Problems estimating the carbon Kuznets curve

Juha V.A. Itkonen*

Department of Political and Economic Studies, Economics, University of Helsinki, P.O. Box 17 (Arkadiankatu 7), FI-00014 University of Helsinki, Finland

Abstract

We discover flaws in the foundations of a recent strand of literature estimating the carbon Kuznetz curve (CKC). The CKC hypothesizes that carbon dioxide emissions initially increase with economic growth but that the relationship is eventually reversed. The recent literature attempts to estimate the CKC by adding energy consumption as a control variable. Due to model misspecifications related to the econometric methodology and database definitions, the results are biased to support the existence of a CKC. Consequently the literature underestimates the need for climate policies.

Keywords: Carbon dioxide emissions, Climate policy, Economic growth, Energy consumption, Environmental Kuznets curve

*Tel.:+358 503182260, fax: +358 9 19128736, E-mail: juha.itkonen@helsinki.fi

Preprint submitted to Energy *January 19, 2012*

1. Introduction

As concerns for climate change and the need for global mitigation action have gained more awareness, also the long-standing debate on the environmental Kuznets curve (EKC) has heated. The EKC hypothesizes a relationship between emissions and output: at low levels of economic development growth increases emissions, but at higher levels of output the relationship is reversed. Graphically this implies emissions are an "inverted U" shaped function of output. When the focus is particularly on carbon dioxide emissions, the relationship is referred to as the carbon Kuznets curve (CKC).

The issue is controversial as the advocates and the opponents of the CKC propose very different development and climate change mitigation policies. If the CKC hypothesis is true, business-as-usual economic growth would ultimately lead to the reduction of emissions, implying synergy between development and mitigation policy goals. The opponents of the CKC typically view that emissions continue to grow as output grows. This implies the need for separate climate policies. (See e.g. 1.)

Since its beginning [namely 2, 3] the EKC-hypothesis has generated an enormous amount of literature.[1] Various problems in estimating the EKC have lead to the use of evermore complicated econometric methods. A recent strand of literature attempts to merge the CKC literature (emissions-output-nexus) with a related topic concerning the relationship between energy consumption and output (energy-output-nexus): in practice, energy consump-

[1]Surveys of the vast literature are provided by, for example, Copeland and Taylor [4], Stern [5], Aslanidis [6], and Kijima et al. [7].

tion is added as a control variable to estimate the CKC. We call this combined framework the *emissions-energy-output (EEO) model*.[2]

In the past new attempts to estimate EKCs have been shortly followed by critique of the methods used. For example Copeland and Taylor [4] and Stern [5] survey different estimation attempts and problems in their statistical analysis. We add to this discussion by considering problems in the recent strand of literature.

We describe three problems concerning the foundations of the recent

[2] In a precursory study of the new strand, Richmond and Kaufmann [8] attempt to estimate the turning point of the CKC with various model specifications. Some of these model specifications use the consumption shares of different fuel types to explain carbon dioxide emissions levels. The influential work by Ang [9] examines the relationship between emissions, energy consumption, and output in France using cointegration methods and a vector error-correction model (VECM). Total energy consumption is included as a regressor. Further studies have used models similar to Ang's [9]: Apergis and Payne [10, 11] extend and apply this method for panel data on South American countries and for the countries of the Commonwealth of Independent States. Pao and Tsai [12] applies this to panel data on BRIC countries (Brazil, Russia, India, and China), and later add foreign direct investment as a regressor [13] and study Brazil alone [14]. Pao et al. [15] study similarly Russia. Similarly Wang et al. [16] study a panel on China's provinces. Soytas et al. [17] use emissions, energy consumption, and output among others variables in a vector autoregression model (VAR) for the United States. Soytas and Sari [18] apply a similar method for Turkey and Lotfalipour et al. [19] for Iran. Halicioglu [20] adds foreign trade and uses an autoregressive distributed lag model (ARDL) model for Turkey. Jalil and Mahmud [21] use an ARDL model for data on China and add foreign trade as an additional explanatory variable, while Jalil and Feridun [22] add financial development to the equation. Acaravci and Ozturk [23] use ARDL for European countries. Sharma [24] investigates the determinants of emissions without adding nonlinearity to output.

strand of literature. The first problem is related to the econometric method most commonly used to estimate the EEO model: the nonlinearity of the CKC model is incompatible with vector autoregression (VAR) models, because it creates a binding yet neglected constraint for the model, which compromises the integrity of the estimators.

Even with a proper estimation method, the second and third problem arise due to the inclusion of energy consumption as an explanatory variable.[3] The second problem arises because emissions are measured indirectly from energy use in the datasets that are used. Carbon dioxide emissions are defined by a linear function of different fuel commodities, because the amount of emissions that each fuel commodity produces is determined by its chemical composition. As a result, controlling for the level of energy use in the model means that only the proportions of fuel types, and subsequently the ”carbon intensity” of the fuel mix, are allowed to vary. Consequently the meaning of the parameters is distorted and the relation estimated is not actually a conventional CKC. The third problem is caused by the dependence between energy use and output (energy-output-nexus). When this dependence exists, the model is biased to exaggerate the shape of a CKC.

The three problems have practical implications for climate change mitigation policy. First, the estimation problem adds uncertainty to the policy conclusions as the statistical properties of the estimators remain unknown.

[3] The articles in question only briefly comment the rationale for doing this. Some argue that it helps to tackle omitted variable bias, but, how it would solve the endogeneity problem, is left without any justification or discussion. Nevertheless, this is not a trivial matter, and is the source of the second and third problem.

The second and third problem reveal that economic growth, in developing countries, increases emissions faster than anticipated and, in developed countries, reduces emissions slower if at all. Hence the EEO model can give the faulty conclusion that environmental problems could be solved simply by business-as-usual growth. This means more mitigation effort is needed both in developing and developed countries.

We discuss the problems related to the recent strand of literature by focusing on the representative one-country EEO model used for example by Ang [9] and Pao and Tsai [14]. Some of the articles of the strand use slightly different estimation methods and models so some of the problems manifest in different ways.[4] But they all have the common feature of controlling for energy in a CKC model which causes the second and the third problem.

In the next section we present the EEO model. In the third section we derive an accounting identity that causes one of the problems in the literature. In the fourth section we describe the aforementioned three problems. In the fifth section we conclude.

[4] For example, Ang [9], Apergis and Payne [10, 11], Pao and Tsai [14], Wang et al. [16] use a very similar methodology. But Richmond and Kaufmann [8] might avoid similar complications as they explain emissions with fuel proportions, not total energy use. Sharma [24] does not include a square of output into the model and hence avoids the first problem. Soytas et al. [17], Soytas and Sari [18], and Lotfalipour et al. [19] use a time series technique known as the Toda-Yamamoto procedure, which does not explicate a long-run model, as do vector error-correction models.

2. EEO model

Next we present the EEO model, introduced by Ang [9], which has been reused and augmented in the recent strand of literature. The EEO model is described by equation

$$c_t = \beta_0 + \beta_1 e_t + \beta_2 y_t + \beta_3 y_t^2 + u_t, \tag{1}$$

where c_t is carbon dioxide emissions, e_t is total energy use, y_t is real GDP measured in local currency, all measured in per capita terms and converted into natural logarithms, and u_t is an error term.

As in a typical CKC-model, the square of output is included to capture the nonlinearity in the CKC. The CKC hypothesis implies that parameter β_2 is positive and β_3 is negative to form an upside-down parabola. The novel feature in the EEO model is the included regressor e_t.

Most commonly the model is estimated using cointegration and vector error-correction modelling (VECM) techniques [see e.g. 25, 26]. The time series on emissions, energy use, and output may include stochastic trends. A long-run relationship between the time series may exist if stochastic trends are common to variables. A common stochastic trend implies that there is a linear combination of the time series such that the combination is stationary. In which case, the time series are said to be cointegrated.

Such a relationship is specified by equation (1) when u_t is stationary. This is considered as the long-run (or steady-state) model. In addition to the long-run model, we can study the dynamic causal relationship between the time series by specifying the VAR model whose corresponding error-correction representation incorporates equation (1). The VAR model describes how the variables vary, in the short-run, around the long-run model. (See e.g. 26.)[5]

The model can be estimated using Johansen's [27] approach, possibly correcting for small sample bias according to Reinsel and Ahn [28].

3. The data and definitions

To consider the CKC literature, it is important to take into account how the carbon dioxide emissions data is produced in the datasets that are used in the literature.[6] Essentially, there are no actual measurements of carbon dioxide emissions. They are simply calculated from energy statistics (see Appendix A).[7]

---

[5]The long-run and short-run models are actually components of the same model. The error term of the long-run model corresponds to the error-correction term of the VECM. (26.)

[6] Most cited articles use data from the World Bank's World Development Indicators (WDI) dataset, which in turn uses carbon dioxide emission data calculated by the U.S. Department of Energy's Carbon Dioxide Information Analysis Center (CDIAC) [29]. In the CDIAC dataset carbon dioxide emissions are calculated from consumed quantities of different fuel commodities and cement manufacturing. The CDIAC dataset uses energy statistics by the United Nations Statistics Division (UNSD) among others. UNSD data is used for the time period analyzed in this paper. The WDI dataset uses energy statistics compiled by the International Energy Agency (IEA). Richmond and Kaufmann [8] use data compiled by the IEA on energy use, and calculates the carbon dioxide emissions by multiplying fuel use by the appropriate carbon content factor.

[7]It is important to note, that the data contains emissions only from domestically used energy. It does not include emissions embodied in imported goods nor does it exclude emissions from exported goods. A country's carbon footprint, which would account for the carbon content of net trade, could have a very different trend compared to domestic emissions from energy use. From this point of view, a decrease in domestic emissions of

To begin we define an important concept: *Carbon intensity* A_t is the average emissions rate of total energy consumption.[8] Carbon intensity measures how much carbon dioxide emissions one unit of energy produces given the mix of different fuel types. That is, carbon intensity depends on the proportions in which different fuel types are used. Appendix A gives a formal definition.

Given this knowledge, we can derive identity

$$C_t \equiv E_t A_t + X_t, \tag{2}$$

where C_t is carbon dioxide emissions, E_t is total energy consumption, and X_t is emissions from gas flaring and cement manufacturing, all measured per capita. Appendix A shows how this identity is derived.

It is important to note, that this is simply an accounting identity derived from the definitions of the dataset, so it must be satisfied in the sample. That is, identity (2) holds by definition in the dataset.

We note that gas flaring and cement manufacturing amount only to a percent of total carbon emissions in the data. To derive an algebraically more convenient form, we assume, from here on, that they can be omitted, i.e. $X_t = 0$. Therefore taking a natural logarithm of equation (2) gives

---

developed countries could be simply due to outsourcing heavily emitting production to developing countries. (See e.g. [30, 4, 31].)

[8]Note that here carbon intensity refers to the ratio of carbon emissions to energy consumption. This is not to be confused with carbon intensity of output which is the ratio of carbon emissions to output.

$$c_t = e_t + a_t, \tag{3}$$

where the variables are the corresponding logarithms of the capital letter variables.

Next we present the three problems in the recent CKC literature.

4. The problems in the recent CKC literature

4.1. Transformations in a VAR model

The first problem relates to the estimation of the VECM and arises because of the simple functional relationship between the regressors y_t and y_t^2.[9] A system of equations entails a restriction to the model's joint distribution [35], but this has not been fully taken into account. More specifically, the assumption of normally distributed i.i.d error terms [27] is in contradiction with the VAR model's equations. A priori, the error terms can not have the assumed distribution given that the model equations hold.

The VAR model consists of equations

$$x_t = a_0 + \sum_{i=1}^{p} A_i x_{t-i} + \varepsilon_t, \qquad t = 0, \ldots, T, \tag{4}$$

where $x_t = (c_t, e_t, y_t, y_t^2)$ is a vector of logarithms of regressors, $\varepsilon_t \in \mathbb{R}^4$ is a vector of error terms, $a_0 \in \mathbb{R}^4$ is a vector of constants, $A_i \in \mathbb{R}^{4\times 4}$ is a matrix of parameters for lag i, and p is the number of lags.

[9] The same source of problems, the dependency between regressors, is noted by Müller-Fürstenberger and Wagner [32] and Wagner [33] who conclude that a square of an unit root is not necessarily an unit root. This problem does not apply here as Johansen's [27] estimation method does not require that all variables have an unit root [See e.g. 34].

The problem can be shown within a simpler setting, so without a loss to generality, we restrict to a model with only two regressors, y_t and y_t^2, and assume that $p = 1$, $a_0 = 0$, and $A_i = [a_{jk}] \in \mathbb{R}^{2\times 2}$. Hence our model consists of equations

$$y_t = a_{11}y_{t-1} + a_{12}y_{t-1}^2 + \varepsilon_{1,t} \quad \text{and} \tag{5}$$

$$y_t^2 = a_{21}y_{t-1} + a_{22}y_{t-1}^2 + \varepsilon_{2,t}, \tag{6}$$

for all $t = 0, \dots, T$.

First, we show that not all error terms of the model can be normally distributed given that model equations (5) and (6) hold. Plugging y_t of equation (5) into equation (6) and rearranging gives

$$\varepsilon_{2,t} = (a_{11}y_{t-1} + a_{12}y_{t-1}^2 + \varepsilon_{1,t})^2 - a_{21}y_{t-1} - a_{22}y_{t-1}^2. \tag{7}$$

We notice that the lagged variables, y_{t-1}, are given at time t. Therefore equation (7) constrains a polynomial relationship between error terms $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$, hence they can not both be normally distributed. In other words, when the lagged variables are given and if $\varepsilon_{1,t}$ is drawn from a normal distribution, then equation (7) determines a non-normal distribution for $\varepsilon_{2,t}$.

Second, we show that the error terms are not independent over time. Plugging lagged equations (5) and (6) into (7) we get

$$\begin{aligned}\varepsilon_{2,t} =& (a_{11}(a_{11}y_{t-2} + a_{12}y_{t-2}^2 + \varepsilon_{1,t-1}) + a_{12}(a_{21}y_{t-2} + a_{22}y_{t-2}^2 + \varepsilon_{2,t-1}) + \varepsilon_{1,t})^2 \\ &- a_{21}(a_{11}y_{t-2} + a_{12}y_{t-2}^2 + \varepsilon_{1,t-1}) - a_{22}(a_{21}y_{t-2} + a_{22}y_{t-2}^2 + \varepsilon_{2,t-1})\end{aligned}$$

where again the right-hand-side regressors are given. Hence, the value of error term $\varepsilon_{2,t}$ depends on $\varepsilon_{1,t-1}$, and therefore they can not be chosen independently, which violates the model assumptions.

This means that the assumption of normally distributed i.i.d error terms, which is required by Johansen's [27] estimation method, can not be satisfied and estimates are not reliable. We also see a much more general property: including a transformation of a regressors into a VAR model as a regressor creates an implicit constraint between error terms.

Even if the problem of estimation would be solved, there would remain other problems of misspecification. To focus on these, we temporarily set aside the aforementioned problem in the subsequent sections.

4.2. The interpretation of the parameters

We now turn to the second problem in the recent literature. Wrong interpretation of the parameters and resulting wrong conclusions arise from the definition of carbon emissions in the dataset (Section 3). It is worth emphasizing, that this problem is not about the estimation of the model, but is related to the specification of the model.

In the context of CKC, the parameter of interest is the causal effect of output on carbon emissions. That is, we want to know how output affects emissions. In model equation (1), the partial derivative

$$\frac{\partial c_t}{\partial y_t} = \beta_2 + 2\beta_3 y_t \tag{8}$$

is interpreted as the partial causal effect of y_t on c_t, i.e. it quantifies the relationship between emissions and output.[10] This would be the Marshallian ceteris paribus change that assumes other variables constant [36, 37]. This term determines the shape of the carbon Kuznets curve.

[10]To be exact, we are interested in the expected conditional partial derivative, but to ease notation, we do the analysis as if it was a deterministic model.

This, however, does not take into account the conceptual dependence between energy and carbon emissions that is captured by identity (3). Recognizing this dependence reveals that the causal effect (8) has a much more narrow interpretation than intended. We give three alternative ways to reach this conclusion.

First, note that calculating the partial derivative (8) requires that total energy use e_t is held constant. Now, from identity (3) we notice that, in this case, the level of carbon dioxide emissions c_t can only change through changes in carbon intensity a_t. The causal effect (8) can be interpreted only as the causal effect of output y_t on emissions c_t through carbon intensity a_t. This ignores the effect of y_t on c_t through energy use e_t. As a result, the model is actually a regression analysis of carbon intensity, instead of carbon emissions.

Second, the problem can be also seen by comparing the causal effect (8) with the derivative of identity (3). Partially differentiating identity (3) with respect to y_t gives

$$\frac{\partial c_t}{\partial y_t} = \frac{\partial a_t}{\partial y_t} + \frac{\partial e_t}{\partial y_t}.$$

If emissions level e_t is held constant, as is required to calculate the causal effect (8), the second term, $\partial e_t / \partial y_t$, is omitted. This means that the causal effect (8), which the EEO literature investigates, is only the first term, $\partial a_t / \partial y_t$. As before, this shows that an important channel of influence is blocked.

Third, a more explicit regression equation can be formulated. Equation (3) can be plugged into equation (1) to eliminate c_t. Rearranging gives equation

$$a_t = \beta_0 + (\beta_1 - 1)e_t + \beta_2 y_t + \beta_3 y_t^2 + u_t. \tag{9}$$

Here we see that model equation (1) is equivalently a regression on carbon intensity a_t, and the functional form between a_t and output y_t is exactly the same as between carbon emissions c_t and y_t. That is, the causal effect of y_t on emissions c_t equals exactly the causal effect of y_t on carbon intensity a_t. Formally,

$$\frac{\partial c_t}{\partial y_t} = \frac{\partial a_t}{\partial y_t} = \beta_2 + 2\beta_3 y_t,$$

which brings us to the same conclusion: "parameter of interest" equals the effect of output onto carbon intensity, i.e. the cleanness of energy, not the amount of emissions, as intended.

In other words, the new and the old CKC literatures are looking at different parameters. What is missing here, is the link between energy use and output. That is, richer economies use more energy. In the next section we consider how adding this missing link changes the picture.

4.3. Bias

The third problem is a misspecification bias rising from the dependence between energy use e_t and output y_t. We begin by looking at the data. First, energy use over different output levels is depicted in Figure 1. The apparent relationship between the variables suggests that more output requires more energy. This basic notion, the details of which are the subject of the immense energy-output-nexus literature, is actually the motivation behind the emissions-energy-output-nexus, and is essential to the CKC hypothesis. Nonetheless, it is unintentionally neglected due to the model formulation, as seen in the previous section.

Second, identity (2) implies that variations in both carbon intensity and energy use are essential for the CKC. This can be seen from Figure 2. Here the

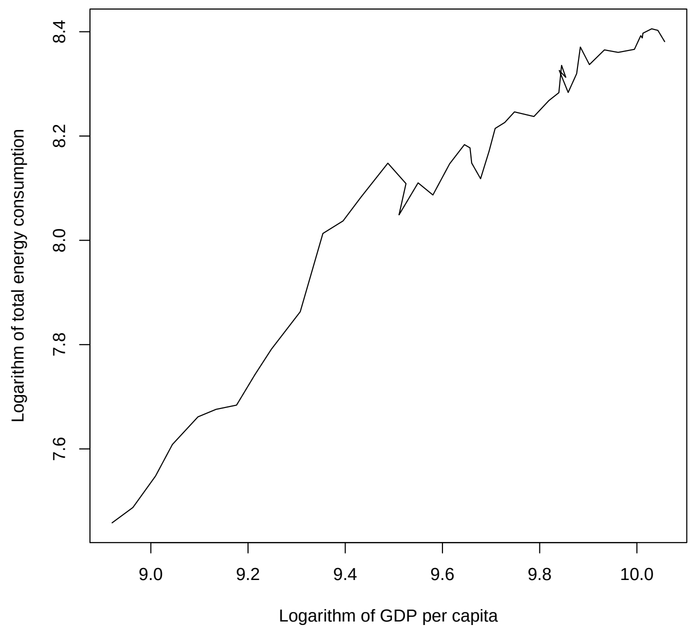

Figure 1: Relationship between the logarithm of total energy consumption per capita and the logarithm of per capita GDP in France, 1960-2006.

development of carbon emissions in France (curve A) has been decomposed in to a growing energy consumption (B) and a declining carbon intensity (C).[11] This shows that, without the growth of energy consumption, emissions in 2006 would be 60% less compared to 1960. On the other hand, without the shift to cleaner fuels, emissions would be 150% higher in 2006.[12] Clearly both

[11]To be more specific, $A = \frac{c_t}{c_{1960}}$, $B = \frac{e_t}{e_{1960}}$, and $C = \frac{c_t}{c_{1960}} / \frac{e_t}{e_{1960}}$. That is, $A = BC$.

[12]Carbon intensity a_t has decreased in France because of a decline in the share of heavily polluting fuels like coal. They have been replaced or outgrown by the use of oil, natural gas and nuclear energy [38]. Especially in the case of France, is seems that nuclear energy

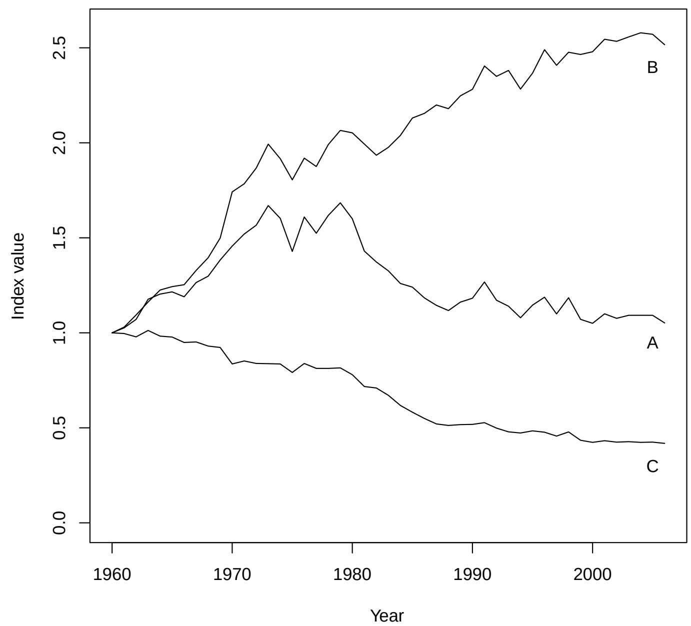

Figure 2: Curve A is the index of carbon emissions, B is a index energy consumption, and C is the carbon intensity. By definition $A = BC$.

factors, energy consumption and carbon intensity, need to be accounted for.

Hence, we need to consider a model where also energy use e_t depends on output y_t. To capture this dependency, we assume for simplicity that there is a linear relationship

$$e_t = \beta_e y_t + v_t, \tag{10}$$

where β_e a strictly positive parameter and v_t is the error term, which captures other factors affecting the relationship.[13]

has had a significant impact [see 39].

[13]This simplified specification ignores other important factors, which might change the

The existence of another cointegration equation can not be ruled out by the cointegration test results. The tests, that are derived from Johansen [27] reject the null hypothesis of zero cointegration equations against the alternative of one *or more* cointegration equations. In other words, the hypothesis, that there is a second cointegration equation like (10), is not rejected at any stage.[14] (See e.g. 41, p. 329; 34; 42, 43.)

Now, instead of just model equation (1), we need to look at system

$$c_t = \beta_0 + \beta_1 e_t + \beta_2 y_t + \beta_3 y_t^2 + u_t \tag{11a}$$

$$e_t = \beta_e y_t + v_t, \tag{11b}$$

where the EEO model is supplemented with the link between energy and output.

This link creates a bias in the parameter of interest. To assess this, we need to calculate a causal effect for system (11), and compare it with the causal effect in EEO model. The magnitude of the causal effect of output y_t on carbon emissions c_t in system (11) can be calculated by applying the implicit function rule, as done in Appendix B. The (total) causal effect is given by

$$\frac{\mathrm{d}c_t}{\mathrm{d}y_t} = (\beta_2 + 2\beta_3 y_t) + \beta_e \beta_1. \tag{12}$$

Now causal effect (12) can be compared with the biased interpretation in expression (8). We see clearly, that the EEO model specification is biased by

---

magnitude of the bias, but they should not affect its existence or direction, which are in focus here.

[14]Furthermore, a false negative occurs here often as the sample size is small and deterministic trends are possible [40].

the term $-\beta_e\beta_1$, which is negative in the plausible case: First, β_e is positive when a larger output implies more energy use. Second, the parameter β_1 should be also positive, as energy use has positive effect on carbon emissions. The bias equals to the causal effect of output on emissions through energy use, which was shown to be missing in EEO model.

The negative bias has two implications for the shape of the CKC.

First, the turning point of CKC is at a higher level of output when bias exists. We show this in Appendix B. This means the turning point will occur later than estimated.

A second implication for the shape is that the unbiased CKC grows quicker and declines more slowly, than the biased one. This is simply because, for all levels of output y_t, the biased causal effect is smaller than the unbiased one. Before the turning point of the biased CKC, carbon emissions are actually growing faster. After the biased CKC has turned, emissions are actually still growing for awhile. And after the true turning point, emissions are declining, but slower then the biased CKC implies.

The unbiased shape draws a more negative picture for the CKC hypothesis. If a CKC were to be found, economic growth would benefit climate policy goals later and to a lesser extent than estimated.

5. Conclusions

We have shown, first, that using a transformation of a regressor as a regressor in a VAR model creates a contradiction with the statistical assumptions. In such case, the standard estimators are not reliable. Hence the reported estimates are not sound.

Second, neglecting the dataset definitions alters the interpretation of the model parameters significantly. As a result, the question answered in the recent CKC literature is not the same as in earlier CKC literature. Only the relationship between carbon intensity and output is estimated, which neglects the possible dependence through energy use. The estimated relationship is not the CKC as a whole and therefore can not be compared with earlier studies.

Third, when energy use depends on output, the model is biased. As a result, the criticized model gives an overly optimistic view of the possibility to achieve climate policy goals simply through economic growth. If there is a turning point, it occurs later than expected. Before turning, output increases emissions faster, and afterwards, emissions drop slower than anticipated.

To answer any relevant questions about the CKC hypothesis, one can not simply combine the energy-output and carbon-output nexuses into one equation, as done in the recent literature. It seems as yet another attempt to find a EKC has failed.

Appendix A. Definition of carbon emissions

In this appendix we derive a identity from the definitions of the dataset. This identity is the source the second and third problem presented in Section 4.

First, the dataset in use (World bank's World Development Indicators, WDI) defines carbon dioxide emissions as a linear function of fossil fuel combustion and cement manufacturing. The amount of carbon dioxide emissions caused by combustion is determined by the chemical composition of the fuel. The emitted amount of carbon dioxide is calculated by multiplying the amount of fuel usage by a constant factor prescribed by the chemical properties of the fuel. Thus, the total carbon dioxide emissions C_t is a linear combination of the usage of oil E_t^{oil}, solid fuels E_t^{solid}, natural gas E_t^{gas}, and gas flaring E_t^{flare}, in addition to emissions from cement manufacturing S_t, all measured in per capita term. More formally, that is,

$$C_t \equiv \alpha_{oil} E_t^{oil} + \alpha_{solid} E_t^{solid} + \alpha_{gas} E_t^{gas} + \alpha_{flare} E_t^{flare} + S_t, \tag{A.1}$$

where α_{oil}, α_{solid}, α_{gas}, $\alpha_{flare} > 0$ are the related ratios of emissions to fuel quantity. [See 29]

Second, total energy use E_t can be defined as the sum of oil E_t^{oil}, solid fuels E_t^{solid}, natural gas E_t^{gas}, and other energy sources E_t^{other}, such as nuclear energy and renewable fuels, which do not cause emissions in the aforementioned sense.[15] Gas flaring does not result in energy production. Therefore

$$E_t \equiv E_t^{oil} + E_t^{solid} + E_t^{gas} + E_t^{other}.$$

To clarify the notation we define two sets of variable: the set of energy commodities affecting carbon dioxide emissions, $\mathfrak{C} = \{oil, solid, gas, flare\}$, and the set of energy commodities that amount to total energy use, $\mathfrak{E} = \{oil, solid, gas, other\}$.

Next let's define the proportions of fuel commodities in terms of total energy use,

$$q_t^i \equiv \frac{E_t^i}{E_t},$$

[15]Variable E_t^{other} does not enter equation (A.1) because possible emissions from such energy are not included in the definition of emissions in the database.

where $q_t^i \geq 0$ for all $i \in \mathfrak{E}$ and $\sum_{i \in \mathfrak{E}} q_t^i = 1$ for any t. By rearranging and plugging this into identity (A.1) to eliminate E_t^i for each i, we get

$$C_t \equiv E_t \sum_{i \in \mathfrak{C} \cap \mathfrak{E}} q_t^i \alpha_i + \alpha_{flare} E_t^{flare} + S_t.$$

By interpreting the sum term as the average emissions rate of energy consumption, we can identify it as *carbon intensity* and denote it by A_t, so that

$$C_t \equiv E_t A_t + \alpha_{flare} E_t^{flare} + S_t. \tag{A.2}$$

This is simply an accounting identity derived from the definitions of the dataset, so it must be satisfied by the observed values.

To derive an algebraically more convenient form, we note that gas flaring and cement manufacturing amount only to a percent of total carbon emissions in the data, thus they can be omitted, i.e. set to zero. Therefore taking a natural logarithm of equation (A.2) gives

$$c_t = e_t + a_t,$$

where the variables are the corresponding logarithms of the capital letter variables.

Appendix B. Mathematical derivations for section 5.3.

The magnitude of the causal effect of output y_t on carbon emissions c_t in system (11) can be assessed by applying the implicit function theorem to get the total derivative

$$\frac{\mathrm{d}c_t}{\mathrm{d}y_t} = -\frac{\begin{vmatrix} -(\beta_2 + 2\beta_3 y_t) & -\beta_1 \\ -\beta_e & 1 \end{vmatrix}}{\begin{vmatrix} 1 & -\beta_1 \\ 0 & 1 \end{vmatrix}}.$$

By calculating the determinants, we get a simplified expression for the (total) causal effect,

$$\frac{\mathrm{d}c_t}{\mathrm{d}y_t} = (\beta_2 + 2\beta_3 y_t) + \beta_e \beta_1. \tag{B.1}$$

Now causal effect (B.1) can be compared with the biased interpretation in expression (8). We see that the EEO model specification is biased by the term $-\beta_e\beta_1$, which is negative in the plausible case.

Next we show that the turning point of CKC is at a higher level of output when bias exists. In the unbiased case the turning point y_t^* is such that the causal effect (12) equals zero. This is equivalent to

$$y_t^* = \frac{-\beta_2 - \beta_e\beta_1}{2\beta_3}.$$

Similarly, in the biased case the turning point y_t^{**} satisfies

$$y_t^{**} = \frac{-\beta_2}{2\beta_3}.$$

Now, when $\beta_e\beta_1 > 0$, adding β_2 to both sides gives $\beta_2 + \beta_e\beta_1 > \beta_2$. Because β_2 is positive and β_3 is negative according to the CKC-hypothesis, we see that

$$\frac{-\beta_2 - \beta_e\beta_1}{2\beta_3} > \frac{-\beta_2}{2\beta_3}.$$

By noting the turning points, we get

$$y_t^* = \frac{-\beta_2 - \beta_e\beta_1}{2\beta_3} > \frac{-\beta_2}{2\beta_3} = y_t^{**}.$$

That is, the true turning point occurs at a higher level of output.

Acknowledgements

Many thanks to Silke Friedrich, Marc Gronwald, Hannu Kivimäki, Markku Lanne, Karen Pittel, Panu Poutvaara, Pentti Saikkonen, and Harri Turunen for helpful comments and discussion. Funding and support from HECER and Ifo Institute is gratefully acknowledged.

References

[1] Brock WA, Taylor MS. Chapter 28 economic growth and the environment: A review of theory and empirics. vol. 1, Part 2 of *Handbook of Economic Growth*. Elsevier; 2005, p. 1749–1821.

[2] Grossman GM, Krueger AB. Environmental impacts of a North American free trade agreement. NBER Working Papers 3914; National Bureau of Economic Research, Inc; 1991.

[3] Grossman GM, Krueger AB. Economic growth and the environment. The Quarterly Journal of Economics 1995;110(2):pp. 353–377.

[4] Copeland BR, Taylor MS. Trade, growth, and the environment. Journal of Economic Literature 2004;42(1):pp. 7–71.

[5] Stern DI. The rise and fall of the environmental Kuznets curve. World Development 2004;32(8):1419–1439.

[6] Aslanidis N. Environmental Kuznets curves for carbon emissions: A critical survey. Working Papers 2009.75; Fondazione Eni Enrico Mattei; 2009.

[7] Kijima M, Nishide K, Ohyama A. Economic models for the environmental Kuznets curve: A survey. Journal of Economic Dynamics and Control 2010;34(7):1187–1201.

[8] Richmond AK, Kaufmann RK. Is there a turning point in the relationship between income and energy use and/or carbon emissions? Ecological Economics 2006;56(2):176–189.

[9] Ang JB. CO_2 emissions, energy consumption, and output in France. Energy Policy 2007;35(10):4772–4778.

[10] Apergis N, Payne JE. CO_2 emissions, energy usage, and output in Central America. Energy Policy 2009;37(8):3282–3286.

[11] Apergis N, Payne JE. The emissions, energy consumption, and growth nexus: Evidence from the Commonwealth of Independent States. Energy Policy 2010;38(1):650–655.

[12] Pao HT, Tsai CM. CO_2 emissions, energy consumption and economic growth in BRIC countries. Energy Policy 2010;38(12):7850–7860. Special Section: Carbon Reduction at Community Scale;

[13] Pao HT, Tsai CM. Multivariate Granger causality between CO_2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of bric (brazil, russian federation, india, and china) countries. Energy 2011;36(1):685–693.

[14] Pao HT, Tsai CM. Modeling and forecasting the CO_2 emissions, energy consumption, and economic growth in Brazil. Energy 2011;36(5):2450–2458.

[15] Pao HT, Yu HC, Yang YH. Modeling the CO_2 emissions, energy use, and economic growth in Russia. Energy 2011;36(8):5094–5100.

[16] Wang S, Zhou D, Zhou P, Wang Q. CO_2 emissions, energy consumption and economic growth in China: A panel data analysis. Energy Policy 2011;39(9):4870–4875.

[17] Soytas U, Sari R, Ewing BT. Energy consumption, income, and carbon emissions in the United States. Ecological Economics 2007;62(3-4):482–489.

[18] Soytas U, Sari R. Energy consumption, economic growth, and carbon emissions: Challenges faced by an EU candidate member. Ecological Economics 2009;68(6):1667–1675. Eco-efficiency: From technical optimisation to reflective sustainability analysis;

[19] Lotfalipour MR, Falahi MA, Ashena M. Economic growth, CO_2 emissions, and fossil fuels consumption in Iran. Energy 2010;35(12):5115–5120. The 3rd International Conference on Sustainable Energy and Environmental Protection, SEEP 2009;

[20] Halicioglu F. An econometric study of CO_2 emissions, energy consumption, income and foreign trade in Turkey. Energy Policy 2009;37(3):1156–1164.

[21] Jalil A, Mahmud SF. Environment Kuznets curve for CO_2 emissions: A cointegration analysis for China. Energy Policy 2009;37(12):5167–5172.

[22] Jalil A, Feridun M. The impact of growth, energy and financial development on the environment in China: A cointegration analysis. Energy Economics 2011;33(2):284–291.

[23] Acaravci A, Ozturk I. On the relationship between energy consumption, CO_2 emissions and economic growth in Europe. Energy 2010;35(12):5412–5420. The 3rd International Conference on Sustainable Energy and Environmental Protection, SEEP 2009;

[24] Sharma SS. Determinants of carbon dioxide emissions: Empirical evidence from 69 countries. Applied Energy 2011;88(1):376–382.

[25] Engle RF, Granger CWJ. Co-integration and error correction: Representation, estimation, and testing. Econometrica 1987;55(2):251–276.

[26] Engle RF, Granger CWJ, Hallman JJ. Merging short-and long-run forecasts : An application of seasonal cointegration to monthly electricity sales forecasting. Journal of Econometrics 1989;40(1):45–62.

[27] Johansen S. Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control 1988;12(2-3):231–254.

[28] Reinsel GC, Ahn SK. Vector autoregressive models with unit roots and reduced rank structure: estimation, likelihood ratio test, and forecasting. Journal of Time Series Analysis 1992;13(4):353–375.

[29] Boden T, Marland G, Andres R. Global, Regional, and National Fossil-Fuel CO_2 Emissions. Oak Ridge, Tenn., U.S.A.: Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy; 2009.

[30] Ross M, Larson ED, Williams RH. Energy demand and materials flows in the economy. Energy 1987;12(10-11):953–967.

[31] Aichele R, Felbermayr G. Kyoto and the carbon footprint of nations. Ifo Working Paper Series Ifo Working Paper No. 103; Ifo Institute for Economic Research at the University of Munich; 2011.

[32] Müller-Fürstenberger G, Wagner M. Exploring the environmental Kuznets hypothesis: Theoretical and econometric problems. Ecological Economics 2007;62(3-4):648–660.

[33] Wagner M. The carbon Kuznets curve: A cloudy picture emitted by bad econometrics? Resource and Energy Economics 2008;30(3):388–408.

[34] Watson MW. Chapter 47 vector autoregressions and cointegration. vol. 4 of *Handbook of Econometrics*. Elsevier; 1994, p. 2843–2915.

[35] Haavelmo T. The statistical implications of a system of simultaneous equations. Econometrica 1943;11(1):1–12.

[36] Heckman JJ. The scientific model of causality. Sociological Methodology 2005;35(1):1–97.

[37] Heckman JJ, Vytlacil EJ. Chapter 70 econometric evaluation of social programs, part i: Causal models, structural models and econometric

policy evaluation. vol. 6, Part 2 of *Handbook of Econometrics*. Elsevier; 2007, p. 4779 – 4874.

[38] Kaufmann RK. A biophysical analysis of the energy/real GDP ratio: implications for substitution and technical change. Ecological Economics 1992;6(1):35–56.

[39] Iwata H, Okada K, Samreth S. Empirical study on the environmental Kuznets curve for CO_2 in France: The role of nuclear energy. Energy Policy 2010;38(8):4057–4063.

[40] Demetrescu M, Lütkepohl H, Saikkonen P. Testing for the cointegrating rank of a vector autoregressive process with uncertain deterministic trend term. Econometrics Journal 2009;12(3):414–435.

[41] Lütkepohl H. New Introduction to Multiple Time Series Analysis. Springer; 2005.

[42] Hamilton JD. Time Series Analysis. Princeton University Press; 1 ed.; 1994.

[43] Johansen S. Likelihood-Based Inference in Cointegrated Vector Autoregressive Models. Oxford University Press; 1995.