Impact of Environmental Regulation on Productivity: Case Studies of Three Industries in Japan

Adisak Chalermthanakom

Ph.D. candidate, Graduate School of Economics, Kyoto University, Japan
E-mail: chua@econs.mbox.media.kyoto-u.ac.jp

Kazuhiro Ueta

Professor, Graduate School of Economics, Kyoto University, Japan
E-mail: ueta@econ.kyoto-u.ac.jp

ABSTRACT

Although firms bear the cost of compliance, strict but flexible environmental regulation may benefit them by spurring the innovation process. However, the relationship between environmental regulation and productivity is unclear. We calculate productivity growth by using data envelopment analysis; we then conduct regression analysis, using panel data on productivity growth by environmental regulation stringency. A one-year lag of environmental regulation stringency is included in the model.

We use data from the automobile, food, and electronics industries in Japan, from the 2003–2009 period. Regarding environmental productivity, the results are likely to support the Porter hypothesis, rather than traditional productivity. The automobile industry's results support the Porter hypothesis in the case of environmental productivity; for traditional productivity, there is the trade-off between environment and economic performance. The results of the food and electronics industries show no positive or negative impact of environmental regulation on traditional or environmental productivity. Different results between the two productivity indices were found for the automobile industry. The benefits of achieving higher productivity should accrue to firms that can expand output while reducing pollution emissions. Policymakers and managers should make use of environmental productivity in their decision-making process, together with more traditional measures of productivity.

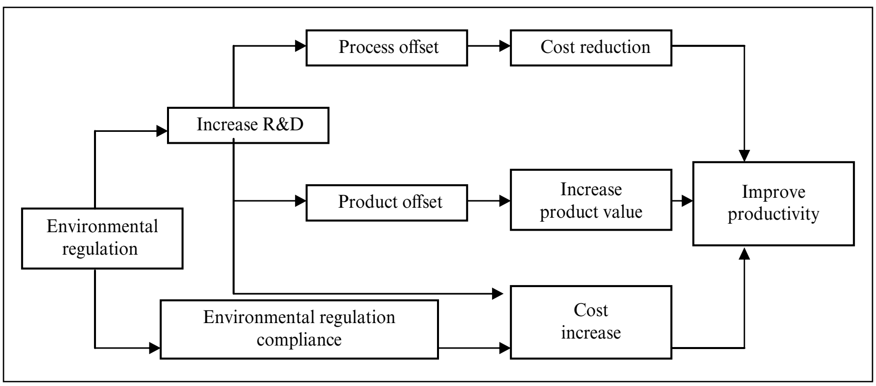
Keywords: Porter hypothesis, environmental regulation, Japanese industries
JEL Classification Number: Q59

1 Introduction

Policymakers usually set environmental regulations, so as to prompt firms to reduce their waste and pollution outputs. However, many economists believe that environmental regulations increase production costs and reduce the productivity and competitiveness of firms. Palmer et al. (1995) describes this problem as embodying a trade-off between productivity and the environment. However, some researchers think that there is not necessarily such a trade-off; for example, Porter and van der Linde (1995) suggest that environmental regulations may be of benefit to firms. This idea is hereafter referred to as the "Porter hypothesis," which implies that environmental regulation provides firms with an incentive to innovate. Regulation can trigger innovation that may eventually increase a firm's productivity, which in the long term may outweigh the short-term private costs of regulation. These positive results to both the environment and firms can be considered a win–win situation deriving from higher productivity among firms. Figure 1 shows schematically how environmental regulation can increase productivity, leading to benefits in terms of both firms and the environment.

This schematic figure presents the Porter hypothesis as argued by Porter and van der Linde, where more stringent and flexible environmental policies are beneficial to the economy because they stimulate innovation that results in improvements in productivity. Firms may try to follow environmental regulations by reducing emissions; however, compliance with such environmental regulations increases costs. With higher abatement costs, firms increase investment in innovation to find more efficient ways of responding to environmental

Figure 1. Schematic Representation of Environmental Regulation Increasing Productivity.



Note: Modified from Ambec and Barla (2006).

regulation. From such innovation, firms might derive a new production process that could reduce production costs, or a new product that could increase output value. This increase or decrease in productivity as a result of environmental regulation depends on whether the benefits from innovation are greater or less than the cost of compliance.

Numerous empirical studies identify the relationship between environmental regulation and productivity. These studies mainly focus on developed countries (Gollop and Roberts, 1983; Dufour et al., 1998; Berman and Bui, 2001; Gray and Shadbegian, 2003; Marklund, 2003; Domazlicky and Weber, 2004; Lanoie et al. 2005; Managi et al., 2005; Hamamoto, 2006; Telle and Larsson, 2007; Van der Vlist et al., 2007). Some studies find that environmental regulation negatively impacts productivity, while others indicate that environmental regulation improves it. At present, the impact of environmental regulation remains controversial and should be tested within the context of various regimes and industries.

Why is the impact of environmental regulation on productivity ambiguous? Perhaps, the data in Figure 1 are suggesting that the Porter hypothesis says that if regulation is not stringent enough to trigger the innovation process, firms may end up pursuing end-of-pipe measures that might ultimately *decrease* their productivity. We hypothesize that tighter environmental regulation triggers the innovation process and provides firms with benefits greater than the cost of compliance, which ultimately improves productivity. The current study examines productivity in terms of both traditional productivity (Malmquist [M] index) and environmental productivity (Malmquist–Luenberger [ML] index). For greater accuracy vis-à-vis pollution discharged to the environment during production, environmental productivity is the appropriate measure, rather than traditional productivity, especially in cases where firms must take all or part of the responsibility for related environmental damage. Firms allocate a portion of resources to pollution countermeasures, such as pollution abatement equipment, and make investments in cleaner production processes; thus, the benefits of achieving higher productivity should accrue to firms that can simultaneously expand output and reduce pollution emissions. This study also examines environmental performance, such as carbon dioxide (CO_2) emissions and waste water discharge, in calculating environmental productivity. The case studies in this study are from the automobile, food, and electronics industries in Japan. Data for this analysis were obtained for the 2003–2009 period, from 17 firms in the automobile industry, 18 in the food industry, and 16 in the electronics industry.

1.1 Case Studies of Japanese Industries

The case studies in this study pertain to manufacturing industries in Japan. Japan had a period of high growth in the 1950s and 1960s, but during that time also encountered severe environmental problems. To correct these environmental issues, Japan established a comprehensive legal system based on the Basic Law for Environmental Pollution (1967). Furthermore, in 1970, the so-called Pollution Diet—a special legislative session in which a set of 14 environmental regulations was enacted—made essential improvements to the complete system of environmental pollution control. The environmental performance of Japan was quite good from 2000 to 2008 (OECD 2010). In terms of the relationship between pollution emissions and socioeconomic activity in Japan, studies have shown that CO_2 has tended to fluctuate with gross domestic product, whereas sulfur oxides have followed a downward trend (decoupling), in spite of economic growth. Nitrogen oxides and waste, too, have shown a decoupling trend since the early 2000s (MOE 2012). Moreover, Japan is quite active in meeting environmental regulation standards such that, as of 2010, the number of certifications in Japan under ISO 14001 was 35,016, accounting for almost 14% of the 250,972 certifications worldwide. These facts have led to the consensus that Japanese firms are successful in decoupling environmental degradation and economic growth, at least in part.

It is better to test environmental regulation and productivity in various industries over the same period, and to take the various contexts into account when making comparisons. We can see different responses to environmental regulation in each industry, because a variety of production technologies and intermediate materials are used therein; differences in the scale of environmental regulation also affect the results. Lighter environmental regulation may not motivate firms to innovate and may result in firms pursuing end-of-pipe abatement strategies. In line with Figure 1, we hypothesize that the impact of tighter environmental regulation may benefit firms in such industries. This study investigates the automobile, food, and electronics industries as case studies, because they are some of the most pollution-intensive industries across a variety of transmission means (e.g., air emissions, waste water discharge, solid waste). In recent years, firms have issued environmental data in corporate sustainability reports or environmental reports. These industries have rather complete data that can be used to calculate productivity and determine the impact of environmental regulation.

2 Methodology and Data

This study uses a two-stage methodology. First, we calculate efficiency by using the data envelopment analysis (DEA) method and then calculating productivity growth. The DEA model is a nonparametric approach to estimating the efficiency score of a firm. DEA uses linear programming (LP) methods to construct a piecewise frontier over the sample decision-making units. The efficiency score is calculated as a function of distance from the constructed frontier. Second, we conduct a regression model for productivity growth by environmental regulation stringency, and other firm-specific variables. This section discusses the methodology used in this analysis.

2.1 Productivity Growth Without Undesirable Output

While there are many ways of estimating productivity growth, this study uses DEA, for several reasons. First, DEA does not require price data, which are rare. Moreover, DEA uses a nonparametric piecewise frontier, so it does not require a large quantity of data—unlike the case of other parametric approaches (Coelli et al., 1998). As mentioned, within our sample, 18 firms are in the food industry, 16 in the electronics industry, and 17 in the automobile industry; given these small samples sizes, DEA is the most suitable method for estimating productivity.

The output-oriented DEA model is defined as:

$$\mathrm{Max}_{\alpha,\lambda} \quad \alpha$$

$$\text{St.} \quad X\lambda \leq x_i,$$
$$Y\lambda \geq \alpha y_i, \quad \text{and}$$
$$\lambda \geq 0,$$

where X is a K × N input matrix, Y is an M × N output matrix, α is a scalar, and λ is an N × 1 vector of constants; x_i and y_i are the input and output of firm i, respectively. When we use LP to solve the DEA model, α is the efficiency score of firm i. Additionally, this DEA model can be defined as the following output distance function:

$$D_o(x, y) = \min\{\delta : (y/\delta) \in P(x)\},$$

where P(x) is the output set.

According to Fare et al. (1994), the M index is employed to calculate productivity growth, using the following equation:

$$M_t^{t+1} = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \times \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right]^{1/2}.$$

Here $t = 1, \ldots,$ T is the time period. The first term on the right-hand side is the output distance function when P(x) is the output set in period t, and the second term is the output distance function when P(x) is the output set in period $t + 1$.

2.2 Productivity Growth With Undesirable Output

In the real world, the fact that economic activity has an effect on the environment cannot be disregarded; traditional productivity (i.e., that which ignores undesirable output production) is not a sufficient metric for firms and policymakers in managing environmental and economic issues. To generate more accurate information on production that emits pollution or otherwise affects the environment, environmental performance productivity is a more appropriate measure of productivity than traditional productivity, especially in cases where firms must bear some or most of the costs of environmental damage. Firms that are able to expand output and reduce pollution simultaneously should be credited for both when calculating productivity. This study considers environmental performance—such as CO_2 emissions and biochemical oxygen demand—in productivity calculations.

Pollution is referred to as an undesirable output. Weakly disposable undesirable output, as discussed by Fare et al. (1989), is widely included as an undesirable output in productivity calculations (Fare et al., 1996; Chung et al., 1997; Fare et al., 2001; Boyd et al., 2002; Marklund, 2003; Domazlicky and Weber, 2004). Our model assumes undesirable output (b) is weakly disposable, such that:

$$\text{if } (y, b) \in P(x) \quad \text{and} \quad 0 \le \theta \le 1, \quad \text{then} \quad (\theta y, \theta b) \in P(x).$$

Additionally, the null-joint between output and undesirable output is assumed, such that

$$\text{if } (y, b) \in P(x) \quad \text{and} \quad b = 0, \quad \text{then } y = 0.$$

These assumptions suggest that good output cannot be produced if undesirable output does not also occur. We can also reduce undesirable output in tandem with an accompanying decrease in good output, while good output and input are maintained according to the strongly disposable DEA model.

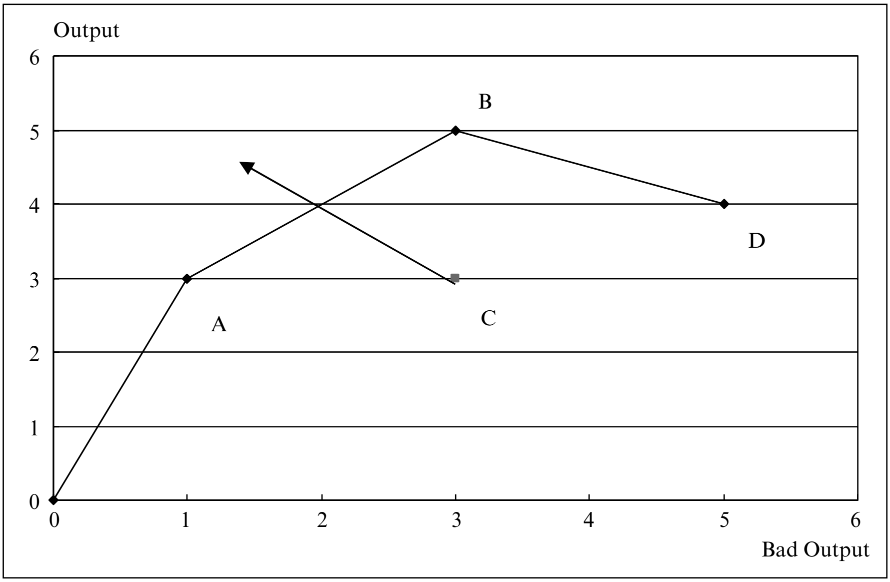
To illustrate the weakly disposable and null-joint assumption, following Domazlicky and Weber (2004), Figure 2 shows the production possibilities set. Suppose there are four firms, each employing the same inputs, with observations represented by points A, B, C, and D: firm A produces $b = 1$ and $y = 3$, firm B produces $b = 3$ and $y = 5$, firm C produces $b = 3$ and $y = 3$, and firm D produces $b = 5$ and $y = 4$.

To measure efficiency and inefficiency, the directional distance function below is applied to show that firms that can produce more good output and reduce undesirable output simultaneously are credited as "efficient firms" (Chung et al., 1997).

$$\vec{D}_o(x, y, b; g) = \max\{\beta : (y, b) + \beta g \in P(x)\},$$

where the direction vector $g = (y, -b)$. According to this example and Figure 2, firm C is the only firm in our set that is inefficient.

Figure 2. Output Possibility Set P(x) and Directional Distance Function.



2.2.1 Methodology Improvement

Fare et al.'s (1989) methodology has a shortcoming: it cannot exclude firm D from the production frontier. Firm D obviously produces less and pollutes more than firm B, so it should be considered an inefficient firm. Thus, we treat bad output as input, even if it contradicts the flow of materials. The benefit of this approach is that the production possibility frontier more closely resembles that in Fare's methodology, except that firm D is no longer classified as an "efficient firm." The other firms can be given the same efficiency score as in Fare's methodology (see Figure 3).

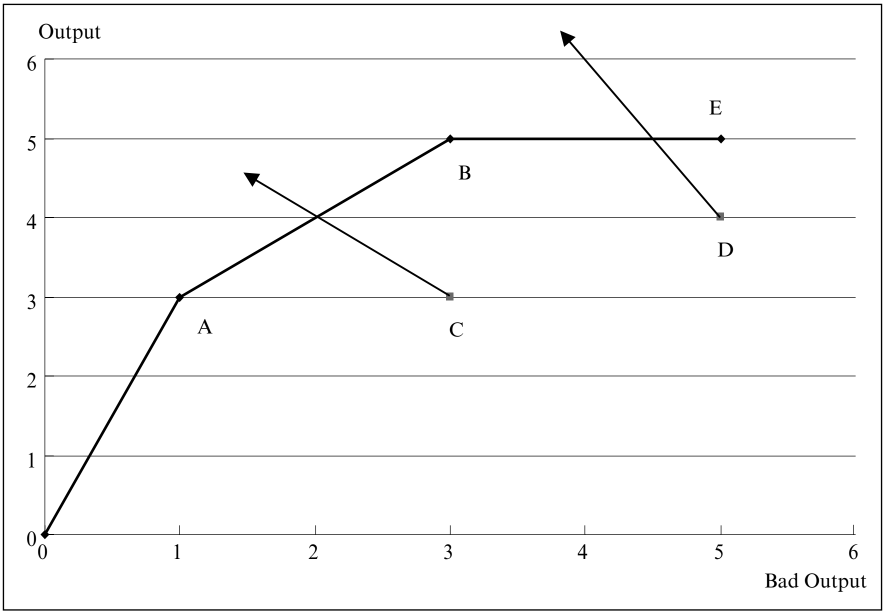
The DEA can be solved as:

$$\text{Max}_{\beta,\lambda} \quad \beta$$
$$\text{St.} \quad X\lambda \le x_i,$$
$$Y\lambda \ge y_i + \beta g_y,$$
$$B\lambda \le b_i + \beta g_b, \quad \text{and}$$
$$\lambda \ge 0,$$

where $(g_y, g_b) = (y_i, -b_i)$.

The β of an inefficient firm is greater than 0, which means that the inefficient firm can produce more βy and produce less βb in order to reach the output possibility frontier.

Figure 3. Output Possibilities When Treating Undesirable Outputs as Inputs.



After solving LP problems for each firm in line with the work of Chung et al. (1997), the ML index is employed to calculate productivity growth, using the following equation:

$$ML_t^{t+1} = \left[\frac{(1+\vec{D}_0^t(y^t, b^t, x^t; g^t))(1+\vec{D}_0^{t+1}(y^t, b^t, x^t; g^t))}{(1+\vec{D}_0^t(y^{t+1}, b^{t+1}, x^{t+1}; g^{t+1}))(1+\vec{D}_0^{t+1}(y^{t+1}, b^{t+1}, x^{t+1}; g^{t+1}))} \right]^{1/2}, \quad (1)$$

where $t = 1, \ldots,$ T is the time period.

Equation (1) is the geometric mean of environmental productivity growth, calculated using period t and period $t + 1$ as the reference technologies.

2.3 Testing the Impact of Environmental Regulation on Productivity

To test the impact of environmental regulation on productivity, an econometric model is applied. However, regression analysis using a productivity index calculated by DEA as a dependent variable may cause autocorrelation; Simar and Wilson (2007) propose a double-bootstrap method to resolve this issue.

Nakano and Managi (2008) and Zhengfei and Oude Lansink (2006) consider the bootstrap method too complex and difficult to apply to empirical research, especially with a panel model and dynamic specification. They apply the system generalized method of moments (GMM) introduced by Arellano and Bover (1995) and Blundell and Bond (1998). In terms of resolving the autocorrelation problem, they claim that system GMM is a valid alternative to the bootstrap method. The current study follows Zhengfei and Oude Lansink (2006): for this reason, we estimate the following equation:

$$Growth_{it} = c + \alpha_1 Growth_{it-1} + \beta_1 ER_{it} + \beta_2 ER_{it-1} + \beta_3 K_{it} + \beta_4 Inputprice_{it} + \varepsilon_{it}$$

$$\varepsilon_{it} = \eta_i + \nu_{it},$$

where the error term ε_{it} consists of individual effect η_t and disturbance term v_{it}, and $Growth_{it}$ is productivity growth. This study uses the M and ML indexes.

The firms' previous-year performance might affect current-year performance: if a firm had high productivity growth in the previous year, it might be difficult to retain a high growth rate in the following year. One-year-lagged productivity growth $Growth_{it-1}$ is included in the regression; however, the lagged dependent variable correlates with the error term. To resolve this autocorrelation, the first-difference model is used to remove individual effect η_i, and the dependent variable before $t - 2$ is used as an instrumental variable in system GMM. Additionally, productivity growth might affect capital K_{it}. This endogeneity problem can be resolved by using all lagged of K_{it} as an instrumental variable. To estimate system GMM, the current study uses the DPD (Dynamic Panel Data) program for Ox, provided by Doornik et al. (2006).

Productivity growth is regressed on one-year-lagged productivity growth $Growth_{it-1}$, environmental regulation stringency (ER_t), one-year-lagged environmental regulation stringency (ER_{t-1}), size of plant, and input price. In determining the relationship between productivity growth and environmental regulation, environmental regulation stringency is no doubt an important variable. Alternative variables—such as environmental preservation cost per production cost, number of firm inspections, facility's perception, and pollution control capital cost—are other possibilities for use in such an evaluation (Iraldo et al., 2011). However, the number of inspections and facility's perception are not available within the dataset, while environmental preservation cost can be extracted from corporate sustainability reports and environmental reports. Additionally, when environmental regulation is more stringent, we can expect that firms will address regulations by increasing their environmental preservation cost per production cost. Similarly, Jaffe and Palmer (1997) use pollution control capital costs, Gray and Shadbegian (2003) use pollution abatement investment, Brunnermeier and

Cohen (2003) use pollution control operating costs, and Lanoie et al. (2008) use investment in pollution control equipment per total cost. The current study uses environmental preservation cost per production cost as a proxy for environmental regulation stringency.

In addition, the lag of environmental regulation is an important dependent variable in the model. More stringent environmental policies will necessarily lead to innovation that ultimately reduces inefficiencies; this, in turn, eventually reduces costs. This process may take some time (Porter and van der Linde, 1995; Ambec and Barla, 2006). A one-year lag of environmental regulation (ER_{t-1}) is included in the econometric model to aid in determining the relationship between productivity growth and environmental regulation. ER_t and ER_{t-1} may be positively or negatively related to productivity growth. The effect of ER_{t-1} should be greater than that of ER_t; therefore, the coefficient of ER_{t-1} should be positive if the innovation process takes time, and benefits accruing from innovation occur within the one-year-lagged period; meanwhile, the coefficient of ER_t may be negative solely on account of compliance costs incurred in the current period, and there has been no time for firms to adapt to the regulation. The size of plant should positively correlate with productivity growth: larger plants should be more productive than smaller plants. Additionally, the input price should relate positively to productivity growth: when the input price increases, firms tend to use less input to produce the same amount of output.

3 Case Studies and Data

In terms of environmental and economic performance, Japan can develop its economy while simultaneously addressing environmental problems to satisfaction. This section describes the characteristics of environmental regulation in Japan as tools for resolving environmental problems.

3.1 Environmental Regulation in Japan

According to the OECD (2010), environmental regulation in Japan emphasizes performance standards and negotiated agreements. Performance standards are widely used when discussing every type of environment issue. High-priority issues include air pollution in urban areas, solid waste, water pollution, environmental protection, and climate change. Another important characteristic of environmental regulation in Japan is negotiated or voluntary agreements. These agreements are the result of negotiations between municipalities and facilities, especially newly established facilities. In addition, municipalities legally have the power to set more stringent standards; in reality, many municipalities set more stringent standards than do their national-level counterparts.

Furthermore, the OECD (2010) found that these approaches—namely, performance standards and negotiated agreements—can persuade businesses that investments in clean technologies can ultimately confer competitive advantages; however, it is questionable, whether these approaches provide sufficient incentive to improve environmental performance and encourage new technologies in the favored direction. Table 1 summarizes environmental regulation in Japan from 1967 to 2007. Environmental regulation in Japan began in 1967 with the enactment of the Basic Law for Environmental Pollution Control. In 1970, essential improvements in environmental law occurred when a set of 14 new environment regulations (comprising the Pollution Diet) was passed; furthermore, at the time of the 1970 Pollution Diet, the Basic Law for Environmental Pollution Control was amended to delete a provision stating that "harmony with sound economic development should be considered" (Tsuru, 1999, p. 249).

The current study looks to evaluate the impact of environmental regulation on productivity growth in three different manufacturing industries in Japan. Owing to differences in technology and intermediate materials, firms respond to environmental regulation in different ways. Case studies of firms in the three industries should provide more information than a case study of a single industry, and the automobile, food, and electronics industries were selected because they are among the most pollution-intensive in Japan. These three industries are also subject to high levels of environmental regulation (Hibiki and Arimura, 2005). In addition, data were readily available with regard to these industries.

Table 1. History of Environmental Laws and Regulation in Japan.

Year	Environmental laws and regulations
1967	Basic Law for Environmental Pollution Control
1968	Air Pollution Control Law
1970	Pollution Diet (a group of 14 environmental regulations)
1970	Water Pollution Control Law
1973	Chemical Substances Control Law
1993	Basic Environmental Law (revision of 1967 law)
1999	Pollutant Release and Transfer Registers Law (PRTR Law)
2000	Basic Law for Establishing a Sound Material-Cycle Society
2002	Soil Contamination Countermeasures Law
2005	Kyoto Protocol became effective
2007	Basic Act on Biodiversity

Table 2. Summary Statistics for Variables Used in Calculating Productivity Growth.

Variables	Automobile	Food	Electronics
Output			
Deflated output (millions of JPY)			
mean	1,444,561.20	253,776.45	2,448,285.25
std. dev.	2,268,802.39	230,032.30	3,361,866.49
Input			
Labor (number of people)			
mean	10,077.92	2,155.60	17,184.77
std. dev.	8,197.13	2,394.75	26,118.00
Plant capital (millions of JPY)			
mean	147,481.19	48,711.20	215,463.84
std. dev.	144,239.64	33,032.16	265,883.59
Undesirable output			
CO_2 (tons)			
mean	283,930.62	145,386.43	939,467.32
std. dev.	322,873.38	134,009.64	1,351,691.45
Waste water discharge (tons)			
mean	3,012,328.81	7,653,451.09	15,141,146.24
std. dev.	3,108,700.60	15,568,188.60	20,290,969.57
Solid waste (tons)			
mean	405.49	1,267.99	8,208.38
std. dev.	1,160.91	2,203.01	19,658.29
PRTR*: Toxic chemicals (tons)			
mean	744.54	N/A	1,199.65
std. dev.	714.55		2,542.54

*Pollutant Release and Transfer Register.

3.2 Data

Table 2 shows the summary statistics for variables used in this study to calculate productivity growth.

The environmental data are from the corporate sustainability and environmental reports of each firm studied, and production data are from each firm's annual securities report. All variables reflect annual values for the 2003–2009 period. As mentioned, the number of observations are 16, 17, and 18 firms in the electronics, automobile, and food industries, respectively; these are the maximum numbers of firms for which data were available.

To determine the relationship between productivity growth and environmental regulation, the econometric model includes independent variables for environmental regulation stringency, input price, and firm size. According to Table 3, the mean of traditional productivity growth (M) is about 0.39–2.50%, while the mean of environmental productivity growth (ML) is likely higher and at around 0.87–1.76%. The automobile industry has the highest environmental preservation cost per production cost; the automobile, food, and electronics industries have cost ratios of 2.94%, 1.74%, and 1.73%, respectively. Environmental preservation cost per production cost is used as a proxy for environmental regulation stringency, so we anticipate the impact of environmental regulation on productivity to be highest in the automobile industry. The average plant size, in millions of JPY, is largest in the electronics (229,778), automobile (148,675), and food industries (48,791), in that order, while the input price index seems to be highest in the food industry (104.82), followed by the automobile (102.72) and electronics industries (100.13).

4 Results

4.1 Estimates of Productivity Growth

When undesirable output is included in the ML calculation, the relation is:

$$\mathrm{ML} = \mathrm{f}(Growth_{it-1}, ER_t, ER_{t-1}, \text{plant size, input price index}).$$

When excluding undesirable output in the M calculation, the relation is:

$$\mathrm{M} = \mathrm{f}(Growth_{it-1}, ER_t, ER_{t-1}, \text{plant size, input price index}).$$

To address autocorrelation by using the productivity index as a dependent variable, the current study uses system GMM, as recommended by Nakano and Managi (2008) and Zhengfei and Oude Lansink (2006). In addition, the Sargan test for overidentifying restrictions and the AR(2) test in Tables 4, 5, and 6 show that system GMM is suitable in addressing the autocorrelation problem, and that the instrumental variables in the model are valid.

Summary statistics for variables used in the productivity growth equations are summarized in Table 3.

4.2 Automobile Industry

Table 4 provides a summary of the regression results for the case study firms in the automobile industry. In the case of the M model, current-period environmental regulation stringency has a significant and negative effect on productivity. However, in the case of the ML model, the coefficient of ER_{t-1} is significantly greater than that of ER_t, and the overall impact of environmental regulation is positive. Environmental regulation in the same time period has a negative effect on produc-

Table 3. Summary Statistics for Variables Used in Productivity Growth Equations.

Variables	Automobile	Food	Electronics
Dependent variables			
ML growth (%)			
mean	1.61	0.87	1.76
std. dev.	5.84	5.17	6.93
M growth (%)			
mean	0.39	0.61	2.50
std. dev.	18.20	10.45	17.33
Independent variables			
Environmental preservation cost per production cost (%)			
mean	2.94	1.74	1.73
std. dev.	2.09	0.91	1.47
Plant capital (millions of JPY)			
mean	148,675.70	48,791.71	229,778.20
std. dev.	144,207.24	33,356.53	277,093.87
Input price index			
mean	102.72	104.82	100.13
std. dev.	2.62	4.49	2.58

Table 4. Relationships Between Productivity Growth and Environmental Regulation Stringency in the Automobile Industry.

	ML	**M**
ER_t	–4.19** (1.67)	–17.57** (8.10)
ER_{t-1}	4.74*** (1.69)	6.80 (10.02)
One-year-lagged productivity growth	–0.20 (0.13)	–0.27* (0.15)
Plant capital	0.000006 (0.000009)	–0.00004 (0.00006)
Input price	–0.56* (0.29)	–3.68*** (0.90)
Sargan test	p = 0.999	p = 0.998
AR(2)	p = 0.826	p = 0.082

Note: n = 85 (five periods and 17 firms). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are standard errors.

tivity growth, because there has not been sufficient time for firms to adapt to the regulation. Nevertheless, after some time has passed, firms can adapt to the earlier environmental regulation and increase their environmental productivity growth (as captured in the one-year-lagged variable for environmental regulation stringency).

4.3 Food Industry

Table 5 provides the regression results for the case study firms in the food industry. For this industry, no conclusion can be drawn regarding the relationship between productivity growth and environmental regulation, because neither the coefficient for ER_t, nor that for ER_{t-1}, is significant. In the case of the M and ML models, the signs of ER_t and ER_{t-1} are as expected, but they are not significant.

4.4 Electronics Industry

Table 6 provides a summary of the regression results for the case study firms in the electronics industry. In the case of the M and ML models, no conclusion

Table 5. Relationships Between Productivity Growth and Environmental Regulation Stringency in the Food Industry.

	ML	M
ER_t	–0.61 (1.29)	–4.58 (5.17)
ER_{t-1}	1.48 (1.32)	6.05 (6.51)
One-year-lagged productivity growth	–0.13 (0.18)	–0.37* (0.19)
Plant capital	–0.00001 (0.00006)	–0.0001 (0.0001)
Input price	–0.43** (0.20)	–0.59*** (0.19)
Sargan test	p = 0.998	p = 0.993
AR(2)	p = 0.086	p = 0.805

Note: n = 90 (five periods and 18 firms). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are standard errors.

can be drawn regarding the relationship between productivity growth and environmental regulation, because neither the coefficient for ER_t, nor that for ER_{t-1}, is significant.

5 Discussion and Concluding Remarks

This study explores the relationship between environmental regulation and productivity. Environmental performance increases when environmental regulation is more stringent, but firms must bear the costs of compliance. When environmental regulation is more stringent, firms have an incentive to improve their production and products in order to meet the environmental requirements, and these improvements can over the long term reduce costs and increase product value. As shown in Figure 1, productivity may increase or decrease, depending on the benefits accrued from innovation and whether the benefits are greater or less than the costs of environmental regulation compliance. This study examined the automobile, food, and electronics industries in Japan between 2003 and 2009, in order to observe any differences in terms of sector or regulation stringency.

This study finds that the impact of environmental regulation on productivity clearly differs by industries within the period of study. We found a trade-off between environment and economic performance in the case of traditional

Table 6. Relationships Between Productivity Growth and Environmental Regulation Stringency in the Electronics Industry.

	ML	**M**
ER_t	1.62 (5.81)	–20.69 (18.01)
ER_{t-1}	–0.03 (5.49)	14.41 (24.00)
One-year-lagged productivity growth	–0.09 (0.10)	–0.07 (0.17)
Plant capital	0.000006 (0.000007)	–0.00000005 (0.00002)
Input price	–0.09 (0.18)	0.79 (0.74)
Sargan test	p = 1.000	p = 0.988
AR(2)	p = 0.909	p = 0.893

Note: n = 80 (five periods and 16 firms). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are standard errors.

productivity in the automobile industry. However, a positive relationship (4.74) was detected in the automobile industry between environmental regulation stringency and environmental productivity growth when adding to the model one year of lag time for environmental regulation (Table 4). Firms can offset the compliance costs of regulation with benefits stemming from innovation, and by decreasing emissions in subsequent years. Thus, the Porter hypothesis is correct in the case of environmental productivity in the automobile industry. Positive relationships were not statistically detected between environmental regulation stringency and productivity growth in the food industry (Table 5). At the same time, no negative relationship was observed, indicating that the compliance costs are of the same magnitude as the benefits of innovation. Therefore, for the food industry, we conclude that environmental regulation does not stimulate productivity growth, but it also does not impede economic performance. The results for the electronics industry resemble those of the food industry, in that no positive or negative relationship was observed. These results imply that there is no trade-off between economic performance and environment protection, and that environmental regulation did not stimulate productivity growth in the 2003–2009 period (Table 6).

To the best of our knowledge, no previous study has tested the Porter hypothesis vis-à-vis various scales of environmental regulation stringency across various industries. The ambiguous results of previous studies may have derived from testing the Porter hypothesis in individual industries only, where there is no variation in the level of environmental regulation stringency. Although some studies have tested the Porter hypothesis with respect to a variety of industries, they did not emphasize differences of scale in environmental regulation stringency. Among the three industries examined here, the automobile industry has the highest ratio of environmental preservation cost per production cost: the automobile, food, and electronics industries had cost ratios of 2.94%, 1.74%, and 1.73%, respectively. We used this ratio as a proxy for environmental regulation stringency, which means that the automobile industry has the highest environmental regulation stringency. Further, the impact of environmental regulation on productivity in the automobile industry is statistically significant and larger than those of the other two industries. When we analyzed in greater detail the environmental preservation cost, we found that it included environmental research and development (R&D). Firms respond to product regulation with environmental R&D, in response to which product offsets occur and output value increases. Of the three industries studied, the automobile industry had the highest ratio of environmental R&D per environmental protection cost: the automobile, food, and electronic industries had R&D ratios of 68.79%, 2.08%, and 27.88%, respectively. The automobile industry might increase its productivity mainly by increasing its output value; in the case of traditional productivity, we found only a negative impact of current-period environmental regulation on productivity. This finding might result from the fact that the period of study is too short to capture any positive impact in subsequent years. However, in the case of environmental productivity, we found environmental regulation to have a positive impact overall. In the case of environmental productivity, we can conclude that tighter environmental regulation motivates firms to respond to the environmental regulation, and that over time, firms can realize a positive impact that stems from the innovation process. That positive impact manifests as product offsets, process offsets, and emission reductions.

Furthermore, previous studies did not compare the results of environmental regulation impact on *both* environmental productivity and traditional productivity. This study, therefore, is the first to make such a comparison and incorporate more information on the discharge of undesirable output to the environment during production. When using environmental productivity (ML index), the results likely support the Porter hypothesis, whereas the use of traditional productivity (M index) does not. In the automobile industry, when testing the impact of environmental regulation using environmental productivity, the magnitude of the current-period environmental regulation stringency (ER_t) coefficient (–4.19) is significantly lower than that of the one-year-lagged environmental regulation stringency (ER_{t-1}) (4.74). However, the magnitude of the ER_t coefficient (–17.56) is significantly greater than that of ER_{t-1} (6.80) when using traditional productivity (Table 4). In the food and electronics industries, neither a positive nor a negative impact from environmental regulation was found (Tables 5 and 6).

These conclusions for all three industries occur within a context where firms use resources, including capital and labor, to reduce pollution emissions.

The results of testing the relationship between environmental regulation and productivity supported the Porter hypothesis with respect to the automobile industry in the case of the environmental productivity index; for the other industries, the Porter hypothesis was not supported. In addition, according to the schematic of the effect of environmental regulation on productivity (Figure 1), policymakers should design environmental regulation that reduces the cost of compliance; they should also stimulate innovation—a part of what the Porter hypothesis describes as a characteristic of good environmental regulation. Japan's approach, which emphasizes performance standards in its environmental regulation, promotes innovation in product and production processes, to some extent.

Overall, this study makes a primary contribution to the understanding of environmental regulation and productivity growth. In this study, these two parameters were assessed within the contexts of three different industries; we explored the potential for variability in response to regulation, on the basis of industrial practices, through the inclusion of both current-period environmental regulation stringency and one-year-lagged environmental regulation stringency. Moreover, we tested the Porter hypothesis by using environmental productivity, deriving differential results and finding more support for the hypothesis than for the case using traditional productivity. Policymakers and managers should also make use of environmental productivity in their decision-making processes. In future research, such analysis should be undertaken with reference to greater numbers of industries and countries. Additional analysis may lead to other findings and conclusions, from different contexts. In addition, it would be useful to test the Porter hypothesis while using a greater lag time for environmental regulation stringency, using data from a longer period: the impact of environmental regulation on productivity may occur over a lag time exceeding one year.

References

Ambec, S. and Barla, P. (2006) "Can environmental regulations be good for business? An assessment of the Porter hypothesis," *Energy Studies Review* 14: pp. 42–62.

Arellano, M. and Bover, O. (1995) "Another look at the instrumental variable estimation of error-components models," *Journal of Econometrics* 68: pp. 29–51.

Berman, E. and Bui, L.T.M. (2001) "Environmental regulation and productivity: evidence from oil refineries," *The Review of Economics and Statistics* 83(3): pp. 498–510.

Blundell, R. and Bond, S. (1998) "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics* 87: pp. 115–143.

Boyd, G.A., Tolley, G. and Pang, J. (2002) "Firm level productivity, efficiency, and environmental performance of the container glass industry," *Environmental and Resource Economics* 23: pp. 29–43.

Brunnermeier, S.B. and Cohen, M.A. (2003) "Determinants of environmental innovation in US manufacturing industries," *Journal of Environmental Economics and Management* 45: pp. 278–293.

Chung, Y.H., Fare, R. and Grosskopf, S. (1997) "Productivity and undesirable outputs: A directional distance function approach," *Journal of Environmental Management* 51: pp. 229–240.

Coelli, T.J., Prasada Rao, D.S. and Battese, G.E. (1998) *An Introduction to Efficiency and Productivity Analysis*, Springer, New York.

Domazlicky, B.R. and Weber, W.L. (2004) "Does environmental protection lead to slower productivity growth in the chemical industry?," *Environmental and Resource Economics* 28: pp. 301–324.

Doornik, J.A., Arellano, M. and Bond, S. (2006) "Panel data estimation using DPD for ox," Economics Discussion Paper, Nuffield College, Oxford University.

Dufour, C., Lanoie, P. and Patry, M. (1998) "Regulation and productivity," *Journal of Productivity Analysis* 9: pp. 233–247.

Fare, R., Grosskopf, S., Lovell, C.A.K. and Pasurka, C. (1989) "Multilateral productivity comparisons when some outputs are undesirable: a non-parametric approach," *The Review of Economics Statistics* 71: pp. 90–98.

Fare, R., Grosskopf, S. and Lovell, C.A.K. (1994) *Production Frontiers*. Cambridge University Press, Cambridge.

Fare, R., Grosskopf, S. and Tyteca, D. (1996) "An activity analysis model of the environmental performance of firms—application to fossil-fuel-fired electric utilities," *Ecology Economics* 18: pp. 161–175.

Fare, R., Grosskopf, S. and Pasurka, C. (2001) "Accounting for air pollution in measures of state manufacturing growth," *Journal of Regional Science* 41: pp. 381–409.

Gollop, F.M. and Roberts, M.J. (1983) "Environmental regulations and productivity growth: the case of fossil-fuelled electric power generation," *Journal of Political Economy* 91(4): pp. 654–674.

Gray, W.B. and Shadbegian, R.J. (2003) "Firm vintage, technology, and environmental regulation," *Journal of Environmental Economics and Management* 46: pp. 384–402.

Hamamoto, M. (2006) "Environmental regulation and the productivity of Japanese manufacturing industries," *Resource and Energy Economics* 28: pp. 299–312.

Hibiki, A. and Arimura, T. (2005) "Environmental policies and firm-level management: practices in Japan," Paper presented at the OECD Conference, *Environmental Policy and Firm-level Management*. Washington, DC.

Iraldo, F., Testa, F., Melis, M. and Frey, M. (2011) "A literature review on the links between environmental regulation and competitiveness," *Environmental Policy and Governance* 21: pp. 201–222.

Jaffe, A.B. and Palmer, K. (1997) "Environmental regulation and innovation: a panel data study," *The Review of Economics and Statistics* 79: pp. 610–619.

Lanoie, P., Patry, M. and Lajeunesse, R. (2005) "Environmental regulation and productivity: new findings on the Porter hypothesis," mimeo, HEC Montréal.

Lanoie, P., Patry, M. and Lajeunesse, R. (2008) "Environmental regulation and productivity: testing the Porter hypothesis," *Journal of Productivity Analysis* 30: pp. 121–128.

Managi, S., Opaluch, J.J., Jin, D. and Grigalunas, T.A. (2005) "Environmental regulations and technological change in the offshore oil and gas industry," *Land Economics* 81(2): pp. 303–319.

Marklund, P. -O., (2003) "Environmental regulation and firm efficiency: studying the Porter hypothesis using a directional output distance function," mimeo; paper provided by Department of Economics, Umeå University, Umeå Economic Studies 619.

Ministry of the Environment (2012). *Annual Report on the Environment, the Sound Material-Cycle Society and Biodiversity in Japan 2012*, Tokyo.

Nakano, M. and Managi, S. (2008) "Regulatory reforms and productivity: an empirical analysis of the Japanese electricity industry," *Energy Policy* 36: pp. 201–209.

OECD (Organisation for Economic Co-operation and Development) (2010), *OECD Environmental Performance Reviews: Japan 2010*, OECD Publishing.

Palmer, K., Oates, W.E. and Portney, P.R. (1995) "Tightening environmental standards: the benefit–cost or the no-cost paradigm?," *Journal of Economic Perspectives* 9(4): pp. 119–132.

Porter, M. and van der Linde, C. (1995) "Towards a new conception of environment–competitiveness relationship," *Journal of Economic Perspective* 9: pp. 97–118.

Simar, L. and Wilson, P.W. (2007) "Estimation and inference in two-stage, semi-parametric models of production processes," *Journal of Econometrics* 136: pp. 31–64.

Telle, K. and Larsson, J. (2007) "Do environmental regulations hamper productivity growth? How accounting for improvements of firms' environmental performance can change the conclusion," *Ecological Economics* 61: pp. 438–445.

Tsuru S. (1999) *The Political Economy of the Environment: The Case of Japan*, Athlone Press, London.

van der Vlist, A.J., Withagen, C. and Folmer, H. (2007) "Technical efficiency under alternative environmental regulatory regimes: the case of Dutch horticulture," *Ecological Economics* 63(1): pp. 65–173.

Zhengfei, G. and Oude Lansink, A. (2006) "The source of productivity growth in Dutch agriculture: a perspective from finance," *American Journal of Agricultural Economics* 88: pp. 644–656.