Pairwise Differencing Forecast of Global Carbon Dioxide Emissions: China vs. Technological Effects

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Abstract

This paper presents forecasts of global carbon dioxide emissions in the near future with reduced form Environmental Kuznets Curve (EKC) estimation via extending the recently proposed pairwise differencing approach by incorporating a model for time related effects. This strategy identifies the income related emission pathways (scale effects), independent from the identification problem of the time effects (compositional and technological effects), so that we are able to analyze some important issues regarding future global CO_2 emission pathways. Firstly, by being consistent with the basic theoretical results in the literature, income effects are responsible for the increase in global carbon dioxide emissions, which is mitigated by the time effects of developed regions. However, we show that these time effects are not likely to compensate for the income effects, indicating a no slow-down in carbon dioxide emissions in the near future. Secondly, although China is an important contributor to the global emissions, a reversal of the global trend is unlikely, even if China's carbon intensive industrial growth would come to a halt.

1 Introduction

Considered as one of the most important factors leading to global warming, carbon dioxide (CO_2) emissions as a result of economic activity lies at the core of the debates on climate change. How much CO_2 will be emitted in the future is important to the international community to understand the urgency and stringency of the measures that should be taken, and central to these discussions is the uncertainty of future emissions. Related to this concern, equally important questions arise considering the role played by the international negotiations in an effort to reduce CO_2 emissions: Firstly, does the rapid carbon intensive industrialization, experienced in the developing regions, like China, constitute a major future threat? Secondly, is the pollution compensating factors, like the state of the advancement in green technologies in the developed world sufficient to reduce future emissions at the regional and global level? Answering these questions requires to disentangle the main determinants of emissions, proposed in the environment and growth literature. These are scale (income) effects on the one hand, and time effects (most importantly, reflecting compositional and technological effects as suggested in the literature (Taylor and Copeland, 2004)) on the other. Fulfilling this requirement, we extend the pairwise differencing approach proposed by Vollebergh et al. (2009), and further developed by Sen et al. (2013), in order to forecast regional and global level CO_2 emissions up to 2050.

The literature on the modeling of CO_2 emissions is predominated by structural models, in which some structural parameters, (such as population growth, income growth, and technological change) are chosen by expert judgements. This subjective uncertainty is the main drawback of these models in forecasting future emissions. For example, in the Special Report on Emission Scenarios (SRES) by the Intergovernmental Panel on Climate Change (IPCC), despite the underlying "no change in policy" assumption (see IPCC (2000) and IPCC (2008)), future forecasts of greenhouse gas emissions range

from a level that is over five times larger than the current level to a reduction by 2100, depending on the subjective uncertainty. These so-called integrated assessment models (IAMs) are based on the IPAT identity (Ehrlich et al., 1971), where the impact (I) is decomposed into three determinants: Population (P), affluence (income per capita), and technology (T). On the other hand, the structural models used in the economics literature are mostly computable general equilibrium (CGE) models. CGE models require large data-sets for calibration, which are disaggregated at the sectoral level, and also depend on some subjective choices for the parameters of the theoretical setting. These models are essential for policy evaluation; however, they are not forecasting models (Auffhammer and Steinhauser, 2012), although they are commonly used for this purpose.

The other approach is reduced form modeling, which is also followed in this paper. The focus of this strand of literature is mostly the in-sample relation between emission per-capita and gross domestic (GDP) per-capita, and the main goal is to test the presence of an inverted U-shaped relation, namely the Environmental Kuznets Curve (EKC) hypothesis. When it comes to forecasting, reduced form modeling has several advantages. Firstly, data requirement is not as intensive as in case of the CGE models. Secondly, the well-established forecasting methods in time series econometrics can be easily incorporated, while in CGE models this is not so straightforward, since sectoral level data for most countries can be found only at irregular intervals. Thirdly, reduced form models provide the benchmark to the forecasts by structural models (Schmalensee et al., 1998). Finally, and most importantly, reduced form models might help in avoiding subjective choices of structural parameters. Hence, these characteristics make reduced form modeling an indispensable complementary tool for forecasting future emissions.

Compared to the structural models, reduced form modeling is not widely exploited for the purpose of forecasting future emission patterns, despite their numerous advan-

tages. Indeed, there are some potential drawbacks of reduced form modeling of emissions, which we take care of in this paper. The first set of problems are regarded with the in-sample estimates of the functional relation between emissions and income in the EKC literature. Firstly, the panel estimation methods, widely used in this literature, suffer from the well-known unit-root, cointegration, and cross-sectional dependence problems (Stern, 2004; Wagner, 2008). Secondly, a non-linear functional specification of a non-stationary exogenous variable requires an appropriate estimation technique and a cointegration test for the hypothesized relation (Muller-Furstenberger and Wagner, 2007). Thirdly, Dijkgraaf and Vollebergh (2005) show that the assumption of parameter homogeneity in the panel estimations is too strong. Due to the last problem, in this paper, we allow the income effects to be heterogeneous across cross-sectional units. This is also necessary, when the main goal is forecasting, where the goal is not just to test an imposed functional relation, but to estimate the functional relation between emission and GDP per capita. This assumption also avoids the panel dimension of the first and second problem[1]. Then, we adopt the estimation strategy "efficient non-stationary nonlinear least squares" (ENNLS) suggested by Chang et al. (2001), which accounts for both the first and second problems in time series estimations.

A second set of problems arise when the reduced form models are used for forecasting. Consider the following IPAT relation underlying the structural models:

$$I = P * A * T$$

Taking logarithms, and relaxing the one-to-one deterministic structure, the EKC literature transforms this identity into the following econometric relation:

[1]See Sen et al. (2013) for the methods applied in the panel context.

$$\log(\frac{I}{P}) = \log(A) + \log(T) + \varepsilon,$$

where ε denotes the error term. Then, the common practice is to estimate this linear econometric model by using CO_2 emission levels as a measure of impact (I), and modeling affluence (A) as a function of GDP per capita. Here, a series of problems arise due to the term T, which reflects not only the effect of technology, but possibly also other factors, such as changes in industrial composition or environmental policy. This term is difficult to measure at a macro level study. In order to circumvent this problem, the EKC literature generally uses time dummies, linear or quadratic time trend, as a proxy for this composite effect. However, such an approach might not properly disentangle the scale effects from the effect of the composite term. The reason is as follows: If the the time effects, constituting the effect of factors other than income, are poorly proxied by the time trends, then their effect will be captured by the error term. Since income and other possible factors are likely to be correlated, an endogeneity problem arises. Therefore, the estimated functional relation between emissions and GDP per-capita captures not only the scale effects, but also other possible factors like technology and industrial composition (see Auffhammer and Carson 2008; Vollebergh et al. 2009, and Sen et al., 2013). In line with this argument, estimated functions in the literature are non-linear, like inverted U-shaped or N-shaped, while properly identified scale effects will not be decreasing in GDP per capita. As a result, forecasts depending on these functional forms can lead to counter - intuitive results, like explosive growth or zero emissions even in the near future. This is elaborated as the identification problem of the time effects by Vollebergh et al. (2009). It is argued that the imposed structure on the time effects (like linear or quadratic time trends) is consequential for the estimated

functional form of the relation between emissions and income (income effects). Once the income effects are identified properly, they constitute the pure scale effects. Such a disaggregation is very useful for forecasting, since the potentially nonlinear total effect is decomposed into its determinants, which are more likely to have monotonic trends, and can be extrapolated more easily, rather than extrapolating possibly non-linear total effects. Moreover, forecasting the individual income and time effects, instead of the total effect can improve the forecasting performance (Lütkepohl, 1984; Lükepohl, 1987; Lütkepohl, 2006). In order to achieve this decomposition, we extend the pairwise differencing approach, first proposed by Vollebergh et al. (2009), and modified to account for the "non-linear specification of non-stationary covariates" in Sen et al. (2013).

In Vollebergh et al. (2009) and Sen et al. (2013) income effects are identified independent of the identification problem of the time effects. In this paper, we further model the time effects econometrically, by treating them as a residual data. Our method allows to analyze the previously raised issues. Our main findings are as follows: Firstly, our forecasts imply that the income effects are rising for all regions, and the time effects of developed regions partially offset the rising income effects. However, the global level forecasts show that the mitigating effect of the time effects are far from creating a slow-down in total effects, so an inverted U-shaped relation as suggested by the EKC hypothesis is not likely to be observed in the future. This first set of results is fully in line with the theoretical arguments in the EKC literature that environmental degradation, due to a growing scale of the economy, is mitigated as the economy grows above a threshold level which induces technological change and sectoral composition towards a more environmental friendly point. Secondly, the income effect of China is a strong contributor to the global emissions, reflecting their recent high growth rates. Moreover, the estimated time effects of China are positive, potentially reflecting their switch to a coal-based energy input mix, in combination with a shift to industrial pro-

duction. However, constructing a scenario by excluding China does not change the global picture. That is, in contrast to what is widely believed, our results indicate that the source of both current and future growth in global emissions is not mainly China, but the insufficient progress in the green technologies of developed regions.

This paper is closely related to the EKC literature, initiated by Grossman and Krueger (1991). The early literature focuses on various indicators for environmental degradation, and analyzes many sub-samples of countries or regions, by employing parametric reduced form models (Shafik and Bandyopadhyay, 1992; Selden and Song, 1994; Panayotou, 1993; Horvath, 1997; Komen et al., 1997; De Bruyn et al., 1998; Stern, 1998). As follows up of this early literature, the attention turned towards the econometric techniques employed in the early literature. First, the parametric estimation of the EKC relation is criticized for being simply a trial and error approach by testing a pre-specified functional form, and as a solution, non-parametric or semi-parametric econometric techniques were employed (Taskin and Zaim, 2000; Millimet et al., 2003; Azomahou et al., 2006). Second, the developments in non-stationary panel data estimation techniques necessitated to revise the earlier findings, by also taking into account the non-linear specification of a potentially non-stationary variable (Stern, 2004; Muller-Furstenberger and Wagner, 2007; Wagner, 2008; Galeotti et al., 2009). Third, Dijkgraaf and Vollebergh (2005) showed that the homogenous parameter assumption in panel estimations is too strong. Allowing heterogeneity, Martinez-Zarzoso and Bengochea-Morancho (2004) used a pooled mean estimator. Fourth, Vollebergh et al. (2009) argued that the empirical EKC literature suffers from a fundamental problem due to the identification of the time effects. They proposed pairwise differencing as a remedy. In this paper, our in-sample estimations are based on the method proposed in Sen et al. (2013), controlling for all these criticisms.

Our paper directly contributes to the literature forecasting global emissions with re-

duced form models. While Holtz-Eakin and Selden (1995) use a quadratic specification, Schmalensee et al. (1998) use a flexible estimator for the income effects. Auffhammer and Carson (2008) forecast the CO_2 emission pathways of China, by aggregating the provincial level forecasts. In a similar manner, Auffhammer and Steinhauser (2012) forecast US emissions, by focusing on model selection. Despite the difference that we present global level forecast, our forecasting strategy is similar in the sense that we also use regional forecasts to construct our global level forecasts. Similar to our approach of dismantling the total effects, disaggregation across regions can also improve the forecasting performance (Giacomini and Granger, 2004; Marcellino et al., 2003). None of the mentioned papers account for potential non-stationarity, parameter heterogeneity, and the identification problem of the time effects. Our approach allows us to figure out the driving force of the change in forecasted emissions, whether it is time effects or income effects of specific regions. Furthermore, our forecasts are fully data-based, while Holtz-Eakin and Selden (1995) and Schmalensee et al. (1998) use IPCC scenarios for future GDP and population forecasts in order to construct global level forecasts of emission per capita. We think our approach is in line with the goal of reducing subjective uncertainty.

The remainder of this paper is organized as follows. Section 2 describes the empirical strategies. Our dataset is described in section 3. In section 4, estimation and forecasting results are analyzed. Finally, section 5 contains the conclusion.

2 Empirical Strategy

In this section, we explain our empirical strategy. We start with a non-technical description of the in-sample estimations (see Sen et al. (2013) for further details). Next, we describe the forecasting procedure.

2.1 In-sample Estimation Strategy

The correlation between per-capita emissions and GDP, documented in the EKC literature, is basically a combination of growing scale of the economy, structural changes in the composition of industries, and the extent to which such developments are affected by technological change or differences in resource availability. In order to gain insight into these structural trends, following the IPAT identity, the reduced form panel estimation technique postulates the general decomposition:

$$y_{it} = f(x_{it}, i) + \lambda(i, t) + \varepsilon_{it}, \tag{1}$$

where the logarithm of emissions per-capita, y_{it}, of region (or country) i in year t is a combination of income effects, f, and time effects, λ. Here, the income effect is modeled as a fully flexible function of GDP per-capita, x_{it}, and both effects are fully heterogenous, ie. region specific. Proper identification of scale effects require to disentangle the effect of x_{it}, from the other unobserved time effects. The common approach is to assume that fixed effects are additively separable from f and λ, which leads to $y_{it} = \alpha_i + f(x_{it}) + \lambda(t) + \varepsilon_{it}$, where the income and time effects are assumed to be homogenous across regions. Furthermore, the commonly applied parametric estimation methods postulate functional forms for f and λ, such as using some degree of polynomials or time dummies. However, as argued by Vollebergh et al. (2009), the choice of such functional forms are arbitrary at some degree, and raises a fundamental problem in the identification of income effects. More specifically, the choice for λ is consequential on the estimated shape of f. This is a more crucial problem, if the goal is not just to test a postulated functional relation, but to identify the functional relation to make future forecasts. Indeed, the results in the EKC literature illustrate how problematic it is to obtain robust estimations of long-term relationship between income and the

environmental quality, even with comparable data sets. Therefore, it is important to be as flexible as possible, while specifying the time effects.

We start with the general form in equation (1), and do not impose any funtional form for the time effects. Instead, we assume that for every region, i, there exist a pair region, k, with equal time effects. This is much weaker than the assumption of equal time effects across all cross-sectional units imposed by the panel estimation methods. Under this weaker assumption that $\lambda(t,i) = \lambda(t,k)$, applying a pairwise differencing leads to the following expression:

$$(y_{it} - y_{kt}) = f(x_{i,t}, i) - f(x_{k,t}, k) + (\varepsilon_{it} - \varepsilon_{kt}) \tag{2}$$

where Vollebergh et al. (2009) impose $E(\varepsilon_{it} - \varepsilon_{kt}|x_{it}, x_{rt}) = 0$. So that, we are able to eliminate time effects without any a priori functional assumption. By estimating equation (2), income effects can be identified up to a constant.

One can impose further restrictions on equation (2), depending on the employed estimation strategy. In Sen et al. (2013), we perform a wide range of estimations, considering several problems. Firstly, we show that homogeneity of income effects across regions is a very strong assumption, driving the inverted U-shaped results in the literature. Dijkgraaf and Vollebergh (2005), by employing a formal test, reach the same conclusion. So, here, we assume full heterogeneity across regions, as well as pairs. Secondly, equation 2 can be estimated both parametrically or non-parametrically. Non-parametric techniques are superior by allowing a fully flexible estimation of functional forms. However, they suffer from over-fitting problem, and end-of sample biases, which deteriorates their usefulness in forecasting. Therefore, in this paper, we perform semi-parametric estimations of equation 2, by using polynomials up to fifth order. In contrast to Vollebergh et al. (2009), we control for nonlinear specification of non-stationary variables, by adopting the estimation strategy "efficient nonstationary nonlinear least

squares" (ENNLS) suggested by Chang et al. (2001). Thus, we also take into account both the non-linearity and non-stationary properties of the variables. Indeed, Sen et al. (2013) shows that per capita emission and GDP series are potentially integrated of order one. Finally, pairwise differencing estimation strategy eliminates cross-sectional dependence and common factor structure problems, prevalent in the panel estimations of the EKC relation.[2]

Following the estimation of income effects, time effects can be obtained from:

$$\begin{aligned} \lambda(t,i) + \varepsilon_{it} &= y_{it} - \hat{f}(x_{it}, i) \\ \lambda(t,k) + \varepsilon_{kt} &= y_{kt} - \hat{f}(x_{kt}, k), \end{aligned}$$

where $\hat{f}(.)$ is the estimated income effects. Under the assumption that $\lambda(t) = \lambda(t,i) = \lambda(t,k)$, the difference between the two expressions is idiosyncratic. Vollebergh et al. (2009) suggest to callibrate $\lambda(t)$ as average of $y_{it} - \hat{f}(x_{it}, i)$ and $y_{kt} - \hat{f}(x_{kt}, k)$. However, note that the assumption of equal time effects is not testable, since fully flexible time effects are not identifiable (Vollebergh et al., 2009). Finally, the total effect is estimated as the sum of estimated income and time effects.

This procedure reveals the time effects as residuals (observed minus estimated income effects). Therefore, one can think of the revealed time effects as a series to be modeled econometrically. In this paper, we extend the methods suggested by Vollebergh et al. (2009) and Sen et al. (2013) by modeling the revealed time effects as univariate autoregressive integrated moving average (ARIMA) processes, possibly with deterministic trends.

In the EKC literature, estimate of function $f(.)$ is interpreted as a combined effect of scale, technological, compositional and other possible effects, since technological change

[2]See Wagner (2008) for a discussion of these problems. Sen at al. (2013) describes how pairwise differencing accounts for these problems.

potentially depends on income and emissions. However, pairwise differencing identifies the pure effect of income growth on emissions. Therefore, estimated income effects are interpreted as scale effects, and time effects reflect a composite effect, which is argued to be dominated by technological change and compositional effects in the theoretical EKC literature (see, for example Taylor and Copeland (2004)). In theory, properly identified scale effects must be increasing in GDP per capita, which puts a check on our results. An inverted U-shaped relation in total emissions can only arise, if the time effects are negative and strong enough to offset the scale effects.

Choosing the pair regions is key to the identification of the income effect in our approach. In theory, there are as many identifications possible as there are potential pairs of regions. In our case, there are eight identifications for each of the nine regions that we compare. Our prior is that, combining two regions with similar time trends will result in a good fit, while combining two regions with different time trends will result in a bad fit. Based on this prior and on the basis of the in-sample fit of equation (2), for each region, we select a corresponding region with a similar time trend. This selection procedure is referred to as the "Goodness-of-Fit (GoF) prior". Note that any specification of the time effect, such as one being fixed and homogeneous across cross-sections, is also based on some prior. Our approach simply makes explicit, from the very beginning, that the empirical evidence on the presence of a possible inverted-U relationship cannot be inferred automatically, but always depends upon one's prior (Heckman, 2000).

Non-parametric estimations may suffer from end-of-sample biases, which may drive out-of-sample predictions. Therefore, we prefer a parametric approach in making in-sample estimations of equation (2) prior to the projections. However, compared to parametric estimation strategies, non-parametric ones have the advantage of imposing far less structure on the income effects. For this reason, we employ non-parametric

estimators for two purposes relating to the in-sample performance. Firstly, we base our pair selection procedure, GoF prior, on non-parametric estimations. Secondly, before carrying out future projections, we check in-sample performance of parametric estimations by checking whether our parametric estimations stay inside the non-parametric confidence intervals. We use smooth-backfitting (SBF) Nadaraya-Watson estimator following Mammen et al. (1999), and as explained in Nielsen and Sperlich (2005). Although SBF does not account for nonstationarity, generalized SBF (GSBF) estimator suggested by Schienle (2011) applies to the cases with multiple nonstationary covariates. GSBF reduces to classical SBF, if there are only two nonstationary covariates, as in our case.

2.2 Forecasting Strategy

In this section we describe our forecasting strategy. We start with forecasting the income and time effects of each region. Next, the total effects of each region is obtained as the sum of forecasted income and time effects. Finally, forecasts of global income, time, and total effects are sum of regional effects weighted with population. Before describing the forecasting method of individual series, we first formulize the aggregation process as follows:

$$\hat{x}_{w,T+h|T} = \sum_{i=1}^{9} \frac{\hat{p}_{i,T+h|T}}{\hat{p}_{w,T+h|T}} \hat{x}_{i,T+h|T} \,, \tag{3}$$

$$\hat{\lambda}_{w,T+h} = \sum_{i=1}^{9} \frac{\hat{p}_{i,T+h|T}}{\hat{p}_{w,T+h|T}} \hat{\lambda}_{i,T+h|T} \,, \tag{4}$$

where $\hat{x}_{w,T+h|T}$ is the predicted levels of income effects for whole world (w), h year ahead the final sample year T, based on the information available at time T. Here, individual regions are indicated with i, and p stands for population. Forecasts of global

time effects are denoted with $\hat{\lambda}_{w,T+h}$. Equations (3) and (4) describe the construction of the global forecasted levels of income and time effects as population weighted averages of the forecasts of income and time effects of individual regions. Now, the forecasts of total effects at the regional and global level can be obtained by multiplying the income and time effects as follows:

$$\hat{y}_{i,T+h|T} = \hat{x}_{i,T+h|T}\hat{\lambda}_{i,T+h|T} \tag{5}$$

$$\hat{y}_{w,T+h|T} = \hat{x}_{w,T+h|T}\hat{\lambda}_{w,T+h|T} \tag{6}$$

where $\hat{y}_{w,T+h}$ is the predicted levels of emission per capita for whole world. Equation (5) and (6) reflects the IPAT identity. Alternatively, one can work with series in logarithms, and the total effects can be derived by summing the logarithms of income and time effects. Next, we describe how the individual series are forecasted.

A simple forecasting technique for the income effects is obtained by regressing the estimated income effects on GDP per capita. We expect that this simple technique may result in a good in-sample fit, since the estimated in-sample income effects are expected to exhibit increasing trends. That is, by disentangling the scale effects from the other possible effects, we can project the income effects into the future with a simple linear extrapolation. Throughout the main text, we present the results of this linear extrapolation for the income effects. We also forecast income effects with univariate ARIMA models which are presented in the appendix.

Inn the previous section, we mentioned that the time effects for each region is modeled as an ARIMA proccess with possible deterministic trends. Our forecasts of individual time effects depend on these chosen in-sample models.

In order to perform the above forecasting procedure, one needs future projections

of regional GDP and the population series. In this paper, instead of using available scenario based projections, we prefer to make data-based econometric forecasts for these series. We think that such an approach is more compatible with the aim of avoiding subjective uncertainity. Our forecasting strategy (which is the same for the time effects and the income effects in the case of univariate ARIMA modeling) is as follows: The forecasting model for each individual series is chosen from a pool of models. Candidate models are combinations of autoregressive and moving average terms up to order three, a linear or a quadratic trend, and we also allow the series to be integrated up to order two. That is, candidate models are in the class of ARIMA models with deterministic trends. In choosing the forecasting model, we do not impose the order of integration a priori based on unit root tests. Instead, we allow the model selection criteria to choose the order of integration for each series as suggested by Chatfield (2002).

As model selection criterion, we use mean squared errors (MSE), mean absolute errors (MAE), and mean absolute percentage errors (MAPE). In the main text, we present the results focusing on MAPE. Our choice of model selection criteria is driven by our preference towards simpler models, since overfitting by including extra terms can result in unintuitive out-of-sample forecasts. Therefore, a criteria based on absolute errors (MAE and MAPE) is prefered to a criteria based on squared errors (MSE). These model selection criteria do not penalize for increasing number of parameters. Accounting for this concern, AIC and BIC are widely used model selection criterion, which we do not prefer. Instead, we employ the forecast comparison test suggested by Diebold and Mariano (2002), which is flexible in terms of controlling for preference towards simpler models. Whenever the Diebold and Mariano (2002) test does not reject the null hypothesis that the predictive accuracy of two models are equal at 5% significance level, we prefer the simpler model, even if it has a larger MSE, MAE, or MAPE. By simplicity, we mean a smaller number of parameters to be estimated.

Taking logarithms of GDP and population series is a common application in econometric modeling for various purposes. In the context of forecasting, the goal of a logarithmic transformation is to obtain a series with a relatively stationary variance. In their simulation, Lütkepohl and Xu (2012) show that a logarithmic transformation improves forecasts, only if the variance of the level variable is stationarized. On the other hand, forecasting in logarithms may result in dramatic distortions in forecast accuracy, if the level variable has already a stationary variance. Based on this finding, we prefer a model in levels to a model in logarithms, whenever the Diebold and Mariano (2002) test indicates that the two model have equal predictive accuracy. Another issue in case of modeling the log-transformed variable is about transforming forecasts back into levels. Simply, exponentiating the log-forecasts in order to obtain level-forecasts is not optimal. Instead, following Granger and Newbold (1976), we apply the following transformation:

$$\hat{y}_{t+h|t} = \exp(\ln(y)\hat{)}_{t+h|t} + \frac{1}{2}\hat{\sigma}^2_{\ln(y)}),$$

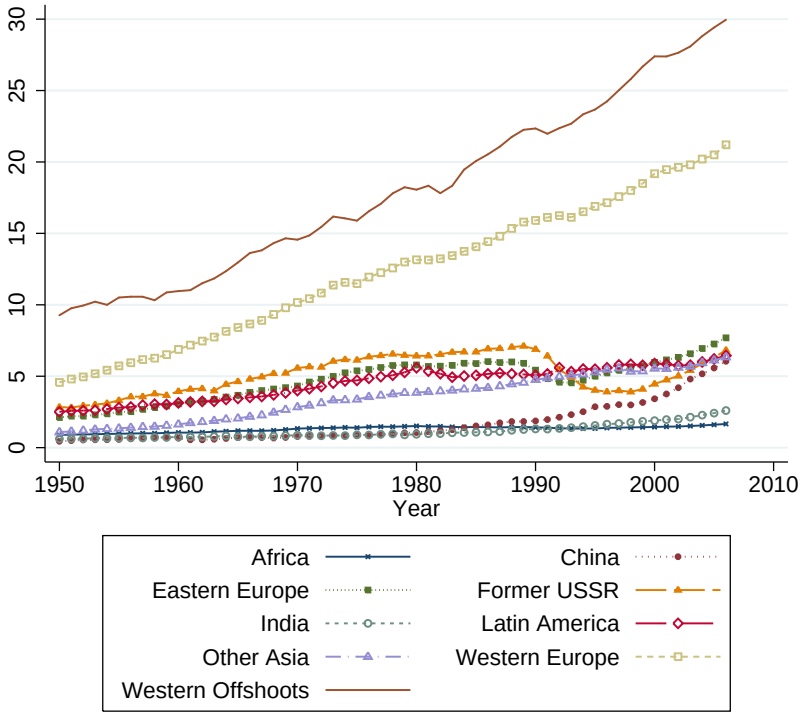
where $\hat{\sigma}^2$ is the mean square error of log - forecasts.

A final issue is about whether to base the model selection on in-sample fit, or out-of-sample fit. In the main text, we present our results based on forecasts derived from models which are chosen according to their in-sample fit. Alternatively, one can divide the sample into an estimation period and a test period, and choose the model which predicts the test period better. Our results depending on different test period lenghts are presented in Appendix.

3 Data and Descriptive Statistics

Our dataset is a balanced panel for all countries, covering the period between 1950 and 2006. CO_2 emission data consist of the sum of emissions from gas, liquid and solid fuels (based on consumption figures), and from gas flaring and cement production (see Boden et al., 1995; Marland et al., 2009). For each type of fuel, data on annual CO_2 emissions result from three aspects: the amount of fuel consumed, the fraction of the fuel that becomes oxidized, and a factor for the carbon content of the fuel. The fuel types incorporated in the calculations are coal, other solid fuels, crude oil, petroleum products, and natural gas. Total energy use and emissions per country are corrected for exports and imports of fuels, as well as for stock changes, international marine bunkers, and non-energy use of fuels, such as chemical feedstock. The estimation of the amounts of CO_2 released through gas flaring are based on the UNSTAT database, supplemented by estimations from DOE/EIA. The estimations of the amounts of CO_2 released from cement manufacturing are based on figures indicating the quantity of manufactured cement, the average calcium oxide content per unit of cement and a factor to convert the calcium oxide content into CO_2 equivalents. Data on GDP and population are taken from Maddison (2009). All figures are expressed in 1990 International Geary-Khamis dollars, using purchasing power parities. We aggregate data on a country by country basis into nine regions: India, China, "Other Asia", western Europe, eastern Europe, former USSR, "Western Oshoots", Africa, and Latin America. In contrast to the division into regions by the IPCC, we distinguish explicitly between Eastern Europe and Former USSR, divide the "old" OECD in western Europe (old EU) and what we indicate as "Western Oshoots" (Australia, Canada, New Zealand, and the United States), while Japan together with the countries of the Middle East are grouped under the name "Other Asia". Finally, we split the IPCC region ALM into Africa and Latin America. Figures 1 and 2 present our basic data.

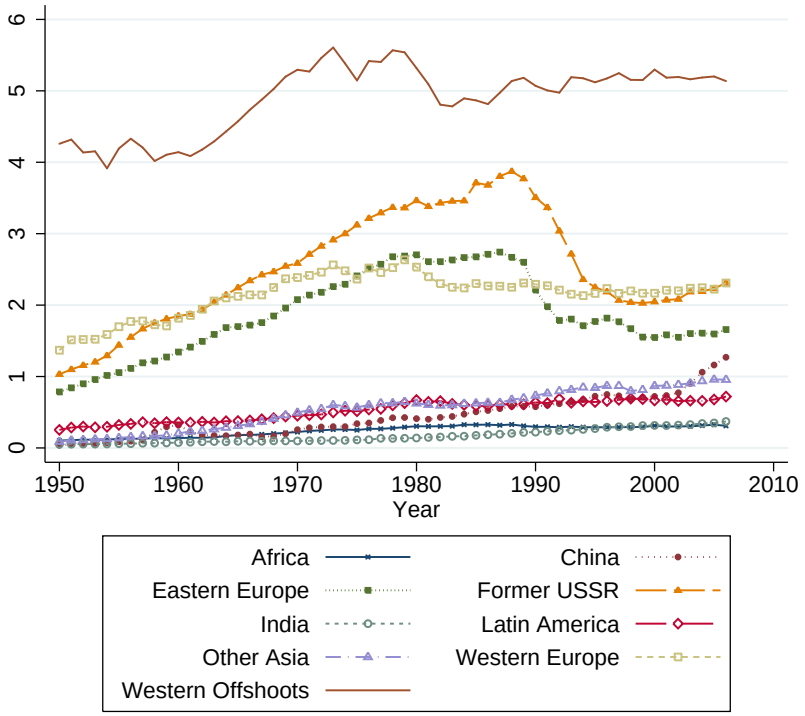
Figure 1: GDP per Capita (Mln. US $ 1990)



Looking at our data on the distribution of GDP per capita (see Figure 1), Western Oshoots have by far the highest income per capita, whereas, in particular, India and Africa are on the lowest end of the scale. Clearly, the distribution has changed remarkably over time. At the beginning of our sample period, there were three clubs with Russia, Eastern Europe, and Latin America forming a rather stable middle-income group. Because of instability in these middle income regions as well as the remarkable growth for Other Asia and China since the 1990s, the set of middle-income countries currently contains five out of our nine regions.

Interestingly, both the distribution and development over time, the region-specific per-capita CO_2 emissions are remarkably different (see Figure 2). The carbon intensity in the Western Offshoots has always been much higher than in any other region, followed by Former USSR, Western and Eastern Europe. Since these emissions reached a peak

Figure 2: Carbon dioxide emission in tonnes per capita



in Western Europe in the 1970s, carbon intensity there has remained more or less constant, whereas Former USSR and Eastern Europe have experienced a strong decline in emissions since the beginning of the 1990s. Most remarkable, however, is the recent, very high growth rate in China. China's growth in carbon intensity since 2001 is almost unprecedented. The only precursor in growth in per-capita carbon intensity since World War II, is the development in Western Offshoots during the 1960s. Indeed, China's per-capita carbon emissions have already reached the level of Eastern Europe of 2009.

Table 1 shows descriptive statistics of the data. Our data-set, aggregated over the regions, contains 9 regions and 57 years, resulting in 513 observations for all variables in our panel of CO_2 emissions. Considering only the mean, median, standard deviation, maximum and minimum values, all variables seem to be right tailed. Taking logarithms of the per capita variables seems to correct for the skewness of the level variables.

Table 1: Descriptive statistics

	Units	Mean	Median	St. Dev.	Min.	Max.
Emission	Tons (mln)	497.632	316.123	444.506	18.174	1832.085
GDP	1990 $ (bln)	2266.119	1357.705	2296.699	185.023	10654.535
Population	Million	486.749	368.697	329.695	87.637	1469.631
Emission pc.	kg.	1480.306	709.261	1523.701	39.262	5607.049
GDP pc.	1990 $	5819.531	4097.832	6057.425	448.022	29955.564
Emission pc. (log)		6.655	6.564	1.249	3.670	8.632
GDP pc. (log)		8.184	8.318	1.012	6.105	10.307

Note: Descriptive statistics are for the period 1950 - 2006. Total number of observation is 513.

4 Results

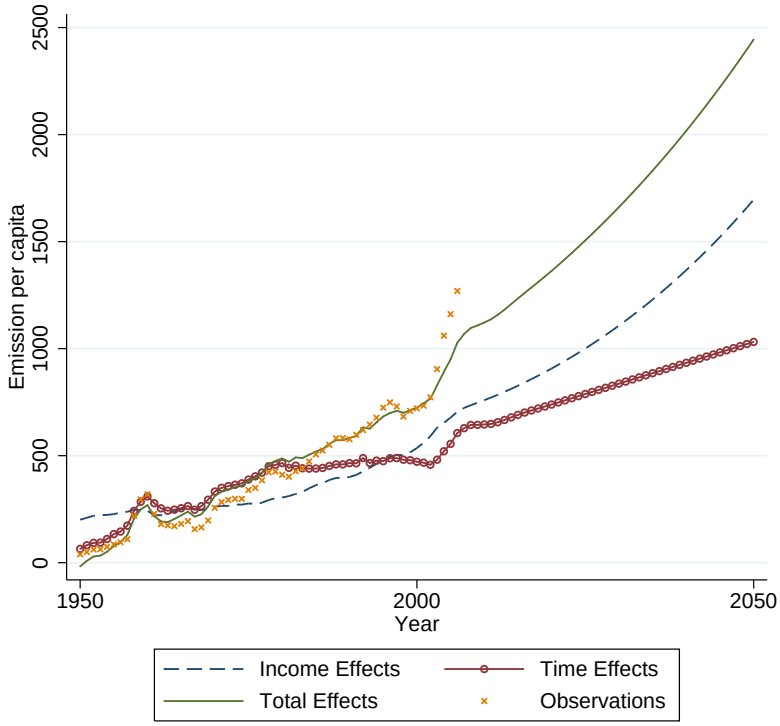
In this section, we present our regional and global emission projections. There are two patterns in the regional forecasts depending on the slope of the time effects. For the developed regions, Western Offshoots and Western Europe, time effects are negatively sloped, possibly indicating that contribution of technological and compositional effects to CO_2 emissions are decreasing. For the other regions, time effects are positively sloped. Here, we only present the results for China, representing the developing regions, and Western Offshoots, representing the developed regions. Interpretations of the results extends to other regions in these two groups.

In the guidence of theoretical arguments in the EKC literature, in the analysis below, we interpret the time effects as a composite effect, reflecting not only the effect of technology but also industrial composition.

4.1 Is the developments in green technologies sufficient to reduce emissions at the regional and global level?

Figure 3 illustrates the in-sample estimates and the projections for China. Since the levels of the curves are not identified in the semi-parametric specifications, we normalize the curves per region in such a way that the average level equals the corresponding

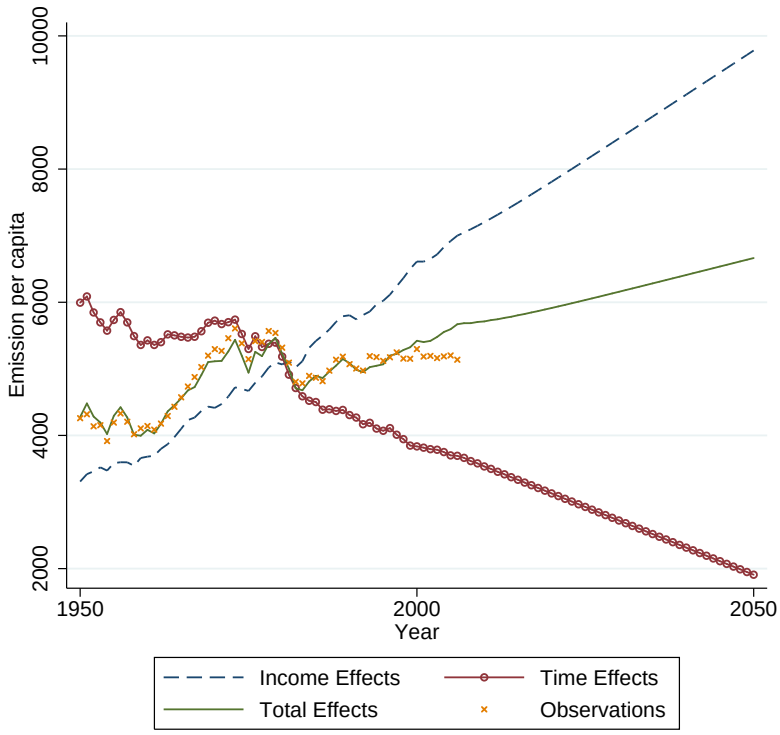
Figure 3: In-sample Estimates and Forecasts for CO_2Emissions Per Capita of China



sample average of the CO_2 emissions per capita. In case of the income effect, we plot the $f(x_{it}, i)$ for a given region, i, as a function of time t, so that we actually plot the income effect using the income level at time t. Thus, moving from 1990 to 1991, the figures show the effect of the change in per-capita income between 1990 and 1991. Similarly, the time effect in the figure represents the estimated technological plus compositional effects for an additional year. Finally, the total effect just consists of the income effect plus the time effect at time t.

The results in Figure 3 illustrates that both income and time effects are increasing for China. That is, both the effect of the growing scale of the economy, and the combined effects of technological change and change in industrial composition are strong contributors to the emissions of China. In the the corresponding future projections, this pattern is not likely to change for the period up to 2050, unless there is a structural

Figure 4: In-sample Estimates and Forecasts for CO_2Emissions Per Capita of Western Off-shoots



change. This pattern is qualitatively the same for other developing regions.

The results for Western Offshoots are presented in Figure 4. Being in line with the theoretical arguments in the EKC literature, income effects are increasing, while time effects are decreasing. Therefore, the technological and compositional effect mitigates the increase in emissions due to a growing scale of the economy. However, the time effects cannot offset the income effects, and the total effects are increasing. Hence, even in the developed world, there is no sign of a slow down in the total emissions.

Our regional in-sample estimates and forecasts illustrate how pairwise differencing leads to results in-line with theory, by allowing for full-flexibility in the specification of the time effects. Thus, properly identified income effects reflect pure scale effects. As is illustrated by the estimated income effects that are increasing.[3] The common inverted

[3]Indeed, for all regions, our estimated income effects are increasing reflecting the emissions as a

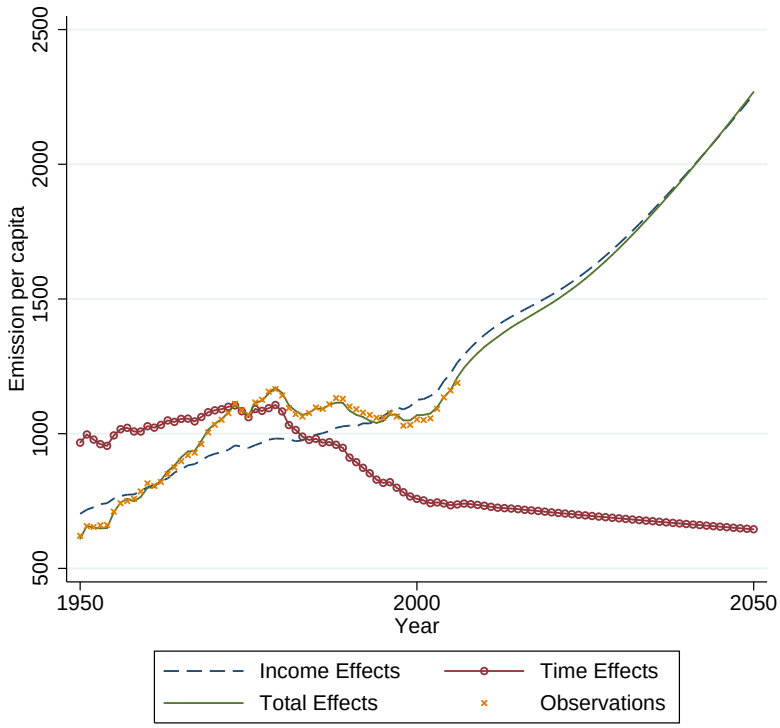
U-shaped and N-shaped findings in the EKC literature likely have to be interpreted as the combined effects of scale, technology, and industrial composition.

The pairwise differencing approach has some important advantages in forecasting. Firstly, the potentially nonlinear total effect is decomposed into its determinants, which are more likely to exhibit monotonic trends. Clearly, the estimated inverted U-shaped or N-shaped total effects in the EKC literature are not appropriate for forecasting purposes, since they often lead to forecasts with explosively increasing emission, or zero emission in the long-run. On the other hand, as illustrated in Figure 3 and 4, our findings indicate that the individual income and time effects are likely to have monotonic trends. Extrapolating these monotonic individual trends are more convenient, by preventing the counter intuitive results stemming from the use of non-linear total effects. Moreover, Giacomini and Granger (2004) show that, forecasting the individual effects, instead of the aggregate effect, can improve the forecasting performance. We achieve such a decomposition, by constructing the global effects, starting from the regional income and time effects.

We forecast the global emissions based on population-weighted averages for each region's best-fit estimates. To compute these global averages, we weight each of our region specific GoF estimates (after transforming our log estimates into levels) of the income and time effects with the region specific population levels. Similarly, we weight the future projections with projections of population levels. The results in Figure 5 provide a concise summary of the development of our region specific findings. The pattern in the time effects are dominated by the developed world. That is, they are decreasing and expected to decrease in the future. However, this trend in time effects are not sufficient to compensate the increasing income effects. As a result, our projection indicates a sharp rise in global emissions.

result of growing scale of the economy. These results are given in the appendix.

Figure 5: In-sample Estimates and Forecasts of Global CO_2 Emission Per Capita



In theory, the effect of industrial composition should constitute a less important role in the time effects at a global level, compared to its role at the regional level. The reason is that, the change in sectoral composition, effecting the emission level, is hypothesized to be mostly driven by a shift of dirty industries from the regions with strict environmental regulations to the regions with less strict regulations (Pollution Haven Hypothesis). Clearly, such an effect should cancel out at the global level, since it is a mere replacement of dirty industries. Another reason for the change in sectoral composition can be the directed technological change towards cleaner technologies, which can be considered as a technological effect rather than a compositional effect. Therefore, in theory, global time effects should constitute technological effects. Given this explanation, we can answer the question whether technological progress will be sufficient to create a slow-down in future emissions. Our global level forecasts illustrate

that such a slow-down is not likely, indicating a pessimistic picture. Although, there is some mitigating effect of technological change in the developed regions, these are far from being sufficient to compensate the effect of growing scale of global economy.

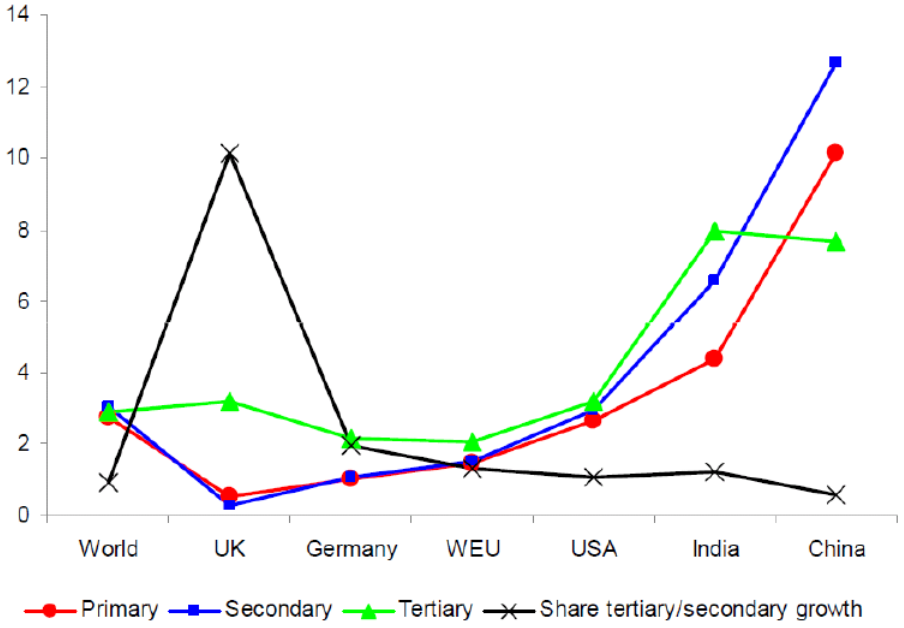
4.2 Deeper into the positive time effects of China

China became the largest CO_2 emitter on the world by 2008, which initiated a torrent of studies explaining the changes in China's carbon emission pathways. Our in-sample estimations and forecasts show that the time effects of China are a strong contributor to global carbon emssions, which is not a situation that is likely to change in the near future. In this section, we present a descriptive study in order to gain insights into the estimated time effects of China. We document two major factors which are likely to have influenced the patterns estimated for the time effect of China. The first one is the strong growth in the industrial sector, reflecting the compositional effects. The second one is the shift in the energy input mix, in particular, the increased use of coal, reflecting the effect of technological change.

We first start with investigating the compositional effects, which is considered as one of the most influential elements composing the time effects. Figure 6 documents a comparison of structural developments in sectoral composition of China, relative to those in regions and countries such as the United States, the European Union, and India. Every point on the figure indicates the percentage change in sectoral gross value added from 1990 to 2006. China has clearly the highest real sectoral growth in both primary and secondary sectors among all regions, and the growth of its tertiary sector is only slightly below that of India. Interestingly, the relative growth in the secondary sector compared to the tertiary sector is the lowest in China. This picture indicates a strong specialization towards the industrial sector in China compared to other regions.

Secondly, in Table 2, we document the energy input mix in China in comparison to

Figure 6: Percentage Change in Sectoral Gross Value Added, 1990 - 2006



Source: the National Accounts Estimates of Main Aggregates, United Nations Statistics Division.

Table 2: Composition of Shares in Total Energy Demand in the US, EU, China, India, and the World, Source: OECD (2009)

	USA			EU		
	1970	1990	2006	1970	1990	2006
Coal	19	24	24	29	28	19
Oil	45	40	39	56	37	35
Gas	32	23	23	8	18	25
Nuclear	0	8	9	1	13	14
Renewables	4	5	5	6	5	8

	China			India			World		
	1971	1990	2006	1971	1990	2006	1971	1990	2006
Coal	51	61	66	25	33	41	26	25	27
Oil	9	13	18	11	19	24	44	37	34
Gas	0	1	3	0	3	6	16	19	21
Nuclear	0	0	1	0	1	1	1	6	6
Renewables	40	24	12	64	44	29	13	13	13

other regions and its development over time. With a 61% coal share in total energy demand, China already had a relatively carbon intensive energy structure in 1990, but this share grew even further to 66% by 2006. The share also by far exceeds that of any other region or country. Clearly, the role of less carbon intensive energy sources, such as gas or nuclear energy, lags far behind in both China compared to the richer countries.

As a result, the more than proportional growth in the industrial sector together with the continued and even expanded exploitation of coal as the major energy input, are likely to explain our exceptional time effect estimates for China.

4.3 Is China the main threat in combating with global warming?

Our finding of a positive time effect for China reflects their recent switch to a coal-based energy input mix, as well as their strong industrial expansion, both of which have contributed to the recent upsurge in global carbon emissions. However, this trend has not co-evolved with a strong enough negative time effect in developed regions, such as Western Europe and Western Offshootss, in order to induce an overall reduction in global per-capita carbon emissions. In fact, the underlying regional trends in emission patterns make a reversal of the overall global trend quite unlikely, for the next decades at least.

These findings strengthens the concerns that high growth rates by China, which is expected to continue for the following decades, may constitute the main problem for the struggle against environmental degradation. In order to analyze if this is the case, we forecast global emissions by excluding China. Figure 7 illustrates the results. Although the recent strong growth in per-capita emissions in China certainly have contributed to the renewed upward overall trend (Figure 5), the same result is obtained

Figure 7: In-sample Estimates and Projections of Global CO_2 Emission Per Capita Excluding China

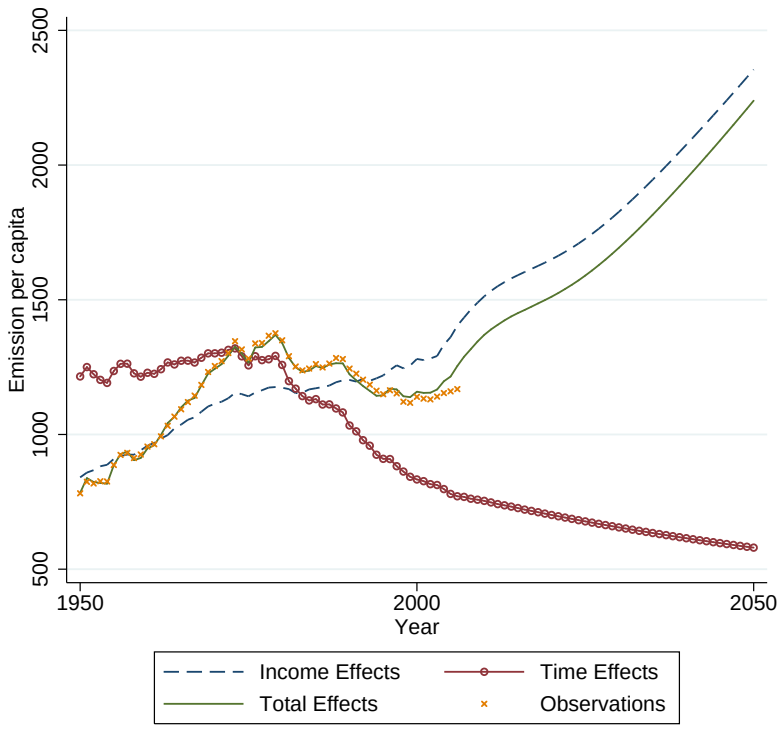
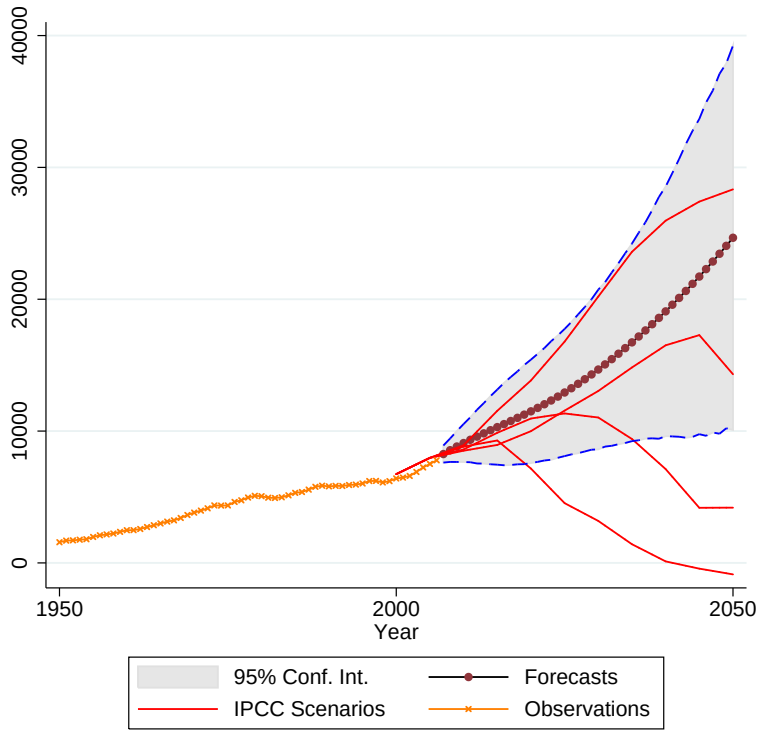


Figure 8: Global CO_2 Emissions and IPCC Scenarios



when we exclude China from the sample. This suggests that the underlying current developments in the other regions have been such that the downward sloping time effect cannot compensate for the strong positive income effect. This remarkable result is at odds with the popular view that particularly China would be the most important threat to the policies that aim at stabilizing global carbon emissions.

4.4 Global Emissions and IPCC Scenarios

5 Conclusion

The pairwise differencing approach is a flexible way to disentangle the scale effects from other factors. Our results show that such a decomposition can reveal some powerful insights about the underlying trends driving the global CO_2 emissions, and provides

a convenient tool to make future forecasts. Our results reveals a pattern consistent with the role of scale effects in the growth and environment literature that the income effects are positive for any region. That is, GDP per capita and corresponding amount of emissions are always positively linked. This shows that pairwise differencing approach is able to identify the scale effects properly. Moreover, we document an extensive analysis that the strong increasing pattern in the estimated time effcts of China is consistent with their rapid industrialization and increased share of coal in their energy input mix.

While, we find a strong income effect leading to a sharp rise in global emissions, the global time effects, dominated by the trends in developed regions, plays a mitigating role, but far from to compensate the strong income effects. As a result, our forecasts do not even imply a slow down in global CO_2emissions up to 2050. We further present an analysis regarding with the recent role of China in the global emissions pathways. We find that the pessimistic pattern revealed by our forecasts is not driven by China alone, but the main problem is the time effects in the developed regions, which is likely to be driven by technological effect, are very weak to compensate the scale effects. A further concern revealed in our forecasts is that the decrease in time effects of developed regions is expected to slow down in the future.

As a final note, there are some points in our analysis that are open to be improved by future research. Firstly, our analysis fully relies on historical data, including the projections of GDP and poulation series, by which we aim to fully avoid subjective uncertainty. However, expert judgements about the future evolution of these series can easily be incorporated in our analysis in order to produce more efficient forecasts. For example, our future forecasts of population for China implies a downturn around 2030, which can be a reasonable forecast due to one-child policy of China. However, if one believes only a slow-down, but not a downturn as a possible scenario, this can be easily introduced as a constraint in the forecasting model. Furthermore, since we are able

to decompose income and time effects, such scenarios can also include expert views on these series.

A second point is that, our pairwise differencing estimations rely on the GoF prior in order to match regions which have similar time effects. In our view, a matching strategy based on an expert judgment can also be legitimate. Indeed, the matching by GoF prior produce intuitive results, such as matching Western Europe with Western Offshoots, or Eastern Europe with Former USSR. Note that, any estimation in the EKC literature applies such prior beliefs, like imposing homogenous income and time effects in the panel estimations. However, using expert judgment can be unfeasible when there are many cross-sectional units, and GoF prior becomes necessity. Using another matching process, possibly relying on observed data relevant to time effects, can be a possible future research avenue.

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A APPENDIX

A.1 More Robustness Checks

1. In sample performance in comparison to non-parametric non-stationary estimation

2. Pairing regions

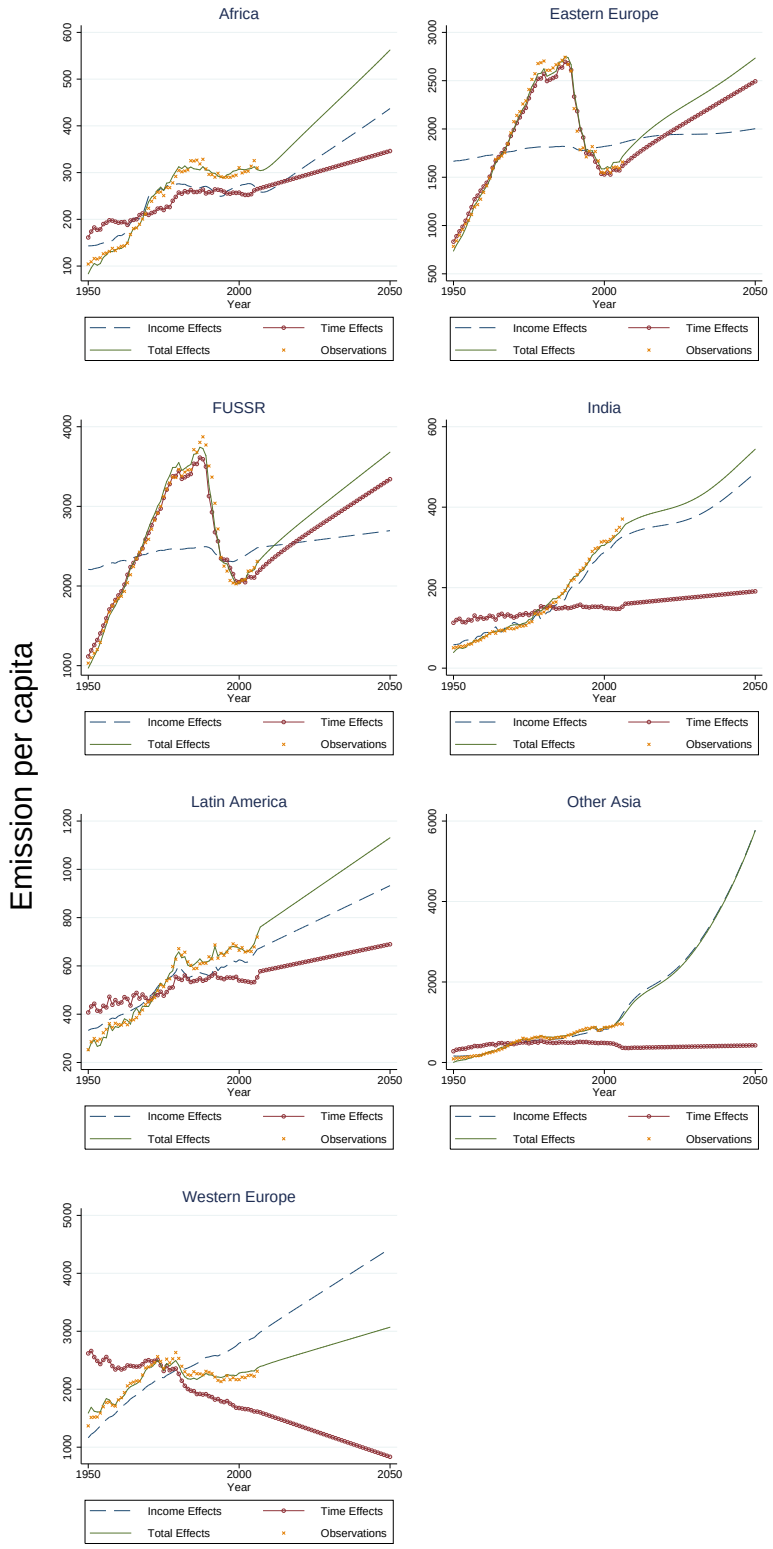
3. Model selection criteria

4. Model selection based on out-of-sample performance

5. Preference towards simplicity in model selection

A.2 Forecasts for Other Individual Regions

Figure 9: Forecasts for All Regions



A.3 Estimation Tables

Table 3: Pairwise Diffrenced ENNLS Estimations for Africa

	(1)	(2)	(3)	(4)	(5)
GDP pc.	0.925***	28.094*	-1299.637***		
	(0.201)	(15.215)	(325.506)		
GDP pc.^{2}		-1.877*	184.195***	-89.955***	
		(1.052)	(45.868)	(23.013)	
GDP pc.^{3}			-8.689***	17.006***	-8.290***
			(2.154)	(4.323)	(2.161)
GDP pc.^{4}				-0.903***	1.764***
				(0.228)	(0.456)
GDP pc.^{5}					-0.100***
					(0.026)
Adjusted R^2	0.783	0.793	0.793	0.792	0.791
AIC	-168.3	-169.8	-170.9	-170.6	-170.4
BIC	-160.3	-159.8	-162.8	-162.6	-162.4
Observations	55	55	55	55	55

Standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Pairwise Diffrenced ENNLS Estimations for CHINA

	(1)	(2)	(3)	(4)	(5)
GDP pc.	0.482***	1.822	7.382	-501.066*	
	(0.111)	(1.579)	(20.974)	(266.863)	
GDP pc.^{2}		-0.091	-0.830	102.627*	-32.909*
		(0.106)	(2.785)	(54.240)	(18.571)
GDP pc.^{3}			0.033	-9.286*	8.986*
			(0.123)	(4.884)	(5.009)
GDP pc.^{4}				0.313*	-0.914*
				(0.164)	(0.505)
GDP pc.^{5}					0.033*
					(0.018)
Adjusted R^2	0.885	0.884	0.880	0.886	0.885
AIC	-31.1	-29.7	-27.4	-29.3	-28.6
BIC	-23.0	-19.6	-15.4	-15.2	-14.5
Observations	55	55	55	55	55

Standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Pairwise Diffrenced ENNLS Estimation for Eastern Europe

	(1)	(2)	(3)	(4)	(5)
GDP pc.	0.085*	0.756	-92.682		116.177
	(0.046)	(1.615)	(58.140)		(504.613)
GDP pc.^{2}		-0.040	11.249	-5.550	
		(0.097)	(7.024)	(3.499)	
GDP pc.^{3}			-0.454	0.898	-3.823
			(0.283)	(0.563)	(14.681)
GDP pc.^{4}				-0.041	0.488
				(0.025)	(1.769)
GDP pc.^{5}					-0.019
					(0.064)
Adjusted R^2	0.058	0.043	0.065	0.065	0.047
AIC	-140.2	-138.4	-139.3	-139.3	-139.4
BIC	-134.2	-130.4	-129.2	-129.2	-129.3
Observations	55	55	55	55	55

Standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Pairwise Diffrenced ENNLS Estimations for FUSSR

	(1)	(2)	(3)	(4)	(5)
GDP pc.	0.132**	0.830	122.677		
	(0.057)	(2.588)	(124.255)		
GDP pc.^{2}		-0.041	-14.531	7.473	
		(0.152)	(14.762)	(7.407)	
GDP pc.^{3}			0.574	-1.179	0.614
			(0.584)	(1.173)	(0.587)
GDP pc.^{4}				0.052	-0.109
				(0.052)	(0.104)
GDP pc.^{5}					0.005
					(0.005)
Adjusted R^2	0.058	0.040	0.044	0.044	0.046
AIC	-140.2	-138.3	-139.3	-137.3	-137.4
BIC	-134.2	-130.3	-131.2	-127.3	-127.3
Observations	55	55	55	55	55

Standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Pairwise Diffrenced ENNLS Estimations for India

	(1)	(2)	(3)	(4)	(5)
GDP pc.	1.294***	11.515***	18.219		
	(0.078)	(1.337)	(27.279)		
GDP pc.^{2}		-0.721***	-1.662	2.168	2.972
		(0.092)	(3.805)	(1.993)	(42.629)
GDP pc.^{3}			0.044	-0.313	-0.542
			(0.177)	(0.370)	(12.052)
GDP pc.^{4}				0.012	0.037
				(0.019)	(1.276)
GDP pc.^{5}					-0.001
					(0.048)
Adjusted R^2	0.961	0.975	0.975	0.975	0.974
AIC	-142.3	-165.9	-163.9	-164.0	-164.0
BIC	-134.3	-157.9	-153.9	-153.9	-153.9
Observations	55	55	55	55	55

Standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Pairwise Diffrenced ENNLS Estimations for Latin America

	(1)	(2)	(3)	(4)	(5)
GDP pc.	0.740***	-3.430	-23.212		
	(0.083)	(3.186)	(150.910)		
GDP pc.^{2}		0.251	2.640	-1.978	
		(0.192)	(18.353)	(9.049)	
GDP pc.^{3}			-0.096	0.309	-0.191
			(0.744)	(1.467)	(0.723)
GDP pc.^{4}				-0.013	0.034
				(0.067)	(0.132)
GDP pc.^{5}					-0.002
					(0.006)
Adjusted R^2	0.975	0.976	0.975	0.975	0.975
AIC	-165.9	-165.8	-165.7	-165.7	-165.7
BIC	-157.9	-155.8	-155.6	-155.7	-155.7
Observations	55	55	55	55	55

Standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Pairwise Diffrenced ENNLS Estimations for Other Asia

	(1)	(2)	(3)	(4)	(5)
GDP pc.	1.321***	15.747***	24.557		-733.896***
	(0.104)	(1.906)	(39.855)		(192.577)
GDP pc.^{2}		-0.922***	-2.057	3.029	
		(0.120)	(5.142)	(2.501)	
GDP pc.^{3}			0.049	-0.417	23.994***
			(0.221)	(0.429)	(6.218)
GDP pc.^{4}				0.016	-3.056***
				(0.021)	(0.790)
GDP pc.^{5}					0.117***
					(0.030)
Adjusted R^2	0.928	0.941	0.940	0.940	0.952
AIC	-130.7	-140.5	-138.4	-138.7	-151.2
BIC	-120.6	-128.5	-124.3	-124.6	-135.1
Observations	55	55	55	55	55

Standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Pairwise Diffrenced ENNLS Estimations for Western Europe

	(1)	(2)	(3)	(4)	(5)
GDP pc.	0.766***	6.278***	40.061**		30.354
	(0.114)	(1.950)	(16.262)		(131.037)
GDP pc.^{2}		-0.311***	-4.137**	2.381**	
		(0.112)	(1.749)	(0.901)	
GDP pc.^{3}			0.144**	-0.327**	-0.526
			(0.063)	(0.129)	(3.087)
GDP pc.^{4}				0.013**	0.048
				(0.005)	(0.335)
GDP pc.^{5}					-0.001
					(0.011)
Adjusted R^2	0.821	0.832	0.833	0.833	0.830
AIC	-232.4	-233.9	-234.7	-234.7	-234.8
BIC	-224.4	-223.8	-224.7	-224.6	-224.7
Observations	55	55	55	55	55

Standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Pairwise Diffrenced ENNLS Estimations for Western Offshoots

	(1)	(2)	(3)	(4)	(5)
GDP pc.	0.639***	5.675**	-91.788*		
	(0.189)	(2.260)	(47.737)		
GDP pc.^{2}		-0.261**	9.449*	-0.740	
		(0.120)	(4.869)	(3.209)	
GDP pc.^{3}			-0.321*	0.122	-0.037
			(0.166)	(0.432)	(0.224)
GDP pc.^{4}				-0.005	0.007
				(0.016)	(0.034)
GDP pc.^{5}					-0.000
					(0.001)
Adjusted R^2	0.833	0.832	0.821	0.829	0.829
AIC	-234.7	-233.9	-232.4	-234.2	-234.2
BIC	-224.7	-223.8	-224.4	-224.1	-224.2
Observations	55	55	55	55	55

Standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$