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The Environmental Kuznets Curve: Tipping Points, Uncertainty and Weak Identification

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Abstract:

We consider an empirical estimation of the Environmental Kuznets Curve (EKC) for carbon dioxide and sulphur, with a focus on confidence set estimation of the tipping point. Various econometric – parametric and nonparametric – methods are considered, reflecting the implications of persistence, endogeneity, the necessity of breaking down our panel regionally, and the small number of countries within each panel. In particular, we propose an inference method that corrects for potential weak-identification of the tipping point. Weak identification may occur if the true EKC is linear while a quadratic income term is nevertheless imposed into the estimated equation. Relevant literature to date confirms that non-linearity of the EKC is indeed not granted, which provides the motivation for our work. Viewed collectively, our results confirm an inverted U-shaped EKC in the OECD countries but generally not elsewhere, although a local-pollutant analysis suggest favorable exceptions beyond the OECD. Our measures of uncertainty confirm that it is difficult to identify economically plausible tipping points. Policy-relevant estimates of the tipping point can nevertheless be recovered from a local-pollutant long-run or non-parametric perspective.

Keywords: Environmental Kuznets Curve, Fieller method, Delta method, CO_2 and SO_2 emissions, Confidence set, Tipping point, Climate policy

Résumé:

À partir de données empiriques, nous estimons la Courbe Environnementale de Kuznets (CEK) pour les émissions de gaz carbonique et de soufre en mettant l’accent sur l’ensemble de confiance du point de chute. Plusieurs méthodes économétriques – paramétriques et non-paramétriques – sont considérées ; ceci reflète les implications de la persistance, de l’endogénéité, de la nécessité de regrouper les pays par régions et du petit nombre de pays dans chaque groupe. En particulier, nous proposons une méthode d’inférence qui corrige pour l’identification potentiellement faible du point de chute. Celle-ci peut survenir si la vraie courbe CEK est linéaire et si un terme quadratique est quand même ajouté au moment de l’estimation. Les écrits antérieurs confirment que la non linéarité de la courbe CEK n’est pas acquise ; c’est d’ailleurs la justification de notre recherche. Pris dans leur ensemble, nos résultats confirment l’existence d’une courbe CEK en forme de U inversé pour les pays membres de l’OCDE, mais non pour les autres pays, même si les résultats pour le SO_2 sont quand même davantage favorables à l’existence d’une telle relation pour d’autres pays. Nos mesures d’incertitude confirment qu’il est très difficile d’identifier des points de chute qui soient acceptables du point de vue économique. Néanmoins, de tels points de chute peuvent être identifiés en adoptant une approche de long terme ou non-paramétrique pour des émissions de nature locale.

Mots clés: Courbe Environnementale de Kuznets, méthode de Fieller, méthode Delta, émissions de CO_2 et de SO_2, ensemble de confiance, point de chute, politique à l’égard du climat

Classification JEL: C52, Q51, Q52, Q56

1 Introduction

The Environmental Kuznets Curve (EKC) describes an inverted "U" relationship between per capita income and pollution levels. Viewed as a stylized feature, the EKC caught the attention of the profession following empirical work by - among others - Grossman and Krueger (1995).[1] Since then, research on the curve has evolved in response to two major challenges, both of which reflect common conceptual problems associated with reduced-form relationships. The first is a lack of compelling theoretical foundations. The second is a plethora of serious and lasting econometric imperfections given available data.[2]

Traditionally, the EKC is estimated using panel data regressions known to be plagued by trending, endogeneity, heterogeneity, and pooling problems. For these reasons, reported estimates are fragile for important parameters, including the coefficient on the quadratic income term.[3] This affects other objects of interest such as policy implications or inference about the *tipping point*, which refers to the level of income where per capita emissions reach their maximum.

Although substantial, this literature has not yet produced a serious consensus view. Even so, developments in econometrics have made applied works on the EKC more credible than it was in the early to mid-nineties. Progress has resulted from attention to functional forms and controls, and to assumptions on trends. Yet despite progress, little attention has been paid to estimation uncertainty about the tipping point. In this paper, we focus on this problem.

We consider an empirical estimation of the EKC for carbon dioxide and sulphur, with a focus on the tipping point. Our panel - of 114 countries for CO_2 and 82 for SO_2 - spanning the period 1960-2007 is disaggregated into several groupings. OECD countries comprise one group while all others are grouped into six geographic regions. Disaggregation is necessary to reduce biases resulting from inappropriately pooling the data when countries are dissimilar. Our estimators take into account the high degree of persistence in the data and the presence of endogeneity. Disaggregating our panel into regions necessarily places models into a "small sample" [in particular small n, where n refers to the number of countries] framework. We thus favour panel data methods that have been proved to work relatively well in the small n context.

Historically, the tipping point has not been a primary object of interest in most of these studies. A voluminous part of this literature has rather focused on assessing the existence of the EKC, which broadly entails the following: at early stages of development, pollution initially

[1] Early studies that found evidence of the EKC include Shafik (1994), Selden and Song (1994), Holtz-Eakin and Selden (1995) and Cole, Rayner and Bates (1997). These studies were generally optimistic about the potential for economic growth to solve environmental problems for several pollutants.

[2] For surveys, see *e.g.* Carson (2010), Wagner (2010),Vollebergh, Melenberg and Dijkgraaf (2009), Brock and Taylor (2005), Cavlovic, Baker, Berrens and Gawande (2000), Dinda (2004), Stern (2001, 2003, 2004, 2010), Yandle, Bhattarai, and Vijayaraghavan (2004), Dasgupta, Laplante, Wang and Wheeler (2002), Levinson (2002), and the references therein. Other works are also discussed below.

[3] The range of published estimates is wide and covers values close to zero for the quadratic component, and controversial income elasticities.

rises with per capita income but then falls as per capita income exceeds some threshold level. Available studies have applied a variety of econometric models and methods, each taking into account a different feature of the data that was previously overlooked. For example (we refer the reader to the above cited surveys for a more exhaustive summary), Stern, Common, and Barbier (1996) argue that heteroskedasticity is present in grouped data. List and Gallet (1999) do not find support for the poolability of the data for U.S. states. Harbaugh, Levinson, and Wilson (2003) find that results (on air pollutants) are sensitive to functional forms, additional covariates, sampling periods and geographic location. To tackle the problem of poolability, Lee, Chiu and Sun (2010) disaggregate their sample of 97 countries into four regions and estimate an EKC for water pollution. They find no EKC in the full sample of countries, but do find EKC's for developed regions. Non-parametric specifications and/or specifications focusing on pollution growth have also been considered; see List, Millimet and Stengos (2003), Azomahou, Lasney and Van (2006), Ordás-Criado, Valente and Stengos (2011), Kalaitzidakis, Mamuneas and Stengos (2011) and the references therein.[4]

A second strand in the recent literature has questioned the feasibility of estimating the EKC by analyzing the time series properties of income per capita and emissions per capita. By investigating whether both variables have a unit root, scholars are questioning the extent to which the time series properties of the data render previous estimates of the EKC spurious. The question of whether income and emissions cointegrate is - in fact - at center stage. Perman and Stern (2003) use panel unit root tests and find that sulphur emissions, global GDP and its square expressed in natural logs are stochastically trending, casting doubt on the general applicability of the EKC hypothesis. In particular, they argue that typical specifications for the EKC are too simple for cointegration to hold. Richmond and Kaufmann (2006) estimate EKCs for CO_2 in a sample of 36 countries over the period 1973–1997. They find CO_2 emissions, fuel mix, and GDP per capita are all nonstationary. Romero-Avila (2008) use a panel stationarity test which allows for multiple breaks and cross-sectional dependence, and find that world per capita income is nonstationary and per capita CO_2 emissions are regime-wise trend stationary. Another example is Jalil and Mahumd (2009) who use a cointegration based analysis to estimate an EKC for China. They find evidence for a long run relationship between per capita CO_2 emissions and per capita income and a Granger causality test indicates that the direction of causation runs from economic growth to emissions. Stern (2010) proposes the between-estimator to address the cross-sectional dependence and time-effect problems documented by Wagner (2008) and Vollebergh, Melenberg and Dijkgraaf (2010). Stern also points out that time-dummies will not capture time-varying technological changes, and the latter may lead to contemporaneous correlation between regressors and country effects and/or residual errors.

Non-stationary time-series tools can provide concise and informative summaries of relations among environmental and growth data. But we should not expect that such analyses will resolve controversies. In this regard, our view conforms with Stern (2010) on one fundamental dimension: empirical work on the EKC confronts inevitable hurdles arising from persistence. For this reason, we do not rely on pre-testing in our analysis of tipping points. Instead, we

[4] A tipping point consistent with our definition may be hard to formulate from a general non-parametric perspective.

consider the most recent panel techniques that have been proved reliable in dynamic contexts with persistent data. Our interest is to understand whether the tipping point can be estimated (given available econometric know-how) with enough precision regardless of the time series properties of the data.

Many researchers (refer to the above cited surveys) report point estimates of the tipping point without worrying about standard errors, and in the few cases where intervals are reported, computation details are often lacking. For instance Holtz-Eakin and Selden (1995) estimate the tipping point at \$35,428, while Cole, Rayner and Bates (1997) estimate a tipping point of \$62,700 for a quadratic function in logs and \$25,100 for a quadratic function in levels. Cole *et al.* (1997) also estimate standard errors for the tipping point and find them to be large. Figueroa and Pasten (2009), who utilize a random coefficients model to analyze sulphur dioxide emissions, find an EKC present in 17 of 28 high income countries and estimate country specific tipping points which range between \$6,201 and \$12,863. Stern (2010), citing supporting evidence from Vollebergh *et al.* (2009), Wagner (2008) and Stern and Common (2001), argues that reported *lower* estimates of tipping points and elasticities are typically biased. Specifically, Stern examines the relationship between sulphur dioxide and carbon dioxide emissions and income using a variety of panel estimation techniques including OLS, first differences, fixed effects, and random effects. However, Stern argues that the between estimator is likely to be the most reasonable estimator of the long run relationship between income and emissions, because it is consistent for both stationary and non-stationary data in the presence of misspecified dynamics and heterogeneous regression coefficients. Stern finds no EKC using the between estimator for both pollutants, but instead a positive linear relationship. Stern also estimates the tipping point for each quadratic model as well as its standard error. With respect to carbon, Stern finds that the between estimator yields either a tipping point insignificantly different from zero (due to the coefficient on GDP squared being positive) using data from Vollenbergh (2009) and \$653,110 using the data from Wagner (2008), with a standard error of \$2,084,513.[5]

In short, while reported confidence intervals for EKC model parameters are often narrow, reported estimates of the tipping points are *all over the map* and suggest substantive disagreements. For the purpose of this paper, more important than the specific estimates is our concern with uncertainty. Providing empirically grounded policy advice requires measurable precision. Accounting for uncertainty carefully could change our conclusions about the strength of evidence on the EKC and might also lead us to question whether such a simple reduced form is answering the most interesting questions about income and emission data. Put differently, far more attention needs to be paid for identification of the tipping point.

The tipping point can be easily defined within a standard EKC regression. To set focus (our framework is formally defined below), let EM_{it}, be per capita emissions in country i and year t, and let GDP_{it} be the logarithm of the country's per capita income. Consider the regression of EM_{it} on: (i) GPD_{it} [with coefficient β_1], (ii) GDP_{it}^2 [with coefficient β_2], and (iii) various

[5] In Stern (2010, Table 4), for the case using Wagner's carbon data, the fixed effects estimated turning point is \$41,678 with a standard error of \$4,043 without time effects and \$15,837 with a standard error of \$1,060 with time effects. This contrasts sharply with the between estimator where the turning point is \$653,110 with a standard error of \$2,084,513.

controls, for $t = 1, \ldots, T$ and $i = 1, \ldots, n$. Then the tipping point corresponds to $\delta = \exp(-\beta_1/2\beta_2)$. Given consistent regression estimates, consistent point estimates for the tipping point follow straightforwardly. It is however rather difficult to derive reliable confidence bounds for a ratio of parameters.

The *Delta* method [defined formally in section 3 and Appendix B] is commonly prescribed for this purpose. In view of its Wald-type form, the method is justified asymptotically for a wide class of models suitable for estimation by consistent asymptotically normal procedures. However, even when the numerator and denominator are identifiable, a ratio involves a possibly discontinuous parameter transformation. More precisely in our case, as $\beta_2 \to 0$, the ratio $-\beta_1/2\beta_2$ becomes weakly identified. This should not be taken lightly since a zero value for β_2 has not been convincingly refuted in the EKC literature.

When a parameter is weakly identified, reliance on usual standard errors can be misleading in the following sense. Usual confidence intervals of the form {estimate $\pm$ asymptotic α-level (say 5%) cut-off point $\times$ asymptotic standard error} will **not** cover the true parameter value with probability $1 - \alpha$ (say 95%).[6] Coverage probabilities can in fact be way below the hypothesized (say 95%) confidence level. So even if standard errors estimated using usual methods are narrow, they still provide a spurious assessment of the true uncertainty. The same holds true for standard bootstrap methods in the case of ratios.[7] Alternative methods based on generalizing Fieller's (1940, 1954) approach [also formally presented in section 3 and Appendix B] that will not suffer from this problem have recently gained popularity.[8] The main difference between the Delta and Fieller method is that the former will achieve significance level control [that is, will cover the unknown true value with the hypothesized probability (say 95%)] only if the ratio is strongly identified [that is if β_2 is far enough form the zero boundary], whereas the latter does not require identification [that is, it is level-correct whether β_2 is zero, local-to-zero or non-zero].[9] In other words, the Fieller method is robust to modeling mistakes resulting from imposing non-linearity of the EKC.

Presuming a false degree of precision is consequential. For example, if the true EKC is linear (see *e.g.* Stern (2010), Kalaitzidakis, Mamuneas and Stengos (2011) and the references therein for supportive arguments) and the econometrician nevertheless imposes a quadratic income term into the estimated equation, then the standard confidence interval for the tipping point will appear quite tight yet will most certainly not cover the true value. Associated decisions are thus misguided (arbitrarily false). For the ratio to be identified, the denominator has to be far enough from zero.[10] It is however worth noting that such a check is hard-wired into the Fieller

[6] See Dufour (1997). Related results can also be found in the so called *weak instruments* literature which is now considerable; see the surveys by Dufour (2003), Stock, Wright and Yogo (2002), and the viewpoint article by Stock (2010). Weak instruments and inference on ratios raise comparable local identification problems.

[7] Bolduc, Khalaf and Yelou (2010) find that the *delta* and bootstrap method are spurious even in the simplest design they consider. Coverage rates collapsing to zero [which means that the probability of the estimated interval to include the unknown true value of the ratio is zero] are also documented for empirically relevant scenarios.

[8] See Zerbe *et al.* (1982), Dufour (1997), Bernard, Idoudi, Khalaf and Yelou (2008) and Bolduc, Khalaf and Yelou (2010).

[9] Applications of Fieller's method in econometrics are scarce; see Beaulieu, Dufour and Khalaf (2011), Bernard, Idoudi, Khalaf and Yélou (2007), Bolduc, Khalaf and Yelou (2010).

[10] For a parallel with the weak-instruments problem and first-stage regression tests, refer to Stock (2010, pages

method: if β_2 is truly zero then the Fieller confidence set will be unbounded and will alert the researcher to this fact. The natural step when non-linearity of the curve is not granted (leading to possible weak identification of the tipping point) is to incorporate this uncertainty into set-estimation, which is what the Fieller method delivers in contrast to the Delta method. The Fieller approach thus comes with an assurance that it will inform us of poor-identification of the tipping point, which has an important potential to generate more reliable policy prescriptions based on the EKC.

We validate the above analysis with non-parametric specification checks, using the spline-based method from Ma, Racine and Yang (2011) and Racine and Nie (2011). In particular, for cases where an inverted-U shape is confirmed, we estimate a tipping point relaxing symmetry. Recall that an EKC is not necessarily symmetric, yet parametric quadratic equations typically impose symmetry. We thus check whether the latter assumption is overly restrictive and whether it affects tipping point estimates importantly.

Our results reveal very serious uncertainty, even when focusing on cases where the coefficient on GDP_{it}^2 is significant and negative. On balance, we find that an EKC exists in the OECD countries but generally not elsewhere, although a local-pollutant analysis suggests more favorable results beyond the OECD. Despite its existence in the OECD, our measures of uncertainty suggest that it is difficult to identify an economically plausible tipping point. Policy relevant estimates of the tipping point can nevertheless be recovered from a local-pollutant long-run or nonparametric perspective.

The paper is organized as follows. Our estimating equations are presented in section 2. In section 3, we summarize our confidence set estimation methods for the tipping point. Our empirical analysis is reported in section 3.1. Section 4 presents concluding arguments. An appendix summarizes our data set and discusses technical details.

2 Framework

We consider the following panel regression

$$EM_{it} = \beta_{0i} + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 IND_{it} + \beta_4 CIE_{it} + \beta_5 EFF_{it} + u_{it} \tag{2.1}$$

where EM_{it} is per capita emissions in country i and year t for $t = 1, \ldots, T$ and $i = 1, \ldots, n$; GDP_{it} is the country's per capita income, and IND_{it}, CIE_{it}, and EFF_{it} are control variables defined in Section 2.1. The intercept β_{0i} includes a country effect. Time effects - often considered in this literature to capture technology - are also included when indicated below. Further assumptions on the residual errors and regressors are discussed in Section 2.2.

This set-up implies an inverted-U form with respect to GDP. The level of income at which the curve reaches a maximum can be solved for and is known as the tipping point. In our context, the tipping point corresponds to

$$\delta = \exp(-\beta_1 / 2\beta_2) \tag{2.2}$$

86-87).

with $\beta_1 > 0$ and $\beta_2 < 0$. Sign restrictions imply that a maximum for the emissions is reached at a positive level of GDP. These restrictions are however not numerically imposed at the estimation stage.

In the context of equation (2.1), $-\beta_1/2\beta_2$ is not identifiable if the true β_2 is close to zero. When parameters are not identifiable on a subset of the parameter space, or when the admissible set of parameter values is unbounded, it is important to use a method for the construction of confidence sets that allows for unbounded outcomes [Dufour (1997); see also the above cited surveys on the parallel weak-instruments literature].[11] Concretely, when a parameter is not identifiable, data will barely carry any information on this parameter. Since any value in its parameter space is more or less equally acceptable, this should be reflected in any appropriate confidence set. In other words, weak-identification should, in principle, lead to diffuse confidence sets that can alert the researcher to the problem. Unfortunately, if usual confidence intervals are constructed when estimating weakly-identified parameters [for example, via an expression with bounded limits such as the commonly used Delta-method discussed below], the expected diffuse intervals often do not obtain even when bootstrapping. Rather, and because of theoretical failures, it is likely to yield very tight confidence intervals that are focused on "wrong" values.

The econometric literature refers to this problem as one of poor coverage. For practitioners, this problem is doubly-misleading. First, estimated intervals would severely understate estimation uncertainty. Secondly, intervals will fail to cover the true parameter value, but in view of their tightness, this will go unnoticed. These problems are averted if one applies a confidence set estimation method such as the Fieller method as proposed in this paper that allows for unbounded outcomes.

2.1 Data, covariates and controls

Data used in this paper are available from the World Bank's World Development Indicators (WDI) online database, and Stern (2005). As a dependent variable, we consider EM_{it} annual per capita CO_2 as well as SO_2 emissions. CO_2 data are collected from the Carbon Dioxide Information Analysis Center, Environmental Sciences Division at the Oak Ridge National Laboratory in Tennessee. For SO_2, we use the dataset from Stern (2005). Annual data for all variables are available for 114 countries for CO_2 emissions and 85 for SO_2 emissions, and will be organized into panels running over the 1960-2005 period.

GDP_{it} measures purchasing power parity corrected per capita income in thousands of constant USD with 2000 as the base year. Three additional variables are included as controls. The first control, IND_{it}, is the share of GDP in a given year derived from industry. It has been observed that the per capita energy use of countries usually peaks at the same time as the industrial share of GDP.[12] This occurs at different times for different countries and reflects the particular experience of each country with respect to industrialization and eventual shifts to a service economy. The second control, CIE_{it}, is the number of kilograms of CO_2 emitted per

[11] Observe that usual confidence intervals of the form {estimate $\pm$ asymptotic cut-off point $\times$ asymptotic standard error} are bounded by construction; the same holds for confidence intervals with bootstrap-based cut-off points or standard errors.

[12] See, for example, Rühl and Giljum (2011).

kilogram of oil equivalent energy. An important determinant of the carbon intensity of energy is the fossil fuel mix used in a country. Coal has twice the CO_2 emissions relative to natural gas per unit of energy and oil products are half way in between. CO_2 intensity of energy depends also on technology and on the efficiency of the combustion process. Lastly, the third control, EFF_{it}, is the percentage of energy a country uses that is derived from fossil fuels. This control takes into account a country's natural resource endowments. While fossil fuels are traded to various extents on world markets and thus are accessible to all countries, some energy sources are available only at the local level. This is the case of hydro and nuclear power, two energy sources that have very low emissions. All these variables are in logs. The coefficients of all three controls are expected to be positive.

In addition to a panel encompassing the full sample of countries, regional panels are segmented into the OECD, Non-OECD Asia (hereafter referred to as Asia), the Middle East & North Africa, Sub-Saharan Africa, South America, and Central American & the Caribbean. A full list of countries included in each region appear in Appendix A.

2.2 Estimation

We first question endogeneity of the regressors in (2.1) in a static context, that is, ignoring persistence in the residual error terms. So we estimate the equation with the error component 2SLS estimator proposed by Baltagi and Li (1992). In static panels, available results on the finite sample [n small relative to T] properties of this estimator support its consideration in our context. Reported results instrument GDP_{it}, its square and CO_2 intensity of energy using first lags of these variables.[13]

We next reconsider the equation when persistence in the residual u_{it} is not ruled out. For example, assuming that u_{it} is a first order autoregressive process suggests the following dynamic representation of (2.1)

$$\begin{aligned} EM_{it} = {} & \beta_{0i} + \rho_0 EM_{i,t-1} + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \\ & \beta_3 IND_{it} + \beta_4 CIE_{it} + \beta_5 EFF_{it} + \\ & \rho_1 GDP_{i,t-1} + \rho_2 GDP_{i,t-1}^2 + \rho_3 IND_{i,t-1} + \rho_4 CIE_{i,t-1} + \rho_5 EFF_{i,t-1} + e_{it} \end{aligned} \tag{2.3}$$

where the residual error term e_{it} is temporally uncorrelated. Instrumental variables (IV) methods [*e.g.* Anderson and Hsiao (1982), Arellano and Bond (1991), and Blundell and Bond (1998)] are typically considered and have been shown to work relatively well with persistent variables, when n is large relative to T.[14] With small n, when applicable [see *e.g.* Bun and Kiviet (2006) for conditions on n relative to T], they can be severely biased and highly imprecise. In contrast, bias-corrected least squares dummy variable (LSDV) estimators [see *e.g.* Kiviet (1995), Judson and Owen (1999), Bruno (2005) and Bun and Carree (2005)] may outperform their IV counterparts when n is small. We thus consider the bias corrected LSDV estimator of Kiviet (1995) with bootstrap standard errors (as in Bruno (2005)). Bias correction of this estimator

[13] Results when all regressors were instrumented are qualitatively similar so we do not report them for space considerations.

[14] Most methods require a dynamically stable model, that is a non-unitary ρ_0 in our case.

requires an initial consistent estimate; we use the Anderson and Hsiao (1982) estimator for this purpose which is better suited for our small n than its GMM counterparts. In contrast with the Baltagi and Li (1992) estimator, Kiviet's bias-corrected LSDV presumes that the regressors may be correlated with the individual-specific effect but are strictly exogenous with respect to e_{it}. So whereas the former works with endogenous regressors in a static context, the latter allows dynamics [as described] yet requires strict exogeneity of GDP and controls. It is worth noting that the above cited IV estimators correct for both dynamics and endogeneity with respect to the residual error yet require a large n and are thus unsuitable for the problem at hand. We thus turn to methods whose validity has been demonstrated for fixed n, and specifically to those proposed by Pesaran, Shin and Smith (1999).

When regressors may be non-stationary, Pesaran, Shin and Smith (1999) provide an alternative econometric framework that allows (2.3) to be viewed as a stable long-run relation with associated error correction form

$$\begin{aligned} \Delta EM_{it} &= -\rho_1 \Delta GDP_{it} - \rho_2 \Delta GDP_{it}^2 - \rho_3 \Delta IND_{it} - \rho_4 \Delta CIE_{it} - \rho_5 \Delta EFF_{it} \\ &\quad + \phi(EM_{i,t-1} - \theta_{0i} - \theta_1 GDP_{it} - \theta_2 GDP_{it}^2 - \theta_3 IND_i - \theta_4 CIE_{it} - \theta_5 EFF_{it}) \\ &\quad + e_{it} \end{aligned} \tag{2.4}$$

where $\phi = \rho_0 - 1$ is negative, $\theta_{0i} = \beta_{0i}/(1-\rho_0)$ and $\theta_j = \left(\beta_j + \rho_j\right)/(1-\rho_0)$, $j = 1, ...5$. Although related, the framework of Pesaran, Shin and Smith (1999) differs from traditional cointegration definitions that require I(1) regressors. In other words, the existence of a long-run relation between the dependant variable and the considered regressors does not rest on whether the regressors are I(1). Consistency requires independence of the regressors and residual errors, yet long-run coefficients can be estimated consistently when regressors are not strictly exogenous by augmenting the lags in the equation. Reported estimates rely on the first lag [as in (2.4)] and impose $\beta_3 = \beta_4 = \beta_5 = 0$ [with short run coefficients $\rho_j \neq 0$] implying that controls, although statistically relevant for short run adjustments, are not required for the postulated relation between emissions and income to be stable in the long-run. This assumption seems empirically crucial and affects the precision of our inference on the tipping point.

We supplement the above analysis with non-parametric graphical robustness checks, using the spline-based method from Ma, Racine and Yang (2011) and Racine and Nie (2011). This method provides a graphical representation of the mean of the emissions series conditional on contemporaneous GPD. The conditional mean is assumed to follow a non-linear and unknown function approximated via best-fit B-splines allowing for heteroskedasticity of unknown form (again assumed to depend on GDP). Further details are in the Appendix. Reported results do not use other controls. Reflecting available technological known-how in this literature, such estimations do not account for the panel structure of the data, nor for its time series properties, and impose stationarity.[15] For this reason, we do not interpret resulting curves from an inferential perspective. Instead, we view them as summary representations of our data. Severe inconsistencies between these curves and our parametric results are nevertheless worth checking

[15] To some extent, aside from the shape restriction, the non-parametric assumptions are not necessarily weaker than *e.g.* our long-run Panel assumptions as in (2.4).

for. In particular, we look for asymmetries in the estimated function in addition to turning points, since - although not required for an EKC - our quadratic parametric equations imposes symmetry.

3 Estimation Uncertainty for Tipping Points

Assuming the considered estimators are consistent and asymptotically normal, the Delta-method provides Wald-type confidence intervals using regular asymptotic theory. To present our set estimators in their simplest form with reference to the problem at hand[16], let us reparametrize equation (2.1) into a panel regression of EM_{it} on $-GPD_{it}$ [with coefficient θ_1], $GDP_{it}^2/2$ [with coefficient θ_2] and all remaining controls, so that the tipping point becomes $\delta = \exp(\theta_1/\theta_2)$, with estimators $\hat{\delta} = \exp(\hat{\theta}_1/\hat{\theta}_2)$. Let

$$\hat{\Sigma}_{12} = \begin{bmatrix} \hat{v}_1 & \hat{v}_{12} \\ \hat{v}_{12} & \hat{v}_2 \end{bmatrix}$$

refer to the subset of the variance/covariance matrix of the estimates that corresponds to $\hat{\theta}_1$ and $\hat{\theta}_2$. The *Delta* method leads to the usual Wald-type $1-\alpha$ level confidence interval:

$$\mathrm{DCS}\,(\delta;\alpha) = \left[\hat{\delta} \pm z_{\alpha/2}\hat{\Sigma}_{\delta}^{1/2}\right],\ \hat{\Sigma}_{\delta} = \hat{G}'\hat{\Sigma}_{12}\hat{G},\ \hat{G} = \hat{\delta}\left(1/\hat{\theta}_2, -\hat{\theta}_1/\hat{\theta}_2^2\right)' \tag{3.5}$$

where $z_{\alpha/2}$ refers to the two-tailed α-level standard normal cut-off point. The solution is presented in Appendix B. The *Delta*-method for $(1-\alpha)$ level thus requires inverting the $\mathtt{t}$-statistic associated with $\mathcal{H}_D(\delta_0) : \delta - \delta_0 = 0$

$$\mathtt{t}_D\,(\delta_0) = \left(\hat{\delta} - \delta_0\right) / \left[\hat{\Sigma}_{\delta}^{1/2}\right],$$

where inverting a test with respect to a parameter means collecting all values (here δ_0) not rejected by this test at the α level. This definition relies on the usual duality between a t-test and a standard confidence interval.

In contrast, the Fieller method inverts an alternative $\mathtt{t}$-statistic

$$\mathtt{t}_F\,(d_0) = (\hat{\theta}_1 - d_0\hat{\theta}_2)/[(\hat{v}_1 + d_0^2\hat{v}_2 - 2d_0\hat{v}_{12})^{1/2}]$$

associated with $\mathcal{H}_F(d_0) : \theta_1 - d_0\theta_2 = 0$, where $d_0 = \log(\delta_0)$. This requires solving for the set of d_0 values that are not rejected at level α using $\mathtt{t}_F\,(d_0)$ and a standard normal two-tailed cut-off $\mathsf{z}_{\alpha/2}$. In other words, we need to collect the d_0 values such that $|\mathtt{t}_F\,(d_0)| \leq z_{\alpha/2}$ or alternatively such that $(\hat{\theta}_1 - d_0\hat{\theta}_2)^2 \leq \mathsf{z}_{\alpha/2}^2(\hat{v}_1 + d_0^2\hat{v}_2 - 2d_0\hat{v}_{12})$, leading to a second degree inequality in d_0. The resulting set denoted FCS$\,(d;\alpha)$ [see (B.4) in Appendix B] will have $(1-\alpha)$ level whether θ_2 is zero or not. The solution for the underlying inequality is provided in Appendix B. FCS$\,(d;\alpha)$ is either a bounded interval, an unbounded interval, or the entire real line $]-\infty,+\infty[$, where

[16] Refer to Appendix B for a detailed discussion.

the unbounded solutions occurs when the denominator is close to zero. Because FCS$(d;\alpha)$ is obtained by projection methods, taking the exponential of its limits provides the desired confidence set for δ.

In parallel, the considered non-parametric method [see Racine and Nie (2011) for details] yields estimates and confidence bands for the point at which the derivative of the estimated function is closest to zero. We take the latter as our tipping point estimate in cases where an inverted-U shape is non-parametrically confirmed. This analysis, as argued above, aims to check for severe inconsistencies between our parametric and non-parametric results. In particular we aim to assess robustness of the tipping point estimates to the symmetry hypothesis underlying our quadratic equations.

3.1 Results

Tables 1-2 report estimates for the emission equation coefficients. For presentation clarity, we report the estimates of the parameters of interest β_j, $j = 1, ...5$; complete results are available upon request. Since sign restrictions have not been empirically imposed, interpretation of the tipping point with respect to an inverted U-shaped curve make sense when $\beta_1 > 0$ and $\beta_2 < 0$. So cases where the estimated β_1 and β_2 are significant at the 5% level and both are correctly signed are reported in bold characters. Except for a few illustrative cases, our analysis will focus on these cases, mainly for concreteness. In our discussion from there on, statistical significance implies a 5% level. Tipping point estimates are reported in Tables 3-5.

From Tables 1 and 2, we see that a statistically insignificant β_2 occurs quite often with both emission series. As argued above, despite no clear consensus, a linear EKC is not necessarily at odds with the current literature. Problems with the Delta method for inference on the tipping point would occur if the true β_2 is zero, so a significant β_2 does not necessarily guarantee identification. We nevertheless view these results as a motivation in support of the Fieller method whose accuracy does not depend on a non-zero β_2. Indeed, unbounded confidence sets are quite prevalent in Tables 3-5, which confirm that the tipping point is indeed hard to pin down from available data.

Another point worth emphasizing concerns the heterogeneity of results across regions, with all estimation methods and both emissions data. Our disaggregate estimation is thus more meaningful than the full sample case, which we nevertheless report for completion and possibly for comparison with available literature. Our discussion will thus focus on our regional estimates.

A few methodological comments emerge from Tables 3-5 that are worth pointing out, given that to the best of our knowledge, identification problems have not been formally discussed in this literature.

1. Conforming with econometric theory, the Fieller and Delta method provide comparable confidence bands when the Fieller set is bounded and tight [as in e.g. Table 5 for the OECD], suggesting strong identification. In this case, the Fieller sets are wider to some extent yet they convey conformable economic content.

2. When the Fieller sets are unbounded and/or very wide suggesting weak identification (which occurs most prominently but not exclusively when a linear curve cannot be refuted)

then the Delta and Fieller sets can be very different and imply very different economic conclusions. For example, they may provide conflicting evidence regarding the statistical significance of the tipping point which may be tested [given the duality between the confidence intervals and Wald tests] by checking whether the reported sets cover zero. Examples of such a conflict include the case of Asia with Carbon and the 2SLS method, the case of Central America with Carbon and the LSDV method, and the noteworthy case of the OECD with Sulphur and the LSDV method. In the latter case, the Delta confidence set is tight and covers zero, whereas the Fieller set although very wide excludes zero. Since β_1 and β_2 are significant at the 5% level and both are correctly signed in this case, results with the Delta method with regards to the tipping point seem puzzling. In contrast, the Fieller method reveals that estimation uncertainty is severe in this case, which undermines the usefulness of the estimated curve with this method and the Sulphur series.

3. Other "pathological" results include cases for which the Delta-method based sets are very tight [examples occur more prominently in table 4] while their Fieller counterparts are unbounded. Econometric theory suggests that such cases illustrate [again, on recalling the duality between confidence intervals and Wald tests] severe spurious rejections with standard methods that do not cater for weak identification. In other words, econometric theory suggests that identification concerns conveyed via unbounded Fieller sets implies that the Delta-method interval may be tightly centered on "wrong" values.[17]

Tables 3-5 suggest further substantive conclusions. When referring to the "existence" of the EKC, a broad definition that prevails in the literature entails the following: emission levels initially rise with per capita income but then eventually fall as per capita income exceeds some threshold level. Viewed collectively, our results suggest that conforming with this definition, the estimated β_1 and β_2 are significant at the 5% level and both are correctly signed mainly in the OECD region. This conclusion while not at odds with the literature needs to be qualified, when interpreting results on the tipping point estimates. Except with the long-run dynamic fixed effects method applied to the OECD region, estimates of the tipping points are either extremely imprecise (practically uninformative), or suggest economically implausible values. Although quite wide, the Delta method does not convey how seriously uninformative these sets truly are.

Consider for example the case of Carbon with the 2SLS estimate form Table 2, in the OECD region. In this case, both estimation methods support an inverted-U curve, yet the confidence intervals suggest a lower bound of at least 46.687, which is disconcerting given our measure of per capita income in thousands of constant 2000 USD. It may be argued that from a purely statistical perspective, both set estimates are not too wide, indicating that δ can be pinned down with enough precision. From an economic perspective, these estimates are much too high to reconcile with meaningful useful theory or useful policy. It is interesting to note that using Sulphur for this same region and this same method rejects the EKC form, which is reflected via highly imprecise estimates of the tipping point. Although wide, the Delta method based bands understate the severity of estimation uncertainty in this case. With the bias-corrected LSDV

[17] Indeed, the above cited econometric literature provides many convincing simulation studies documenting this problem with standard Wald-type tests.

method, we find support for the curve with both emission series for the OECD countries. Yet the estimate uncertainty regarding the tipping point is much more pronounced than with the 2SLS method, so for all practical purposes, LSDV-based confidence intervals are non-informative.

On balance, results via our long-run approach in Table 5 for the OECD are informative and consistent with EKC predictions. Confidence bands suggest, in addition to statistical precision, turning points that are economically reasonable given our measurement scale for GDP. These results may be attributed to various methodological considerations. First, it matters importantly to account for dynamics in estimating the EKC. Second, avoiding methods that are not designed for fixed n is commendable. The bias-corrected LSDV method is in principle applicable, yet the bias-correction assumes strictly exogenous regressors. The pooled long-run inference methods are designed for fixed n and large T. "How large is large" is of course a usual question with annual data. The fact remains that fixed n-and-T panel data methods are unavailable to date, so given the emissions series at hand and the importance of a regional analysis, one may argue that dynamic fixed effects are, among available methods, best suited for our purpose. Perhaps more importantly, in contrast to other cointegration methods, dynamic fixed effects do not require one to take a stand regarding the I(1) properties of regressors. Given available mixed results in this literature, this is worth pointing out. Of course this presumes that the considered long-run relations are stable and that estimations with further lags (to control for potential endogeneity of regressors) provide conformable results. Our results for the OECD region do not seem to refute these assumptions.

It is worth noting that our estimated turning points are generally lower with SO_2 than with CO_2. This suggests that results with local pollutants may be more relevant from a policy perspective. Since European countries share some common regulations with regards to local pollutants, we revisit our analysis of the OECD countries with focus on Europe. Results reported in Table 6 support our main message: policy-relevant estimates of the tipping point are recovered via a dynamic long-run econometric perspective. From a technical perspective and comparing Table 6 to the OECD results from Table 5, note that a decreased sample size costs statistical precision with the CO_2 data. With this series, we find sizable differences in confidence bands when including and excluding the long run control variables. Interestingly, the SO_2 case is more stable, which supports our reliance on local pollutants in analyzing this sub-sample. This also leads us to revisit the Central America results, since a local pollutant argument may be relevant for this sub-sample with SO_2 data. Indeed, Table 5 suggests evidence in favour of an EKC with reasonable tipping points in this case as well.

Finally, our non-parametric analysis reported in Figures 1-2 may help further understand the above results. Indeed, for most non-OECD countries, observed best fit curves deviate arbitrarily and dramatically from an expected EKC. Even if a formal statistical test is not intended, such inconsistencies [between the postulated parametric quadratic form and its non-parametric best-fit counterpart] may justify - at least in part - the severe uncertainties we find via parametric estimates of the tipping point. In contrast, non-parametric curves for the OECD countries are globally in line with our parametric results; the same observation holds for Central America with SO_2. Some asymmetry in cases where an EKC was found is suggested yet appears minor. Some of the observed clustering and bunching-up may also be attributed to the fact that dynamic and country effects are not accounted for. For reference [and because reported figures are in a log-scale] companion non-parametric tipping point set estimates conformable with Tables 1-6 are reported in Table 7. Although non-parametric confidence bands in Table 7 are tighter than their parametric counterparts from Tables 5 and 6, both convey fairly comparable substantive information. This is worth noting, because (in contrast with our parametric methods) non-parametric estimations do not account for the panel, endogeneity and time series structure of the data, and require stationarity.

4 Conclusion

Despite some overemphasis on methodology in recent works, important advances in econometrics have made empirical work on the EKC seem more credible than it was in the early nineties. Our contributions to estimating the EKC focus on the precision of the tipping point estimate, under various assumptions regarding endogeneity and persistence, and functional form. Taken collectively, our results suggest that except from a local-pollutant long-run or non-parametric perspective, confidence sets around the tipping point are sufficiently wide that the policy relevance of the EKC is greatly undermined even in the OECD. From a constructive perspective, we view these results as a motivation for further work aiming to improve identification of the curve, and for finite sample motivated panel data methods.

The fact that a long-run approach holds promise - although noteworthy - should not be viewed as evidence in favour of a cointegration approach to the EKC. In the same vein, our non-parametric estimations - although informative - are not intended to disqualify parametric estimations (recall that as considered, the former are not necessarily less restrictive than the latter). Rather, our main conclusion is that regardless of the statistical assumptions one is comfortable maintaining in this context, interpreting the shape of the curve should not be the whole story. We should and do ask whether data supports a plausible tipping point. To do so, statistical methods that account for a weakly identified tipping point should be preferred, because of the nature of the problem under study. Indeed, if the question taken to the data is whether a non-linear effect is present, then methods that impose the linear case away - which causes weak identification - cannot be adequate.

Table 1 - Carbon Emissions Equation

		All	OECD	Asia	SS-Africa	M. East	S. America	C. America
2SLS	GDP	0.550	**1.262**	0.427	0.336	0.883	0.497	-0.007
		(0.00)	**(0.00)**	(0.00)	(0.00)	(0.00)	(0.00)	(0.95)
	GDP^2	0.002	**-0.113**	0.065	0.128	0.011	-0.037	0.362
		(0.633)	**(0.00)**	(0.00)	(0.00)	(0.47)	(0.52)	(0.00)
	CIE	0.349	0.352	0.434	1.152	0.085	0.093	-1.134
		(0.00)	(0.00)	(0.00)	(0.00)	(0.24)	(0.15)	(0.00)
	EFF	0.755	0.698	1.084	0.432	0.533	0.795	2.587
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	IND	0.123	0.237	0.337	0.244	-0.035	0.176	0.809
		(0.00)	(0.00)	(0.00)	(0.00)	(0.70)	(0.01)	(0.00)
DLSDV	GDP	0.208	**0.347**	0.114	0.251	0.170	0.049	0.313
		(0.00)	**(0.00)**	(0.00)	(0.02)	(0.00)	(0.58)	(0.00)
	GDP^2	0.002	**-0.039**	0.014	0.044	0.017	0.033	0.092
		(0.69)	**(0.00)**	(0.01)	(0.23)	(0.23)	(0.36)	(0.01)
	CIE	0.182	0.083	0.090	0.597	0.197	0.050	0.136
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)
	EFF	0.295	0.148	0.320	0.304	0.019	0.240	0.365
		(0.00)	(0.00)	(0.00)	(0.00)	(0.95)	(0.00)	(0.00)
	IND	0.046	-0.005	0.078	0.033	-0.040	0.048	0.050
		(0.02)	(0.82)	(0.04)	(0.56)	(0.45)	(0.34)	(0.28)
DFE (A)	GDP	**0.934**	**2.837**	1.097	1.020	0.758	1.033	1.496
		(0.00)	**(0.00)**	(0.00)	(0.011)	(0.00)	(0.04)	(0.00)
	GDP^2	**-0.115**	**-0.530**	-0.045	0.331	-0.044	-0.086	-0.139
		(0.00)	**(0.00)**	(0.59)	(0.13)	(0.44)	(0.69)	(0.41)
DFE (B)	GDP	0.619	**1.645**	0.494	0.379	0.758	0.532	0.356
		(0.00)	**(0.00)**	(0.00)	(0.014)	(0.00)	(0.18)	(0.18)
	GDP^2	-0.007	**-0.191**	0.047	0.070	-0.048	0.049	0.199
		(0.66)	**(0.00)**	(0.14)	(0.38)	(0.38)	(0.77)	(0.04)
	CIE	0.331	0.30	0.270	0.885	0.307	0.121	0.165
		(0.00)	(0.03)	(0.02)	(0.00)	(0.00)	(0.36)	(0.09)
	EFF	0.768	0.913	1.047	0.457	2.847	0.741	0.830
		(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)	(0.00)
	IND	0.154	0.403	0.594	0.049	-0.307	0.034	0.028
		(0.02)	(0.02)	(0.00)	(0.66)	(0.16)	(0.86)	(0.79)

2SLS: Baltagi and Li (1992); equation: (2.1), with time dummies; GDP, GDP^2, CIE instrumented using first lags. DLSDV: Kiviet (1995); equation: (2.3) with time dummies and $\rho_j = 0$, $j = 1, ...5$. DFE: Pesaran, Shin and Smith (1999); equations (2.3) with $\rho_j = 0$, $j = 3, ...5$ (Case A) and relaxing the latter constraints (case B). In bold: β_1 and β_2 significant at 5% with $\beta_1 > 0$ and $\beta_2 < 0$.

Table 2 - Sulphur Emissions Equation

		All	OECD	Asia	SS-Africa	M. East	S. America	C. America
2SLS	GDP	0.819	1.062	0.784	-0.723	2.184	0.252	-3.046
		(0.00)	(0.01)	(0.00)	(0.03)	(0.00)	(0.18)	(0.00)
	GDP^2	-0.054	-0.327	0.016	0.038	0.286	0.305	1.537
		(0.06)	(0.14)	(0.66)	(0.01)	(0.00)	(0.46)	(0.00)
	CIE	-0.099	1.829	0.184	-1.056	-1.902	-0.213	0.766
		(0.43)	(0.00)	(0.13)	(0.78)	(0.00)	(0.07)	(0.32)
	EFF	0.449	-0.846	0.719	1.772	1.184	0.850	2.027
		(0.04)	(0.13)	(0.00)	(0.00)	(0.50)	(0.00)	(0.00)
	IND	0.052	0.190	0.668	3.556	-1.006	0.583	-0.469
		(0.73)	(0.65)	(0.01)	(0.00)	(0.03)	(0.011)	(0.00)
DLSDV	GDP	0.231	**0.621**	0.244	-0.096	0.270	-0.096	-1.998
		(0.00)	**(0.03)**	(0.011)	(0.66)	(0.37)	(0.62)	(0.02)
	GDP^2	-0.021	**-0.127**	0.007	-0.048	-0.044	0.058	0.980
		(0.14)	**(0.03)**	(0.72)	(0.56)	(0.44)	(0.54)	(0.00)
	CIE	-0.041	0.180	-0.002	0.174	-0.131	0.008	0.063
		(0.37)	(0.05)	(0.96)	(0.08)	(0.21)	(0.89)	(0.74)
	EFF	0.053	-0.187	0.274	0.374	-0.374	0.177	0.604
		(0.60)	(0.33)	(0.02)	(0.14)	(0.83)	(0.28)	(0.28)
	IND	0.060	-0.101	-0.041	0.117	0.035	0.070	0.209
		(0.41)	(0.60)	(0.77)	(0.42)	(0.89)	(0.58)	(0.51)
DFE (A)	GDP	**0.825**	**3.115**	0.513	**1.194**	0.934	-0.423	-2.196
		(0.00)	**(0.00)**	(0.03)	**(0.00)**	(0.03)	(0.68)	(0.03)
	GDP^2	**-0.155**	**-0.666**	-0.118	**-0.313**	-0.172	0.574	1.209
		(0.00)	**(0.00)**	(0.21)	**(0.04)**	(0.06)	(0.26)	(0.01)
DFE (B)	GDP	**0.564**	**3.092**	0.169	-0.065	1.256	-1.199	-2.073
		(0.00)	**(0.00)**	(0.41)	(0.88)	(0.02)	(0.21)	(0.06)
	GDP^2	**-0.081**	**-0.627**	-0.041	-0.088	-0.170	0.850	1.037
		(0.05)	**(0.00)**	(0.59)	(0.53)	(0.06)	(0.05)	(0.02)
	CIE	-0.065	1.058	0.114	-0.054	-0.620	0.170	0.370
		(0.57)	(0.00)	(0.57)	(0.80)	(0.00)	(0.59)	(0.39)
	EFF	0.896	-0.680	1.095	1.861	-4.030	1.973	0.456
		(0.00)	(0.18)	(0.01)	(0.00)	(0.20)	(0.04)	(0.63)
	IND	0.193	-0.301	0.182	-0.011	0.244	-0.327	0.785
		(0.32)	(0.52)	(0.073)	(0.97)	(0.52)	(0.68)	(0.14)

2SLS: Baltagi and Li (1992); equation: (2.1), with time dummies; GDP, GDP^2, CIE instrumented using first lags. DLSDV: Kiviet (1995); equation: (2.3) with time dummies and $\rho_j = 0$, $j = 1, ...5$. DFE: Pesaran, Shin and Smith (1999); equations (2.3) with $\rho_j = 0$, $j = 3, ...5$ (Case A) and relaxing the latter constraints (case B). In bold: β_1 and β_2 significant at 5% with $\beta_1 > 0$ and $\beta_2 < 0$.

Table 3: Set estimates for the tipping point using panel 2SLS

Region	Tipping Point	Delta Method	Fieller Method
		Carbon Dioxide	
All	$2.6E+21$	$(-2.2E+23, 2.2E+23)$	$(-\infty, 0) \cup (1.04E+08, \infty)$
OECD	95.76	$(46.687, 144.835)$	$(61.35, 176.06)$
Asia	.039	$(-0.011, 0.091)$	$(0.006, 0.107)$
SS-Africa	.269	$(0.054, 0.485)$	$(0.061, 0.477)$
M. East	$5.52E-18$	$(-6E-16, 6E-16)$	$(-\infty, 0.0001) \cup (8E+10, \infty)$
S. America	797.92	$(-12965.8, 14561.6)$	$(-\infty, 0.211) \cup (11.17, \infty)$
C. America	1.009	$(0.729, 1.29)$	$(0.708, 1.279)$
		Sulphur	
All	1854.92	$(-10137.13846.8)$	$(-\infty, 0) \cup (73.40, \infty)$
OECD	25.86	$(-27.92, 79.64)$	$(-\infty, 0.07) \cup (9.49, \infty)$
Asia	$8.02E+10$	$(0, 8.073E+12)$	$(-\infty, 0.0004) \cup (78.90, \infty)$
SS-Africa	$8.02E-05$	$(-0.005, 0.0054)$	$(-\infty, 0.44) \cup (3.16, \infty)$
M. East	45.22	$(-11.62, 102.06)$	$(19.82, 824.63)$
S. America	0.66	$(-0.32, 1.647)$	$(-\infty, 1.47) \cup (1.21E+08, \infty)$
C. America	2.69	$(2.489, 2.899)$	$(2.49, 2.91)$

Estimating equation: (2.1), with time dummies. Method: error component 2SLS from Baltagi and Li (1992). GDP, GDP^2 and CO_2 Intensity are instrumented using the first lag of each. All confidence sets are at the 5% level.

Table 4. Set estimates for the tipping point using dynamic bias-corrected LSDV

Region	Tipping Point	Delta Method	Fieller Method
		Carbon Dioxide	
All	$1.45E+21$	$(-127.35, 2.57E+23)$	$(-\infty, 0) \cup (46852, \infty)$
OECD	56.924	$(2.613, 138.23)$	$(19.47, 814.4)$
Asia	0.036	$(-7.44, 0.184)$	$(-\infty, 0.336) \cup (9E+9, \infty)$
SS-Africa	0.059	$(-9.93, 0.481)$	$(-\infty, 1.02) \cup (29.66, \infty)$
M. East	0.008	$(-20.61, 0.146)$	$(-\infty, 1.07) \cup (149.1, \infty)$
S. America	0.765	$(-4.722, 4.178)$	$(-\infty, \infty)$
C. America	0.199	$(-3.80, 0.637)$	$(0.00004, 0.724)$
		Sulphur	
All	223.19	$(-1100.2, 1546.6)$	$(-\infty, 6.69E-05) \cup (9.34, \infty)$
OECD	11.44	$(-4.42, 27.29)$	$(1.81, 10390.11)$
Asia	$1.12E-08$	$(-1.1E-6, 1.13E-06)$	$(0.14, 11.26)$
SS-Africa	0.36	$(-1.98, 2.71)$	$(-\infty, \infty)$
M. East	21.68	$(-52.1, 95.49)$	$(-\infty, \infty)$
S. America	2.29	$(-2.23, 6.81)$	$(-\infty, \infty)$
C. America	2.77	$(1.42, 4.11)$	$(1.36, 4.40)$

Estimating equation: (2.3) with time dummies and $\rho_j = 0$, $j = 1, ...5$. Relaxing the latter constraints increases uncertainty with both emission series. Method: bias-corrected LSDV with bootstrap standard errors from Kiviet (1995) and Bruno (2005). All confidence sets are at the 5% level.

Table 5. Set estimates for the tipping point using long-run dynamic fixed effects

Region	Tipping Point	Delta Method	Fieller Method
Carbon, Case A [no long-run controls]			
All	52.34	$(-8.69, 113.4)$	$(21.34, 296.5)$
OECD	17.22	$(9.75, 24.67)$	$(11.78, 33.45)$
Asia	227.3	$(-1553.5, 2008.1)$	$(-\infty, 0) \cup (7.44, \infty)$
SS-Africa	0.214	$(-0.332, 0.761)$	$(-\infty, 0.786) \cup (421.4, \infty)$
M. East	2620.5	$(-34028, 39269)$	$(-\infty, 0.08) \cup (26.25, \infty)$
S. America	391.96	$(-9220.7, 10004.5)$	$(-\infty, 0.91) \cup (5.83, \infty)$
C. America	218.96	$(-2054.9, 2492.8)$	$(-\infty, 0.13) \cup (9.45, \infty)$
Carbon, Case B [with long-run controls]			
All	53.33	$(-10.9, 117.6)$	$(21.25, 330.1)$
OECD	16.59	$(10.69, 22.48)$	$(12.05, 26.89)$
Asia	36605	$(-925231, 998443)$	$(-\infty, 0.0005) \cup (15.53, \infty)$
SS-Africa	0.266	$(-0.264, 0.796)$	$(-\infty, .8) \cup (675938, \infty)$
M. East	66.49	$(-136.2, 269.2)$	$(-\infty, 0) \cup (12.17, \infty)$
S. America	12.87	$(-15.95, 41.71)$	$(-\infty, 0.11) \cup (4.84, \infty)$
C. America	10.39	$(-5.67, 26.47)$	$(-\infty, 0) \cup (4.54, \infty)$
Sulphur, Case A [no long-run controls]			
All	14.27	$(-0.15, 28.69)$	$(6.42, 73.43)$
OECD	10.38	$(7.35, 13.4)$	$(7.84, 14.59)$
Asia	8.80	$(-31.59, 49.2)$	$(-\infty, 0.008) \cup (1.10, \infty)$
SS-Africa	6.74	$(-6.34, 19.83)$	$(2.04, 1.61E + 22)$
M. East	15.09	$(-9.64, 39.82)$	$(-\infty, 8.39E - 07) \cup (2.41, \infty)$
S. America	1.45	$(-0.43, 3.32)$	$(-\infty, \infty)$
C. America	2.48	$(1.41, 3.54)$	$(1.25, 4.33)$
Sulphur, Case B [with long-run controls]			
All	33.16	$(-54.95, 121.26)$	$(-\infty, 0) \cup (6.89, \infty)$
OECD	11.77	$(7.22, 16.31)$	$(8.46, 20.29)$
Asia	7.67	$(-71.68, 87)$	$(-\infty, \infty)$
SS-Africa	0.69	$(-3, 4.39)$	$(-\infty, \infty)$
M. East	40.05	$(-43.8, 123.89)$	$(-\infty, 0) \cup (6.84, \infty)$
S. America	2.03	$(0.63, 3.41)$	$(0, 7.01)$
C. America	2.72	$(1.21, 4.22)$	$(0.87, 6.28)$

Estimating equation: (2.3) with $\rho_j = 0$, $j = 3, ...5$ (Case A) and relaxing the latter constraints (case B). Method: dynamic fixed effects applied to the error correction form (2.4), from Pesaran, Shin and Smith (1999). All confidence sets are at the 5% level.

Table 6. Results focusing on Europe

CO_2	Tipping Point	Delta Method	Fieller Method
Panel 2SLS	106.38	$(13.42, 199.35)$	$(53.25, 355.08)$
Dynamic Bias Corrected LSDV	83.69	$(-14.77, 182.15)$	$(32.49, 445.03)$
Dynamic Fixed Effects - with long run controlls	50.81	$(-0.12, 101.74)$	$(25.65, 436.67)$
Dynamic Fixed Effects - no long run controlls	13.67	$(8.31, 19.04)$	$(9.28, 26.38)$
SO_2	Tipping Point	Delta Method	Fieller Method
Panel 2SLS	7.64	$(5.29, 9.98)$	$(5.81, 12.01)$
LSDV	21.52	$(-2.11, 69.16)$	$(3.38, 11703.3)$
Dynamic Fixed Effects - with long run controls	14.43	$(5.11, 23.74)$	$(8.81, 55.62)$
Dynamic Fixed Effects - no long run controls	12.5	$(6.08, 18.91)$	$(7.84, 29.29)$

Refer to Tables 1-5 for the definition of estimation methods. European countries are selected out of the OECD list reported in the Appendix for each emission series.

Table 7. Non parametric tipping point estimates, selected sub-samples

CO_2	Tipping Point Estimate	Estimated Confidence Bands
OECD	17.61	$(15.73, 19.42)$
Europe	15.60	$(14.61, 16.50)$
SO_2	Tipping Point Estimate	Estimated Confidence Bands
OECD	10.83	$(9.07, 11.71)$
Europe	14.77	$(12.38, 15.91)$
Central America	2.10	$(0.63, 3.35)$

Refer to the Appendix for the description of the estimation method. European countries are selected out of the OECD list reported in the Appendix for each emission series.

Appendix

A List of countries

Countries used for the CO_2 equation

OECD.[18] (27 countries). Albania, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Italy, Japan, Malta, Netherlands, New Zealand, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States

Asia. (17 countries) Bangladesh, China, India, Indonesia, Kazakhstan, Kyrgyzstan, Malaysia, Mongolia, Pakistan, The Philippines, Singapore, Sri Lanka, Tajikistan, Thailand, Turkmenistan, Uzbekistan, Vietnam

Sub-Saharan Africa. (16 countries) Angola, Benin, Botswana, Cameroon, Congo, Cote d'Ivoire, Gabon, Ghana, Kenya, Namibia, Nigeria, Senegal, South Africa, Togo, Zambia, Zimbabwe

The Middle East & North Africa. (16 countries) Algeria, Bahrain, Egypt, Eritrea, Iran, Jordan, Kuwait, Lebanon, Morocco, Oman, Saudi Arabia, Sudan, Syria, Tunisia, United Arab Emirates, Yemen

South America. (11 countries) Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guatemala, Paraguay, Peru, Uruguay, Venezuela.

Central America & The Caribbean. (10 countries). Costa Rica, Dominican Republic, El Salvador, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Trinidad & Tobago.

Other. (17 countries) Armenia, Azerbaijan, Belarus, Bulgaria, Croatia, Czech Republic, Georgia, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russia, Slovakia, Slovenia, Ukraine.

Countries used for the SO_2 equation

OECD. (27 countries). Albania, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Italy, Japan, Malta, Netherlands, New Zealand, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.

Asia. (12 countries). Bangladesh, China, India, Indonesia, Malaysia, Mongolia, Pakistan, Philippines, Singapore, Sri Lanka, Thailand, Vietnam.

Sub-Saharan Africa. (11 countries). Botswana, Cameroon, Cote d'Ivoire, Gabon, Ghana, Kenya, Senegal, South Africa, Togo, Zambia, Zimbabwe.

[18] The list of OECD countries includes countries that have been in the OECD for the majority of the time frame of this study, with the exceptions of Albania and South Korea. The latter two are included because, in our judgement, are anomalies with respect to their geographic peers and Albania is included because this group corresponded closest to its characteristics.

The Middle East & North Africa. (13 countries) Algeria, Bahrain, Egypt, Iran, Jordan, Kuwait, Morocco, Oman, Saudi Arabia, Sudan, Syria, Tunisia, United Arab Emirates.

South America. (10 countries). Argentina, Bolivia, Brazil, Chile, Colombia, Guatemala, Paraguay, Peru, Uruguay, Venezuela.

Central America & The Caribbean. (7 countries). Costa Rica, Dominican Republic, El Salvador, Honduras, Mexico, Panama, Trinidad & Tobago.

Other. (2 countries**).** Bulgaria, Romania.

B The Fieller method

Consider the general model $(\mathcal{Y}, \{P_\theta : \theta \in \Theta\})$, $\Theta \subset \mathbb{R}^p$, $p \geq 1$, where $\mathcal{Y}$ is the sample space and P_θ is a probability distribution over $\mathcal{Y}$ indexed by $\theta = (\theta_1, \theta_2, ..., \theta_p)'$. Our object of interest are functions of θ of the form $h(\theta) = \exp(L'\theta/K'\theta)$ where L and K are nonstochastic $p \times 1$ vectors. Given a sample of size T, assume a consistent and asymptotically normal estimator of θ is available $\hat{\theta} = (\hat{\theta}_1, \hat{\theta}_2, ..., \hat{\theta}_p)' \overset{asy}{\sim} \mathrm{N}(\theta, \Sigma_\theta)$ where Σ_θ is estimated consistently by $\widehat{\Sigma}_\theta$. The discontinuity set $\{\theta \in \Theta : K'\theta = 0\}$ is clearly non-empty. In this context, the *Delta* method exploits the following regular asymptotic result:

$$h(\hat{\theta}) \overset{asy}{\sim} N\left(h(\theta), \frac{\partial h\left(\hat{\theta}\right)}{\partial \theta'} \hat{\Sigma}_\theta \frac{\partial h'\left(\hat{\theta}\right)}{\partial \theta}\right). \tag{B.1}$$

For the same problem, Fieller's method inverts a Wald-type test associated with the hypothesis $L'\theta - d_0 K'\theta = 0$ for a collection of fixed d_0 values. For the ratio case presented in section 3, Fieller's method involves assembling all d_0 values such that $\theta_1 - d_0\theta_2 = 0$ is not rejected at the $\alpha\%$ using the **t**-statistic $\left(\hat{\theta}_1 - d_0\hat{\theta}_2\right) / \left(d_0^2\hat{v}_2 - 2d_0\hat{v}_{12} + \hat{v}_1\right)^{1/2}$ which is asymptotically standard normal under the null hypothesis. This requires the solution to the following inequality in d_0

$$\mathrm{FCS}(\delta; \alpha) = \left\{d_0 : \left(\hat{\theta}_1 - d_0\hat{\theta}_2\right)^2 \leq z_{\alpha/2}^2 \left(\hat{v}_1 + d_0^2\hat{v}_2 - 2d_0\hat{v}_{12}\right)\right\},$$

leading to the second-degree-polynomial inequality for d_0:

$$A\delta_0^2 + 2B\delta_0 + C \leq 0 \tag{B.2}$$

$$A = \hat{\theta}_2^2 - z_{\alpha/2}^2\hat{v}_2, \quad B = -\hat{\theta}_1\hat{\theta}_2 + z_{\alpha/2}^2\hat{v}_{12}, \quad C = \hat{\theta}_1^2 - z_{\alpha/2}^2\hat{v}_1. \tag{B.3}$$

Except for a set of measure zero, $A \neq 0$. Similarly, except for a set of measure zero, $\Delta = B^2 - AC \neq 0$. Real roots

$$d_{01} = \frac{-B - \sqrt{\Delta}}{A}, \quad d_{02} = \frac{-B + \sqrt{\Delta}}{A}$$

exist if and only if $\Delta > 0$, so

$$\text{FCS}\,(d;\alpha) = \left\{ \begin{array}{ccc} & [d_{01}, \quad d_{02}] & if \quad A > 0 \\ ]-\infty, & d_{01}] \cup [d_{02}, \quad +\infty[& if \quad A < 0 \end{array} \right. . \tag{B.4}$$

Bolduc, Khalaf and Yelou (2010) further show that: (i) if $\Delta < 0$, then $A < 0$ and $\text{FCS}\,(d;\alpha) = \mathbb{R}$; (ii) $\text{FCS}\,(d;\alpha)$ contains the point estimate $\hat{\theta}_1/\hat{\theta}_2$ and thus cannot be empty, and (iii) asymptotically, Fieller's solution and the *Delta* method give similar results when the former leads to an interval, *i.e.* when the denominator is far from zero. Taking the exponential of the limits of $\text{FCS}\,(d;\alpha)$ provides a confidence set for $\exp(d)$.

C B-splines

Using the method introduced by Ma, Racine and Yang (2011), we estimate the conditional expectation of emissions via the following relationship:

$$EM_{it} = f(GDP_{it}) + \sigma(GDP_{it})u_{it}, \quad f(.) \text{ and } \sigma(.) \text{ unknown}, \tag{C.5a}$$

which provides a graphical representation [with confidence bands] of the mean of emissions conditional on GDP, disregarding the dynamic properties of the model and its panel structure. This method uses a B-spline function for $f(.)$, which is a linear combination of B-splines of degree m defined as follows

$$B(x) = \sum_{c=0}^{N+m} b_c B_{c,m}(x), \quad x \in [k_0, k_{N+1}]$$

where b_c are denoted "control points", $k_0, ..., k_{N+1}$ are known as a knot sequence [an individual term in this sequence is known as a knot],

$$B_{c,0}(x) = \left\{ \begin{array}{cc} 1 & k_c \leq x < k_{c+1} \\ 0 & otherwise \end{array} \right\}$$

which is referred to as the 'intercept', and

$$\begin{aligned} B_{c,j+1}(x) &= a_{c,j+1}(x)B_{c,j}(x) + [1 - a_{c+1,j+1}(x)]B_{c+1,j}(x), \\ a_{c,j+1}(x) &= \left\{ \begin{array}{cc} \frac{x-k_c}{k_{c+j}-k_c} & k_{c+j} \neq k_c \\ 0 & otherwise \end{array} \right\}. \end{aligned}$$

The unknown function $f(GDP_{it})$ is estimated by least squares as

$$\widehat{\mathrm{B}}(GDP_{it}) = argmin_{\mathrm{B}(GDP_{it,g})} \sum_{i=1}^{n} \sum_{t=1}^{T} [EM_{it} - B(GDP_{it})]^2 .$$

Explicitly, this requires the estimation of the control points b_c. Underlying best fit parameters are selected by cross-validation; see Racine and Yang (2011) for further details. Further description of this R-package is available at: http://cran.r-project.org/web/packages/crs/crs.pdf.

To obtain tipping point estimates comparable to those in Tables 1-5, and because reported curves in figures 1-2 are in a log-scale conforming with our estimating equations, we refit curves in levels and compute the confidence bands at the point were the derivative of the estimated functions is the closest to zero. These are reported in Table 7 for selected sub-samples.

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Figure 1. Non-parametric Conditional Mean Estimates, CO2 on GDP

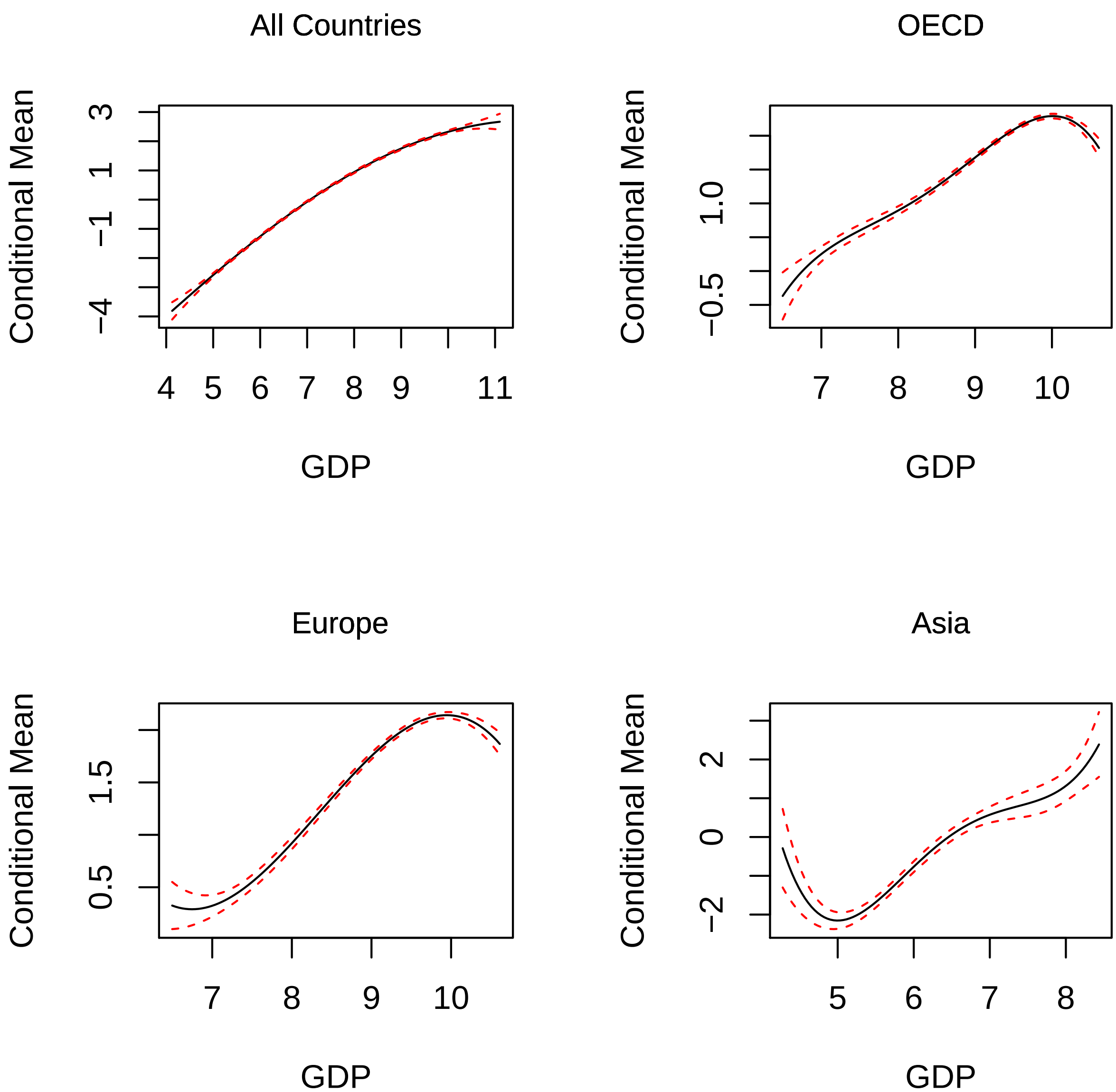

Figure 1. Non-parametric Conditional Mean Estimates, CO2 on GDP - continued

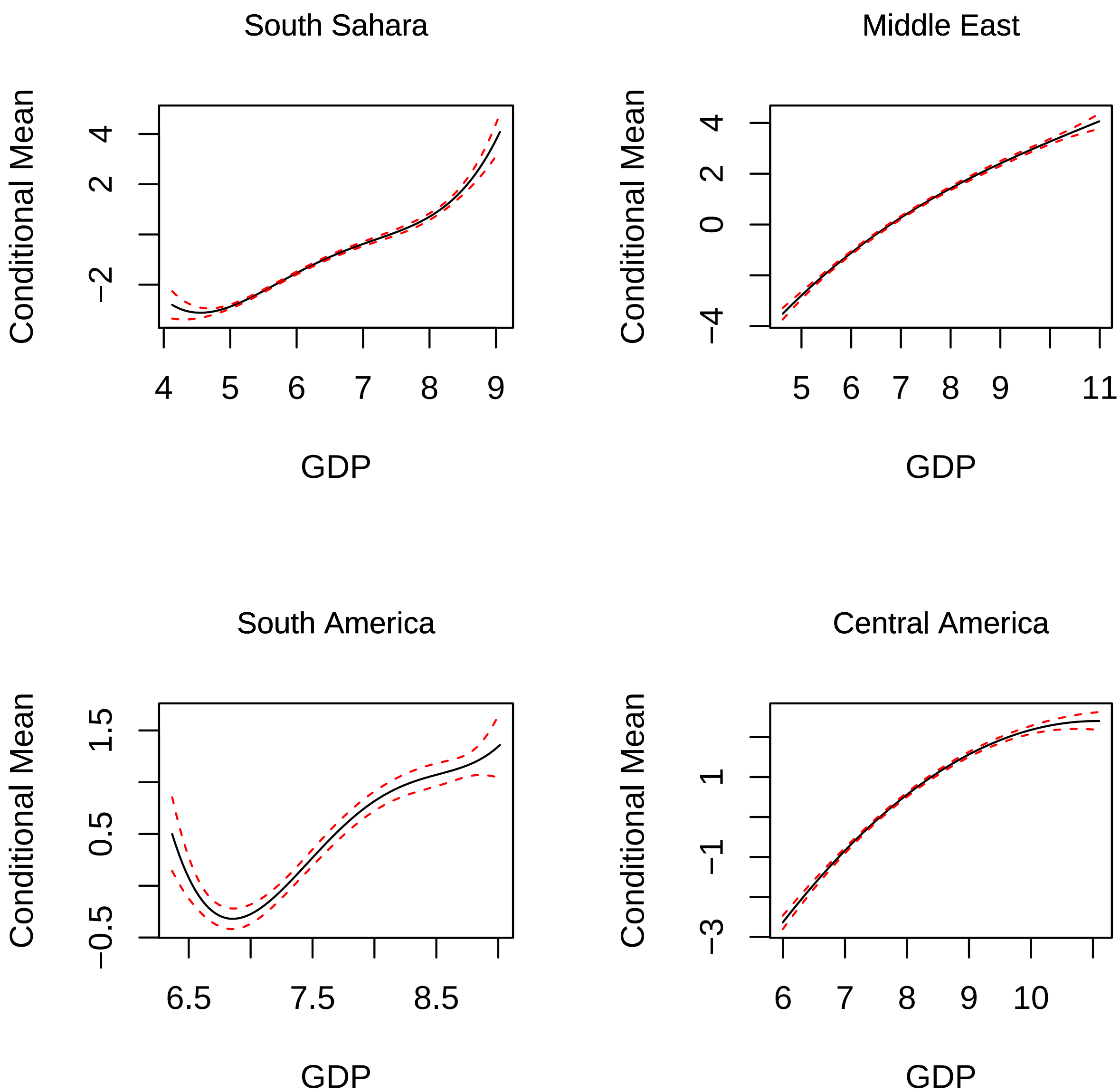

Figure 2. Non-parametric Conditional Mean Estimates, SO2 on GDP

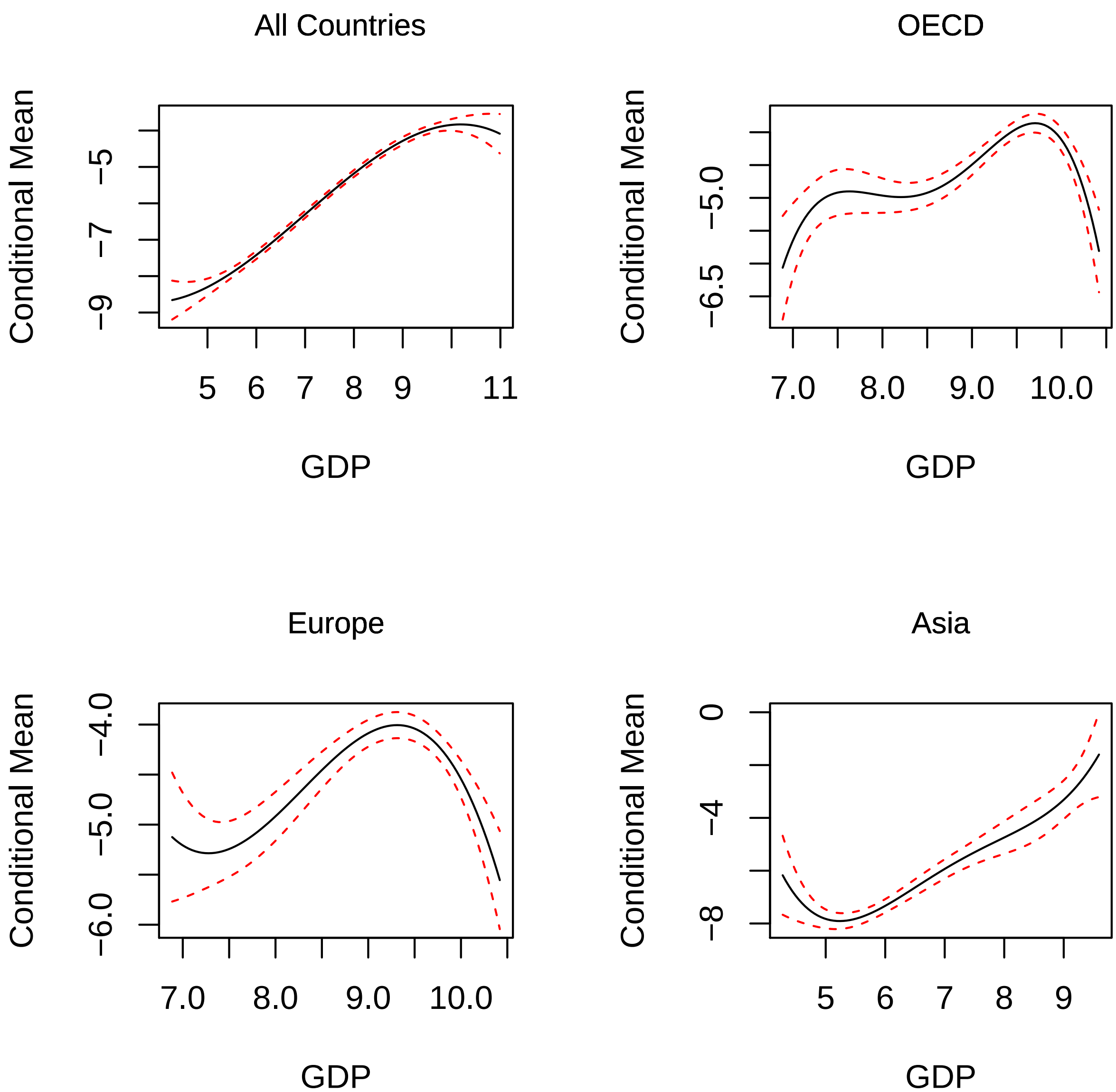

Figure 2. Non-parametric Conditional Mean Estimates, SO2 on GDP - continued