Energy Price-Induced and Exogenous Technological Progress: Analysis of the Economic and Environmental Effects

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Abstract

In this paper, we distinguish between factor/output substitution and shifts in the production technology frontier. Our model includes the by-products of carbon dioxide and sulfur dioxide emissions where the function requires the simultaneous expansion of good outputs and reductions in emissions. We estimate a directional output distance function for 80 countries over the period 1971–2000 to measure the exogenous and oil price-induced technological change. On average, we find substantial oil price-induced technological progress at the world level when long-term oil prices are rising, although the growth rate is more volatile in developed countries than in developing countries. The results also show that developed countries experience higher exogenous technological progress in comparison with developing countries, and the gap between the two has increased during the period of our study.

Keywords: Price-Induced Technological Change, Exogenous Technological Change, Environmental Effects.

1. Introduction

Technological advancements play a crucial ameliorating role in managing the long-standing problems of climate change and energy security through reducing energy consumption. Economists often cite the use of energy (or carbon) taxation to reduce the emission of greenhouse gases. However, in most environmental policy models, technological change is incorporated as an exogenous variable. Several empirical studies analyze the relationship between energy prices and energy-saving induced innovation.[1] This study extends the literature by explicitly incorporating environmental variables, such as carbon dioxide (CO_2) and sulfur dioxide (SO_2), and attempts to find how the changes in oil prices are related to induced innovations that are not only energy saving, but also emission reducing. That is, the question to be addressed is whether increases in oil prices lead to a reduction in energy consumption and emissions.

Changes in production factors are expected to change the constraints and incentives that affect technological change (TECH). The importance of relative prices as a stimulator of TECH is traceable to Hicks (1932) who argues that "… a change in relative prices of factors of production is itself a spur to invention, and to invention of a particular kind—directed to economizing the use of a factor which has become relatively expensive (pp.124–125)." In general, the theory of induced innovation addresses the effects of relative prices on the direction of TECH (Hayami and Ruttan, 1971).

It is expected that the increase in long-term oil prices will economies the use of oil and substitute it with other relatively cheap energy inputs such as coal. The change in the composition of energy inputs has implication for emissions. For example, the decrease in oil use as a result of higher oil prices may lead to increase in the use of coal and as a result the emissions of carbon, in the absence of any regulation, will be higher.

Most empirical studies are conducted using firm-level industrial data and measure TECH either in terms of inputs (e.g., investments and research and development (R&D) expenditures in energy-saving innovations) or in terms of outputs (e.g., the number of patents

[1] These studies empirically measure the induced technological progress due to changes in the environmental policy parameters. The literature in this field includes Litchtenberg (1986, 1987), Lanjouw and Mody (1996), Jaffe et al. (2003), Newell et al. (1999), Nordhaus (2002), and Popp (2002).

filed, granted or cited in the area of energy-saving innovations). For example, Popp (2002) tests the induced innovation hypothesis using United States patent data from 1970 to 1994 to estimate the effect of energy prices on innovations. However, patent statistics can be misleading since many patents never see commercial application, many innovations are not patented, and some are subdivided into multiple patents, each covering one or more aspects of the innovation (e.g., Basberg, 1987). In addition, changes in patent policies over time may again make patent counts a misleading indicator of innovation, particularly over longer time periods (Managi, et al., 2005). Similarly, Newell et al. (1999) provide evidence of energy price-induced technological progress using a product-characteristics framework. They find that energy prices are positively associated with the energy efficiency of electrical appliances. Gallagher et al. (2006) note this problem in their measures of TECH when technologies are often not well defined and discrete, as described below.

The TECH needs to be estimated in terms of measures of market penetration, the economic benefits of technologies, technological learning, energy efficiency, and changes in the energy mix (Gallagher et al., 2006) and the transformation function is the best instrument for measuring the rate and direction of TECH (Jaffe et al. 2003). The transformation function describes a production possibility frontier. It is the set of combinations of inputs and outputs that are technically feasible at a given point in time. The movement of this frontier represents TECH. We estimate a directional output distance function for a sample of 80 countries over the period 1971–2000 to measure exogenous and energy price-induced TECH.

TECH is similar in nature to any investment process, as it requires time and adjustments that are not instantaneous, and the choice of technology is influenced by long-term prices. TECH is therefore decomposed into two parts, namely exogenous technological change (ETCH), and energy price-induced technological change (ITCH). A time-trend variable is used to measure ETCH.[2] Similarly, the inclusion of long-term oil prices as a shift factor in the transformation function is used for measuring ITCH.

[2] Technological progress occurs because of both inducements and advancements in general science and technology. Therefore, a time trend is included as an argument for the country-specific transformation frontier to account for the impact of scientific innovation on the production technology (Lansink et al., 2000, p. 500, footnote 1).

There is a considerable theoretical and empirical literature on the measurement of induced innovation effects.[3] This literature typically analyzes the inducement effect in the framework of a conventional representation of production technology, including cost, production and profit functions. Distinguishing between factor/output substitution and shifts in the production technology frontier is problematic with such conventional representations. This is because current and long-run prices appear along with the input–output vectors. As a result, the comparative static relations of the stated price-induced innovation model do not follow basic economic conditions. That is, the direct derivatives of the demand and supply functions with respect to prices cannot be signed given the presence of the cross-derivatives (Celikkol and Stefanou, 1999; Caputo and Paris, 2005).

Moreover, traditional measures of productivity do not account for the production of harmful by-products, such as CO_2 and SO_2 emissions, which may lead to environmental damage. Some recent studies include environmental externalities and conclude that measures including environmental indicators differ from traditional measures.[4] We use a directional output distance function as a representation of the production technology. This function simultaneously seeks to expand "good" outputs and contract "bad" (pollution) outputs. It is then particularly well suited to the task of providing a measure of technical efficiency in the full input–output space and satisfies all properties assured by more conventional representations.

The paper is organized as follows. Section 2 outlines the theoretical structure of the study. Section 3 presents an empirical model for the stochastic estimation of the directional output distance function. The data are described in Section 4. Section 5 discusses the results of the study and the conclusions are presented in Section 6.

[3] See Hayami and Ruttan (1971), Binswanger (1974, 1978), Thirtle and Ruttan (1987) for recent literature reviews.

[4] See, for example, Hailu and Veeman (2000), Färe et al. (2005), Managi et al. (2005), Kumar (2006), and Managi and Jena,(2000).

2 Theoretical Framework

2.1. The Directional Output Distance Function

Suppose that a country employs a vector of inputs (such as labor, capital and energy use), $x\in\Re^K_+$ to produce a vector of "good" outputs (such as GDP), $y\in\Re^M_+$, and "bad" outputs (such as SO_2 and CO_2), $b\in\Re^N_+$. The technology is now defined as:

$$T = \{(x, y, b; t, q) : x \text{ can produce } (y, b) \text{ at time t and long run oil price q}\} \quad (1)$$

The output is strongly or freely disposable if $(y, b)\in T$ and $(y', b') \le (y, b) \Rightarrow (y', b') \in T$. This implies that if an observed output vector is feasible, then any smaller output vector is also feasible. This assumption excludes production processes that generate bad outputs that are costly to dispose of. For example, concerns about pollutants (such as CO_2 and SO_2) imply that these should not be considered freely disposable. In such cases, bad outputs are considered as being weakly disposable: $(y, b)\in T$ and $0 \le \theta \le 1 \Rightarrow (\theta y, \theta b) \in T$. This implies that pollution is costly to dispose of and abatement activities typically divert resources away from the production of desirable outputs and thus lead to lower good outputs for any given inputs. Moreover, good outputs are assumed to be null-joint with the bad outputs.[5]

More formally, the directional output distance function is defined as:[6]

$$D(x, y, b; g, t, q) = \max_{\beta}\{\beta : (y + \beta \cdot g_y, b - \beta \cdot g_b) \in T\}. \quad (2)$$

This function requires the simultaneous reduction in bad outputs and expansion in good outputs. The computed value of β (β^*) provides the maximum expansion of good outputs and contraction of bad outputs if a firm has to operate efficiently given the directional vector g. The vector $g = (g_y, -g_b)$ specifies the direction an output vector ($(y,b)\in T$) is scaled so

[5] Null-jointness implies that a firm cannot produce good outputs in the absence of bad outputs, i.e. *if* $(y,b)\in T$ and b=0, then y=0..

[6] See Färe et al. (2005) for the properties of the directional output distance function.

as to reach the boundary of the output set at the point $(y+\beta^* \cdot g_y, b-\beta^* \cdot g_b) \in T$ by expanding the good outputs and contracting the bad outputs where $\beta^* = D(x, y, b; g, t, q)$.

The directional output distance function derives its properties from the production technology T (Färe et al., 2005). The advantage of this function is that it allows one to consider nonproportional changes in output, since it is possible to expand good outputs, while contracting the bad outputs. This property is very useful in the study of the input–output choices of a polluting firm facing environmental regulation. 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. Moreover, the directional output distance function and revenue function are duals to each other (Färe et al., 2001; Färe et al., 2005).

2.2. Malmquist–Luenberger Productivity Indicators

We extend the Malmquist–Luenberger measure of productivity change (PCH) to a measure that also accounts for ITCH. The productivity indicator is traditionally decomposed into technological change (TECH), or shifts in the production frontier, and efficiency change (EFFCH), or the movement of inefficient production units relative to the frontier which may be termed as 'catch-up'effect.. We now further decompose TECH into ETCH and ITCH, i.e., $TECH = ETCH + ITCH$, as illustrated in Figure 1.

Suppose the direction of expansion $(g_y, -g_b)$ is denoted by g. The output (b^t, y^t) vector in period t is denoted by $\boldsymbol{a}$, and the vector (b^{t+1}, y^{t+1}) in period $(t+1)$ is denoted by $\boldsymbol{d}$. The two technologies are T^t and T'^{t+1}. The shift in technology from T^t to T'^{t+1} is a combination of technological shift due to ETCH and ITCH, i.e., shift in the production technology from T^t to T^{t+1} is induced by the factors such as the general advancement in science and technology and the shift from T^{t+1} to T'^{t+1} is due to the change in relative prices. Therefore, we obtain:

$$\begin{aligned} EFFCH &= (b-a) \\ TECH &= (d-b) = ((d-c)+(c-b)) = ITCH + ETCH \end{aligned} \tag{3}$$

Thus, EFFCH measures how close the observation $\boldsymbol{a}$ is to the technology T^t and TECH measures the shift in the production technology.

Following Färe et al. (2005), the directional output distance function is parameterized using a (additive) quadratic flexible functional form. In our case, with one good output (GDP= y), two bad outputs ($CO_2 = b_1$ and $SO_2 = b_2$), three inputs (labor = x_1, capital = x_2, and energy = x_3), a time trend and long-run oil prices, the particular functional form is (see Managi et al. (2006) for alternative specification for multiple output stochastic production analysis):

$$\begin{aligned} D^{kt}(x^{kt}, y^{kt}, b^{kt}; g, t, q) &= \alpha_0 + \sum_{n=1}^{3} \alpha_n x_n^{kt} + \beta_1 y^{kt} + \sum_{m=1}^{2} \beta_m b_m^{kt} + \gamma_1 t + \gamma_2 q^t + \frac{1}{2}\sum_{n=1}^{3}\sum_{n'=1}^{3} \alpha_{nn'} x_n^{kt} x_{n'}^{kt} \\ &+ \sum_{n=1}^{3} \delta_{n1} x_n^{kt} y^{kt} + \sum_{m=1}^{2}\sum_{n=1}^{3} \delta_{nm} x_n^{kt} b_m^{kt} + \sum_{n=1}^{3} \eta_{n1} x_n^{kt} t + \sum_{n=1}^{3} \eta_{n2} x_n^{kt} q^t + \frac{1}{2}\beta_{11} y^{kt} y^{kt} + \sum_{m=1}^{2} \beta_{1m} y^{kt} b_m^{kt} + \mu_{y1} y^{kt} t \\ &+ \mu_{y2} y^{kt} q^t + \frac{1}{2}\sum_{m=1}^{2}\sum_{m'=1}^{2} \beta_{mm'} b_m^{kt} b_{m'}^{kt} + \sum_{m=1}^{2} \mu_{m1} b_m^{kt} t + \sum_{m=1}^{2} \mu_{m2} b_m^{kt} q^t + \frac{1}{2}\gamma_{11} t^2 + \phi t q^t + \frac{1}{2}\gamma_{22} q^{t\,2} + \psi G \end{aligned} \tag{4}$$

with

$$\alpha_{nn'} = \alpha_{n'n};\ \beta_{mm'} = \beta_{m'm};\ \beta_1 - \sum_{m=1}^{2} \beta_m = -1;\ \beta_{1m} - \sum_{m=1}^{2} \beta_{mm'} = 0;\ \beta_{11} - \sum_{m=1}^{2} \beta_{1m} = 0; n = 1,2,3;\ m = 1,2$$

and $g = (1,-1)$, where 1 refers to g_y and –1 refers to $-g_b$, where t is a time trend, q is long-run oil prices, and G is a group dummy. The countries are grouped in two categories, developed and developing, based on per capita income following the World Bank classification.

Specification (4) allows for neutral and biased TECH. The effect of neutral ETCH is captured by the coefficients γ_1 and γ_{11} and the effect of neutral ITCH is captured by the coefficients γ_2 and γ_{22}. The extents of input-biased ETCH and ITCH is estimated by the coefficients η_{n1} and η_{n2}, respectively. The effects of changes in output due to ETCH and ITCH (i.e., output biased TECH) are estimated by the coefficients μ_{y1}, μ_{m1}, μ_{y2} *and* μ_{m2}, respectively. In addition, the interaction between ITCH and ETCH response is captured by the coefficient ϕ.

We parameterize the directional output distance function in quadratic form so that we are able to apply Diewert's (1976) *Quadratic Identity Lemma*.[7] Using this lemma, changes in the directional output distance function (4) from one period to the next can be written as:

$$\begin{aligned}(D^t - D^{t+1}) &= 0.5\left[\frac{\partial D^t}{\partial y}+\frac{\partial D^{t+1}}{\partial y}\right](y^{t+1}-y^t)+0.5\sum_{m=1}^{2}\left[\frac{\partial D^t}{\partial b}+\frac{\partial D^{t+1}}{\partial b}\right](b^{t+1}-b^t)\\ &+0.5\sum_{n=1}^{3}\left[\frac{\partial D^t}{\partial x_n}+\frac{\partial D^{t+1}}{\partial x_n}\right](x_n^{t+1}-x_n^t)+0.5\left[\frac{\partial D^{t+1}}{\partial t}+\frac{\partial D^t}{\partial t}\right]+0.5\left[\frac{\partial D^{t+1}}{\partial q}+\frac{\partial D^t}{\partial q}\right](q^t-q^{t+1})\end{aligned} \tag{5}$$

where D^t is short for $D(x^t, y^t, b^t; g, t, q)$. Let *PCH* be the productivity index defined as:

$$\begin{aligned}PCH &= -0.5\left[\frac{-\partial D^{t+1}}{\partial y}+\frac{-\partial D^t}{\partial y}\right](y^{t+1}-y^t)+0.5\sum_{m=1}^{2}\left[\frac{\partial D^t}{\partial b}+\frac{\partial D^{t+1}}{\partial b}\right](b^{t+1}-b^t)\\ &+0.5\sum_{n=1}^{3}\left[\frac{\partial D^{t+1}}{\partial x_n}+\frac{\partial D^t}{\partial x_n}\right](x_n^{t+1}-x_n^t)\end{aligned}. \tag{6}$$

This *PCH* index can be broadly defined as the difference of the weighted-average rates of change in outputs and inputs, where the weights are the derivatives of directional output distance function with respect to the (negative) good outputs and the (positive) bad outputs and inputs, respectively. Rearranging equation (6), *PCH* can be decomposed as:

$$PCH = \underbrace{(D^{t+1}-D^t)}_{EFFCH} \underbrace{-0.5\left[\frac{\partial D^{t+1}}{\partial t}+\frac{\partial D^t}{\partial t}\right]}_{ETCH} \underbrace{-0.5\left[\frac{\partial D^{t+1}}{\partial q}+\frac{\partial D^t}{\partial q}\right].(q^{t+1}-q^t)}_{ITCH}. \tag{7}$$

Equation (7) provides a meaningful decomposition of *PCH* into changes in EFFCH, ETCH, and ITCH. Negative values of the derivatives of the directional output distance function with respect to the time trend and the long-run oil prices imply a positive change in ETCH and ITCH, respectively. Therefore, the negative value of each component of the *PCH* productivity index implies a positive change in total factor productivity.[8]

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[7] Orea (2002) used the quadratic identity lemma for parametric decomposition of the Malmquist productivity index using an output distance function.

[8] In the discussion, we have multiplied each of the components by minus one for the sake of convention.

TECH, both exogenous and induced, can be further decomposed into two categories: changes associated with shifts in the transformation function and changes in output decisions regarding the production of a particular output from a change in relative prices along the new transformation function (Färe et al., 1997). The shift in the transformation function can be further subdivided into two categories: neutral TECH and biased TECH. Neutral TECH implies a shift in the technological frontier such that it becomes possible to produce fewer bad outputs and more good outputs with the same input quantities. Biased TECH implies the change in the slope of the frontier and the decision point of the firm is not on the ray, even when the relative prices are constant.

This decomposition of TECH can be illustrated with Figure 1. Suppose a representative country uses some fixed quantity of inputs to produce GDP and sulfur emissions. Furthermore, assume that the country takes a decision at point ***a***, given technological possibilities represented by T^t. Assume also that, at some time $t+1$, technological possibilities have improved, as represented by the shift of the frontier from T^t to T^{t+1}. Accordingly, the production decision to be taken is situated at point ***d***.

We can decompose the movement from point ***b*** and ***d*** into the movements from ***b*** to ***d'***, and from ***d'*** to ***d***. Point ***d'*** is the point on the new frontier that does not lie on a ray. Hence, the movement from ***b*** to ***d'*** represents a combination of biased and neutral technological change. The movement from point **b** to ***d*** represents neutral technological progress and the movement from ***d'*** to ***d*** measures the effect on the lesser production of SO_2 emissions between time t and $t+1$, referred to as bias in the production of outputs or biased TECH. The following subsection 2.3 deals with the measurement of output and input biases in a directional output distance function.

2.3. Output and Input Biases

Antle (1984) develops a profit-based multifactor measure of biased TECH. He defines the impact of technological progress on input decisions for factor n as the proportionate change in the cost share of elasticity of factor n due to proportionate changes in the exogenous variables and long-run factor prices.

One can derive the output supply functions as the derivative of the revenue function with respect to output prices. Similarly, we can derive the inverse of the output supply functions as the derivative of the directional output distance function with respect to the output quantities. The measures of output bias for exogenous and induced technological change can be expressed as follows.

$$\frac{\varepsilon_i}{\varepsilon} = -\frac{\partial \ln D}{\partial \ln y_i} \bigg/ -\sum_{i=1}^{3} \frac{\partial \ln D}{\partial \ln y_i}$$
$$B_{it}^{E} = \frac{\partial \ln(\varepsilon_i / \varepsilon)}{\partial \ln t} \tag{8}$$
$$B_{it}^{I} = \frac{\partial \ln(\varepsilon_i / \varepsilon)}{\partial \ln q}$$

The output bias associated with technological progress is:

$$\text{i}^{\text{th}} \text{ output} \begin{Bmatrix} Increa\sin g \\ Neutral \\ \mathrm{Re}\,ducing \end{Bmatrix} \text{ when } B_{it} \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} 0 \tag{9}$$

for y_i: *GDP*, CO_2, SO_2. We treat good and bad outputs asymmetrically. Therefore, a positive sign indicates GDP increasing (or augmenting) and emissions reducing (or saving) technological change. The input biases can be developed in a similar manner. That is, a positive sign indicates input decreasing and a negative sign indicates input increasing technological change.

3. Estimation

The directional output distance function can be computed using either linear programming (LP) or stochastic frontier techniques. Econometric estimation of distance functions has some advantages over the LP approach. Other than allowing for the appropriate treatment of measurement errors and random shocks, several statistical hypotheses can be tested (such as the significance of parameters, the separability between outputs and inputs and between good and bad outputs, and monotonicity properties of distance functions).[9] The stochastic specification of the directional output distance function takes the form:

[9] However, stochastic methods have their own disadvantages. These include the requirement for distributional assumptions concerning the inefficiency and error terms, and the problem of imposing non-linear monotonicity constraints in the estimation process.

$$0 = D(x, y, b; 1, -1, t, q) + \varepsilon \tag{10}$$

where $\varepsilon = v - \mu$, and $v \sim N(0, \sigma_v^2)$, μ is the one-sided systematic error term, and $\mu \sim iidG(P, \theta)$, and P and θ are the shape and scale distribution parameters, respectively.

To estimate equation (10), we employ the translation property of the directional output distance function. The translation property implies that:

$$D(x, y + \alpha, b - \alpha; 1, -1, t, q) + \alpha = D(x, y, b; 1, -1, t, q)\,. \tag{11}$$

By substituting $D(x, y + \alpha, b - \alpha; 1, -1, t, q) + \alpha$ for $D(x, y, b; 1, -1, t, q)$ in (10) and taking α to the left-hand side, we obtain:

$$-\alpha = D(x, y + \alpha, b - \alpha; 1, -1, t, q) + \varepsilon \tag{12}$$

where $D(x, y + \alpha, b - \alpha; 1, -1, t, q)$ is the quadratic form given by (4) with α added to y and subtracted from b. Thus, one is able to obtain variation on the left-hand side by choosing an α that is specific to each country. In this study, this is the variable SO_2.

The parameters of the quadratic distance function (4) and the value of the directional output distance function, which is the measure of technical inefficiency, can be estimated using either corrected ordinary least square (COLS) [10] or maximum likelihood (ML) methods. The COLS approach is not as demanding as the ML method, which requires maximization of the likelihood function. The ML method is asymptotically more efficient than the COLS estimator, but the properties of the two estimators in finite samples can be analytically determined. The finite sample properties of the half-normal frontier model are investigated in a Monte Carlo experiment by Coelli (1995), where the ML estimator is found to be significantly superior to the COLS estimator where the contribution of technical inefficiency effects to the total variance term is large.

Greene (2003) shows that the gamma model has the virtue of providing a richer and more flexible parameterization of the inefficiency distribution in the stochastic frontier model than either of the canonical forms (half-normal or exponential). Moreover, gamma

[10] See Lovell *et al.* (1994) for an application of COLS to the Shephard output distance function. Also see Färe *et al.* (2005) for the directional output distance function.

specification enjoys essentially the same properties as the normal/half-normal model with the additional advantage of the flexibility of a two-parameter distribution. The primary advantage is that it does not require that the firm-specific inefficiency measures be predominately near zero (Greene, 1990). One can test down from the gamma to the exponential by testing if the shape parameter (*P)* equals 1.0, as the gamma distribution is a generalization of the exponential distribution. The present study adopts the ML estimation approach while assuming a gamma distribution for the one-sided error term.

4. Data

The *Center for Air Pollution Impact and Trend Analysis* produced a comprehensive database on sulfur emissions incorporating time and spatial variations from 1850 to 1990. Their estimates are considered superior to others in terms of their extent and spatial and temporal resolution. Stern (2005) extended this database to include more recent data. Carbon dioxide and population data are provided from the *World Development Indicators*. Per capita income defined as 1990 GDP per capita (measured in real PPP-adjusted dollars) is taken from the *Penn World Table 6.1*. The capital labor ratios and labor force data are obtained from the *Extended Penn World Table*. The data set covers an unbalanced panel of 80 countries from 1971 to 2000.

In constructing the productivity indices, the resource constraint consists of the net, fixed, standardized, capital stock, the labor force, as measured by the number of employed workers, and energy use measured in kilotons (kt) of oil equivalents. The country selection is based on the availability of all of the required variables and the choice of study period is based both on the availability of data and oil price volatilities. The sample size is 2093 observations 610 for developed countries and 1483 for developing countries. The list of name of the countries is provided in the appendix.

In terms of energy consumption, oil accounts for most of the consumption of hydrocarbons. Although the use of natural gas has risen in the past few decades, there is a high positive correlation between oil and natural gas prices. Moreover, oil accounts for about 35% of global annual use of primary energy, with much of that oil sourced from politically unstable regions (Gallagher et al., 2006). Therefore, we assume oil price volatility induces energy-saving innovations.

Country-specific oil price variables are difficult to measure and have been influenced by price controls, high and varying taxes on petroleum products, exchange rate fluctuations and country specific price index variations. Most of the empirical literature applies the $US world oil price as a common indicator of global market disturbances that affect all countries (e.g., Burbidge and Harrison, 1984). Following the literature, we apply the oil price indices since our data set is an unbalanced panel. The oil price indices are calculated by taking 1970 as the base year.

Changes in long-run prices induce the development of new technologies leading to shifts in the technology frontier. Therefore, it is important to model long-run prices, which depend on current and past price information, as arguments in the production technology frontier to separate the scarcity response from the biased ITCH. Therefore, a three-year moving average of past energy prices is included in the frontier function to account for price-induced ITCH. We use three-year data since most recent years have the greatest information content (Lansink et al., 2000). This choice of long-term energy prices is also consistent with an adaptive expectation model of prices, in which expected future prices depend on a weighted average of past prices (Popp, 2002). The price trend and time trend is not correlated and simple correlations using our data in this study is 0.00009.

5. Results

The directional output distance function is estimated using mean normalized input and output data since we face convergence problems in the models given the numerical size of the outputs and inputs (see Färe et al., 2005). This normalization implies $(x, y, b) = (1, 1, 1)$ for a hypothetical country that uses the mean level of inputs and produces the mean level of outputs.

As mentioned earlier, we follow the ML estimation procedure for the estimation of the directional distance function, and the one-sided error term is assumed to be independently and identically gamma distributed (i.i.γ). Table 1 provides the parameter estimates of the directional distance function. In fact, we estimate four specifications of the same basic directional distance function. In Specification 1, only the input–output vectors are included. In Specification 2, we include the trend variable as the shift parameter. In Specification 3, two shift parameters are included: the time trend and long-run relative energy prices. As noted, we divide the countries into two groups (developed and developing) and include the group dummy in the estimation (Specification 4). The selection among specifications is based on a log-likelihood ratio (LR) test. Table 2 provides the LR test statistics. Based on these LR test statistics, Specification 4 is selected for further analysis, as the country-group dummies are statistically significant, even at the 1% level.[11]

As in Table 1, most of the ML coefficients are accurately estimated. Technical inefficiency is correctly identified within the composed error term: (i) the LR test on the one-sided error is highly significant; (ii) the share of technical inefficiency in the total variance is high, i.e., 95%; and (iii) it appears to have a gamma distribution with $\theta = 4.038$ and $P = 0.35$. The estimated parameters in Specification 4 indicate that the first-order coefficients on the output and inputs have the expected values regarding economic behavior. After examining the signs of the second-order parameters, it would appear that they also involve interesting results. These, however, require a more detailed analysis to measure their final influence. Thus, using the estimated coefficients presented in Table 1, we are able to verify that the resultant distance functions satisfy the regularity conditions of convexity on inputs and concavity on outputs for the large majority of observations.[12]

The parameters associated with the trend and long-term energy price variables are of specific interest. Negative parameters indicate positive changes in technology, and a positive parameter indicates technological regression. The LR test statistics on these parameters allows us to reject the null hypotheses of no ETCH and ITCH (see Table 2). We find the absence of a neutral ETCH because the coefficient of time is not statistically significant. Rather, we observe the presence of biased or embodied ETCH, since the coefficients of the interaction terms between the time trend and the outputs and inputs are statistically significant. The coefficient of long-term energy prices is negative and statistically significant

[11] An important issue in efficiency studies is the credibility of the assumption that all production processes can actually reach the best practice production frontier. In the present study, it would be incorrect when measuring technical efficiency to assume that all countries have access to the best-practice manufacturing frontier. This is because the specialized journals, technological fairs, and multinational global marketing strategies that guarantee innovations are not readily equally available to all firms in all countries.

[12] We find that the monotonicity conditions with respect to GDP and CO_2 are satisfied by 98% and 100% of the observations, but not with respect to SO_2. With respect to the inputs (labor, capital and energy) these conditions are satisfied by 88%, 100%, and 12% of the observations, respectively.

indicating the presence of neutral ITCH due to changes in energy prices. The coefficients of the interaction terms between the outputs and energy prices, and inputs and energy prices indicate embodied ITCH.

5.1. Levels of Inefficiency and Presence of a Catch-up Effect

Country-specific technical inefficiency, EFFCH, ITCH, ETCH, TCH and PCH are estimated for each country in each year over the period 1971–2000.[13] The pooled sample average level of inefficiency (value of the directional distance function) is 0.076. This implies that countries operating around the average values of inputs and outputs have the potential to increase GDP and simultaneously decrease the quantities of SO_2 and CO_2 emissions by about 8%. In developed countries, the potential to increase GDP and reduce bad outputs is higher (11.5%) than in developing countries (5.5%).

We find that the world witnessed a small decline in the catch-up effect in the order of magnitude of –0.2% per annum. Moreover, the magnitude of the catch-up effect is the same across the two groups (Figure 2a). Of the sample of 80 countries, Poland observed the highest catch-up effect of about 2% per year followed by Romania with 1.6%. The countries that witnessed an annual decline in the catch-up effect of more than 1% include the following: Thailand (–2.3%), Australia (–2%), Mexico (–1.8%), Spain and Italy (–1.3%), and Iran (–1.1%). On average, of the 80 countries, 26 caught up with the world output frontier and 51 observed a decline in EFFCH.

5.2. Magnitude of Exogenous and Energy Price-induced Technological Change

The average annual value of total factor productivity (or PCH) aggregates the effects of EFFCH, ETCH and ITCH. The world PCH has increased by about 0.26% per annum. This can be mainly attributed to progress in general technologies (exogenous technological progress) of a magnitude of 0.46% per annum.[14] During the study period, 54 countries

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[13] Country and time-specific inefficiency and the components of total factor productivity are not reported because of space restrictions. Similarly, the results concerning the direction of technological change are not reported here. These results are available from the authors upon request.

[14] The low value of ETCH growth may imply that factors accumulate. This is also discussed in the sub-section on the direction of input bias. This finding is consistent with Kumar and Russell (2002) and even with growth accounting studies (e.g., Hall and Jones, 1999).

observed positive productivity change. The United Kingdom experienced the highest growth rate with 3.2% per annum. The growth in productivity change can be attributed to the catch-up effect and TECH.

Recall that we decomposed TECH effect into two components: ETCH and ITCH. The developed countries witnessed higher exogenous technological progress in comparison with developing countries and the gap between the groups in the growth of ETCH has increased over time (see Figures 2b and 3). Seventy-one countries witnessed exogenous technological progress and France observed the highest growth rate in exogenous technological progress of the magnitude of 3.8% per annum. The nine countries that experienced a decline in ETCH are all developing countries.[15] In the developing countries, Brazil (2.5%), Mexico (1.2%) and India (1.15%) experienced a more than 1% per annum progress in ETCH. This suggests that although technological progress has contributed positively to growth in most countries, the pattern is very dissimilar. This indicates that developed countries have benefited more than developing countries from exogenous technological progress.[16]

At the world level on average, we observe the absence of energy price-induced technological progress and the entire progress in TECH can be attributed to progress in ETCH. Figures 2c and 3 reveal that both of the county groups witnessed substantial energy price-induced technological progress when long-term oil prices were rising, although the growth rate of ITCH is more volatile in developed countries when compared with developing countries. This finding is consistent with the level of energy consumption in the economies of both groups. In the developed economies, both per capita and aggregate energy consumption are much higher than in developing economies so the magnitude of ITCH is expected to be higher. In fact, developed countries account for more than half of the total final consumption of energy. Fifty-three countries observed an outward shift in the production frontier due to changes in long-term oil prices, although the magnitude of this progress was negligible.

We need to keep in mind the nature of these economies and the level of use of energy in production and consumption activities. In developing countries, the level of energy

[15] These include Benin, Bangladesh, Bolivia, Ivory Coast, Haiti, Mozambique, Nicaragua, Senegal and Togo.

[16] A similar kind of trend is observed by Kumar and Russell (2002) using a sample of 55 countries over the period of 1965–1990.

consumption is lower than in developed countries. Therefore, to understand the implications of changes in long-term oil prices, the obvious way is to analyze the country-specific results. Because of space constraints, we limit the analysis to the results for the USA, Japan and India, by way of examples. We consider these three economies for further analysis because of their size and aggregate consumption of energy. The USA and the Japan together account for about 75% of estimated public sector spending in the area of energy research, development and demonstration (ERD&D) by IEA countries (Gallagher et al., 2006). Although there are no systematic and detailed data on public ERD&D spending in developing countries, data from India indicate that the Indian Government also invests a significant amount in this area (about 0.9 billion 2000 PPP$ in 1996–1997; see Sagar, 2002). The results of these three countries are presented in Figures 4a through 4c.

In all three economies, we observe a stable growth path in the ETCH. The US economy experienced an exogenous technological progress of about 2% per annum, followed by the progress in ETCH in India of 1.15% per annum. The annual growth rate of ETCH in Japan was only 0.92%.[17] The path of EFFCH in all three countries is quite volatile. On average, the contribution of EFFCH to productivity change is negligible. However, India and Japan observed a decline in EFFCH (–0.046% and –0.019% per annum) and the USA observed a growth in EFFCH (0.008% per annum).

The annual growth path of ITCH is of particular interest. Figures 4a and 4b show that the growth path of ITCH is very volatile and it is consistent with the changes in long-term oil prices. The USA and Japan observe a high growth rate in ITCH when oil prices were rising and a decline in the growth of ITCH when oil prices were declining. The growth rate was highest during the period when the oil prices were peaking. This finding is consistent with the expenditure in the area of ERD&D in these economies. Public ERD&D in OECD countries showed a significant upward spike in the wake of the oil crises of the 1970s. These expenditures peaked in the early 1980s and thereafter declined significantly (Gallagher et al., 2006). In developed economies, it is the private sector, not the public sector that invests in ERD&D technology. Although the exact figures of private investment in ERD&D are not

[17]This finding corroborates evidence provided by Fare et al. (1994) and Kumar and Russell (2002), although their samples comprise different groups of countries and sample periods. They also use data envelopment analysis (DEA) techniques for measuring exogenous technological change.

available, some data certainly support this position. The National Science Foundation's annual survey of industrial R&D indicates that (public and private) funds for industrial energy R&D showed an almost continual decline during the 1980s and 1990s, with the 1999 levels about one-fifth of their peak values in 1980 in real terms.[18]

Moreover, the growth rate of ITCH during the 1970s and 1980s in Japan was higher than that of the USA, but was lower in the 1990s. These findings are consistent with the dependence of these countries on imported oil and with structural changes in energy consumption.[19]

During the study period, India observed growth in ETCH and a positive change pattern in ITCH during the early 1980s when oil prices were at their peak and then positive changes in ITCH during 1995–1997 and in 2000 (Figure 4c). During the 1970s oil crises, India observed an absence of growth in ITCH.

5.3. Direction of Output Bias

Gallagher et al. (2006) identify three major challenges for the energy-saving innovations: reducing its dependence on oil, global warming, and making clean energy available to the underprivileged populations of developing countries. Global warming is caused by the higher use of energy resources and existing energy (oil) prices are incapable of internalizing the environmental externalities. Energy taxation may help in reducing CO_2 emissions. Thus, the output biases help in determining whether higher energy price-induced technological progress reduces CO_2 emissions and causes an internalization of the externalities.

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[18] http:\\www.nsf.gov/statistics/iris/research_hist.cfm?index=21 as quoted in Gallagher et al. (2006).

[19] Japan's dependence on imported crude oil is nearly 100%. Theoretically, the effect of a price rise on the Japanese economy should be extensive. However, the structural pattern of energy consumption in 1990s Japan differs for the first and second oil crises. During the crises, crude oil's share in energy consumption in Japan was nearly 80%, but this had fallen below 50% by the late 1990s. Moreover, Japan has taken steps to cushion the impact of a rise in crude oil prices through strategic stockpiles and by raising the efficiency of energy consumption. The ratio of energy consumption to GDP declined rapidly from the middle of the 1970s to the first half of 1980 and mildly after that until the beginning of the 1990s. Since then, it has been flat or has risen only slightly. Between 1973 and 2000 it fell 33%, reflecting Japan's increased energy consumption efficiency (Ono, 2005). However, the US dependence on oil in energy consumption has declined slightly from about 46% in 1973 to 38% in 2000.

The annual averages of the output biases arising from ETCH and ITCH are shown in Figures 5a to 5f. Exogenous output bias results indicate that the world observed GDP reducing and emission-increasing technological progress during the study period. Similarly, the output bias resulting from the induced innovation indicates that energy price changes lead to technological change that favors the increase in emissions but against GDP. This finding is consistent with the observed increasing aggregate trend throughout the world. Though some industries are cleaner and becoming more efficient in their environmental management, an aggregated trend at the macro level shows pollution is increasing.

Across the world input-increasing progress is observed. Note that we observe varying results at the country level. In developing countries, the direction of technological change is similar to the direction observed at the world level, i.e., GDP-reducing and emission-increasing. However, in developed countries, we find that the direction of technological progress is both GDP and emissions-increasing. Moreover, in developed countries, the direction of technological progress in the 1970s was GDP increasing and emissions-reducing when the long-term oil price was rising. However, the direction was GDP and emissions-increasing during the 1980s and 1990s.

The directions of the output bias of technological progress in the three countries are shown in Table 3. The annual average values for four different periods are reported, (i) 1971–1981, the period during which long-term prices had an increasing trend; (ii) 1982–1988, the period during which long-term prices displayed a decreasing trend; (iii) 1989–1992, the period when the world faced increasing oil prices; and (iv) 1993–1999, the period when the world witnessed a downward trend in long-term oil prices. Since 2000, oil prices have been rising. The output bias results reveal that the USA experienced emission-reducing and GDP-increasing technological progress during the 1970s and 1980s, but during the last two periods, the direction of technological progress was both GDP and emissions reducing. The direction of technological progress was identical for exogenous and energy price-induced technological changes. However, the magnitude of emissions-reducing technological progress due to long-term energy prices was higher than the technological progress caused by general science and technologies in all of the periods except 1989–1992.

Similarly, Japan observed an identical direction of technological progress either exogenous or energy price-induced. During the 1970s and during the fourth period, technological progress was GDP-increasing and emissions-reducing. However, it was both GDP and emissions-reducing during the 1980s and early 1990s. With respect to CO_2 emissions, the magnitude of ITCH bias was higher than the ETCH bias during 1970s and 1990s, but during the period 1982 to 1992, the magnitude of the bias was lower. Although the technological progress was SO_2 emissions-reducing during the study period, the magnitude of the energy price-induced technological progress was lower than the exogenous technological progress during the 1980s and the 1990s. The direction of technological change (either exogenous or energy price-induced) was GDP-increasing and emissions-reducing in India until the early 1990s. During 1992–1999, the bias of ETCH was both GDP and emissions reducing, but the direction of ITCH was GDP increasing and emissions reducing. Except during the period 1989–1992, the magnitude of CO_2 emissions-reducing ITCH bias was larger than the ETCH bias and the magnitude of the SO_2 emissions-reducing ITCH bias was larger than the ETCH bias throughout the study period.

5.4. Direction of Input Bias

Similar to the output bias results, the input bias arising from energy price-induced innovation and exogenous technological change are estimated using equation (7) for each input, country, and time period. For the different countries, the average annual values of the input bias arising from ETCH and ITCH are reported in Figures 5g to 5l. Exogenous and energy price-induced input bias results indicate that the world observed input-increasing technological change during the study period.

In Table 4, we present the results for the directions of the input bias for technological progress in the USA, Japan and India. Throughout the study period, the USA observed the direction of technological progress, either exogenous or energy price-induced, that is labor and capital using and energy saving. The magnitude of the ITCH bias against energy consumption was higher than the ETCH bias. In Japan throughout the study period, the direction of ITCH was energy saving, but the direction of ETCH was energy using. The direction of ITCH was labor and capital using, but the direction of ETCH was labor and capital saving from 1982 to 1999. In India, the direction of ITCH was labor and capital saving and energy using throughout the study period. The direction of ETCH was labor and capital saving and energy using during 1971 to 1988, but it was all inputs (capital, labor and energy) saving from 1989 to 1999.

6. Conclusions

A change in relative factor prices stimulates inventions directed at saving the factors that have become relatively expensive. The theory of induced innovation addresses the impact of relative prices on the direction of technological change (Hayami and Ruttan, 1971; Jaffe et al., 2003).

This study contributes to the literature by distinguishing between factor/output substitution and shifts in the production technology frontier. Furthermore, our model includes the by-products of CO_2 and SO_2 emissions, whereby the function requires a simultaneous reduction in emissions and the expansion of good outputs. This study finds how the changes in energy prices are related to induced innovations that are not only energy saving but also measure the impact on emissions. That is, we test whether the increase in energy prices leads to a reduction in energy consumption and sulfur dioxide emission.

We measure technological change in terms of the economic benefits of technologies by using a production possibility frontier. In particular, a directional distance function is applied to measure technological change in 80 countries over the period 1971 to 2000. The technological change effect is decomposed into its exogenous and endogenous effects. The results show that developed countries experienced higher exogenous technological progress in comparison with developing countries and the gap between the two groups has increased over the sample period.

On average and across the world, we observe an absence of energy price-induced technological progress; most of the technological progress is attributed to exogenous technological progress. However, we find that both groups of countries observed substantial energy price-induced technological progress when long-term oil prices were rising, although the growth rate is more volatile in developed countries than in developing countries.

On the one hand, we find that the direction of technological progress was GDP-increasing and emissions-reducing in the 1970s in the developed countries when oil prices were rising. However, the direction was both GDP- and emissions-increasing during the 1980s and the 1990s. The result that only increasing energy prices encourages energy-saving technological progress, is consistent with the theoretical arguments of price-induced technological progress. The results on the output bias provide important implications for the environmental (or carbon) taxation debate; for example, energy prices induce technological progress that internalizes the externalities. The output bias leads to technological change biased in favor of emissions and against GDP. On the other hand, technological change is GDP-reducing and emission-increasing in developing countries. These results imply that developing countries are insensitive to increasing energy prices. Therefore, we need to be careful about the interpretation of energy price increases or energy taxation with regard to developing countries. Moreover, the heterogeneity of results recalls that future research could be directed towards more in-depth analyses of individual countries on this issue.

Appendix. List of the Countries

Argentina, Australia, Austria, Belgium, Benin, Bangladesh, Bolivia, Brazil, Canada, Switzerland, Chile, Cote d`Ivoire, Cameroon, Colombia, Costa Rica, Cyprus, Denmark, Dominican Republic, Ecuador, Egypt, Spain, Ethiopia, Finland, France, Gabon, United Kingdom, Greece, Ghana, Guatemala, Hong Kong, Honduras, Haiti, Hungary, Indonesia, India, Ireland, Iran, Iceland, Israel, Italy, Jamaica, Jordan, Japan, Kenya, Korea, Republic of Sri Lanka, Luxembourg, Morocco, Mexico, Mozambique, Malaysia, Nigeria, Nicaragua, Netherlands, Norway, Nepal, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Paraguay, Romania, Senegal, Singapore, El Salvador, Sweden, Syria, Togo, Thailand, Trinidad &Tobago, Tunisia, Tanzania, Uruguay, United States, Venezuela, South Africa, Zambia, Zimbabwe.

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Table 1: Parameter Estimates of Directional Output Distance Function

	Specification 1		**Specification 2**		**Specification 3**		**Specification 4**	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.0032	-0.920	0.0117	3.995	0.0225	2.919	0.0160	3.810
GDP	-0.5990	-46.105	-0.3887	-55.832	-0.4020	-27.345	-0.3844	-35.014
SO_2	*-0.0609*		*-0.0164*		*-0.0605*		*-0.0279*	
CO_2	0.4619	27.523	0.6277	72.464	0.6585	36.571	0.6435	51.020
Labor	0.1360	25.709	0.1093	33.236	0.1374	30.595	0.1021	29.305
Capital	0.3609	27.540	0.1332	13.854	0.2207	14.387	0.1539	12.637
Energy	-0.2752	-11.872	-0.4571	-34.465	-0.5582	-24.247	-0.4406	-24.309
$(GDP)^2$	0.1263	6.297	0.2115	15.871	0.1867	13.167	0.1939	18.503
$(SO_2)^2$	*-0.2898*		*-0.5165*		*-0.5076*		*-0.3811*	
$(CO_2)^2$	0.1901	8.998	0.3039	23.921	0.3420	22.744	0.1695	13.947
$(Labor)^2$	0.0063	3.380	0.0013	1.208	-0.0015	-0.991	0.0058	5.123
$(Capital)^2$	0.0383	7.115	0.0205	4.832	0.0442	10.834	-0.0024	-0.586
$(Energy)^2$	0.2999	6.557	0.5114	16.952	0.4533	13.786	0.4743	20.135
$GDP \cdot SO_2$	*-0.1768*		*-0.3045*		*-0.3315*		*-0.1783*	
$GDP \cdot CO_2$	0.3031	8.141	0.5160	22.364	0.5182	19.456	0.3723	19.044
GDP · Labor	0.0419	16.930	0.0261	16.514	0.0333	18.496	0.0274	19.347
GDP · Capital	-0.0766	-7.676	-0.1368	-20.987	-0.1369	-19.765	-0.1083	-18.269
GDP · Energy	-0.1942	-6.435	-0.3344	-16.775	-0.2941	-13.652	-0.3090	-19.931
$SO_2 \cdot CO_2$	*0.1130*		*0.2120*		*0.1762*		*0.2028*	
SO_2 · Labor	*0.0382*		*0.0546*		*0.0596*		*0.0471*	
SO_2 · Capital	*0.0312*		*0.0036*		*0.0350*		*-0.0270*	
SO_2 · Energy	*0.0208*		*0.0731*		*0.1018*		*-0.0055*	
CO_2 · Labor	0.0037	0.934	-0.0285	-15.758	-0.0263	-11.476	-0.0197	-13.291
CO_2 · Capital	-0.1078	-9.654	-0.1404	-20.750	-0.1719	-22.248	-0.0812	-12.807
CO_2 · Energy	-0.2150	-7.726	-0.4075	-23.109	-0.3959	-19.399	-0.3035	-20.212
Labor · Capital	-0.0242	-2.466	0.0730	18.195	0.0525	11.451	0.0480	12.995
Labor · Energy	-0.1913	-11.563	-0.1618	-18.555	-0.1696	-16.039	-0.1721	-20.464
Capital · Energy	0.2611	8.555	0.4876	25.403	0.4720	22.132	0.4083	23.983
Time			-0.0003	-0.879	0.0008	0.697	0.0007	1.006
$(Time)^2$			2.10E-05	0.988	-6.53E-05	-1.301	-5.44E-05	-1.611
GDP · Time			-0.0039	-11.751	-0.0028	-6.261	-0.0034	-8.733
SO_2 · Time			*0.0001*		*0.0007*		*0.0006*	
CO_2 · Time			-0.0039	-10.503	-0.0035	-6.636	-0.0039	-9.211
Labor · Time			-0.0011	-7.799	-0.0008	-3.826	-0.0009	-5.858
Capital · Time			0.0081	16.929	0.0064	12.172	0.0083	16.242
Energy · Time			0.0091	14.095	0.0067	8.116	0.0079	11.300
EnergyPrice					-0.0064	-1.641	-0.0059	-2.571
$(Energy\ Price)^2$					0.0012	1.237	0.0013	2.270
GDP · Energy Price					-0.0199	-7.373	-0.0111	-5.381

SO_2 · Energy Price					*0.0056*		*0.002*	
CO_2 · Energy Price					-0.0255	-8.091	-0.0131	-5.548
Labor · Energy Price					-0.0006	-1.566	-0.0002	-0.593
Capital · Energy Price					0.0029	1.472	-0.0026	-1.648
Energy · Energy Price					0.0297	7.716	0.0194	6.776
Energy Price · Time					6.06E-05	0.272	2.40E-05	0.179
Group Dummy							-0.0073	-3.323
θ	7.6430	14.5170	4.3281	20.155	6.0328	23.128	4.0382	20.500
P	0.4511	15.5170	0.3637	19.139	0.4024	17.258	0.3528	21.293
σ_v	0.0134	29.4460	0.0157	29.299	0.0240	35.646	0.0132	25.941
Loglikelihood function	2310.12		2737.40		2740.89		2796.12	

Note: Parameters in *Italic* are calculated by applying the translation property of the directional distance function. Number of observation: 2093.

Table 2: Tests of Hypotheses for Functional Form of Directional Output Distance Function

Null Hypothesis	Log Likelihood Ratio Test Statistics (λ)	Critical χ^2	Decision Level (at 1% level)
H_0: $\gamma_1=\gamma_2=\gamma_{11}=\eta_{11}=\eta_{21}=\eta_{31}=\mu_1=0$	854.56	18.48	Reject H_0
H_0: $\gamma_1=\gamma_2=\gamma_{11}=\eta_{11}=\eta_{21}=\eta_{31}=\mu_1=\gamma_2=\gamma_{22}=\eta_{12}=\eta_{22}=\eta_{32}=\mu_2=\phi=0$	861.54	29.1	Reject H_0
H_0: $\psi_{13}=0$	110.46	6.63	Reject H_0

λ = -2{Log(Likelihood (H_0)- Log(Likelihood (H_1))}

Table 3: Average Annual Output Biases in USA, Japan, and India

Period	GDP Biased Exogenous technological Change	CO_2 Biased Exogenous technological Change	SO_2 Biased Exogenous technological Change	GDP Biased Energy Price Induced technological Change	CO_2 Biased Energy Price Induced technological Change	SO_2 Biased Energy Price Induced technological Change
USA						
1971-1981	5.03E-02	2.77E-02	2.51E-02	8.99E-02	4.85E-02	4.38E-02
1982-1988	2.34E-01	6.51E-02	5.87E-02	2.31E-01	7.95E-02	7.31E-02
1989-1992	-3.85E-01	3.98E-02	3.17E-02	-1.58E-01	1.64E-02	1.31E-02
1993-2000	-3.96E-02	2.49E-02	1.56E-02	-1.08E-02	6.47E-03	4.11E-03
Japan						
1971-1981	1.09E-02	2.27E-02	1.50E-02	2.97E-04	4.17E-02	2.77E-02
1982-1988	-2.36E-01	5.12E-02	3.20E-02	-2.56E-01	4.75E-02	3.00E-02
1989-1992	-3.10E-01	6.69E-02	4.17E-02	-1.13E-01	2.54E-02	1.58E-02
1993-2000	6.00E+00	1.12E-01	7.64E-02	1.50E+00	2.68E-02	1.82E-02
India						
1971-1981	7.96E-01	7.37E-01	7.22E-01	1.08E+00	9.79E-01	9.52E-01
1982-1988	2.37E+00	2.19E+00	2.16E+00	3.08E+00	2.92E+00	2.89E+00
1989-1992	8.54E-01	2.49E-01	2.19E-01	3.50E-01	1.03E-01	9.03E-02
1993-2000	-2.63E-02	1.41E-01	1.13E-01	1.88E-02	3.72E-02	3.00E-02

Table 4: Average Annual Input Biases in USA, Japan, and India

Period	Labor Biased Exogenous technological Change	Capital Biased Exogenous technological Change	Energy Biased Exogenous technological Change	Labor Biased Energy Price Induced technological Change	Capital Biased Energy Price Induced technological Change	Energy Biased Energy Price Induced technological Change
USA						
1971-1981	-1.14E-02	-5.79E-03	4.40E-03	-1.10E-02	-1.25E-02	1.27E-02
1982-1988	-2.09E-02	-6.69E-03	4.10E-03	-1.02E-02	-1.24E-02	1.26E-02
1989-1992	-2.40E-02	-5.87E-03	3.06E-03	-4.55E-03	-5.71E-03	5.80E-03
1993-2000	-2.72E-02	-5.32E-03	2.21E-03	-3.01E-03	-3.85E-03	4.03E-03
Japan						
1971-1981	-1.73E-03	-1.63E-03	-4.71E-03	-1.17E-02	-2.28E-02	1.86E-02
1982-1988	7.13E-02	1.69E-02	-2.05E-02	-4.33E-03	-2.05E-02	2.87E-02
1989-1992	1.26E-01	2.88E-02	-3.05E-02	-6.31E-04	-9.20E-03	1.07E-02
1993-2000	1.37E-01	3.55E-02	-3.45E-02	-8.41E-05	-5.77E-03	6.01E-03
India						
1971-1981	5.48E-02	4.53E-02	-2.34E-03	2.82E-02	1.98E-02	-2.42E-03
1982-1988	1.00E-01	9.76E-02	-2.02E-03	3.20E-02	2.32E-02	-3.40E-03
1989-1992	1.13E-01	1.20E-01	1.92E-03	1.52E-02	1.11E-02	-1.60E-03
1993-2000	1.31E-01	1.45E-01	1.18E-02	1.07E-02	7.92E-03	-6.80E-04

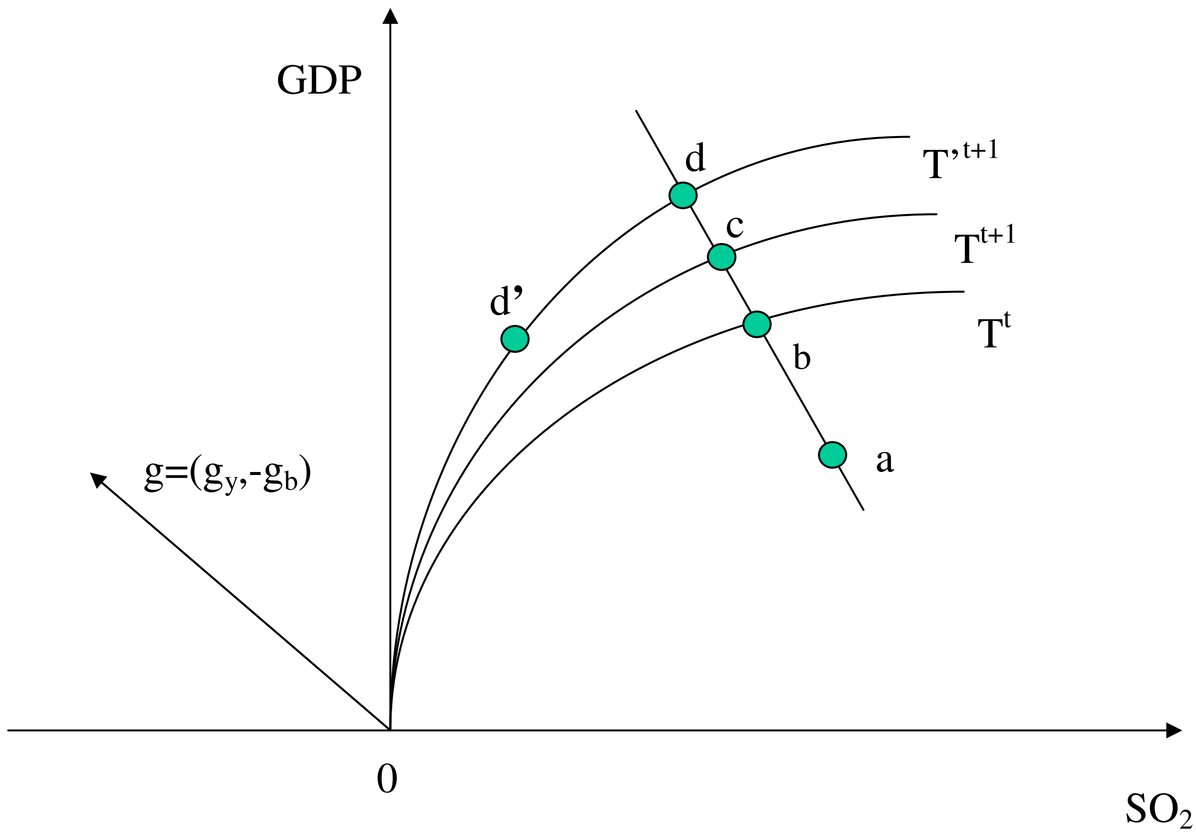


Figure 1: Decomposition of Productivity Indicators

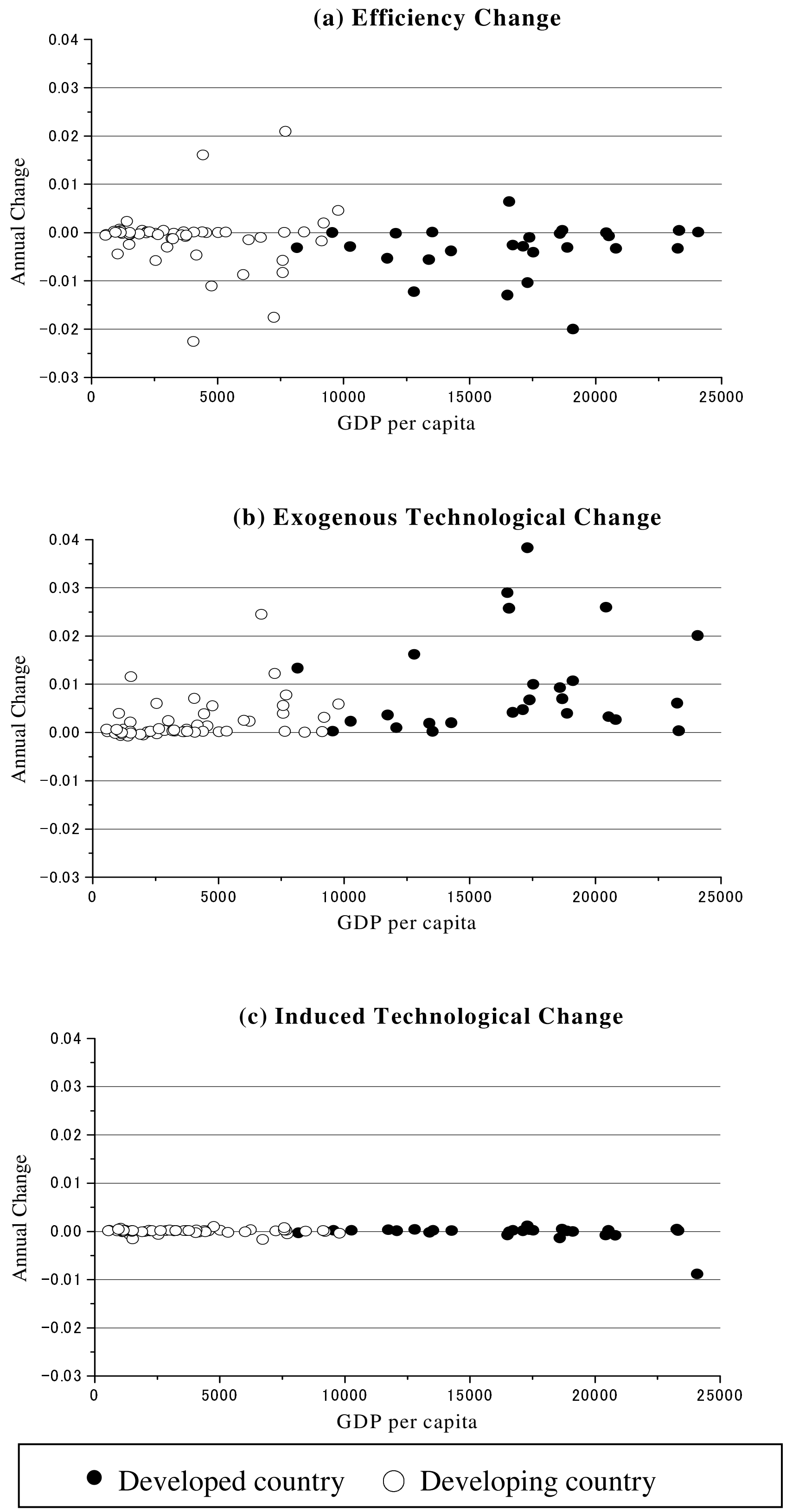
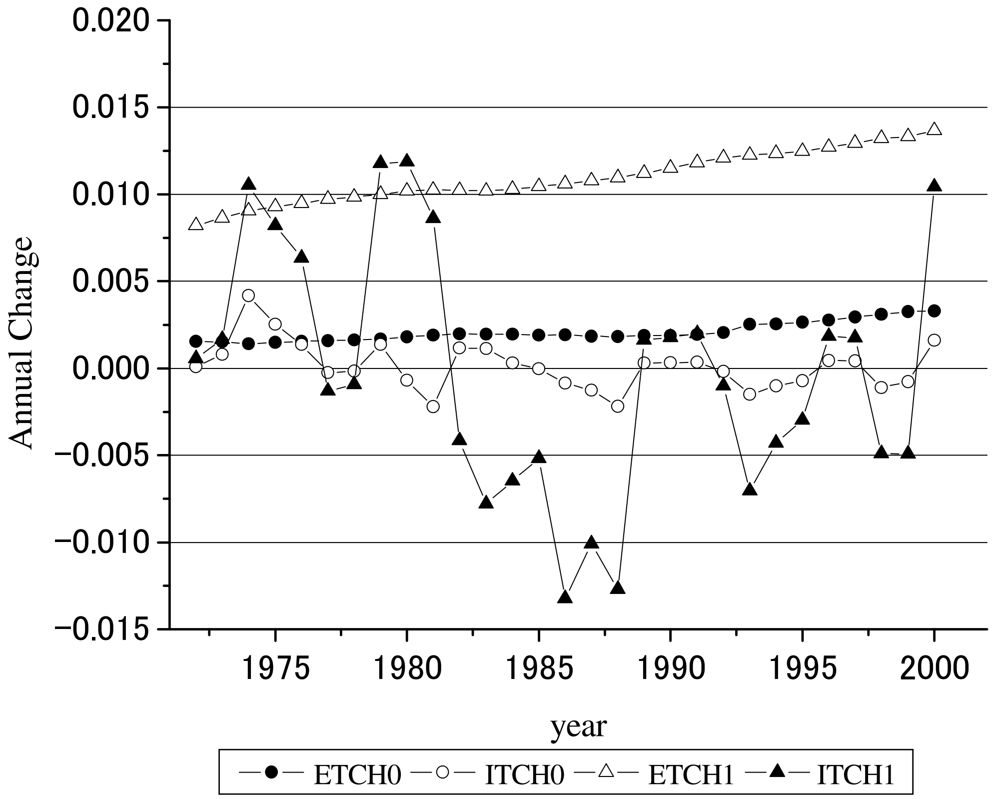


Figure 2: Decomposition of Technological Change



Note: ETCH0: Exogenous Technological Change (ETCH) in developing countries; ITCH0: Induced Technological Change (ITCH) in developing countries; ETCH1: ETCH in developed countries; ITCH1: ITCH in developed countries.

Figure 3: Exogenous and Induced Technological Change

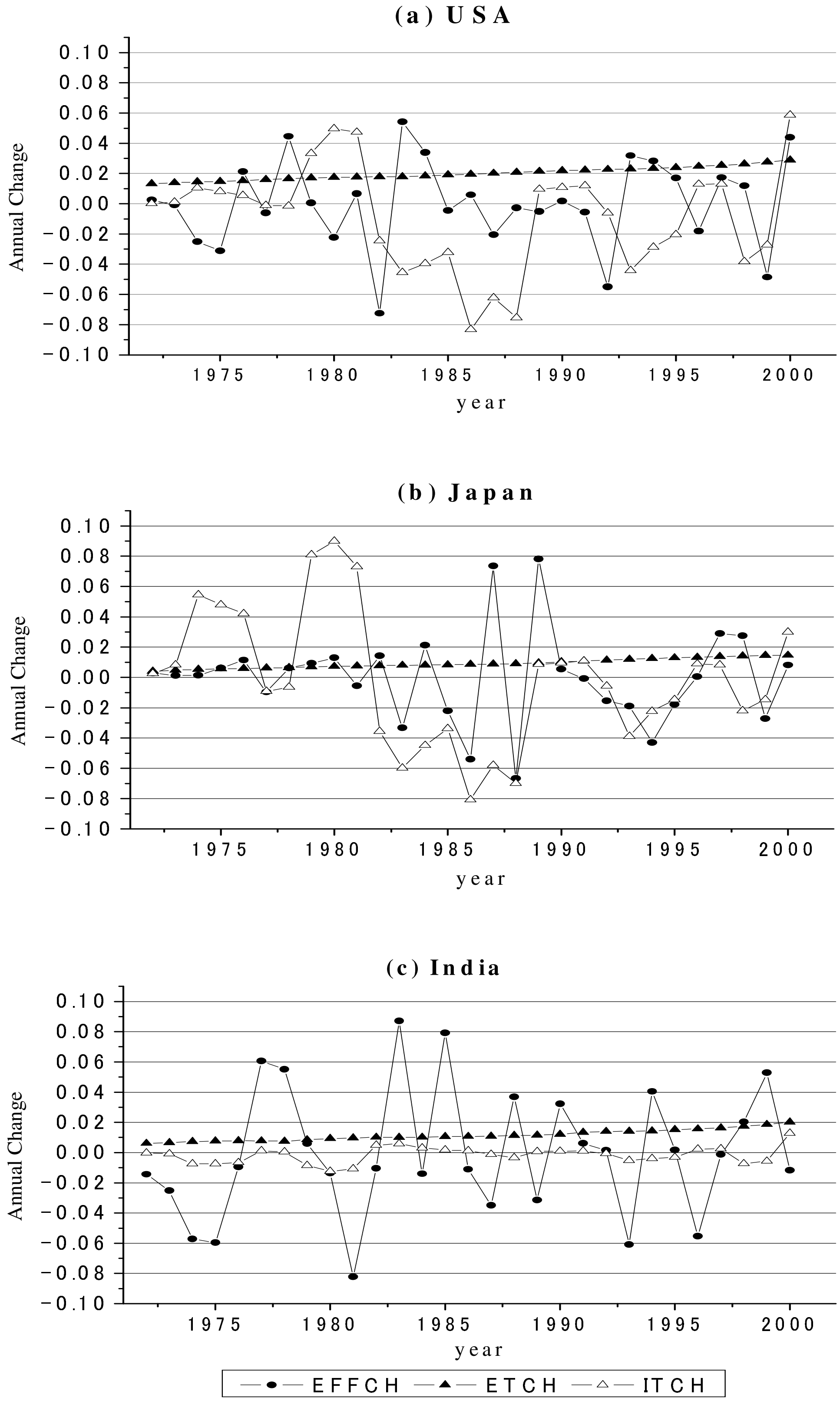


Figure 4: Technological Changes in USA, Japan, and India

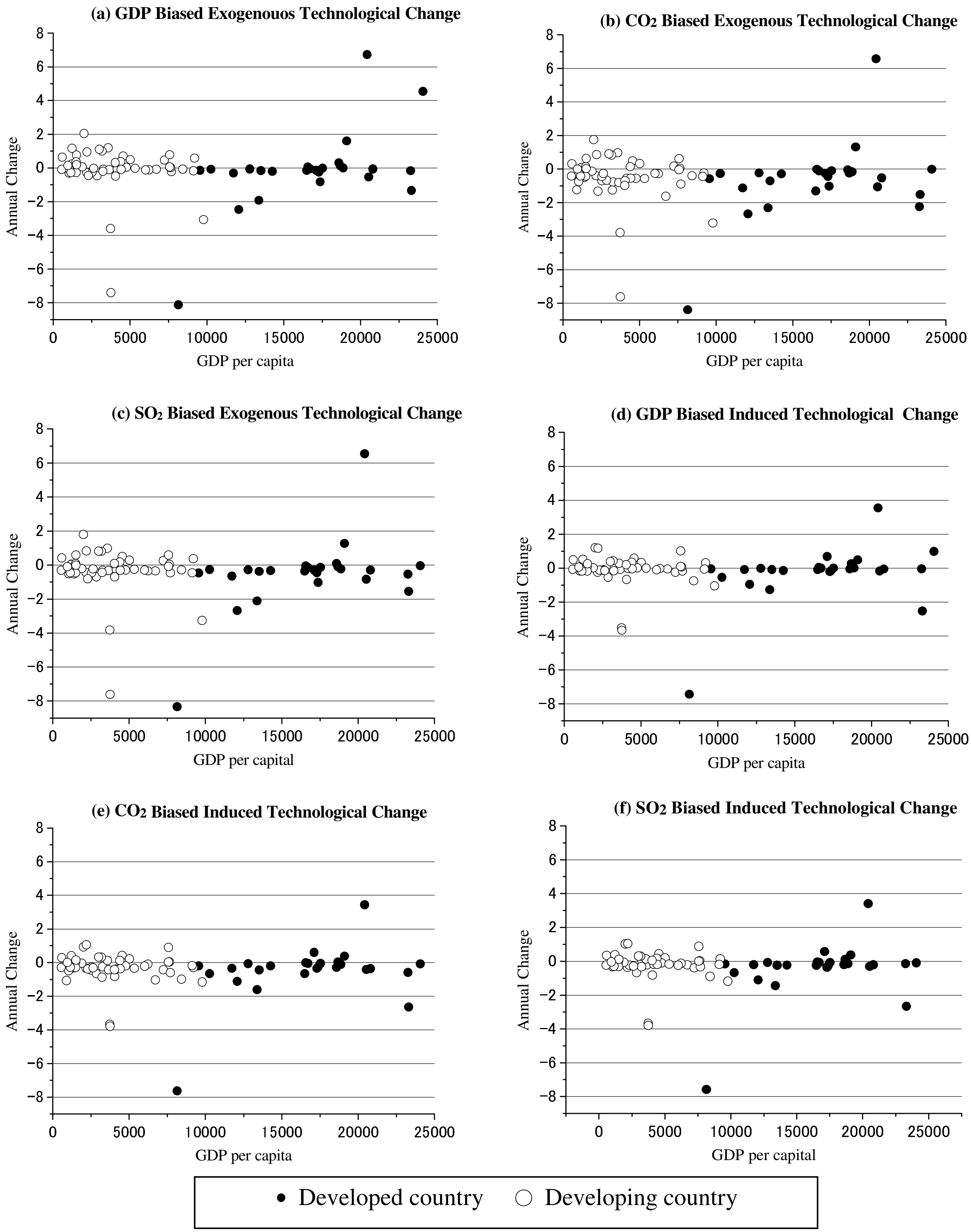


Figure 5: Biased Technological Changes

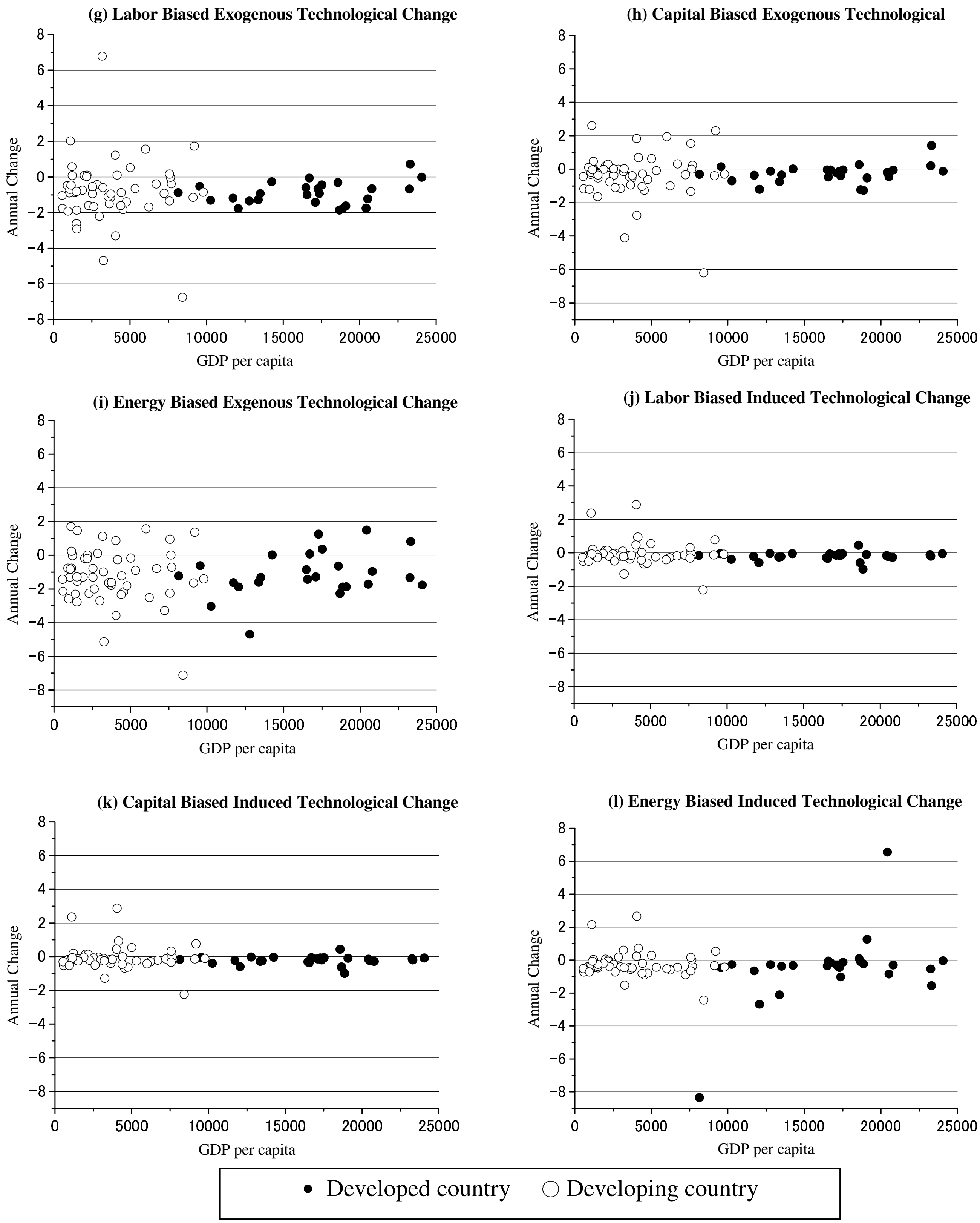


Figure 5: (continued…)