology transfers occur and emerging economies adopt greener production methods, the global production network will eventually become more sustainable, and CO_2 emissions per value added will converge across countries. This will in turn promote convergence in emissions per capita.

The assessment of convergence in CO_2 emissions has received considerable attention in the empirical literature.[4] Most studies tested for convergence in CO_2 per capita across different groups of countries, but their results remain broadly inconclusive.[5] In contrast, a smaller number of studies investigated convergence in carbon efficiency, pointing invariably towards the existence of convergence across countries.[6] However, all these studies focused on production-based emissions, while cross-country convergence in CO_2 embodied in consumption has not yet been investigated.[7]

We evaluate international convergence in CO_2 emissions per capita and per value added derived from national production- and consumption-based inventories worldwide. We put forward a Bayesian assessment of β-convergence that is based on the theoretical model by Ordás Criado et al. (2011) and extends the empirical model developed by these authors. Our model also allows for potential group-specific dynamics of convergence using Bayesian shrinkage priors. Our convergence test is robust to heteroscedasticity and accounts for potential endogeneity between the growth rates of emissions and GDP per capita by means of instrumental variables (IV) estimation.

[3] The Paris Agreement recognizes the need to support developing countries in order to facilitate the effective implementation of the objectives identified in the Agreement (Paris Agreement, Art. 2).

[4] See Pettersson et al. (2014) and Stern (2017) for comprehensive surveys of the literature on convergence in pollution emissions.

[5] The findings of the literature range from evidence for convergence (Strazicich and List, 2003; Nguyen, 2005; Ezcurra, 2007; Romero-Ávila, 2008; Lee et al., 2008; Westerlund and Basher, 2008; Lee and Chang, 2009; Brock and Taylor, 2010; Jobert et al., 2010; Huang and Meng, 2013; Yavuz and Yilanci, 2013; Anjum et al., 2014; Hao et al., 2015; Wu et al., 2016; Zhao et al., 2015) over the existence of convergence clubs (Nguyen, 2005; Aldy, 2006; Lee and Chang, 2008; Panopoulou and Pantelidis, 2009; Barassi et al., 2011; Ordás Criado and Grether, 2011; Camarero et al., 2013; Herrerias, 2013; Wang et al., 2014; Burnett, 2016) to no evidence for convergence (Aldy, 2007; Barassi et al., 2008; Nourry, 2009).

[6] See Anjum et al. (2014), Camarero et al. (2013) and Panopoulou and Pantelidis (2009).

[7] Aldy (2007) investigates convergence of CO_2 emissions across US states. This is the only study so far that also covers consumption inventories. The author did not find evidence for convergence for either CO_2 production or for CO_2 consumption per capita. In contrast to Aldy, our study covers economies at different development states, thus being the first one to evaluate global convergence patterns in CO_2 consumption.

Our contribution is twofold. First, we assess international convergence in production- and consumption-based carbon emissions for the first time by using a comprehensive dataset on comparable CO_2 emission inventories recently published by Fernández-Amador et al. (2016). The dataset covers 178 economies (grouped in 66 countries and 12 composite regions) and extends over 14 years after the Kyoto Protocol ratification.The focus on both inventories allows to account for the increasing detachment between CO_2 per capita generated by production activities and CO_2 embodied in final consumption in a period of rapidly expanding global production networks, which permit cross-border sourcing of carbon in final consumption. In addition, we analyze CO_2 emissions per value added (carbon intensity or efficiency) and draw conclusions on whether the detected patterns are driven by efficiency effects. While CO_2 per capita offers important insights on convergence stemming from the expansion of production or consumption in a country, convergence in CO_2 intensity provides information on whether countries that use more pollutant production methods eventually catch up with environmentally more efficient economies.

Second, our structural model presents some interesting features. It uses a Bayesian stochastic search variable selection prior (SSVS, George and McCulloch, 1993) to test for the existence of group-specific convergence dynamics; the groups comprise the European Union (EU), the OECD, and the countries that ratified Annex I of the Kyoto Protocol. The model is robust to heteroscedasticity; it is based on Student-t-distributed errors for which the degrees of freedom are estimated endogenously. Furthermore, for the first time in the context of t-distributed errors, it formulates a flexible Cholesky-prior to instrument potentially endogenous regressors; this prior has been proposed by Lopes and Polson (2014) in the framework of normal distributions.

Our results point to the existence of country-specific conditional convergence in all four emission inventories. The speed of convergence implies a half-life of 2.8–3.1 years for emissions per capita and 3.2–5 years for emission intensities. Yet, convergence towards global steady states, though conditioned on the political and economic structures, is much slower for emission intensities, implying a half-life of 20–24 years, whereas emissions per capita do not show convergence towards such global steady states. Moreover, we do not find support for the existence of group-specific convergence dynamics for countries belonging to the OECD, the EU, or the Annex I of the Kyoto Protocol. These findings evince the ineffectiveness of environmental policies implemented in developed economies and pose doubts on the feasibility of an effective global action against climate change.

The next section reviews the literature on convergence. Section 3 describes the data. In section 4, we explain the specification of the convergence test. Section 5 presents the results and section 6 concludes.

2 Literature review

Convergence tests received considerable attention in the empirical literature evaluating the predictions of Solow's (1956) growth model. Early studies tested whether countries starting out from low income levels experienced higher subsequent growth rates, either conditional on or unconditional of control variables (β-convergence).[8] Later studies suggested that β-convergence could be driven by regression to the mean (see Friedman, 1992; Quah, 1993) and tested whether the dispersion of income across countries was narrowing over time (σ-convergence).[9] Yet, Sala-i-Martin (1996) pointed out the merits of β-convergence for providing insights into growth dynamics. Although β-convergence is not sufficient for σ-convergence, it is a necessary condition (Sala-i-Martin, 1996; Young et al., 2008) and provides valuable information whenever alternative tests for convergence cannot be applied.[10]

Besides cross-sectional convergence tests, also time-series approaches have been developed. Several authors investigated stochastic convergence of income levels via unit root testing, that is, whether income shocks are of permanent or temporary nature.[11] While these approaches got increasingly popular as more data became available over time, Bernard and Durlauf (1996) pointed out that they are grounded on the assumption that the economies in the sample are near their long-run equilibria. In this sense, the use of time series tests may be invalid if the data are driven by transition dynamics.[12]

Similar to the Solow model for economic growth, there are theoretical models that predict convergence of pollution emission levels across countries over time (e.g. Brock and Taylor, 2010; Ordás Criado et al., 2011). Like the Solow model, these boil down econometrically to an equation of conditional β-convergence.

[8] Earlier studies focused on unconditional convergence, while more recent studies tested for conditional convergence, i.e. convergence after allowing for heterogeneity across countries by accounting for additional determinants of economic growth. While unconditional convergence was often found for OECD countries it was generally rejected for samples including non-OECD countries. If countries converge to different steady states, unconditional convergence models might result in biased coefficient estimates as the model used for estimation is miss-specified (see Barro and Sala-i Martin, 2004). See for example Baumol (1986); Barro (1991); Barro and Sala-i Martin (1992); Mankiw et al. (1992); Barro and Sala-i Martin (2004).

[9] See for example Quah (1993); Barro and Sala-i Martin (1992); Sala-i-Martin (1996); Young et al. (2008). Phillips and Sul (2007b) developed a test for identifying club convergence groups, which corresponds to a test of conditional σ-convergence (see Phillips and Sul, 2007b). Phillips and Sul (2007a) provided a short empirical application of the test, to convergence in economic growth.

[10] See e.g. Ravallion (2003) who applies β-convergence tests to international income inequality.

[11] See for example Carlino and Mills (1993); Quah (1993); Bernard and Durlauf (1996); Evans and Karras (1996).

[12] See also Panopoulou and Pantelidis (2009), Jobert et al. (2010) and Ordás Criado and Grether (2011) for surveys on β-, σ- and stochastic convergence.

Empirical studies on convergence in CO_2 production per capita led to heterogeneous conclusions. For OECD countries, Strazicich and List (2003), Romero-Ávila (2008), Lee et al. (2008), Lee and Chang (2009), Jobert et al. (2010), and Yavuz and Yilanci (2013) found evidence for convergence. Lee and Chang (2008) and Barassi et al. (2011) reported convergence only for a subgroup of countries, and Barassi et al. (2008) did not detect evidence for convergence.[13]

A growing number of studies included developing countries in their samples. Ezcurra (2007), Westerlund and Basher (2008), Brock and Taylor (2010), and Anjum et al. (2014) provided evidence for convergence across countries of different income status. Panopoulou and Pantelidis (2009), Ordás Criado and Grether (2011), and Herrerias (2013) detected several convergence clubs,[14] and Nguyen (2005) and Aldy (2006) found convergence only in sub-groups or clubs of developed economies. Nourry (2009) failed to detect evidence for cross-country convergence.

Some authors focused on convergence across regions in China and the US. For China, Huang and Meng (2013) detected overall convergence and Wu et al. (2016) found evidence for club convergence. For the US, Burnett (2016) found a club of 26 converging states, while convergence for the US as a whole was rejected. While all these studies focused on CO_2 production inventories, Aldy (2007) additionally assessed consumption of CO_2 per capita in the US states, but did not find convergence in either measure.

The heterogeneous findings of the literature on CO_2 convergence are in line with the mixed evidence for the existence of an environmental Kuznets curve (EKC). The EKC hypothesis suggests that as national income levels rise, pollution first increases with income, but after a certain level of income has been reached this mechanism is reversed.[15] If income levels are positively correlated with CO_2 emissions, the existence of an EKC relationship would ultimately lead to emission convergence (Stern, 2017). However, even though empirical studies find a positive relationship between economic growth and CO_2 emissions, the evidence favoring an EKC-type relationship is restricted to time-series or panel studies covering OECD economies.[16]

[13] Studies for OECD countries focused mainly on stochastic and β-convergence. For more details on the concept of convergence used by the respective studies, see Table A.1 in the Appendix.

[14] Panopoulou and Pantelidis (2009) and Herrerias (2013) applied the Phillips and Sul (2007b) test for convergence clubs. Ordás Criado and Grether (2011) found evidence for income-specific and regional convergence clubs especially for the sub-period 1980–2000.

[15] See Dasgupta et al. (2002), Kaika and Zervas (2010), and Stern (2004, 2017) for reviews and Fernández-Amador et al. (2017) for a summary of the most recent evidence.

[16] Schmalensee et al. (1998) is an exception, finding support for an inverse-U relationship using nonparametric techniques. More recently, Aslanidis and Iranzo (2009) and Fernández-Amador et al. (2017) found that the income-elasticity of CO_2 emissions decreases slightly after income per capita passes a certain threshold, such that relative decoupling increases with economic growth, though there is no evidence of absolute decoupling and an EKC relationship. Fernández-Amador et al. (2017) also provided evidence for a similar pattern in CO_2 consumption-based inventories.

Improvements in carbon efficiencies (i.e. CO_2 per value added) are an important requirement for reaching the turning point postulated by the EKC. High-income countries generally are more carbon efficient than less developed economies (Fernández-Amador et al., 2016). This can be explained by their stronger preferences for a cleaner environment, better access to cleaner technology and potential for carbon leakage. Carbon leakage will impede convergence in carbon emission intensities, as firms with larger emission intensity might relocate to countries with less stringent environmental regulation. However, if the rapid increase in international trade induces transfers of green technology to less developed countries, their carbon efficiency could improve more rapidly (Grossman and Helpman, 1995), which would contribute to convergence in carbon intensities. Thus, although most studies focused on CO_2 emissions per capita, evaluating convergence in carbon intensities provides additional insights in the convergence patterns across countries.[17]

Among the existing studies on convergence in the intensity of CO_2 emissions from production activities, Camarero et al. (2013) identified four convergence clubs among 22 OECD countries using the test for club-convergences developed by Phillips and Sul (2007b). Anjum et al. (2014) and Panopoulou and Pantelidis (2009) provided evidence for convergence in a panel of 136 and 128 countries, respectively. Focusing on Chinese regions, the results of Hao et al. (2015) and Zhao et al. (2015) suggest convergence of emission intensity, while Wang et al. (2014) found evidence for club convergence.[18]

3 Data

CO_2 emissions per capita and per value added derived from production and consumption inventories are available from the emissions database constructed by Fernández-Amador et al. (2016). Following Fernández-Amador et al. (2016), we define carbon intensities as carbon per value added rather than per GDP. For production inventories, value added is computed as value added embodied in production, whereas for consumption-based inventories, it is calculated as value added embodied in consumption. Therefore, both emission inventories and value added are measured at the same stage of the supply chain. The dataset consists of a balanced panel of national production- and consumption-based carbon emission inventories from fossil fuel combustion covering 66 countries and 12 composite regions (encompassing a total of 178 economies) over the years 1997, 2001, 2004, 2007 and 2011 (390 data-points). It relies on input-output, trade and energy data of several releases of the Global Trade Analysis Project (GTAP) database.

[17] Anjum et al. (2014) reported that the negative correlation between initial emission and subsequent emission growth is stronger for CO_2 intensity than for CO_2 per capita.

[18] All of these studies define CO_2 intensity as CO_2 per GDP. In our analysis we refer to CO_2 intensity as CO_2 per value added.

To test for the presence of β-convergence, we compute the growth rates of the four emission inventories, which we consecutively use as dependent variables in the empirical analysis. Since the data-points are unequally spaced in time (3 to 4 periods), we calculate the average growth rate of emissions between years $t - s$ and t, where s is the number of periods between two observations.[19] The resulting average annual growth rates allow to evaluate convergence in the large-N, small-T panel dataset, for which time-series methods cannot be used.[20]

Our baseline control variables are derived from the theoretical model by Ordás Criado et al. (2011) (equations 28 and 29 in their paper) and include the growth rate of purchasing-power parity (ppp) adjusted real GDP per capita over the period considered (based on data from the World Development Indicators, WDI, dataset) and the lagged level of CO_2 emissions, which should capture the scale effect of economic growth on emissions and potential convergence forces, respectively. The lagged level of ppp-adjusted GDP per capita is added in order to capture potential non-linearities in the relationship between economic growth and emissions.

To limit potential omitted variable bias (see Barro and Sala-i Martin, 2004), we add a large set of additional control variables capturing economic, structural and institutional characteristics of the individuals in the sample, and include individual-, and time dummies (see Table A.2 in the *Appendix* for details). We derive trade flows as a share of GDP as well as value added shares of different sectors of the economy (agriculture, energy, light manufacturing, heavy manufacturing, textiles, water services, construction, trade and transport, and remaining services) from the GTAP database. Data on population density, the share of fossil fuels and nuclear energy in total energy production, and rents from fossil fuel production as a share of GDP are available from the WDI database. A democracy index is sourced from the Polity IV database. Finally, in order to investigate group-specific convergence patterns, we generate dummy variables for members of the EU, OECD, and Annex I of the Kyoto Protocol.

[19] This corresponds to calculating average yearly growth rates. For a similar method see Ravallion (2003), who accounts for the unequal spacing in time between measures of income inequality for large-N, small-T panel data by regressing the difference in inequality between time t and the initial period t_1 on a constant and initial inequality in time t_1, both multiplied by a time trend $(t - 1)$. In contrast to Ravallion's data our panel is balanced in the sense that for every individual we observe all variables in the same points in time. Thus, we can also exploit the variation of the data across time and use initial emissions in year $t - s$ instead of in year t_1 as a regressor.

[20] Bernard and Durlauf (1996) pointed out that the power of time series tests may be weak when the dynamics do not occur near the steady state. In this sense, time-series approaches to test for stochastic convergence may not be particularly suitable in our context, because data on CO_2 emissions covering a global sample of countries are very likely to be driven by transition dynamics rather than being near the steady state.

4 Econometric model

We develop a Bayesian test for beta convergence as an extension of the model proposed by Ordás Criado et al. (2011).[21] Let E_{it} be, alternatively, the natural logarithm of CO_2 emissions per capita or per value added in country i at time t, where $i \subseteq [1, \dots, N]$ and $t \subseteq [1, \dots, T]$, and let $G_{i,t,s} = (E_{i,t} - E_{i,t-s})/s$ be the average growth rate of E_i over the period $t - s$ and t. The test is defined by the following recursive structural model with selection equation:

$$
\begin{aligned}
G_{i,t,s} &= \beta E_{i,t-s} + \pi_0 g_{i,t,s} + \pi_1 Y_{i,t-s} + \sum [\lambda_r z_{r,i,t-s}] + \\
&\quad + \delta_t + \alpha_i + \sum [\beta_j d_j E_{i,t-s}] + \epsilon_{1,it} && (1)\\
g_{i,t,s} &= \alpha_{iv} + \beta_{iv} L(g_{i,t,s}) + \epsilon_{2,it} && (2)\\
(\epsilon_{1,it}, \epsilon_{2,it}) &\sim t(0, \Sigma, \nu) && (3)
\end{aligned}
$$

The growth rate of emissions ($G_{i,t,s}$) depends on the logarithm of the level of emissions in country i at period $t - s$ ($E_{i,t-s}$), the growth rate of real GDP per capita over the period $t - s$ and t ($g_{i,t,s}$), the logarithm of real GDP per capita of country i in $t - s$ ($Y_{i,t-s}$), a set of control variables as described in the data section ($z_{j,i,t-s}$), time effects (δ_t), and individual dummies (α_i). Furthermore, d_j are dummy variables for group membership in the EU, OECD and Annex I of the Kyoto Protocol. The parameter associated with $E_{i,t-s}$ is the parameter of interest; in particular, $\beta < 0$ provides evidence for convergence.

The relationship between the growth rates of emissions and GDP per capita is potentially endogenous. Thus, we follow Barro and Sala-i Martin (1992) and instrument the growth rate of GDP per capita with its growth rate in the previous period, denoted $L(g_{i,t,s})$, where $L(\cdot)$ is the lag operator.[22]

[21] Ordás Criado et al. (2011) test for convergence in sulfur oxides and nitrogen oxides. They regressed the average growth rates of emissions over the period $t - 5$ to t on the level of emissions at the initial period of the growth rate ($t - 5$), the growth rate of GDP over $t - 5$ and t, GDP in $t - 5$, and time and individual dummies by OLS and a non-parametric model. The authors also addressed endogeneity between CO_2 emissions and GDP by instrumenting with GDP and its growth rate lagged 5 periods (as in Barro and Sala-i Martin 1992). They did not find evidence for heteroscedasticity in the estimation results.

[22] For the first period in our sample, 1997–2001, we use the growth rate for a period of the same length, 1993–1997.

The priors for the parameters in (1)–(2) are collected in the following set of equations:

$$\begin{aligned}
\beta, \pi_0, \pi_1, \lambda_r, \delta_t, \alpha_{iv}, \beta_{iv} &\sim N(0,\phi) &(4)\\
\alpha_i &\sim N(0,\psi) &(5)\\
\beta_j &\sim (1-\gamma_j)N(0,\kappa_0^2) + \gamma_j N(0,\kappa_1^2) &(6)\\
\gamma_j &\sim Bernoulli(p) &(7)
\end{aligned}$$

The priors of the parameters β, π_0, π_1, λ_r, δ_t, α_{iv}, and β_{iv} follow a normal distribution with zero mean and precision $\phi = 0.2$.[23] We estimate the individual effects using the dummy variables approach, where α_i is normally distributed with precision $\psi = 0.5$.[24] An intercept of the model can be retrieved as $\overline{\alpha} = \frac{1}{N}\sum_i^N \alpha_i$. Three aspects of the prior elicitation deserve special explanation: the shrinkage prior for the specific groups considered, the prior of the degrees of freedom of the Student–t, and the prior for the errors' covariance matrix in the structural IV model.

Equations (6)–(7) characterize a hierarchical SSVS shrinkage prior (see George and McCulloch, 1993) that grants flexibility for the data to discriminate among models including group-specific convergence dynamics (for EU, OECD, and Annex I membership). Each group-specific prior on β_j is modeled using a mixture of two normals with different precisions κ_0^2 and κ_1^2. $\kappa_0^2 > \kappa_1^2$ so that when $\gamma_j = 0$, β_j is restricted to be estimated around 0, whereas when $\gamma_j = 1$, β_j remains unrestricted. We set $\kappa_0^2 = 10$ and $\kappa_1^2 = 1$. To reflect the absence of prior beliefs about the existence of specific group convergence we set $p = 0.5$.

The model (1)–(3) allows for heteroscedasticity in the error terms. It follows from (3) that the vector of errors is distributed as a bivariate Student–t with mean vector $\mu = (0,0)'$, and covariance matrix $\nu(\nu-2)^{-1}\Sigma$, given $\nu > 2$ and Σ is a 2×2 positive definite symmetric matrix. The degrees of freedom parameter ν is estimated endogenously with prior

$$\begin{aligned}
\nu &= \lfloor 1/u \rfloor &(8)\\
u &\sim U(0,m)\ , &(9)
\end{aligned}$$

where the function $\lfloor 1/u \rfloor$ rounds the values of ν to the nearest integer to $1/u$. U in equation (9) stands for an uniform distribution where the parameter m is set to 0.3, such that ν is an integer within the interval $[3,\infty)$ (see Gelman and Hill, 2007). The estimation of ν renders the specification in (1)–(3) rather flexible. Small values of ν will yield heteroscedasticity-

[23] The precision is defined as the inverse of the variance. A precision of 0.2 implies a variance of 5.

[24] Note that the precision of the individual dummies is larger than the precision of the rest of the parameters, as suggested e.g. by Lancaster (2008).

robust parameter estimates, while as ν increases the errors' distribution will approach normality (homoscedasticity).[25]

In order to complete the prior for the covariance matrix in (3), we propose a Cholesky-based prior for Σ. Lopes and Polson (2014) have shown the better performance of this type of prior compared to the more widely used approach of specifying an inverted Wishart prior for Σ for IV-models in the context of normal-distributed errors.[26] More specifically, we model the components of the error vector based on the recursive conditional regressions arising from the Cholesky decomposition of $\Sigma = ADA'$, such that $D = diag(\Sigma_{1|2}, \Sigma_{22})$ and A is an upper triangular matrix with ones in the main diagonal and upper triangular component $a_{12} = \Sigma_{12}/\Sigma_{22}$. Thus, equation (3) can be re-written in recursive conditional form, using the specification of the conditionals of a multivariate Student–t:[27]

$$\begin{aligned} \epsilon_{1|2,it} &\sim t(a_{12}\epsilon_{2,it}, \Sigma_{1|2}, \nu + d_2) && (10) \\ \epsilon_{2,it} &\sim t(0, \Sigma_{22}, \nu) \ , && (11) \end{aligned}$$

where $\Sigma_{11} = \Sigma_{1|2} + \Sigma_{12}^2/\Sigma_{22}$, and $d_2 = 1$ is the dimension of $\epsilon_{2,it}$. We must specify priors for Σ_{22}, the conditional variance $\Sigma_{1|2}$, and for the parameter a_{12}, which calibrates the strength of the correlation between $\epsilon_{1,it}$ and $\epsilon_{2,it}$. We assign Σ_{22}^{-1} and $\Sigma_{1|2}^{-1}$ a gamma prior with shape and scale parameters $a, b = 0.001$ so that we remain uninformative about the precision of the model. a_{12} follows a normal prior centered at zero and with precision $\tau = 0.2$.

$$\begin{aligned} \Sigma_{22}^{-1}, \Sigma_{1|2}^{-1} &\sim \Gamma(a, b) && (12) \\ a_{12} &\sim N(0, \tau) && (13) \end{aligned}$$

A Markov Chain Monte Carlo (MCMC) algorithm is used to carry out Bayesian inference. Standard Gibbs-sampling can be applied to all priors specified, including the SSVS prior,

[25] We regard the priors for the parameters of interest $(\beta, \pi_0, \pi_1, \lambda_j, \delta_t, \alpha_{iv}, \beta_{iv}, \alpha_i, \beta_j)$ as informative. Geweke (1993) shows that under informative (normal) priors for the slopes, both the first and the second moments of the slopes exist. When the priors of the slopes are uninformative, $\nu > 2$ ensures existence of the first moments, while $\nu > 4$ ensures existence of the second moments.

[26] Cholesky-based priors have been applied to high dimensional stochastic volatility models (Lopes, 2011), longitudinal models (Pourahmadi, 1999), and IV-models in the context of normal distributions (Lopes and Polson, 2014). Alternatively, we could use an inverted Wishart prior for Σ, $\Sigma \sim IW(v_0, \Sigma_0)$, with parameters v_0 and Σ_0 (we explain the derivation of the IV-prior in terms of covariance matrices, because this is common in the literature). Priors for covariance matrices and variances have usually been addressed by means of inverted Wishart and inverted Gamma distributions, respectively, while Wishart or Gamma distributions have been used as priors for precision matrices and precisions. Wishart priors have been extensively used in the framework of Bayesian instrumental variable models under normal-distributed errors (see e.g. Kleibergen and Zivot, 2003; Lancaster, 2008; Rossi, 2005).

[27] See Nadarajah and Kotz (2005) for the characterization and properties of the multivariate Student–t distribution.

equations (6)-(7), the degrees of freedom parameter, equations (8)-(9), and the Cholesky-based priors for covariance of the t-distributed error terms, equations (12)-(13).[28] The vector of parameters to estimate is $P = (\beta, \pi_0, \pi_1, \lambda_r, \delta_t, \alpha_i, \alpha_{iv}, \beta_{iv}, \beta_j, \gamma_j, \nu, \Sigma_{22}^{-1}, \Sigma_{1|2}^{-1}, a_{12})$. We implement three Markov chains from which, after a burn-in of $7.5 \cdot 10^5$ draws, we retain a posterior sample of $7.5 \cdot 10^5$ draws each.[29] We apply a thinning of 3, ending up with a mixed posterior sample of $7.5 \cdot 10^5$ draws. We average across the posterior sample to calculate the posterior means, standard errors and quantiles of the coefficients, and the posterior inclusion probabilities (PIP) of the coefficients associated with specific group convergence. The PIPs of the coefficients for group convergence show the posterior probability of observing specific dynamics associated with those groups.

It should be noted that the model proposed is a dynamic panel model. Nickell (1981) showed that incidental parameters yield inconsistent OLS or Maximum Likelihood (ML) estimates in dynamic panels with short time dimension. The phenomenon is a consequence of having a limited number of observations from which each incidental (individual-specific) parameter is estimated, which in turn contaminates the estimation of the common parameters and, in particular, of the dynamic (autoregressive) parameter.[30] The literature has proposed alternative estimators with the aim of correcting Nickell´s (1981) bias. In particular, four lines have been developed—IV estimators, generalized method of moments (GMM) estimators, analytical corrections for the least squares dummy variable (LSDV) estimator, and bootstrap-based bias corrected estimators (see Everaert and Pozzi, 2007, for a review of these lines). In particular, Everaert and Pozzi (2007) put forward a bias correction procedure for the LSDV estimator based on the iterative boostrap proposed by Tanizaki (2000; 2004, Ch. 5). Everaert and Pozzi (2007) carried out a comparison with the other methods available in the literature in a Monte Carlo experiment, and found that the bootstrap-corrected LSDV estimator performs as well as analytical corrections in terms of bias, while it is easier to implement than those, and outperforms GMM estimators in samples with small time dimension.

Nickell´s (1981) bias affects the likelihood estimator in the context of dynamic panels. Since the Bayesian estimation approach is partially based on the likelihood of the model, Bayesian posterior estimates may inherit some bias from it. However, the use of informa-

[28] See George and McCulloch (1993) for details on the Gibbs sampler for the SSVS prior, Geweke (1993) for the Gibbs sampler applied to Student–t parameters, and Lopes and Polson (2014) for the details of the Gibbs sampling for IV-estimation in the context of the normal distribution.

[29] That was sufficient for the chains to show mixing and the estimates of the coefficients to convergence to their ergodic distribution.

[30] The concept of incidental parameter and the problem of limited information to estimate incidental parameters was first defined by Neyman and Scott (1948). Lancaster (2000) and Moon et al. (2015) offer rigurous treatments of the incidental parameters problem.

tive priors for the individuals effects and the slope parameters may atenuate the effect of the likelihood-inherited bias in the Bayesian estimator.

Several authors have studied the analogies between non-parametric and Bayesian bootstrap approaches. A connection between the non-parametric bootstrap and Bayesian inference has been suggested, for example, by Rubin (1981), Efron (1982), and Newton and Raftery (1994). Hastie et al. (2009, Ch, 8) characterized the non-parametric bootstrap as a nonparametric, noninformative approximation to Bayesian inference implemented by perturbing the data instead of perturbing the parameters. Weng (1989) showed that even though the Bayesian and non-parametric bootstraps can be interchanged in a first-order sense, they are different in a second-order asymptotic sense. Newton and Raftery (1994) and Efron (2011) have shown the connection between both the non-parametric and the parametric bootstrap and MCMC, respectively.

In the context of dynamic panels, Maddala and Hu (1996) showed Monte Carlo evidence that the iterative Bayesian estimator resulted in the smallest mean square error (MSE) in dynamic panels with individual random coefficients when compared to some classical estimators. Hsiao et al. (1999) also conducted a Monte Carlo study to investigate the small sample performance of the estimators of the means of short-run coefficients in the dynamic panel data model with coefficient heterogeneity, where there is no consistent estimator of the mean parameters unless N and T both tend to infinity. In such models, the authors found that the Bayesian approach performs fairly well even when T is small, whereas indicated that some consistent estimators may have disastrous implications in panels with very small T. In this vein, the non-parametric iterative bootstrap implemented by Everaert and Pozzi (2007) and the Gibbs sampling approach used to carry out inference from our econometric model present a high degree of analogy. Our posterior inference is based on the mean of the mixed posterior sample resulting from the Gibbs sample after thinning. In addition, it is based on informative priors. Therefore, we expect that our posterior estimates do not suffer from considerable bias.

As a robustness check, we estimate an alternative (homoscedastic) model where the priors in equations (3), (10), and (11) are replaced, respectively, by

$$(\epsilon_{1,it}, \epsilon_{2,it}) \sim N(0, \Sigma) \tag{14}$$

$$\epsilon_{1|2,it} \sim N(a_{12}\epsilon_{2,it}, \Sigma_{1|2}) \tag{15}$$

$$\epsilon_{2,it} \sim N(0, \Sigma_{22}) \tag{16}$$

where again $a_{12} = \Sigma_{12}/\Sigma_{22}$ and the equations (8) and (9) for the prior of the degrees of freedom ν are eliminated. Therefore, the model collapses to the Bayesian IV-model proposed by Lopes and Polson (2014). The Gibbs sampling algorithm for estimating this model's posterior is simplified by deleting the steps corresponding to the marginal density of ν.

5 Results

We implement two types of IV models with t-distributed errors that differ in the inclusion or exclusion of individual-specific dummy variables. The *DV-conditional heteroscedastic model* includes a set of economic, political and structural controls, and individual dummy variables. It constitutes a test for (fully) conditional convergence. The *conditional heteroscedastic model* does not include individual effects and is only conditioned on economic, political and structural variables. This model provides evidence on a stronger assumption about convergence than the *DV-conditional heteroscedastic model*, as it approximates the concept of convergence by global convergence.

Table 1 summarizes the results of the IV model with t-distributed errors and individual dummy variables (*DV-conditional heteroscedastic model*). The results of the *conditional heteroscedastic model* (without individual dummies) are available in Table 2.[31] The four columns of the tables report the posterior means of the parameter estimates from the outcome (upper panel) and the selection equations (middle panel), the PIPs of the regressors associated with specific-group convergence and the half-life derived from the convergence estimates (lower panel), the estimated degrees of freedom (ν) for the t-distribution, the Bayesian R^2 and the number of observations of the regressions for the four CO_2 inventories (CO_2 per capita and per value added for production and consumption inventories). The asterisks next to the parameter estimates indicate whether the parameter is different from zero at the 99%, 95% or 90% (equal-tailed) credibility interval (CI).

The estimated degrees of freedom for the t-distribution (ν) turn out to be very low (between 4 and 6), pointing towards the existence of heteroscedasticity for each of the four inventories. For the *conditional model* in Table 2 the degrees of freedom are slightly lower than for the *DV-conditional model* in Table 1. The Bayesian R^2 are relatively high throughout, indicating that the included regressors explain a large part of the variation in the growth rates of all four inventories. In particular, our *DV-conditional convergence model* explains 85% of the variation in growth of CO_2 emissions per capita embodied in production activities, while it accounts for $73\% - 75\%$ of the variation in the growth rate

[31] Furthermore, we report the results of the *DV-conditional* and *conditional homoscedastic models* (normal-distributed errors with and without individual dummies) in Tables A.4 and A.5 in the *Appendix*.

of emissions per capita embodied in consumption inventories and in emissions per value added. The explanatory power of the *conditional model* is around $10\% - 15\%$ lower.

In all specifications we instrument the growth rate of income per capita in order to account for potential reverse causality (see Barro and Sala-i Martin 1992). The results of the selection equations are shown in the middle panel of the tables. The coefficient of lagged income per capita growth, which we use as an instrument, is positive with a CI of 99% in each specification, pointing towards a high relevance of this variable for explaining the contemporaneous growth rate of income per capita. At the same time it is exogenous, as emission growth cannot affect on lagged growth rates of income per capita. a_{iv}, the strength of the correlation between the errors of the two equations, is relatively low but for the carbon emissions per value added derived from production activities.

5.1 DV-conditional convergence

For the *DV-conditional convergence model* in Table 1, the posterior mean of the parameter connected to lagged emissions (convergence parameter) reveals a negative effect of lagged emissions on emission growth for all four emission inventories, at a CI level of 99%. This provides strong evidence for convergence in all four CO_2 emission inventories. The magnitudes of the posterior mean of the convergence parameter are larger in absolute value for emissions per capita than for carbon intensities.

Given the size of the convergence parameters, β, it is possible to calculate the time needed for countries to halve their emissions gap towards their country-specific steady states. Assuming that the average emission trajectories observed in the sample remain unchanged, the half-life of emissions amounts to 3.1 years for CO_2 per capita production, 2.8 years for CO_2 per capita consumption, 3.2 years for CO_2 intensity production, and 5 years for CO_2 intensity consumption.[32] These rather fast convergence rates implied by our estimates are in line with the findings of Westerlund and Basher (2008) and Jobert et al. (2010) for CO_2 per capita from production. Westerlund and Basher (2008) reported a half-life of CO_2 emissions per capita of between 3.1 and 6.1 years in a sample of developed and developing countries.[33] Jobert et al. (2010) found the half-life of CO_2 emissions to be between 2.2 and 3.4 years for various OECD countries.[34] Thus, our results confirm that the findings

[32] The half-life provides an indication of the speed of convergence. It is defined as the time required to eliminate half of the initial gap between actual emissions levels and the steady state. The half-life is calculated as $\frac{ln(0.5)}{1-e^{(-\beta)}}$ (see Romer, 2012, p. 26).

[33] The half-life in their sample of developed countries was estimated to lie between 4.2 and 6.2 years; this is longer than the half-life estimated in their pooled sample including developing countries.

[34] These figures correspond to estimates of conditional convergence. For unconditional convergence the authors reported a half-life between 4 and 8.5 years.

	(1) CO_2 pc prod.	(2) CO_2 pc cons.	(3) CO_2 va prod.	(4) CO_2 va cons.
		Outcome equation		
Constant	-0.2853 *	-0.1822	-0.1640	-0.0679
Ln(emissions)	-0.2033 ***	-0.2223 ***	-0.1959 ***	-0.1305 ***
Ln(emissions)·EU	0.0005	-0.0001	-0.0122	-0.0039
Ln(emissions)·OECD	0.0003	-0.0007	-0.0021	-0.0008
Ln(emissions)·Annex I	-0.0006	-0.0004	0.0003	0.0002
Ln(income pc)	0.0776 ***	0.0741 ***	-0.0006	0.0019
Income pc growth	0.3734	0.5522	-1.2302 **	-0.7552
Ln(pop. density)	-0.122 ***	-0.1358 **	0.0493	0.0350
Fossil rents	0.0019 **	0.0028 ***	-0.0002	-0.0013
Nuclear %	-0.0012	-0.0001	-0.0030	-0.0018
Fossil fuels %	0.0002	0.0004	-0.0003	-0.0006
Openness	0.0000	-0.0002	0.0000	0.0000
Political regime	-0.0022 **	0.0001	-0.0049 **	-0.0024
VA energy %	0.0003	0.0006	0.0007	0.0005
VA light manufacturing %	0.0007	0.0008	0.0013	0.0005
VA heavy manufacturing %	0.0009	0.0013 *	0.0002	-0.0011
VA textiles %	0.0009	-0.0010	0.0036	-0.0016
VA water services %	0.0037	0.0058	0.0019	-0.0064
VA construction %	-0.0029 **	-0.0014	-0.0039 *	-0.0023
VA trade and transport %	0.0007	0.0008	0.0012	0.0007
VA other services %	0.0016 ***	0.0012 **	0.0025 ***	0.0016 **
2004	0.0218 ***	0.0272 ***	-0.0629 ***	-0.0861 ***
2007	0.0085	0.0238 ***	-0.0994 ***	-0.1072 ***
2011	0.033 *	0.0257	-0.0762 **	-0.1058 ***
Individual dummies	yes	yes	yes	yes
		Selection equation for income pc growth		
Constant	0.0240 ***	0.0240 ***	0.0239 ***	0.0239 ***
Income pc growth, lagged	0.3361 ***	0.3337 ***	0.3349 ***	0.3356 ***
a_{iv}	0.1106	0.0547	1.1206 **	0.7065
PIP EU	0.0039	0.0049	0.2247	0.0954
PIP OECD	0.0132	0.0070	0.0528	0.0204
PIP Annex I	0.0033	0.0033	0.0197	0.0159
Half-life	3.0746	2.7843	3.2030	4.9724
ν	4.9775	5.3817	5.9000	5.4898
R^2	0.8479	0.7482	0.7403	0.7326
N	312	312	312	312

Note: * CI 90%, ** CI 95%, *** CI 99%. All variables but group dummies and income pc growth enter in lagged values. The Half-life is calculated as $ln(0.5)/(1-e^{-\beta})$. We evaluate all explanatory variables at their means.

Table 1: Results t-distribution, DV-conditional model

of earlier studies covering a smaller number of countries also hold for sample of countries comprising the whole world.

We do not find support for the existence of specific convergence dynamics for EU, OECD or Annex I members. The PIPs of the group-specific regressors are usually smaller than 10%, with the exception of the group of EU countries in the model for CO_2 production per value added, with a PIP of 22% (column (3)). This implies that the estimation algorithm tends to exclude group-specific dynamics. Consequently, the slope estimates of the group-specific regressors are very low in magnitude for all inventories and not different from zero at any of the CI levels considered.

Some of the control variables capturing a country's economic and institutional characteristics have a significant effect on emission growth. Higher per capita income is associated with higher growth rates of CO_2 per capita, while a higher growth rate of income per capita lowers the growth rate of emission intensity of production activities. This highlights, on the one hand, the role of energy—and thus energy-derived CO_2 emissions—as a necessary input for production and consumption patterns, but, on the other hand, also shows that economic growth is connected to some carbon efficiency gains. Population density has a negative effect on the growth rate of CO_2 per capita. The opposite is true for the share of rents from fossil fuel production in GDP. With respect to the variables related to the energy mix of an economy, there are no effects from the shares of fossil fuel or nuclear energy in total energy used. Noteworthy, trade openness does not affect emissions growth for any of the inventories considered. Yet, democratic political regimes are connected to lower growth rates in CO_2 embodied in production; that is, democracy may be a channel through which citizens' preferences are revealed. Regarding the sectoral shares in value added, only three sectors are relevant at a CI level of at least 90%. These are heavy manufacturing, with a positive effect on the growth rate of CO_2 per capita embodied in consumption, the construction sector, which lowers the growth rate of both production-based CO_2 emissions per capita and per value added, and services not included elsewhere, which are connected to higher emission growth rates for all inventories considered.[35] The time dummies are different from zero at the selected credibility intervals in most cases. For carbon emissions per capita, they point towards an increase in emissions from 2001 onwards as compared to the reference period 1997–2001. For CO_2 per value added, by contrast, the results indicate a decrease in emission intensities over time, with a slight rebound during 2007–2011 for production inventories.

[35] The negative impact of the construction sector may be related to the low carbon intensity of this sector during the period analyzed. It should be noted that estimations do take the value added share of agriculture as the benchmark sector and exclude it from the specifications in order to avoid multicollinearity.

5.2 Conditional convergence without individual dummies

The *DV-conditional model* analyzed above includes individual-specific effects and is thus concerned with convergence towards individual-specific steady-states. A stronger assumption is that convergence occurs towards a common steady-state, which is determined by economic and political factors. In order to test for international convergence towards a common level of emissions per capita or per value added, we also estimate models without individuals specific effects. The results from *conditional convergence models* without individual dummies, displayed in Table 2, show a slightly different pattern of convergence. The convergence parameter (of lagged emissions) is still relevant at the 99% CI level for CO_2 intensities (columns (3) and (4)), but it a has much lower value than in the *DV-conditional model*; it indicates a half-life of 20 and 24 years for the CO_2 intensity of production and consumption, respectively. For CO_2 per capita inventories (columns (1) and (2)) the convergence parameter turns irrelevant, pointing towards the absence of convergence. Group-specific convergence patterns remain unimportant, with PIPs that are even lower than for the conditional models (below 2%).

Also for some of the control variables the CI changes. While some variables turn irrelevant for explaining emissions growth—income per capita, population density, heavy manufacturing, construction—some others gain relevance, namely the share of fossil fuels in energy production, the share of value added in the energy sector, textiles, and trade and transport. Surprisingly, higher fossil rents in GDP are connected to a lower growth rate of the CO_2 intensity of consumption patterns.

To sum up, our findings provide strong evidence for convergence towards country-specific steady states for all four CO_2 inventories (*DV-conditional model*). Nevertheless, international convergence towards common steady states that are determined by political and economic structures cannot be detected for CO_2 emissions per capita (*conditional model*) and global conditional convergence towards common steady states can only be confirmed for CO_2 intensities. Convergence towards these global conditional steady states is, however, much slower than the convergence towards country-specific steady states in CO_2 intensities.

The evidence for convergence in CO_2 intensities irrespective of the specification used to test for convergence is consistent with the existence of carbon efficiency gains of production activities and, through global production networks, of consumption patterns, as observed for 1997–2011 by Fernández-Amador et al. (2016). In addition, carbon intensities of production activities show faster convergence than those associated with final consumption. This suggests that technology transfer may induce technological spillovers and technology adoption, which might play an important role for the convergence dynam-

	(1) CO_2 pc prod.	(2) CO_2 pc cons.	(3) CO_2 va prod.	(4) CO_2 va cons.
	Outcome equation			
Constant	-0.1235 ***	-0.0812 *	-0.0452	0.0008
Ln(emissions)	-0.0030	-0.0050	-0.0345 ***	-0.0286 ***
Ln(emissions)·EU	0.0002	0.0002	-0.0005	-0.0005
Ln(emissions)·OECD	0.0002	0.0003	0.0001	0.0000
Ln(emissions)·Annex I	0.0004	-0.0005	0.0006	0.0004
Ln(income pc)	-0.0008	-0.0004	-0.0007	0.0019
Income pc growth	0.7050 ***	0.7517 **	0.4723	0.9728 **
Ln(pop. density)	-0.0010	-0.0025	-0.0011	-0.0010
Fossil rents	0.0004	0.0002	-0.0007	-0.0009 *
Nuclear %	-0.0002	0.0000	0.0000	0.0001
Fossil fuels %	0.0000	0.0000	0.0005 ***	0.0003 **
Openness	-0.0001	0.0000	-0.0001	-0.0001
Political regime	-0.0001	0.0007	-0.0030 ***	-0.0019 **
VA energy %	0.0008 *	0.0006	0.0004	0.0001
VA light manufacturing %	0.0009	0.0005	0.0010	-0.0003
VA heavy manufacturing %	0.0008	0.0001	0.0000	-0.0010
VA textiles %	0.0066 ***	0.0054 ***	0.0051 *	0.0023
VA water services %	0.0014	0.0014	-0.0032	-0.0075
VA construction %	0.0009	-0.0004	0.0032	0.0017
VA trade and transport %	0.0011 **	0.0007	0.0007	-0.0001
VA other services %	0.0014 ***	0.0008	0.0006	-0.0003
2004	0.035 ***	0.0407 ***	-0.0769 ***	-0.0886 ***
2007	0.014 **	0.0218 ***	-0.0888 ***	-0.0954 ***
2011	0.0383 **	0.0238	-0.0415	-0.0822 ***
Individual dummies	no	no	no	no
	Selection equation for income pc growth			
Constant	0.0238 ***	0.0240 ***	0.0239 ***	0.0238 ***
Income pc growth, lagged	0.3429 ***	0.3354 ***	0.3361 ***	0.3384 ***
a_{iv}	-0.0788	0.0998	-0.3062	-0.6815
PIP EU	0.0019	0.0040	0.0092	0.0073
PIP OECD	0.0019	0.0023	0.0109	0.0071
PIP Annex I	0.0021	0.0032	0.0151	0.0066
Half-life			19.7466	23.8910
ν	4.1685	5.1104	5.2182	5.1730
R^2	0.7541	0.6100	0.6049	0.6598
N	312	312	312	312

Note: * CI 90%, ** CI 95%, *** CI 99%. All variables but group dummies and income pc growth enter in lagged values. The Half-life is calculated as $ln(0.5)/(1-e^{-\beta})$. We evaluate all explanatory variables at their means.

Table 2: Results t-distribution, conditional model

ics detected. Notwithstanding, trade openness does not seem to drive this result. By contrast, consumption-based CO_2 emissions per capita converge faster than emissions per capita embodied in production in the *DV-conditional model*. This result is consistent with converging consumption bundles (per capita), as a result of increasing globalization and the homogenization of consumer tastes.

Although some previous studies have found evidence for group-specific convergence patterns for OECD and EU members (e.g. Aldy, 2006; Nguyen, 2005; Ordás Criado and Grether, 2011; Panopoulou and Pantelidis, 2009; Westerlund and Basher, 2008), none of our models provides evidence for differences in convergence dynamics implied by membership in the OECD, EU, or Annex I of the Kyoto protocol. Therefore, climate change policies of industrialized countries such as the OECD or the EU have not been effective in accelerating emission convergence among developed economies (see also Westerlund and Basher, 2008, who found slower convergence for OECD countries). Also the binding commitments of the Kyoto Protocol have been largely ineffective in accelerating emission convergence among Annex I countries (see also Ordás Criado and Grether, 2011).

6 Conclusion and discussion

We tested for international convergence in CO_2 per capita and per value added derived from production and consumption patterns across a global sample of countries for the 1997–2011 period. In so doing, we put forward a Bayesian test for convergence that is robust to heteroscedasticity, accounts for endogeneity between the growth rate of CO_2 emissions and economic growth, and allows for the existence of group-specific convergence among members of the EU, the OECD, and the Annex I of the Kyoto Protocol.

Our findings suggest that all four emission inventories converge towards country-specific steady states. International convergence towards global steady states determined by economic and political structures is only found for CO_2 intensities. Although global convergence in carbon intensities provides a first step in contributing to convergence in per capita emissions, these convergence forces are not strong enough to promote convergence in CO_2 per capita. These results are consistent with the findings of the EKC literature for carbon emissions that composition and technique effects are outweighted by scale effects (see e.g. Fernández-Amador et al., 2017). The short half-lives calculated show that both emissions per capita and intensities are close to their country-specific steady states. However, actual levels of carbon emissions have proven to be unsustainable. This highlights the current incompatibility between economic growth and the 2°C target, and the need for further environmental policies to keep global warming under control while maintaining reasonable economic growth rates.

The historical responsibility for atmospheric CO_2 concentrations corresponds to developed economies. However, those economies, represented in our sample by three groups—OECD, EU, and the countries that ratified the Annex I of the Kyoto Protocol—have not experienced faster group convergence. This lack of specific patterns of convergence among developed economies, despite the environmental policies implemented in these countries, shows the difficulties in achieving effective agreements and policies to take action against global warming.

The absence of international convergence in emissions per capita, which are already beyond sustainability targets, poses doubts on the feasibility of the targets agreed without a significant change in the international institutional framework and strict implementation of new, stronger abatement policies. The lack of a stabilization of emissions in industrialized economies at sustainable emission levels may discourage developing economies to accept a cap on emissions. In addition, the idiosyncratic, country-specific convergence dynamics in emissions may further complicate the design of multilateral policy frameworks aimed at global emissions reduction. Even though there is an urgency for multilateral approaches to fight climate change that encompass developed and developing countries, developed economies should implement national environmental policies to promote carbon efficiency and less polluting sources of energy in order to reinforce the international action against global warming.

A Online Appendix

Study	Dep.-Var.	Type	Coverage	Conditional?	Finding
		Panel 1: OECD countries			
Barassi et al. (2008)	CO_2/Pop. (r)	st.	21 OECD (1950-2002)	NO	NO
Barassi et al. (2011)	CO_2/Pop. (r)	st.	18 OECD (1870-2004)	NO	YES: 13/18
Camarero et al. (2013)	CO_2/GDP	σ	22 OECD (1980-2008)	YES	YES: 4 clubs
Jobert et al. (2010)	CO_2/Pop.	β	22 EUR (1971-2006)	both	YES
Lee et al. (2008)	CO_2/Pop. (r)	st.	21 OECD (1960-2000)	YES	YES
Lee and Chang (2008)	CO_2/Pop. (r)	β, st.	21 OECD (1960-2000)	YES (st.)	YES: 7/21
Lee and Chang (2009)	CO_2/Pop. (r)	st.	21 OECD (1950-2002)	YES	YES
Romero-Ávila (2008)	CO_2/Pop. (r)	st.	23 OECD (1960-2002)	YES	YES: cond.
Strazicich and List (2003)	CO_2/Pop. (a+r)	β, st.	21 OECD (1960-1997)	both	YES
Yavuz and Yilanci (2013)	CO_2/Pop	st.	G7 (1960-2005)	both	YES: cond.
		Panel 2: Developed and developing countries			
Aldy (2006)	CO_2/Pop. (a+r)	σ, st., distr. dyn.	88 (1960-2000)	NO	YES: OECD
Anjum et al. (2014)	CO_2/Pop.	β	136 (1971-2010)	YES	YES
	CO_2/GDP			YES	YES
Brock and Taylor (2010)	CO_2/Pop.	β, σ	173 (1960-1998)	both	YES
Ezcurra (2007)	CO_2/Pop. (r)	σ, distr. dyn.	87 (1960-1999)	both	YES: both
Herrerias (2013)	CO_2/Pop.	σ, st.	58-162 (1980-2009)	both	NO: st. YES: clubs
Nguyen (2005)	CO_2/Pop. (r)	β, st.	100 (1966-1996)	both	YES: β YES: OECD, st.
Nourry (2009)	CO_2/Pop.	st.	127 (1950-2003)	NO	NO
Ordás Criado and Grether (2011)	CO_2/Pop. (a+r)	σ, distr. dyn.	166 (1960-2002)	both	NO: overall YES: groups
Panopoulou and Pantelidis (2009)	CO_2/Pop. CO_2/GDP	σ	128 (1960-2003)	YES	YES: 2 clubs
Westerlund and Basher (2008)	CO_2/Pop. (r)	st.	28 (1870/1901-2002)	YES	YES
		Panel 3: Regions within countries			
Aldy (2007)	CO_2/Pop. (a+r) prod. + cons	σ, st., distr. dyn.	US (1960-1999)	NO	NO
Burnett (2016)	CO_2/Pop.	σ	US (1960-2010)	YES	YES: 1 club
Hao et al. (2015)	CO_2/GDP	β, st.	China (1995-2011)	both	YES
Huang and Meng (2013)	CO_2/Pop.	β	China (1985-2008)	NO	YES
Wang et al. (2014)	CO_2/GDP	σ	China (1995-2011)	YES	YES: 3 clubs
Wu et al. (2016)	CO_2/Pop. (r)	σ, distr. dyn.	China (2002-2011), 286 cities	both	YES: overall
Zhao et al. (2015)	CO_2/GDP	β	China (1990-2010)	YES	YES YES: clubs

Note: The table gives an overview over the CO_2 convergence literature. CO_2/Pop. and CO_2/GDP denotes whether the used dependent variable is per capita emissions or emissions intensitiy. Relative (to the group average) per capita emissions are denoted by (r), (a+r) denotes if absolute and relative per capita emissions were used. β, σ and st. denotes beta, sigma and stochastic convergence, respectively. Some studies follow the work of Quah (1996) and apply non-parametric kernel estimations to assess the entire distribution of emissions, see also Romero-Ávila (2008). We denote those studies by "distr. dyn.".

Table A.1: Covergence literature - overview and results

Variable	Description	Source
	Dependent variables	
Δ(ln CO_2 p.c., prod.)	First difference of log of production-based CO_2 emissions per capita, divided by the length of the period. Emission data is based on raw data on fossil fuel consumption taken from GTAP.	Fernández-Amador et al. (2016)
Δ(ln CO_2 p.c., cons.)	First difference of log of consumption-based CO_2 emissions per capita divided by the length of the period. Constructed from a MRIOT, based on GTAP data.	Fernández-Amador et al. (2016)
Δ(ln CO_2 va, prod.)	First difference of log of production-based CO_2 emissions per value added, divided by the length of the period. Emission data is based on raw data on fossil fuel consumption taken from GTAP.	Fernández-Amador et al. (2016)
Δ(ln CO_2 va, cons.)	First difference of log of consumption-based CO_2 emissions per value added , divided by the length of the period. Constructed from a MRIOT, based on GTAP data.	Fernández-Amador et al. (2016)
	Control variables	
ln(Income pc)	Log of real GDP (PPP) per capita.	WDI
ln(pop. density)	Log of number of inhabitants per square kilometer.	WDI
Fossil fuels %	Share of fossil fuels in total energy production[a].	WDI
Nuclear %	Share of nuclear energy in total energy production[a].	WDI
Fossil rents	Rents from fossil fuel production as share of GDP[a].	WDI
Political regime	Polity2 political regime index.	Polity IV
Openness	Trade openness calculated as (X+M)/GDP.	GTAP
VA agr %	Share of VA in agriculture relative to total VA.	GTAP
VA egy %	Share of VA in energy sectors to total VA.	GTAP
VA lmf %	Share of VA in light manufacturing sectors relative to total VA.	GTAP
VA hmf %	Share of VA in heavy manufacturing sectors relative to total VA.	GTAP
VA tex %	Share of VA in textile sectors relative to total VA.	GTAP
VA wtr %	Share of VA in water services relative to total VA.	GTAP
VA cns %	Share of VA in construction relative to total VA.	GTAP
VA t_t %	Share of VA in trade and transport relative to total VA.	GTAP
VA oser %	Share of VA in remaining services sectors relative to total VA.	GTAP
Annex I	Dummy = 1 for members of Annex I of the Kyoto Protocol.	United Nations
EU	Dummy = 1 for members of the European Union	EU
OECD	Dummy = 1 for OECD members.	OECD

[a] Values for composite regions were obtained as GDP weighted averages. If data was missing for individual group members, group averages were used.

Table A.2: Definition of variables and data sources

	N	Mean	Std. dev	Min	Max
Dependent variables					
Growth CO_2 pc prod.	312	0.0101	0.0594	-0.3357	0.2664
Growth CO_2 pc cons.	312	0.0144	0.0576	-0.1940	0.2483
Growth CO_2 va prod.	312	-0.0275	0.0850	-0.3178	0.3219
Growth CO_2 va cons.	312	-0.0217	0.0735	-0.2316	0.2623
Control variables					
Ln(CO_2 pc prod.)	312	1.1993	1.4195	-2.6818	3.6089
Ln(CO_2 pc cons.)	312	1.3106	1.3204	-1.9832	3.5690
Ln(CO_2 va prod.)	312	-0.0727	0.7463	-1.8546	2.2377
Ln(CO_2 va cons.)	312	0.0362	0.5812	-1.0788	2.0602
EU	312	0.3013	0.4596	0.0000	1.0000
OECD	312	0.3686	0.4832	0.0000	1.0000
Annex I	312	0.3429	0.4755	0.0000	1.0000
Ln(income pc)	312	12.5369	1.6209	8.9704	16.5477
Income pc growth	312	0.0376	0.0295	-0.1096	0.1497
Ln(pop. density)	312	4.2848	1.4593	0.8781	8.8357
Openness	312	0.8261	0.4765	0.1761	3.2739
Political regime	312	6.2276	5.2041	-7.0000	10.0000
Nuclear %	312	0.1019	0.1833	0.0000	0.8357
Fossil %	312	0.5732	0.3111	0.0000	1.0000
Fossil rents	312	0.0409	0.0823	0.0000	0.4756
VA energy %	312	0.1467	0.1801	0.0001	0.7603
VA light manufacturing %	312	0.0705	0.0462	0.0003	0.3640
VA heavy manufacturing%	312	0.1231	0.0607	0.0015	0.4548
VA textiles %	312	0.0191	0.0195	0.0000	0.1267
VA water services %	312	0.0032	0.0027	0.0000	0.0233
VA construction %	312	0.0473	0.0308	0.0001	0.1596
VA trade and transport %	312	0.2256	0.1291	0.0424	0.7712
VA other services %	312	0.2825	0.1790	0.0008	0.6331

Table A.3: Descriptive statistics

	(1) CO_2 pc prod.	(2) CO_2 pc cons.	(3) CO_2 va prod.	(4) CO_2 va cons.
		Outcome equation		
Constant	-0.1932	-0.1222	-0.1502	-0.0832
Ln(emissions), lagged	-0.2133 ***	-0.2347 ***	-0.1971 ***	-0.1347 ***
Ln(emissions)·EU, lagged	0.0001	-0.0002	-0.0097	-0.0060
Ln(emissions)·OECD, lagged	0.0000	-0.0002	-0.0021	-0.0006
Ln(emissions)·Annex I, lagged	0.0000	0.0001	0.0002	0.0001
Ln(Income pc), lagged	0.0782 ***	0.0717 ***	-0.0038	-0.0048
Income pc growth	0.1227	0.2985	-1.3502 **	-0.8494
Pop. Density	-0.1434 ***	-0.1405 ***	0.0569	0.0584
Fossil rents	0.0021 **	0.0032 ***	-0.0005	-0.0013
Nuclear %	-0.0006	0.0003	-0.0039 *	-0.0022
Fossil fuels %	0.0003	0.0005	-0.0004	-0.0003
Openness	0.0000	0.0000	0.0000	-0.0001
Political regime	-0.0023 **	0.0006	-0.0055 ***	-0.0026
VA energy %	-0.0002	0.0004	0.0006	0.0004
VA light manufacturing %	0.0007	-0.0001	0.0013	-0.0004
VA heavy manufacturing %	0.0007	0.0011	0.0005	-0.0007
VA textiles %	0.0009	-0.0013	0.0039	-0.0018
VA water services %	0.0073	0.0044	0.0048	0.0010
VA construction %	-0.0031 **	-0.0007	-0.0045 **	-0.0034
VA trade and transport %	0.0005	0.0007	0.0013	0.0007
VA other services %	0.0015 ***	0.0011 *	0.0027 ***	0.0014 *
2004	0.0296 ***	0.0258 ***	-0.0554 ***	-0.0779 ***
2007	0.0216 ***	0.0301 ***	-0.0888 ***	-0.0928 ***
2011	0.0554 **	0.0315	-0.0647 *	-0.1151 ***
Individual dummies	yes	yes	yes	yes
		Selection equation for income pc growth		
Constant	0.0248 ***	0.0248 ***	0.0245 ***	0.0246 ***
Income pc growth, lagged	0.3001 ***	0.3006 ***	0.3070 ***	0.3040 ***
a_{iv}	0.2433	0.2131	1.2112 **	0.7520
PIP EU	0.0116	0.0074	0.1946	0.1295
PIP OECD	0.0252	0.0115	0.0544	0.0284
PIP Annex I	0.0046	0.0052	0.0201	0.0172
Half-life	2.9154	2.6203	3.1815	4.8071
R^2	0.6412 ***	0.5331 ***	0.5795 ***	0.5093 ***
N	312	312	312	312

Note: * CI 90%, ** CI 95%, *** CI 99%. All variables but group dummies and income pc growth enter in lagged values. The Half-life is calculated as $ln(0.5)/(1-e^{-\beta})$. We evaluate all explanatory variables at their means.

Table A.4: Results normal distribution, DV-conditional model

	(1) CO_2 pc prod.	(2) CO_2 pc cons.	(3) CO_2 va prod.	(4) CO_2 va cons.
		Outcome equation		
Constant	-0.1533 **	-0.1230 **	-0.0243	0.0330
Ln(emissions), lagged	-0.0028	-0.0079 *	-0.0395 ***	-0.0305 ***
Ln(emissions)·EU, lagged	0.0002	0.0003	0.0006	0.0002
Ln(emissions)·OECD, lagged	-0.0003	-0.0004	0.0001	-0.0003
Ln(emissions)·Annex I, lagged	-0.0001	0.0004	0.0004	0.0000
Ln(Income pc), lagged	0.0001	0.0010	0.0009	0.0019
Income pc growth	0.7720 *	0.6318	0.3172	0.6959
Pop. Density	-0.0024	-0.0040	-0.0050	-0.0040
Fossil rents	0.0006	0.0002	-0.0006	-0.0009
Nuclear %	-0.0002	0.0001	0.0000	0.0000
Fossil fuels %	0.0001	0.0000	0.0007 ***	0.0004 **
Openness	-0.0001	0.0000	-0.0002 *	-0.0001
Political regime	-0.0003	0.0008	-0.0037 ***	-0.0028 ***
VA energy %	0.0004	0.0009	-0.0003	-0.0002
VA light manufacturing %	0.0004	0.0004	0.0005	-0.0004
VA heavy manufacturing %	0.0013 *	0.0004	-0.0001	-0.0009
VA textiles %	0.0087 ***	0.0067 ***	0.0052 *	0.0012
VA water services %	0.0094	0.0072	-0.0022	-0.0071
VA construction %	0.0001	0.0001	0.0014	0.0014
VA trade and transport %	0.0013 **	0.0012 *	0.0005	0.0000
VA other services %	0.0017 ***	0.0012 **	0.0006	-0.0002
2004	0.0511 ***	0.0418 ***	-0.0678 ***	-0.0851 ***
2007	0.0257 ***	0.0292 ***	-0.0826 ***	-0.0892 ***
2011	0.0638 **	0.0216	-0.0210	-0.0842 ***
Individual dummies	no	no	no	no
		Selection equation for income pc growth		
Constant	0.0247 ***	0.0248 ***	0.0247 ***	0.0247 ***
Income pc growth, lagged	0.3019 ***	0.3012 ***	0.3023 ***	0.3031 ***
a_iv	-0.2451	0.1027	-0.1682	-0.4731
PIP EU	0.0122	0.0135	0.0175	0.0119
PIP OECD	0.0044	0.0066	0.0151	0.0129
PIP Annex I	0.0044	0.0054	0.0159	0.0106
Half-life		87.3940	17.2037	22.3813
R^2	0.2057 ***	0.2494 ***	0.2701 ***	0.3615 ***
N	312	312	312	312

Note: * CI 90%, ** CI 95%, *** CI 99%. All variables but group dummies and income pc growth enter in lagged values. The Half-life is calculated as $ln(0.5)/(1 - e^{-\beta})$. We evaluate all explanatory variables at their means.

Table A.5: Results normal distribution, conditional model

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