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Zhiyang Shen
IESEG School of Management (CNRS LEM 9221)

Jean-Philippe Boussemart
University of Lille 3 and IESEG School of Management (LEM-CNRS 9221)

Hervé Leleu
CNRS (LEM, UMR 9221) and IESEG School of Management

IESEG School of Management
Lille Catholic University
3, rue de la Digue
F-59000 Lille
www.ieseg.fr
Tel: 33(0)3 20 54 58 92
Fax: 33(0)3 20 57 48 55

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Zhiyang SHEN[a*], Jean-Philippe BOUSSEMART[b], Hervé LELEU[c]

[a] IÉSEG School of Management, CNRS, Univ. Lille, UMR 9221 - LEM, F-59000 Lille, France
email: z.shen@ieseg.fr

[b] Univ. Lille, CNRS, IÉSEG School of Management, UMR 9221 - LEM, F-59000 Lille, France
email: jp.boussemart@ieseg.fr

[c] CNRS, IÉSEG School of Management, Univ. Lille, UMR 9221 - LEM, F-59000 Lille, France
email: h.leleu@ieseg.fr

Abstract
Unlike most previous research, which has focused on estimating carbon shadow prices at regional or sectoral levels, this paper attempts to estimate carbon shadow prices at a worldwide level. A non-parametric robust framework estimates carbon shadow prices for 119 countries from all continents in 12 large groups. Our empirical results reveal that the global carbon shadow price is increasing by around 2.24% per annum and reached 2845 US dollars per ton in 2011. Regional carbon shadow prices present significant disparities and evolve within different categories over the analyzed period. We find a substantial sigma convergence process of carbon shadow prices among countries during 1990–2007 while divergence appears after the global financial crisis. We then analyze the relationship between carbon shadow prices and the implementation of the Kyoto Protocol.

JEL Classification: D24, Q56

Keywords: Undesirable Output, Carbon Shadow Price, Robust Frontier, Weak Disposability.

Corresponding author: Zhiyang SHEN, IÉSEG School of Management, 3 rue de la Digue, 59000 Lille France. Tel: +33(3) 20 54 58 92. Email: z.shen@ieseg.fr

1. Introduction

According to record of the U.S. National Centers for Environmental Information, 2014 was the warmest year ever, globally. Global warming threatens the survival of people all over the world, and scientists attribute climate change to emissions of greenhouse gases, such as carbon dioxide emissions. Carbon emissions have no real prices, but the opportunity costs for producers can be shown by carbon shadow prices—the amount of revenue that producers have to give up for a certain amount of carbon emission abatement—which provides useful information for environmental regulators. Nowadays, governments make great efforts to reduce carbon emissions and carry out different pricing approaches for carbon taxes. A popular approach is to set a gradually decreasing upper limit on carbon emissions and to allow exchanges of emissions permits in the market (Kossoy et al., 2015). Thus, the right to emit carbon dioxide changes from being a common resource good that is rivalrous but not excludable to a private good that is both rivalrous and excludable. When an amount of carbon emissions has a real price, is the price reasonable or fair to each producer? Lee et al. (2014) find that the carbon shadow price increases as the abatement level increases over time in South Korean electricity generating plants. Molinos-Senante et al. (2015) argue that the estimation of the carbon shadow price for non-power enterprises can provide incentives for reducing greenhouse gas emissions. The objective of this paper is to investigate the carbon shadow price at the worldwide level for its economic implications and references for global carbon pricing.

To estimate the shadow prices of undesirable outputs, both parametric and non-parametric methods, such as translog and quadratic functional forms or data envelopment analysis (DEA), tend to be used in the literature. Zhou et al. (2015) compare carbon abatement costs among Shanghai industrial sectors using the parametric and non-parametric approaches, with both the Shephard input/output and directional distance functions. Their results indicate that the type of distance functions plays a tiny role in estimating carbon shadow prices. However, the choice between parametric and non-parametric approaches affects the final prices significantly.

Compared to the parametric approach, a non-parametric framework based on activity analysis modeling makes it possible to explore the entire production technology, incorporating environmental elements without any particular specifications of functional forms. Zhou et al. (2008) classify two groups in modeling pollution-generating technologies among activity analysis models: one uses data transformation or treats undesirable outputs as inputs based on free disposability assumption while the other uses original data based on a weak disposability assumption. The latter approach is introduced by Färe et al. (1989), such that desirable and undesirable outputs can only be decreased proportionately by a uniform abatement factor. Kuosmanen et al. (2005) propose an improvement by setting non-uniform abatement factors for variable returns to scale (VRS) models; Kuosmanen and Matin (2011) develop the dual formulation for this model. The applications of Kuosmanen's model is available from Mekaroonreung and Johnson (2009), Berre et al. (2013), Berre et al. (2014), and Lee and Zhou (2015).

Recently, several pollution-generating technologies have been proposed in non-parametric models and debates have been generated on selecting the right way to model undesirable outputs, such as by-production technology, materials balance principles, and weak G-disposability, etc. Indeed, the choice of modeling technologies including environmental dimensions should be based on different criteria, according to the research question, the level of analysis (micro versus macro), and the types of pollution that are included in the production technology (SO_2, CO_2, NO_X, …).

In detail, weak disposability emphasizes the symbiosis between good and bad outputs, which suggests that pollution is difficult to abandon. Some pollutions are easily disposed of by the introduction of additional equipment. For example, most sulfides and nitrides are soluble in water, and a simple chemical treatment may deal with them effortlessly. Even if some of them are difficult to dissolve in water, they can be removed by inexpensive approaches (e.g., nitric oxide can be oxidized to nitric dioxide, which is soluble in water). Consequently, these pollutions can be at a null level in the final production. At this time, the traditional weak disposability assumption is not relevant, and results may not provide useful and precise information for environmental regulators. However, some other types of pollution, such as carbon dioxide, are difficult to dispose of, and therefore the weak disposability assumption seems more appropriate. Murty and Russell (2002) introduce the by-production approach, combining two sub-technologies, namely, intended production technology and residual generation technology. Their intersection indicates the right trade-offs in production activities (Murty et al., 2012). On the basis of the laws of thermodynamics/mass conservation, material balance principles require the balance of materials' bounds between physical inputs and outputs using weak G-disposability. These two last approaches (by-production and material balance) require detailed data, such as pollution-generating inputs, that may be not available for country-level analyses, which often retains

CO_2 as a bad output linked to GDP. Consequently, the weak disposability assumption still seems an appropriate manner to model the production technology at the macro level.

Reviews of environmental modeling technologies in a non-parametric framework can be found in Zhou et al. (2008), Song et al. (2012), Oude-Lansink and Wall (2014), Zhang and Choi (2014), and Dakpo et al. (2015), etc. Zhou et al. (2014) summarize the literature on shadow price estimation for undesirable outputs. They note that most of the previous papers focusing on the shadow prices of undesirable outputs are conducted at the micro level for energy plants or polluted firms because of data availability and that there is a lack of studies exploring this field across different countries at a macro level. Yörük and Zaim (2005) discover a positive correlation between environmental productivity and climate protocol among OECD countries. Wei et al. (2013) argue that carbon shadow prices are positively correlated with the technology level of thermal power enterprises. However, most papers ignore the relationship between carbon shadow prices and environmental protocol.

That being so, this paper investigates the global carbon shadow prices for 119 countries, both developed and developing, using a robust non-parametric model based on the weak disposability assumption in the first stage. In the second stage, we analyze the impact of the Kyoto Protocol on the evolution of carbon shadow prices. The rest of the paper is structured as follows: Section 2 reviews environmental production technology and proposes a robust DEA model for estimating carbon shadow prices; Section 3 introduces the data and presents the empirical results; Section 4 presents the conclusions.

2. Methodology

2.1 Model specification

In order to measure the worldwide carbon shadow price through a model of pollution-generating technology, we start from the Shephard's definition of weakly disposable technology (Färe & Grosskopf, 2003). Introduced by Shephard (1970, 1974), weak disposability and the null-joint condition are two classical assumptions usually used to model a pollution-generating technology. Weak disposability implies that proportional decreases in good and bad outputs are achievable through a scaling down of production activity through the introduction of an abatement factor, θ. From an economic point of view, desirable and undesirable outputs are joint outputs. In addition, the null-joint condition means that the desirable outputs cannot be made if the undesirable outputs are at the null level.

Let $\mathbf{x}=(x_1,...,x_N)\in R_+^N$ denote the vector of inputs, and $\mathbf{y}=(y_1,...,y_M)\in R_+^M$ and $\mathbf{z}=(z_1,...,z_J)\in R_+^J$ the vectors of desirable and undesirable outputs for a country, respectively. The technology and its corresponding output set are denoted by T and P:

$$T=\{(\mathbf{x},\mathbf{y},\mathbf{z}):\mathbf{x}\text{ can produce }(\mathbf{y},\mathbf{z})\} \qquad (1)$$

$$P(\mathbf{x})=\{(\mathbf{y},\mathbf{z}):(\mathbf{x},\mathbf{y},\mathbf{z})\in T\} \qquad (2)$$

Weak disposability and null-jointness assumptions can be defined as:

$$\text{If } (\mathbf{y},\mathbf{z})\in P(\mathbf{x}) \text{ and } 0\le\theta\le 1 \text{ then } (\theta\mathbf{y},\theta\mathbf{z})\in P(\mathbf{x}) \qquad (3)$$

$$\text{If } (\mathbf{y},\mathbf{z})\in P(\mathbf{x}) \text{ and } \mathbf{y}=\mathbf{0} \text{ then } \mathbf{z}=\mathbf{0} \qquad (4)$$

The directional distance function measures gaps between the observed production plans (countries) and the production frontier or the benchmark defined by the best practices. The inefficiency scores δ estimate these distances. Based on the Färe and Grosskopf axiomatic (FG), the production technology and directional distance function for an observed sample of K decision-making units (DMUs or countries) are defined by:

$$\hat{T}_{FG}=\left\{(\mathbf{x},\mathbf{y},\mathbf{z}):\mathbf{x}\in R_+^N,\,\mathbf{y}\in R_+^M,\,\mathbf{z}\in R_+^J,\ \theta\sum_{k=1}^{K}\mu_k y_k^m\ge y_{k'}^m,\ m=1,\cdots,M,\ \theta\sum_{k=1}^{K}\mu_k z_k^j=z_{k'}^j,\ j=1,\cdots,J,\right.$$
$$\left.\sum_{k=1}^{K}\mu_k x_k^n\le x_{k'}^n,\ n=1,\cdots,N,\ \sum_{k=1}^{K}\mu_k=1,\ \mu_k\ge 0\ \ k=1,...,K,\ 0\le\theta\le 1\right\} \qquad (5)$$

$$D_{T_{FG}}(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z}) = \sup_{\delta}\left\{\ \delta\in\Re_+ :\ (\mathbf{x},\mathbf{y}+\boldsymbol{\delta}\times\mathbf{g_y},\mathbf{z}\text{-}\boldsymbol{\delta}\times\mathbf{g_z})\in T_{FG}\ \right\} \qquad (6)$$

Next, the primal non-linear program under a VRS technology is denoted as:

$$\hat{D}_{T_{FG}}(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z}) = \max_{\delta,\mu,\theta} \ \delta$$
$$s.t. \ \theta\sum_{k=1}^{K}\mu_k y_k^m \geq y^m + \delta g_y^m \quad \forall m = 1,\cdots,M$$
$$\theta\sum_{k=1}^{K}\mu_k z_k^j = z^j - \delta g_z^j \quad \forall j = 1,\cdots,J$$
$$\sum_{k=1}^{K}\mu_k x_k^n \leq x^n \quad \forall n = 1,\cdots,N \qquad \text{(NLP1)}$$
$$\sum_{k=1}^{K}\mu_k = 1$$
$$\mu_k \geq 0 \quad \forall k = 1,...,K$$
$$0 \leq \theta \leq 1$$

The nonzero vector $(\mathbf{0},\mathbf{g_y},\mathbf{g_z})$ suggested by Chung et al. (1997) is intended to maximize desirable outputs and to minimize undesirable outputs simultaneously. To measure the carbon shadow price for each country, we employ output vector as the direction $(\mathbf{0},\mathbf{g_y},\mathbf{g_z})=(\mathbf{0},\mathbf{y},\mathbf{z})$, starting from a country sample of K DMUs. In NLP1, the production technology is non-linear, and this abatement effort is conventionally unique, shared with all countries under the VRS assumption. The corresponding VRS linearization related to a uniform abatement has been developed correctly by Zhou et al. (2008) and Sahoo et al. (2011). In order to maintain the convexity of the technology, Kuosmanen (2005) proposes non-uniform abatement factors as θ_k. The resulting technology is given by:

$$\hat{T}_{KU} = \left\{ (\mathbf{x},\mathbf{y},\mathbf{z}) : \mathbf{x} \in R_+^N, \mathbf{y} \in R_+^M, \mathbf{z} \in R_+^J, \sum_{k=1}^{K}\theta_k\mu_k y_k^m \geq y_{k'}^m, \ m = 1,\cdots,M, \ \sum_{k=1}^{K}\theta_k\mu_k z_k^j = z_{k'}^j, \ j = 1,\cdots,J, \right.$$
$$\left. \sum_{k=1}^{K}\mu_k x_k^n \leq x_{k'}^n, \ n = 1,\cdots,N, \ \sum_{k=1}^{K}\mu_k = 1, \ \mu_k \geq 0 \ \ k = 1,...,K, 0 \leq \theta_k \leq 1 \ \ k = 1,...,K \right\} \qquad (7)$$

Kuosmanen technology also leads to a straightforward linearization of Equation 7. Using changes of variables $\mu_k = \lambda_k + \sigma_k$ and $\lambda_k = \theta_k\mu_k$, the primal linear program under a VRS technology is defined as:

$$
\begin{aligned}
&\hat{D}_{T_{KU}}(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_{\mathbf{y}},\mathbf{g}_{\mathbf{z}}) = \max_{\delta,\lambda,\sigma}\ \delta \\
s.t.\ &\sum_{k=1}^{K}\lambda_k y_k^m \geq y^m + \delta g_y^m \quad \forall m = 1,\cdots,M \\
&\sum_{k=1}^{K}\lambda_k z_k^j = z^j - \delta g_z^j \quad \forall j = 1,\cdots,J \\
&\sum_{k=1}^{K}(\lambda_k + \sigma_k)x_k^n \leq x^n \quad \forall n = 1,\cdots,N \\
&\sum_{k=1}^{K}(\lambda_k + \sigma_k) = 1 \\
&\lambda_k \geq 0 \quad \forall k = 1,\ldots,K \\
&\sigma_k \geq 0 \quad \forall k = 1,\ldots,K
\end{aligned}
\tag{LP1}
$$

Kuosmanen and Podinovski (2009) argue that their model can provide new economic insights into weak disposability while Shephard's model violates the convexity axiom.

2.2 Shadow prices of undesirable outputs

Thanks to a non-parametric DEA approach, the shadow prices of outputs and inputs can be deduced from marginal values related to the constraints in the primal model even when the information of market prices is incomplete. These marginal values have no economic sense as absolute values, but their ratio may be interpreted as input marginal productivities, which can be derived from the Lagrangian method (Equation 8).

$$
\frac{\omega_x}{\omega_y} = -\frac{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_{\mathbf{y}},\mathbf{g}_{\mathbf{z}}) / \partial x}{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_{\mathbf{y}},\mathbf{g}_{\mathbf{z}}) / \partial y} \tag{8}
$$

In the same manner, the ratio of shadow prices of carbon emissions to GDP can be understood as the opportunity cost of reducing one extra unit of carbon emissions by giving up a certain unit of GDP. This ratio may provide useful information for producers and regulators to make trade-offs between economic benefits and environmental impacts in terms of negative externality. Although the shadow prices of undesirable outputs can usually be obtained by using the Lagrangian method (cf. Equation 9), the duality can bridge the gap between the production technologies and may provide more explicit economic representations than the primal model can.

$$\frac{\omega_z}{\omega_y} = -\frac{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z})/\partial z}{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z})/\partial y} \qquad (9)$$

Kuosmanen and Matin (2011) develop the dual formulation of LP1 to derive the shadow prices of bad outputs, which provides an economic interpretation for weak disposability. In Kuosmanen's initial model, the shadow prices of bad outputs are unconstrained, allowing negative and positive values. Consequently, bad outputs are allowed to involve benefits or costs in production activity that could generate ambiguous economic signals. We therefore change the equality sign to inequality ($\leq$) in the second constraint of LP1, meaning that bad outputs can only produce costs (negative revenues).

Finally, we compute the corresponding constrained dual model for each country (*k'*) as:

$$\begin{aligned}
&\hat{D}(\mathbf{x}_{k'},\mathbf{y}_{k'},\mathbf{z}_{k'};\mathbf{0},\mathbf{g_y},\mathbf{g_z}) = \min_{\phi,\pi_x,\pi_y,\pi_z} [\ \phi - \ (\sum_{m=1}^{M}\pi_y^m y_{k'}^m - \sum_{j=1}^{J}\pi_z^j z_{k'}^j - \sum_{n=1}^{N}\pi_x^n x_{k'}^n)] \\
&s.t.\ \sum_{m=1}^{M}\pi_y^m y_k^m - \sum_{j=1}^{J}\pi_z^j z_k^j - \sum_{n=1}^{N}\pi_x^n x_k^n \leq \phi \quad \forall k = 1,\cdots,K \\
&-\sum_{n=1}^{N}\pi_x^n x_k^n \leq \phi \quad \forall k = 1,\cdots,K \\
&\sum_{m=1}^{M}\pi_y^m g_y^m + \sum_{j=1}^{J}\pi_z^j g_z^j = 1 \qquad\qquad \text{(LP2)} \\
&\pi_y^m \geq 0 \quad \forall m = 1,\dots,M \\
&\pi_z^j \geq 0 \quad \forall j = 1,\dots,J \\
&\pi_x^n \geq 0 \quad \forall n = 1,\dots,N
\end{aligned}$$

The shadow prices of inputs and good and bad outputs—defined by ω_x, ω_y, and ω_z—can be directly computed from LP2 by the estimated values of π_x, π_y, and π_z (Equations 10 and 11). In LP2, the objective function is to minimize the profit inefficiency of the evaluated country (*k'*) by minimizing the difference between optimal shadow profit ϕ and the shadow profit for *k'* derived from the best shadow prices and observed inputs and outputs $(\sum_{m=1}^{M}\pi_y^m y_{k'}^m - \sum_{j=1}^{J}\pi_z^j z_{k'}^j - \sum_{n=1}^{N}\pi_x^n x_{k'}^n)$ (Berre et al., 2013).

$$\frac{\hat{\omega}_x}{\hat{\omega}_y} = -\frac{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z})/\partial x}{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z})/\partial y} = \frac{\pi_x}{\pi_y} \tag{10}$$

$$\frac{\hat{\omega}_z}{\hat{\omega}_y} = -\frac{\partial \hat{D}_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z})/\partial z}{\partial \hat{D}_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z})/\partial y} = \frac{\pi_z}{\pi_y} \tag{11}$$

A methodological point deserves discussion at this stage. It is well known that when linear programs are degenerate, several shadow prices are obtained and multiple solutions exist. This is generally a problem because we cannot decide easily which solution must be kept. Our approach, developed in the next section, circumvents this obstacle through a sub-sampling approach. While a large number of replications are computed, we can expect that the average shadow prices calculated from their empirical distributions are representative.

2.3 Estimation approach: A robust DEA model

The directional distance function defined in (6) makes it possible to evaluate gaps between the observed production plan and the relevant production frontier defined by best practices. As the true frontier is unknown, this distance function in a general multi-output, multi-input framework is gauged through LP1 or LP2. Owing to their non-parametric nature, these linear programs permit the avoidance of eventual bias effects on efficiency scores and shadow prices resulting from the arbitrary choice of the functional forms of technology necessary for econometric methods. However, this enveloping technique has a major drawback: it is difficult to incorporate statistical noise into the empirical estimations. Therefore, estimated shadow prices may be significantly influenced by potential outliers belonging to the production set. This issue can be resolved through successive sub-sampling frontier estimations rather than only one traditional full frontier. Consequently, in our empirical analysis, the presence of potential outliers is taken into account by applying an estimation strategy proposed by Kneip et al. (2008) and Cazals et al. (2002), from which consistent estimators can be derived. More precisely, partial frontiers are constructed from a large number of Monte-Carlo replications ($b=1,\cdots,B$), by selecting different random sub-samples of size I ($I \in K$) with replacement and based on the initial observed DMUs. Their corresponding production sets are now defined as:

$$\hat{T}_{KU}^{b} = \left\{ (\mathbf{x},\mathbf{y},\mathbf{z}) : \mathbf{x} \in R_{+}^{N},\ \mathbf{y} \in R_{+}^{M},\ \mathbf{z} \in R_{+}^{J},\ \sum_{k=1}^{I} \lambda_k y_k^m \geq y_{k'}^m,\ m=1,\cdots,M,\ \sum_{k=1}^{I} \lambda_k z_k^j \leq z_{k'}^j,\ j=1,\cdots,J, \right.$$
$$\left. \sum_{k=1}^{I} (\lambda_k + \sigma_k) x_k^n \leq x_{k'}^n,\ n=1,\cdots,N,\ \sum_{k=1}^{I} (\lambda_k + \sigma_k) = 1,\ \lambda_k \geq 0\ \ k=1,...,I,\ \sigma_k \geq 0\ \ k=1,...,I \right\} \tag{12}$$

This leads to defining the directional distance function relative to each sub-sample (b) as:

$$\hat{\delta}_{k'}^{b}(y_{k'}^m, z_{k'}^j, x_{k'}^n) = \max \left\{ \delta : (y_{k'}^m + \delta y_{k'}^m, z_{k'}^j - \delta z_{k'}^j, x_{k'}^n) \in \hat{T}_{KU}^{b} \right\} \tag{13}$$

Finally, robust values of the shadow prices of inputs and good and bad outputs are obtained from their empirical distributions as:

$$\begin{aligned} \hat{\pi}_x &= \frac{1}{B} \sum_{b=1}^{B} \hat{\pi}_x^b \\ \hat{\pi}_y &= \frac{1}{B} \sum_{b=1}^{B} \hat{\pi}_y^b \\ \hat{\pi}_z &= \frac{1}{B} \sum_{b=1}^{B} \hat{\pi}_z^b \end{aligned} \tag{14}$$

This robust frontier approach is characterized by the number of replications (B) and the size (I) of the sub-samples. The number of the Monte-Carlo replications has to be large enough to check the sensitivity of the final results. If the sub-sample size reaches infinity, one gets back to the shadow prices of LP2 because each country of the entire sample has a high probability of selection into the sub-technology. By contrast, with too small values for I, the referent production set might be inappropriate. As a result, through a relevant choice between these two parameters, the robust frontier approach implies a trade-off between a pertinent definition of the technology and a control of the outlier bias effects.

3. Data and results

3.1. Data

In order to estimate global carbon shadow prices, we try to integrate as large a number as possible of country samples from all over the world. Our data covers 119 countries in 12 groups for the period from 1990 to 2011: 20 countries from Africa (Angola, Benin, Botswana, Cameroon, Côte d'Ivoire, Democratic Republic of the Congo, Ethiopia, Gabon, Ghana, Kenya, Morocco, Mozambique, Nigeria, Republic of the Congo, Senegal, Sudan, Togo, Tunisia, Zambia, and Zimbabwe), 10 countries from Asia (Bangladesh, Brunei Darussalam, Malaysia, Mongolia, Nepal, Pakistan, Philippines, Singapore, Sri Lanka, and Thailand), 4 countries from the BRI(C)S (Brazil, India, Russian Federation, and South Africa), 5 countries from CIVET (Colombia, Egypt, Indonesia, Turkey, and Viet Nam), 11 countries from the Middle East (Bahrain, Islamic Republic of Iran, Iraq, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, and Yemen), 14 countries from the Non-OECD Americas (Argentina, Bolivia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Panama, Peru, Trinidad and Tobago, Uruguay, and Venezuela), 21 countries from Non-OECD Europe and Eurasia (Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Malta, Republic of Moldova, Romania, Serbia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan), 3 countries from the OECD Americas (Canada, Chile, and Mexico), 5 countries from OECD Asia Oceania (Australia, Israel, Japan, New Zealand, and Republic of Korea), 24 countries from OECD Europe (Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom), and the two biggest carbon emitters, China, and the United States of America (USA), respectively.

We use two inputs, one desirable output, and one undesirable output: capital stock, labor force, real GDP, and carbon dioxide emissions, respectively. Capital stock is measured using the perpetual inventory method at current purchasing power parities in 2005 US million dollars. The labor force is measured as number of persons employed, in millions. Real GDP is measured as output-side at current purchasing power parities in 2005 US million dollars. Carbon emissions are based on sectoral approach in million tons. The first three are taken from the Penn World Table 8.1 (Feenstra et al., 2015) and the last from fuel combustion highlights (International Energy Agency, 2014).

Table 1 shows the average growth rates of inputs and outputs. China, the Middle East, CIVET, and Asia have the top four growth rates of capital stock (all higher than 6%), possibly because of their proactive investment policies and good financing environment. We note that a negative growth in labor force appears only in Non-OECD Europe and Eurasia (-0.34%) and that the global trend is increasing, at 1.43%. The growth rates of real GDP in the Middle East, China, and Africa, the three highest, respectively, are all above 5%. China has the highest growth rate of carbon emissions (5.91%) and has been the largest emitter, rather than the USA, since 2008. Although the USA has a high level of carbon emissions, it is increasing at only 0.6%. Europe has negative growth in carbon emissions (-0.15%) thanks to effective and efficient environmental policies. We also notice that Non-OECD Europe and Eurasia has a negative trend in carbon emissions (-1.78%), reflecting the economic downturn after the collapse of the former Soviet Union.

Table 1 about here

3.2. Empirical results

Because we may have introduced outliers into production technology owing to the disparate scales of national economies and carbon emissions among countries, a robust frontier approach is implemented. We simulate $B = 1000$ replications with a sub-sample size $I = 90$ out of the 119 countries in the initial sample. The robust shadow prices are computed by the mean values of the 1000 replications in the first stage.

In Figure 1, the evolution of the carbon shadow price at a worldwide level is measured by the average value of each group in logarithm terms. The carbon shadow price is significantly increasing, at an annual rate of 2.24% (t-value=6.81). This first result is in line with Table 1, which clearly shows that the growth rate of real GDP is around twice as high as that for CO_2. This suggests that pollution issues have been taken more into account by most of countries, particularly in Non-OECD Europe, OECD Europe, and the USA. The worldwide carbon shadow price is evaluated at around 1213 US dollars per ton in 1990 and experiences a steady fifteen-year growth between 1991 and 2005 to around 2191 US dollars per ton in 2005. A significant decrease in the carbon shadow price is observed between 2005 and 2009, followed by a substantial rise for 2009–2011; its mean value is around 2845 US dollars per ton in 2011.

Figure 1 about here

The kernel densities of carbon shadow prices are plotted in Figure 2. In most regions, carbon shadow prices are distributed around 600 US dollars per ton in 1990 and 2400 US dollars per ton in 2011. The right side shift of the kernel density peaks between these two periods confirms the positive growth for carbon shadow prices. Simultaneously, their distribution is significantly more dispersed.

Figure 2 about here

For a specific group of countries, the regional carbon shadow prices show clustering characteristics. In Figure 3, three groups of carbon shadow prices can be easily identified at the beginning of the sample period. The first group includes Africa, Asia, and the Non-OECD Americas, presenting the highest carbon shadow prices. The second group contains China and the USA, which record the lowest carbon shadow prices. These levels indicate that their marginal abatement costs of carbon emission are very low. The third group contains the rest of the regions, with shadow prices between the first and the second groups' levels.

Figure 3 about here

We find that the three groups evolve into five new bunches of countries at the end of the sample period. First, Africa still has the highest carbon shadow prices. The new second group is composed of Asia, the Non-OECD Americas, and Non-OECD Europe and Eurasia. Their carbon shadow prices are just below the African level. The third group gathers OECD Europe, the Middle East, and CIVET. These three groups have relatively high carbon shadow prices, which indicates that they have less of an impact on global warming. The rest of the regions except China comprises the fourth group. The fourth group and China dominate the lowest carbon shadow prices, which implies that they contribute much of the world's pollution. In other words, they produce GDP without considering environmental costs. However, all countries have to share the pollution and pay for carbon taxes.

We note that the carbon shadow prices of the BRI(C)S, OECD Asia Oceania, and the OECD Americas tend to be of a similar level while OECD Europe is detached from the other

OECD groups during this evolution. The growth of carbon shadow prices in OECD Europe indicates that effective and efficient environmental policies has been carried out.

On the whole, developed countries have lower carbon shadow prices, developing regions dominate higher carbon marginal abatement costs, and BRICS countries have a relatively low opportunity cost of carbon abatement. This result is consistent with Maradan and Vassiliev (2005), who point out that the marginal carbon abatement cost is generally higher in developing countries than in developed ones even if carbon shadow prices in some developing countries are lower than those in high-income countries.

The growth rates of carbon shadow prices for each region are displayed in Table 2. Most of the observed regions reveal significantly increasing trends in carbon shadow prices while the BRICS countries record negative growths. These results can be summarized as follows:

1) Favored emerging economies show rapid economic development, and their economic growth is essentially dependent on high energy consumption, implying carbon emissions;

2) countries with higher carbon emissions have lower opportunity costs for reducing pollution; and

3) shadow price distributions show substantial disparities among countries.

Table 2 about here

As shown in Figure 4, one can observe a sigma convergence of carbon shadow prices over the period 1990–2007. The decline of variation coefficient is around -3.6% per year and is statistically significant (t-value = -14.43). Conversely, a sigma divergence is detected between 2008 and 2011. This phenomenon may be correlated with the global financial crisis triggered in the USA. Woo et al. (2015) argue that environmental efficiency is being affected by the global financial crisis. Our results show that this crisis may potentially affect carbon shadow prices.

Figure 4 about here

Finally, in order to examine the impact of the Kyoto Protocol on the carbon shadow prices, we conduct a regression analysis. Historically, the Kyoto Protocol was adopted at the third session of the conference of the parties (COP 3) in 1997. It was open for signature from 1998 to 1999 and received 84 signatures at that time, but 191 states are now party to it.[1] The effect of the Kyoto Protocol (*KP*) is tested in a fixed effect panel model. According to the date of entry into force, a dummy variable is created for each country and year (cf. Appendix). We add to the regression equation the ratio of carbon emissions to GDP as a control variable (CO_2/GDP), with ε denoting the error term (cf. Equation 15). Time-fixed effects are also introduced through parameter α_t . Consistent with the robust approach we used to compute shadow prices, our estimation strategy is to run a regression per sub-sampling replication and to build confidence intervals for parameters of interest from the empirical distribution of the fixed effects estimators. The regression model is defined by Equation 15, and the results are presented in Table 3 and Figure 5.

$$\ln CSP_{it} = \alpha_t + \beta_0 + \beta_1 \ln(CO_2 / GDP)_{it} + \beta_2 Dummy(KP)_{it} + \varepsilon_{it} \quad (15)$$

Table 3 about here

Figure 5 about here

According to our findings, we conclude that the implementation of the Kyoto Protocol has not a very effective impact on the evolution of carbon shadow prices. The kernel density of β_2 displayed in Figure 5 shows that the distribution of the parameters is mostly positive, but we cannot reject the finding that zero belongs to this distribution at the 5% level. Therefore, we have to conclude that the Kyoto Protocol did not significantly affect the pollution regulations of engaged states. This emphasizes that further cooperation and efforts at carbon reduction among countries, such as the Copenhagen Accord of 2009 and the Paris climate conference of 2015, were necessary.

4. Conclusions

[1] Sourced from the United Nations Framework Convention on Climate Change: http://unfccc.int/kyoto_protocol/status_of_ratification/items/2613.php

Global warming and carbon pricing were the core issues of the last conference of the parties (COP 21) in Paris in 2015. Most states support the idea of carbon pricing to bring down emissions. A remaining question is the best way that governments can price carbon emissions. Currently, two main types of mechanism can be used: emissions-trading systems, which essentially fix the quota for emissions, leading to an ex-post market price for carbon, and taxes that directly set a price on carbon without constraining ex-ante the volume of emissions. At the moment, given the difficulty of fixing a carbon price, governments favor the first option.

Our analysis is more in line with the second mechanism and could help policy makers to evaluate levels of carbon pricing among different countries and to fix relevant carbon taxes. Through a non-parametric robust frontier, we estimate worldwide carbon shadow prices, incorporating desirable and undesirable outputs, for a sample of 119 countries. According to our empirical results, the carbon shadow price is increasing at a rate of 2.24% per annum, reaching 2845 US dollar per ton in 2011, which suggests that carbon abatement may become increasingly challenging at the worldwide level. However, significant disparities are observed among groups of countries and over time. A significant sigma convergence of carbon shadow prices is observed among regions between 1990 and 2007, while a divergence is detected over the period 2007–2011. This means that economic fluctuations and shocks may affect carbon shadow prices.

In this paper, we conclude that the Kyoto Protocol has had no significant impact on carbon shadow prices. Therefore, countries need to keep engaging in Kyoto resolutions. A new agreement was adopted at the Paris climate conference, which included more countries and ambitious targets. While the necessity of carbon pricing is more and more commonly shared among parties, the main question relates to the uniqueness of the CO_2 tax. Our main conclusion suggests that unique carbon pricing for countries with different levels of economic development and pollution may be unfair or unreasonable. Carbon taxes should be settled according to the respective social capabilities of states.

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Table 1. Average growth rates of inputs and outputs 1990–2011

Regions	Capital Stock	Labor Force	Real GDP	CO_2
Africa	4.95%	2.68%	5.65%	3.28%
Asia	6.28%	2.26%	4.18%	4.62%
BRI(C)S	2.78%	1.73%	3.95%	1.43%
CIVET	7.24%	1.77%	3.85%	4.62%
Middle East	7.61%	3.68%	8.49%	4.83%
Non-OECD Americas	5.16%	2.05%	4.61%	3.17%
Non-OECD Europe and Eurasia	2.03%	-0.34%	2.44%	-1.78%
OECD Americas	3.20%	1.98%	3.15%	1.78%
OECD Asia Oceania	4.05%	0.41%	2.03%	1.52%
OECD Europe	3.73%	0.75%	2.91%	-0.15%
China	11.05%	1.00%	6.72%	5.91%
USA	3.73%	0.93%	2.72%	0.60%
Total	4.68%	1.43%	3.69%	2.02%

Table 2. Average growth rates of carbon shadow prices 1990–2011

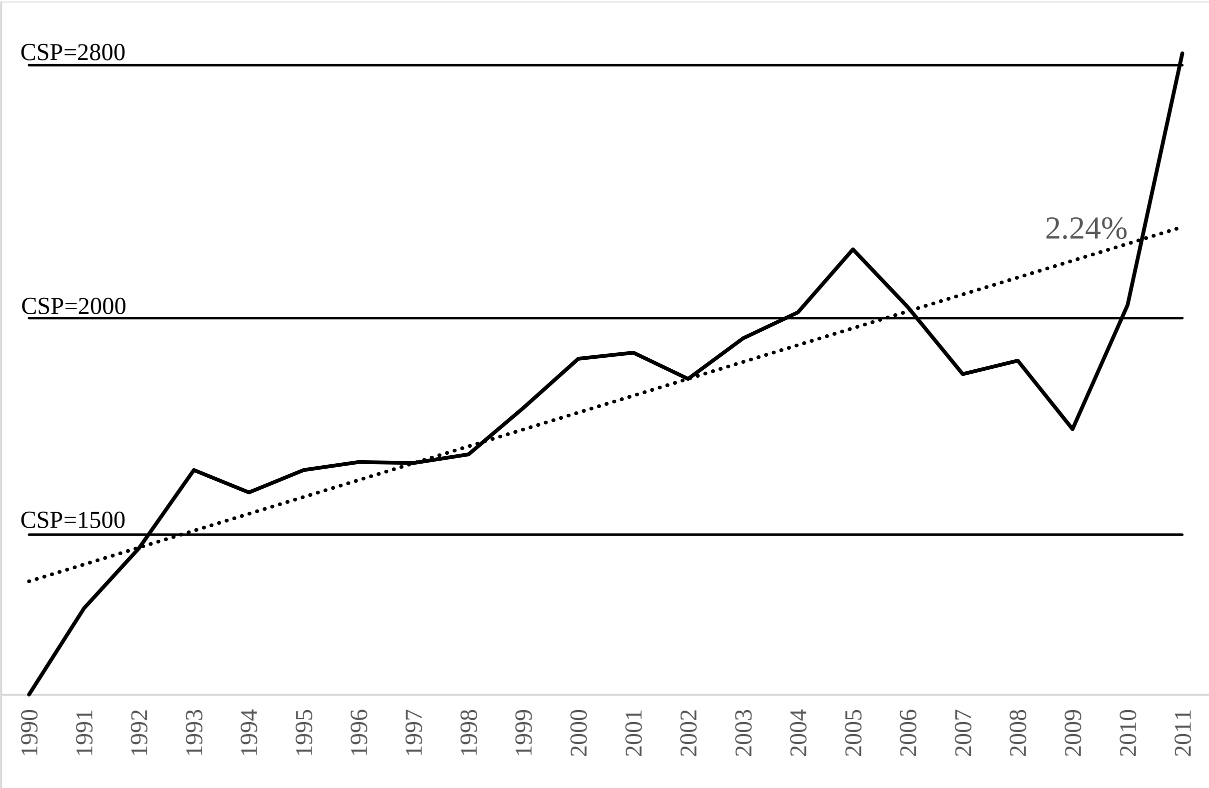
Regions	coefficient	t-value
Africa	1.00%	1.69
Asia	0.79%	2.65
BRI(C)S	-0.97%	-1.01
CIVET	5.22%	12.55
Middle East	2.28%	3.70
Non-OECD Americas	3.10%	6.80
Non-OECD Europe and Eurasia	3.56%	2.58
OECD Americas	0.74%	0.76
OECD Asia Oceania	4.43%	4.25
OECD Europe	7.01%	14.97
China	-4.81%	-5.03
USA	2.31%	3.05
Total	2.24%	6.81

Table 3. Estimates of the Kyoto Protocol equation (15)

Coefficient	**Mean estimation**	**Lower bound (2.5%)**	**Upper bound (97.5%)**	**Significance at 5% level***
β_0	6.521	5.426	7.516	Yes
β_1	-0.048	-0.200	0.096	No
β_2	0.198	-0.060	0.455	No

*A coefficient is significantly different from 0 if the confidence interval does not include 0.

Figure 1. Shadow prices of carbon emissions at worldwide level (in logarithmic terms)



CSP: Carbon shadow price ($/ton)

Figure 2. Kernel density of carbon shadow prices

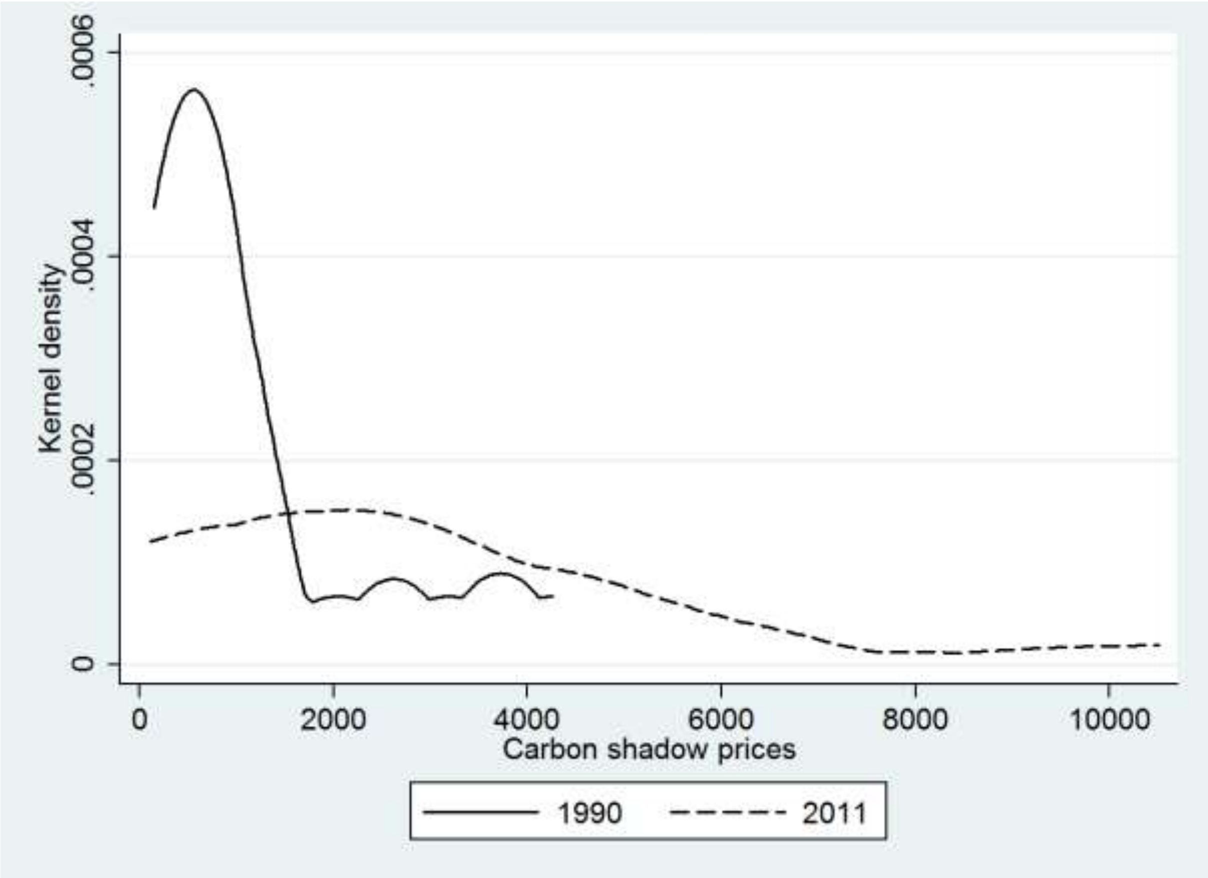
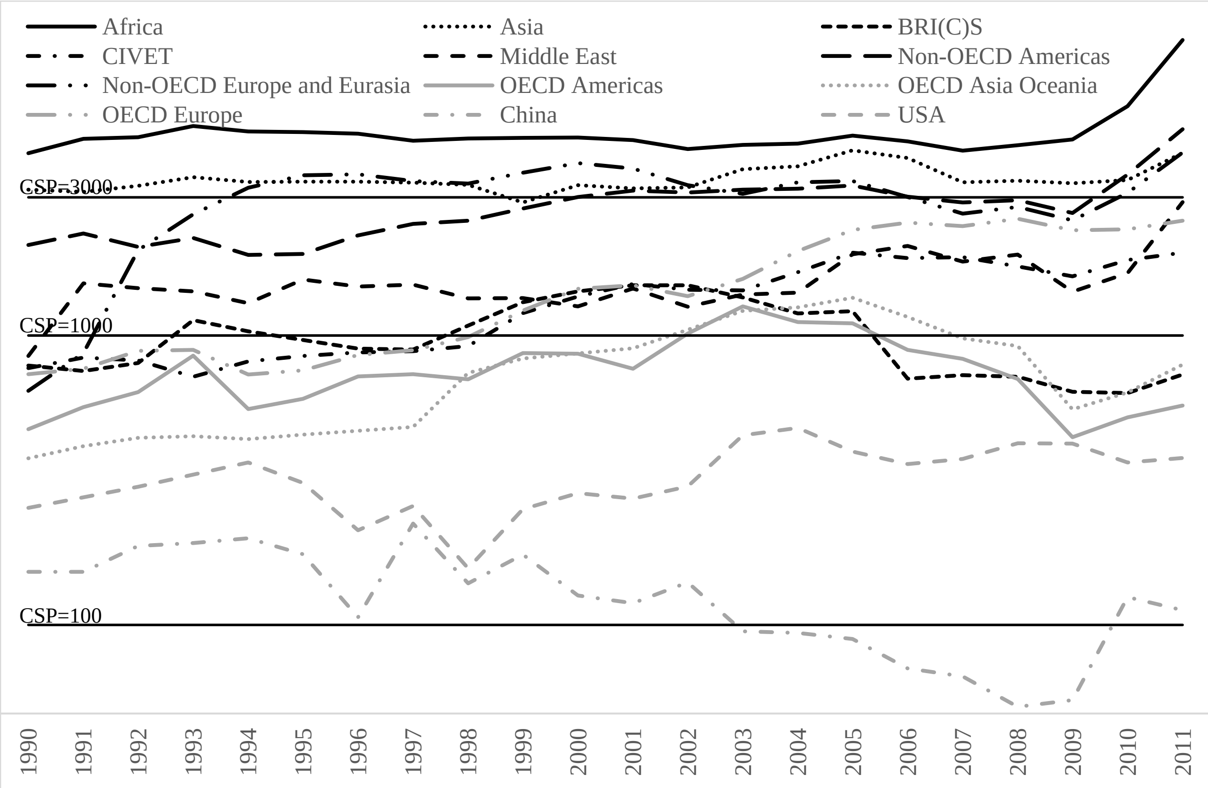


Figure 3. Shadow prices of carbon emissions (in logarithmic terms)



CSP: Carbon shadow price ($/ton)

Figure 4. Variation coefficient of shadow prices

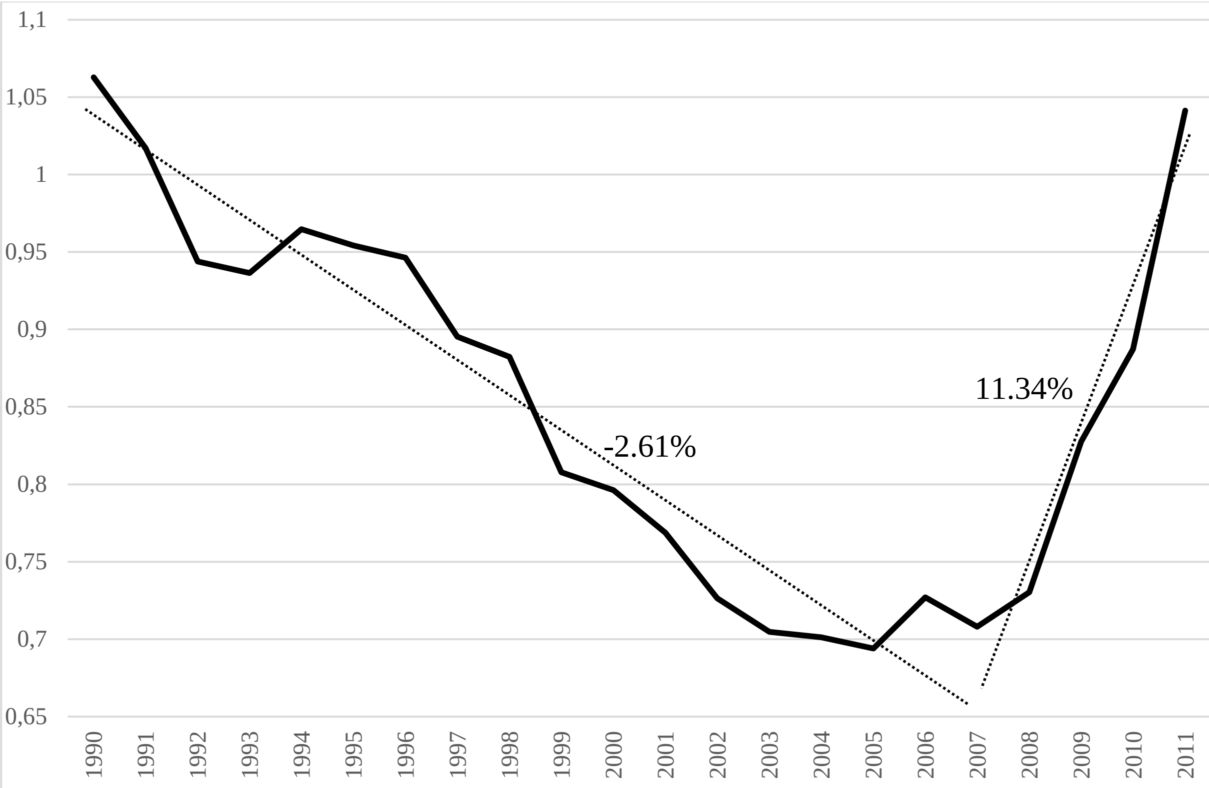
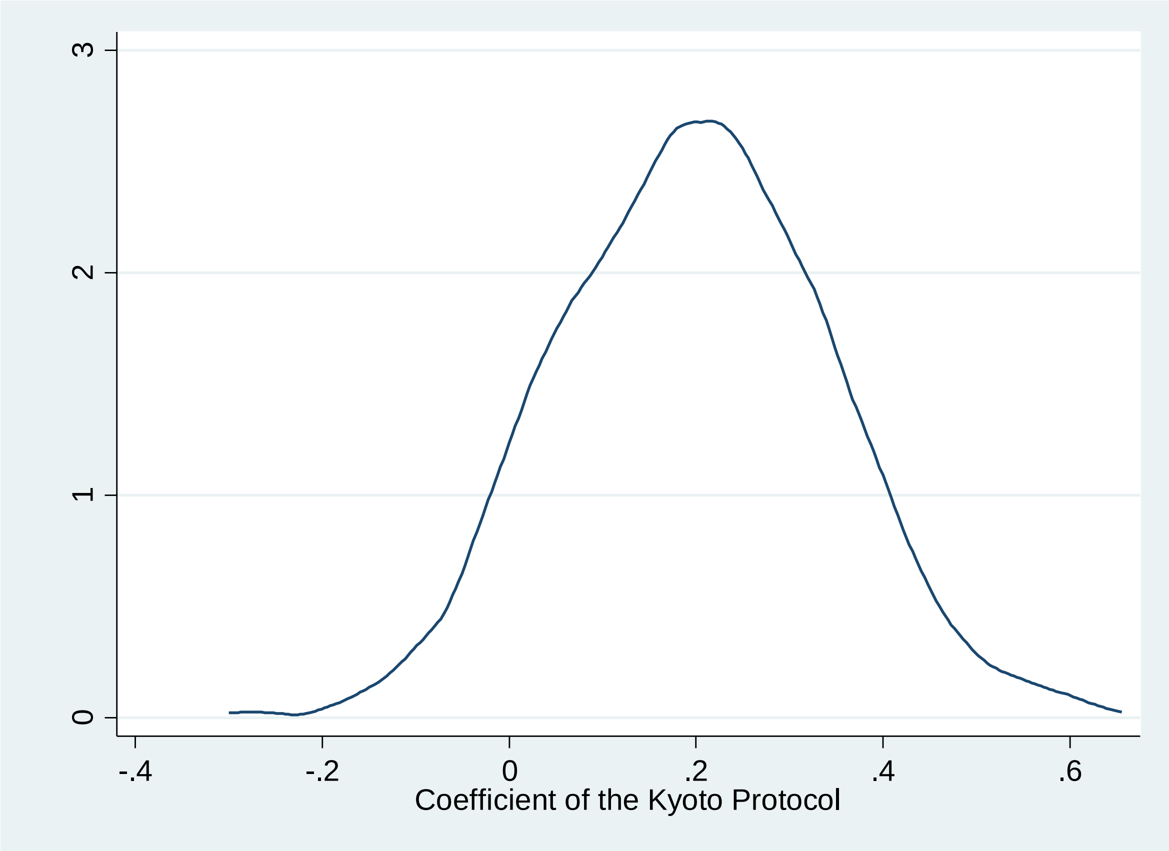


Figure 5. Kernel density of coefficient of the Kyoto Protocol



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Appendix: Implementation dates of the Kyoto Protocol

Country	Entry into force	Country	Entry into force	Country	Entry into force
ALBANIA	30-Jun-05	GEORGIA	16-Feb-05	PERU	16-Feb-05
ANGOLA	6-Aug-07	GERMANY	16-Feb-05	PHILIPPINES	16-Feb-05
ARGENTINA	16-Feb-05	GHANA	16-Feb-05	POLAND	16-Feb-05
ARMENIA	16-Feb-05	GREECE	16-Feb-05	PORTUGAL	16-Feb-05
AUSTRALIA	11-Mar-08	GUATEMALA	16-Feb-05	QATAR	11-Apr-05
AUSTRIA	16-Feb-05	HONDURAS	16-Feb-05	R. KOREA	16-Feb-05
AZERBAIJAN	16-Feb-05	HUNGARY	16-Feb-05	R. MOLDOVA	16-Feb-05
BAHRAIN	1-May-06	ICELAND	16-Feb-05	ROMANIA	16-Feb-05
BANGLADESH	16-Feb-05	INDIA	16-Feb-05	RUSSIAN	16-Feb-05
BELARUS	24-Nov-05	INDONESIA	3-Mar-05	SAUDI ARABIA	1-May-05
BELGIUM	16-Feb-05	IRAN	20-Dec-05	SENEGAL	16-Feb-05
BENIN	16-Feb-05	IRAQ	26-Oct-09	SERBIA	17-Jan-08
BOLIVIA	16-Feb-05	IRELAND	16-Feb-05	SINGAPORE	11-Jul-06
BOSNIA & H.	15-Jul-07	ISRAEL	16-Feb-05	SLOVAKIA	16-Feb-05
BOTSWANA	16-Feb-05	ITALY	16-Feb-05	SLOVENIA	16-Feb-05
BRAZIL	16-Feb-05	JAMAICA	16-Feb-05	SOUTH AFRICA	16-Feb-05
BRUNEI D.	18-Nov-09	JAPAN	16-Feb-05	SPAIN	16-Feb-05
BULGARIA	16-Feb-05	JORDAN	16-Feb-05	SRI LANKA	16-Feb-05
CAMEROON	16-Feb-05	KAZAKHSTAN	17-Sep-09	SUDAN	16-Feb-05
CANADA	16-Feb-05	KENYA	26-May-05	SWEDEN	16-Feb-05
CHILE	16-Feb-05	KUWAIT	9-Jun-05	SWITZERLAND	16-Feb-05
CHINA	16-Feb-05	KYRGYZSTAN	16-Feb-05	SYRIAN A. R.	27-Apr-06
COLOMBIA	16-Feb-05	LATVIA	16-Feb-05	TAJIKISTAN	29-Mar-09
CONGO	13-May-07	LEBANON	11-Feb-07	THAILAND	16-Feb-05
COSTA RICA	16-Feb-05	LITHUANIA	16-Feb-05	TOGO	16-Feb-05
COTE D’IVOIRE	22-Jul-07	LUXEMBOURG	16-Feb-05	TRINIDAD & T.	16-Feb-05
CROATIA	28-Aug-07	MALAYSIA	16-Feb-05	TUNISIA	16-Feb-05
CYPRUS	16-Feb-05	MALTA	16-Feb-05	TURKEY	26-Aug-09
CZECH R.	16-Feb-05	MEXICO	16-Feb-05	TURKMENISTAN	16-Feb-05
D. R. CONGO	21-Jun-05	MONGOLIA	16-Feb-05	UKRAINE	16-Feb-05
DENMARK	16-Feb-05	MOROCCO	16-Feb-05	UK	16-Feb-05
DOMINICAN R.	16-Feb-05	MOZAMBIQUE	18-Apr-05	USA	None
ECUADOR	16-Feb-05	NEPAL	15-Dec-05	URUGUAY	16-Feb-05
EGYPT	12-Apr-05	NETHERLANDS	16-Feb-05	UZBEKISTAN	16-Feb-05
EL SALVADOR	16-Feb-05	NEW ZEALAND	16-Feb-05	VENEZUELA	19-May-05
ESTONIA	16-Feb-05	NIGERIA	10-Mar-05	VIET NAM	16-Feb-05
ETHIOPIA	13-Jul-05	NORWAY	16-Feb-05	YEMEN	16-Feb-05
FINLAND	16-Feb-05	OMAN	19-Apr-05	ZAMBIA	5-Oct-06
FRANCE	16-Feb-05	PAKISTAN	11-Apr-05	ZIMBABWE	28-Sep-09
GABON	12-Mar-07	PANAMA	16-Feb-05		

Sourced from the United Nations Framework Convention on Climate Change.