

Article

The Links between Environmental Innovation and Environmental Performance: Evidence for High- and Middle-Income Countries

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Abstract: Technology innovation plays an increasingly prominent role in addressing global environmental challenges. In particular, environmental technology innovation (environmental innovation) is the most powerful and realistic alternative to achieve environmental sustainability and sustainable development. A better understanding of how environmental innovation affects the environment and how the effect differs by country is needed. This study analyzes how environmental innovation affects environmental improvement by a dynamic panel model using the System Generalized Method of Moments (GMM) estimation. We use panel data from 33 high-income countries and 36 middle-income countries for the period 1996–2011, to compare their environmental pollution patterns, and determine how environmental innovation affects air pollution reduction as measured by sulfur dioxide (SO_2) and carbon dioxide (CO_2) emissions. The results reveal that environmental innovation improves the environment in some countries over time. The effect is particularly beneficial in high income countries. It is evident that environmental innovations reduce SO₂ and CO₂ emissions in high-income countries with time interval, while it does not in middle-income countries. The study also identifies that the relationship between per capita income and SO₂ and CO₂ emissions has a different pattern between high- and middle-income countries. The inverted U-shaped pattern supporting the hypothesis of the Environmental Kuznets Curve (EKC) exists in high-income countries. The examination of the trade effect on pollution emissions provides mixed results; however, trade clearly increases SO₂ and CO₂ emissions in middle-income countries. This study contributes to empirical literatures on the effect of environmental innovation on environmental improvement. And it has significant implications for understanding the importance of direction and role of environmental innovation for environmental sustainability and sustainable development.

Keywords: environmental innovation; environmental pollution; EKC; SO₂ and CO₂ emissions

1. Introduction

The world has experienced unprecedented economic growth, but it was a mainly unsustainable development accompanied with a significant increase in pollutant emissions. As a result, the world faces challenging environmental problems that threaten human survival, including environmental pollution and climate change stemming from rapid population growth, development of industrialization and urbanization, and soaring energy demand. These environmental challenges and threats are a direct challenge to environmental sustainability, and more fundamentally they threaten our present and future. Therefore, in order for mankind to continue to grow in a sustainable way, it is necessary to improve the efficiency of resources and energy and move towards a sustainable economy that uses less resources and energy. If we do so, the close links between resource consumption and



economic growth can be severed. And furthermore, sustainable development ensuring simultaneous environmental sustainability and economic growth can be achievable. Environmental sustainability is fundamental to sustainable development. Given the growing importance of environmental sustainability, environmental technological innovation (hereinafter referred to as environmental innovation) is the most realistic alternative for achieving environmental sustainability. In recent years, environmental innovation has emerged as the most powerful means to overcome environmental challenges and threats. Environmental innovation is crucial in that it can play a prominent role in transforming the "trade-off relations" between economic growth and environmental improvement into mutually cooperative "win-win relations", and contribute to further achieving sustainable development [1]. In this respect, environmental innovation is increasingly emphasized not only in solving the environmental problems of the present generation, but also in ensuring the environmental sustainability of future generations. In general, environmental innovation refers to an environmentally motivated innovation aimed at reducing negative environmental externalities. Environmental innovation includes products, processes, and management innovations that are less harmful to the environment than relevant alternatives [2,3]. The vast literature on environment has focused on analyzing the factors of environmental innovation while acknowledging the full value of environmental innovation. Most notably, the Porter hypothesis, which postulates the links between environmental regulation and environmental innovation, holds that strict and well-designed environmental regulations can induce efficiency and environmental innovation that help environmental improvement without increasing production costs (i.e., without compromising competitiveness). The hypothesis has influenced numerous studies on environmental innovation. As a result, many researchers have been primarily interested in environmental regulation as an input of environmental innovation, and productivity improvement as an outcome of environmental innovation. But the environmental improvement as another outcome of environmental innovation has received relatively less attention. This observation suggests that previous studies on environmental innovation may not be enough to verify a critical role of environmental innovation in improving the environment. Furthermore, some researchers have doubts about whether environmental innovation can induce an absolute pollution reduction. For example, Kemp and Pearson [4] claim that environmental innovation does not necessarily promise absolute decline in environmental damage. According to their arguments, even if less environmentally harmful technologies replaced more environmentally harmful technologies, if the new technologies replaced are used more than before, environmental damage may not be reduced because all the technologies cause environmental damage, to some extent, during the production process and product use. Yet, there are only a few empirical studies on the overall effect of environmental innovation on environmental improvement [5–7].

Although environmental improvement should be the ultimate goal of environmental innovation, the empirical assessment of whether environmental innovation contributes to environmental improvement has been insufficient and has not received much academic attention. From this point of view, the environmental performance of environmental innovation has not been fully understood. This observation is especially important for policy-makers who need to design environmental policies and regulations to induce environmental innovation that meets environmental imperatives, and to evaluate their effectiveness.

In this study, we are entirely focusing on investigating the direct effect of environmental innovation on environmental improvement in terms of outcome rather than input aspect of innovation. It is also necessary to consider environmental regulation as a factor affecting environmental innovation, which is the main aspect emphasized by Porter hypothesis. However, recognizing the realistic consideration that it is difficult to make an accurate comparison of environmental regulation between countries, a detailed analysis of these issues is left for future research.

Therefore, the objective of this study is to seek to evaluate how environmental innovation directly affects environmental improvement using a dynamic panel model, the System Generalized Method of Moments (GMM) estimator [8,9] to consider the impact of past environmental pollution

on the current environmental pollution. In order to compare environmental pollution patterns and determine how differently environmental innovation affects the environment according to income level, this study uses panel data from 33 high-income countries and 36 middle-income countries due to environmental patent data constraints. This study regresses environmental patents on the level of environmental pollution (measured by sulfur dioxide (SO₂) emissions and carbon dioxide (CO_2) emissions), while controlling for key variables such as trade, income, foreign direct investment, and other conditions. This study contributes to empirical literatures on the effect of environmental innovation on environmental improvement. The results reveal that environmental innovation has an effect in some countries over time, though not all countries. The effect is particularly beneficial to high-income countries. This finding suggests the need for a better understanding of the direction and role of environmental innovation for environmental improvement. The results also find that middle-income countries are not following an identical income-environment path (inversed U-shaped curve) as high-income countries. It indicates that the Environmental Kuznets Curve (hereinafter referred to as EKC) hypothesis, which postulates an inverted U-shaped relationship between economic growth and pollution emissions, is more applicable to high-income countries with higher environmental demands and capacities than middle-income countries. The rationale for this interpretation is that as income grows, environmental concerns grow as well [10,11]. As a result, the demand for environmental-friendly products increases as income increases. In addition, high-income countries may be better able to meet the higher requirements for environmental protection through their institutional environmental capacities [12]. It is also likely that economic growth increases the utilization of cleaner capital and technology [13]. The remainder of this paper comprises the following: Section 2 provides a literature review on the environmental performance of environmental innovation, Section 3 addresses the data and methodology, Section 4 discusses the estimation results, and Section 5 provides a summary and conclusion.

2. Literature Review

As mentioned earlier, relatively little research attention has been devoted to the effect of environmental innovation on the environment. Notably, most of the research is not cross-country panel data analysis, but single-country industry-level analysis [5], or survey-based study [6,7]. As an empirical study that examined the linkage between environmental innovation and environmental performance, Carrion-Flores and Innes [5] estimated a simultaneous panel data model of environmental innovation and toxic air pollution. They identified bi-directional causal links between environmental innovation (environmental patent) and pollution emissions, using a panel of 127 US manufacturing industries over the 16-year period 1989–2004. They found that environmental innovation is a key driver of reductions in US toxic emissions, and tighter emission standards trigger environmental innovation rather than environmental innovation contributes to long-run emission reduction more substantively, and furthermore the long-term pollution reduction effect of innovation induced by strict standards is small.

Horbach et al. [6] also examined the links among environmental regulation, environmental innovation, and environmental performance. Using a unique dataset of the German Community Innovation Survey conducted in 2009, they identified specific determinants of environmentally friendly innovation by area of environmental impact. They highlighted that positive environmental impacts are derived through clear environmental targets or side-effects of innovation. First, they found that environmentally friendly innovations are triggered by regulations and cost saving motivations. Second, they identified the areas that may be conducive to cost saving relative to others. The findings suggested that end-of-pipe oriented areas such as air emissions (SO₂, NO_x) are strongly motivated by present and future regulation, whereas energy consumption is mainly driven by cost savings. Thus, they suggested that different forms of environmental impact require different policy measures, since some environmental technologies are more market motivated, while end-of-pipe technologies are more regulation driven.

Conducting a questionnaire-based survey involving 124 Taiwanese firms from eight industry sectors, and using structural equation modeling, Chiou et al. [7] found that "greening" suppliers through environmental innovation significantly enhance environmental performance. Their results indicate that environmental product and process innovations may be more effective than environmental managerial innovation in improving environmental performance. However, they pointed out that these results may also reflect that managerial innovation affects environmental performance indirectly, compared to other forms of innovation.

The empirical study of Carrion-Flores and Innes [5] and survey-based studies of Horbach et al. [6] and Chiou et al. [7] all confirm the positive effect of environmental innovation on environmental pollution reduction. However, these studies are not cross-country panel analyses and do not analyze the same sources of pollution, so they have potential limitations to address the general effects of environmental innovation on environmental improvement.

In terms of the effect of economic growth on the environment, there have been numerous empirical EKC literatures identifying the nonlinear relationship between income and environmental pollution by using econometric models and methods. However, discussions continue on appropriate specification and estimation strategies [14]. In particular, Wagner [14] indicated that the EKC and related literatures have econometric problems to identify the long-run relationship of EKCs since these studies have used linear cointegration or non-cointegration tests with the quadratic and cubic specifications of GDP. He showed that using appropriate cointegration methods leaded much less evidence for cointegrating EKCs compared to linear cointegration tests.

This study seeks to differentiate from previous studies as follows: First, this study uses cross-country panel data analysis rather than firm or industry-level analysis for a single country. Second, this study examines heterogeneous effects of environmental innovation on environmental improvement between high-income countries and middle-income countries, by grouping countries by income level. Third, this study compares the emission patterns of SO₂, which is the most common environmental pollutant, and CO₂, which is not a pollution gas, but, as a greenhouse gas, is the main cause of climate change. Fourth, this study analyzes the relationship between income level and environmental pollution within a revised EKC model with a quadratic term of GDP per capita in the panel context. In this study, we apply a system GMM estimation for the dynamic panel models to overcome endogeneity with a short sample from 1996 to 2011 and panel data for 69 countries. Wagner [14] pointed out that SUR or panel approaches are important to identify cross-country differences in policies.

3. Data and Methodology

3.1. Data

This study tests for the effect of environmental innovation on the environmental improvement by using panel data compiled from the World Bank's World Development Indicators for 1996 to 2011. The data for 69 countries are grouped into high- and middle-income countries according to the World Bank's 2011 country classification by income (Table 1). Table 2 defines the variables used in the study and provides summary statistics. To measure the environmental pollution, this study uses SO₂ emissions and CO₂ emissions per capita, which are widely used as environmental quality indicators in environmental economics papers, as dependent variables; environmental patents, which are most frequently used as an innovation activity indicator, as an independent variable; and trade (% of GDP), real GDP per capita, FDI net inflow (% of GDP), political system, and population density, as control variables. These control variables to affect environmental pollution emissions are mainly based on the existing EKC literature and Potoski and Prakashi [15].

| High Income (33) | | Middle Income (36) | | | | | |
|------------------|---------------------|--------------------|---------------------------|-------------|--|--|--|
| | | Upper | Lower Middle (9) | | | | |
| Australia | Luxembourg | Algeria | Panama | Armenia | | | |
| Austria | The Netherlands | Argentina | Peru | Sri Lanka | | | |
| Belgium | New Zealand | Belarus | Romania | Guatemala | | | |
| Canada | Norway | Brazil | Russian Federation | Mongolia | | | |
| Croatia | Poland | Bulgaria | South Africa | Morocco | | | |
| Cyprus | Portugal | Chile | TFYR of Macedonia | Pakistan | | | |
| Czech Rep. | Rep. of Korea | China | Thailand | Philippines | | | |
| Denmark | Saudi Arabia | Colombia | Tunisia | India | | | |
| Estonia | Singapore | Costa Rica | Turkey | Egypt | | | |
| Finland | Slovakia | Ecuador | Uruguay | 0,11 | | | |
| France | Spain | Iran | 0, | | | | |
| Germany | Sweden | Jordan | | | | | |
| Greece | Switzerland | Kazakhstan | | | | | |
| Hungary | Trinidad and Tobago | Latvia | | | | | |
| Ireland | United Kingdom | Lithuania | | | | | |
| Italy | USA | Malaysia | | | | | |
| Japan | | Mexico | | | | | |

Table 1. Country Classification.

Note: World Bank Classification (GNI per capita in US \$, 2011); High Income (>12,475), Upper Middle Income (4036~12,475), Lower Middle Income (1026~4035), Lower Income (\leq 1025).

| Variable | Contents | Source | Obs. | Mean | Std. Dev. |
|-----------------------|--|-----------------------|------|----------|-----------|
| ln_SO ₂ | Log (SO ₂ emission per capita kilo grams) | UNEP | 897 | 3.027408 | 0.906473 |
| ln_CO ₂ | Log (CO ₂ emission per capita metric tons) | World Bank WDI | 1035 | 1.843427 | 0.677143 |
| ln_ENVP | Log (Environmental Patents, EPO) | OECD Patents Database | | | |
| t-1 | | | 1515 | 1.109302 | 1.616113 |
| t-2 | | | 1414 | 1.097339 | 1.60942 |
| t-3 | | | 1313 | 1.084565 | 1.601894 |
| TRADE | Trade (% of GDP) | World Bank WDI | 1099 | 86.13171 | 56.51306 |
| ln_(GDP) | Log (GDP per capita) (constant 2010 US\$) | World Bank WDI | 1099 | 9.016548 | 1.271173 |
| ln_(GDP) ² | [Log (GDP per capita)] ² (constant 2010 US\$) | World Bank WDI | 1099 | 82.91255 | 22.81949 |
| FDI | FDI net inflow (% of GDP) | World Bank WDI | | | |
| t-1 | | | 1021 | 4.752078 | 14.6096 |
| | Log (Polity Index) | | | | |
| ln_POL | * Autocratic -10 | Polity IV Project | 1104 | 3.246734 | 0.264559 |
| | ~Democratic +10 | | | | |
| POP | Population Density (People per sq.km of land area) | World Bank WDI | 1096 | 198.5379 | 756.7396 |

Table 2. Variables and Summary of Statistics.

3.1.1. SO₂ and CO₂ Emission Level

The burning of fossil fuels and biomass is the most significant source of air pollutants such as SO₂, CO₂, NOx. SO₂ is one of a group of highly reactive gasses known as "sulfur oxides", and is linked to several adverse effects on the respiratory system [16]. The largest sources of SO₂ emissions are fossil fuel combustion at power plants and other industrial facilities, and smaller sources of SO₂ emissions include industrial processes such as extracting metal from ore, and the burning of high sulfur-containing fuels by locomotives, large ships, and non-road equipment [16]. In general, SO₂ emissions are widely used to measure environmental quality or environmental performance, as the emissions immediately cause human health or environmental problems. Unlike SO₂, CO₂ is not a direct harm to humans and the environment, but it has a considerable global negative impact as a greenhouse gas and a purely global externality. Thus, this study uses SO₂ and CO₂ emissions data are extracted from the Edgar v. 4.2 estimation data in UNEP and World Bank (WDI), respectively.

3.1.2. Environmental Patents

Research and development (R&D) and patents are usually used as significant and reliable indicators to estimate technological innovation. Output measures such as patents are preferable

to input measures such as R&D, because R&D data is not available at the segmented industrial level and for private R&D expenditures [17]. Most importantly, patents are preferred in the literature as they are more likely to indicate commercial market output than input measures such as R&D [17] and provide detailed information on each invention [18]. Thus, this study uses environmental patent data to construct a measure of environmental innovation. Patent data were obtained from the OECD's patent database, based on the counts of international patent applications classified as "general environmental management" entered into the European Patent Office (EPO)—World Patent Statistical (PATSTAT) database, based on a selection of IPC classes targeting specific areas of environment-related technology, classified by inventor country and priority date. Specifically, this study uses successful patent applications rather than granted patents to measure innovation on the basis that the date of application is when the inventor recognizes that a potentially valuable invention has been made, as Jaffe and Palmer [19] point out. Patents within the category of general environmental management include major sectors related to environmental technologies, designed to reduce environmental externalities in production processes. In particular, this study includes (1-year, 2-year, and 3-year) lagged patents to incorporate feedback over time since environmental patents can influence the environment (SO₂ and CO₂ emissions) with a time delay.

3.1.3. Trade

Trade directly or indirectly affects the environment. It can directly increase pollution emissions by boosting industrial activities and transportation, and indirectly decrease it, by encouraging environmental awareness through an income effect that indicates when a country reaches a certain income level, people can afford and therefore begin to demand a cleaner environment, increased demand for environmentally friendly products. This demand for a clean environment leads to the adoption of environmental infrastructures and regulations. Eiras and Schaeffer [20] argue that countries with an open economy have higher scores than average environmental sustainability scores and are twice as high in environmental sustainability scores than a closed economy. It indicates that the causality between trade openness and environmental quality can work in different directions. Therefore, this study includes a trade variable to verify whether trade openness works toward increasing or decreasing environmental pollution. Trade data were extracted from the World Bank WDI database.

3.1.4. Foreign Direct Investment (FDI) Net Inflow

FDI inflow can also affect the environment. FDI is often regarded environmentally beneficial because it can stimulate the transfer of new technologies, skills, and production methods. However, according to Mabey and McNally [21], FDI traditionally tends to depend on natural resource use and extraction, such as oil, gas, and mineral production. Moreover, resource or pollution intensive industries are more likely to be located in countries with less stringent environmental standards. They argue that FDI inflows to host countries that lack regulatory capacities for environmental protection are more likely to lead to environmental degradation. Therefore, this study includes FDI inflow as a factor that can affect the environment of the host country. FDI inflow data are taken from the World Bank WDI database.

3.1.5. GDP per Capita

GDP per capita is a measure of income. Income is regarded as an important factor that affects the environment of a country. The squared term of GDP per capita indicates the nonlinear relationship between income and the environment, which is well known as the Environmental Kuznets Curve [22]: an inverted U-shaped relationship. The EKC was named after the Kuznets Curve that Simon Kuznets first postulated a (inverted U-shaped) relationship between income level and inequality degree in his 1954 presidential address to the American Economic Association. The idea underpinning EKC is that environmental quality worsens in the initial stage of growth but reaches a peak at a

threshold level appropriately called a "turning point", and begins to decline as countries become rich enough to afford a cleaner environment [22,23]. In 1991, EKC was first introduced by Grossman and Krueger, who conducted a pioneering work on the North American Free Trade Agreement (NAFTA). Grossman and Krueger [24] examined the link between per capita incomes and environmental quality and suggested that the general Kuznets Curve relating income and inequality could be applied to the relationship between income and pollution. Their work led to a flourishing of literature on EKC. Numerous scholars [25–30] hypothesized that the relationship between economic growth and environmental quality could be either negative or positive, as it is not necessarily directly correlated with the process of a country's economic development [22]. Using cross-country data, they found that some pollutants including SO₂ follow an inverted U-shaped curve with respect to the change of per capita incomes and examined the turning points of the EKC. However, each of these studies revealed different turning points depending on particular modelling strategies, sampling techniques, variables, and so on [31]. Some empirical works found new results, suggesting that the turning point is falling and moving to the left as growth generates less pollution in the early stages of industrialization, and starts decreasing at lower income levels, this known as the "Revised EKC" [32]. This study attempts to verify whether the inverted U-shaped relationship between income and the environment that EKC hypothesis suggests, is applicable to SO_2 and CO_2 . GDP per capita data are extracted from the World Bank WDI database.

3.1.6. Polity (Democracy Level)

Polity measures the level of democracy of a country. Some studies argue that more democratic governments are more capable of protecting the environment than less or non-democratic governments [33,34], while others assert that democracy leads to excessive resource use by individuals or find a weak relationship between democracy and the environment [35]. To capture the impact of democracy on the environment, this study takes account of the polity as a factor that may affect the environment. The polity index ranges from -10 (strongly autocratic) to +10 (strongly democratic) and the data is drawn from the Polity IV project database.

3.1.7. Population Density (Population Pressure)

Many studies have sought to determine the relationship between population dynamics (e.g., population size, growth, density, age and gender composition, migration, urbanization, etc.) and environmental changes. This study also uses population density to control the human impact on the environment; i.e., population pressure. Population density data are extracted from the World Bank WDI database.

3.2. Methodology

Our analysis is based on the methodology proposed by Potoski and Prakashi [15] to address dynamics in pollution emissions to consider the impact of past environmental pollution on current pollution. This study models the effect of environmental innovation on the environment, controlling for income and other relevant factors by using panel data. It compares high-income countries and middle-income countries as the effect of environmental innovation may vary depending on the national income level. To estimate the effect of environmental innovation on pollutant emissions, the effect of past levels of pollutant emissions on current emission levels should be taken into account. Thus, this study estimates the following dynamic panel data regression model, including a lagged dependent variable as an explanatory variable:

$$lnEMS_{it} = \beta_{1}lnEMS_{it-1} + \beta_{2}lnENVP_{it-j} + \beta_{3} TRADE_{it} + \beta_{4}ln(GDP)_{it} + \beta_{5}ln(GDP)^{2}_{it} + \beta_{6}FDI_{it-1} + \beta_{7}lnPOL_{it} + \beta_{8}POP_{it} + \sigma_{i} + v_{t} + u_{it}$$
(1)

where *i* and *t* denote country and year, respectively. σ_i represents unobservable country-specific effects and v_t common time effects. u_{it} is the idiosyncratic error term, which includes the effects of all time-varying unobservable factors except for idiosyncratic linear trends and common time effects. The dependent variable *EMS* is environmental pollution emissions as measured by SO_2 and CO_2 emissions per capita in period t for country i. The independent variable ENVP is environmental patent applications that measure environmental innovation activities, which is the main interest in this model. It is used to explore the direct effect of environmental innovation on environmental pollution reduction. The lags of ENVP take account of the time interval before environmental innovation influences the environment. Environmental innovation can directly affect environmental pollution emissions, but it can also indirectly affect environmental pollution emissions since environmental innovation is linked to GDP per capita. Environmental innovation can indirectly increase pollution emissions through the positive effect of increasing GDP per capita. Therefore, the indirect effect of patent through economic growth on environmental pollution emissions can be considered. Castiglione, Infante, and Smirnova [36] conducted an analysis on both the direct effect and indirect effect of the independent variable on the dependent variable. They analyzed the indirect effect of the rule of law through increasing economic growth on the environmental tax. However, we are mainly focusing on investigating the direct effect of environmental innovation on pollution reduction with panel data grouped into high- and middle-income countries rather than the indirect effect of environmental innovation on pollution increase through the contribution to economic growth. Therefore, the analysis of these indirect effects is left for future study. GDP denotes GDP per capita and $(GDP)^2$ is the squared term of GDP per capita. As to the need to consider the nonlinear relationship between income and the environment over time, Dinda [30] explains: "(i) the progress of economic development, from clean agrarian economy to polluting industrial economy to clean service economy; (ii) tendency of people with higher income having higher preference for environmental quality, etc." Thus, this study includes a nonlinear trend between income and environmental pollution in the model to illustrate how income can change environmental quality over time by testing the EKC hypothesis. The EKC hypothesis postulates that environmental quality is transformed in association with changes in per capita income. Specifically, income increases environmental pressure in the early phase of economic growth, but after reaching a certain level or "turning point", it starts to decrease. Thus, if the EKC hypothesis is valid, the coefficients of GDP and (GDP)² will be positive and negative values, respectively. However, it does not mean that high income automatically brings environmental pollution reduction since, unless appropriate political institutions are established, higher income does not necessarily guarantee environmental improvement. Political factors sometimes add further complexity to the environment-related debate [37,38], for instance, the civil and political freedom to express discontent with environmental quality. Thus, this study includes POL, the level of democracy, as a political factor, to describe the direct effect of a country's political system on environmental quality. TRADE represents the share of international trade in GDP, indicating the economy's openness, and detects the effect of trade on the environment. Foreign direct investment inflow (FDI) is often characterized as environmentally beneficial, but it must also be acknowledged that economic growth induced by FDI may derive from the sacrifice of natural environments; accordingly, the impact of FDI on host-country's environments is also considered in the model. POP, as a measure of population density, is included to account for population pressure on the environment in the model.

To examine the heterogeneous effects of income on the environment, this study conducts a comparative analysis between high-income countries and middle-income countries. The classification of countries by income level accords with the World Bank's 2011 criteria. The estimation model contains lagged dependent and control variables to consider the possible time delay between the onset of intervention from the independent variables and subsequent effect on the dependent variable (environmental improvement or deterioration). Thus, this model considers 1-year, 2-year, and 3-year lagged variables of environmental patents to observe how environmental innovation activities affect environmental quality over time. Equation (1) is a dynamic panel model that may contain lagged

dependent variables correlated with the error term. In this case, the ordinary least square (OLS) and fixed effect (FE) are inconsistent. Specifically, the fixed effects estimators could be upward biased in the presence of endogeneity [39]. To obtain consistent estimators, the application of an appropriate instrumental variables estimator (2SLS) or GMM is required. GMM estimators are based on an assumption of no serial correlation in the error, thus permitting the use of lags in the dependent variable as instruments for identification of the parameter on the endogenous lagged dependent variable. The GMM method in the estimation of dynamic panel models developed by Arellano and Bond [40] uses level variables of the dependent variable as instruments. However, Brudell and Bond [9] identified the poor performance of the first-differenced GMM estimator (DIF) and extended GMM estimator labeled "system GMM estimator", which uses lagged first differences of dependent variables as additional instruments, and yields less bias and greater precision, even in the smaller sample size compared to the DIF estimator that can be downward biased when the series are persistent and the sample size is small [41]. In particular, it obtains estimated coefficients in a system containing both first-differenced and levels equations. Hence, it enables a reduction of endogeneity problems by eliminating unobserved heterogeneity and omitted variable bias through first differencing, and by reducing potential biases from simultaneity and reverse causality by using the past as an instrument for the present [42]. Furthermore, system GMM is known to be a more efficient estimation than DIF GMM and is particularly useful when the autoregressive coefficient is close to unity [43] (approximately 0.7~0.9 in Tables 3 and 4). Therefore, this study adopts system GMM estimation to conduct the dynamic panel data analysis. The Arellano–Bond test on autocorrelations (AR (1), AR (2)) and the Sargan (or Hansen J) test on over-identifying restrictions were conducted, the results presented in Tables 3 and 4.

4. Estimation Results

Tables 3 and 4 report the estimation results of the effect of environmental innovation on SO_2 emissions, and CO_2 emissions, respectively. In the case of SO_2 emissions (Table 3), environmental innovation is beneficial to the environment of high-income countries over time. In column (4), the 3-year lagged environmental patents contributes to a reduction in SO_2 emissions in high income countries by 4.9%, whereas in middle income countries it has insignificant impact on SO₂ emissions. It can be interpreted that environmental patent activities in high-income countries, which have far more favorable conditions for commercialization and on-site adoption of patents based on the higher innovation capacity, have the effect of reducing SO₂ emissions, and the effect starts to appear after at least three years. In addition, trade does not increase SO₂ emissions in high-income countries, but increases in middle-income countries in columns (5) to (8). It indicates that trade promotes pollution-emitting activities in middle-income countries rather than in high-income countries. In columns (1) to (4), the EKC relationship between income and SO_2 emissions exists in the high-income countries as the coefficient of per capita income has a significant positive value, and the coefficient of the squared term of per capita income has a significant negative value. This suggests that as incomes rise, SO_2 emissions increase, but this increasing trend is weakened as the income level improves and shifts downward after the peak. Therefore, the EKC trend observed in high income countries can be interpreted as resulting from adopting pollution reduction measures to reduce SO₂ emissions due to increased social pressures and environmental awareness in high-income countries. FDI inflow does not have a significant impact on SO₂ emission reduction in either high- or middle-income countries. However, a democratic political system has a positive effect on SO₂ emission reduction in high-income countries, as shown in columns (1) to (3). Population density increases SO_2 emissions in middle-income countries, but does not in high-income countries, see columns (1) to (8). It can be interpreted that SO_2 emissions have already been greatly reduced in high-income countries since enormous regulation and control efforts were put into place during the 1980s to reduce SO_2 emissions as a result of experiencing severe acid rain damage caused by SO_2 emissions [44].

| | SO ₂ per Capita | | | | | | | |
|-------------------------|----------------------------|-------------------------|-----------------------------|-------------------------|------------------------------|------------------------------|------------------------------|------------------------------|
| Variables | High Income | | | | Middle Income | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ln_SO _{2t-1} | 0.7380 *** (0.056) | 0.7379 *** (0.057) | 0.7550 *** (0.058) | 0.7098 *** (0.064) | 0.7571 *** (0.055) | 0.7556 *** (0.055) | 0.7434 *** (0.055) | 0.7492 *** (0.054) |
| ln_ENVP_t | -0.0219 (0.022) | | | | -0.0199 (0.030) | | | |
| ln_ENVP _{t-1} | | -0.0197 (0.021) | | | | 0.0076 (0.030) | | |
| ln_ENVP _{t-2} | | | 0.0259 (0.023) | | | | -0.0275 (0.031) | |
| ln_ENVP _{t-3} | | | | -0.0486 * (0.026) | | | | -0.0068 (0.030) |
| TRADE _t | -0.0002 (0.001) | -0.0002 (0.001) | 0.0006 (0.001) | -0.0004 (0.001) | 0.0036 *** (0.001) | 0.0036 *** (0.001) | 0.0038 *** (0.001) | 0.0034 *** (0.001) |
| ln_(GDP) _t | 3.1821 * (1.694) | 3.0967 * (1.697) | 3.7505 ** (1.708) | 3.3884 * (1.787) | 0.4912 (0.759) | 0.4891 (0.759) | 0.4596 (0.763) | 0.5439 (0.732) |
| ln_(GDP) ² t | -0.1695 ** (0.086) | -0.1653 * (0.086) | -0.2020 ** (0.087) | -0.1793 ** (0.091) | -0.0075 (0.048) | -0.0079 (0.048) | -0.0061 (0.048) | -0.0102 (0.047) |
| FDI _{t-1} | -0.0009 (0.001) | -0.0008 (0.001) | -0.0008 (0.001) | -0.0008 (0.001) | -0.0060 (0.005) | -0.0064 (0.005) | -0.0067 (0.005) | -0.0065 (0.005) |
| ln_POL_t | -0.5708 ** (0.228) | -0.5669 ** (0.228) | -0.6339 *** (0.241) | -0.4038 (0.363) | -0.0882 (0.136) | -0.0888 (0.136) | -0.1219 (0.147) | -0.1043 (0.155) |
| POPt | 0.0000 (0.000) | 0.0000 (0.000) | 0.0000 0.0000 | 0.0000 (0.000) | 0.0041 *** (0.001) | 0.0038 *** (0.001) | 0.0043 *** (0.001) | 0.0041 *** (0.001) |
| Observations | 382 | 382 | 351 | 320 | 429 | 429 | 393 | 357 |
| Number of Country | 33 | 33 | 33 | 33 | 36 | 36 | 36 | 36 |
| Sargan p-value | 0.974 | 0.981 | 0.995 | 0.993 | 0.999 | 0.999 | 0.997 | 0.961 |
| Hansen <i>p</i> -value | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| AR (1) p-value | 0.012 | 0.013 | 0.015 | 0.018 | 0.069 | 0.070 | 0.058 | 0.027 |
| AR (2) p-value | 0.209 | 0.199 | 0.223 | 0.175 | 0.279 | 0.279 | 0.249 | 0.258 |

| Table 3. System Generalized Method of Moments (GMM)—Estimation Results (SO ₂) | Table 3. System | Generalized M | lethod of Moments | (GMM) |)—Estimation Results | $(SO_2).$ |
|---|-----------------|---------------|-------------------|-------|----------------------|-----------|
|---|-----------------|---------------|-------------------|-------|----------------------|-----------|

Note: (1) Standard errors are in parenthesis; (2) *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively; (3) Time dummies are included, but their results are not reported.

In the case of CO₂ emissions (Table 4), environmental innovation has a beneficial effect on the environment of high-income countries over time. In columns (4), 3-year lagged environmental innovation reduces CO_2 emissions in high income countries by 2.3%, whereas in middle-income countries it has no significant effect. It can be interpreted that the reduction of CO₂ emissions represents the legacy of environmental technology developed largely in high-income countries. Trade has a small, but significant effect to increase CO₂ emissions in middle-income countries, suggesting that trade encourages CO_2 emitting (industrial) activities in middle-income countries. In columns (1) to (4), the EKC relationship between income and CO_2 emissions is present in high-income countries. This can be interpreted as being the result of enhancing environmental regulations and investments related to environmental pollution and climate change mitigation in high-income countries. FDI inflow helps to reduce CO_2 emissions in middle-income countries, as per columns (5) to (7). A democratic political system has significantly positive effect on CO₂ emissions reduction in both high- and middle-income countries, as shown in columns (1) to (3) and (5) to (8), indicating that democratic governance contributes to environmental improvement and its effect is greater in high-income countries. The population density is found to have a small but significant effect in the reduction of CO_2 emissions in high-income countries. This result can be interpreted that large population pressure has a beneficial effect in reducing CO₂ emissions in high-income countries. It means that, with growing concern about CO₂ increases as the main cause of global warming, there are more people per unit area that demand CO₂ emissions reduction than SO₂ emissions reduction in high-income countries.

| | CO ₂ per Capita | | | | | | | |
|---------------------------|------------------------------|------------------------------|------------------------|-----------------------------|------------------------------|------------------------------|------------------------------|------------------------------|
| Variables | | High I | ncome | - Middle Income | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ln_CO _{2t-1} | 0.8722 *** (0.038) | 0.8725 *** (0.037) | 0.8537 *** (0.037) | 0.8437 *** (0.039) | 0.8943 *** (0.027) | 0.8934 *** (0.027) | 0.9108 *** (0.028) | 0.8477 *** (0.032) |
| ln_ENVP_t | -0.0011 (0.010) | | | | 0.0047 (0.008) | | | |
| ln_ENVP _{t-1} | | -0.0018 (0.010) | | | | 0.0067 (0.008) | | |
| ln_ENVP _{t-2} | | | -0.0044 (0.010) | | | | 0.0011 (0.009) | |
| ln_ENVP _{t-3} | | | | -0.0226 ** (0.011) | | | | -0.0022 (0.009) |
| TRADE _t | 0.0005 (0.000) | 0.0005 (0.000) | 0.0004 (0.000) | 0.0005 (0.000) | 0.0008 *** (0.000) | 0.0008 *** (0.000) | 0.0007 *** (0.000) | 0.0008 *** (0.000) |
| ln_(GDP)t | 2.1202 *** (0.779) | 2.1310 *** (0.769) | 2.1875 *** (0.772) | 1.8643 ** (0.820) | 0.0650 (0.222) | 0.0553 (0.222) | 0.1127 (0.225) | 0.0015 (0.228) |
| $ln_(GDP)^2_t$ | -0.1044 *** (0.039) | -0.1048 *** (0.038) | -0.1088 *** (0.039) | -0.0922 ** (0.041) | 0.0027 (0.013) | 0.0030 (0.013) | -0.0013 (0.014) | 0.0092 (0.014) |
| FDI _{t-1} | -0.0004 (0.001) | -0.0004 (0.001) | -0.0004 (0.001) | -0.0004 (0.001) | -0.0030 ** (0.001) | -0.0029 ** (0.001) | -0.0030 ** (0.001) | -0.0020 (0.001) |
| ln_POLt | -0.1471 ** (0.061) | -0.1466 ** (0.061) | -0.1292 ** (0.062) | -0.1141 (0.076) | -0.0966 *** (0.036) | -0.0957 *** (0.036) | -0.0821 ** (0.038) | -0.1221 *** (0.040) |
| POPt | -0.0001 *** (0.000) | -0.0001 *** (0.000) | -0.0001 *** (0.000) | -0.0001 *** (0.000) | 0.0001 (0.000) | 0.0001 (0.000) | 0.0001 (0.000) | 0.0005 (0.000) |
| Observations | 448 | 448 | 417 | 386 | 497 | 497 | 461 | 425 |
| Number of Country | 33 | 33 | 33 | 33 | 36 | 36 | 36 | 36 |
| Sargan (p-value) | 0.066 | 0.526 | 0.009 | 0.870 | 0.771 | 0.739 | 0.678 | 0.646 |
| Hansen (p-value) | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| AR (1) (<i>p</i> -value) | 0.003 | 0.002 | 0.001 | 0.004 | 0.000 | 0.000 | 0.000 | 0.000 |
| AR (2) (p-value) | 0.332 | 0.338 | 0.569 | 0.391 | 0.805 | 0.735 | 0.730 | 0.588 |

Table 4. System GMM—Estimation Results (CO₂).

Note: (1) Standard errors are in parenthesis; (2) *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively; (3) Time dummies are included, but their results are not reported; (4) AR(1) and AR(2) are tests for first-order and second-order serial correlation, asymptotically N(0,1); (5) Sargan and Hansen tests are for the overidentifying restrictions for the GMM estimators, asymptotically χ 2.

The reliability of the system GMM estimate is checked with a Sargan test for the validity of the overidentifying restrictions, and the Arellano–Bond [40] test for serially uncorrelated error terms. In the Sargan statistic, the *p*-values of the result in column (3) (Table 4) rejected the null hypothesis that overidentified restrictions are valid. However, the Sargan test is *only valid* under the *i.i.d.* assumption (every residual is independent and identically distributed) on the disturbance terms. Thus, it might mean that the Sargan test should be rejected due to heteroscedasticity. In this case, the Hansen J test can be used, because it also tests the validity of the overidentifying restrictions and is also robust to heteroscedasticity. This study, therefore, conducts the Hansen J test for all models including the model where the Sargan test is rejected. The diagnostic statistics of the dynamic models suggest that the models perform well. In all models presented in Tables 3 and 4, the Arellano–Bond test shows that the null hypothesis is rejected in the first order but not in the second order, suggesting no significant autocorrelation for AR (2). The Sargan test or Hansen J test suggests that the instruments used are valid in all models.

5. Summary and Conclusions

Environmental innovation can have positive environmental impact. However, previous literature has been insufficient in empirically assessing the environmental performance of environmental innovation. This observation is especially important for policy-makers who need to understand the direction of environmental innovation incentivized by government policies and encourage environmental innovation that meets environmental imperatives. This study attempts to evaluate how environmental innovation impacts environmental improvement using a system GMM estimator

for a dynamic modeling [8,9]. This study uses panel data from 33 high-income countries and 36 middle-income countries to compare their environmental pollution patterns and determine how environmental patents affect environmental pollution reduction with respect to SO_2 emissions and CO_2 emissions.

This study has found that environmental innovation appears to improve the environment in some countries over time, though not all countries. The effect is particularly beneficial to high-income countries with a dominant position in economic strategy and a regulatory system that induces environmental innovation, and the legacy of environmental technology developed largely as a result. The results also show that the inverted U-shaped relation between income and pollution exists for SO₂ and CO₂ in high-income countries but does not exist in middle-income countries, providing partial empirical support for the EKC hypothesis. It can be interpreted that the middle-income countries have not reached the turning point yet or they may follow patterns that are not the same as high-income countries in the process of economic growth. The examination of the effect of trade does not provide sufficient evidence that trade encourages environmental pollution. However, the pollution-inducing effect of trade seems to be clear in the middle-income countries. This study provides significant and useful implications for understanding the importance of the direction and role of environmental innovation; i.e., whether environmental innovation is aimed at improving the environment or productivity.

However, this study has some limitations, as it used environmental patent applications as an indicator of environmental innovation. As the OECD [17] pointed out, not all innovations are patentable, not all patentable inventions are patented, and not all patented inventions are eventually commercialized and adopted, due to different economic values. Therefore, not all environmental innovation activities involve environmental patents. Nonetheless, environmental patent is a useful indicator to measure environmental innovation, which is the most powerful realistic alternative for environmental sustainability and sustainable development. In this regard, environmental innovation should be considered in all areas where innovation is studied, for achieving sustainable development. Future research on environmental innovation should include this issue. Furthermore, environmental taxes can be a significant factor in reducing environmental pollution and creating environmental innovations in high-income countries. However, there are data constraints on countries other than EU countries for environmental taxes, thus this matter should be addressed in a future study.

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References

- 1. Organization for Economic Co-operation and Development (OECD). *Voluntary Approaches to Environmental Policy: An Assessment;* OECD: Paris, France, 2000.
- 2. Chen, Y.; Lai, S.; Wen, C. The influence of green innovation performance on corporate advantage in Taiwan. *J. Bus. Value Ethics* **2006**, *67*, 331–339. [CrossRef]
- 3. Chen, Y. The driver of green innovation and green image-green core competence. *J. Bus. Value Ethics* **2008**, *81*, 531–543. [CrossRef]
- 4. Kemp, R.; Pearson, P. *Final Report MEI Project about Measuring Eco-Innovation;* Deliverable 15 of MEI Project (D15) Project Report Maastricht; University of Maastricht: Maastricht, The Netherlands, 2007.

- Carrion-Flores, C.; Innes, R. Environmental innovation and environmental performance. J. Environ. Econ. Manag. 2010, 59, 27–42. [CrossRef]
- Horbach, J.; Rammer, C.; Rennings, K. Determinants of Eco-Innovations by Type of Environmental Impact— The Role of Regulatory Push/Pull, Technology Push and Market Pull. *Ecol. Econ.* 2012, 78, 112–122. [CrossRef]
- Chiou, T.; Chan, H.; Lettice, F.; Chung, S.H. The influence of greening the suppliers and green innovation on environmental performance and competitive advantage in Taiwan. *Transp. Res. Part E* 2011, 47, 822–836. [CrossRef]
- 8. Arellano, M.; Bover, O. Another look at the instrumental-variable estimation of error-components models. *J. Econ.* **1995**, *68*, 29–52. [CrossRef]
- 9. Brundell, R.; Bond, S. Initial conditions and moment restrictions in dynamic panel data models. *J. Econ.* **1998**, *87*, 115–143. [CrossRef]
- 10. Beckerman, W. Economic Growth and the Environment: Whose Growth? Whose Environment? *World Dev.* **1992**, *20*, 481–496. [CrossRef]
- 11. World Bank (WB). World Development Report; Oxford University Press: New York, NY, USA, 1992.
- 12. Neumayer, E. Weak versus Strong Sustainability; Edward Elgar: Cheltenham/Northampton, UK, 2003.
- 13. Van Alstine, J.; Neumayer, E. The Environmental Kuznets Curve. In *Handbook on Trade and the Environment*; Gallagher Kevin, P., Ed.; Edward Elgar: Cheltenham/Northampton, UK, 2010.
- 14. Wagner, M. The Environmental Kuznets Curve, Cointegration and Nonlinearity. J. Appl. Econ. 2015, 30, 984–1067. [CrossRef]
- 15. Potoski, M.; Prakashi, A. Do Voluntary Programs Reduce Pollution? Examining ISO 14001's Effectiveness across Countries. *Policy Stud. J.* 2013, *41*, 273–294. [CrossRef]
- 16. Environmental Protection Agency (EPA). Global Greenhouse Gas Emissions Data. 2015. Available online: http://www3.epa.gov/climatechange/ghgemissions/global.html (accessed on 20 November 2017).
- 17. Organization for Economic Co-operation and Development (OECD). *Measuring Environmental Innovation Using Patent Data*; OECD: Paris, France, 2015.
- 18. Popp, D. *Using the Triadic Patent Family Database to Study Environmental Innovation;* OECD Environment Directorate Working Paper ENV/EPOC/WPNEP/RD; OECD: Paris, France, 2005.
- 19. Jaffe, A.B.; Palmer, K. Environmental regulation and innovation: A panel data study. *Rev. Econ. Stat.* **1997**, *79*, 610–619. [CrossRef]
- 20. Eiras, A.; Schaefer, B. *Trade: The Best Way to Protect the Environment*; Heritage Foundation Backgrounder No. 1480; Heritage Foundation: Washington, DC, USA, 2001.
- 21. Mabey, N.; McNally, R. Foreign Direct Investment and the Environment: From Pollution Havens to Sustainable Development; WWF-UK Report; OECD: Paris, France, 1999.
- 22. Cialani, C. Economic growth and environmental quality: An econometric and decomposition analysis. *Manag. Environ. Qual. Int. J.* 2007, *18*, 568–577. [CrossRef]
- 23. Frankel, J. *Environmental Effects of International Trade;* Expert Report No. 31 to Sweden's Globalization Council; Harvard University: Cambridge, MA, USA, 2009.
- 24. Grossman, G.M.; Krueger, A.B. *Environmental Impacts of the North American Free Trade Agreement;* NBER Working Paper No. 3914; National Bureau of Economic Research: Cambridge, MA, USA, 1991.
- 25. Shafik, N.; Bandyopadhyay, S. *Economic Growth and Environmental Quality: Time-Series and Cross-Country Evidence*; Policy Research Working Paper; World Bank: Washington, DC, USA, 1992.
- 26. Panayotou, T. *Empirical Tests and Policy Analysis of Environmental Degradation at Different Stages of Economic Development;* World Employment Programme Research Working Paper; ILO: Geneva, Switzerland, 1993.
- 27. Seldon, T.M.; Song, D. Environmental Quality and Development: Is There a Kuznets Curve for Air Pollution Emissions? *J. Environ. Econ. Manag.* **1994**, 27, 147–162. [CrossRef]
- 28. Shafik, N. Economic Development and Environmental Quality: An Economic Analysis. *Oxf. Econ. Pap.* **1994**, *46*, 757–773. [CrossRef]
- 29. Copeland, B.R.; Taylor, M.S. Trade, Growth, and the Environment. J. Econ. Lit. 2004, 42, 7–71. [CrossRef]
- 30. Dinda, S. Environmental Kuznets Curve hypothesis: A Survey. Ecol. Econ. 2004, 49, 431–455. [CrossRef]
- 31. Neumayer, E. Is Economic Growth the Environment's Best Friend? Z. Umweltpolit. Umweltr. 1998, 21, 161–176.
- 32. Dasgupta, S.; Laplante, B.; Wang, H.; Wheeler, D. Confronting the Environmental Kuznets Curve. *J. Econ. Perspect.* **2002**, *16*, 147–168. [CrossRef]

- 33. Barrett, S.; Graddy, K. Freedom, Growth and the Environment. Environ. Dev. Econ. 2000, 5, 433–456. [CrossRef]
- 34. Frankel, J.; Rose, A.K. *Is Trade Good or Bad for the Environment? Sorting out the Causality*; NBER Working Paper Series; National Bureau of Economic Research: Cambridge, MA, USA, 2002.
- 35. Neumayer, E. Do democracies exhibit stronger international environmental commitment? A cross-country analysis. *J. Peace Res.* 2002, *39*, 139–164. [CrossRef]
- Castiglione, C.; Infante, D.; Smirnova, J. Is There Any Evidence on the Existence of an Environmental Taxation Kuznets Curve? The Case of European Countries under Their Rule of Law Enforcement. *Sustainability* 2014, 6, 7242–7262. [CrossRef]
- 37. Li, Q.; Reuveny, R. Democracy and environmental degradation. Int. Stud. Q. 2006, 50, 935–956. [CrossRef]
- 38. Buitenzorgy, M.; Mol, A. Does democracy lead to a better environment? Deforestation and the democratic transition peak. *Environ. Resour. Econ.* **2011**, *48*, 59–70. [CrossRef]
- 39. Ulku, H. R&D, Innovation and Output: Evidence from OECD and non-OECD countries. *Appl. Econ.* **2008**, *39*, 291–307.
- 40. Arellano, M.; Bond, S. Some test of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud.* **1991**, *58*, 277–297. [CrossRef]
- 41. Brundell, R.; Bond, S. GMM Estimation with persistent panel data: An application to production functions. *Econ. Rev.* **2000**, *19*, 321–340. [CrossRef]
- 42. Ammari, A.; Kadria, M.; Ellouze, A. Board structure and firm performance: Evidence from French firms listed in SBF 120. *Int. J. Econ. Financ. Issues* **2014**, *4*, 580–590.
- 43. Na, K.Y.; Han, C.; Yoon, C.H. Network effect of transportation infrastructure: A dynamic panel evidence. *Ann. Regional Sci.* **2013**, *50*, 265–274. [CrossRef]
- 44. Environmental Protection Agency (EPA). *Acid Rain Program. 2001 Progress Report;* National Center for Environmental Economics Office of Policy U.S. Environmental Protection Agency: Durham, NC, USA, 2001.



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