Substitute or Complement? Assessing Renewable and Non-renewable Energy in OECD Countries

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Abstract

Elasticity of interfuel substitution between renewable and non-renewable energy is a key to establish effective climate change policy.This is the first study estimating the elasticity of substitution between different fossil fuels and renewable resources. We use twelve manufacturing industry level data for the OECD countries over 1995 to 2009. We find complementally relationship from non-renewable energy to renewable energy in eight industries while substitute relationship holds for four industries. In particular, food and pulp industries have strong complementally relationship.

Keywords: *Fossil fuels, Renewable energy, Morishima elasticity of substitution, Directional distance function, shadow price of* CO_2, *OECD countries*
JEL Classification: L60, Q20, Q42

1. Introduction

Climate change threatens future well-being and stability. Large cuts in the carbon emissions are required to mitigate negative effects of climate change. It necessitates a transformation of world economies from fossil fuel based to de-carbonized economies, and technical change plays a major role in de-carbonizing the production, investment, and consumption activities (Kumar and Yalew, 2012; Managi et al., 2012). Therefore, the substitution of renewable resources for fossil fuels is at the heart of climate change mitigation policy.

Acemoglu et al. (2012) analyze technical change in the growth model with environmental and resource constraints to discuss the substitution pass from fossil fuels (dirty inputs) to renewable (clean inputs) resources. The elasticity of substitution is a key in understanding the evolution of technical change between fossil fuels and renewable resources. Because of the lack of elasticity estimates in the literature, they assume two different values of elasticity where both of them are high (Acemoglu et al., 2012). As a future research, they suggest to estimate the relevant elasticity of substitution between fossil fuels and renewable using industry-level data. We contribute to this task by estimating the Morishima elasticity of substitution (MES) between different fossil fuels and renewable resources using industry level data for the OECD countries. Market demand of renewable resources has been growing over years. Total renewables supply grew by 2.4% per annum between 1971 and 2008 while 1.3% per annum for total primary energy supply in OECD countries (OECD, 2010). Behind this background, there are three reasons which are increasing of fossil fuel price, cost of renewable energy decrease due to technological progress, and policy target to reduce GHG emissions. According to Apergis and Payne (2014), real coal prices, and real oil prices are each positive and statistically significant to renewable energy consumption. In 2008, European commission set the 20-20-20 target which is targeted to reduce 20% of GHG emission, decrease 20% of primary energy use, and increase 20% of renewable energy use.

Inter-fuel substitution is seen as a promising venue in meeting the growing challenge of climate change and industries have substituted fuels considering their constraints. There have been a large number of empirical studies to quantify the potential for switching between electricity and other fuels focusing on fossil fuels (Halvorsen, 1977; Jones, 1995; Bjørner and Jensen, 2002; Stern, 2012). They found that electricity is generally a weak substitute for other energy inputs (such as coal, oil, and gas). But none of these studies estimate the substitutability between conventional fossil fuels (including electricity) and renewable resources.

Steinbuks (2012) suggests the use of industry level data to avoid measurement error associated with aggregation over industries. It is clear that the required investment and know-how for switching energy vary by industries because the reasons of energy use are different (Fujii and Managi, 2013) (e.g. intermediate materials or combustion; see Appendix 1 for detail). That is elasticity is different over industries. Additionally, relative price between renewable and non-renewable energy is different among industries and change over time due to technological progress that needs to be controlled (Kuper and van Soest, 2003).

We also test the effect of Kyoto protocol on the estimation of shadow price of carbon dioxide (CO_2). Kyoto protocol is the first market mechanism and international agreement to reduce greenhouse gas emissions. Industrial sector might change their energy use strategy after Kyoto protocol adopted or enforced. Another objective of this study is to understand how each manufacturing sector changes the energy use after Kyoto protocol, focusing on the inter-fuel elasticity, shadow price of CO_2, and productive efficiency.

Our results show there is complementally relationship between renewable and non-renewable energy. Some of the manufacturing sectors might have complementally relationship between renewable and non-renewable energy because of their industrial characteristics (see Karltorp and Sandén (2012) for technological reason). Thus, we clarify that elasticity by industries and also find shadow price increases after the Kyoto protocol.

The rest of the paper is organized as follows: Section 2 introduces previous studies about inter-fuel energy substitution and methodological development of elasticity index. Section 3 describes our methodology. Section 4 presents the data used in the study. Results on the basis of the parameters of directional output distance function are discussed in Section 5. The paper concludes in Section 6.

2. Background

2-1. Interfuel energy substitute

Interfuel substitution and the substitutability of energy and other factors of production determine the effects of output growth and fuel prices on the demand for energy and indirectly to the CO_2 emissions. They have been of interest in a large number of energy demand studies since the early 1970s (see Stern, 2012 for extensive review). Most of them use a flexible functional form for the underlying aggregator function (e.g., Pindyck 1979). This approach of energy demand involves specifying a twice differentiable translog functional form of cost function, and applying Shephard's lemma to derive the resulting cost share (or input-output) equations.

Using these equations with relevant data, they estimate the parameters of the demand for fuels. These include the own- and cross-price elasticities as well as the elasticities of substitution. Although the role of energy in the structure of production has been the focus of a large number of empirical studies, the evidence on inter-factor and inter-fuel substitutability is mixed. The early studies by Berndt and Wood (1975) and Magnus (1979) all use time series data for a single country and found substitutability between energy and labor, but complementarity between energy and capital. Also, Fuss (1977) find oil, gas and coal to be substitutes using Canadian data, but found no substitutability between each of these energy inputs and electricity. Moreover, Pindyck (1979) find energy and labor to be substitutes and also energy and capital to be substitutes, and not complements as earlier studies had indicated.

Some recent studies focus on the specific industries in one country (Fujii et al., 2010; Assaf et al., 2011; Barros et al., 2012). Floros and Vlachou (2005) analyze interfuel substitution and effect of carbon tax using manufacturing sectors data in Greek. They find that electricity and diesel, and electricity and mazout are substitutes, while diesel and mazout are complement in most manufacturing sectors. Bousquet and Ladoux (2006) estimate substitution of fossil fuels in France. They conclude that increasing the price of energy possibly modifies the number of energy used by the firm.

Many of the literature ignore the theoretical regularity conditions of microeconomic theory (see Serletis et al. 2009). Serletis et al. (2009) estimate the inter-fuel elasticity of substitution for a set of developed and developing countries using the time-series of 1980 to 2006. They estimate the elasticities not only at the aggregate level but at sectoral level also. They apply the normalized quadratic cost function and estimate the corresponding input-output equations subject to the theoretical regularity conditions of Diewert and Wales (1987).

2-2. Elasticity of substitution and productive inefficiency

Measurement of inter-fuel substitution elasticity is important for the energy and climate change mitigation policy. In the literature two approaches are used for measuring the inter-fuel partial substitution elasticity between two variables[1]. Balckorby and Russell (1989)

[1]Most of the conventional studies employ the Allen elasticity of substitution to measure substitution behavior and structural instability in a variety of contexts. In the context of two inputs, the relationship is unambiguous and the inputs must be substitutes. However, when there are more than two inputs, the relationship becomes complex and depends on the direction taken toward the point of approximation.

finds that the Allen elasticity of substitution is uninformative in the case of more than two inputs and suggest the use of MES. MES examines how changes in the price ratio of inputs affect the quantity ratio of inputs. Inputs are Morishima substitutes (complements) if an increase in the price ratio of inputs causes quantity ratio to increase (decrease). In this study we examine MES between coal, electricity, natural gas, oil and oil products, and renewable resources used in the various industries in OECD countries.

To estimate MES between different fuels and to obtain shadow prices of CO_2 emissions, we model a production process that consider both the production of good output (value added) and CO_2 emissions. We apply the directional output distance function of a multi-output production frontier models (Chambers et al., 1996). In production theory, the directional output distance function is dual to the revenue function (Managi, 2010). One can exploit that duality to derive shadow price estimates for CO_2 emissions. Directional distance function can be estimated either parametrically or non-parametrically. Here, we apply parametric estimation[2].

Parametric estimation of directional output distance function can be provided both econometrically or deterministically. Econometric estimation has the advantages in providing space for statistical noise and testing the various hypotheses over the deterministic estimation. Parameterization must satisfy the axiomatic properties of the directional output distance function and enable the computation of marginal effects. This limits the set of possible functional forms considerably. The functional form captures the economically relevant information that exhaustively characterizes the behavior of economic agents. The flexible functional form also needs to provide a second order differential approximation (Chambers, 1988).

Recently, Färe et al. (2010) use Monte Carlo simulations to demonstrate the apparent greater ability in practice of the quadratic directional output distance function, compared to the translog (also flexible and can be likewise restricted to satisfy homogeneity) Shephard output distance function to characterize the output set. Their results suggest that the output set is better parameterized via a quadratic output directional distance function than with a translog Shephard output distance function. Similarly Färe et al. (2008) find, while examining

[2]Nonparametric estimation constructs the feasible output set as a convex, linear combination of all input and output observations. The model satisfies the assumptions made to characterize the production structure. It also assesses performance by measuring each observation's directional distance to the corresponding output frontier, as a piece-wise linear combination of the outer most output observations. Nonparametric estimation does not, however, generate the smooth, differentiable output frontier required to solve for unique shadow values, and does not offer a tractable way to evaluate the economic tradeoffs facing each of the observations.

the regularity conditions, the quadratic function has fewer monotonicity violations than the translog function, so the quadratic function performs better than the translog function based on monotonicity and curvature violations. Therefore we use quadratic form and estimate it as a frontier function.

3. Model

3.1 The directional output distance function

To measure inter-fuel MES we use a directional output distance function. A directional output distance function seeks to expand the vector of marketable outputs such as value added, $y \in \Re^{M}_{+}$, and reduce CO_2 emissions, $b \in \Re^{N}_{+}$, by employing a vector of inputs (such as labor, capital, materials and various forms of energy use), $x \in \Re^{l}_{+}$. The function inherits its properties from the production technology, P(x). The production technology is defined as:

$$P(x) = \{(x, y, b) : x \text{ can produce } (y, b)\}. \tag{1}$$

The production technology may be modeled in alternative ways. The outputs are strongly or freely disposable if $(y, b) \in P(x)$ and $(y', b') \leq (y, b) \Rightarrow (y', b') \in P(x)$. This implies that if an observed output vector is feasible, then any output vector smaller than that is also feasible. This assumption excludes production processes that generate pollutants that are costly to dispose of. Concerns for CO_2 emissions reduction require that these should not be considered freely disposable. In such cases, CO_2 emissions are considered weakly disposable: $(y, b) \in P(x)$ and $0 \leq \theta \leq 1 \Rightarrow (\theta y, \theta b) \in P(x)$. This implies that CO_2 emissions disposal is costly and that abatement activities would typically divert resources away from the production of marketable outputs, leading to lower marketable outputs for given inputs or the employment of more resources for a given level of marketable output. Marketable outputs are assumed to be null-joint with the pollutants.[3] Formally, the directional output distance function is defined as:

$$D\left(x, y, b; g\right) = \max_{\beta} \left\{ \beta : \left(y + \beta \cdot g_y, b - \beta \cdot g_b \right) \in P\left(x\right) \right\}. \tag{2}$$

[3] Null-jointness implies that a firm cannot produce marketable outputs in the absence of pollutants, i.e., if $(y, b) \in P(x)$ and $b = 0$ then $y = 0$.

This function requires a simultaneous reduction of CO_2 emissions and expansion of marketable outputs. The computed value of β (i.e., $\beta*$) provides the maximum expansion of marketable outputs and reduction of CO_2 emissions if a firm has to operate efficiently given the directional vector g. The vector $g = (g_y, -g_b)$ specifies the direction in which an output vector ($(y,b) \in P(x)$) is scaled, so as to reach the boundary of the output set at the point $(y + \beta^* \cdot g_y, b - \beta^* \cdot g_b) \in P(x)$. This is accomplished by expanding marketable outputs and reducing CO_2 emissions, where $\beta^* = D(x, y, b; g)$.

The directional output distance function derives its properties from the output possibility set, P(x) (see Färe et al., 2005).[4] These properties include monotonicity conditions for marketable outputs and pollutants, and, from its definition, a translation property that is the additive counterpart to the homogeneity property of the Shephard distance functions. The translation property implies that:

$$D(x, y + \alpha, b - \alpha; g_y, -g_b) + \alpha = D(x, y, b; g_y, -g_b). \tag{3}$$

Moreover, the advantage of a directional output distance function is that it allows one to consider disproportional changes in outputs, and makes it possible to expand one output while reducing another. The distance function takes the value of zero for technically efficient output vectors on the frontier, whereas positive values imply inefficient output vectors below the frontier. The higher the value, the more inefficient is the output vector.

3.2 The Morishima elasticity of substitution (MES)

A directional output distance function can be used to measure the interaction between different outputs, as it completely describes the production technology, including curvature. The curvature measures the ease with which marketable outputs can be substituted with pollutants, and the ease with which pollutants are substituted for one another in the production process. The curvature can be quantified using the concept of MES, which is the ratio of relative change in the shadow prices of marketable output and pollution to the relative change in pollution intensity (i.e., the ratio of bad output to good output). Following Blackorby and Russell (1989), the indirect MES between outputs may be defined as:

[4] For the properties of directional output distance functions, see Färe et al. (2005).

$$M_{ij} = \frac{d\ln(p_i / p_j)}{d\ln(x_j / x_i)}, \tag{4}$$

where p stand for the prices of energy inputs. In terms of directional output distance function, the MES following Färe et al. (2005) between different fuels can be specified as:

$$M_{ij} = x_j^* \left(\frac{D_{ij}}{D_i} - \frac{D_{jj}}{D_j} \right) \tag{5}$$

Where x^* are the frontier values of energy inputs. The sign and magnitude of M_{ij} is of particular interest. It reveals the ease of substitution or complementarity between two energy inputs. Positive signs of MES imply that energy inputs are substitutes for one another, i.e., the reduction in the relative shadow price ratio of two energy inputs due to a reduction in the relative intensities of energy inputs. But a negative sign implies that the two fuels are complements to one another, i.e., reductions in one fuel lead to reductions in the other fuel. Moreover, the MES are not symmetric, i.e., $M_{ij} \neq M_{ji}$. This is as it should be and allows for asymmetry in the substitutability of different inputs.[5]

3.3 Marginal abatement costs of CO_2

The output distance function projects the observed output vector onto the boundary of the output set by increasing all outputs proportionally including pollutants. However, in case of a directional output distance function, it is possible to project to the frontier in a direction that decreases pollutants and increases marketable output. Färe et al. (2005) estimated the marginal abatement cost for SO_2 emissions using a directional output distance function. Murty et al. (2007) and Kumar and Managi (2011) estimated the marginal abatement cost functions for air and water pollutants, respectively. The derivation of marginal abatement

[5]The MES measures the effect of change in the price of one output to the output ratio of the same output and one other. The MES has the special feature of being asymmetric that is $M_{ij} \neq M_{ji}$, unless the directional distance function is a member of the CES-Cobb-Douglas family. Asymmetry implies that the MES evaluates the substitutability with respect either the one or the other price. When the number of outputs exceeds two, any substitution elasticity is partial. An equal percentage change of the one or the other output price incurs different changes to the optimal output ratio, and therefore the substitution elasticity is inherently asymmetric (Blackbory and Russel, 1989).

costs using a distance function requires the assumption that one observed output price is its shadow price. Let y_1 denote the marketable output, and assume that the observed marketable output price equals its absolute shadow price ($r_1^o = r_1^s$). Färe et al. (2005) have shown that the marginal abatement cost for pollutant, b_i (i = 2,..., N) can be derived as,

$$r_i^s = r_1^o \frac{\partial D / \partial b_i}{\partial D / \partial y}, \qquad i = 2,3,...., N. \tag{6}$$

In our case there is a single bad output, CO_2 emissions. Firms can follow different approaches to reduce the CO_2 emissions, i.e., they can reduce the value added produced by the firms or increase the production efficiency of fossil fuels consumption or switch from the use of fossil fuels to renewable or use a mix of these different options. Following either of these options or a mix of options involves costs for the firms. Therefore, the shadow price derived using equation (7) can be interpreted as the cost of abatement of CO_2 emissions.

3.4. The empirical model

The directional output distance function is parameterized using an (additive) quadratic flexible functional form following Färe et al. (2005). The capital-labour-energy (KLE) production function specification is utilized for this study. Capital, labour and energy are taken as three inputs. Output is accordingly defined as total value of output minus the value of materials. This specification is based on the assumption that in the gross output production function, materials input is separable from capital, labour and energy.[6] For studying the role energy input in the production process in manufacturing industries, particularly the issues of energy substitution by other inputs, the KLE production function specification is arguably better than the KLEM (capital, labour, energy and materials) specification. It may be contended in this context that economic output is created by capital, labour and energy. Materials used are a passive partner in the production process and do not contribute to value addition which is the essence of economic output (Lindenberger and Kummel, 2002). It may be added that a number of earlier studies have used the KLE specification. These include

[6] For a discussion on separability, see Berndt and Christensen (1973). See also, Pindyck (1979) and Pyo and Ha (2007).

Kemfert and Welscth (2000) and Klacek et al. (2007). Also mentionable here is the study undertaken by Pindyck (1979) who assumed that labour, capital and energy are as a group weakly separable from materials input.

In our case, the particular form is expressed as follows, with one marketable net output (y_1), CO_2 emissions, two non-energy inputs (number of employees= x_1, and capital stock= x_2) and five energy inputs (coal = x_3, electricity = x_4, natural gas = x_5, oil = x_6 and renewable = x_7) :

$$D(x,y,b;g)=\alpha_0+\sum_{l=1}^{7}\beta_l x_l+\alpha_1 y+\alpha_2 b+\gamma_1 t+\frac{1}{2}\sum_{i=1}^{7}\sum_{i=1}^{7}\beta_{ij}x_i x_j+\sum_{i=1}^{7}\delta_{i1}x_i y+\sum_{i=1}^{7}\delta_{i2}x_i b$$
$$+\sum_{i=1}^{7}\delta_{it}x_i t+\frac{1}{2}\alpha_{11}y^2+\alpha_{12}yb+\alpha_{1t}yt+\frac{1}{2}\alpha_{22}b^2+\alpha_{2t}bt+\frac{1}{2}\gamma_{11}t^2+\sum \phi_I I+\sum \phi_c C \tag{7}$$

with

$$\beta_{ij}=\beta_{ji},\alpha_{12}=\alpha_{21},\alpha_1-\alpha_2=-1,\alpha_{11}=\alpha_{22}=\alpha_{12},\gamma_{1i}=\gamma_{2j}$$

Those constraints follow from the translation property, and $g=(1,-1)$, where 1 refers to marketable output and –1 refers to CO_2 emissions direction vector. Furthermore, *t* is time trend, and *I* are industry dummies and *C* are countries dummies. Time trend and its square capture neutral technological change, and its interaction terms with inputs and outputs measures embodied technological change. Industry and country dummies account for industry and country heterogeneity respectively.

The function in equation (7) can be estimated using stochastic techniques. Following Färe et al. (2005), the stochastic specification of directional distance function takes the form:

$$0=D(x,y,b;1,-1,t)+\varepsilon \tag{8}$$

where $\varepsilon=v-\mu$ with $v\sim N(0,\sigma_v^2)$ and μ (one-sided error term) is assumed to be exponentially distributed.

To estimate (8) we utilise the translation property of the directional output distance function. As in Färe et al. (2005), we choose the directional vector g = (1,-1), where 1 refers to g_y and -1 refers to $-g_b$, (see Figure 1). This choice of direction is consistent with revenue maximization hypothesis. The translation property implies that:

$$D(y+\alpha, b-\alpha; 1, -1, t,) + \alpha = D(x, y, b; 1, -1, t) \tag{9}$$

By substituting $D(b-\alpha, y+\alpha; -1, 1, t) + \alpha$ for $D(x, b, y; -1, 1, t)$ in (8) and taking α to the left hand side, we obtain:

$$-\alpha = D(b-\alpha, y+\alpha; -1, 1, t) + \varepsilon \tag{10}$$

where $D(b-\alpha, y+\alpha; -1, 1, t)$ is the quadratic form given by (4) with α added to y and subtracted from b. Thus one is able to get variation on the left-hand side by choosing an α that is specific to each industry. In our case it is CO_2 emissions.[7]

<Figure 1 about here>

The parameters of the quadratic distance function, as specified in equation (9), is estimated using maximum likelihood (ML) methods. Moreover, Greene (2000) shows that the gamma/exponential model has the virtue of providing a richer and more flexible parameterisation of the inefficiency distribution in the stochastic frontier model. Gamma/exponential specification enjoys essentially the same properties as normal/half-normal model with the additional advantage of the flexibility of a two-parameter distribution. The primal advantage is that it does not require that the firm-specific inefficiency measures be predominately near zero (Greene, 1990). The present study adopts ML estimation approach and assumes exponential distribution for one-sided error term.

To estimate the directional distance function, we divide each input and output by its industry specific mean value following Färe et al. (2005). To invoke the translation property for estimating the directional output distance function, we choose α for each observation equal to the industry specific index value of the CO_2 emissions.[8] Since the dataset covers 16 countries and 12 industries, we use country and industry dummies in the estimation of the directional distance function to account for country and industry specific effects in the pooled sample of 2,800 observations.

[7]The results were not affected by the choice of α. The parameters obtained alternatively with the other inputs as α showed little difference.

[8]The index value of the value added for an observation is its value added normalized by the industry specific mean value added.

4. Data

We use 16 OECD countries and 12 industries dataset from 1995 to 2009 (see Appendix 2)[9]. Financial data, which are value added, number of employees, and real fixed capital stock data were obtained from EU-KLEMS[10]. EU-KLEMS uses perpetual inventory methods for measuring the capital stock. For the aggregation over the different asset classes EU-KLEMS assumes that aggregate capital services are a translog function of the services of individual assets and the flow of capital services for each asset class is proportional to its stock. This implies that the fixed capital stock is a translog quantity index of individual assets in a particular industry (Timmer et al., 2007). All financial data were deflated to 2005 prices.

The sector-level CO_2 emissions and energy consumption data were obtained from three databases published by the International Energy Agency (IEA): (1) CO_2 Emissions from Fuel Combustion 2011 edition, (2) Energy Balances of OECD countries 2011 edition, and (3) Energy Statistics of OECD countries 2011 edition. The CO_2 emissions data for coal, oil, and natural gas were obtained directly from the CO_2 Emissions from Fuel Combustion database. However, this database does not include electricity-derived CO_2 emissions; therefore, we estimated electricity-derived CO_2 emissions as the sectoral electricity consumption amount (kWh) multiplied by the CO_2 coefficient (ton-CO_2/kWh) for each country[11].

To understand inter-fuel substitution among the non-renewable energy use, we categorized energy data into five groups: coal, oil, natural gas, electricity, and renewable energy following the definition given by IEA (see Appendix3). Renewable energy include biodiesels, biogases, bio-gasoline, geothermal, hydro, municipal waste (renewable), other liquid biofuels, primary solid biofuels, solar photovoltaic, solar thermal, tide, wave and ocean, and wind.

Table 1 shows that mean value of each data by industries. From Table 1, CO_2 emission is high in electricity, chemical and metal industries. Electricity, metal and mineral industries have high carbon intensity (sale per CO_2 emission), while construction and transportation equipment industries have low carbon intensity. This is because main energy

[9] Chemical industry includes coal chemical and petro chemical industries. Non-metallic minerals industry includes cement industry and ceramic industry.

[10] The EU-KLEMS is financial database published by the Groningen Growth and Development Centre. EU KLEMS stands for EU level analysis of capital, labour, energy, materials and service inputs (http://www.euklems.net/).

[11] Because we have difficulty to distinguish the electric power production source by type of industry, we apply the each country's overall average CO_2 coefficient score to estimate electricity-derived CO_2 emissions from industrial sectors. CO_2 coefficient depends on the power generation technology and portfolio of electricity power generation (see Appendix 3).

sources for production are different among industries (see Appendix 1). For example, Metal industry uses coal both as a fuel and for oxidation-reduction reactions in shaft furnaces. In this case, without technological innovation of the intermediate material technology, it is difficult to reduce coal consumption while maintaining the same level of steel production. Thus, coal energy has large share in total energy use in Metal industry (see Table 1).

<Table 1 about here>

Meanwhile, electricity, food, pulp, and wood industries have large share of renewable energy use comparing with other industries. Renewable energy of electricity sector comes from hydro and geothermal. Other three industrial sectors use renewable energy comes from primary solid biofuel[12] which is generated by plant and wood (see Appendix 4). Thus, manufacturing sectors which use wood and plant as intermediate material have advantage to correct materials of biofuels which is generated by production process.

5. Results

5.1. Technical inefficiency and potential improvement

The estimated parameters for the directional output distance function are presented in Table 2. We estimate two specification of the model; one using two energy inputs namely, renewable and non-renewable. Recall that non-renewables is the sum total of coal, electricity, natural gas, crude oil, oil products and heat energy use. The other specification of the model includes five separated energy variables in the estimation of directional distance function namely, coal, electricity, natural gas, oil and oil products, and renewable energy sources.

<Table 2 about here>

We find that the ML estimation parameters are statistically significant. Most of the first-order parameters have the expected signs and are statistically significant. Looking at the second-order parameters, it appears that they reveal interesting results. These, however, require a more detailed analysis to understand their ultimate influence. Thus, using the

[12]According to IEA (2011), primary solid biofuels are defined as any plant matter used directly as fuel or converted into other forms before combustion.This covers a multitude of woody materials generated by industrial process or provided directly by forestry and agriculture (firewood, wood chips, bark, sawdust, shavings, chips, sulphite lyes also known as black liquor, animal materials/wastes and other solid biofuels).

estimated coefficients, we are able to verify that the resulting distance functions satisfy regularity conditions (monotonicity and concavity conditions) for average values. For the directional output distance function to be well behaved, it needs to be non-negative and the constraints of monotonicity[13], symmetry, and the translation property need to hold. In a stochastic estimation of the distance functions, translation and symmetry properties are imposed, and monotonicity is tested for afterwards. We find that the monotonicity condition with respect to value added is satisfied by most of the observations. With respect to CO_2 emissions all observations satisfy the monotonicity condition. Since we have used quadratic specification of directional output distance function implying non-homogeneity of the distance function. Chow test statistics of estimated parameters show that none of the industries are operating under the constant returns to scale.[14]

Note that in both of the specification while estimating the directional output distance function we have included country and industry specific dummies to capture the country and industry specific heterogeneities. We find that industry and country specific dummies are statistically significant in both the specifications. Out of 11 industry specific dummies 8 and 6 are statistically significant in specification 1 and 2 respectively. Similarly, we observe that in first specification out of 15 country-specific dummies 10 are statistically significant and in the second specification all the country-specific dummies are statistically different from zero (appendix 5). The statistically significance of country-specific dummies reflects the heterogeneity regarding institutional arrangements/environmental regulation framework observed among the OECD countries. For example, the United States has not rectified the Kyoto Protocol and the European Union countries have implemented the Emission Trading System (ETS). Such heterogeneity in institutional arrangements may have impact on environmental technological innovations and adoptions and on the substitution possibilities between non-renewable and renewable energy sources.

The parameters associated with the time trend variable are of specific interest. Negative parameters indicate positive changes in the technology, and a positive parameter indicates technological regression. We find presence of neutral and embodied technological change as the coefficients of time and its interaction terms with outputs and inputs are statistically significant. In both of the specification we find presence of neutral technological progress as the first order coefficient of neutral technological progress is negative, but the

[13](i) $D_y(x,y,b;g) \le 0$, (ii) $D_b(x,y,b;g) \ge 0$, (iii) $D_{yy}(x,y,b;g) \le 0$, (iv) $D_{by}(x,y,b;g) \le 0$.

[14] In the first specification the F statistics is 334.86 and in the second specification its value is 251.53.

second order coefficient is positive implying that though there is neutral technological progress that increases good output and reduces carbon emissions but further technological progress requires more efforts. The coefficients of interaction terms of time and inputs variables reflect the presence of embodied technological progress. Application of the econometric approach for estimating parameters allows us to test whether the distribution of the inefficiency term is significantly different from zero. The log-likelihood ratio test helps reject the null hypothesis of zero inefficiency, i.e., the energy intensive industries in the OECD countries are not operating at the frontier P(x), on average. The inefficiency estimates of $E(\mu|\varepsilon)$ (i.e., the value of the directional distance function) are obtained for each observation.

Table 3 shows industry-specific average estimates of technical inefficiency. For a representative energy intensive industry in the OECD countries and using the overall sample mean of inputs to produce the sample mean of outputs, the estimated value of the directional output distance function is 0.11 for specification 1 and 0.16 for specification 2. We find that the mining industry is the most inefficient, chemical and food industries are the most efficient in specification 1. In specification 2, construction industry is the most inefficient, and pulp industry is the most efficient of the model, industry in OECD countries. The reason that pulp industry is evaluated as efficient is that technological progress of biofuel use. The main renewable energy source in pulp industry is black liquor and investment and running cost of black liquor use become cheaper over year due to the technological progress (e.g. Black liquor gasification, see Naqvi et al. (2010)). This technological advance allows pulp industry to reduce CO_2 emissions without huge financial stress.

Non-zero inefficiency score indicates that production is not technically and environmentally efficient. Because inefficiency score represent how many percentage industrial sectors are available to potentially increase value added and decrease CO_2 emissions simultaneously without increasing input, we can estimate potential improvement amount of value added and CO_2 emissions. From Table 3, 12 manufacturing industries could, on average and without changing resources or developing technology, increase value added by US$ 5.72 to 7.04 trillion depending on the specification of the model used and reduce CO_2 emissions by 6.38 to 7.84 million ton-CO_2.

<Table 3 about here>

We also find that electricity, chemical, metal, and machinery industries have large potential to reduce CO_2 emissions. On the other hand, construction, mining, textile, and wood industries have small potential to reduce CO_2 emissions. Construction and transport industries have large potential of value added but potential CO_2 reduction is small. Then, we suggest setting high priority to increase value added in these two industries to achieve economic development in low carbon society. While, electricity, metal, and mineral industry have large potential to reduce CO_2 emissions but value added increase potential is small comparing with CO_2 reduction potential. Therefore, high priority for CO_2 reduction policy targeting inefficient production in these three sectors is effective to reduce CO_2 emissions.

5.2. Elasticity and asymmetry inter-fuel substitution

Recall that the MES measures the relative change in shadow prices for different fuels due to relative changes in fuel quantities. As these are indirect elasticities, the higher its value (in absolute terms), lower is the degree of interaction between fuels. The MES at the industry level are shown in Tables 4. Negative score of MES represents complementally relationship and positive score shows substitutability.

<Table 4 about here>

From Table 4, there are substitution relationship in fossil fuel and renewable energy ($m56 > 0$) in four industries, namely, electricity, machinery, mining and transport as a general expectation. Note that the substitution possibilities are highest in the electricity industry and lowest for the transport industry. Meanwhile, we find complementally relationship between non-renewable energy and renewable energy ($m56 < 0$) in metal, chemical, construction, food, mineral, pulp, textile, and wood industries. In particular, food and pulp industries have strong complementally relationship. One interpretation of this result is these two industries have advantage to produce biofuels by waste of production such as wood chip and plant stalk. In the meantime, waste amount of production usually depend on the production scale in manufacturing sectors, implying available amount of primary solid biofuels have positive relationship with the amount of total energy supply (Bright et al., 2010). Thus, complementally relationship between renewable and non-renewable energy can exist.

However, the main reasons of complementally relationship are different among industries. From table 4, strong complementally relationship from renewable energy to non-renewable energy in food industry ($m52 > 1$) but not in pulp industry ($m52 < 1$). This is because usage of renewable energy is different between pulp and food industry. Food industry is able to substitute natural gas and oil for combustion by primary solid biofuels in production process. In the meantime, pulp and paper industry use oil products as both combustion and intermediate material input, which make difficult to substitute oil product by biofuels (Wetterlund et al., 2011).

From Table 4, we observe asymmetric substitutional relationship between renewable and non-renewable energy. Especially asymmetric relationship between renewable and electricity is observed in electricity and machinery industries. There are several previous studies focusing on asymmetric inter-fuel substitution (e.g., Gately and Huntington, 2002; Griffin and Schulman, 2005) while, most of them focus on the inter-fuel substitution relationship among non-renewable energies. From our result, we find that there is asymmetric inter-fuel substitution relationship between renewable and non-renewable energy. Additionally, this relationship is different among industry.

Our results do not support high possibility of substitution between fossil fuels and renewable resources in their simulations. This may be possible in the very long-run as the innovation widens the range of technological possibilities. But in the medium to short run at least these possibilities are less likely because neither gas nor coal can easily substitute for liquid fuels used in internal combustion engines. The elasticity is due to the inertia of existing equipment and to the technical constraints imposed on the system by the energy carriers that transform primary into final energy and into specific end-use energy services.

5.3. Shadow price of CO_2

Table 5 provide industry specific shadow prices of CO_2. From Table 5, the shadow price differs by industry. Construction and machinery industries have high shadow prices. Meanwhile chemical, electricity, mineral, pulp industries have low shadow prices. It is supposed to be that in the industries there are possibilities of inter-fuel (fossil fuel to renewable) substitution lower should be the price of mitigating the CO2 emissions. This is weakly confirmed by the relationship between the shadow prices of CO2 emissions and the Morishima elasticity of substitution between fossil fuels and renewable. For example, we find complementarity between fossil fuels and renewable and the shadow prices are higher in this industry. Similarly it is supposed that the firms/industries which are technically inefficient they can mitigate the carbon emissions simply by increasing the technical efficiency and the shadow prices should be low for these firms/industries. But our results do not support this hypothesis. This may be due to the technological constraints faced by those firms which are technically inefficient. That is, these firms are technical inefficient due to the constraints of technological lock-ins which are making it costly to dispose off the carbon emission and shadow prices are higher as well it is difficult to find the possibilities of substitution between fossil fuels and renewable.

Moreover, because most OECD countries ratified Kyoto protocol, we consider industrial sector shift their strategy to more low carbon after Kyoto protocol adopted (in 1997) or Kyoto protocol into force (in 2005). Then, we divide our dataset into two groups which are "*before Kyoto*" and "*after Kyoto*" to check the differences of shadow price of CO_2 between two groups. We apply the student t-test to check the significance of difference.

<Table 5 about here>

From Table 5, there is a statistically significant difference before and after Kyoto protocol adopted (in 1997) in metal, chemical, electricity, mineral, pulp, textile, transport, and wood industries. In these industries, the shadow price in *after Kyoto* is significantly higher than *before Kyoto*. Additionally, we observe statistically significant differences of the shadow price before and after Kyoto protocol into force (2005) in all industries except construction and mining sectors. One interpretation of these results is increase of renewable energy use share which is more costly than fossil fuels. Main energy source in wood industries are renewable energy, especially primary solid biofuels (see Table 1). From our dataset, renewable energy use share in total energy use was increased from 26.5% before Kyoto to 38.8% after Kyoto in wood industry. According to Carriquiry et al. (2011), cost of biofuel energy is much higher than fossil fuels. This information implies that shadow price of CO_2 increases due to expansion of biofuel energy use in wood industry.

In general, we expect that CO_2 shadow prices would be higher in sector where there is little substitution possibilities. However, we find in several sectors where renewables and fossil fuels are found to be complements, and CO_2 shadow prices are low. They might be the sectors where the shadow prices can keep low by better management of CO_2 and therefore substitution possibilities do not have to be searched for.

6. Conclusions

Elasticity of inter-fuel substitution between renewable and non-renewable energy is important to understand effective climate change mitigation policy. Because of the lack of elasticity estimates between renewable and non-renewable in the literature, numerical modeling needs to assume specific number and these are substitute. We estimate the Morishima elasticity of substitution between different fossil fuels and renewable resources using industry level data for the OECD countries.

Substitution relationship from non-renewable energy to renewable energy holds for four industries. We find complementally relationship between non-renewable energy and renewable energy in metal, chemical, construction, food, mineral, pulp, textile, and wood industries. In particular, food and pulp industries have strong complementally relationship. Strong substitution relationship might be possible in the very long-run as the innovation widens the range of technological possibilities. But in the medium to short time period at least these possibilities are less likely because renewable energy have difficulty to substitute for fossil fuels used as intermediate products. The elasticity is due to the inertia of existing equipment and to the technical constraints imposed on the system by the energy carriers that transform primary into final energy and into specific end-use energy services.

We also found shadow price of CO_2 increased after Kyoto protocol adopted in nine industries, and after into force in ten industries. Further researchers need to investigate more disaggregated analysis to capture the technological differences in detail. Additionally, elasticity estimation focusing developing countries is also needed because that is important information to set the target and obligation of post-Kyoto protocol.

Because difficulty of substitution between fossil fuels and renewable energy is different among industries, developing countries which will be industrialized need to select the plant location considering with industrial characteristics and easiness of biomass procurement, especially food industry and pulp and paper industry which have advantage to substitute renewable energy from fossil fuels. Intergovernmental Panel on Climate Change (IPCC) pointed that bio-energy with carbon capture and storage (BECCS) is effective approach to reach atmospheric concentration levels of about 450ppm CO_2 equivalent by year 2100 in their fifth assessment report reports (IPCC, 2014). However, BECCS faces the task of land use problems (Tavoni and Socolow, 2013). Therefore, location layout of industrial sector is needed to consider substitution elasticity between renewable energy and fossil fuel, and applicability of new GHG emission management approach.

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Table 1: Mean value of data variables, 15-year mean values

(Figures in second rows in parenthesis are standard deviations)

	Value added Billion U.S.$	CO_2 Million ton-CO_2	Employee 1000 person	Capital Billion U.S.$	Coal Peta joule	Oil Peta joule	Gas Peta joule	Electricity Peta joule	Renewable Peta joule
Metal	33.75	33.47	476.41	62.96	45.75	20.27	127.72	102.76	0.12
	(49.87)	(47.84)	(591.41)	(98.90)	(60.69)	(28.69)	(205.08)	(142.50)	(0.44)
Chemical	47.90	30.42	388.83	84.83	25.01	60.86	149.05	107.33	1.62
	(83.90)	(66.25)	(526.25)	(131.71)	(56.40)	(111.38)	(396.58)	(212.95)	(5.44)
Construction	88.65	2.09	1,465.86	47.67	0.05	22.44	3.11	2.56	3.05
	(143.41)	(3.29)	(2,070.89)	(2.16)	(0.24)	(39.73)	(6.28)	(2.50)	(8.04)
Electricity	32.68	217.16	130.89	207.25	1,834.62	163.62	526.81	82.26	210.83
	(64.29)	(503.48)	(199.91)	(336.76)	(4,638.18)	(300.09)	(1,064.28)	(168.36)	(388.42)
Food	29.87	11.94	415.62	46.21	10.00	25.91	64.97	38.62	7.37
	(46.88)	(23.01)	(535.50)	(59.35)	(30.89)	(39.92)	(141.87)	(65.32)	(19.33)
Machinery	25.00	12.92	367.86	38.63	1.64	15.45	44.50	66.48	0.06
	(37.21)	(23.94)	(452.54)	(64.68)	(3.64)	(23.49)	(97.80)	(114.64)	(0.20)
Mining	23.20	2.52	73.35	81.03	0.84	5.64	2.21	11.83	0.01
	(58.67)	(5.26)	(145.07)	(219.71)	(1.75)	(12.88)	(4.52)	(27.37)	(0.05)
Mineral	9.32	15.81	137.96	18.07	51.38	38.23	62.59	29.98	2.02
	(12.81)	(21.37)	(150.34)	(21.13)	(85.09)	(46.79)	(104.36)	(37.47)	(4.55)
Pulp	26.67	14.79	345.63	37.34	16.03	22.75	55.43	64.97	71.25
	(50.13)	(31.39)	(543.74)	(56.24)	(38.73)	(42.98)	(131.33)	(110.08)	(187.72)
Textile	9.61	4.17	271.14	18.47	1.60	8.15	16.67	17.03	0.18
	(13.37)	(7.85)	(324.03)	(25.47)	(3.79)	(15.27)	(31.97)	(31.25)	(0.56)
Transport	29.32	4.68	365.36	56.18	1.50	5.90	19.73	21.22	0.01
	(49.99)	(10.39)	(516.29)	(96.07)	(5.51)	(13.64)	(48.02)	(41.90)	(0.04)
Wood	5.10	2.35	100.31	7.96	0.24	7.14	5.99	10.65	20.79
	(8.40)	(6.90)	(134.88)	(9.70)	(0.93)	(23.97)	(19.61)	(25.24)	(63.18)
All	30.09	29.36	378.27	58.88	165.72	33.03	89.90	46.31	26.43
	(65.72)	(158.55)	(798.37)	(142.42)	(1,428.58)	(105.34)	(367.58)	(109.43)	(138.90)

Table 2: Estimated coefficients of directional output distance function

Variable	Specification 1			Specification 2		
	Coefficient		z-stat	Coefficient		z-stat
GDP	-0.21	***	-15.96	-0.47	***	-24.62
$(GDP)^2 = (CO_2)^2 = GDP \times CO_2$	0.03	***	6.44	0.01	*	1.34
GDP×employee = CO_2×employee	0.04	***	7.33	0.08	***	10.33
GDP×capital = CO_2×capital	-0.03	***	-10.63	-0.02	***	-3.38
GDP×renewable = CO_2×renewable	-0.01	***	-5.05	-0.00	*	-1.59
GDP×nonrenewable = CO_2×nonrenewable	-0.08	***	-12.27	-		
GDP×coal = CO_2×coal	-			0.01	***	5.88
GDP×electricity = CO_2×electricity	-			-0.03	***	-5.21
GDP×gas = CO_2×gas	-			0.00		0.32
GDP×oil = CO_2×oil	-			-0.04	***	-8.52
CO_2	0.79		-	0.53		-
y1time = y2time	0.01	***	9.31	0.00	***	3.51
employee	0.01		0.98	0.12	***	4.47
employee × employee	0.02	***	2.34	-0.03	***	-2.48
employee × capital	-0.04	***	-6.97	-0.06	***	-6.02
employee × renewable	0.00	*	1.34	0.02	***	5.48
employee × non-renewable	-0.06	***	-7.09	-		
employee × coal	-			-0.03	***	-6.38
employee × electricity	-			-0.02	***	-2.58
employee × gas	-			-0.01		-1.18
employee × oil	-			0.01	***	2.19
employee × time	-0.00		-0.17	-0.01	***	-3.30
capital	0.23	***	18.96	0.36	***	15.30
capital × capital	0.01		1.04	0.02	***	2.49
capital × renewable	0.00		1.25	-0.01	***	-4.76
capital × non-renewable	0.04	***	9.17	-		
capital × coal	-			-0.00		-0.69
capital × electricity	-			0.01		0.76
capital × gas	-			-0.05	***	-9.37
capital × oil	-			0.03	***	6.57
capital × time	-0.01	***	-6.38	-0.00	**	-2.07
coal	-			-0.04	***	-8.14
coal × coal	-			0.00	***	9.74
coal × electricity	-			-0.01	***	-4.75
coal × gas	-			-0.00		-1.23
coal × oil	-			0.00		1.13
coal × renewable	-			0.00		0.13
coal × time	-			0.00	*	1.84
electricity	-			-0.23	***	-11.86
electricity × electricity	-			0.02	***	2.35
electricity × gas	-			0.03	***	6.56
electricity × oil	-			0.02	***	4.66

electricity × renewable	-			0.00		0.35
electricity × time	-			0.01	***	3.61
gas	-			-0.05	***	-3.31
gas × gas	-			-0.01	***	-3.43
gas × oil	-			0.00	**	2.07
gas × renewable	-			-0.00	***	-2.54
gas × time	-			-0.00		-0.21
oil	-			-0.08	***	-7.95
oil × oil	-			0.01	***	3.76
oil × renewable	-			0.00		-0.17
oil × time	-			-0.00	***	-2.92
renewable	-0.01	***	-5.81	0.00		0.74
renewable × renewable	-0.00	***	-2.36	-0.00		-1.71
renewable × non-renewable	0.01	***	5.68	-		
renewable × time	-0.01	***	-6.27	-0.00		-1.33
non-renewable	-0.63	***	-38.78	-		
non-renewable × non-renewable	0.15	***	16.26	-		
non-renewable × time	-0.01	***	-6.27	-		
time	-0.00		-1.50	-0.00		-1.46
$time^2$	0.00	**	2.03	0.00	**	2.08
constant	0.11	***	3.20	-0.14	***	-2.69
$\ln\sigma_v^2$	-5.976	***	-76.74	-4.477	***	-44.14
$\ln\sigma_u^2$	-4.196	***	-77.44	-3.090	***	-34.28
σ_v	0.050 (0.002)			0.1066 (0.005)		
σ_u	0.123 (0.003)			0.2134 (0.010)		
σ^2	0.018 (0.001)			0.057 (0.003)		
λ	2.435 (0.005)			2.001 (0.015)		
Log-likelihood	2149.09			1137.78		
Observations	2880			2880		

Note:*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Estimates of technical inefficiency and CO_2 reduction potential:

Means and Standard Deviation (figures in second rows in parenthesis are standard errors)

	Specification 1			Specification 2		
	Inefficiency score	Potentially value added increase (Trillion U.S.$)	Potentially CO_2 emissions reduction (million ton-CO_2)	Inefficiency score	Potentially value added increase (Trillion U.S.$)	Potentially CO_2 emissions reduction (million ton-CO_2)
Metal	0.117	5.086	6.611	0.152	5.330	6.152
	(0.008)	(0.672)	(0.885)	(0.007)	(0.643)	(0.887)
Chemical	0.085	6.787	4.872	0.148	6.783	3.887
	(0.005)	(1.432)	(1.277)	(0.004)	(0.781)	(0.521)
Construction	0.126	10.117	0.192	0.201	32.797	0.870
	(0.009)	(2.146)	(0.027)	(0.013)	(5.500)	(0.157)
Electric	0.107	8.458	62.900	0.156	5.875	49.300
	(0.008)	(2.092)	(14.200)	(0.006)	(1.118)	(12.700)
Food	0.091	5.306	2.649	0.158	6.037	2.972
	(0.006)	(1.031)	(0.621)	(0.006)	(1.048)	(0.646)
Machinery	0.136	6.973	5.422	0.175	6.154	4.496
	(0.011)	(1.273)	(1.093)	(0.008)	(0.975)	(0.871)
Mining	0.137	7.487	0.877	0.160	5.504	0.641
	(0.011)	(1.743)	(0.180)	(0.007)	(1.320)	(0.132)
Mineral	0.099	1.444	2.613	0.151	1.315	2.536
	(0.006)	(0.179)	(0.373)	(0.005)	(0.120)	(0.306)
Pulp	0.105	6.537	4.077	0.143	5.363	2.976
	(0.007)	(1.238)	(0.906)	(0.004)	(0.893)	(0.578)
Textile	0.123	2.603	1.722	0.153	1.756	1.020
	(0.012)	(0.539)	(0.373)	(0.006)	(0.235)	(0.173)
Transport	0.118	6.821	1.533	0.154	6.575	1.204
	(0.009)	(1.419)	(0.373)	(0.006)	(1.008)	(0.252)
Wood	0.107	0.971	0.639	0.160	1.021	0.584
	(0.007)	(0.178)	(0.175)	(0.007)	(0.163)	(0.151)
All	0.113	5.716	7.845	0.159	7.043	6.383
	(0.002)	(0.385)	(1.236)	(0.002)	(0.536)	(1.091)

Table 4: Inter-fuel Morishima Elasticity of Substitution by Industry (figures in second rows in parenthesis are standard errors)

Industry	m56	m65	m12	m21	m13	m31	m14	m41	m15	m51	m23	m32	m24	m42	m25	m52	m34	m43	m35	m53	m45	m54
Metal	-1.485	-0.063	0.517	0.336	-0.249	0.120	-0.864	0.186	-0.003	-0.606	-0.264	-0.192	1.988	0.947	-0.009	-3.227	-0.886	0.059	0.033	1.692	-0.003	-1.134
	(0.692)	(0.019)	(0.041)	(0.029)	(0.022)	(0.010)	(0.966)	(0.103)	(0.009)	(0.247)	(0.023)	(0.015)	(2.246)	(1.080)	(0.010)	(1.414)	(0.965)	(0.241)	(0.009)	(0.641)	(0.009)	(0.541)
Chemical	-0.522	-0.033	0.640	0.425	-0.387	0.143	-2.762	0.369	-0.036	0.643	-0.233	-0.144	6.396	1.682	-0.039	2.748	-2.775	-0.039	-0.011	-2.492	-0.035	0.885
	(0.898)	(0.023)	(0.118)	(0.087)	(0.093)	(0.028)	(2.962)	(0.266)	(0.062)	(0.457)	(0.035)	(0.012)	(6.888)	(1.848)	(0.062)	(2.366)	(2.961)	(0.098)	(0.062)	(2.109)	(0.062)	(0.684)
Construction	-1.558	-0.048	0.551	-0.192	-0.403	-0.042	0.033	-0.075	0.016	0.078	-0.415	-0.268	-0.116	-0.102	0.013	-0.452	0.038	-0.187	0.057	-1.755	0.017	1.018
	(1.670)	(0.008)	(0.071)	(0.567)	(0.113)	(0.179)	(0.008)	(0.180)	(0.065)	(1.478)	(0.062)	(0.188)	(0.015)	(0.046)	(0.065)	(2.041)	(0.012)	(0.026)	(0.065)	(1.954)	(0.065)	(0.860)
Electricity	2.135	-0.021	0.113	-0.048	0.022	-0.002	0.076	-0.030	0.015	0.128	-0.256	-0.175	-0.145	-0.058	0.012	-0.187	0.037	-0.134	0.039	-0.642	0.016	-0.122
	(1.763)	(0.027)	(0.154)	(0.132)	(0.101)	(0.042)	(0.054)	(0.042)	(0.037)	(0.169)	(0.029)	(0.023)	(0.124)	(0.074)	(0.038)	(1.017)	(0.052)	(0.042)	(0.037)	(0.524)	(0.037)	(0.659)
Food	-6.650	-0.102	-0.694	-1.313	0.683	-0.406	0.136	-0.430	-0.753	0.767	-0.231	-0.169	-0.227	-0.104	-0.756	16.712	0.070	-0.152	-0.727	-4.101	-0.752	8.552
	(5.676)	(0.049)	(0.889)	(1.195)	(0.687)	(0.378)	(0.036)	(0.380)	(0.559)	(0.328)	(0.024)	(0.010)	(0.031)	(0.009)	(0.559)	(16.426)	(0.012)	(0.015)	(0.559)	(3.356)	(0.559)	(9.176)
Machinery	3.595	-0.023	0.517	0.344	-0.234	0.119	-0.031	0.115	-0.000	0.300	-0.459	-1.946	0.059	0.162	-0.008	1.068	-0.179	-0.279	0.022	-1.138	-0.005	0.714
	(6.099)	(0.041)	(0.060)	(0.058)	(0.046)	(0.019)	(0.028)	(0.021)	(0.025)	(0.310)	(0.177)	(2.328)	(0.064)	(0.088)	(0.025)	(1.123)	(0.158)	(0.171)	(0.025)	(1.138)	(0.026)	(0.635)
Mining	5.905	0.271	0.047	-0.054	0.143	0.013	0.102	-0.036	-6.428	30.433	-0.295	-0.206	-0.157	-0.107	-6.434	-5,977.681	0.010	-0.228	-6.406	-0.332	-6.427	6.763
	(4.574)	(0.272)	(0.063)	(0.101)	(0.103)	(0.031)	(0.020)	(0.033)	(6.428)	(29.901)	(0.049)	(0.026)	(0.028)	(0.025)	(6.428)	(6,004.616)	(0.008)	(0.027)	(6.426)	(1.285)	(6.428)	(6.792)
Mineral	-4.426	-0.017	0.592	0.393	-0.327	0.139	0.082	0.105	0.127	-1.012	-0.291	-0.163	-0.207	-0.123	0.117	-2.884	0.066	-0.172	0.148	3.159	0.123	0.245
	(2.894)	(0.035)	(0.063)	(0.053)	(0.051)	(0.018)	(0.008)	(0.015)	(0.224)	(0.717)	(0.032)	(0.012)	(0.018)	(0.014)	(0.224)	(3.373)	(0.007)	(0.014)	(0.224)	(3.657)	(0.224)	(1.398)
Pulp	-5.464	-0.171	0.393	0.169	-0.158	0.062	0.121	0.031	-0.021	0.189	-0.221	-0.211	-0.280	-0.149	-0.024	0.643	0.089	-0.139	0.005	0.839	-0.019	-0.148
	(3.296)	(0.102)	(0.482)	(0.589)	(0.413)	(0.187)	(0.044)	(0.187)	(0.027)	(0.242)	(0.024)	(0.017)	(0.048)	(0.021)	(0.027)	(1.836)	(0.020)	(0.013)	(0.027)	(0.734)	(0.027)	(0.562)
Textile	-2.000	0.000	0.641	0.447	-0.356	0.153	0.101	0.123	0.000	-0.301	-0.267	-0.039	-0.255	-0.110	0.000	2.753	0.146	-0.164	0.000	-0.676	0.000	2.048
	(1.454)	(0.000)	(0.093)	(0.076)	(0.058)	(0.027)	(0.023)	(0.022)	(0.000)	(0.151)	(0.038)	(0.122)	(0.053)	(0.018)	(0.000)	(2.795)	(0.053)	(0.025)	(0.000)	(0.493)	(0.000)	(2.196)
Transport	55.371	0.674	0.300	-0.201	-0.088	-0.051	0.076	-0.081	-0.025	-0.043	-0.399	-0.269	-0.134	-0.015	-0.029	-0.124	0.011	-0.198	-0.006	-0.370	-0.024	0.073
	(56.256)	(0.713)	(0.167)	(0.334)	(0.116)	(0.105)	(0.015)	(0.107)	(0.025)	(0.223)	(0.072)	(0.053)	(0.022)	(0.022)	(0.025)	(1.236)	(0.008)	(0.025)	(0.024)	(0.726)	(0.025)	(0.601)
Wood	-2.435	-0.114	0.071	-0.056	-0.066	-0.000	0.056	-0.027	-0.017	0.205	0.270	-0.425	-0.229	-0.338	-0.011	2.364	0.022	-0.136	0.005	-3.458	-0.016	0.488
	(2.642)	(0.057)	(0.147)	(0.109)	(0.079)	(0.034)	(0.014)	(0.037)	(0.028)	(0.179)	(0.390)	(0.214)	(0.098)	(0.208)	(0.029v	(2.827)	(0.006)	(0.025)	(0.028)	(3.517)	(0.028)	(0.397)

Note: 1. Coal, 2. Electricity, 3. Natural gas, 4. Oil and oil products, 5. Renewables, 6. Total non-renewables

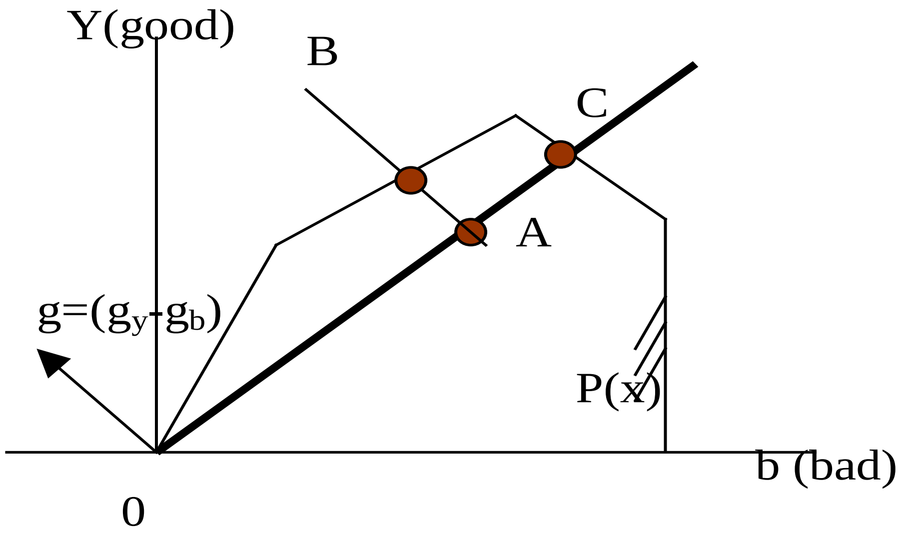
Table 5: Shadow Prices of CO_2 by industry (U.S.$ per ton-CO_2)

(Mean values for the observations satisfying monotonicity conditions)

Industry	Mean value of Shadow price			Shadow price difference	p >|t|	Mean value of Shadow price		Shadow price difference	p >|t|
	1995-2009	1995-1997	1998-2009			1995-2005	2006-2009		
Metal	7.507	4.334	8.300	3.966	0.000	5.867	12.016	6.150	0.000
Chemical	7.259	4.373	7.981	3.608	0.000	4.373	10.898	6.525	0.000
Construction	19.267	3.878	23.179	19.301	0.538	5.307	59.678	54.371	0.059
Electricity	7.181	4.293	7.914	3.621	0.000	5.722	11.389	5.667	0.000
Food	7.399	4.566	8.118	3.552	0.000	6.186	10.899	4.713	0.000
Machinery	13.962	4.615	16.336	11.721	0.373	6.594	34.311	27.717	0.020
Mining	7.838	4.858	8.587	3.728	0.154	7.144	9.706	2.562	0.278
Mineral	6.908	4.318	7.555	3.237	0.000	5.670	10.311	4.641	0.000
Pulp	7.677	4.370	8.504	4.134	0.000	5.660	13.223	7.563	0.000
Textile	7.891	5.533	8.487	2.954	0.003	6.200	12.692	6.492	0.000
Transport	8.050	4.445	8.960	4.515	0.035	5.995	13.882	7.887	0.000
Wood	8.685	4.916	9.627	4.711	0.000	6.540	14.583	8.043	0.000
All	9.076	4.544	10.218	5.674	0.036	6.067	17.484	11.417	0.000

*Note:*Right side p-value is result of two tailed student's t-test for mean value differences between before and after Kyoto protocol adopted (1997) and into force (2005).

Figure 1: Shephard Output and Directional Distance Functions



Appendix 1. Main purpose of energy use by type of industry

	Coal / peat	Oil/petroleum products	Natural gas	Electricity
Food	Private power generation, Fuel for boiler	Fuel for equipment, Packaging materials, Private power generation,	Fuel for equipment, Private power generation	Fuel for automation production equipment
Wood	Private power generation, Fuel for boiler	Fuel for equipment, Private power generation	Fuel for equipment,	Fuel for automation production equipment
Chemical	Material for coal product, Private power generation, Fuel for boiler	Material for petroleum product, Petroleum solvent, Private power generation,	Fuel for equipment, Private power generation	Fuel for automation production equipment
Pulp	Private power generation, Fuel for boiler	Ink for printing, Fuel for equipment, Petroleum solvent	Fuel for equipment, Private power generation	Fuel for automation production equipment
Minerals	Material for cement, Fuel for boiler	Material for cement, Fuel for equipment, Thermal source	Fuel for equipment, Private power generation	Fuel for equipment, (e.g. Electric cement mill)
Metal	Material for cokes product, Fuel for equipment, Private power generation	Fuel for equipment, Private power generation, Thermal source	Fuel for equipment, Private power generation	Fuel for equipment, (e.g. Electric arc furnaces)
Machinery	Private power generation	Fuel for equipment, Petroleum product for painting, Grease, Petroleum solvent,	Fuel for equipment, Private power generation	Fuel for automation production equipment
Transport	Private power generation	Fuel for equipment, Petroleum product for painting, Grease, Petroleum solvent,	Fuel for equipment, Private power generation	Fuel for automation production equipment
Construction	Material for coal tar	Fuel for construction equipment, Material for asphalt,	Fuel for equipment, Private power generation	Fuel for equipment

Appendix 2. Data sample description

Time period	1995-2009
Country	(1) Australia, (2) Austria, (3) Czech Republic, (4) Denmark, (5) Finland, (6) Germany, (7) Italy, (8) Japan, (9) Korea, (10) Netherlands, (11) Portugal, (12) Slovenia,(13) Spain, (14) Sweden, (15) United Kingdom, (16) United States
Industry type	(1) Metal, (2) Chemical, (3) Construction, (4) Electricity, (5) Food, (6) Machinery, (7)Mining, (8) Mineral, (9) Pulp, (10) Textile, (11) Transport, (12) Wood
Energy type	(1)Coal, (2) Electricity, (3) Natural gas, (4) Oil, (5) Renewable energy

Appendix 3. Definition of fuel data

Coal (coal, coal product and peat)	*Anthracite*	*BKB/peat briquettes*	*Brown coal*	*Coal tar*	*Coke oven coke*
	Coking coal	*Gas coke*	*Hard coal*	*Lignite*	*Other bituminous coal*
	Patent fuel	*Peat*	*Sub-bituminous coal*		
Oil (petroleum product and crude oil)	*Additives/blending components*	*Aviation gasoline*	*Bitumen*	*Crude oil*	*Crude/NGL/feedstocks (if no detail)*
	Ethane	*Fuel oil*	*Gas/diesel oil*	*Gasoline type jet fuel*	*Kerosene type jet fuel*
	Liquefied petroleum gases (LPG)	*Lubricants*	*Motor gasoline*	*Naphtha*	*Natural gas liquids*
	Non-specified oil products	*Other hydrocarbons*	*Other Kerosene*	*Paraffin waxes*	*Petroleum coke*
	Refinery feedstocks	*Refinery gas*	*White spirit & SBP*		
Natural gas	*Blast furnace gas*	*Coke oven gas*	*Gas works gas*	*Natural gas*	
	Other recovered gases				
Electricity	*Elec/heat output from non-specified manufactured gases*	*Electricity*	*Electric boilers*		
Renewable Energy	*Biodiesels*	*Biogases*	*Biogasoline*	*Charcoal*	*Other recovered gases*
	Municipal waste (renewable)	*Non-specified primary biofuels and waste*	*Other liquid biofuels*	*Primary solid biofuels*	*Geothermal*
	Other sources	*Solar photovoltaics*	*Solar thermal*	*Tide, wave and ocean*	*Wind*
	Hydro				

Appendix 4. Breakdown of renewable energy use share in total renewable energy by industries

	Metal	Chemical	Construction	Electricity	Food	Machinery	Mining	Minerals	Pulp	Textile	Transport	Wood
Biodiesels	0.00%	0.00%	15.99%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Biogases	0.00%	16.47%	2.63%	2.86%	1.86%	1.56%	0.00%	0.05%	0.06%	0.10%	52.78%	0.00%
Biogasoline	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Geothermal	0.00%	0.00%	0.00%	16.39%	0.00%	0.00%	0.00%	0.00%	0.49%	0.00%	0.00%	0.00%
Hydro	0.00%	0.00%	0.00%	60.41%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Municipal waste (renewable)	1.20%	2.14%	0.00%	4.67%	0.04%	0.62%	28.26%	7.68%	0.09%	0.10%	0.00%	0.00%
Other liquid biofuels	0.15%	0.27%	0.00%	0.19%	0.06%	1.56%	10.87%	0.09%	0.48%	0.00%	8.33%	0.00%
Primary solid biofuels	98.65%	81.12%	80.43%	10.06%	98.03%	96.26%	60.87%	92.19%	98.87%	99.80%	38.89%	99.99%
Solar photovoltaics	0.00%	0.00%	0.00%	0.15%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Solar thermal	0.00%	0.00%	0.95%	0.14%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Tide, wave and ocean	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Wind	0.00%	0.00%	0.00%	5.13%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Appendix 5. Coefficient score of country and industry dummy variables

Country and industry name	Specification 1 Coefficient		Specification 1 z-score	Specification 2 Coefficient		Specification 2 z-score
Australia	-0.142	***	-4.230	0.162	***	3.420
Austria	-0.025		-0.740	0.279	***	5.680
Czech Republic	-0.078	**	-2.320	0.243	***	5.030
Denmark	-0.046		-1.370	0.283	***	5.720
Finland	-0.010		-0.290	0.282	***	5.660
Germany	-0.170	***	-5.390	0.254	***	6.100
Italy	-0.194	***	-5.910	0.178	***	3.850
Japan	-0.170	***	-5.210	0.129	***	2.860
Korea	-0.169	***	-5.110	0.106	**	2.210
Netherlands	-0.018		-0.550	0.283	***	5.920
Portugal	-0.061	*	-1.820	0.244	***	4.960
Slovenia	-0.030		-0.890	0.276	***	5.530
Spain	-0.112	***	-3.360	0.239	***	5.060
Sweden	0.067	**	2.000	0.368	***	7.270
United Kingdom	-0.095	***	-2.930	0.322	***	7.470
United States		-			-	
Basic metals and fabricated metal	-0.024	***	-2.820	-0.016		-1.010
Chemical, rubber, plastics and fuel	-0.016	*	-1.950	-0.014		-0.920
Construction	-0.058	***	-5.920	-0.024		-1.400
Electricity, gas and water supply	-0.014	*	-1.670	0.010		0.600
Food , beverages and tobacco	-0.050	***	-6.060	-0.039	**	-2.520
Machinery, nec	0.004		0.470	0.020		1.280
Mining and quarrying	0.119	***	11.550	0.077	***	4.600
Other non-metallic mineral	-0.067	***	-8.100	-0.044	***	-2.830
Pulp, paper, paper , printing and publishing	-0.009		-1.060	-0.035	**	-2.300
Textiles, textile , leather and footwear	-0.022	***	-2.590	-0.025		-1.630
Transport equipment	0.000		0.000	-0.037	**	-2.400
Wood and of wood and cork		-			-	