연구논문 「환경정책」제30권 특별호 2022. 12: 1-22
DOI http://dx.doi.org/10.15301/jepa.2022.30.S.1
pISSN 1598-835X eISSN 2714-0601

Interrelationships Among Environmental Regulations, Technological Innovations, and Productivity in South Korea*

Byung Min Soon** · Dong Won Shin***

Abstract: Because environmental policies have increasingly become stricter in response to relevant challenges, policymakers are now paying more attention to regulations that affect productivity. Focusing on conditions in Korea, this study used the Granger causality test to investigate causal relationships between environmental regulations, technological innovation, and productivity. The main results indicate that productivity is influenced by (1) technological innovation and (2) the innovation results from strengthened environmental regulations in separate sectors (i.e., manufacturing and non-manufacturing). These findings highlight some policy implications. As the environmental protection expenditure increases due to environmental regulations, the government and companies increase the number of R&D workers and spend more on technological innovation. Meanwhile, a suitable circumstance must be established to generate product and process innovations. The government and companies should make investments to construct this circumstance in response to environmental regulations. Finally, because regulations and innovations change productivity slowly, it is important to engage in long-term environmental policy projects.

Key Words: Environmental regulation, Technological innovation, Productivity, Granger-causality, Green growth, Green Economy

I. Introduction

There are arguments on whether environmental regulations increase or

* This work was supported by Korea Environment Institute as 「A Study on the Improvement of Environmental Regulations to Promote the Green Economy (Ⅲ)(GP21-87-02)」and 「A survey on Key Technology Innovations for Carbon Neutrality: Cost Database Framework and Strategy(RE2022-01)」.

** Author, Assistant Professor, Department of Agricultural Economics, Chungnam National University, Daejeon, Korea

*** Corresponding Author, Senior Research Fellow, Division for Climate and Energy, Korea Environment Institute, Sejong, Korea

decrease productivity. According to Porter's hypothesis, environmental regulations create technological innovation and improve productivity (Porter and van der Linder, 1995). On the other hand, Jaffe et al. (1995) argued that government intervention for environmental regulation disturbs market competitiveness because environmental regulation increases production costs. Increasing production costs makes profit lower and reduces investment.

Many studies focused on the relationship between two primary variables respectively, i.e., technological innovation and productivity, and environmental regulation. For instance, some studies have defined the relationship between environmental regulation and technological innovation (Jaffe et al., 1997; Pickman, 1998; Brunnermeier et al., 2003), environmental regulation and productivity (Morris, 2018; Bhatnagar, 1998; Lee, 2011), and technological innovation and productivity (Albrizio et al., 2017; Lanoie et al., 2008). However, studies are scarce on the dynamic relationship among the three variables.

The objective of our study is to find dynamic causality among environmental regulations, technological innovation, and productivity. To do this, we used proxy variables to estimate dynamic causality: environmental protection expenditure and revenues (EPER) for environmental regulation, Research and Development personnel for technological innovation, and total factor productivity for productivity. With these variables, the Granger causality test from the error correction model (ECM) examines the dynamic relationship among the three variables, and variance decomposition shows how much of each variable is explained by exogenous shocks to other variables.

This article will be presented in the following order: Section II reviews previous studies regarding relationships between environmental regulation, technological innovation, and productivity. Section III introduces the time series analysis to examine the dynamic causality among the three variables. Section IV presents estimation results, and the last section has the article's conclusion.

II. Literature Review

The relationship between environmental regulation and technological innovation is more important now due to increasing mutual interaction. Jaffe (1997) found that environmental protection expenditure positively impacts R&D investment over time in the manufacturing industry. Pickman (1998) used linear regression to determine the number of patents related to solving environmental problems such as pollution reduction expenditures. These results indicate that the relationship between environmental regulation and technological innovation is positive, and the bigger the company, the more effective the technological innovation is. Brunnermeier et al. (2003) also analyzed how environmental regulation affects technological innovation in the U.S. manufacturing industry. The study shows that firm's technological innovation are closely related to the need for environmental protection through regulation.

Morris (2018) verified that technological innovation increases productivity by a cross-sectional survey of firms. The result shows that, in the manufacturing and service industries, productivity is driven up by technological innovation. Lee (2011) also found that technological innovation raised productivity in Korea: production costs pushed up by environmental regulations do not affect the firms' competitiveness while the regulations result productivity increase by boosting R&D activity.

The Organization for Economic Co-operation and Development (OECD) is an international organization consisting of 39 countries and defines international standards for environmental issues as well as social, economic and environmental challenges over 60 years. Albrizio (2017) analyzed how environmental policies in OECD countries affect productivity in industries and firms. The research shows that higher productivity allows firms that achieved a dominant position in the marketto reduce costs as they adapt to environmental regulations and have a short-term boost in profit. However, Albrizio (2017) also found that environmental regulations might cause their productivity to diminish. Lanoie et al. (2008) found that environmental regulations in the Canadian manufacturing industries positively affected productivity. Their findings are based on environmental regulatory results from 17 manufacturing industries in Quebec from 1985 to 1994. These results indicate that industries under high competitiveness in the world market tend to increase technological innovation, which will, in turn, lead to reduced production costs and increased profits (Lanoie et al. 2008).

There is a lack of empirical studies focusing on the relationship among environmental regulations, technological innovation and productivity. Lee and Ji (2011) estimated the impact of three variables (environmental regulation, technological innovation, and productivity) using a sequential model. The study assumes that an environmental protection expenditure change R&D expenditure, and then R&D expenditures affect value added. However, this study does not indicate the causality among the these three variables. Pan et al. (2019) also analyzed causality tests among the three variables. However, they used a directed graph that explores contemporaneous causality patterns. Since the causes of the three variables can be intermingled over time, our study uses a Granger-causality test to examine the dynamic causative features among the variables.

Ⅲ. Research Framework and Data Description

1. Research Methods

The panel unit root test is used to find the panel data of the three variables, which are stationary time series. With variables that are part of the non-stationary time series, the data is spurious regression, which provides misleading statistical results of the relationship between the variables. To avoid spurious regression, an unit root test is needed. We used the LLC test, IPS test, ADF-Fisher, and PP-Fisher tests to find panel data that are stationary.

The autoregressive process is considered for the panel data as follows:

$$y_{it} = a_i y_{it-1} + b_i x_{it} + u_{it}, \quad i = 1,2,....,N, t = 1,2,...., T_i \qquad (1)$$

where x_{it} represents the exogenous variable for each industry, N is the number of industries, T_i represents the periods of industry i, and a_i represents the autoregression coefficients. If $|a_i| < 1$, then, y_i is a stationary variable. If $|a_i| = 1$, then y_i is a non-stationary variable.

1) Panel cointegration test

The Johansen-Fisher panel cointegration test proposed by Engle and Granger (1987) indicates that if panel data have a unit root, the first-order differential sequence is applied to make the stationary sequence. Since analysis using variables through the first differentiation approach could lose the long-term effect, we used the Johansen-Fisher cointegration test to find a long-term relationship with a level variable. This test is a non-parametric test in which the coefficients are not homogeneous (Pan et al. 2019; Maddala and Wu 1999). We confirm cointegration among variables through trade statistic (λtrace-panel) and maximum Engen-value statistic (λmax-panel). If π_i is the p-value of the Johansen-Fisher cointegration test for cross-sectional data, the λtrace-panel and λmax-panel are test statistics for the aggregate panel data according to the calculations of Pan et al. (2019) and expressed here as follows:

$$\lambda_{trace-panel} = -2\sum_{i=1}^{N}\ln(\pi_{trace,i}) \sim \chi^2_{2N} \text{ and}$$

$$\lambda_{\max-panel} = -2\sum_{i=1}^{N}\ln(\pi_{\max,i}) \sim \chi^2_{2N}. \tag{2}$$

When unstable variables are cointegrated, we utilize the error correction model (ECM) to estimate the long and short-term effects. ECM has a term error-correction inferring that the last period's error affects its short-run dynamics. So, we used ECM with the three variables and then explored the Granger-causality analysis.

2) Granger-causality test

Granger (1969) and Engle and Granger (1987) proposed the Granger causality test. We use the Granger causality test to examine dynamic causality patterns. Early Granger causality is based on the unrestricted vector autoregression model (VAR) with levels of variables. More recent Granger causality tests have been used to enhance the cointegration methods. We first check cointegration among variables. When a long-term relationship exists among variables that are cointegrated, we built an error correction model (ECM) to explore the dynamic causality pattern. The Granger causality test is calculated as follows:

$$\triangle y_t = a_0 + a_1 \widehat{e_{t-1}} + \sum_{i=1}^{p} \beta_i \triangle y_{t-i} + \sum_{j=1}^{q} \gamma_{t-j} \triangle x_{t-j} + \epsilon_t . \qquad (3)$$

where y_t is one of the variables for environmental regulation, technological innovation, and productivity; hence, x_t represents variables except for yt. Δ is the first difference operator and represents the 3 by 3 matrix of short-run coefficients. A vector of disturbance term has a mean zero and a 3 by 3 covariance matrix is the speed of the adjustment at which dependent variables return to equilibrium after other variables have been distorted from equilibrium. The lower the adjustment coefficient is, the slower the market forces are. $\widehat{e_{t-1}}$ represents the error correction term that measures deviations from the long-term relationship among variables.

One hypothesis is that x_t does not allow the Granger-causality test to cause y_t.

$$H_0 : \gamma_1^k = \cdots\cdots = \gamma_p^k = 0 \tag{4}$$

If we reject the null hypothesis, we can conclude that x_t Granger test causes y_t. We check causality based on the F statistic. Since VECM includes lag variables, we can find causality between variables over time by conducting the Granger-causality test.

The Granger-causality and directed acyclic graph (DAG) tests are standard tools for finding causality among the variables. The Granger-causality test can identify the causal relationship among variables, while the DAG test is contemporaneous (Swanson and Granger, 1997; Pan et al., 2019). Variables used in our study can slowly affect each other. Therefore, the DAG test that simultaneously provides a causality pattern among variables does not fit our study.

The variance decomposition is used to examine how a shock to each variable affects the other variables in the autoregression, which is a widely used method for analyzing the relative effects of variables. It enables us to determine how much error in a variable significantly affects an error in the variables including our own variable. The variance decomposition indicates how one of three variables in our study significantly affects the other variables. For example, the variance of environmental protection expenditures and revenues (EPERs) contributes to R&D workers and the total factor productivity (TFP).

2. Variable Selection

1) Environmental regulation

Environmental protection expenditures and revenues (EPERs) are used as a proxy variable for environmental regulation. The increase in environmental regulation means that public and private sectors can increase the EPER. This paper's introduction immediately identified EPER as the variable affecting the investments in research and development (R&D), and it is often used as the variable when determining environmental regulations (Jaffe et al. 1997; Pickman, 1998; Brunnermeier et al. 2003; Pan et al. 2019). We employ EPER published by the Bank of Korea to analyze the environmental market's efficiency and size.

2) Technological innovation

Several variables represent technological innovation: R&D investment, R&D workers, and patents. (Jaffe et al. 1997; Pickman, 1998; Brunnermier et al. 2003; Bhatnagar, 1998; Pan et al. 2019). The variable - R&D workers, surveyed the Korea Institute of S&T Evaluation and Planning, is used as a proxy for technological innovation variables.

3) TFP

Total factor productivity (TFP) is usually measured as the ratio of aggregated production factors primarily, made up of labor (workers) and capital to the sum of total labor, capital (money, buildings, machines) and intermediate input based on an output elasticity that follows the constant patterns of the Cobb-Douglas production function. Since technological innovation strengthens competitiveness in the long term, TFP adapts to economic growth effects of technological innovations.

According to Porter's hypothesis (Porter and van der Linder, C. 1995;

Ambec et al. 2020), technological innovations from the environmental regulation contribute to increased productivity. Once a relationship among the three variables with proxy variables is defined, the results will show how tightening environmental regulation increases R&D workers and consequently improve productivity as shown in ⟨Figure 1⟩. Understanding the relationship between environmental regulation, technological innovation, and productivity can provide us with an idea of whatan effective environmental policy could be.

⟨Figure 1⟩ Linkage among three variables

⟨Table 1⟩ Literature review

Authors	Variables		
	Environmental Regulation	Technological Innovation	Productivity
	Environmental Regulation and Technological Innovation		
Jaffe et al. (1997)	Environmental Pollution Prevention Expenditure	Patent, R&D expenditure	
Pickman (1998)	Environmental Pollution Prevention Expenditure	Environmental patent	
Brunnermeier et al. (2003)	Environmental Pollution Prevention Expenditure	Patent	
	Technological Innovation and Productivity		
Morris (2018)		Innovation score	Technical investment score
Bhatnagar (1998)		Environmental patent	Price cost margin, Sales, Workers
Lee (2011)		Capital-labor ratio, R&D stock	Output
	Environmental Regulation and Productivity		
Albrizio et al. (2007)	Environmental Policy Rigidity Index		TFP
Lanoie et al. (2008)	Pollution Prevention Facility Investment Ratio		TFP

Environmental Regulation, Technological Innovation, and Productivity			
Lee and Ji (2011)	Environmental Pollution Prevention Expenditure	R&D expenditures	Added value
Pan et al. (2019)	Command control of environmental regulation, Market incentive environmental regulation	Patent	Energy consumption/GDP

3. Data Description

We collected panel data for three variables from 2012 to 2018 in the manufacturing and non-manufacturing sectors. We matched available data from 14 industries. The manufacturing sector in the study consists of the following eight industries: 1) petrochemical, 2) primary metal, 3) assembly metal, 4) wood paper, 5) nonmetal, 6) food and beverage, 7) transportation equipment, 8) fiber and leather, as well as the other manufacturing industries. The non-manufacturing sector inlcludes services, such as electric and gas, agricultural fishery, construction, and mine industries.

〈Table 2〉 shows that EPER in the manufacturing sector is more significant than that in the non-manufacturing sector. In contrast, the R&D workers and TFP in the manufacturing sector are less significant than those in the non-manufacturing sector. The minimum and maximum values of R&D workers in the manufacturing sector are much larger than those in the non-manufacturing sector, which means that the transportation industry is relatively larger than the rest of the manufacturing sector combined?. The minimum and maximum value of TFP in the manufacturing sector is larger than that of the non-manufacturing sector, even though the mean value in the manufacturing sector is smaller than that in the non-manufacturing sector.

〈Table 2〉 Data Description

Variable		Unit	Mean	S.D	Min	Max
EPER	all	Billion won	610	596	22	1,872
	manu	Billion won	648	669	24	1,872
	Non-manu	Billion won	541	435	22	1,464
R&D worker	all	Number of people	13,502	18,588	32	79,777
	manu	Number of people	13,026	14,253	1,176	44,788
	Non-manu	Number of people	14,358	24,782	32	79,777
TFP	all	%	0.26	2.07	-6.52	7.49
	manu	%	0.01	1.74	-4.66	7.49
	Non-manu	%	0.69	2.53	-6.52	5.45

Note: manu and non-manu represent manufacturing and non-manufacturing, respectively.

Ⅳ. Results

1. Panel data unit root test

A panel unit root test is required to conduct the empirical analysis using the panel data approach. 〈Table 3〉 represents the unit root test results. LLC (Levin et al. 2002), IPS (Im et al. (2003), Fisher-ADF, and Fisher-PP methods (Fisher 1932) confirm stationarity for each panel data (Choi et al. 2001). The LLC test rejects the null hypothesis of a unit root for the three variables in levels and presents the first differences. However, IPS, Fisher-ADF, and Fisher-PP tests failed to reject the null hypothesis of a unit root for the variables, EPER and R&D workers, in levels. The first differences in these two variables generate stationarity as tests reject the null hypothesis. Hence, EPER and R&D workers are integrated into order one. The unit root test for TFP indicates that the TFP variable is stable, so the total factor productivity (TFP) is integrated of order zero.

〈Table 3〉 Results of panel unit root test

Method	Levels			First difference		
	EPER	R&D workers	TFP	EPER	R&D workers	TFP
LLC	−2.33***	−1.81**	−7.87***	−8.45***	−6.74***	−10.64***
IPC	0.76	2.19	−2.34***	−1.97**	−1.45*	−3.01***
Fisher−ADF	18.66	14.71	51.97***	50.13***	43.55**	60.50***
Fisher−PP	18.73	22.08	72.67***	66.49***	51.06***	90.78***

Note: ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

2. Panel data cointegration test

Johansen cointegration test (Engle and Granger 1987) detects unstable and stable variables to see if they will move together in the long run. Since EPER and R&D workers are the variables that are integrated under order one and TFP is integrated under order zero, we have a precondition of the cointegration test. In 〈Table 4〉, Fisher's test results imply no more than one relationship among these three variables based on the panel data for all sectors. Moreover, three of the variables are separated into manufacturing and non-manufacturing sectors, which means they are cointegrated.

〈Table 4〉 Results of panel cointegration test

No. of Cointeg	λtrace			λmax		
	All	Manu	Nonmanu	All	Manu	Nonmanu
None	54.87***	48.70***	37.35***	52.06***	42.67***	24.01***
At most 1	2.81	6.02	13.34	2.58	5.32	13.21*
At most 2	0.23	0.70	0.13	0.23	0.70	0.13

Note: ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively. Manu and Non−manu represent manufacturing and non−manufacturing, respectively.

3. Granger-causality test

We use the Granger-causality approach to find dynamic causal patterns among EREP, R&D workers, and TFP. We find first dynamic causality in the whole industry, including 14 industries. The results show that EPER Granger causes R&D workers at the 10% significant level, and R&D workers Granger causes TFP under the 5% significant level. Therefore, we can conclude that productivity would be affected by the change in the R&D workers resulting from environmental regulation increase. Since TFP Granger causes R&D workers and EPER Granger causes TFP, causal patterns among the three variables are not considered one-way causality.

In the manufacturing sector, we reject the null hypothesis that EPER does not Granger cause R&D workers at the 10% significant level, and R&D workers do not Granger cause TFP. The rest of the Granger causality tests show no Granger causality. Hence, the relationship among the three variables shows that EPER Granger causes R&D workers and R&D workers Granger causes TFP. Compared to the results from all sectors, Granger causality in the manufacturing sector flows in a one-way direction (EPER -〉 R&D workers -〉 TFP).

In the non-manufacturing sector, we reject the null hypothesis that EPER does not Granger cause R&D workers at the 1% significant level and R&D workers do not Granger cause TFP at the 5% significant level. The rest of the Granger causality tests showed no Granger causality. Hence, the results eidentify the causal relationship that is equal to those in the manufacturing sector. Through the Granger causality test in both manufacturing and non-manufacturing sectors, we found that environmental regulation can improve productivity with technological innovation. However, the Granger causality test does not show how much each variable contributes to change in the other variables. The variance decomposition can provide the impact size.

〈Table 5〉 Results of Granger-causality

Hypothesis	F-statistic	Granger-causality
All sectors		
EPER does not Granger causes R&D workers	8.49*	O
R&D workers does not Granger causes EPER	3.31	X
R&D workers does not Granger causes TFP	10.01**	O
TFP does not Granger causes R&D workers	8.28*	O
EPER does not Granger causes TFP	9.91**	O
TFP does not Granger causes EPER	0.88	X
EPER → R&D workers → TFP		
Manufacturing sector		
EPER does not Granger causes R&D workers	6.64*	O
R&D workers does not Granger causes EPER	1.66	X
R&D workers does not Granger causes TFP	7.46*	O
TFP does not Granger causes R&D workers	5.21	X
EPER does not Granger causes TFP	2.83	X
TFP does not Granger causes EPER	0.76	X
EPER → R&D workers → TFP		
Non-manufacturing sector		
EPER does not Granger causes R&D workers	10.09***	O
R&D workers does not Granger causes EPER	2.94	X
R&D workers does not Granger causes TFP	6.96**	O
TFP does not Granger causes R&D workers	0.56	X
EPER does not Granger causes TFP	0.11	X
TFP does not Granger causes EPER	0.07	X
EPER → R&D workers → TFP		

Note: ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

Our study shows causality among environmental regulation, technological innovation, and productivity to be identical to previous studies. Pan et al. (2019) showing the same results used the number of patents for technological innovation and energy consumption per

GDP for energy efficiency, meanwhile, they found contemporaneous causality patterns. The research of Lee and Ji (2011) shows the same results as our study, however, it fail to prove the relationship among the three variables. Even though their study used a differenct method from ours it does support our contention that productivity can be positively affected by technological innovation which has been partly promoted by environmental regulation.

4. Variance decomposition

Based on the dynamic causality from the Granger causality test, the variance decomposition of the vector error correction model (VECM) is used to discuss the relationship among variables. 〈Table 6〉 shows that a variable is influenced by itself and other variables in the first, fifth, and tenth phase of the forecast period The results imply how much a variable contributes to the other variables when exogenous shocks exist.

Variables significantly affect each other. In the variance decomposition of TFP in 〈Table 6〉, TFP is solely affected, which is explained by EPER and R&D workers with a percentage contribution of 2.07% and 8.88% respectively, in the first phase of the forecast period. The contribution of TFP is reduced while the contribution of EPER and R&D workers to TFP increased over time. In the variance decomposition of R&D workers, the contribution of EPER to R&D workers is larger than that of TFP. In the case of the variance decomposition of TFP, the contribution of R&D workers to TFP is greater than that of EPER. These results imply that EPER and R&D workers change TFP in the long term. Moreover, compared with TFP, EPER have significant effects on R&D workers. Although EPER and R&D workers have effect on TFP, the impact size of R&D workers is relatively larger than that of EPER.

〈Table 6〉 Variance decomposition in all sector

Period	EPER	R&D workers	TFP
Variance decomposition of EPER			
1	100.00	0.00	0.00
5	83.59	13.74	2.66
10	51.44	41.70	6.84
Variance decomposition of R&D workers			
1	2.56	97.43	0.00
5	19.35	74.35	6.28
10	22.35	67.41	10.23
Variance decomposition of TFP			
1	2.07	8.88	89.03
5	32.45	48.44	19.09
10	31.48	51.99	16.52

It is shown that manufacturing and non-manufacturing sectors have the same dynamic causality, however, the contribution size of TFP look different in the two sectors. TFP is affected by EPER and R&D workers, and the impact of EPER on TFP is larger than that of R&D workers on TFP in the manufacturing sector. In the non-manufacturing sector, TFP is affected by EPER and T&D workers in the same way as shown with the variance decomposition in the manufacturing sector. The contribution of EPER and R&D workers to TFP in the non-manufacturing sector, meanwhile, is larger than that of the two variables to TFP in the manufacturing sector. These results indicate that strengthening environmental regulation affects R&D workers and TPF. The effect of environmental regulations on R&D workers and TFP in the non-manufacturing sector is relatively large compared with their effects in the manufacturing sector. Therefore, when we implement environmental regulation in the manufacturing sector, its impact on the TFP would be moving slowly compared with the impact in the non-manufacturing sectors such as services and agriculture or fisheries.

〈Table 7〉 Variance decomposition in the manufacturing and non-manufacturing sector

Sector	Period	EPER	R&D workers	TFP
Manufacturing sector	Variance decomposition of EPER			
	1	100.00	0.00	0.00
	5	83.71	14.77	1.50
	10	83.13	15.11	1.74
	Variance decomposition of R&D workers			
	1	2.51	97.48	0.00
	5	13.41	85.38	1.19
	10	14.71	83.97	1.30
	Variance decomposition of TFP			
	1	1.66	0.62	97.70
	5	15.24	4.98	79.76
	10	15.31	5.51	79.17
Non-manufacturing sector	Variance decomposition of EPER			
	1	100.00	0.00	0.00
	5	78.72	20.48	0.79
	10	74.62	24.51	0.85
	Variance decomposition of R&D workers			
	1	0.46	99.53	0.00
	5	44.66	55.03	0.29
	10	46.76	52.54	0.68
	Variance decomposition of TFP			
	1	47.67	0.15	52.16
	5	53.68	28.69	17.62
	10	57.65	33.06	9.27

Ⅴ. Conclusions

Our study investigated the causal relationship among environmental regulation, technological innovation, and productivity in Korea. We employed EPER as a proxy for environmental regulation, R&D workers for technological innovation, and TFP for productivity. The Granger-causality from the ECM system is used to examine dynamic causality among the three variables. Lastly, we used the variance decomposition to analyze how the shock of each variable impacts the other variables in the auto-regression.

The main results imply that the level of productivity is influenced by technological innovations caused by stronger environmental regulations. Moreover, these causal relationships were identified in the cases that we separated all sectors into manufacturing and non-manufacturing sectors. The variance decomposition shows that the contribution size of EPER and R&D workers on TFP is different in the manufacturing and non-manufacturing sectors. The contribution of EPER and R&D workers to TFP in the non-manufacturing sector is larger than the contribution of the two variables to TFP in the manufacturing sector. Consequently, we emphasize the relationship of the three variables with dynamic causality. Each variable's impact on the others in the non-manufacturing sector is bigger than in the manufacturing sector.

Our study supports some policy implications: As the environmental protection expenditure from the environmental regulation increases, government and companies accordingly increase R&D workers and spend more money on improving technological innovations. Given the fact that TFP is positively impacted by R&D expenditure, it is necessary to develop the environmental regulation policies towards generating technological innovations. We also have opportunities to invest in product and process innovation in order to improve productivity. A suitable circumstance generating product and process innovations should be set up, and the government and companies need to commit money in order to foster the circumstances in responding to environmental regulation. In addition, since regulation and innovation with regards to the environment slowly change productivity, we need to design long-term environmental policy projects.

This analysis has some limitations. We used proxy variables for environmental regulation, technological innovation, and productivity. The proxy variables used in this study are limited because of data availability. If we had other proxy variables, the dynamic causality results would differ. The environmental protection expenditures in the level of public, company and private sectors could affect productivity respectively, but we employ them as a whole in this study. Also, this study does not prove if the improvement of environmental regulation affects technological innovation and productivity: The increase of EPER might not mean the improvement of environmental regulation. To examine the impact of the improvement of environmental regulation on productivity, it is worthwhile to the corporate data. We expect that a future research will address these limitations and come up with solutions to broaden this research area.

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Byung Min Soon: Assistant Professor in the department of agricultural economics at Chungnam National University. He was a research fellow at the Korea Rural Economic Institute (KREI). He received a Ph.D. in Agricultural and Applied Economics from the University of Missouri. His primary research focuses on environmental policy analysis, international trade, and price analysis (soonbm@cnu.ac.kr).

Dong Won Shin: Senior Research Fellow at the Korea Environment Institute (KEI). He received a Ph.D. in Agricultural and Applied Economics at the University of Missouri. The main areas of interest are environmental policy in climate and energy, air pollution, technology and innovation adoption(dwshin@kei.re.kr).

Received: 15 October 2022
Revised: 25 October 2022
Accepted: 12 November 2022