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Grazing the Commons: Global Carbon Emissions Forever?

ABSTRACT

This paper presents the results from our investigation of the per-capita, long-term relation between carbon dioxide emissions and gross domestic product (GDP) for the world, obtained with the use of a new, flexible estimator. Consistent with simple economic growth models, we find that regional, population-weighted per-capita emissions systematically increase with income (scale effect) and usually decline over time (composition and technology effect). Both our in-sample results and out-of-sample scenarios indicate that this negative time effect is unlikely to compensate for the upward-income effect at a global level, in the near future. In particular, even if China's specialization in carbon-intensive industrial sectors would come to a halt, recent trends *outside* China make a reversal of the overall global trend very unlikely.

Keywords: CO₂ Emissions; Environmental Kuznets Curve; Panel Data; (Semi)parametric Estimation

JEL Codes: C33 O50 Q40

I. Introduction

How many carbon emissions from fossil-fuel use will be added to the global carbon stock in the future, and, perhaps even more important in international negotiations, by whom? A question that is at least as important is the question of whether there is any sign of a slowdown. Predictions of the flow of human-induced carbon emissions and their regional distribution are uncertain. Indeed, as observed by the Intergovernmental Panel on Climate Change (IPCC, 2004), roughly half of the estimated variation in the mean global temperature by 2100 applies to the uncertainty on the future emissions paths themselves.¹ Results from typical Integrated Assessment Models (IAMs) show a large variety in expected emission patterns for the (distant) future. Predictions on the flow of greenhouse gas (GHG) emissions, according to long-term scenarios in the IPCC Special Report on Emissions Scenarios (SRES), vary from a level that is over five times larger than the current flow to even a reduction by 2100, depending on structural parameter choices such as population growth, economic or income growth, and technological change (Van Vuuren and Riahi, 2008).

The difficulty in choosing these parameter levels for making structural, long-term model predictions is well-known. The IAMs used by the IPCC typically fix these levels by applying a mix of subjective expert judgement and calibration. Only recently, attention has grown for the potential implications of the (subjective) uncertainty related to key parameter values (Den Elzen and Van Vuuren, 2007). One important example is given by the parameters that fix the relationship between carbon emissions from fossil-fuel use and economic growth (measured as Gross Domestic Product, GDP), in particular, for developing countries such as China. According to the well-known Environmental Kuznets Curve (EKC) hypothesis, rising income correlates with lower (per-capita) emissions after

¹The other half of this range is due to the fact that it is not known how sensitive climate will be to increasing concentrations of greenhouse gases.

some initial upturn due to (endogenous) mechanisms induced by growing concerns over increasing emissions at higher income levels (Grossman and Krueger, 1995). Using a spline-based estimator, Schmalensee et al. (1999) indeed confirm the EKC hypothesis for carbon emissions in their world sample. According to the hypothesis, China's recent and in history almost unparalleled growth in per-capita carbon emissions would be temporary. The current, rising trend will soon be followed by a decline, because the recent, strong growth in the industrial sector as well as the strong penetration of coal in the fuel mix 'automatically' will come to an end. Recent estimates by Brock and Taylor (2009) also provide further support for this hypothesis.

However, our findings are quite different. With the use of a new flexible estimator, both our in-sample estimates and our out-of-sample scenarios for regional and global per-capita carbon emissions leave little room to expect a global EKC pattern in the near future. In contrast to what is now widely believed, we find that developments in China are not solely responsible for the current global increase in per-capita carbon emissions. Indeed, our (anomalous) 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 unmistakably 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, or 'Western Offshoots' (Australia, Canada, New Zealand, and the United States), 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 decade at least, despite the current world economic crisis.

Our results are based on a new estimator that makes our priors explicit from the very beginning. Such priors are often only implicit in the existing literature on panel EKC estimations. Indeed, as explained by Vollebergh et al., (2009), existing reduced

form EKC estimations suffer from a fundamental identification problem, due to the need to disentangle the income from the time effect. Estimation is then only possible after imposing untestable identifying assumptions. However, this creates model ambiguity because choosing between different identified models becomes arbitrary, which, to a large extent, may drive the estimation results (Manski, 2000). Instead, we start with the data and impose only very weak identifying assumptions on the common decomposition that characterizes all EKC estimates, that is, the separation of the long-term development paths into an income and time effect. Given this decomposition, we only assume a common time trend between two (related) regions, allowing for fully flexible income and time effects. Given this identification, our estimator provides reasonable and robust results and produces the standard expected signs of similar theoretical decompositions in models of (green) economic growth into a positive scale (income) effect, on the one hand, and a negative composition and technique (time) effect, on the other (for example, Stokey, 1998; Andreoni and Levinson, 2002; Brock and Taylor, 2009). However, the estimated negative time effects are such that they do not compensate for the upward-income effect at the global level, in the near future. As a consequence, the world may face the enormous challenge of inducing a much stronger negative time effect by stimulating carbon-extensive sectoral and technological change – at least if the aim is to reduce CO₂ emissions.

II. Estimation Approach

Using a panel for estimating correlations between per-capita emissions and income is a very efficient procedure to gain insight into structural trends in the data. Observations on per-capita emissions and GDP basically reflect all combined effects of countries that grow in size (income growth), structural developments in the composition of industries

and their emission intensities, and the extent to which such developments are affected by (induced) technological change or differences in (fossil-fuel) resource availability. The main interest in this correlation stems from the idea that, at higher levels of income, countries – after some initial neglect – would become engaged in actions that reduce emissions even if they are heterogeneous.

The simplest decomposition to reveal such underlying trends is one in income and time effects. Indeed, the reduced form estimation technique, commonly applied in the Environmental Kuznets Curve (EKC) literature, postulates exactly this decomposition. To date, this literature starts with observed panel data (y_{rt}, x_{rt}) , with $r \in \mathcal{R}$, where \mathcal{R} denotes a set of cross-sections, such as regions, and $t \in \mathcal{T}$, with typically $\mathcal{T} = \{1, 2, \dots, T\}$, representing time. Then identifying assumptions that separate the effect of the independent variable from the unobserved effects are applied to allow for proper inference (Heckman, 2000). Panel data, in particular, offer the advantage of allowing for controls at the individual or cross-sectional level, and allow for time controls to capture these unobserved effects. The standard approach typically postulates the following decomposition:

$$y_{rt} = f(x_{rt}, r) + \lambda(r, t) + \epsilon_{rt}. \quad (1)$$

and subsequently imposes further restrictions on the possible functions λ and f (by restricting the choices of λ and f to some restricted classes of functions Λ and Φ). Well-known examples are time or region-specific fixed effects or homogeneous polynomials up to some order. In this way (f, λ) becomes identifiable.

However, the choice between specifications becomes arbitrary at a certain point.² For

²See Vollebergh et al. (2009) for an explanation why a fundamental identification dilemma plagues such reduced form estimations based on panel data. Both cross-sectional and time controls can be specified at different degrees of heterogeneity and flexibility and this raises the fundamental dilemma of how much flexibility to allow when specifying the estimation equation. With fully flexible time-effects that are also cross sectionally specific, all variation in the data will be captured by these control variables, whereas with restrictive time and cross-section effects, too much variation in the data might be attributed to the independent variable(s).

instance, both functions f and λ can be assumed to be homogeneous over cross-sections, with the only exception being the region-specific constant terms of the function f . Such an approach assumes that every region reacts similarly to shifts in the independent variable, for example, according to a similar third-order polynomial, even if the cross-sectional units are allowed to differ in their intercepts. Clearly, such an assumption imposes very strong *ex ante* restrictions, much stronger than would be needed to identify f and λ in (1). Also, in the case of a semi-parametric estimation framework potential misspecification remains a problem if a homogeneity assumption is applied to the time effect of all cross-sectional units. The vast variety of papers in the EKC literature on carbon emissions illustrates how problematic it is to obtain robust estimations of long-term relationship between economic growth and the environment – even with comparable data sets.

It has recently been demonstrated that allowing full flexibility in the link function f while imposing a very weak restriction on the function λ not only generates robust estimates for income-CO₂, but also for income-SO₂ relationships (see Vollebergh et al., 2009). Moreover, and in contrast to the standard EKC literature, the results obtained also match fundamental theoretical models and basic intuition. The results obtained for the income effect clearly seem to capture the first main driver behind changes in total pollution, which is the overall size of the economy (‘scale’), whereas the time effect reflects the combined effect of changes in the mix of sectors comprising the economy (‘composition’), together with the technologies employed in production and abatement (‘technique’).

The approach followed by Vollebergh et al. (2009) employs a non-parametric estimator based on the very simple assumption that – given the decomposition (1) – cross-sectional time effects are pairwise similar. So, in our ‘most reasonable’ decomposition we assume only that it is not (fully) region-specific: for each $r \in \mathcal{R}$ we assume the existence of at least one $s \in \mathcal{R}$, with $s \neq r$, such that for all $t \in \mathcal{T}$ we have $\lambda(r, t) = \lambda(s, t)$. Note that

if λ does not satisfy such a requirement, it cannot really be distinguished from possible idiosyncratic effects. Using the assumption $\lambda(r, t) = \lambda(s, t)$ for all $t \in \mathcal{T}$ for a given pair (r, s) we are able to identify and estimate $f(x, r)$ and $f(x, s)$ by taking differences:

$$y_{rt} - y_{st} = f(x_{rt}, r) - f(x_{st}, s) + (\epsilon_{rt} - \epsilon_{st}), \quad t = 1, 2, \dots, T, \quad (2)$$

combined with the assumption that $E(\epsilon_{rt} - \epsilon_{st} | x_{rt}, x_{st}) = 0$. This approach allows full flexibility in f and λ , while the assumption $E(\epsilon_{rt} - \epsilon_{st} | x_{rt}, x_{st}) = 0$ guarantees that it is reasonable to classify the effects captured by ϵ_{rt} as being idiosyncratic.

The unknown regression functions $f(x, r)$ and $f(x, s)$ of equation (2) can be identified (up to their levels) and estimated by applying Linton and Nielsen’s method (see Linton and Nielsen, 1995), while imposing their regularity conditions and additional distributional assumptions. Appendix A describes the technical details, including our estimator for the time effect $\lambda(r, t)$.³ Given that any pair of cross-sectional units (r, s) can be used, our approach leaves $N(N - 1)/2$ possible relationships for a sample of N cross-sections. We face model ambiguity, due to a lack of identification (Manski, 2000).⁴ To deal with this ambiguity, we proceed by employing priors over the cross-sectional units. Such priors can be used to express one’s clearly subjective views about which countries or regions are less or more likely to have common time trends. Note, however, 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 can no longer be inferred ‘automatically,’ but always depends upon one’s prior (Heckman, 2000).

³Note that this specification also implicitly accounts for potential endogeneity if the time trend captures technological change which – in turn – depends on (the levels of) emissions and income. In the original Linton-Nielsen estimator, the confidence band is based on the assumption of homoskedasticity. Vollebergh et al. (2009) extend the asymptotic limit distribution by also allowing for the possibility of heteroskedasticity.

⁴Note the important difference with the additional restrictions imposed within the standard literature (in particular on the time-effects included). These restrictions can be tested.

In our empirical application, we examine all possible pairs and base our inference on the combination of these possible pairs. We use different priors to investigate the sensitivity to the prior choice.

III. Data

Our analysis applies to quantifying equation (1) with $y = \log(E/P)$ and $x = \log(Y/P)$, with E reflecting CO₂ emissions, Y the GDP level and P the population size, and with the controls r and t referring to country/region and year, respectively. Note that the control for country/region reflects persistent cross-section specific differences, such as fossil-fuel availability and prices, regulatory differences and preferences, and that the control for time picks up changes over time, such as changing prices or technologies. We use a balanced panel for all countries, for the period between 1950 and 2006. CO₂ 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 and 2009). For each type of fuel, data on annual CO₂ 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 feedstocks. The estimation of the amounts of CO₂ released through gas flaring are based on the UNSTAT database, supplemented by estimations from DOE/EIA. The estimations of the amounts of CO₂ 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 carbon dioxide

equivalents. Data on Y and P are taken from Maddison (2006). 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 Offshoots,’ Africa, and Latin America.⁵ 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 Offshoots’ (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.

[INSERT FIGURE 1]

Looking at our data on the distribution of GDP per capita (see Figure 1), ‘Western Offshoots’ 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.⁶

[INSERT FIGURE 2]

Interestingly, both the distribution and development over time, the region-specific per-capita CO₂-emissions are remarkably different (see Figure 2). The carbon intensity

⁵Note that – after aggregation – we divide the overall amount of income and emissions by overall population of this region to obtain per-capita income and emissions.

⁶Considering China’s rate of growth over the past 10 years, it is likely that, by 2018, it will have reached the 2006 real income level of a country such as Portugal (which is at the lower bound of traditional OECD countries).

in the ‘Western Offshoots’ has always been much higher than in any other region, followed by Russia, western and eastern Europe. Since these emissions reached a peak in western Europe in the 1970s, carbon intensity there has remained more or less constant, whereas Russia and eastern Europe have experienced a strong decline in emissions since the beginning of the 1990s, and have ended up even (far) below the level of western Europe. 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.

[INSERT TABLE I]

Table I shows descriptive statistics of the data. Our data-set, aggregated over the regions, contains (9 regions \times 57 years =) 513 observations for all variables in our panel of CO₂ emissions. Finally, our data does not seem to suffer from unit root problems.⁷

IV. Main Results

As explained in section II, we estimate our pairwise model by applying (2) and using the Linton and Nielsen (LN) method (Linton and Nielsen, 1995). Choosing the ‘right’ combination of regions is key to the identification of the income-related effect in our pairwise procedure. In theory there are as many identifications possible as there are potential pairs of regions that is, in our case eight identifications for each of the nine regions.⁸ Our prior is that combining two regions with similar time trends will result in

⁷We found ambiguous results using the KPSS test (see Kwiatkowski et al., 1992). Indeed, results largely depend on the modeling assumptions of the test itself, which, as is well known, strongly affect the size and power of this test.

⁸Although nothing prevents our estimation approach from being applied at the underlying individual country level, the number of possible potential pairs would be extremely large. This would even become

a good fit of equation (1), 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 (1), 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’. In this section the results for this prior are presented.⁹

For the GoF prior to work we start from (1) and estimate this equation for each region using all possible pairs, that is, for each region there are eight other likely candidates to assume a common time effect. Subsequently, selection between these estimates then follows on the basis of the lowest sum of squared errors (our ‘prior GoF’). We find that the best fits usually confirm our expectations, such as western Europe versus ‘Western Offshoots’ (and vice versa) and China versus Other Asia. However, and perhaps somewhat more surprisingly, we also observe pairs such as India versus former USSR (and vice versa).

Figure 3 shows in-sample estimates for each of the nine regions (in logs). 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 sample average of the logarithm of CO₂ emissions per capita. In case of the income effect we plot the $f(x_{rt}, r)$ for a given r 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 figure shows the effect of the change in per-capita between 1990 and 1991. Similarly, the time effect in the figure represents the estimated effect of time for an additional year. Finally, the total effect just consists of the time t income effect plus the time effect of time t (but at the level of the sample average of the logarithm of CO₂ emissions per capita).

infinite if we would also allow for the construction of ‘artificial’ regions, by taking, for example, convex combinations of countries or regions.

⁹See Appendix B for a robustness assessment of the choice for this prior. Interestingly, Vollebergh et al. (2009) observe that a Goodness-of-Fit measure has little discriminatory power (see footnote 20 on p.36) in their sample of 24 ‘traditional’ OECD countries for the two priors they present in their paper: a rather involved ‘author’ based assessment of pairs and a simple Bayesian approach for these 24 countries.

[INSERT FIGURE 3]

Our first important finding is the rather robust *positive* pure income-related effect which – in most cases – is even less or more linear (thus, exponential in levels). In other words, the income related effect positively influences per-capita emission levels for most income levels within our regions, including those of a relatively poor region such as India. Only for certain regions, such as former USSR and to a lesser extent eastern Europe, we find a somewhat different pattern. This could easily be explained by the somewhat anomalous development due to the initial collapse of these economies after 1989 and their recovery since the end of the 1990s. Note that these results are in stark contrast to the results usually presented in the empirical literature on EKC. Instead, the estimates confirm again the finding by Vollebergh et al. (2009) of there being no empirical support for an inverted U of the income effect as such. Even the richest regions in our sample, ‘Western Offshoots’ and western Europe, show an almost linear rise in this income effect.

What really makes a difference in emission reduction is the pattern of the time-effect. Even with an upward income effect, the overall emission pattern might still produce an ‘overall’ inverted U shape, if the time effect would (more than) compensate for the upward income effect. As noted before this time effect typically reflects unmeasured temporal variability that is correlated with CO₂ emissions and captures the combined effect of sectoral and technological change. The estimated region-specific time effects show an inverted U shape or even a linear downward trend for most regions. The richer regions in our sample have the strongest negative time effect, although this effect is not enough to compensate for the income effect entirely. Apparently, the richer countries have succeeded in combining per-capita growth (in income) with a reduction in emissions due to a shift to less CO₂-intensive sectors as well as by technological improvements in the remaining sectors. This pattern – although with some delay – could be observed even for poorer regions such as India and Latin America. The estimations for China provide the only

exception to this rule of a downward trend in the time effect.

[INSERT FIGURE 4]

We also include estimates for the world based on *population-weighted averages* for each region's best-fit estimates. To compute these global averages we weigh each of our region specific GoF estimates (after transforming our log estimates into levels) against the region specific population levels. We consider as average one where all curves are at the same level (see Figure 4a).¹⁰ The results provide a concise summary of the development of global per-capita carbon emissions reflecting our region specific findings of both income- and time-related effects. Nevertheless, the income effect is positive with some slowdown after the two oil crises of the 1970s and the breakdown of the former USSR and Eastern Europe. In contrast, the time effect is downward sloping with a structural break around 1980.¹¹ This result is dominated by the 'Western Offshoots' and western Europe, in particular, in case of the average at the regions' own levels, but also in case of the average at equal levels.

The combined income and time effect shows the large impact of the oil crises of the 1970s. After 1980 global per-capita emissions stabilized due to a combined effect of a slowdown in the pace of the income effect and a somewhat stronger negative time effect. For the last decade we clearly observe a strong upward trend, again due to an increase in the income effect and some slowdown in the time effect. Although the recent strong growth in per-capita emissions in China certainly have contributed to this renewed upward overall trend, the same result is obtained when we exclude China from the sample (see Figure 4b). This suggests that the underlying current developments in other regions have been such that the downward sloping time effect can no longer compensate for the strong positive income effect since about 2000. Indeed, we observe a flattening trend

¹⁰Levels matter due to changing population weights over time. However, the average where each region-specific curve is at the average level of the region itself yields comparable results.

¹¹Lanne and Liski (2003) found a structural break in 1978.

in the time effect for this period, combined with a sometimes even strong increase in the income effect in most regions. This remarkable result is at odds with the popular view that particularly China would be the most important threat to policies that aim at stabilizing global carbon emissions. The next section returns to this important finding and discusses its underlying mechanisms, as well as their likely implications for future emission developments.

V. Analyzing the Results

Our reduced form estimates show little sign of a structural slowdown in global per capita carbon emissions. Building on the different, but also sometimes strongly diverging patterns between regions, our population weighted global emission pattern shows a rapid overall increase since 2000. Moreover, this effect does not depend on the inclusion or exclusion of China. This section provides a deeper understanding of the likely mechanisms behind these findings as well as some further explorations of scenarios that could help predict global future emission pathways based on real data.

A. Income level, negative time effects, and China

We start with a more extensive analysis of the likelihood of an inverted U for CO₂ emissions with income, that is the likelihood that emissions at some point will decline when income rises. Several authors report that such an effect applies even to the more or less unregulated CO₂ case (for example, Holtz-Eakin and Selden, 1995; Schmalensee et al., 1998), although others challenge this view (for example, Azomahou et al., 2006). On the face of it our results seem to confirm the inverted U conjecture for CO₂-emissions because the regions with the highest per-capita income levels, such as ‘Western Offshoots’ and western Europe, also show overall stabilizing emission patterns. In fact, we identify

a *positive* correlation between emissions and income independent of the income level. Stabilization in both regions only took place because the *negative time effect* more or less compensates for the upward income effect, in particular, since the oil crises of the 1980s.¹²

Indeed, the question of whether emissions decline after a country passes some threshold income level crucially depends on time effects being strong enough to compensate for a positive income effect. Thus, using our identification procedure, the likelihood of finding such strong negative time effects should increase as income rises. At first glance, the estimated time effects in our sample seem to back up such a likelihood. Three of the nine regions with a clear declining trend over the whole period are also the richest regions, and the richer the region, the stronger the negative time effect is. However, counter-evidence exists as well, such as the inverted-U time effect for the poor India region and the strong rising time effect for China, with income levels per capita currently comparable with those of Latin America, Russia, and eastern Europe. A final anomalous sign is the reduced rate of decline in the time effect for the richest regions already mentioned in the previous section.

From our global perspective, however, it is not only the level of income that matters, but also the co-evolution of region-specific developments and their weight in the overall estimate. If declining time effects in a high-income region with a smaller population is due to regional specialization in carbon-intensive production methods in a lower income region with a (much) larger population (for example, China), our population-weighted global per-capita estimate would suggest that a global inverted U is very unlikely for the near future.¹³ Indeed, much of the global economic expansion in the last decade has been

¹²Only recently has the time effect slowed down and has been no longer able to compensate enough for the (still) positive income effect and overall emissions have been increasing again.

¹³The population-weighted OECD average that resulted from applying our GoF prior to the whole OECD sample of Vollebergh et al. (2009), resembles our findings for western Europe and ‘Western Offshoots’, in particular after the oil crises (see Figure C in Appendix B).

due to China specializing in carbon-intensive production which is also reflected in our positive time effect for China. Understanding this exceptional ‘China effect’ seems key to understanding the global development in carbon emissions.

China, in 2008, overtook the United States as the world’s largest emitter of CO₂. This happened much earlier than was previously anticipated. For instance, the IPCC expected this to happen not before 2020 (IPCC, 2000). This unexpected increase in carbon emissions in China invoked a torrent of studies explaining how China’s past carbon emission trajectory has changed from a dramatic decline in energy intensity from the onset of economic reform in the late 1970s until 2000 to its subsequent equally dramatic increase in energy intensity since 2003. Apart from concerns over the reliability of both carbon emission and growth data for China, little discord exists on whether the general trend in the data does describe real changes in China (compare, for example, Aufhammer and Carson, 2008; Van Vuuren and Riahi, 2008).

Two major factors are likely to have influenced our overall estimate of the time effect for China: i) the absolute rise in the per-capita level of energy consumption, due to the strong growth in the industrial sector; ii) the shifting role of fuel input, in particular, the increased use of coal. Figure 5, derived from the National Accounts Estimates of Main Aggregates, United Nations Statistics Division, documents structural developments in sectoral composition for China, relative to those in regions and countries such as the United States, the EU and India between 1990 and 2006, measured as the annual growth in Gross Value Added (at constant 1990 prices in US dollars). Clearly, China has had the highest real sectoral growth in both primary and secondary sectors, and the growth of its tertiary sector is only slightly below that of India. Furthermore, China has had the lowest growth in its secondary, relative to that in the tertiary sector, indicating China’s specialization in the industrial sector. For all other regions and countries (with the exception of France), this figure is above 1, indicating that specialization has been

in tertiary activity. For India, this figure is twice as high, while for the United Kingdom this figure is even a factor of ten higher.

[INSERT FIGURE 5]

Further evidence of an exceptional development for China is the decomposition of total energy demand in its main energy sources as well as their developments over time. With a 61% coal share in total energy demand, China already had a relatively CO₂-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 (see Table II, derived from OECD, 2009). Although the coal share in India has been growing as well, its level of 41% is still well below that of China. Clearly, the role of less carbon intensive energy sources, such as gas or nuclear energy, lags far behind in both China and India compared to the richer countries. These figures are even more extreme if one looks at the energy sources used for electricity generation (not in the table) for which China almost exclusively relies on coal (81%).

[INSERT TABLE II]

The more than proportional growth in the industrial sector together with the continued and even expanded exploitation of coal as the major energy input, explains our exceptional time effect estimates for China. Technological change has not been able to compensate for the strong carbon intensification of the energy system together with its strong growth in industrial activity, both in absolute and relative terms. Here, globalization is key. Decomposition analysis indicates that the rise in energy demand in China is not only for domestic purposes, but is strongly export based (for example, Jiang and Hu, 2008). Moreover input-output analysis of the carbon content of trade flows by Aichele and Felbermayr (2010) suggests statistical evidence of Kyoto commitments affecting car-

bon trade, whereas, on average, the Kyoto protocol has led to substantial carbon leakage in the rich countries.

Some authors believe that the exceptional increase in carbon emissions in China is unlikely to continue forever and should slow down for good reasons (for example, Van Vuuren and Riahi, 2008). As a consequence, overall global per-capita emissions would start to decline ‘automatically’ if global income levels would continue to grow. This view favors the carbon EKC hypothesis. Our estimations of the concurrent trends in rich regions, such as ‘Western Offshoots’ and western Europe, and Other Asia, would suggest a different prospect, however. If recent findings by Levinson (2009) for air quality emissions linked to US imports would also apply to carbon emissions, one would expect the time effect profiles for these regions to be much more negative than those actually observed in our data. Indeed, the positive time trend we find for China suggests that the importing (rich) regions are expanding consumption by growing industrial activity with a typical more carbon intensive energy profile abroad (in particular, in China). However, the time trends for the rich countries suggest this shift will not be enough to correct for the carbon-intensive activities at home. The negative time effects for the richer regions would not only be insufficient to compensate for the positive scale effects at home, they would also contribute to the existing upward global carbon emission trend, even if China is excluded.¹⁴

Our estimates illustrate that a simple unweighed inverted U panel approach of the correlation between emissions and income could be misleading. First, estimations should take account of differences in relative weights between cross sections, in particular if the likelihood of observing declining time trends would be concentrated in (very) small countries (such as Luxembourg; see Vollebergh et al., 2009). Second, if highest income countries also are most likely to show (strong enough) negative time effects, one should

¹⁴These observations, however, cannot simply be carried over to India, which has experienced more growth in the less carbon-intensive service sector.

still be very careful to make inferences about the existence of an inverted U of the total effect. Such an approach could easily undervalue the possibility that trends reflect developments in global specialization and, therefore, could even be ‘explained’ by the upward trend in another region (or countries). Indeed, if recent income growth is strongly correlated with more than proportional growth in energy supply and demand in the export sector and if fuel inputs would become more carbon intensive, technological improvements have to be very substantial to compensate for these upward tendencies in order to produce an overall negative global time effect. Our region-specific estimates provide little evidence of such a trend, not only for China (such as Aufhammer and Carson, 2008), but also for the world as a whole.

B. ‘As if’ Scenarios and Scenarios for the Future

Our estimates of global per-capita carbon emissions do not provide an optimistic picture for the near future. First, according to our estimation, the increasing scale of the global economy is likely to continue its effect of increasing per-capita carbon emissions – given that we have not found any evidence whatsoever of a different income effect at higher income levels. Second, regions tend to differ in the extent to which their time effect might compensate for this positive scale effect. In particular, the anomalous time trend in China and, to a lesser extent, the recovery in Russia and eastern Europe create major challenges for the world. These challenges will even be larger as the observed negative time effect for ‘Western Offshoots’ and western Europe is also driven by international specialization in industrial activity in China. Third, our estimations suggest a reversal of this trend is not simply solved by China participating in some post-Copenhagen agreement, because other regions in the world might simply take over China’s role of providing a carbon-based bandwagon to world industrial development.

To illustrate what the development path of richer regions, such as ‘Western Offshoots’,

would have been without the option of outsourcing industrial activity to China, we constructed ‘as if’ scenarios using estimated time effects for different regions. Figure 6, first of all, repeats both income and time effect for ‘Western Offshoots’ based on our GoF procedure explained in section IV. Subsequently, we ask what would have happened if this region had followed the same development as China, that is, a gradual expansion of coal intensity combined with an intensification of the industrial sector. Thus, we combine the estimated time effect for China based on the GoF pairwise estimation for China versus ‘Other Asia’ with the income effect for ‘Western Offshoots’. As one might expect, this leads to a steep and continuous increase in emissions.¹⁵ When using the India time effect instead, the overall pattern looks like an inverted U because the time trend declines at the end of the period. Both ‘as if’ scenarios illustrate that per-capita emissions in ‘Western Offshoots’ would have been dramatically higher with a coal-based energy mix and without the option for technological change and outsourcing. To put these findings into perspective, ‘Western Offshoots’ would have contributed an additional 130,000 Mt of carbon to the overall amount of human-induced carbon emissions had it followed the Chinese time pattern.¹⁶ Similar findings would apply to the other rich region, western Europe. Conversely, and for the sake of comparison, we include in the bottom panels of Figure 6 ‘as if’ emission paths for India and China, replacing their own time effects by the time effect of ‘Western Offshoots’. Clearly, the time effect of ‘Western Offshoots’ would be nearly strong enough to avoid an increase in per-capita emissions in China and also, but to a lesser extent, in India.

¹⁵Of course, it is unlikely that the time trend for China would be driven only by export to ‘Western Offshoots’. Other relatively rich countries also have been targeted by the Chinese export industry due to international specialization.

¹⁶This equals the total difference in emissions in Mt per-capita between ‘Western Offshoots’ following the time pattern of China and its own time pattern times the actual population between 1950 and 2006. We also assume that the time pattern for China also would be driven by export to other relatively rich countries (western Europe and Other Asia). Therefore we assume that only 37% of the total effect can be attributed to ‘Western Offshoots’, which is equal to the share of GDP of ‘Western Offshoots’ in the overall sum of GDP in all rich regions together.

[FIGURE 6]

Apart from building such ‘as if’ scenarios, we also study extrapolations of per-capita emission trends into the near future. Our forecasts are simple linear extrapolations (in logs) of in-sample region-specific income and time ‘trends’. Using a linear regression we link the income effect to GDP per capita and then extrapolate GDP per capita. We account for structural breaks, including oil crisis for ‘Western Offshoots’, Other Asia, and western Europe (i.e., we extrapolate the trend after 1973), the breakdown of the Russian and East European economies (i.e., extrapolation after 2000), and the economic crisis in Africa and Latin America of the late 1970s (i.e., extrapolation after 1979). Finally, we weigh each of these region specific forecasts (transformed to levels) again by population, extrapolated out-of-sample, to obtain our global estimates in levels (see Figure 7). The first panel presents the weighted results, the other nine panels show the region-specific results.¹⁷

[FIGURE 7]

Based on our region-specific forecasts it is very unlikely that global per-capita CO₂ emissions will follow a downward trend in the near future. Apparently, the underlying trends in most regions and their weight in the final, aggregated forecast is such that the negative time effects will not suffice to compensate for the upward income effects. Indeed, there is little evidence that the income effect slows down, whereas forecasts of the negative time effect indicate that they do not provide large enough compensation to get the overall level down for most regions. In other words, we do not find any indication of an inverted U for the overall, global per capita CO₂ emissions.

[FIGURE 8]

¹⁷We also tried various alternative (but related) scenarios, but all scenarios more or less produce the same outcome.

Given this negative result, we finally investigate whether any alternative scenario would produce a more promising future scenario. Carbon emissions are still very closely linked to the fuel input mix and the carbon content of these fuels because typical abatement options for CO₂ emissions, such as carbon capture and storage (CCS), have been rarely applied in the past. Moreover, international regulation of CO₂ emissions is often hardly binding, despite some coordinated efforts such as the Kyoto protocol or the EU Emission Trading System (EU ETS). To explore what might happen when binding regulations for CO₂-emissions would be implemented, we create a scenario based on similar estimations for SO₂-emissions, in particular for the pair ‘Western Offshoots’ versus western Europe. Both regions typically started to regulate these emissions at the beginning of the 1970s and again around 1985 (see also Popp, 2006). This is clearly illustrated by the data (see Figure 8a). Similar to the CO₂-case, we also find an upward income effect for both regions. However, here the time effect is now strongly negative and even compensates for the upward income effect. If this time effect for ‘Western Offshoots’ would be a representative proxy for stringent regulation of CO₂-emissions, the picture becomes much gloomier. With the strongly negative time effect for SO₂-emissions an overall reduction in per-capita CO₂-emissions at world level should certainly be possible (see Figure 8b, the analogue of Figure 4, with aggregation at regional levels, but this time reported in logs).¹⁸

VI. Conclusion

The EKC approach is a very comprehensive way to explore structural mechanisms behind the stylized facts of global per-capita CO₂ emissions and GDP. The results show how a simple decomposition in income and time effect may yield powerful insights despite its

¹⁸Some likely conditions for such a prospect already exist, such as the large number of patents available for carbon emission reduction technologies (for example, Dechezlepetre et al., 2009).

sensitivity to the (necessary) choice of the prior. Consistent with the scale effect in the international trade literature, our findings support a positive link between income and emissions, irrespective of whether or not a region is rich. However, the conjecture that higher income as such would correlate with a *negative* effect on emissions is rejected. In our data we do not observe any evidence for time related effects that are strong enough to more than offset the positive scale effect. In fact, we find evidence for the opposite. China (and to a lesser extent Africa) appears to be an important exception to the rule of an inverted U or declining time effect even though its per-capita income level now approaches that of regions such as Eastern Europe. Moreover, the overall global, rising per-capita trend that we observe is even visible when we exclude China.

The new estimation approach applied in this paper has shown that the EKC literature is not necessarily approaching a dead end as, for instance, Stern and Common (2001) argue. In fact, the new flexible estimator exploited in this paper produces reasonable results for the simple decomposition that characterizes overall developments for each of our nine regions. For these regions the very different patterns for these regions over time, including severe economic crises in Latin America, eastern Europe, and Russia, and structural changes in the composition of sectors and energy use, are clearly reflected in our estimates. Because our approach follows the data, regional differences are also likely to be better represented in our region specific results. This is clearly illustrated by our findings for China. At first glance, the *positive* time effect we find might look like an anomalous result. Closer inspection, however, reveals the opposite. This finding not just reflects recent fundamental changes in the Chinese economy and its energy system, but also summarizes (very recent) findings in other fields of research, such as decomposition or convergence analysis. Further research along this line seems promising given that this data-driven approach is relatively easy to implement.

There are some caveats too. First of all, our approach is a per-capita analysis. So,

deriving trends in overall carbon emissions also requires better insight into population growth. Furthermore, subjective judgements cannot be avoided when applying the estimator described in this paper, is the case with the use of the GoF prior for global per-capita carbon emissions. One of the strong advantages of this approach, however, is that this judgement should be made explicit from the very beginning and not hidden, for instance, by choosing a (parametric) second-order polynomial estimator with homogeneous time trend. In addition, the choice of relevant pairs also clearly suffers from what might be called ‘irrelevancy.’ A specific pairwise comparison of countries that have little in common is likely to lead to irrelevant results. This shows that expert judgement in choosing priors is necessary.

Finally, we believe that our global per-capita estimates contain some important lessons. The first, well-known lesson is that future developments of global world carbon emissions depend strongly on the emission pathway that China is going to follow. The second, more surprising lesson is that the recent upsurge in global per-capita carbon emissions is not only due to these recent changes in China, but also to developments in other regions. Our findings show that the global pathway also strongly depends on what happens in *other* regions, like the slow down of the negative time effect in western Europe and ‘Western Offshoots.’

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Tables and Figures

Table I
Descriptive statistics^a

Variable	Unit	Mean	Std Dev	Minimum	Maximum
Income	bln 1990 \$	2,266	2,297	185	10,655
Carbon	mtons	498	445	18	1,832
Population	mln	487	330	88	1,470
Per-capita income	1990 \$	5,820	6,057	448	29,956
Per-capita carbon	kg	1,480	1,524	39	5,607

a) Descriptive statistics are for the period 1950-2006 (N = 513)

Table II
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

Figure 1. GDP per Capita (US \$ 1990)

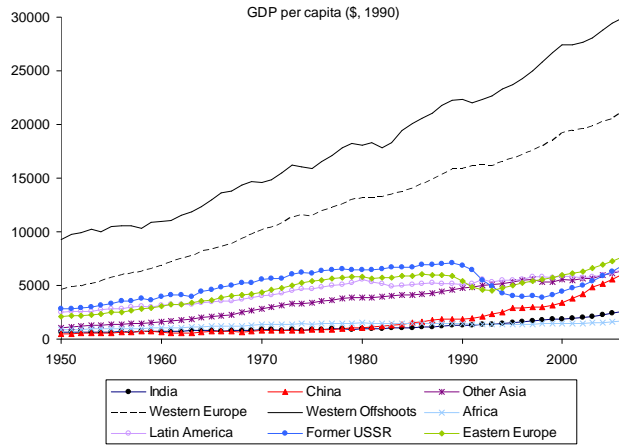


Figure 2. Carbon Dioxide Emissions in kg per Capita

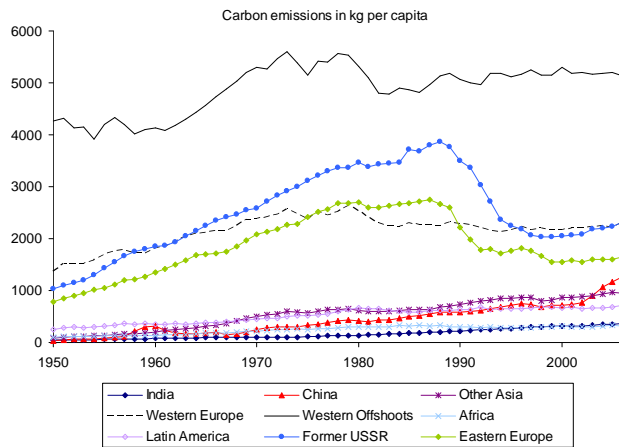


Figure 3a. Estimation results for nine regions based on best fit analysis

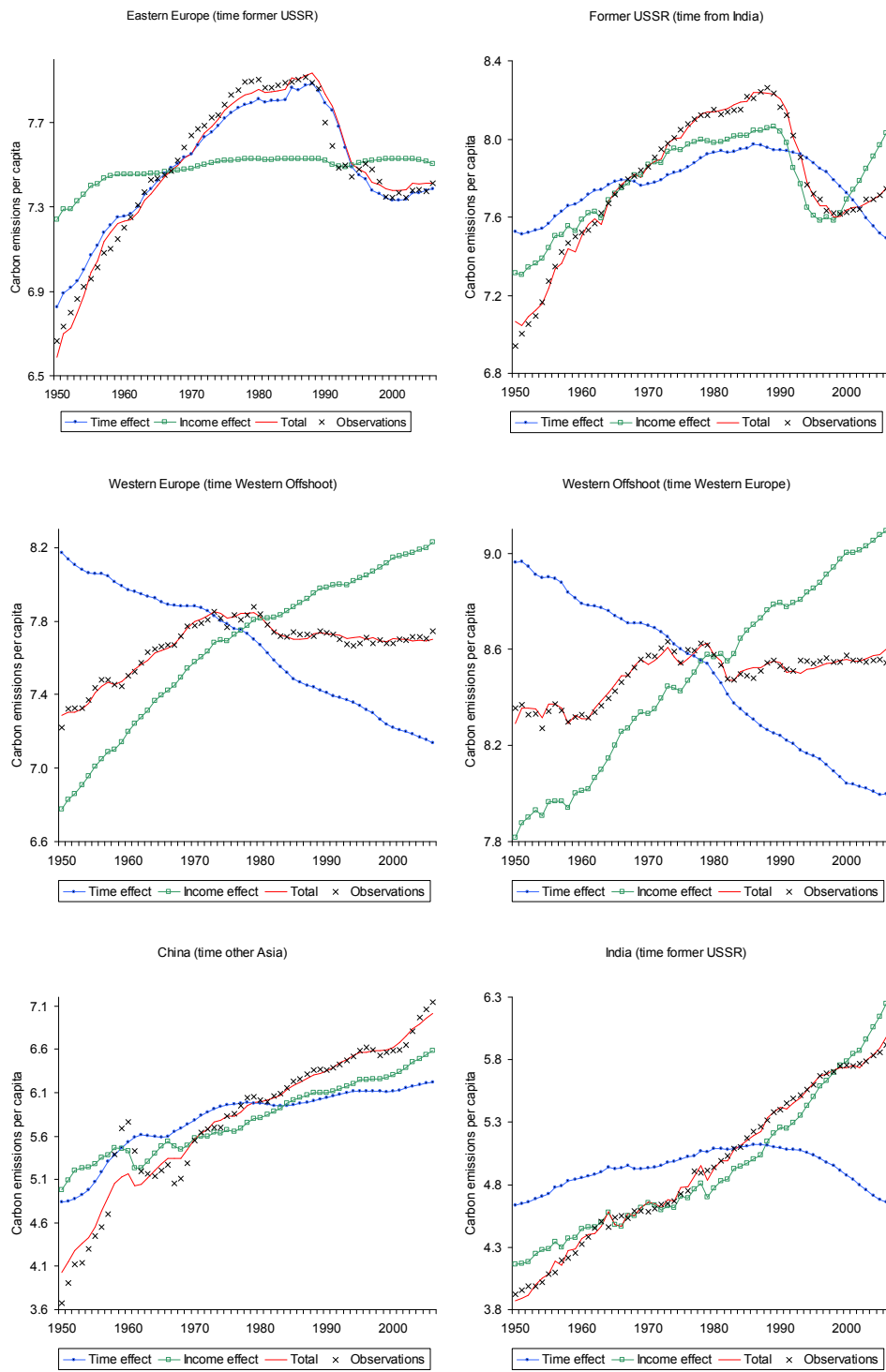


Figure 3b. Estimation results for nine regions based on best fit analysis

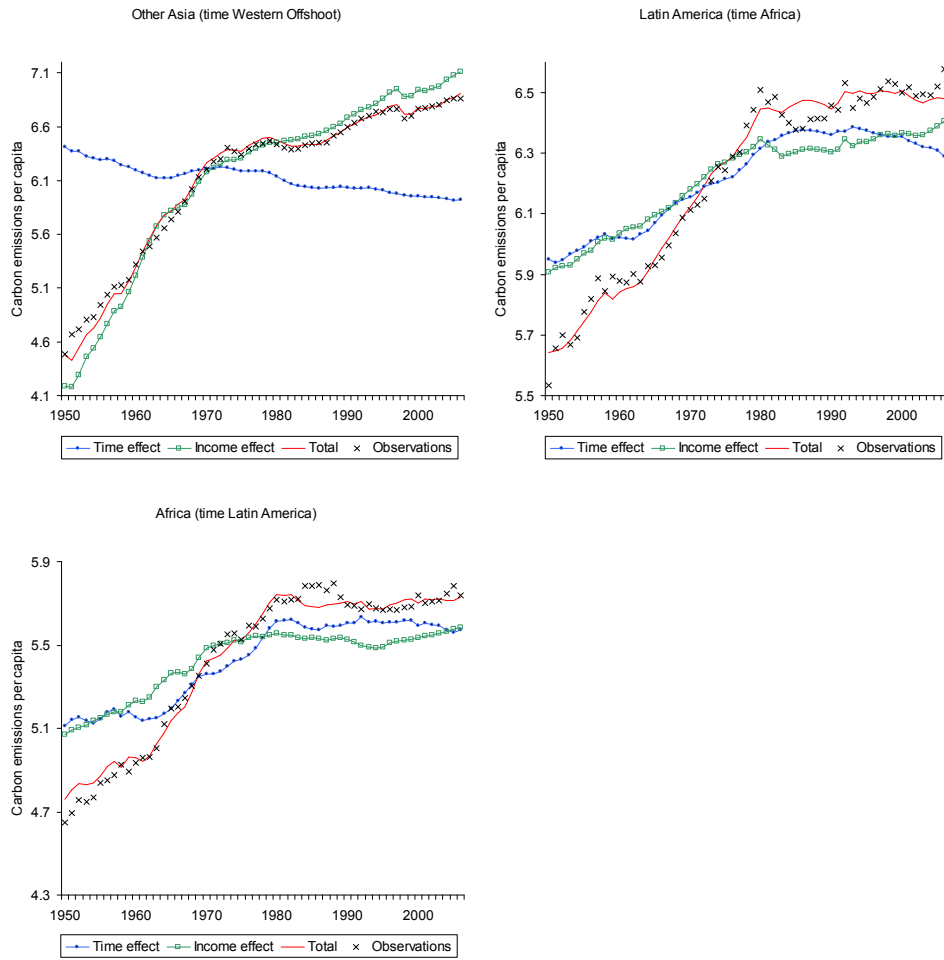


Figure 4a. Estimation results for the World

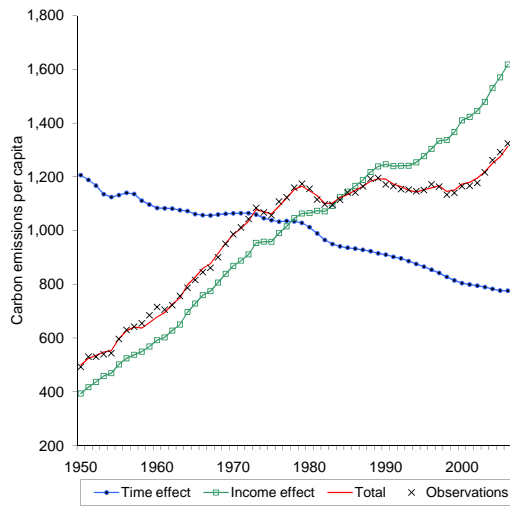


Figure 4b. Estimation results for the World excluding China

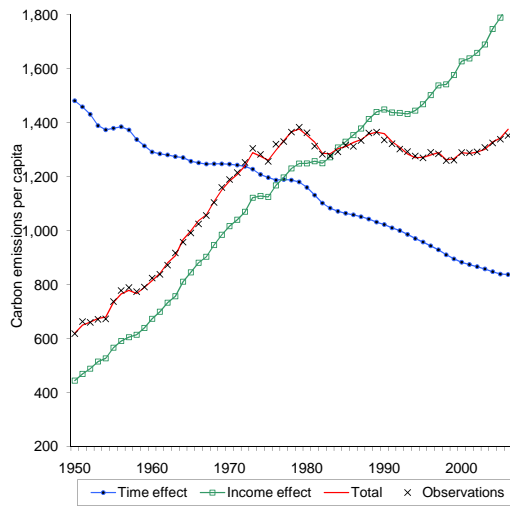
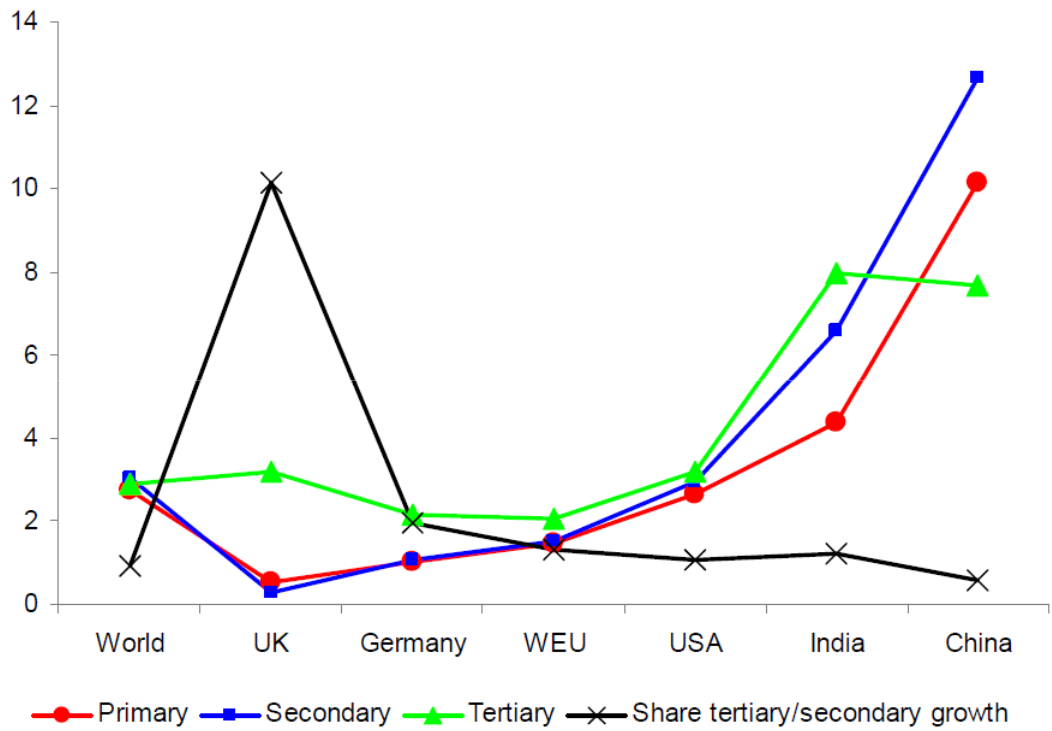


Figure 5. Percentage change sectoral Gross Value Added, 1990-2006



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

Figure 6. Alternative Regional Scenarios

'As If' Scenarios based on varying time effects

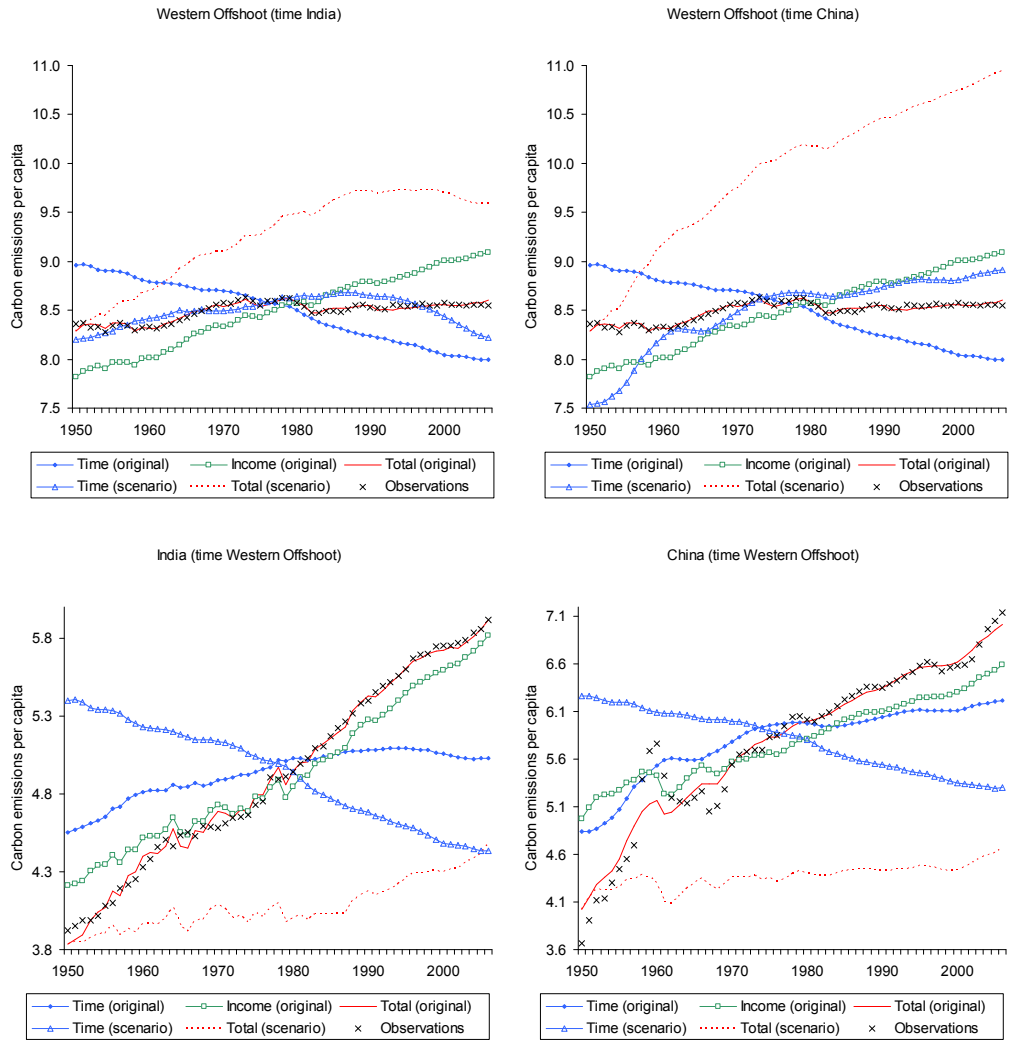


Figure 7a. Regional Forecasts

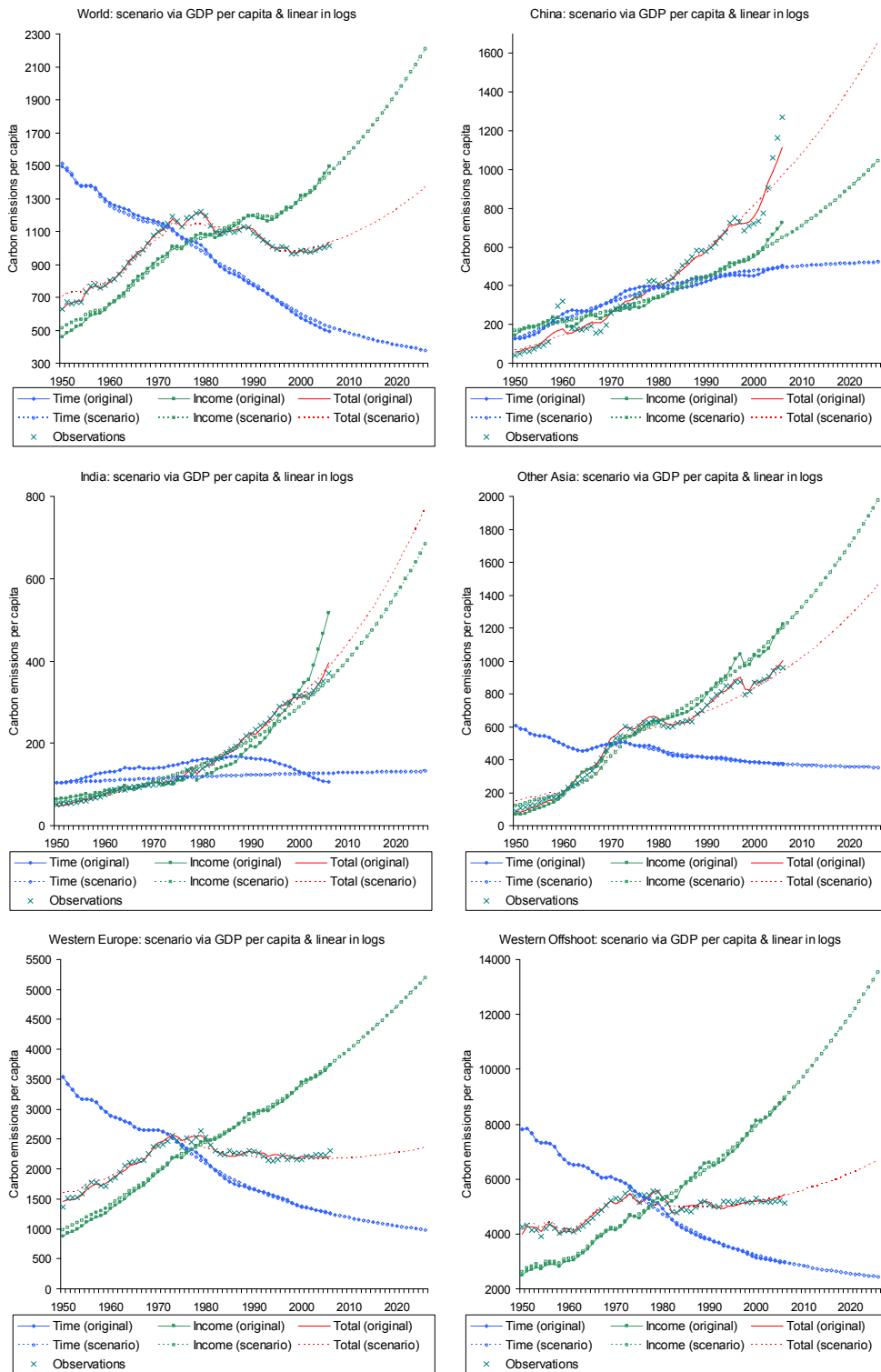


Figure 7b. Regional Forecasts

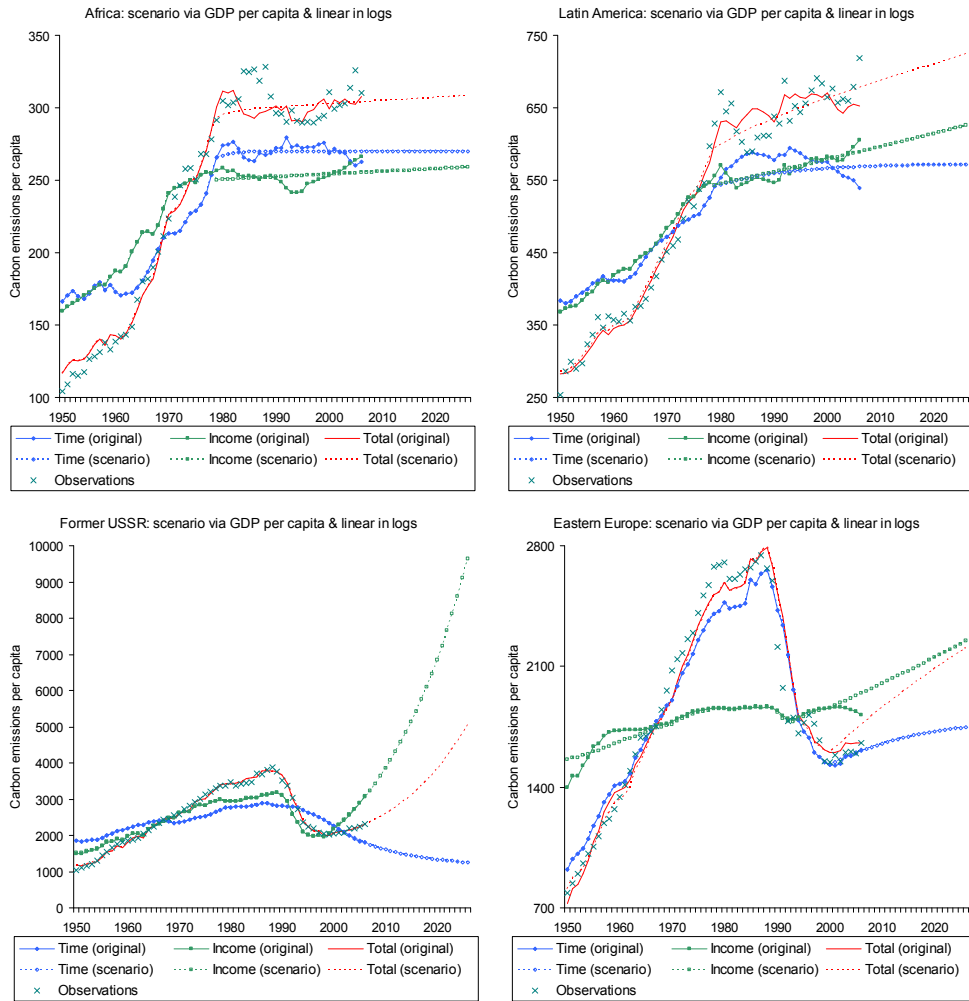


Figure 8a. Estimation Results for SO2

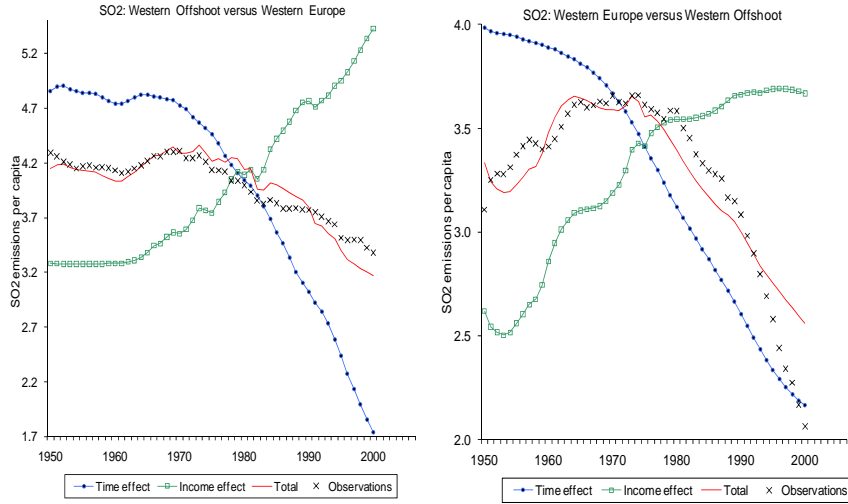
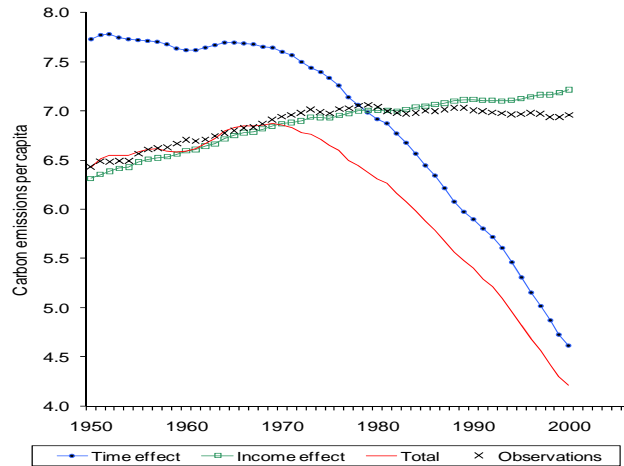


Figure 8b. World Scenario for CO2

(With time effect SO2 Western Offshoot versus Western Europe)



Appendix A: Econometric Background

In this appendix we explain the estimation approach of the model described in Section II in more detail. The estimation approach proceeds as follows. First, consider the auxiliary nonparametric regression

$$y_{rt} - y_{st} = \ell(x_{rt}, x_{st}, r, s) + \epsilon_{rs,t} \quad E(\epsilon_{rs,t} | x_{rt}, x_{st}) = 0. \quad (3)$$

One can estimate ℓ nonparametrically, using a standard Kernel estimator. Next, consider some distribution \mathbb{Q} over x_{st} . Then taking expectation of $\ell(x_{rt}, x_{st}, r, s)$ with respect to \mathbb{Q} , keeping x_{rt} fixed, we find

$$E_{\mathbb{Q}}(\ell(x_{rt}, x_{st}, r, s)) = f(x_{rt}, r) + E_{\mathbb{Q}}(f(x_{st}, s)) = f(x_{rt}, r) + c_{\mathbb{Q}}, \quad (4)$$

with $c_{\mathbb{Q}}$ some constant depending on \mathbb{Q} . Thus, $f(\cdot, r)$ can be estimated nonparametrically up to a constant by calculating $E_{\mathbb{Q}}(\ell(\cdot, x_{st}, r, s))$, using for h its nonparametric estimator. Similarly, $f(\cdot, s)$ can be estimated nonparametrically (up to a constant) by using an auxiliary distribution \mathbb{Q} over x_{rt} . Similar to Linton and Nielsen (1995), we used the empirical distribution functions of x_{rt} and x_{st} to form the auxiliary distribution \mathbb{Q} .

Note that, given the fundamental separability assumption (1), this procedure can be seen as the ultimate reduced form estimation of the inverted U curve, because identifying the inverted U relation between income and emissions no longer depends on the effects of the time variables. Furthermore, assuming that two arbitrary regions have the same time effect does not impose *a priori* a specific structure on this time effect; it would still allow *any* structure, as long as this structure applies to both regions under consideration. So, the only remaining choice is to select the appropriate combination of cross-sectional units (r, s) according to the assumption $\lambda(r, t) = \lambda(s, t)$.

However, this choice cannot be made on the basis of the data alone. To illustrate this, notice that the time effects $\lambda(r, t)$ and $\lambda(s, t)$ might be retrieved from

$$\begin{aligned} y_{rt} - f(x_{rt}, r) &= \lambda(r, t) + \epsilon_{rt}, \\ y_{st} - f(x_{st}, s) &= \lambda(s, t) + \epsilon_{st}, \end{aligned} \tag{5}$$

using the estimated functions f on the two left-hand sides. However, allowing full flexibility for each t , we only had one observation to retrieve $\lambda(r, t)$ (namely, $y_{rt} - \hat{f}(x_{rt}, r)$), one observation to retrieve $\lambda(s, t)$ ($y_{st} - \hat{f}(x_{st}, s)$), and only two observations to retrieve $\lambda(t) = \lambda(r, t) = \lambda(s, t)$. Although this allows estimation of the time effects,¹⁹ it does not allow a *consistent* estimation of fully flexible time trends, since this would require many cross-sectional observations. In other words, $\lambda(t)$, $\lambda(r, t)$, and $\lambda(s, t)$ are not identified and, as a consequence, we are unable to consistently test a hypothesis such as $H_0 : \lambda(t) = \lambda(r, t) = \lambda(s, t)$.

Appendix B: Some Additional Results

The results presented in Section IV might be sensitive to the assumption that allows regions to have a time effect in common. Moreover, no *a priori* reason exists for excluding any particular pair of region (see section II). Other combinations of countries yield quite different results in some cases, but also sometimes produce low GoFs. One example is that of applying a (Bayesian) uniform prior that gives each likely candidate an equal weight and then looks at the average of all 9 pairs (‘world’). With such a prior the findings on, in particular, western Europe and ‘Western Offshoots’ are quite different (see Figure A).

[INSERT FIGURE A]

¹⁹A simple estimator for $\lambda(t)$ consists of taking the average of $y_{rt} - \hat{f}(x_{rt}, r)$ and $y_{st} - \hat{f}(x_{st}, s)$.

However, for some of these estimates the in-sample predictions perform poorly. This suggests that time effects between certain regions are unlikely to be similar. The case of the pairwise comparison for ‘Western Offshoots’ with its best and worst fit is most illustrative. Combining ‘Western Offshoots’ with its worst fit (China) instead of its best fit (Western Europe, shown in Figure 3) yields even opposite results for the time and income effect (not presented). However, pairing ‘Western Offshoots’ with China is hardly convincing, considering some elementary GoF statistics.²⁰ We observe such extreme cases for each region. Therefore, a uniform prior approach for our sample suffers from this large variation between region pairs and this is the main reason why we prefer our GoF prior for this sample.²¹

For our selection of country pairs based on the GoF prior, we conducted a further robustness check by testing whether the GoF of our selected pair could be improved (at the margin) by allowing for the second and third best country specific time effects (in terms of GoF). This ‘time weighted’ test works as follows. Our initial choice yields for each region a one other region b as best fit, based on its in-sample predictive power. Then we test whether weighted combinations with the two next best other regions c and d yield an improvement of the overall GoF. Here, we first let the data decide on which weights should be attached to region c and d . To be more specific, we optimize the fit by optimizing over $w \in [0; 1]$, when region a has the same time effect as the following w -specific ‘artificial region’:

$$(1 - w) \times \mathbf{region\ b} + w \times (w_c \times \mathbf{region\ c} + w_d \times \mathbf{region\ d})$$

²⁰For ‘Western Offshoots’, for instance, the variance of errors is 0.0006 and the average absolute errors is 0.0181 for its best fit (with Western Europe) and 0.0345 and 0.1254 for its worst fit (with China).

²¹Apparently, the more homogeneous sample of ‘traditional’ OECD countries studied by Vollebergh et al. (2009) does not suffer from this problem (see also section V).

where $w_c \geq w_d$, satisfying $w_c + w_d = 1$, are based on the fits, when regions c and d have the same time trend as region a .²²

[INSERT FIGURE B]

Figure B illustrates the results for the optimal w for each of the nine regions. Our initial findings for all but one region only slightly change when we allow for this optimization procedure. Indeed, in most cases w is zero or close to zero. Only for China do we find some difference, although the improvement in fit is very minor. With an optimal w of close to 0.9, we find a more increasing time effect in the earlier period, followed by some flattening and a slight decrease, although the time effect is rising again at the end of the sample.²³ However, the total time effect (difference between end period and first period) in both cases is almost the same.

The general picture emerges that the income effect is positive, irrespective of the income level, which is perfectly in line with standard theory of economic growth. The time effects reflect region-specific patterns as might also be expected from this theory, in particular, if one allows for international trade (Copeland and Taylor, 2003). Our findings also corroborate decomposition analyses as well as earlier findings in (per-capita) convergence analysis. For instance, Rezek and Rogers (2008) present a decomposition of CO₂-emissions for developed countries (21 countries, 1971-2000) in scale, composition (substitution between sectors), and productivity effects, concluding that for most countries the CO₂-saving productivity effect is not large enough to offset the additions in CO₂-emissions due to the scale effect. This is perfectly in line with our estimates for Western Europe and ‘Western Offshoots’. Sun (1999) also shows that, for a sample of

²²Assume SSE_c represents the sum of squared error, when we estimate the model, assuming that regions a and c have the same time trend. Define SSE_d similarly. The weight w_c is then given by $w_c = (1 - SSE_c) / ((1 - SSE_c) + (1 - SSE_d))$, and $w_d = 1 - w_c$.

²³The reason for this finding is that the second and third best pair for China are – a little surprising in our view – Russia and eastern Europe. Clearly, these regions went through very different evolutions since the end of the 1980s.

OECD countries between 1960 and 1995, the GDP growth effect is always positive and nearly always larger than the sum of changes in the CO₂ emission coefficient, energy intensity, and sectoral composition (it is only negative in the 1980-1985 period). Finally, our findings are also consistent with the earlier analysis by Aldy (2006) who observed convergence of CO₂ emissions per capita for the original 24 OECD countries, but could not find emission convergence for a global sample of 88 countries. Indeed, the strong negative time effect that we identify for Western Europe and ‘Western Offshoots’ is not representative for the other regions in our sample, in particular not for China.

[INSERT FIGURE C]

Finally, Figure C presents the population-weighted OECD average that resulted from applying our GoF prior to the whole OECD sample of Vollebergh et al. (2009), resembling our findings for western Europe and ‘Western Offshoots’, in particular after the oil crises.

Additional Figures Appendix B

Figure Aa. Estimation results for nine regions using a uniform prior

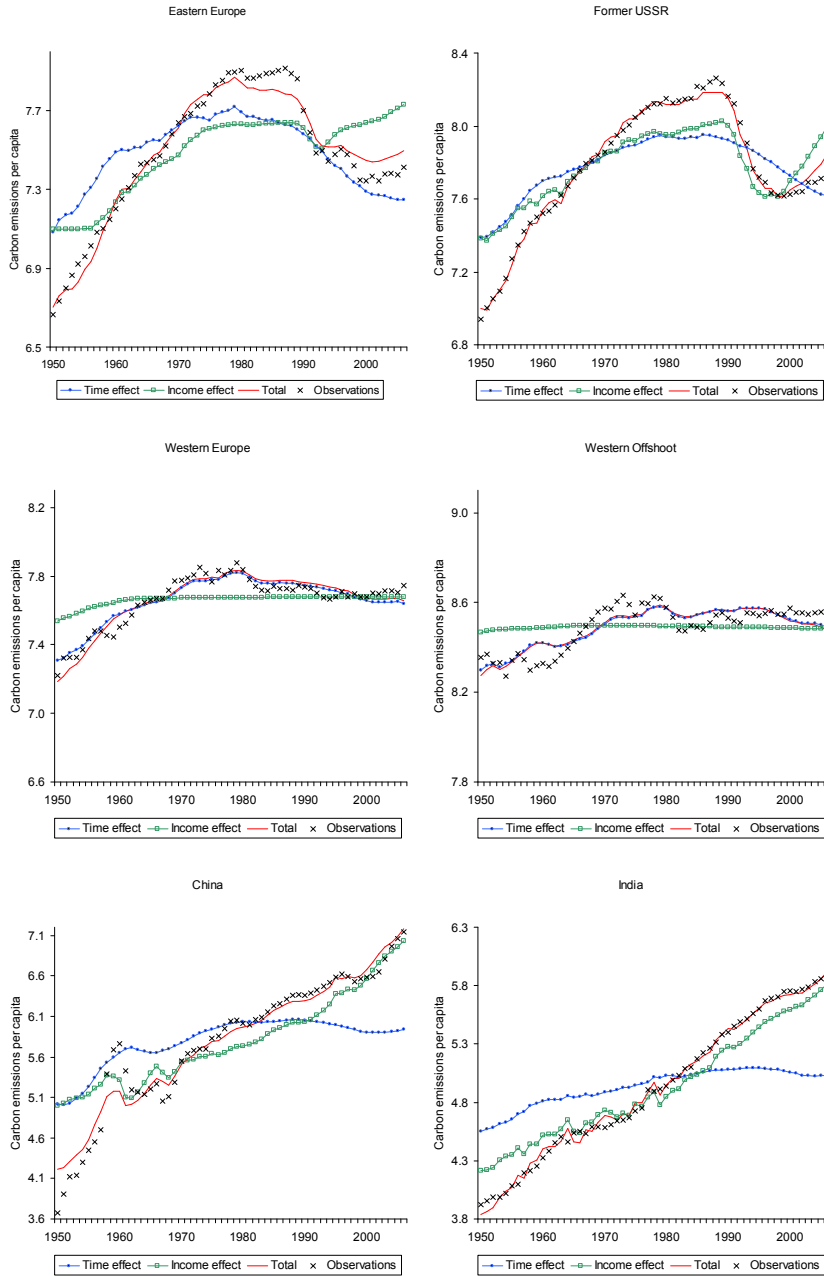


Figure Ab. Estimation results for nine regions using a uniform prior

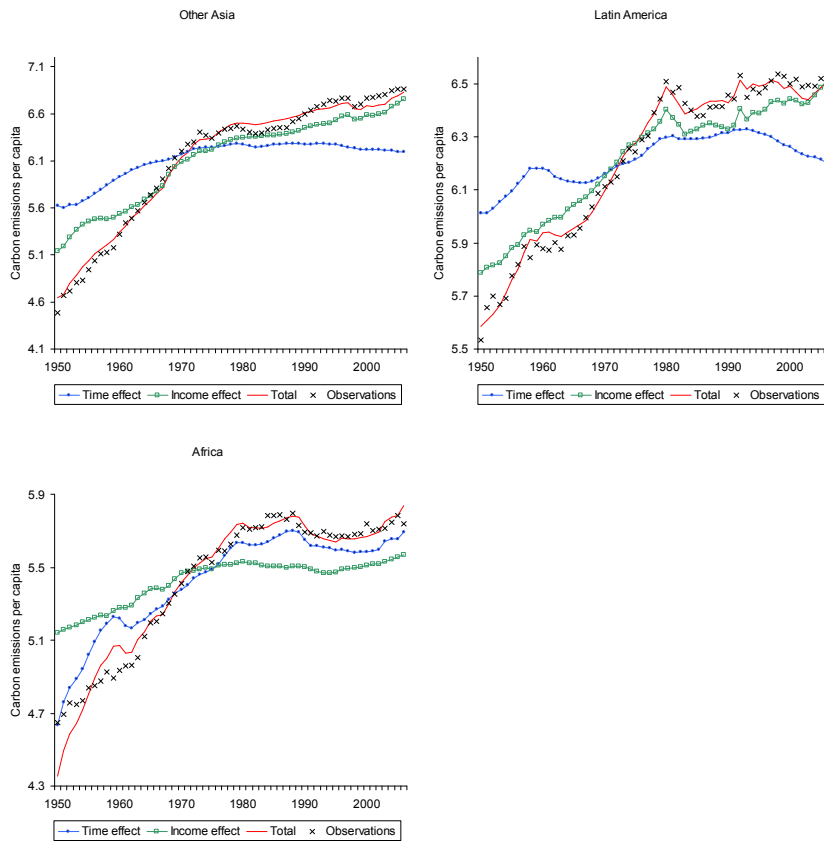


Figure Ba. Robustness Check

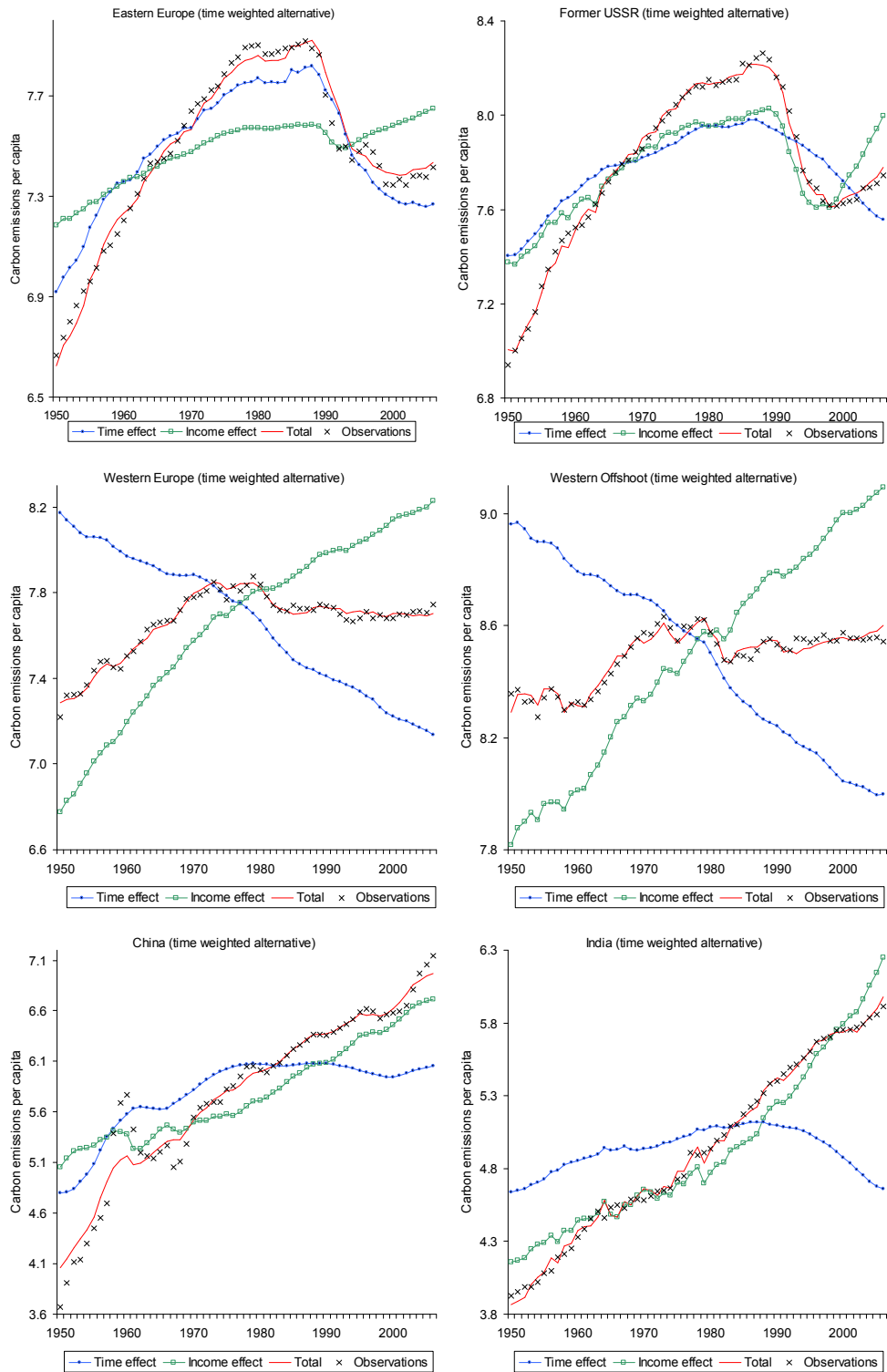


Figure Bb. Robustness Check

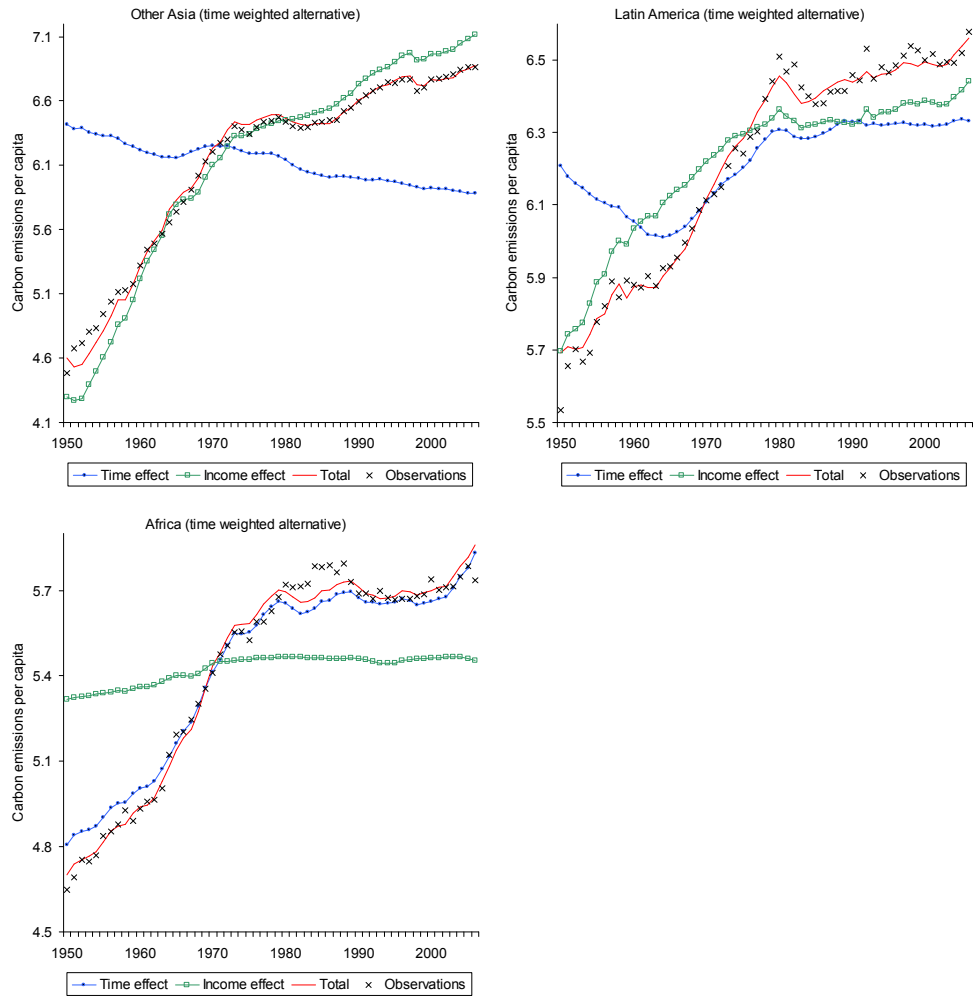


Figure C. Estimation results OECD, weighted by population

