May 2023 Vol.45, No.2

KDI Journal of Economic Policy

KDI Korea Development Institute

KDI Journal of Economic Policy

Statement of Purpose

The KDI Journal of Economic Policy (KDI JEP) is a professional journal published on a quarterly basis. The Journal publishes papers on the academic and policy issues related to the development of Korea's economy. The KDI Journal of Economic Policy welcomes innovative and insightful academic papers on all areas of economics with an emphasis on empirical analysis that contain solid policy implications. KDI JEP is published in English starting in 2015, volume 37 number 1.

The Journal aims to disseminate research outcomes and policy recommendations not only to experts at academia and research institutes but also to policy-makers and the general public. First published in March 1979, the original objective was to circulate ongoing- and past researches conducted in KDI, a leading economic think-tank of South Korea. Starting in August, 2001, the Journal has accepted manuscripts from outside in order to provide the readers more diverse perspectives on Korea's policy initiatives. The Journal now actively seeks and welcomes submissions by researchers at home and from abroad who have genuine interests in the Korean economy.

The contents of papers published in KDI JEP contain personal views of the authors, and thus do not represent the objectives of the Journal or the mission statements of KDI.

Editorial Board

KDI Journal of
Economic Policy

May 2023 VOL. 45, NO. 2

Articles

KDI Journal of Economic Policy 2023, 45(2):1-20
http://dx.doi.org/10.23895/kdijep.2023.45.2.1

Improving Social Acceptance for Carbon Taxation in South Korea†

By YEOCHANG YOON*

Carbon pricing is in the spotlight as an economically efficient policy to limit global warming and reduce greenhouse gas emissions. We examine how policymakers can improve social acceptance of a carbon tax, which is the main obstacle in implementing the policy. We conduct a survey experiment to analyze this topic and adopt two different interventions focusing on the use of revenue from a carbon tax and types of information to be provided. Regarding revenue use, we consider 1) tax reductions, 2) lump-sum transfers, and 3) green project investments. For information types, we focus on 1) the economic value of a carbon tax, and 2) the environmental value of a carbon tax. We find that lump-sum transfers have negative impacts on social acceptance of a carbon tax. For those who perceive climate change as a serious issue, moreover, both lump-sum transfers and tax reductions have negative impacts on acceptability. Regardless of the type of information provided, on the other hand, the social acceptance of a carbon tax is increased after the provision of information. Furthermore, the impact of information provision on the social acceptance interacts with the revenue use impacts. When the revenue use and the type of information are consistent with the aim of the policy, the effects of these strategies can be amplified.

Key Word: Carbon Tax, Carbon Pricing Mechanism, Climate Change, Policy Design
JEL Code: Q54, C99

I. Introduction

Increasing concern surrounding climate change has led to a global effort to reduce greenhouse gas (GHG) emissions. The EU, the United States, and many other countries have declared carbon neutrality goals to reach by 2050 and submitted the

* Associate Fellow, Korea Development Institute (E-mail: yoonyeochang@kdi.re.kr)
* Received: 2022. 11. 14
* Referee Process Started: 2023. 1. 27
* Referee Reports Completed: 2023. 4. 11
† Part of the paper is based on Yeochang Yoon, 2021, *Carbon Taxation Policy in Korea*, Policy Study 2021-08, KDI (in Korean).

updated their 2030 nationally determined contributions (NDCs). South Korea has also declared a goal of achieving net zero emissions by 2050 and raised their emissions reduction goal from 26.3% to 40% by 2030, compared to 2018 levels. Several different policies have been considered to achieve these ambitious targets. Carbon pricing is one of the most important instruments to help emitters reduce their emissions by internalizing the external costs of GHG emissions (Stiglitz, 2019). In relation to this, discussions of the Carbon Border Adjustment Mechanism have arisen and are applying pressure to adjust and improve the current carbon pricing mechanism. As a result, the importance of improving domestic carbon pricing mechanisms is an important topic in Korea.

Korea has an explicit carbon pricing mechanism, emissions trading system (ETS) as well as implicit carbon pricing through energy taxes. The Korean ETS was launched in 2015, covering a relatively wide range of sectors.[1] Although the ETS price is expected to surge to achieve the updated NDC targets and net zero emissions,[2] the imbalanced cost burden will become more serious between ETS and non-ETS sectors. On the other hand, Korea's current energy tax system has been criticized for being unbalanced across different industrial sectors and fuel types and for failing to reflect external costs sufficiently. The sustainability of the current energy tax system is also a subject of debate as the number of green cars increases. Hence, reforming the current energy tax system with the implementation of a carbon tax in non-ETS sectors is considered to be an effective and simple means of applying external costs to the tax rate while allowing the flexible use of tax revenue to fund various policies (Goulder and Parry, 2008).

This paper examines ways to address the crucial issue of public support for a carbon tax when implemented in Korea. Public opposition is the largest obstacle when implementing a carbon tax (Carattini *et al.*, 2018). Despite the fact that a carbon tax is considered to be the most economically efficient policy to reduce emissions, public opposition has made many countries reluctant to implement such a policy. Australia abolished a carbon tax in 2014, and the state of Washington failed to pass related bills in 2016 and 2018. In Korea, the main target would be the non-ETS sector, i.e., small- and medium-sized firms as well as transport and buildings (Yoon, 2021).

This paper studies a survey experiment conducted to analyze how to improve the social acceptance of a carbon tax using different ways to apply carbon tax revenues and different types of information.[3] Several tax revenue uses are considered, such as reductions of existing taxes, lump-sum transfers to households, and investments in green projects. The information provided includes details of a carbon tax with emphasis on either its economic value or its environmental value. To the best of the authors' knowledge, this paper is the first attempt to investigate how carbon taxation acceptability in Korea is contingent upon the utilization of the tax revenues. In addition to prior research, this study analyzes the impact of the interaction between

[1]The Korean ETS covers about 73.5% of national GHG emissions, while the EU ETS covers about 39% of the EU's total GHS emissions.

[2]The IMF expects the global carbon price to rise to $75 per ton of CO_2 by 2030, while the average price of the Korean ETS in 2021 was around $20.

[3]Anderson *et al.* (2019) and Douenne and Fabre (2020) point out that the main reasons for the opposition not only include the carbon tax itself but also the policy design and information provided.

the use of tax revenues and types of information provided on the social acceptability of carbon taxation.

The analysis of tax revenue uses shows that lump-sum transfers reduce support in general. Categorizing individuals based on concern over climate change specifically shows that reductions of existing taxes may have positive effects on support for a carbon tax when an individual does not consider climate change to be a serious issue. On the other hand, when an individual considers climate change to be serious, tax revenue uses beyond investments in green projects show negative effects. Thus, green project investment is a revenue application that does not show negative impacts on support in general and at different levels of climate concern as well.

Dolsak *et al*. (2020), who employed a methodology similar to ours to study this issue in the United States, also found a similar order of effects on acceptability across various revenue uses. They found that using the revenue from carbon taxation for mitigation efforts increased overall acceptability, while lump-sum transfers or tax reductions did not improve acceptability. Our study similarly demonstrates that investments in green projects are more acceptable than lump-sum transfers.[4] Moreover, our study shows that investments in green projects are more favorable for acceptability than both lump-sum transfers and tax reductions, particularly among individuals with a greater awareness of climate change.

Providing information improves subjects' acceptance of a carbon tax in the short run, regardless of the type of information. In addition, differences in the acceptance change according to how the tax revenue is used remain constant even after efforts to improve acceptance via information provision. This implies that when designing and implementing a carbon tax, differences in acceptance according to the policy design should be considered. Furthermore, tax revenue uses and the provision of information enhance the acceptance of a carbon tax when their implications are consistent with each other. Therefore, the aim of the policy, the design of the policy, and the information provided should be consistent overall to improve the social acceptance of such a policy.

The remainder of the paper is structured as follows. Section II reviews the literature on the acceptability of a carbon tax. Section III explains how the survey experiment is designed to investigate the impacts of the different revenue uses and information types on social acceptance, and Section IV analyses the results. Section V provides the conclusion and policy implications.

II. Literature Review

A. *Different Revenue Uses from a Carbon Tax*

Concerns surrounding a carbon tax arise due to the negative effects on the economy, the possibility of aggravating income distribution, or the questionable impact on reducing greenhouse gas emissions. These concerns are strongly related

[4]Mildenberger *et al.* (2022), who studied certain Canadian provinces and Switzerland as they implemented lump-sum transfers as a use of tax revenues from a carbon tax, also demonstrated that the impact of utilizing tax revenues through lump-sum transfers on acceptability is limited.

to how the revenue from a carbon tax will be used.

First, carbon tax revenue can be used to reduce existing taxes, including income taxes, consumption taxes, and corporate taxes, which is an approach closely related to the double-dividend hypothesis. Pearce (1991) was the first to propose the double-dividend hypothesis, which states that the implementation of a carbon tax can achieve both economic and environmental benefits while holding government revenue constant. This arises because a carbon tax will not only improve the environment by providing incentives to reduce GHG emissions but will also improve the effectiveness of the entire tax system by reducing reliance on highly distortionary taxes.

To alleviate the negative impact on income distribution, revenue can be used to support low-income households or provide lump-sum transfers to all households. It is possible that a carbon tax will be regressive, increasing the burden of energy costs relative to income. Lump-sum transfers can benefit low-income households who receive higher proportions relative to income, meaning that a carbon tax could be progressive (Metcalf, 2009; Goulder *et al*., 2019; Fremstad and Paul, 2019).

Investing the carbon tax revenue into green infrastructure and R&D is another way to use the revenue. This approach not only induces efforts in the short run but also promotes GHG emissions reductions in the long run by establishing the infrastructure for energy and industrial transformation. Furthermore, this strategy promotes technological breakthroughs through investments in R&D, thereby maximizing the effects of efforts to reduce emissions (Jaffe *et al*., 2005; Kim *et al*., 2015; Lilliestam *et al*., 2020).

B. *Change in Acceptance by Revenue Use*

Using carbon tax revenues in different ways can affect public support for a carbon tax (Saelen and Kallbekken, 2011; Jagers and Hammar, 2009; Baranzini and Carattini, 2017). Maestre-Andres *et al.* (2019) reviewed various studies of the effect of revenue use on public support. They found that most studies reported that using the revenue for environmental projects is the most preferred, while people have concerns about distributional effects. Many people are skeptical whether a carbon tax will effectively reduce GHG emissions and whether the revenue should be used to reinforce emissions reduction efforts. Using the revenue for lump-sum transfers, on the other hand, showed contradictory results. Kaplowitz and McCright (2015) found that policy acceptability increased via a tax rebate in the U.S., while Jagers *et al.* (2019) showed that it decreased public support in the Swedish case. Beuermann and Santarius (2006) and Dresner *et al.* (2006) noted that the use of revenue as tax reduction is the preferred measure among economists but is at the same time the most unpopular way of using revenue among the public.

Dolsak *et al.* (2020) conducted a survey similar to that here to assess changes in acceptance for different method of revenue use, in their case tax reduction, compensation to the low-income households, mitigation, and adaptation. Support was found to vary among groups depending on how the revenue is to be used, ranging from 47.4% to 61.4%. In particular, using the revenue for mitigation generates 6.3% higher support relative to the control group for which no particular revenue use is proposed. The rate is consistently high regardless of political inclination or income level. For other revenue uses, the rate of support varies depending on political inclination and income level.

C. *Changes in Acceptance by Information Provision*

Information provision has been discussed as another way to improve the acceptance of a carbon tax. Carattini *et al.* (2018), Hammar and Jagers (2006), and Jagers and Hammar (2009) showed that providing information regarding the mitigating effects of a carbon tax on GHG emissions reduction could help to address concerns surrounding the effectiveness of a carbon tax and thereby could increase acceptance. Douenne and Fabre (2020) showed that concern over climate change is the crucial factor behind the acceptance of a carbon tax and proposed an information campaign regarding climate change in order to increase acceptance.

Concerns over climate change have also led to discussions regarding the effectiveness of information provision. In relation to this, van der Linden *et al.* (2015) revealed that scientific consensus information has a positive impact on climate change concerns. On the other hand, Cook and Lewandowsky (2016) showed that such information may have different effects across countries. The information improved overall awareness in Australia but led to potentially negative effects in the U.S. depending on the individuals' political inclinations.

III. Design of the Survey Experiment

This research investigates the impacts of different revenue uses and information provision on acceptance for a carbon tax. To analyze these effects, a combination of a between-subject design and a within-subject design is considered. Both of these designs are adopted to assess not only each effect, but also their interactions.

The between-subject design is used to analyze the impact of different revenue uses on acceptance. Subjects are divided into four groups, with each group receiving a different revenue use proposal. These are denoted as the control group, tax reduction group, lump-sum transfers group, and green projects investment group. P_0 is the control group, for which the revenue use is not specified. For P_1 tax reduction, for P_2 lump-sum transfers, and for P_3 green project investments are suggested as the revenue use method, respectively.

TABLE 1—POLICY INTERVENTIONS[5]

Revenue Use	Frame	Message
P_0	Control Group	-
P_1	Tax Reduction	Reduction in income tax and consumption tax → Environmental achievement + economic achievement
P_2	Lump-sum Transfers	Lump-sum transfers to all citizens → Reduced burden on low-income households
P_3	Green Projects	Technological innovation + investment into infrastructure → GHG emission reduction in long-run

[5]The full messages are provided in the appendix.

TABLE 2—INFORMATION INTERVENTIONS

Information Type	Frame	Message
I_1	Economic Value	Economic damage following climate change + Positive effect of a carbon tax on the economy
I_2	Environmental Value	Environmental damage following climate change + Positive effect of a carbon tax on the environment

To compare the types of information, the groups were divided based on whether they receive information about the economic value of a carbon tax or the environmental value of a carbon tax.[6] I_1 receives information on the economic value of a carbon tax, including information such as the environmental damage from climate change and the economic contribution of a carbon tax. In addition, the information includes the message that a carbon tax is believed to be the most efficient way to reduce GHG emissions by most economists. I_2 receives information on the environmental value of a carbon tax, including the environmental damage following climate change and the environmental contribution of a carbon tax. This group also receives the consensus message that most climate scientists agree that climate change is caused by human behavior, as used in van der Linden *et al.* (2015).

A within-subject design separates the revenue use groups into two groups and provides different information in order to analyze changes in acceptance following the provision of information. As presented in Table 3, subjects were categorized here into eight groups. Below, Group 3 receives a lump-sum transfer as a means to use the revenue and information about the economic value.

The procedure of the survey experiment is shown in Figure 1. Prior to surveying acceptance, truncated information regarding a carbon tax was provided, after which a quiz was given to assess the subjects' basic understanding of a carbon tax. An additional survey was only conducted with subjects who answered the quiz properly.[7] The proposed carbon tax rate was a rate of ₩30,000/tCO_2e, similar to the average price of the ETS allowance in 2020. Then, with the different revenue uses proposed for the different treatment groups, carbon tax acceptance was surveyed on a scale of 21 encompassing integers between –10 and 10. Given the question 'Do you support the implementation of a carbon tax?', -10 indicates "Strongly Disagree," while 10 indicates "Strongly Agree." In addition, a different type of information was provided to each group, acceptance of a carbon tax was resurveyed, and sociodemographic factors including the level of climate change concern were surveyed during the post-survey step.

TABLE 3—GROUP DESIGN

	P_0	P_1	P_2	P_3
I_1	Group 1	Group 2	Group 3	Group 4
I_2	Group 5	Group 6	Group 7	Group 8

[6]This study categorizes information into two types in order to distinguish the separate effects of different types of information and to analyze their interaction with the use of tax revenue.

[7]Overall, 74.99% of the subjects passed the quiz.

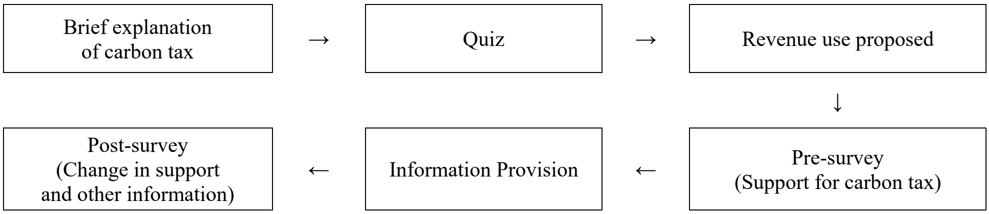


FIGURE 1. SURVEY EXPERIMENT PROCEDURE

TABLE 4—SURVEY EXPERIMENT DESIGN

	First Round	Second Round	
	Main Survey	*Resurvey*	*New Survey*
Number of Subjects	3,200 Subjects (8 Groups x 400 Subjects)	400 Subjects (8 Groups x 50 Subjects)	1000 Subjects (10 Groups x 100 Subjects)
Survey Period	2021. 6. 28. ~ 2021. 7. 6.	2021. 9. 23. ~ 2021. 10. 6.	

The important parts of the message in each step were highlighted in bold, such that only reading the highlighted part would be enough to understand the message. To ensure sufficient reading of each message, the “Next” button was deactivated for a certain time so that subjects could not immediately move on to the next message without reading the message. Furthermore, subjects could not access previous questions.

The survey was divided into two rounds and both were conducted online. In the first round, the *Main Survey* was presented to eight groups following the above procedure. Each group included 400 subjects; hence, 3,200 subjects in total were surveyed. Subjects were initially stratified based on gender and age and were then randomly assigned to either the control group or to one of the treatment groups. The second round was conducted three months after the first round, with 50 subjects from each group of the first round being selected randomly for the *Resurvey* to assess the long-term effects and external validity of the experiment.[8] The *New Survey* in the second round included new subjects not from the first round to avoid any confounding effects caused by the time point of the survey experiment.[9] In the *New Survey*, there were two tax reduction groups – the income tax reduction group and the consumption tax reduction group – because their impacts on income distribution may be different. Hence, we used ten groups. However, the two groups were later merged because no significant changes were found between them.

IV. Analysis

A. *Summary Statistics and Basic Data Analysis*

Prior to analyzing the results of the survey experiment, Table 5 presents the summary statistics of the survey data. The *Main Survey* includes 3,200 subjects, and

[8]The *Resurvey* excluded the quiz from the first round and followed the same procedure used in the pilot survey of the *Main Survey*.
[9]The new subjects were asked the same questions that were asked in the first round.

TABLE 5—SUMMARY STATISTICS OF THE MAIN VARIABLES

	Main Survey (First-Round)	*New Survey* (Second-Round)
Gender (Female=1)	0.5 (0.5)	0.5 (0.5)
Education (Undergraduate or higher=1)	0.84 (0.37)	0.87 (0.34)
Age	39.97 (11.75)	39.32 (10.87)
Household Income (₩4 million/month or higher=1)	0.61 (0.49)	0.64 (0.48)
Married	0.56 (0.50)	0.57 (0.49)
Child	0.30 (0.46)	0.34 (0.47)
Location (Capital Area=1)	0.56 (0.50)	0.56 (0.50)
Religion	0.41 (0.49)	0.38 (0.49)
Politics†	-0.54(3.67)	-0.68(3.47)
Climate Concern	6.05 (3.69)	4.91 (3.59)
Sample size	3,200	1,000

Note: 1) † The variable politics is investigated on a scale ranging from -10 to +10, where a higher value indicates a conservative position and a lower value indicates a progressive position; 2) Figures in the table represent the average value, and ( ) represents the standard deviation.

TABLE 6—AVERAGE ACCEPTANCE RATE FOR EACH GROUP

	Pre-Survey	Post-Survey	
Full Sample	1.36 (4.88)	2.07 (4.88)	
Control Group (P_0)	1.74 (4.90)	Group 1 (I_1)	2.27 (4.80)
		Group 5 (I_2)	2.57 (4.75)
Tax Reduction (P_1)	1.39 (4.82)	Group 2 (I_1)	2.35 (4.67)
		Group 6 (I_2)	2.05 (5.14)
Lump-sum Transfers (P_2)	0.65 (4.92)	Group 3 (I_1)	1.51 (4.80)
		Group 7 (I_2)	1.28 (5.04)
Green Projects (P_3)	1.69 (4.81)	Group 4 (I_1)	2.08 (4.98)
		Group 8 (I_2)	2.41 (4.73)

Note: Figures in the table represent the average value of acceptance, and ( ) represents the standard deviation.

the *New Survey* includes 1,000 subjects, meaning that a total of 4,200 subjects were surveyed in this part of the experiment. In each survey, subjects are equally distributed into each group based on gender and age.[10]

The average value of acceptance for a carbon tax, as shown in Table 6, is 1.36 for the full sample based on the pre-survey. If a value of acceptance above 0 is categorized as indicating support a carbon tax, the rate of support is 48.9% in the full sample. In the post-survey conducted after the information was provided, the average value of acceptance is 2.07 and the rate of support is 61.2% in the full sample.

B. *Policy Effect*

An ordered probit model is employed to analyze changes in the acceptance of a

[10]It should be noted that climate change concern was reduced in the second round relative to that in the first round. This issue will be addressed further in the analysis part concerning policy effects.

carbon tax for each type of revenue use. The dependent variable is the acceptance of a carbon tax, surveyed at a scale of 21 with a range from -10 to +10.[11] An explanatory variable is a dummy variable for policy intervention, P_j, which represents the type of the revenue use, with $j = 0, 1, 2, 3$. P_0 equals 1 for groups 1 and 5 and equals 0 otherwise. Similarly, P_1 equals 1 for groups 2 and 6, P_2 equals 1 for groups 3 and 7, and P_3 equals 1 for groups 4 and 8. Other independent variables that have an effect on the acceptance of a carbon tax are also chosen, in this case gender, education, age, household income, marriage status, having a child, residential location, and religion.

We begin by assessing differences in the effects across revenue use by comparing the control group (P_0) with the treatment groups (P_1, P_2, P_3).[12] As shown in column (1) of Table 7, earmarking the revenue use lowers acceptance compared to this outcome in the control group. In other words, earmarking the revenue use has negative effects on the acceptance of a carbon tax. As shown in column (2) of Table 7, the negative impact of the earmarking of revenue use is due to lump-sum transfers. Specifically, for each revenue use, acceptance is significantly lower when lump-sum transfers are suggested, which results in a negative impact from earmarking. On the other hand, tax reductions and green project investments do not have significant effects on acceptance under the full sample.

Assessing the effects of the socio-demographic factors on acceptance shows that household income, education, and the level of climate concern have positive effects in general. These findings correspond to the analysis in Thalmann (2004) and Hsu *et al.* (2008), who found that education and income level have positive effects on the acceptance of a carbon tax, and Kotchen *et al.* (2017), who analyzed the effects of opinions about global warming on the acceptance of a carbon tax. Among the politically more conservative, acceptance is lower, which is consistent with Dolsak *et al.* (2020).

[11] In general, five-point or seven-point Likert scales are commonly used for measurements to avoid complexity (Cox, 1980; Weng, 2004; Hawthorne *et al*., 2006). However, in Fryer *et al*. (2019), a 17-point Likert scale was used to capture changes in subjects' beliefs about climate change after the provision of information. Our study employs greater granularity in the measurements to investigate the interaction between the use of carbon tax revenue and the types of information provided.

[12] Carattini *et al.* (2018) reviewed the literature on the relationship between the use of the revenue from a carbon tax and acceptance. They showed that the effect of earmarking the revenue from carbon taxation on acceptability depends on how the revenue is utilized, and even with the same revenue use, there can be differences between countries.

TABLE 7—ACCEPTANCE OF CARBON TAX WITH VARIOUS REVENUE USES

		(1) Earmarking Effect	(2) Policy Effect
Non-Control Groups ($P_j = 1,\ j = 1,2,3$)		-0.093** (0.037)	-
Policy Change	Tax Reduction ($P_1 = 1$)	-	-0.051 (0.044)
	Lump-sum Transfers ($P_2 = 1$)	-	-0.231*** (0.046)
	Green Projects ($P_3 = 1$)	-	-0.006 (0.046)
Gender		0.002 (0.032)	0.003 (0.032)
Education		0.143*** (0.045)	0.144*** (0.045)
Age		0.001 (0.002)	0.001 (0.002)
Household Income		0.060* (0.034)	0.067* (0.034)
Married		-0.002 (0.053)	-0.012 (0.053)
Child		0.036 (0.044)	0.037 (0.044)
Location		0.044 (0.032)	0.037 (0.044)
Religion		0.020 (0.032)	0.018 (0.033)
Politics		-0.051*** (0.004)	-0.051*** (0.004)
Climate Concern†		0.793*** (0.054)	0.795*** (0.054)
Surveyed Date (*New Survey*=1)		-0.133*** (0.037)	-0.142*** (0.038)
Cutoffs††		✓	✓
Sample Size		4,200	4,200
Pseudo R^2		0.0198	0.0210

Note: 1) † The climate change variable is used as a dummy variable to improve the accuracy of the empirical model analysis. It is set to 1 if the response variable is positive and 0 otherwise; 2) †† Because this study uses a 21-point Likert scale, there are 20 cutoffs in the ordered probit model. Given these numerous cutoffs, we omitted them from the table; 3) *, **, and *** correspondingly represent significance at the 10%, 5%, and 1% levels, and ( ) is the standard error; 4) The analysis above includes the results of the pre-survey from the *Main Survey* and *New Survey*.

C. *Differences in Policy Effects According to the Level of Climate Concern*

For a deeper analysis of the differences in acceptance across revenue use types, the subjects are categorized based on their level of climate concern. On a scale from -10 to 10, they are classified as having low climate concern when the score is negative and high climate concern when the score is non-negative.

As shown in Table 8, the results when including and excluding the *New Survey*, respectively, show differences in acceptance across different categories of climate concern among the tax reduction group. Only looking at the *Main Survey* in columns (1) to (3) of Table 8 shows that when climate concern is low, the suggestion of a tax reduction increases acceptance. When climate concern is high, however, revenue

TABLE 8—ACCEPTANCE OF A CARBON TAX WITH VARIOUS TYPES OF REVENUE USE DEPENDING ON THE LEVEL OF CLIMATE CONCERN

		Main Survey and *New Survey*			
		(1) Low Climate Concern	(3) High Climate Concern	(4) Low Climate Concern	(6) High Climate Concern
Revenue Uses	Tax Reduction	0.304* (0.174)	-0.081 (0.054)	0.151 (0.149)	-0.062 (0.046)
	Lump-sum Transfers	0.253 (0.171)	-0.252*** (0.054)	0.170 (0.154)	-0.265*** (0.048)
	Green Projects	0.272 (0.172)	-0.013 (0.054)	0.155 (0.156)	-0.024 (0.048)
Gender		0.165 (0.135)	-0.007 (0.039)	0.250** (0.117)	-0.009 (0.034)
Education		0.310* (0.161)	0.108** (0.054)	0.229 (0.143)	0.136*** (0.048)
Age		-0.015** (0.007)	0.003 (0.002)	-0.014** (0.006)	0.003 (0.002)
Household Income		-0.162 (0.129)	0.132*** (0.041)	-0.210* (0.113)	0.089** (0.036)
Married		0.337 (0.211)	-0.009 (0.063)	0.245 (0.180)	-0.036 (0.055)
Child		-0.196 (0.180)	-0.001 (0.054)	-0.043 (0.153)	0.045 (0.046)
Location		0.051 (0.121)	0.024 (0.039)	0.018 (0.106)	0.045 (0.034)
Religion		-0.015 (0.130)	0.047 (0.040)	-0.041 (0.115)	0.024 (0.035)
Politics		-0.044** (0.018)	-0.052*** (0.005)	-0.042*** (0.0153)	-0.053*** (0.005)
Surveyed Date (*New Survey*=1)		-	-	-0.543*** (0.129)	-0.108*** (0.039)
Cutoffs		✓	✓	✓	✓
Sample Size		332	2,868	431	3,769
Pseudo R^2		0.0153	0.0100	0.0250	0.0101

Note: *, **, and *** correspondingly represent significance at the 10%, 5%, and 1% levels, and ( ) is the standard error.

uses other than green project investments lead to lower acceptance at a significant level.

On the other hand, the results that include the *New Survey* in columns (4)-(6) of Table 8 show that the effects of a tax reduction are not significant, although their signs remain the same with the cases of the *Main Survey* only. Another point is that when climate concern is low, the negative effect of the survey date in the *New Survey* is estimated to be quite significant. This is different from the results among subjects whose climate concern level is medium or high. Between the first round (late June of 2021 to early July of 2021) and the second round (late September of 2021 to early October of 2021), a draft of the Carbon Neutrality Roadmap was announced and the NDC target was discussed in Korea. Andersen *et al*. (2019) showed that once policies related to carbon neutrality come under official scrutiny, costs related to GHG reduction are realized and related negative information spreads through various media, likely leading to this difference in the results. In particular, this effect appears more pronounced when climate concern is low.

D. *Change in Acceptance after Information Provision*

Thus far, we have focused on the pre-survey to analyze the changes in acceptance among each type of revenue use. Next, in order to analyze the improvement in acceptance following the provision of information, we investigate both pre-survey and post-survey outcomes. To analyze differences according to the type of information, we use an indicator variable, I_2. This variable equals 1 when the provided information focuses on the environmental value of a carbon tax and equals 0 otherwise.

The dependent variable in column (1) of Table 9 is the difference in acceptance before and after information provision. The constant term, estimated to be positive with statistical significance, implies that information provision has a positive effect

TABLE 9—CHANGE IN ACCEPTANCE AFTER INFORMATION PROVISION

		(1) Change in Acceptance by Information	(2) Post-Survey Acceptance
Revenue Use	Tax Reduction	0.077* (0.046)	-0.007 (0.044)
	Lump-sum Transfers	-0.002 (0.047)	-0.221*** (0.046)
	Green Projects	-0.057 (0.047)	-0.031 (0.046)
Information Type ($I_2 = 1$)		0.010 (0.033)	0.008 (0.031)
Gender		0.222*** (0.033)	0.076** (0.032)
Education		0.008 (0.047)	0.141*** (0.045)
Age		-0.001 (0.002)	0.000 (0.002)
Household Income		0.001 (0.035)	0.060* (0.034)
Married		0.061 (0.055)	0.023 (0.052)
Child		-0.085* (0.046)	0.015 (0.044)
Location		-0.045 (0.033)	0.009 (0.032)
Religion		-0.035 (0.034)	0.039 (0.033)
Politics		0.003 (0.005)	-0.497*** (0.004)
Climate Concern		0.298*** (0.056)	0.918*** (0.054)
Surveyed Date (*New Survey*=1)		-0.052 (0.039)	-0.187*** (0.037)
Cutoffs		✓	✓
Sample Size		4,200	4,200
Pseudo R^2		0.0071	0.0239

Note: *, **, and *** correspondingly represent significance at the 10%, 5%, and 1% levels, and ( ) is the standard error.

on acceptance, at least in the short run. On the other hand, the information type was not related to significant differences in acceptance, except in the case of tax reductions.

Column (2) in Table 9, which presents the analysis results for the post-survey acceptance of a carbon tax after information provision, shows that lump-sum transfers still have a negative effect on significance. The implication here is that despite having provided information to improve acceptance, the effect of revenue use on post-survey acceptance remains similar to the level of pre-survey acceptance.

E. *Interaction between the Policy Effect and Information Effect*

Additionally, we analyzed whether providing a different type of information with each revenue use would lead to heterogeneous effects. These results show an interaction effect between the uses of revenue and the types of information. Given a tax reduction as the type of revenue use, information pertaining to the economic values of a carbon tax has a positive effect on acceptance. For green project investments, on the other hand, information about the environmental value of a carbon tax has a positive effect on acceptance. In other words, when P_1 and I_1 are combined or when P_3 and I_2 are combined, the positive effect of information

TABLE 10—INFORMATION PROVISION EFFECT DEPENDING ON REVENUE USE AND INFORMATION TYPE

	(2) Control Group	(3) Tax Reduction	(4) Lump-sum Transfers	(5) Green Projects
Information Type	0.050	-0.147**	-0.037	0.199***
($I_2 = 1$)	(0.068)	(0.061)	(0.067)	(0.068)
Gender	0.158**	0.236***	0.264***	0.257***
	(0.069)	(0.062)	(0.068)	(0.068)
Education	-0.083	-0.037	0.021	0.129
	(0.096)	(0.087)	(0.096)	(0.096)
Age	-0.010**	0.005	-0.004	0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Household Income	-0.076	0.041	0.044	0.012
	(0.074)	(0.066)	(0.074)	(0.072)
Married	0.325***	-0.080	0.102	-0.033
	(0.112)	(0.101)	(0.116)	(0.112)
Child	-0.225**	-0.101	-0.099	0.082
	(0.095)	(0.084)	(0.096)	(0.093)
Location	0.058	-0.030	-0.072	-0.130*
	(0.069)	(0.062)	(0.068)	(0.069)
Religion	-0.023	-0.012	0.063	0.114
	(0.071)	(0.065)	(0.070)	(0.071)
Politics	0.012	0.006	-0.007	-0.001
	(0.010)	(0.008)	(0.010)	(0.009)
Climate Concern	0.166	0.448***	0.199*	0.341***
	(0.120)	(0.101)	(0.113)	(0.117)
New Survey	-0.092	-0.101	0.136	-0.109
	(0.085)	(0.065)	(0.083)	(0.084)
Cutoffs	✓	✓	✓	✓
Sample Size	1,000	1,200	1,000	1,000
Pseudo R^2	0.0076	0.0123	0.0081	0.0135

Note: *, **, and *** correspondingly represent significance at the 10%, 5%, and 1% levels, and ( ) is the standard error.

provision on acceptance is greater. However, such interaction effects are not observable in P_0 or P_2.

P_1 denotes a type of revenue use designed to achieve goals not only on the environmental frontier but also on economic frontiers, and I_1 emphasizes the economic value of a carbon tax. Similarly, P_3 is suggested to maximize emissions reduction while I_2 emphasizes the environmental value of a carbon tax. Hence, information provision interacts with revenue use in affecting acceptance levels and shows greater effects when the policy design and information provision match with regard to their goals.

F. *Long-run Effect*

The *Resurvey* in the second round was conducted on 50 individuals per group (for a total of 400 individuals) from the first round of surveys three months after the first round of the surveys. In the *New Survey* of the second round, new individuals were also surveyed simultaneously.

To analyze the long-run effect of the *Main Survey*, we analyze whether resurveyed individuals who were surveyed three months prior display greater acceptance relative to newly surveyed individuals.[13] Columns (1) and (2) in Table 11 show the analysis results regarding their acceptance levels. (1) does not include climate concern as an independent variable, while (2) includes this variable.

As shown in column (1) of Table 11, having participated in the first round of surveys has a positive effect on acceptance. In addition, the comparison of the results in (1) and (2) shows that *Resurvey* affects acceptance indirectly through climate concern. The results in (3) confirm a positive effect of *Resurvey* on climate concern. As explained previously, it is possible that some negative news was delivered between the first and the second round. However, resurveyed individuals who were previously exposed to information about a carbon tax appear to be less affected by negative news.

Such results support the inoculation theory, which states that exposure to related information prior to being exposed to arguments surrounding climate change will allow individuals to be less affected by future arguments or information related to climate change, as discussed by McGuire (1970), Compton *et al.* (2021), and others. Hence, resurveyed individuals who had prior exposure to information related to a carbon tax show higher climate concern relative to newly surveyed individuals and thus a greater level of acceptance of a carbon tax.

[13]The individuals surveyed in the first-round of the *Main survey* did not show significant differences in their acceptability in the *Resurvey*, which took place three months later.

TABLE 11— DIFFERENCES IN ACCEPTANCE BETWEEN THE *NEW SURVEY* AND THE *RESURVEY*

		(1) Pre-Survey Acceptance	(2) Pre-Survey Acceptance	(3) Climate Concern
Revenue Use	Tax Reduction	-0.023 (0.075)	0.005 (0.075)	-
	Lump-sum Transfers	-0.197** (0.083)	-0.212** (0.083)	-
	Green Projects	-0.011 (0.083)	-0.025 (0.084)	-
Gender		0.084 (0.055)	0.030 (0.056)	0.211*** (0.056)
Education		0.210** (0.082)	0.206** (0.082)	0.022 (0.082)
Age		0.000 (0.003)	0.000 (0.003)	0.002 (0.003)
Household Income		0.016 (0.060)	-0.009 (0.060)	0.008 (0.061)
Married		-0.090 (0.090)	-0.080 (0.090)	-0.079 (0.090)
Child		0.195** (0.077)	0.182** (0.077)	0.102 (0.077)
Location		0.082 (0.056)	0.079 (0.056)	0.022 (0.056)
Religion		0.006 (0.057)	0.001 (0.057)	0.062 (0.058)
Politics		-0.069*** (0.008)	-0.062*** (0.008)	-0.044*** (0.008)
Climate Concern		-	1.122*** (0.099)	-
Resurvey		-0.162 (0.062)	-0.155** (0.062)	-0.448*** (0.063)
Cutoffs		✓	✓	✓
Sample Size		1,400	1,400	1,400
Pseudo R^2		0.0152	0.0333	0.0150

Note: *, **, and *** correspondingly represent significance at the 10%, 5%, and 1% levels, and ( ) is the standard error.

V. Conclusion

Although imposing a price on carbon is considered to be the most economically efficient policy to reduce GHG emissions, many jurisdictions have failed to introduce a carbon tax, or the price was not high enough to encourage reduction due to public support. Thus, it is crucial to question how social acceptance for a carbon tax can be improved.

This paper conducted a survey experiment to analyze changes in social acceptance levels for a carbon tax depending on the use of the revenue and the types of information provided. First, public support can be changed depending on the use of the revenue. In general, lump-sum transfers have negative impacts on social acceptance for a carbon tax. Moreover, the impact of revenue use on social acceptance can vary with the level of climate concern; with low climate concern, tax reductions have a positive impact, while with sufficiently high climate concern, tax reduction and lump-sum transfers are likely to have negative impacts. On the other hand, green project investments do not have a negative effect on support for a carbon tax, even at different levels of climate concern.

Second, information provision increases support, but no significant differences in the effect of different information types were observed in the full sample. This implies that differences in support across different revenue uses may remain the same, even after certain interventions, such as the provision of information. Thus, differences in support across different revenue uses should be considered in advance when introducing a carbon tax. Moreover, when the policy design and information type are consistent with the aim of the policy, the information effect can be amplified.

Once discussions concerning a carbon tax implementation intensify, individuals will be exposed to other information not included in the surveys. This may have an impact on the interaction effect of revenue use as described above and on information provision; nevertheless, the order in which information is provided remains important. Rabin and Schrag (1999), Wilson (2014) and others studied the potential for confirmation bias, showing that the order in which an individual receives various types of information has an impact on their decision-making process. Under these circumstances, the initial information received plays a significant role in their decision-making process. This type of interaction effect can be utilized by first providing information aligned with the policy's objective when implementing a carbon tax. Hence, there is a need to provide information related to the estimated GHG emissions reduction effect and the estimated environmental and economic value that follows.

APPENDIX

A. *Basic Description of a Carbon Tax*

As concerns about climate change continue to grow and efforts to reduce greenhouse gas emissions become more global, the implementation of a carbon tax has been discussed in Korea.

A carbon tax internalizes the cost of greenhouse gas emissions, providing an incentive to reduce emissions and improve economic efficiency. Setting a price for greenhouse gas emissions increases the cost of fossil fuels, which release a large amount of carbon, and promotes the use of renewable energy and high-efficiency appliances.

The implementation of a carbon tax may result in an increase in electric charges or gas bills. For example, if the tax rate is ₩30,000/tCO_2e, the average household's monthly electric charges could increase by ₩3,158, depending on the amount of electricity used.

B. *Control Group* (P_0)

Concerns surrounding climate change have gradually increased. To reduce greenhouse gas emissions and tackle climate change, a carbon tax can be implemented to set a price for carbon, which may make fossil fuels more expensive.

C. *Tax Reduction* (P_1)

There is concern that the implementation of a carbon tax will increase overall taxation. However, the revenue generated from a carbon tax can be used to reduce labor income taxes and consumption taxes, which can improve not only environmental performance but also economic performance by improving the distortionary tax system.

D. *Lump-sum Transfers* (P_2)

There is concern that the implementation of a carbon tax may have a negative impact on income distribution, especially for low-income households. However, the revenue generated from a carbon tax can be used to provide lump-sum transfers, which can be distributed equally among all households to mitigate the increased burden on low-income households.

E. *Green Project Investment* (P_3)

If the revenue from a carbon tax is used for green project investments, the impact of the tax on emissions reduction can be maximized. By using the revenue for R&D investments and to offset energy transition costs, beneficial long-run effects on emissions reduction can be expected.

F. *Economic Value of Information* (I_1)

According to the Korea Meteorological Administration, typhoons and heavy rains caused economic damage amounting to 1.285 trillion won in 2020, which is more than three times the annual average of the damage from these disasters over the past ten years. Climate change increases production costs by damaging firms' production facilities, creating difficulties in the supply of energy and production inputs and negatively impacting agricultural productivity. These effects reduce the total agricultural production and increase farm prices.

The EU and the United States plan to implement what is known as a carbon border adjustment mechanism that imposes a carbon tariff on carbon-intensive products imported into their markets. As a result, the economic costs of greenhouse gas emissions will be increased for the steel and petrochemical industries.

In contrast, a survey of economists found that approximately 75% of people believe a carbon tax is the most efficient way to tackle climate change. Specifically, a carbon tax is more cost-effective than subsidies or a renewable portfolio standard.

Therefore, the implementation of a carbon tax can efficiently reduce greenhouse gas emissions and mitigate the economic damage caused by the transition to a low-carbon economy.

G. *Environmental Value of Information* (I_2)

According to the Korea Meteorological Administration, the average daily maximum temperature in June of 2020 was 28.0°C and the average daily temperature was 22.8°C. Both were the highest recorded since 1973. There were 2.0 heat wave days, which was also 1.4 days more than the average heat wave days in June.

Climate change raises sea levels, increases the frequency of natural disasters and abnormal weather, and has negative impacts on the global environment and ecosystems. According to the IPCC, the global average surface temperature has increased by approximately 1°C since the Industrial Revolution. If this trend continues and the increase exceeds pre-industrial levels by 2°C, a significant threat to the global ecosystem and civilization arises, as sea levels will rise and the arctic permafrost will melt.

Furthermore, 97% of climate scientists agree that humans are the cause of global warming. Human activities have increased greenhouse gas emissions by 70% from 1970 to 2004, leading to climate change.

Therefore, implementing a carbon tax can limit sea level rises and the environmental damage caused by natural disasters and abnormal weather.

References

Anderson, S., I. Marinescu, and B. Shor. 2019. “Can Pigou at the polls stop us melting the poles?” *NBER Working.*

Baranzini, A. and S. Carattini. 2017. “Effectiveness, earmarking and labeling: testing the acceptability of carbon taxes with survey data,” *Environmental Economics and Policy Studies*, 19: 197-227.

Beuermann, C. and T. Santarius. 2006. “Ecological tax reform in Germany: handling two hot potatoes at the same time,” *Energy Policy*, 34: 917-929.

Carattini, S., A. Baranzini, P. Thalmann, F. Varone, and F. Vöhringer. 2017. “Green taxes in a post-Paris world: Are millions of nays inevitable?” *Environmental Resource Economics*, 68: 97-128.

Carattini, S., M. Carvalho, and S. Frankhauser. 2018. “Overcoming public resistance to carbon taxes,” *WIREs Climate Change*, 9.

Cook, J. and S. Lewandowsky. 2016. “Rational irrationality: modeling climate change belief polarization using Bayesian networks,” *Topics in Cognitive Science*, 8: 160-179.

Compton, J., S. van der Linden, J. Cook, and M. Basol. 2021. “Inoculation theory in the post-truth era: Extant findings and new frontiers for contested science, misinformation, and conspiracy theories,” *Social and Personality Psychology Compass*, 15(6).

Cox, E. P. 1980. “The optimal number of response alternatives for a scale: A review,” *Journal of Marketing Research*, 17(4), 407-422.

Dolsak, N., C. Adoplph, and A. Prakash. 2020. “Policy design and public support for carbon tax: evidence from a 2018 U.S. National online survey experiment,” *Public Administration*, 98(4): 905-921.

Douenne, T. and A. Fabre. 2020. “French attitudes on climate change, carbon taxation, and other climate policies,” *Ecological Economics*, 169.

Dresner, S., L. Dunne, P. Clinch, and C. Beuermann. 2006. “Social and political responses to ecological tax reform in Europe: An introduction to the special issue,” *Energy Policy*, 34: 895-904.

Fremstad, A. and M. Paul. 2019. “The impact of a carbon tax on inequality,” *Ecological Economics*, 163: 88-97.

Fryer, R. G., P. Harms, and M. O. Jackson. 2019. “Updating Beliefs when Evidence is Open to Interpretation: Implications for Bias and Polarization,” *Journal of the European Economic Association*, 17(5): 1470-1501.

Goulder, L. H. and W. H. Parry. 2008, “Instrument choice in environmental policy,” *Review of Environmental Economics and Policy*, 2(2).

Goulder, L. H., M. A. C. Hafstead, G. Kim, and X. Long. 2019. “Impacts of a carbon tax across US household income groups: What are the equity-efficiency trade-offs?” *Journal of Public Economics*, 175: 44-64.

Hammar, H. and S. C. Jagers. 2006. “Can trust in politicians explain individuals’ support for climate policy? The case of CO2 tax,” *Climate Policy*, 5: 613-625.

Hawthorne, G., J. Mouthaan, D. Forbes, and R. W. Novaco. 2006. “Response categories and anger measurement: Do fewer categories result in poorer measurement?” *Social Psychiatry & Psychiatric Epidemiology*, 41, 164-172.

Hsu, S., J. Walters, and A. Purgas. 2008. “Pollution tax heuristics: An empirical study of willingness to pay higher gasoline taxes,” *Energy Policy*, 36: 3612-3619.

Jaffe, A. B., R. G. Newell, and R. N. Stavins. 2005. “Tale of two market failures: technology and environmental policy,” *Ecological Economics*, 54: 164-174.

Jagers, S. C. and H. Hammar. 2009. “Environmental taxation for good and for bad: the efficiency and legitimacy of Sweden’s carbon tax,” *Environmental Politics*, 18(2): 218-237.

Jagers, S. C., J. Martinsson, and S. Matti. 2019. “The impact of compensatory measures on public support for carbon taxation: an experimental study in Sweden,” *Climate Policy*, 19(2): 147-160.

Kaplowitz, S. A. and A. M. McCright. 2015. "Effects of policy characteristics and justifications on acceptance of a gasoline tax increase," *Energy Policy*, 87: 370-381.

Kim, S., S. T. Kim, and Y. J. Chun. 2015. "Environmental regulation, process innovation and social cohesion in Korea," *Indian Journal of Science and Technology*, 8(15).

Kotchen, M. J., Z. M. Turk, and A. A. Leiserowitz. 2017. "Public willingness to pay for a US carbon tax and preferences for spending the revenue," *Environmental Research Letters*.

Lilliestam, J., A. Patt, and G. Bersalli. 2020. "The effect of carbon pricing on technological change for full energy decarbonization: A review of empirical ex-post evidence," *WIREs Climate Change*, 12(1).

Maestre-Andrés, S., S. Drewsa, and J. van den Bergh. 2019. "Perceived fairness and public acceptability of carbon pricing: a review of the literature," *Climate Policy*, 19(9).

McGuire, W. J. 1970. "A vaccine for brainwash," *Psychology Today*, 3(9), 37-64.

Metcalf, G. E. 2009. "Designing a carbon tax to reduce U.S. greenhouse gas emissions," *Review of Environmental Economics and Policy*, 3(1): 63-83.

Mildenberger, M., E. Lachapelle, K. Harrison, and I. Stadelmann-Steffen. 2022. "Limited evidence that carbon tax rebates have increased public support for carbon pricing," *Nature Climate Change*, 12, 121-122.

Pearce, D. 1991. "The role of carbon taxes in adjusting to global warming," *Economic Journal*, 101(407): 938-948.

Rabin, M. and J. L. Schrag. 1999. "First impressions matter: a model of confirmatory bias," *The Quarterly Journal of Economics*, 114(1): 37-82.

Saelen, H. and S. Kallbekken. 2011. "A choice experiment on fuel taxation and earmarking in Norway," *Ecological Economics*, 70: 2181-2190.

Stiglitz, J. E. 2019. "Addressing climate change through price and non-price interventions," *European Economic Review*, 119: 594-612.

Thalmann, P. 2004. "The public acceptance of green taxes: 2 million voters express their opinion," *Public Choice*, 119: 179-217.

van der Linden, S., E. Mailbach, and A. Leiserowitz. 2015. "Improving public engagement with climate change: five "Best Practice" insights from psychological science," *Perspectives on Psychological Science*, 10(6): 758-763.

Weng, L. J. 2004. "Impact of the number of response categories and anchor labels on coefficient alpha and test-retest," *Educational and Psychological Measurement*, 64(6): 956-972.

Wilson, A. 2014. "Bounded memory and biases in information processing," *Econometrica*, 82(6): 2257-2294.

Yoon, Y. 2021. *Carbon Taxation Policy in Korea*, Policy Study, 2021-08, KDI (in Korean).

LITERATURE IN KOREAN

윤여창. 2021. 『탄소세 도입 방안에 대한 연구』, 정책연구시리즈 2021-18, 한국개발연구원.

KDI Journal of Economic Policy 2023, 45(2):21-50
http://dx.doi.org/10.23895/kdijep.2023.45.2.21

The Role of Digital Technology in Climate Technology Innovation†

By KARAM JO*

In this paper, I empirically estimate the relationship between digital technology and climate technology using the United States Patent and Trademark Office's patent database. I find that innovation in digital technology increases the number of patents for climate technology by 17.3% on average, with digital data-processing technology and machine-learning-related technologies especially playing a key role in this relationship. Designing and implementing detailed policies that take into account the relationship between the two technologies will help us reduce the time required to achieve carbon neutrality and shift to the digital economy.

Key Word: Digital Technology, Climate Technology, ICT Energy Consumption, Energy Efficiency
JEL Code: O31, O33, O38, Q48, Q54, Q55, Q58

I. Introduction

Climate change and the digital transformation are two of the most important phenomena that have been transforming our daily lives, and they will continue to do so for many years to come. Consequently, researchers have extensively studied both topics in recent years, and governments in various countries are currently discussing and creating policies to address these changes.[1] In terms of technological development, the two phenomena could be either complementary or confrontational. For instance, the implementation of smart grid technology, which can be widely adopted with the help of digital transformation, could help mitigate climate change by promoting efficient electricity usage, distribution, and trade (European

* Associate Fellow, Korea Development Institute (E-mail: karamjo@kdi.re.kr)
* Received: 2023. 1. 19
* Referee Process Started: 2023. 1. 29
* Referee Reports Completed: 2023. 4. 11
† This paper is written based on Jo (2023, forthcoming). I thank two anonymous referees for their valuable comments. Minsu Song provided excellent research assistance. All remaining errors are mine.

[1]The literature on the effect of climate change on the economy is extensive. Nordhaus (2019) can be a good starting point to follow this literature. Han *et al.* (2021) is a good example documenting various studies and policies related to the digital transformation. Kim and Kim (2020) documents climate policies implemented abroad, including in the EU. Also, Jang *et al.* (2020) compares the EU's Green Deal and Korea's Green New Deal

Commission, 2020). In this case, the advancement of digital technology helps mitigate climate change. However, the proliferation of digital transformation could also accelerate climate change. Data centers, which support digital transformation, consume energy intensively and contribute to heat emission problems. Consequently, the direct negative impact of the digital transformation process on climate change grows as the number of data centers increases.[2] Moreover, the semiconductor manufacturing industry, which is crucial for the digital transformation, is a major energy-intensive sector. As the transition to clean renewable energy is not yet complete, some of the energy required for semiconductor manufacturing must be produced using fossil fuels. Therefore, the increasing demand for semiconductors due to the digital transformation will raise greenhouse gas (GHG) emissions and have an adverse effect on the climate.

Nonetheless, the microfabrication process, which is the primary technological breakthrough in the semiconductor manufacturing industry, allows semiconductors to process the same information while using less energy.[3] As a result, this innovation reduces the amount of electricity used in all places that utilize semiconductors, from typical households to data centers. In fact, Masanet *et al*. (2020) demonstrates that although the volume of information processed increased by 550% from 2010 to 2018, the electric power required by data centers only rose by 6%. This improvement was due to the enhanced efficiency of microprocessors and the reduction of idle power usage, resulting in a swift decline in the amount of electric power required to process the same amount of information.

More direct examples of climate technologies which use digital technologies include building efficiency technologies and sustainable agriculture technologies. By utilizing digital technologies, building owners and operators can monitor and adjust their heating, ventilation, and air conditioning (HVAC) systems more efficiently, resulting in reduced energy usage and lower carbon emissions. Similarly, digital technologies can help reduce fertilizer and water use. Digital tools such as sensors and drones can be used to monitor crop growth and soil conditions, enabling farmers to make more informed decisions about when and how much to water and fertilize their crops. By optimizing these inputs, farmers can reduce waste and improve yields while also minimizing the environmental impact of their farming practices. These are just a few of the examples showing how the integration of digital technologies in climate technologies can offer new opportunities to reduce greenhouse gas emissions and mitigate the effects of climate change while also increasing efficiency and productivity in various sectors. These climate technologies would not exist if digital technologies were not present.

Innovation in digital technology can help mitigate climate change through various channels, as is clear from these previous examples. Thus, climate policies that can lower the returns from investments in digital technologies, such as those that hamper the construction and expansion of data centers or semiconductor manufacturing facilities, could adversely affect climate change prevention efforts by reducing the

[2]According to IEA (2022), electricity used by data centers amounts to approximately 0.9-1.3% of the total electricity used worldwide in 2021, and data centers contribute about 0.6% of the energy-related greenhouse gas emissions. Also, the demand for digital services has been increasing rapidly.

[3]According to Samsung, for example, their three nano-fabrication processes achieve a 23% performance increase and a 45% power consumption reduction compared to their prior fabrication process (https://bit.ly/3R0isXQ).

innovation rate of digital technology. Because digital transformation and climate change affect each other in various dimensions, the European Union, for example, seeks to understand the interaction between the two and makes an effort to design policies reflecting these relationships.[4] In Korea, however, we lack discussions of the relationship between digital transformation and climate change and its mid- to long-term effect in terms of policy design. Also, to the best of my knowledge, there is no study examining the relationship between digital technology and climate technology and discussing its policy implications.

Thus, in this paper, I study the relationship between digital technology and climate technology to enrich our understanding of the relationship between the digital transformation and climate change. Then, I derive implications related to the relationship between climate policy and digital transformation policy. To do this, I empirically estimate the relationship between digital technology and climate technology using the United States Patent and Trademark Office's (USPTO) patent database. I use patent technology classification codes included in the patent data to classify patents for digital technology and patents for climate technology and examine the relationship between the two technologies using detailed sub-classifications for each technology. By using country information for inventors and owners for each patent included in USPTO's patent data, I construct and use country-technology-year-level data in the analysis.

In the empirical analysis, I find the following results. First, innovation in digital technology increases the number of patents for climate technology by 17.3% on average, and digital data-processing technology and machine-learning-related technologies especially play a key role in this relationship. Second, digital data-processing technology and machine-learning-related technologies positively affect developments in smart-grid-related technologies. Lastly, digital technology particularly helps with advancements in energy-saving building technologies, GHG processing and reduction technologies, technologies to reduce the energy used by information and communication technology (ICT), and green transportation technologies. However, statistically significant results on the effects of climate technologies on digital technology could not be found for the purposes of this paper. Designing and implementing detailed policies that take into account the relationship between the two technologies will help us to reduce the time required to achieve carbon neutrality and shift to the digital economy.

The rest of this paper is organized as follows. Chapter II introduces previous studies related to this paper. Chapter III explains the data and measures used in the empirical analysis. Chapter IV explains the empirical model specification and presents the analysis results. Chapter V discusses policy implications. Finally, Chapter VI concludes the paper.

[4] European Union Committee, "Digitalisation for the benefit of the environment: Council approves conclusions," press announcement, 2020. 12. 17 (https://www.consilium.europa.eu/en/press/press-releases/2020/12/17/digitalisation-for-the-benefit-of-the-environment-council-approves-conclusions/).

II. Literature Review

Numerous studies have examined the impact of digital transformation on climate change, focusing mainly on its effect on energy consumption. Horner *et al.* (2016) have analyzed these studies and explained how ICT (which includes computers, mobile devices, and networks) can both decrease or increase energy consumption. The direct energy effect of ICT stems from its energy usage during its operation and manufacturing. The indirect energy effect is the result of changes in energy consumption when ICT is used to modify the way we use existing products and services. Examples of the latter include using smart building technologies to adjust air flows in real time or reducing air travel through online conferences. Moreover, e-commerce has altered the energy use composition for goods transportation. Horner *et al.* (2016) suggest that the indirect energy effect does not necessarily reduce energy use, as e-commerce has increased freight volumes to improve delivery outcomes. Nevertheless, previous research suggests that the indirect energy effect has the potential to reduce energy use significantly depending on efficient technology usage and consumer behavior.

Koomey *et al.* (2011) focus on examining advancements in microprocessor technology and how these have contributed to reducing energy consumption. They show that the computation per kilowatt-hour for microprocessors doubled every 18 months from 1946 to 2009 owing to the development of computer technology and transistor miniaturization. Also, because the theoretical limit for the computation per kilowatt-hour improvement is 2.5×10^6 times higher than what was realized up to 2009, there is much room for improvement in energy use, even in 2023 if we assume that the speed of improvement has remained the same since 2009. This suggests that, during the diffusion of digital transformation, energy usage across the economy could be reduced by decreasing ICT's energy consumption through these developments. Koomey *et al.* (2011)'s findings exemplify the economic significance of digital technology's impact on climate change, which is further elaborated on in this paper.

IEA (2022), on the other hand, compiles recent research findings on electricity consumption and GHG emissions resulting from the digital transformation. Compared to 2015, the number of internet users increased by 60%, internet data traffic rose by 440%, the overall processed data volume by data centers rose by 260%, and electricity usage by data centers and transmission networks increased by 10-60% and 20-60%, respectively, in 2021. In 2020, the share of GHG emissions from data centers out of the total GHG emissions was 0.6%, and the share of energy-related GHG emissions was 0.9%. Based on 2021 data, the global share of electricity used by data centers and transmission networks was around 2-2.7%. Thus, despite rapid diffusion, electricity consumption from digital transformation did not increase as quickly due to ICT energy efficiency improvements, the increased use of renewable energy by ICT firms, and economy-wide decarbonization efforts in the electric grid. Nonetheless, the IEA (2022) emphasizes that we need to reduce our electricity consumption by half by 2030 to reach the net-zero goal, despite these efforts.

While promoting efficient energy use is an important way by which the digital transformation can mitigate climate change, as demonstrated by the studies mentioned earlier, there are many other ways in which the digital transformation can contribute to this effort. According to CODES (2022), digital transformation efforts can move towards improving climate and social sustainability by sharing values and objectives, mitigating negative impacts on the environment and society, and driving innovation. The Global e-Sustainability Initiative (GeSI) (2015) highlights how ICT can reduce greenhouse gas emissions in crucial sectors such as manufacturing, agriculture, construction, and energy through automation and optimization, going beyond merely reducing their energy consumption. For instance, ICT is expected to have a positive impact on the environment by, for instance, increasing grain production by 30% in 2030 compared to 2020 through smart farming and significantly reducing water and oil consumption. The Royal Society (2020) not only documents empirical facts but also suggests specific ways to use digital technology to mitigate climate change. First, constructing data infrastructure to monitor GHG emissions can help data-based services reduce GHG emissions by providing stable and immediate access to data. Secondly, increasing efforts to use renewable energies in the digital sector can help them lower their GHG emissions. Finally, research and innovation can help find new ways for digital transformation efforts to mitigate GHG emissions.

Previous studies have shown that digital technology, or ICT, can help mitigate GHG emissions through efficiency gains in various tasks and by automation and improved electricity usage. In addition to these findings, I contribute to this literature by highlighting the potential for digital technology developments to impact the progress of climate technology directly.

III. Data and Measures

In this section, I explain the data and measures used to estimate the relationship between digital technology and climate technology. I provide a detailed explanation of how I construct the necessary measures using US patent data, as there are many factors to consider to use this data properly. The key in this section is the construction of a digital technology shock that is plausibly exogenous to firms' other decisions that affect their climate technology development. Several papers, such as those by the OECD (2020), Kim *et al.* (2018), Miranda-Agrippino *et al.* (2019), and Sharma and Narayan (2022), particularly the last two, use patent databases to a construct technology shock. Miranda-Agrippino *et al.* (2019) construct an exogenous instrument variable for a technology news shock using residuals from the regression of the growth rate of the number of patent applications to its own lag along with predictions of macro-variables, monetary policy variables, and fiscal policy variables. They analyze the effects of these variables on macro and financial variables. Sharma and Narayan (2022) construct a technology shock using the detrended number of patent applications each year, where they detrend the number of patent applications using the previous five-year average number of patent applications for each year. The constructed technology shock is used to analyze the effect of this variable on stock returns.

Although there have been several efforts to estimate a technology shock using patent databases, there is no general method by which to do so. The key is to find changes in technology that are exogenous to the dependent variables of interest, and in this paper, I define a technology shock as a sharp increase (spike) in innovative technological development for each technology field. A detailed discussion of this measure is given in subsection C.

A. *Data*

I use the USPTO's patent database to ascertain the levels of development in digital technology and climate technology for each OECD member country.[5] The USPTO patent database provides detailed information on ultimately granted patent applications filed by individuals or firms worldwide, including abstracts, lists of previous patents cited, technology classes, lists of inventors, and names and addresses of owners and inventors. The USPTO patent database used for the analysis here contains a set of ultimately granted patent applications from 1976 to 2021. As is well known in previous studies that also use the USPTO patent database, it takes from one year to even as long as ten years, three years on average, for filed patent applications to be granted (see Figure 1-A). Thus, the patent granted year is too far away from the year the innovation occurred. Although the application year may not be the exact year the innovation occurred as well owing to the time required to prepare the patent application documents, this gap should be narrower. Thus, following the previous studies, I use the application year as a proxy for the year the technological innovation occurred.

Also, because the USPTO patent database contains only ultimately granted patent applications and given that the granting process excessively long, the number of patent applications filed falls rapidly after 2016, as shown in Figure 1-B. For example, most of the patent applications filed with USPTO in 2021 were under review as of 2021. Thus, the number of ultimately granted patent applications among the 2021 cohort is very low. Therefore, despite the possibility that the actual number of patent applications filed as well as the quality of the applications in 2021 may equal those factors for 2016 and thus that the number of ultimately granted patent applications counted in 2030 is identical in both years, the number of ultimately granted 2021 patent applications should be very low if counted in 2021. In other words, because the patent application examination process is long, the number of patents created by firms, hence in the economy in 2021, becomes observationally low compared to that in 2016 in the 2021 version of the USPTO patent database. To correct for such bias coming from this type of examination lag, I use patent applications filed up to 2016 in the subsequent analyses. Furthermore, I use the patent applications filed by entities in the 38 OECD member countries in the upcoming analyses, as these should be comparable in terms of the quantity, quality, and composition of the technologies.

To classify the technology of each patent, I use USPTO's Cooperative Patent Classification (CPC) scheme in the following analyses, which USPTO constantly updates to maintain time consistency throughout all of the years the patent data are available. There are nine codes in the 1-digit CPC section, 130 in the 3-digit CPC class, and 670 in the 4-digit CPC subclass. Table 1 shows the number of patent

[5]I download and use the March 29, 2022 version of PatentsView's bulk download service for the USPTO patent database. PatentsView (www.patentsview.org) is owned and maintained by the USPTO.

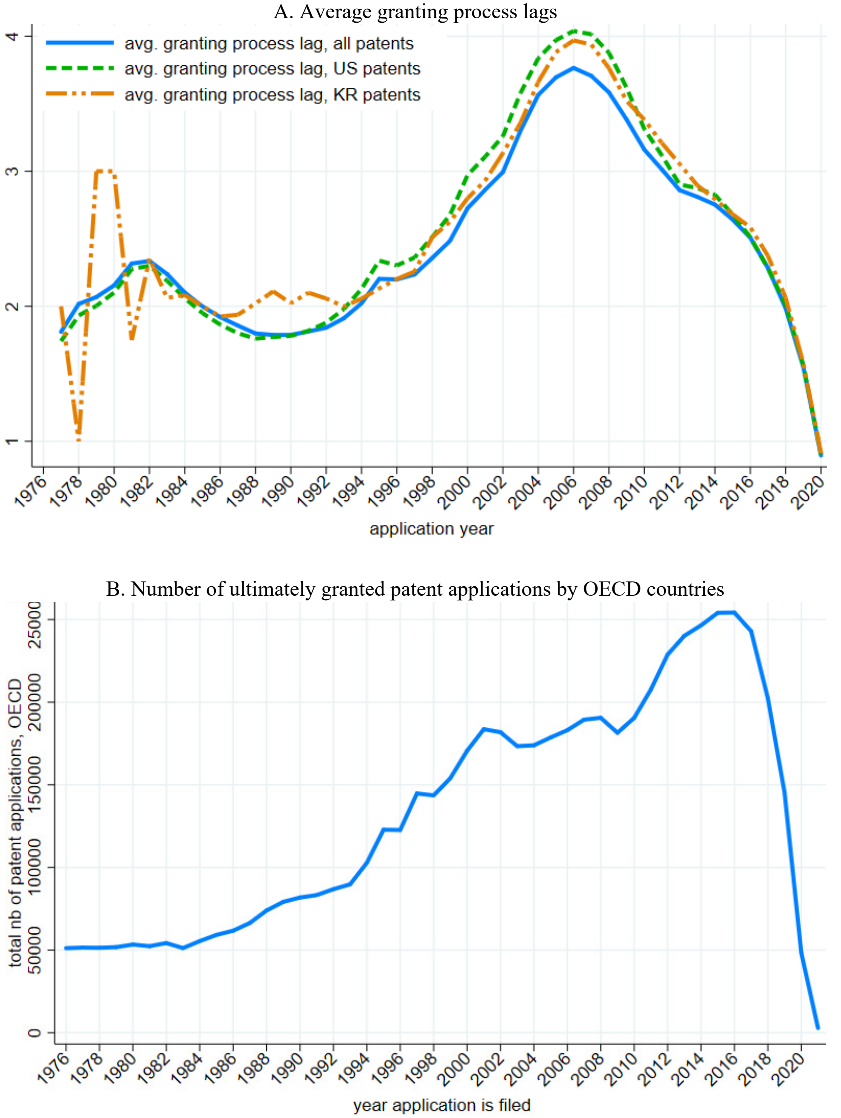


FIGURE 1. USPTO PATENT APPLICATIONS

TABLE 1—TOP 10 PATENTING OECD MEMBER COUNTRIES

Country	Number of Patents	CPC4	CPC3
United States	137,923	586	122
Japan	48,397	494	117
Korea	20,120	393	112
Germany	13,688	480	118
France	5,244	390	114
United Kingdom	4,283	362	111
Switzerland	3,861	338	106
Canada	3,675	375	107
Netherlands	3,469	296	102
Sweden	2,870	269	96

applications and the number of CPC codes for the top ten OECD member countries in terms of the total number of patent applications in 2016. Table A1 in the Appendix shows the same information for all 38 OECD member countries. For more detailed explanations and analyses of the USPTO patent database, I refer to Hall *et al.* (2001).

B. *Climate Technology and Digital Technology Definitions*

As briefly explained previously, USPTO assigns one or more CPC codes to each patent to classify the technologies each patent contains. Among these CPC codes, Y02 is the code USPTO additionally assigns to patents to track the developments in technologies related to mitigation and adaptation to climate change. This code was initially developed jointly by the European Patent Office (EPO), the United Nations (UN), and the International Centre on Trade and Sustainable Development (ICTSD) and used thereafter. To develop an automated way to assign Y02 to relevant patents, climate technology experts from the three institutions first applied textual analysis to all available descriptions in the patent database, such as abstracts and claims, to select patents broadly related to climate technology. The experts then manually inspected and removed false matches using additional information, such as technology classifications, to finalize the assignment. This routine is developed as an algorithm that can automatically assign Y02 to new patents under the supervision of patent experts, and this algorithm has been maintained and updated constantly. See Veefkind *et al.* (2012) for a more detailed explanation. Thus, in this paper, I classify patents assigned to Y02 as patents for climate technology. For example, Y02C under Y02 is for technologies to capture, store, sequestrate, or dispose of GHG, and especially Y02D is for technologies to lower the power consumption of ICT products by, for instance, low-power computing.

Among CPC classes, G06 pertains to technologies for computing, calculating, and counting. Under G06, six subclasses, G06F, G06K, G06N, G06Q, G06T, and G06V, are codes assigned to technologies related to digital transformation technologies. Thus, I classify patents assigned to these six subclasses as patents for digital technology. For example, one of the CPC groups under G06N, G06N 20/00, is for machine-learning-related technologies, and one of the CPC groups under G06F, G06F 1/32, is for technologies for lowering device power consumption levels by processing digital data.

Figure 2 shows digital and climate technology development trends worldwide, where the degree of development is measured as the share of patent applications for digital and/or climate technology from the total number of patent applications filed each year.[6] Because each patent is assigned to one or more CPC, there are cases in which a patent is assigned to both digital technology and climate technology. In such cases, I include the patents in both pools of patents for digital and climate technologies when counting the number of patents in the corresponding pools. Then, I additionally define climate + digital technology — technology used for both climate change mitigation and digital transformation — and compute a trend for the

[6]Henceforth, I will use the term patent as an ultimately granted patent application. Also, the year corresponding to any measures constructed using the patents are the year the patent applications are filed.

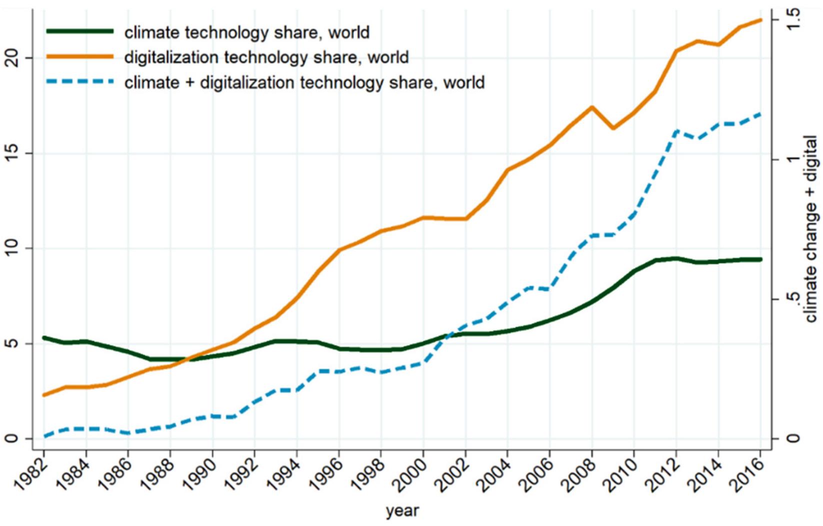


FIGURE 2. TRENDS FOR DIGITAL AND CLIMATE TECHNOLOGIES

development of such technology separately. The share of patents for climate technology among the patents registered with USPTO stagnated in the 1980s and 1990s and then showed a steady increase in the 2000s. This was followed by another period of stagnation after 2010. In contrast, the share of patents for digital technology showed a steady increase in all periods. Also, the share of patents for climate + digital technology, such as G06F 1/32, showed a steady increase in all periods as well.

C. *Different Revenue Uses from a Carbon Tax*

To estimate the effect of digital technology on climate technology and vice versa, I define a rapid increase (spike) in the number of innovative technological improvements as a technology shock for each technology and compute as follows. Just as research papers, patents are required to cite all of the previous patents their technological improvements are based on or related to. Thus, previous studies using the patent database use the number of forward citations received as a measure of the quality or degree of improvement (innovation) each patent contains. Thus, I define patents with the number of forward citations received above the 99th percentile of the forward citation distribution for all patents worldwide as patents related to innovative technological improvements.

In this paper, I use the technology-year mean-adjusted values for the number of forward citations received, where the technology is defined at CPC4-level. As is well documented in Hall *et al*. (2001), both the number of patents created each year and the corresponding trend vary across different technologies. Thus, the number of patents which could potentially cite a specific patent may differ for each technology and year. Also, patents that were created in early periods have the potential mechanically to receive more citations compared to recent patents. In an extreme case, patents created today should have received zero citations. Due to these reasons, for example, a patent related to internal combustion engines created in 1990 and that received 2,000 forward citations could have a lower degree of innovation than an AI-related patent created in 2021 that received 50 forward citations. Thus, it is necessary to adjust for these biases in the number of forward citations to use this measure correctly to assess the quality of patents or the degree of innovation each patent contains. To do this, I compute the average number of forward citations received by patents in each technology-year and divide the number of forward citations each patent in each technology-year received by this average number accordingly.[7]

Then, I define the share of the number of patents for innovative technological improvements from all patents as a measure of the degree of innovative technological improvement for each technology. Here, I use the technology-year mean-adjusted number of forward citations received when counting the number of patents to take the quality of innovation into account. Finally, I compute the DHS (Davis, Haltiwanger, and Schuh, 1998) growth rate of this degree of innovative technological improvement for each technology-year, defining the year when the growth rate is above the 75th percentile of the growth rate distribution for each technology as the year the technology shock (spike) occurred for that technology. According to this methodology, the years the digital technology shock occurred within the regression sample period (1983 to 2016, a total of 34 years) are 1983, 1987, 1989, 1991, 1995, 1999, 2001, 2003, 2004, and 2010 (a total of ten years). For 2010, such digital technology shocks include a total of 495 versatile patents, such as “Electronic Device with Text Error Correction Based on Voice Recognition Data” (Apple, US8719014), “System and Method for Calculating the Thermal Mass of a Building” (Ecofactor Inc., US8131497), Digital Mapping System (Google LLC, US7894984), and “Controlling Power Consumption of a Mobile Device Based on Gesture Recognition” (Qualcomm Inc., US9086875). We could think of other ways to measure a digital technology shock, such as finding an exogenous shock to digital technology, including government policy changes, and using them as instrument variables. However, I was unable to find such exogenous variations.

IV. Empirical Analysis

In this section, I estimate the effect of digital technology on climate technology for various levels of technological aggregation.

A. *Model Specifications*

To estimate the effect of digital technology (a subset of G06 defined previously) on climate technology (Y02), I estimate the following regression model:

$$\log(npat_{cjt}) = \beta_1 I_j^{\{climate\ tech\}} \times I_{t-s}^{\{digital\ shock\}} + \delta_{ct} + \delta_{cj} + \alpha + \varepsilon_{cjt} \tag{1}$$

The dependent variable $\log(npat_{cjt})$ that represents the developments in

[7]Henceforth, the terms number of citations, number of forward citations, and number of patents refer to this technology-year mean-adjusted number of forward citations received.

technology j is the number of patent applications for each technology (j) in each country (c) in year t. As explained previously, I use the technology-year mean-adjusted number of forward citations received when counting the number of patent applications to take into account the quality of innovation, where CPC4 is used for the technology classification. The independent variable $I_j^{\{climate\ tech\}}$ is a dummy variable equal to one if technology j belongs to the climate technology Y02, and $I_{t-s}^{\{digital\ shock\}}$ is a dummy variable equal to one if we observe a digital technology shock in year $t-s$. Thus, the coefficient in front of the interaction term $I_j^{\{climate\ tech\}} \times I_{t-s}^{\{digital\ shock\}}$, β_1 estimates the additional effect of digital technology shock s years ago on climate technology compared to all other technologies. Because it takes time for the USPTO examiners to evaluate the patent applications submitted to the USPTO, to protect their rights, and to make the information available to the public, s should be more than one year. Also, because other firms need time to learn the available information and apply it to their technological developments and then spend more time preparing and submitting patent applications to the USPTO, s should be more than two years. Thus, I use $s=3$ in the baseline regression analysis. To test the robustness of the results, I also use various values of s and report the results in Table B1 in the Appendix. The coefficient estimate for the effect of a digital technology shock in the same year on climate technology, however, is small and statistically insignificant.

δ_{ct} is a country-year fixed effect to control for country-level transitory components that could affect technological development trends and the patent application submission difference across countries. Given that $I_{t-s}^{\{digital\ shock\}}$ is absorbed by δ_{ct}, it is not included as an independent variable separately. δ_{ct} is a country-technology fixed effect to control for the difference in the compositions of technological developments across countries. Because $I_j^{\{climate\ tech\}}$ is absorbed by δ_{cj}, it is not included as an independent variable separately. α is a constant term. As we need to use the three-year prior technology shock in this regression, I limit the analysis sample period to the years 1983 to 2016 (34 years). There are 38 countries with 666 CPC4 in this regression sample, and the total number of observations is 241,402. The mean and standard deviation of the dependent variable $\log(npat_{cjt})$ are 1.97, and 1.78, respectively. The number of years in which a digital technology shock amounts to ten, as explained previously.

B. *Baseline Result*

Table 2 shows the baseline regression results for no fixed effects, the country-year fixed effect only, the country-technology fixed effect only, and both the country-year and the country-technology fixed effects included. As shown in the figure, the estimates for β_1 are positive and statistically significant for all combinations of fixed effects. The results for the main specification in column four show that a digital technology shock additionally increases the number (technology-year-adjusted number of forward citations received) of climate-technology-related patents by 1.24 ($\exp(0.213)$), compared to all other technologies. As the average number of climate-technology-related patents each year is 7.17 ($\exp(1.97)$), this result shows that a digital technology shock increases the number of climate-technology-related patents

TABLE 2—EFFECT OF A DIGITAL TECHNOLOGY SHOCK ON CLIMATE TECHNOLOGY

Dependent Variable: $\log(npat_{cit})$	(1)	(2)	(3)	(4)
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$	0.455***	0.756***	0.307*	0.213**
	(0.031)	(0.036)	(0.153)	(0.102)
Constants	1.625***	1.621***	1.627***	1.629***
	(0.013)	(0.001)	(0.028)	(0.001)
Observations	241,402	241,402	241,402	241,402
Fixed effects	no	ct	cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

by around 17.3% on average. This is an important result showing that, in addition to the previous findings that the digital transformation process helps mitigate climate change by reducing energy use in various ways, the development of digital technology additionally helps mitigate climate change by promoting the development of climate technology, which is very important in the long run. Thus, it is clear that government policies related to the development of digital technology should have an important effect on the development of climate technology.

C. *Technology Shock Measure Validation and Robustness Test*

To test whether the technology shock measure used for the previous analysis captures a simple trend or spurious relationship between digital technology and climate technology, first I regress the current (t) climate technology on the future ($t+s$) digital technology shock measure. Because I need to compute the future technology shock, I limit the regression sample period so that it ranges from 1983 to 2013. The first column of Table 3 shows the result for $s=3$. As shown in the table, the coefficient is small and statistically insignificant. Thus, there is a low possibility that the current digital technology shock measure simply captures spurious relationships. Table B2 in the Appendix shows the results for $s=1$ and $s=2$. We can observe that the coefficient for $s=1$ is statistically significant at 10%. This may stem from the possible release of information for the developed technology before patent application submission, or the large sample size (221,532 observations). However, this result requires further analysis. For $s=2$, the result is statistically insignificant.

The second column in Table 3 shows the estimate of the effect of a digital technology shock on all technologies. This is computed to test whether we obtain the baseline results not because the digital technology shock measure indeed captures its effect on climate technology but because it captures its effect on overall technology or because there is merely a spurious relationship. However, the resulting coefficient estimate is small and statistically insignificant, implying that the possibility of such concerns actually coming to be is low.

The third column in Table 3 shows the estimate of the effect of a climate technology shock on digital technology. This reverse causality estimation allows us to test whether the baseline results are driven by a simple correlation or a common trend between digital technology and climate technology and not by the effect of

TABLE 3—ROBUSTNESS CHECK FOR THE EFFECT OF DIGITAL TECHNOLOGY SHOCK I

Dependent Variable: $\log(npat_{cit})$	(1)	(2)	(3)	(4)
$I_i^{\{climate\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$	0.023 (0.111)			
$I_{t-3}^{\{digital\ shock\}}$		0.104 (0.063)		
$I_i^{\{digital\ tech\}} \times I_{t-3}^{\{climate\ shock\}}$			0.346 (0.210)	0.346 (0.210)
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$				0.213** (0.102)
Constants	1.645*** (0.002)	1.564*** (0.053)	1.629*** (0.001)	1.626*** (0.002)
Observations	221,532	241,402	241,402	241,402
Fixed effects	ct, cj	cj	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

digital technology. This test is important as there is no strong reason as to why climate technology can directly affect digital technology. As shown, the result is statistically insignificant. Thus, the baseline result is likely not capturing a simple correlation.

The fourth column of Table 3 shows the result including $I_i^{\{digital\ tech\}} \times I_{t-3}^{\{climate\ shock\}}$ in the baseline regression specification (1) to estimate the effect of digital technology on climate technology, controlling for the effect of a climate technology shock on digital technology. As shown, the coefficient estimates are identical to those before.

Finally, Table 4 shows whether the baseline results hold even after controlling for the effect of past (three years prior) climate technology shocks on climate technology itself. I run this test as the baseline estimates could be biased if climate technology shocks happened to occur simultaneously with digital technology shocks. However, even when controlling for climate technology shocks, the effect of a digital technology shock remains statistically identical to the baseline result. Furthermore, as shown in the fourth column, the effect of a climate technology shock becomes statistically insignificant after controlling for full fixed effects. All of the results above suggest that the baseline regression result more likely identifies the (causal) effect of digital technology on climate technology than otherwise.

Additionally, I estimate the effect of a digital technology shock on climate + digital technology, as briefly explained in the previous section. Although the share of patents for this type of technology is quite small (0.6% of the total number of patents), as shown in Figure 2, it could be used as an additional robustness test for the baseline results, removing the indirect effect of digital technology, as it is an aspect of climate technology that directly uses digital technology. In this regression analysis, the dependent variable is the country-year-level logged citation-adjusted number of forward citations for patents pertaining to climate + digital technology, and the independent variable is the yearly-level dummy variable for a digital technology shock. Thus, I include the country-fixed effect only in this regression. These results are reported in Table B3 in the Appendix. The coefficient estimate of 0.304 is similar to the baseline result. However, the statistical significance is low

TABLE 4—ROBUSTNESS CHECK FOR THE EFFECT OF DIGITAL TECHNOLOGY SHOCK II

Dependent Variable: $\log(npat_{cit})$	(1)	(2)	(3)	(4)
$I_i^{\{climate\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$	0.324***	0.562***	0.299*	0.207**
	(0.060)	(0.071)	(0.149)	(0.100)
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{climate\ shock\}}$	0.243***	0.360***	0.160	0.101
	(0.076)	(0.090)	(0.132)	(0.089)
Constants	1.624***	1.620***	1.626***	1.628***
	(0.012)	(0.001)	(0.028)	(0.002)
Observations	241,402	241,402	241,402	241,402
Fixed effects	no	ct	cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

(10%) as the regression sample is at the country-year level, with the number of observations equal to 1,197.

Furthermore, I estimate the effect of a digital technology shock on climate technology after separating climate + digital technology from digital technology and climate technology to remove any potential bias that could arise due to a potentially mechanical relationship between a digital technology shock and some of the climate technologies that are actually climate + digital technologies. As reported in the second column of Table B4 in the Appendix, the coefficient estimate is statistically identical after reassigning the climate + digital technology. For comparison purposes, the first column shows the baseline result.

Finally, Table B5 in the Appendix shows the estimate of the effect of digital technology on climate technology, estimated by directly regressing the (logged) number of patent applications for climate technology on the three-year lagged (logged) number of patent applications for digital technology. The advantage of the baseline model over this regression model is that we can isolate the effect of digital technology on climate technology from other factors that could shift both technologies simultaneously, such as a spurious common trend. Additionally, we can estimate the effect of digital technology specific to climate technology by comparing it to the effects of other technologies. Nonetheless, this exercise can also confirm the robustness of the baseline results. Here, only country and time-fixed effects are separately included in this regression specification, as we only have the country-year variations.

As shown in the first column, the coefficient estimate of 0.333 is statistically identical to the baseline estimate of 0.213 reported in Table 2. The second column in Table B5 estimates an additional effect of the year the digital technology shock occurred on climate technology by testing the interaction between the three-year lagged (logged) number of patent applications for digital technology and the digital technology shock measure used in the baseline model. Unless these years are special with regard to the development of climate technology notwithstanding the fact that these are years digital technology shocks occur, all of the digital-technology-specific effects should be absorbed by the number of patent applications for digital technology. Consistent with this perceptive, we have a statistically insignificant and small coefficient for the interaction term. All of the tests above confirm that the baseline estimate of the effect of digital technology on climate technology is robust to many other specifications.

D. *Extension I*

To understand how digital technology affects climate technology in more detail, I extend the baseline regression specification and run several additional analyses. In the first extension, I test whether digital technology affects climate technology differentially in Korea compared to other OECD member countries. I run this test as we need to find causes and find ways to improve the relationship between the two technologies if we find that the effect is lower in Korea. To do this, I additionally test the interaction of a dummy variable for Korea ($I_c^{\{korea\}}$) with the baseline specification. As shown in the second row of the first column in Table 5, the result is statistically insignificant for the triple-interaction term. Thus, the relationship between the two technologies is due to their specific characteristics at the technology level, and I could not find evidence that their relationship is different in Korea due to government policies or the level of technological development.

The next extension is to estimate the effect of digital technology on smart grid technology (Y04), and this result is reported in the second column of Table 5. The coefficient estimate, however, is statistically insignificant. This may stem from the fact that AI-related technological development, which is expected to have a large impact on smart grid technology, showed major developments after 2016. Thus, this result requires further analysis after compiling a longer dataset. Furthermore, this result may be driven by the fact that we are actually combining various detailed digital technologies and using an aggregated form of digital technology in the analysis. If some of these detailed digital technologies have offsetting effects on smart grid technology, such a result would arise. The results when testing the validity of the above extension analyses are reported in Table B6 in the Appendix.

TABLE 5—EFFECTS OF A DIGITAL TECHNOLOGY SHOCK, KOREA SPECIFICITY TEST, SMART GRID

Dependent Variable:	(1)	(2)
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$	0.206**	
	(0.098)	
$\times\ I_c^{\{Korea\}}$	0.153	
	(0.162)	
$I_i^{\{smart\ grid\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$		0.209
		(0.140)
Constants	1.629***	1.631***
	(0.001)	(0.000)
Observations	241,402	241,402
Fixed effects	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

E. *Extension II*

Because the technology shock measure used in this paper is a dummy variable that assumes zero or one at the annual level, it cannot be a good measure of fine technology classifications because we would not be able to separate different fine technologies' movements correctly with annual-level zero one values if these fine technologies co-move in a broad sense. With this limitation in mind, I estimate the effects of finely defined digital technologies in the digital technology used in the baseline analysis on climate technology and examine the effect of digital technology in detail.

Table 6 shows the results for Electric Digital Data Processing (G06F), Computing Arrangements Based on Specific Computational Models (Machine Learning-related technologies, G06N), and Image Data Processing or Generation in General (G06T).[8] We see that climate technology is significantly affected by these three technologies, which exist at the heart of digital technologies. These findings not only help us to understand the detailed role of the digital transformation on climate change mitigation as explored in the previous studies but also highlight the additional importance of digital technological developments on climate change mitigation. I will discuss this in detail in the next section, where I analyze the effects of digital technology on finely defined climate technologies. I report the regression results to test the validity of these results using the future technology shock in Table B7 in the Appendix.

In addition to these aspects, I estimate the effects of finely defined digital technology on smart grid technology. These results are reported in Table 7. In the previous analysis using aggregated digital technology, the estimated coefficient was statistically insignificant. Here, I find statistically significant results at the 10% level for data-processing-related technology and machine-learning-related technology. In fact, it may be possible to obtain statistically more stable (significant) results for these in a few years when a longer dataset becomes available, as machine-learning-related technologies improved rapidly after 2016, and smart grid technology is also relatively new. The robustness test for these analyses using a future technology

TABLE 6—EFFECTS OF DETAILED DIGITAL TECHNOLOGY SHOCKS ON CLIMATE TECHNOLOGY

Dependent Variable:	(1)	(2)	(3)
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{data\ processig\ tech\ shock\}}$	0.269***		
	(0.095)		
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{machine\ learning\ tech\ shock\}}$		0.276***	
		(0.085)	
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{image\ processing\ tech\ shock\}}$			0.316***
			(0.090)
Constants	1.627***	1.629***	1.628***
	(0.002)	(0.001)	(0.001)
Observations	241,402	241,402	241,402
Fixed effects	ct, cj	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

[8]I also ran the same analyses for other detailed digital technologies, but I couldn't find any statistically significant results in those cases. Thus, the results for these other technologies are not reported to save space. These detailed digital technologies include image and video recognition technologies, counting technologies, and computing technologies.

TABLE 7—EFFECTS OF DETAILED DIGITAL TECHNOLOGY SHOCKS ON SMART GRID TECHNOLOGY

Dependent Variable:	(1)	(2)
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{data\ processig\ tech\ shock\}}$	0.224*	
	(0.115)	
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{machine\ learning\ tech\ shock\}}$		0.258*
		(0.136)
Constants	1.631***	1.631***
	(0.000)	(0.000)
Observations	241,402	241,402
Fixed effects	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

shock is reported in Table B8 in the Appendix.

F. *Extension III*

Finally, I analyze the effects of digital technology on finely defined climate technology. As shown in Tables 8 and 9, digital technology has clear effects on six finely defined climate technologies out of eight: Climate Change Mitigation Technologies Related to Buildings (Y02B); Capture, Storage, Sequestration or Disposal of GHG (Y02C); Climate Change Mitigation Technologies in ICT (Y02D); Reduction of GHG Emissions, Related to Energy Generation, Transmission or Distribution (Y02E); Climate Change Mitigation Technologies in the Production or Processing of Goods (Y02P); and Climate Change Mitigation Technologies Related to Transportation (Y02T).[9] Below are some examples that can help us understand what these findings mean and how they are materialized in the real world.

In 2016, Google was able to reduce the electricity they used to dissipate the heat produced by their data center servers by 40% and lower the data center's power

TABLE 8—EFFECTS OF A DIGITAL TECHNOLOGY SHOCK ON DETAILED CLIMATE TECHNOLOGIES I

Dependent Variable:	(1)	(2)	(3)
$I_i^{\{green\ building\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$	0.347**		
	(0.148)		
$I_i^{\{GHG\ processing\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$		0.239**	
		(0.090)	
$I_i^{\{ITC\ power\ saving\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$			0.401*
			(0.231)
Constants	1.631***	1.631***	1.631***
	(0.000)	(0.000)	(0.000)
Observations	241,402	241,402	241,402
Fixed effects	ct, cj	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

[9]The remaining two climate technologies are Technologies for Adaptation to Climate Change (Y02A) and Climate Change Mitigation Technologies Related to Wastewater Treatment or Waste Management (Y02W).

TABLE 9—EFFECTS OF A DIGITAL TECHNOLOGY SHOCK ON DETAILED CLIMATE TECHNOLOGIES II

Dependent Variable:	(1)	(2)	(3)
$I_i^{\{energy\ GHG\ reduction\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$	0.351**		
	(0.158)		
$I_i^{\{green\ production\ or\ processing\ of\ goods\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$		0.183*	
		(0.097)	
$I_i^{\{green\ transfortation\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$			0.346**
			(0.133)
Constants	1.631***	1.631***	1.631***
	(0.000)	(0.000)	(0.000)
Observations	241,402	241,402	241,402
Fixed effects	ct, cj	ct, cj	ct, cj

usage effectiveness (PUE) by 15% by finding a way to control the building's HVAC efficiently using DeepMind's machine learning technology.[10] A lower PUE implies higher energy efficiency. Google expects that this technology could lower electricity and water used in power plants and semiconductor manufacturing factories. Google's effort in this way to apply digital technology newly to climate technology gave birth to several startups with HVAC optimization of buildings as their business focus. One example is BrainBox AI, and such innovations by these startups have reduced GHG emission levels of residences, hotels, airports, and grocery stores by 20~40%. Also, according to BrainBox AI, their customers were able to lower their electricity bills by 25%.[11] US969723 is the patent filed by BrainBox AI in February of 2019 to the USPTO, which was granted in January of 2021, and this patent is for a system and methods of optimizing HVAC control in a building or network of buildings. This technology, categorized as G06N (machine learning-related technology), processes HVAC-related historical data, weather forecasts, and occupancy rates through machine learning to find and utilize the optimal HVAC requirements. This new technology started by Google clearly demonstrates the large contribution to Climate Change Mitigation Technologies Related to Buildings (Y02B). Also, as Google claims, this new technology will make an important contribution to the development of the technology categories of Reduction of GHG Emissions, Related to Energy Generation, Transmission or Distribution (Y02E), and Climate Change Mitigation Technologies in the Production or Processing of Goods (Y02P). This type of machine-learning-based technology will contribute to climate change mitigation by helping to improve existing technologies and heralding the birth of new technologies.

Image Data Processing or Generation technology (G06T) helps mitigate climate change in various fields. It helps computers to analyze video data from traffic cameras in real time to control traffic signals and solve the traffic congestion problem, which ultimately lowers GHG emissions. This technology also helps analyze satellite images to find methane gas leaks. The Carbon Mapper Satellite

[10]Google DeepMind, "Deep Mind AI Reduces Google Data Centre Cooling Bill by 40%," 2016. 7. 20 (https://www.deepmind.com/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-by-40).

[11]*Forbes*, "These Are the Startups Applying AI To Tackle Climate Change," 2021. 6. 20 (https://www.forbes.com/sites/robtoews/2021/06/20/these-are-the-startups-applying-ai-to-tackle-climate-change/?sh=4926ee727b26).

Sensor, developed by joint partners including Planet Labs, NASA, the state government of California, and the University of Arizona, is a good example of using image data-processing technology to find areas with methane gas and carbon dioxide leaks.[12] Owing to such image data-processing technologies, we are able to find problematic areas in real time and mitigate climate change by solving the problems using GHG processing technologies (Y02C). This type of technology will also be used in new areas and will greatly help us to mitigate climate change in the near future. I will discuss examples where data-processing-related technologies, such as technologies for power consumption reductions using data processing, are used for climate technologies, including ICT-related electricity consumption reduction technology, in the next section while discussing policy implications. The analysis results using a future technology shock to test the validity of the results above are reported in Table B9 and B10 in the Appendix. I also analyzed the effects of finely defined digital technologies on finely defined climate technology. I do not include the results from this analysis because they are not stable, which may be due to the possible limitation of the technology shock measure used, as discussed previously, or due to the mismeasurement issue that can arise when dividing data too finely. I plan to re-run this analysis once I find a way to measure a technology shock in a continuous manner.

V. Discussion

In this section, I discuss policy implications derived from the previous analysis results. Here, I focus on government policies that could help promote development in the area of digital technology.

A. *Policies for supporting development in technologies for reducing power consumption by ICTs*

As shown in previous studies and by the real-world examples discussed in the previous sections, the digital transformation, especially that of AI technology that uses high-performance computers and data centers, will play an even more significant role in climate change mitigation. Moreover, as illustrated by the previous analysis results in this paper and the results from other papers, it is not easy for us to disagree that digital technology can mitigate climate change by improving and being combined with climate technology. However, it is also a fact that high-performance computers and data centers negatively affect climate change due to their intensive power consumption. As I introduced in the previous sections, many existing studies and policy institutions worry about and discuss this intensive energy use as it pertains to digital technology. Koomey *et al.* (2011) and the IEA (2022) show that although developments in digital technology improve energy efficiency even more rapidly than performance improvements, there is room for improving energy efficiency even more, and we need to speed this up to accomplish the net-zero goal by 2050. For

[12] https://www.satimagingcorp.com/applications/environmental-impact-studies/global-warming/

these reasons and because the pace of the digital transformation and electrification of energies will increase, the importance of technologies for reducing ICT power consumption levels will progressively increase.

Figure 3 shows a specific example where data-processing-related technology (G06F), including technologies for power consumption through data processing, is applied to a technology for reducing power consumption by ICTs. This is a patent about reducing energy consumption by computer processors, which was applied for by Intel in 2011 and granted in 2015. As written in the corresponding abstract at the bottom right, this technology identifies idle processes among the processes executed in the computer processors, combines them, and reduces the power used by these idle processes.

Technologies that can help reduce the electricity use of ICT products, such as computer-related products, not only greatly help mitigate climate change but also help expedite the digital transformation by lowering the energy cost of firms. Also,

US009075610B2

(12) **United States Patent**
Weissmann et al.

(10) **Patent No.: US 9,075,610 B2**
(45) **Date of Patent: Jul. 7, 2015**

(54) **METHOD, APPARATUS, AND SYSTEM FOR ENERGY EFFICIENCY AND ENERGY CONSERVATION INCLUDING THREAD CONSOLIDATION**

(75) Inventors: **Eliezer Weissmann**, Haifa (IL); **Efraim Rotem**, Haifa (IL); **Avinash N. Ananthakrishnan**, Hillsboro, OR (US); **Alon Naveh**, Ramat Hasharon (IL); **Hisham Abu Salah**, Majdal shams (IL); **Nadav Shulman**, Tel Mond (IL)

(73) Assignee: **Intel Corporation**, Santa Clara, CA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 557 days.

(21) Appl. No.: **13/327,692**

(22) Filed: **Dec. 15, 2011**

(65) **Prior Publication Data**

US 2012/0185709 A1 Jul. 19, 2012

(51) **Int. Cl.**
G06F 1/26 (2006.01)
G06F 1/32 (2006.01)

(52) **U.S. Cl.**
CPC ***G06F 1/3243*** (2013.01); ***G06F 1/3234*** (2013.01); *Y02B 60/32* (2013.01); *Y02B 60/1239* (2013.01)

(58) **Field of Classification Search**
CPC G06F 1/32; G06F 1/324; G06F 1/329; G06F 1/3203; G06F 1/3234; G06F 1/3287; G06F 1/3293; G06F 9/5077; G06F 9/5094; G06F 9/4533; G06F 9/5083; G06F 9/4856; G06F 9/50; G06F 9/505; G06F 9/5061; G06F 9/5088; Y02B 60/142; Y02B 60/144; Y02B 60/148; Y02B 60/162
USPC 713/300, 320, 322, 323, 324; 718/100, 718/102, 104, 105, 107, 108
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

8,533,719	B2 *	9/2013	Fedorova et al.	718/102
2010/0037038	A1 *	2/2010	Bieswanger et al.	712/220
2010/0146513	A1 *	6/2010	Song	718/104
2011/0055838	A1 *	3/2011	Moyes	718/102
2011/0219246	A1 *	9/2011	Arai	713/320
2011/0246995	A1 *	10/2011	Fedorova et al.	718/103
2012/0137289	A1 *	5/2012	Nolterieke et al.	718/1
2012/0272243	A1 *	10/2012	Nolterieke et al.	718/1
2012/0284549	A1 *	11/2012	Abdul et al.	713/323

* cited by examiner

Primary Examiner — Mohammed Rehman
(74) *Attorney, Agent, or Firm* — Trop, Pruner & Hu, P.C.

(57) **ABSTRACT**

An apparatus, method and system is described herein for thread consolidation. Current processor utilization is determined. And consolidation opportunities are identified from the processor utilization and other exaction parameters, such as estimating a new utilization after consolidation, determining if power savings would occur based on the new utilization, and performing migration/consolidation of threads to a subset of active processing elements. Once the consolidation is performed, the non-subset processing elements that are now idle are powered down to save energy and provide an energy efficient execution environment.

19 Claims, 6 Drawing Sheets

FIGURE 3. EXAMPLE OF A DATA-PROCESSING-RELATED TECHNOLOGY (G06F) APPLIED TO A TECHNOLOGY FOR REDUCING POWER CONSUMPTION BY ICTS

as shown in the previous regression analysis results, the development of such digital technology facilitates the development of climate technology. To summarize, technologies for reducing power consumption levels by ICTs represent a solution to the worrying issues of increasing energy consumption and higher GHG emissions levels induced by the digital transformation. Also, through the development of technologies capable of reducing power consumption by ICTs, we can potentially increase the net energy reduction through the digital transformation process while also helping climate technologies to advance. Thus, if we can explicitly support the development of technologies that reduce power consumption by ICTs through climate policies, not only will this also help reduce climate change, but it will have a positive effect on the digital transformation.

B. *Policies for removing factors that could hamper investment incentives for digital technology*

Although climate policies are uniformly applied to all areas to accomplish GHG emission goals overall, we can redesign these policies so that we can apply different measures, such as lowering the restrictions or slowing down the policy implementations for areas where we expect to see a rapid reduction of GHG emissions in an innovative way in near future due to, for instance, technological development. By doing so, although we may not be able to meet our short-term goal, we can achieve a larger GHG emission reduction in the mid to long term. As technology-related investments are sensitively affected by the expected returns, regulations in general harm firms' technological development incentives by lowering the expected return from an investment. Samsung, for example, is said to be facing difficulties in fulfilling its RE100 goal due to an increase in electricity use caused by the production of semiconductors with new technologies, local renewable energy prices, and supply issues.[13] Although participating in the RE100 initiative is thus far voluntary (i.e., although participation is in part due to market pressure, it is not enforced by the government), it is clear that this type of new friction can impact investment returns. This arises because the power supply problem negatively affects semiconductor production and lowers profits by increasing the unit production cost, which in turn lowers expected returns from investments in technological developments. Importantly, however, semiconductors produced using new technologies can do the same tasks using considerably less electricity compared to the existing types, as briefly explained previously. Thus, technological developments in the semiconductor industry can play an important role in significantly improving the net GHG emission reduction effect of the digital transformation.

Continuing the example of semiconductors, firms in this industry always make their mid to long-run roadmaps for technological developments available to the public and attempt to accomplish their innovations accordingly. Thus, it is easy for us to evaluate mid to long-run improvements in the power efficiency and reductions of GHG emissions in this industry compared to those in other industries. By comparing the evaluated expected GHG emissions reduction from using one unit of

[13] *Chosun Biz*, "Enormous Power Consumption of Semiconductor's EUV Process… RE100 Joined Samsung in Trouble," 2022. 9. 20 (https://biz.chosun.com/it-science/ict/2022/09/20/CTXMIP6IRJBQNJB5F3FTP2JRJI/).

new semiconductor (where the evaluation takes into account inter-generational technological development spillovers that could arise due to the sequentiality of innovation) with the GHG emissions from producing one unit of new semiconductor, we could adjust the strength of climate policy enforcement in this industry based on the net GHG emissions reduction level. For other digital technologies, we could guide firms to make their technological development roadmaps available to the public so that we could similarly adjust the strength of climate policy enforcement. Thus, we will be able to expedite the GHG reduction speed at the national level if we confirm other cases similar to those in the semiconductor industry and design detailed policies so that we can promote the development of products and technologies related to energy consumption reductions by adjusting the speed of the green transformation (low-carbon transformation) for production facilities. Also, proper government support for producing the products necessary for the digital transformation, such as semiconductors, would greatly help with the digital transformation. However, these relaxations of regulation should be done while traditional environmental regulations, such as those pertaining to wastewater management, are strictly enforced.

Finally, we could consider policies that support the production and development of products that can lower the electricity consumption of consumer electronics, that is, policies that directly support the development and production of low-power consumption products in general. The Korean government currently indirectly supports the development and production of highly energy-efficient consumer electronics by encouraging the demand for such products through an expenditure subsidy program for top-rated energy-efficient products. However, there is no policy of direct support for such products. The reason for considering direct support for the development and production of highly energy-efficient consumer electronics is ultimately to reduce the time and effort required to accomplish carbon neutrality by reducing the level of electricity production through the use of fossil fuels as the total amount of electricity used could be reduced by reducing the electricity used by each product.

Identical to the semiconductor case, we can measure the energy reduction rates of new products (degree of reduction for energy use compared to existing products) by using the level of electricity use for each product, which is a measure currently used for computing the energy efficiency rating. Furthermore, by using this energy reduction rate of new products, we can also compute how much the GHG emissions are reduced due to the development and production of new products. Then, based on this measure, we could fine-tune the timing and degree of climate policies imposed on each firm. Also, for firms planning to use renewable energies, we could provide benefits such as prioritizing renewable energy use or could provide subsidies based on firms' energy reduction rates of new products. These types of detailed policy support are not possible only through conventional demand-based indirect support. We will be able to expedite the carbon reduction speed at the national level if we can increase the production and demand for products that consume relatively less power.

VI. Conclusion

With regression analyses using the USPTO's patent database, I find in this paper that developments in various digital technologies, especially technologies related to data processing and machine learning, help development in climate technology. Thus, we need a discussion that includes policies for inducing developments in technologies that could serve as bases for developments in climate technology as an aspect of climate policies. For example, although technologies such as microfabrication processes and technology for the efficient use of energy will become more important, the development and production of products using such technologies could be environmentally unfriendly in the short to medium term. In such cases, we could relax the environmental regulation applied to firms proportional to the positive effect their new products will have on the environment. This will help us gradually transit to an environmentally friendly production process without hindering technological development. Also, we must consider finding important technologies that could serve as bases for developments in climate technology and include these technologies in the existing policies on carbon-neutrality-related investment subsidization. Because developments and improvements in digital technology are already the goals of policies for the digital transformation, simply coordinating this goal with climate policy could help us achieve both the digital transformation and climate change mitigation sooner. In contrast, whether slowing down the digital transformation and developments in digital technology could help achieve our climate change mitigation goals remains unclear, as I could not find any evidence that climate technology can affect development in digital technology, and many existing studies show that digital technology can play an important role in climate change mitigation in the mid to long term.

APPENDIX

A. *Additional Tables*

TABLE A1—OECD MEMBER COUNTRIES

Country	Number of Patents	CPC4	CPC3
Austria	1,057	212	85
Australia	1,026	231	87
Belgium	975	204	87
Canada	3,675	375	107
Switzerland	3,861	338	106
Chile	57	33	25
Colombia	23	17	15
Costa Rica	1	1	1
Czech Republic	123	59	31
Germany	13,688	480	118
Denmark	968	174	74
Estonia	16	14	10
Spain	495	160	72
Finland	993	207	84
France	5,244	390	114
United Kingdom	4,283	362	111
Greece	31	14	9
Hungary	35	22	15
Ireland	1,031	152	63
Israel	2,124	206	72
Iceland	58	14	12
Italy	1,903	337	102
Japan	48,397	494	117
Korea	20,120	393	112
Lithuania	15	11	8
Luxembourg	387	111	66
Latvia	9	7	7
Mexico	93	57	38
Netherlands	3,469	296	102
Norway	470	128	64
New Zealand	187	77	38
Poland	94	67	38
Portugal	63	40	24
Sweden	2,870	269	96
Slovenia	23	18	16
Slovak Republic	11	9	9
Turkey	111	67	42
United States	137,923	586	122

B. *Robustness Check*

TABLE B1—EFFECTS OF A DIGITAL TECHNOLOGY SHOCK ON CLIMATE TECHNOLOGY ($s = 0,1,2$)

Dependent Variable:	(1)	(2)	(3)
$I_i^{\{climate\ tech\}} \times I_t^{\{digital\ shock\}}$	0.117		
	(0.100)		
$I_i^{\{climate\ tech\}} \times I_{t-1}^{\{digital\ shock\}}$		0.190*	
		(0.102)	
$I_i^{\{climate\ tech\}} \times I_{t-2}^{\{digital\ shock\}}$			0.206**
			(0.101)
Constants	1.630***	1.629***	1.629***
	(0.001)	(0.001)	(0.001)
Observations	241,402	241,402	241,402
Fixed effects	ct, cj	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

TABLE B2—EFFECTS OF A FUTURE DIGITAL TECHNOLOGY SHOCK ON CLIMATE TECHNOLOGY ($s = 1,2$)

Dependent Variable:	(1)	(2)
$I_i^{\{climate\ tech\}} \times I_{t+1}^{\{digital\ shock\}}$	0.181*	
	(0.097)	
$I_i^{\{climate\ tech\}} \times I_{t+2}^{\{digital\ shock\}}$		0.081
		(0.105)
Constants	1.643***	1.644***
	(0.001)	(0.001)
Observations	221,532	221,532
Fixed effects	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

TABLE B3—EFFECTS OF A DIGITAL TECHNOLOGY SHOCK ON
TECHNOLOGY COMBINING CLIMATE AND DIGITAL TECHNOLOGY

Dependent Variable:	(1)	(2)
$I_i^{\{climate+digital\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$	0.304*	
	(0.153)	
$I_i^{\{climate+digital\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$		0.188
		(0.161)
Constants	0.575***	0.605***
	(0.119)	(0.131)
Observations	1,197	1,121
Fixed effects	c	c

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

TABLE B4—EFFECTS OF A DIGITAL TECHNOLOGY SHOCK ON CLIMATE TECHNOLOGY, EXCLUDING TECHNOLOGY COMBINING CLIMATE AND DIGITAL TECHNOLOGY

Dependent Variable: $\log(npat_{cit})$	(1)	(2)
$I_i^{\{climate\ tech\}} \times I_{t-3}^{\{digital\ shock\}}$	0.213**	0.192**
	(0.102)	(0.094)
Constants	1.629***	1.630***
	(0.001)	(0.001)
Observations	241,402	240,801
Fixed effects	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

TABLE B5—EFFECTS OF A DIGITAL TECHNOLOGY SHOCK ON CLIMATE TECHNOLOGY, DIRECTLY USING THE NUMBER OF PATENTS FOR DIGITAL TECHNOLOGY AND CLIMATE TECHNOLOGY

Dependent Variable: $\log(npat_{ct}^{climate})$	(1)	(2)
$\log(npat_{ct-3}^{digital})$	0.333***	0.313***
	(0.037)	(0.041)
$\log(npat_{ct-3}^{digitla}) \times I_{t-3}^{\{digital\ shock\}}$		0.024
		(0.018)
Constants	1.458***	1.464***
	(0.072)	(0.073)
Observations	1,138	1,138
Fixed effects	c, t	c, t

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

TABLE B6—ROBUSTNESS TEST FOR EXTENDED REGRESSION ANALYSIS I

Dependent Variable:	(1)	(2)
$I_i^{\{climate\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$	0.046	
	(0.046)	
$\times I_c^{\{Korea\}}$	-0.109	
	(0.199)	
$I_i^{\{climate\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$		-0.040
		(0.158)
Constants	1.646***	1.646***
	(0.000)	(0.000)
Observations	221,494	221,532
Fixed effects	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

TABLE B7—ROBUSTNESS TEST FOR EXTENDED REGRESSION ANALYSIS II-I

Dependent Variable:	(1)	(2)	(3)
$I_i^{\{climate\ tech\}} \times I_{t+3}^{\{data\ processig\ tech\ shock\}}$	0.047		
	(0.130)		
$I_i^{\{climate\ tech\}} \times I_{t+3}^{\{machine\ learning\ tech\ shock\}}$		-0.106	
		(0.070)	
$I_i^{\{climate\ tech\}} \times I_{t+3}^{\{image\ processing\ tech\ shock\}}$			0.169
			(0.104)
Constants	1.645***	1.642***	1.643***
	(0.002)	(0.001)	(0.001)
Observations	221,532	221,532	221,532
Fixed effects	ct, cj	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

TABLE B8—ROBUSTNESS TEST FOR EXTENDED REGRESSION ANALYSIS II-II

Dependent Variable:	(1)	(2)
$I_i^{\{smart\ grid\ tech\}} \times I_{t+3}^{\{data\ processing\ tech\ shock\}}$	-0.135	
	(0.165)	
$I_i^{\{smart\ grid\ tech\}} \times I_{t+3}^{\{machine\ learning\ tech\ shock\}}$		0.058
		(0.218)
Constants	1.646***	1.645***
	(0.000)	(0.000)
Observations	221,532	221,532
Fixed effects	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

TABLE B9—ROBUSTNESS TEST FOR EXTENDED REGRESSION ANALYSIS III-I

Dependent Variable:	(1)	(2)	(3)
$I_i^{\{green\ building\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$	-0.001		
	(0.171)		
$I_i^{\{GHG\ processing\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$		-0.068	
		(0.090)	
$I_i^{\{ITC\ power\ saving\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$			0.156
			(0.215)
Constants	1.645***	1.646***	1.645***
	(0.000)	(0.000)	(0.000)
Observations	221,532	221,532	221,532
Fixed effects	ct, cj	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

TABLE B10—ROBUSTNESS TEST FOR EXTENDED REGRESSION ANALYSIS III-II

Dependent Variable:	(1)	(2)	(3)
$I_i^{\{green\ reduction\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$	0.083		
	(0.174)		
$I_i^{\{green\ production\ or\ processing\ of\ goods\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$		-0.015	
		(0.110)	
$I_i^{\{green\ transportation\ tech\}} \times I_{t+3}^{\{digital\ shock\}}$			-0.044
			(0.150)
Constants	1.645***	1.646***	1.646***
	(0.000)	(0.000)	(0.000)
Observations	221,532	221,532	221,532
Fixed effects	ct, cj	ct, cj	ct, cj

Note: 1) Statistical significance levels: ***p<0.01, **p<0.05, *p<0.1; 2) Standard errors in parentheses.

References

CODES. 2022. "Action Plan for a Sustainable Planet in the Digital Age."

Chosun Biz. 2022. "Enormous Power Consumption of Semiconductor's EUV Process… RE100 Joined Samsung in Trouble," Sep. 20 (https://biz.chosun.com/it-science/ict/2022/09/20/CTXMIP6IRJBQNJB5F3FTP2JRJI/).

Davis, Steven J., John C. Haltiwanger, and Scott Schuh. 1998. *Job creation and destruction*, MIT Press Books 1.

European Commission, Directorate-General for Energy, Alaton, C., Tounquet, F. 2020. "Benchmarking smart metering deployment in the EU-28: Final Report, Publications Office" (https://data.europa.eu/doi/10.2833/492070).

European Union Committee. 2020. "Digitalisation for the benefit of the environment: Council approves conclusions," press announcement, Dec. 17.

Forbes. 2021. "These Are the Startups Applying AI To Tackle Climate Change," Jun. 20 (https://www.forbes.com/sites/robtoews/2021/06/20/these-are-the-startups-applying-ai-to-tackle-climate-change/?sh=4926ee727b26).

Google DeepMind. 2016. "Deep Mind AI Reduces Google Data Centre Cooling Bill by 40%," July. 20 (https://www.deepmind.com/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-by-40).

Global e-Sustainability Initiative. 2015. "SMARTer2030, ICT solutions for 21st century challenges," Belgium, GeSI, Accenture Strategy.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2001. "The NBER patent citation data file: Lessons, insights and methodological tool," NBER Working Paper No. 8498.

Han, Jaepil, Jahyun Koo, Jungwook Kim, Sungmin Han, Jonggwan Lee, and Gyuyup Lee. 2021. *Digital Transformation Strategy for Digital-Based Growth*, Research Monograph 2021-07, Korea Development Institute (in Korean).

Horner, Nathaniel C., Arman Shehabi, and Inês L. Azevedo. 2016. "Known unknowns: Indirect energy effects of information and communication technology," *Environmental Research Letters*, 11(10).

IEA. 2022. "Data Centres and Data Transmission Networks," IEA, Paris (https://www.iea.org/reports/data-centres-and-data-transmission-networks).

Jang, Youngwook, Taehyung Oh, Hyunjin Lee, and Hyungjoon Yoon. 2020. "Policy Implications of the European Green Deal for the Korean Green New Deal," Korea Institute for International Economic Policy World Economy Today, 20(24) (in Korean).

Jo, Karam. 2023(forthcoming). "Analysis of the Relationship between Climate Technology and Digital Technology and Policy Implications," in Yong Hyeon Yang *et al*., *Low Carbon Economy Conversion Strategy and Policy Challenges*, Research Monograph, KDI (in Korean).

Kim, Dosung, Sung Han Cho, Jungsoo Lee, Min Seok KIM, and Nam-Hyun Kim. 2018. "A Study on the Competitive Analysis of Digital Healthcare in Korea through Patent Analysis," *Journal of Digital Convergence*, 16(9): 229-237 (doi:10.14400/JDC.2018.16.9.229).

Kim, Soohyung and Changhoon Kim. 2020. *Trends and Implications of the European Green Deal*, Korea Energy Economics Institute (in Korean).

Koomey, Jonathan, Stephen Berard, Marla Sanchez, and Henry Wong. 2011. "Implications of historical trends in the electrical efficiency of computing," *IEEE Annals of the History of Computing*, 33(3): 46-54.

Masanet, Eric, Arman Shehabi, Nuoa Lei, Sarah Smith, and Jonathan Koomey. 2020. "Recalibrating global data center energy-use estimates," *Science*, 367(6481): 984-986.

Miranda-Agrippino, Silvia, Sinem Hacioglu Hoke, and Kristina Bluwstein. 2019. "When creativity strikes: news shocks and business cycle fluctuations," Working Paper.

Nordhaus, William. 2019. "Climate change: The ultimate challenge for economics," *American Economic Review*, 109(6): 1991-2014.

OECD. 2020. "OECD Digital Economy Outlook 2020," OECD Publishing, Paris (https://doi.

org/10.1787/bb167041-en).

Royal Society. 2020. “Digital technology and the planet: Harnessing computing to achieve net zero UK.”

Samsung Newsroom. 2022. Jun. 30 (https://bit.ly/3R0isXQ).

Satelite Imaging Corportaion (https://www.satimagingcorp.com/applications/environmental-impact-studies/global-warming/).

Sharma, Susan Sunila and Paresh Kumar Narayan. 2022. “Technology shocks and stock returns: A long-term perspective,” *Journal of Empirical Finance*, 68: 67-83.

Veefkind, V., J. Hurtado-Albir, S. Angelucci, K. Karachalios, and N. Thumm. 2012. “A new EPO classification scheme for climate change mitigation technologies,” World Patent Information, 34(2): 106-111.

LITERATURE IN KOREAN

장영욱·오태현·이현진·윤형준. 2020, 「유럽 그린딜이 한국 그린뉴딜에 주는 정책 시사점」, KIEP 오늘의 세계경제, 20(24).

김수현·김창훈. 2020, 『유럽 그린딜의 동향과 시사점』, 수시 연구 보고서 2020-01.

한재필·구자현·김정욱·한성민·이종관·이규엽. 2021, 『디지털 기반 성장을 위한 디지털 전환 정책과제』, 연구보고서 2021-07.

조가람. 2023(근간 예정), 「기후기술과 디지털기술의 관계분석과 시사점」, 양용현 외, 『저탄소경제 전환 전략과 정책과제』, 연구보고서, 한국개발연구원.

KDI Journal of Economic Policy 2023, 45(2):51-69
http://dx.doi.org/10.23895/kdijep.2023.45.2.51

Population Aging in Korea: Importance of Elderly Workers†

By JAEJOON LEE*

Korea's population is aging at a faster pace than any other major country, and the adverse impact of this trend on the economy is predicted to be significant. This paper focuses on the macroeconomic effects of population aging with particular attention paid to the pace of aging in Korea. According to our analysis, it is difficult to offset the decline in the labor supply driven by rapid population aging, even if the labor force participation rate of the working-age population rises to a significantly high level. We suggest a re-orientation of policy directions to correspond to the behavioral changes of economic agents. Policies must focus on promoting labor force participation among the elderly while pushing towards human capital advancement and higher productivity.

Key Word: Korean Economy, Population Aging, Economic Growth
JEL Code: J11, E66

I. Introduction

Population aging has become the dominant demographic trend on a global scale. Korea is not an exception; rather, its population aging is predicted to proceed at faster pace than those of any other OECD country. We note that population is a relatively sluggish factor compared to other determinants of economic growth, but corresponding impacts will be less uncertain and more significant. If population aging in Korea progresses at such a rapid pace, economic growth will slow down substantially (i.e., Bank of Korea, 2017; IMF, 2015).

Regarding the relationship between population aging and economic growth, a standard approach is to assume age-specific behavior with respect to labor, savings and investments and to assess the implications of any changes in the relative sizes of different age groups. Obviously, as a population ages, there are fewer workers in

* Senior Fellow, Korea Development Institute (E-mail: jjoonlee@kdi.re.kr)
* Received: 2022. 11. 3
* Referee Process Started: 2022. 11. 16
* Referee Reports Completed: 2023. 4. 11
† This paper is based on the presentation prepared for the KDI-EWC Conference 2020. The author thanks all the participants for their comments at that event. The views expressed in this paper are those of the author and not necessarily those of the KDI.

the active workforce. A widely accepted proposition is that a decrease in the working-age population share is associated with a decrease in the rate of economic growth. These results are robust across different methodologies and are broadly consistent with the literature on demographic effects on growth (see Bloom *et al.*, 2007; Kelly and Schmidt, 1995; 2007). In this regard, Gordon (2016) points out demographic change as a type of “headwind” to the long-run economic growth of developed countries, as older workers will reduce productivity and show low labor force participation rates. Hence, demographic change requires policy actions to ensure economic stability and social cohesion. Our concern is that policy responses in an ordinary manner may not mitigate the impacts of the unprecedented demographic transition in Korea.

This study started from the following research question. The economic analysis of population aging is, in general, based on the life-cycle hypothesis. However, this method has a flaw in that it does not adequately reflect the endogenous responses of economic agents. In particular, the extension of life expectancy may bring changes in life-time decisions such as those related to the labor supply, saving/consumption, human capital, and others. Acemoglu and Restrepo (2017) present empirical evidence that population aging across countries is not associated with a decline in growth per capita, which is contrary to the conventional perception. We expect that the economic consequences of population aging can differ from popular dismal predictions depending on policy responses and institutional changes.

The paper proceeds as follows. Section II shows how rapidly Korea’s demographic change will proceed through a comparison with major countries, and from a macroeconomic perspective, we determine the impact population aging will have on Korea’s economic growth. Section III presents issues from a policy perspective. We conjecture that the impact of population aging will mainly be found in the scarcity of the labor force and that standard policy responses will be to provide some additional labor supply. We examine the effects of these policies on economic growth through a scenario analysis, demonstrating that increasing the labor supply within the working-age population is limited with regard to the ability of this strategy to offset the slowdown in growth. We propose to utilize the labor of the elderly and look into the status of the elderly worker’s labor market in Korea. Considering the generational change in the level of education, we find supportive evidence of a positive role of such a workforce. Section IV concludes the paper and suggests a re-orientation of the policy response to population aging in Korea.

II. Demographic Changes and the Macroeconomic Impact in Korea

A. *The Pace of Population Aging*

Korea has experienced relatively rapid population aging (see OECD, 2018). The old-age dependency ratio[1] doubled only in two decades, rising from 11.2% in 2000 to 23.6% in 2020. Population aging is basically driven by mortality (or longevity),

[1]The measure of aging, admittedly well stylized, is the old-age dependency ratio, which is the elderly (65+) population / the working-age (15-64) population.

fertility, and the population structure. For Korea, all three factors have acted to accelerate the aging of the population. As Korea experienced high economic growth, socio-economic conditions rapidly improved and the country experienced a significant rise in life expectancy, i.e., from 75.9 in 2000 to 83.4 years in 2020. The fertility rate has also changed rapidly, recently dropping further to 0.84 in 2020, the lowest level among OECD countries (see Figure 1). The baby-boomer generation born in 1955~1963[2] resulted in age-specific imbalances in the population structure. As they reach retirement age, rapid aging is expected to continue. We pay attention here to the forward pace of aging in Korea.

Looking ahead, the pace of Korea's population aging will be accelerating in the near future. Remarkably, the UN projects that in 2050 Japan will have the highest share of the population aged 65 and over, at 80.7%, among OECD countries, but the change in the ratio from 2020 to 2050 will be largest in Korea. Figure 2 shows

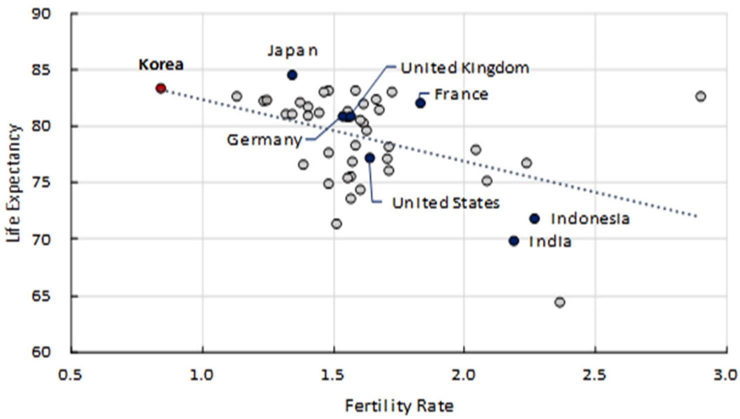


FIGURE 1. LIFE EXPECTANCY AND TOTAL FERTILITY (2020)

Source: World Development Indicators, "Life expectancy at birth & the total fertility rate."

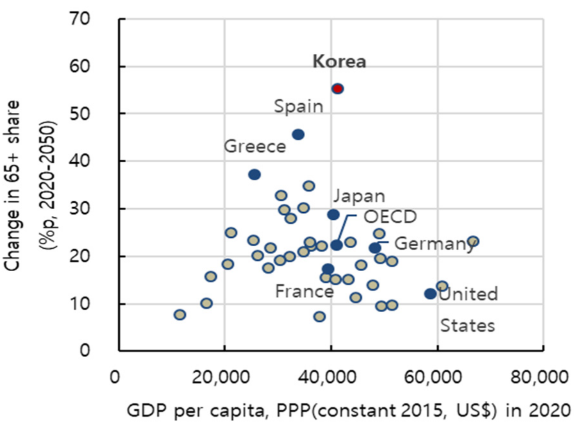


FIGURE 2. CHANGES IN THE 65+ SHARE, 2020-2050, VERSUS THE INCOME LEVEL

Source: Author's calculations based on data from United Nations 2020.

[2]For the definition of baby boomers in Korea, see Hwang (2012).

projections of future changes in the old-age dependency ratio in OECD countries, arranged according to per capita income. Korea is located at the highest changes in the 65+ share with the middle level of per capita income among OECD countries.[3]

Accordingly, the next three decades will be the most important period regarding the population aging phenomenon and how it affects the Korean economy. The pace of population aging will be unprecedented. The response to offset the adverse effects of aging is, therefore, the most critical and urgent issue at present.

B. *Macroeconomic Impacts*

There is a large body of literature on the economic effects of population aging (e.g., Clark *et al*., 2013; Lee, 2016). Here, we focus on the main impacts on macroeconomic variables related to economic growth.

Regarding the production side, population aging has significant impacts on economic growth through the labor supply channel. As fertility declines and a growing number of elderly enter into retirement, the size of the labor force is projected to shrink in the near future. Accordingly, economic growth will also decelerate if other factors are fixed. In the Korean case, the working-age population began to decrease in 2017, and this trend is expected to continue. According to data from Statistics Korea displayed in Figure 3, the working-age population in 2050 will have decreased by a third from its 2017 peak.

Meanwhile, the impact of the labor shortage on economic growth is relatively direct, but it can be, in part, offset by the responses of economic agents in several dimensions (Bloom *et al.*, 2000). For instance, workers are expected to work longer due to longer longevity with better labor fundamentals, such as those related to health and education. Labor force participation may increase because more women can enter the labor market as fertility declines. Human capital can also increase through the mechanism of the quantity vs. quality trade-off. Firms may invest more

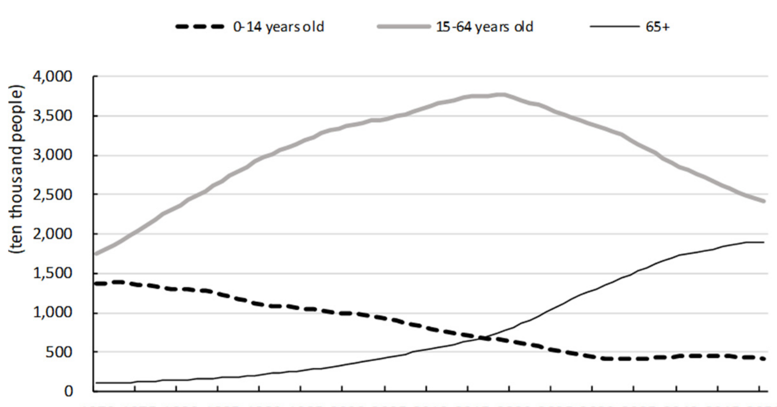


FIGURE 3. POPULATION PROJECTIONS FOR KOREA

Source: Statistics Korea, "Population Projections for Korea 2020~2070", 2021.

[3]The old-age dependency ratio in Korea is predicted to rise to 78.8% in 2050, and the magnitude of the change will be 55.2%p.

in capital-intensive technologies to respond to the scarcity of labor. All of these responses mitigate the negative effects of the labor shortage on economic growth. Overall, the aggregate labor supply will vary depending on the rate of participation in the labor force by gender and age. It is questionable, however, as to whether this factor will be able to make up for the absolute decline in the working-age population. We look into this in the next section by means of a simulation.

On the consumption/savings side, demographic changes affect aggregate savings mainly by altering the relative sizes of age cohorts. According to the life-cycle theory, population aging tends to decrease savings because an increasing number of elderly dependents start to de-cumulate their assets. However, households may tend to increase their income and savings when longevity is expected to increase, a phenomenon entangled with the savings behavior outcomes. We examine the relevant data in order to observe households' responses in Korea.

Figure 4 shows the age profiles of labor income and consumption in Korea. For a comparison over time, they are standardized by dividing by the average labor income

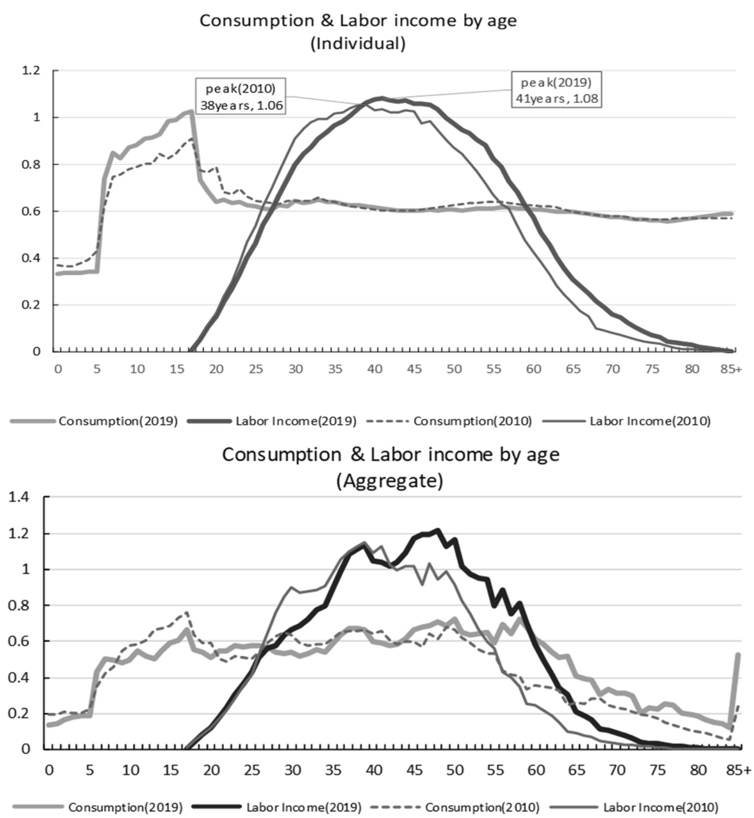


FIGURE 4. CONSUMPTION AND LABOR INCOME BY AGE

Note: For comparability, each age profile is divided by the average level of labor income for the age range of 30-49. Labor income is an average across males and females based on pretax wages and salaries plus employer-provided benefits; it includes two-thirds of self-employment income. Consumption refers to household consumption expenditures on health and education allocated to recipients of these. It includes public in-kind transfers such as public education, health care, and long-term care.

Source: Statistics Korea, "Population Projections for Korea 2020~2070", 2021.

across age range of 30-49 for each year. The upper panel in Figure 4 shows the per capita age patterns of consumption and labor income in 2010 and 2019. The shapes in both years are broadly similar; consumption exceeds labor income at younger ages and older ages, and the ages in between have substantial surpluses. We note that there are some differences between 2010 and 2019. First, the labor income profile in 2019 shifts to the right, which means that labor income peaks later and is slightly higher. This indicates that the elderly tend to work longer and that their labor income remains substantial, even into their 60s. We think that the shift of the labor income curve is likely due to the aging population because both curves depict the size relative to the prime worker group in the age range of 30-49. In particular, this phenomenon may reflect an improvement in labor productivity, which is expected to occur as life expectancy is extended with better health (see Burtless, 2013). However, there is a possibility that it may appear as a result of the unique seniority-based wage practice in Korea. Distinguishing them is an interesting topic but requires separate research. Second, the consumption curve has remained almost flat since this cohort was in their 20s, differing from the rising pattern of consumption in the elderly observed in developed countries (see Lee, 2016). This rising consumption for older citizens may reflect increases in expenditures for health and life care, and in 2019 consumption increases slightly for the elderly above the age of 78, meaning that increasing consumption by the elderly may be in progress. Third, there is upsurge in consumption for children of school ages, reflecting intensive expenditures on early education. A noticeable difference is that the consumption of school-aged children rose significantly in 2019. There may be many reasons for recent increase in education expenditures. Among them, the theoretical prediction that fertility and human capital investment have an inverse relationship is suitable as an explanation, reflecting an important behavioral change in the aging society.

On the whole, the labor income curve shifted to the right, whereas the consumption curve has scarcely changed since this cohort was middle-aged, indicating that the timing of dis-savings by the elderly has been delayed and that the sizes of individual deficits have decreased. Looking at the aggregate data, however, it appears that the total deficit for the elderly increased significantly in 2019. The lower panel in Figure 4 shows that the beginning of dis-saving is postponed from age of 56 to 60 and that the size of the deficit by the elderly increases from 20.4% to 25.2% of the aggregate income level of those in the age range of 30-49.[4] Even given an increase in individual savings in preparation for the aging population, total savings may decrease as a whole in the economy, suggesting a likely reduction of both the source of capital accumulation and future growth.

n sum, according to the life-cycle hypothesis, economic incentives and behaviors differ depending on the stage of life, and the older generation's economic characteristics gradually dominate the overall economy as population aging progresses. The characteristics of this cohort are that they work less and spend the assets they saved in their previous life stages. Thus, as the proportion of this older generation increases, the labor and capital factors of production as a whole will gradually be reduced, causing a decline in economic growth (see Figure 5). In particular, many studies indicate the burdens of pension and health insurance due to

[4]The end point in lower panel of Figure 4 is the sum for those aged 85+.

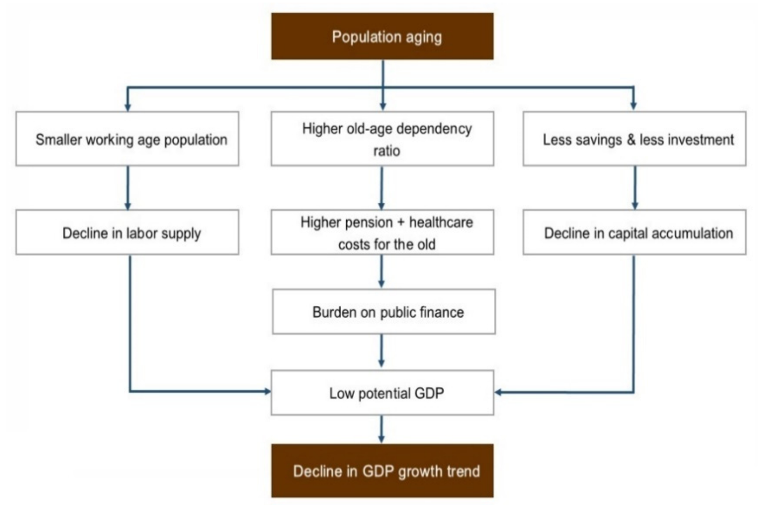


FIGURE 5. MACROECONOMIC IMPACTS OF POPULATION AGING

the increased number of elderly citizens. Among these studies, the IMF (2015) predicts that the Korean economy will need approximately 10% of GDP for population aging for financial burdens such as medical expenses and public pensions. If other conditions remain the same, most of the impact channels of population aging, such as the decline in labor supply, the slowdown in capital accumulation, and the increased financial burden, will negatively affect economic growth in the long run.

III. Policy Issues

From a policy perspective, the aging of the population presents many challenges. The nature of this unprecedented problem means that policymakers have no earlier references for guidance on how the upcoming disturbances work and how they can manage them. In this section, the expected effect of policies that affect the labor supply will be assessed.

A. *Alternative Labor Supply*

1. Scenario Analysis

The impending issue with population aging in Korea is whether the standard policies to increase the labor supply are sufficient to alleviate the adverse impact as the working-age population shrinks. We simulate scenarios in which the labor force participation (LFP) rate of Korea's economy rises to a certain level and calculate this effect on GDP growth using a model of growth accounting (see Appendix: Simulation for Economic Growth).

As noted earlier, Korea’s working-age population (15-64) began to decline in 2017. If labor force participation (LFP) rates were to remain at their current levels

TABLE 1—SIMULATION RESULTS: GDP GROWTH RATES FOR THE ALTERNATIVE LABOR SUPPLY[5]

Time	Baseline	Scenario 1	Scenario 2	Scenario 3
2021~2030	2.0	1.7	1.8	1.9
2031~2040	1.3	0.9	0.9	1.1
2041~2050	1.0	0.6	0.7	0.8

for each age/gender group, the size of the labor force would peak in 2022 and then fall by nearly 20% by 2050. The baseline scenario is the case in which the LFP rate for each age group in the next 30 years is fixed at the initial level of 2017. Baseline in the second column in Table 1 shows the results. The average GDP growth rate for the 2021–2030 period is expected to be 2.0%, and it will continue to fall. The average growth rate for 2041–50 will drop to 1.0%.

Scenario 1 assumes that Korea's LFP rate for each gender/age group changes to the average for G7 countries. As shown in the third column of Table 1, Korea's growth prospects do not improve. Contrary to expectations, the average GDP growth rates for all forecast periods are lower than those in the Baseline Scenario. One of the reasons for the slower growth in this case is that the G7 average LFP rates (henceforth LFPs) for males aged 35 to 64 are not higher than that of Korea.[6]

We look for some specific LFPs to be benchmarked among developed countries. Korea has relatively large gaps between genders in terms of wages and LFPs. Among the potential sources of labor force in Korea, women's participation in economic activities has much room to increase and can be expected to make up for the labor shortage caused by the aging population. In this regard, Sweden has the smallest gap between men and women in terms of economic activity, and both men and women have higher participation rates than in Korea in all working-age groups. Thus, we examine the effect of the increase in LFP relative to the Swedish case in Scenario 2. Second, the LFP for the elderly in Korea was relatively high, but it is expected gradually to decrease as the pension system becomes fully developed in the future. We look at the case in which the economic activity of the elderly follows a country with relatively high LFP for the elderly among developed countries. In Scenario 3, Japan is chosen as another benchmark case because those aged 65+ participate in economic activity more compared to any other developed country. The fourth and fifth columns in Table 1 show the simulation results for additional scenarios. Scenarios 2 and 3 have slightly higher growth projections during all forecast periods than Scenario 1, but the overall growth trend is still lower than that in the Baseline Scenario.

Why does the economic growth trend not improve even if the labor force participation rate rises to the levels found in developed countries? We note that there are several differences in the characteristics of the LFP in benchmarked countries. First, the participation rate is generally high in the 15–64 age group. Second, the LFP difference between men and women is small. Finally, the LFP for those aged 65+ is

[5]The main results are based on the analysis in Lee (2019).

[6]Some characteristics of the labor force's age structure in Korea are as follows: 1) The LFP rate between ages 15 and 35, which is broadly defined as youth, is lower than the OECD average. 2) The LFP of men aged 35–55, i.e., the prime working-age group, is slightly higher, but women's LFP for the same age range is lower than the OECD average. 3) The LFP rate at 55+ is much higher than the OECD average. For the LFPs of other countries, see the table in the Appendix.

far lower than that of the 15-64 age group. We found that these characteristics play a critical role in our simulation.

In the prediction of the Korean economy, the absolute size of the working population will continue to decline and the elderly population aged 65+ will grow at a steady pace up to 2050. Therefore, as long as the LFP of the population aged 65+ remains lower than it is at present, such as in Scenarios 1, 2 and even 3, the overall labor supply will not increase enough to realize higher economic growth, even if the LFP of the working-age population rises to a higher level. These findings from the simulation mean that even if the LFP of Korea approaches the level of any developed country, it will not be able to offset the labor supply shortage due to population aging.[7]

A standard policy measure for population aging is to encourage participation in economic activity by all working-age groups, especially women and young people. The results of the simulation here,[8] however, imply that in Korea, the pace of population aging is so fast that an alternative labor supply from the working-age population may be insufficient to compensate for the adverse effects on economic growth.

2. Other Measures for the Labor Supply

There is no doubt that the super-low fertility rate in Korea is one of the most serious socio-economic problems, but we must also note that raising the fertility rate is not a direct solution to the current population aging issue. Considering the variety of birth determinants and individual preferences, it is difficult to find effective instruments for raising the fertility rate. Even with successful policies for birth, two or three decades will be required for newborn children to reach their prime working age to thus provide sufficient human resources. Therefore, an increase in fertility is neither an easy nor a timely measure to deal with the aging population.

Migration from relatively young developing countries could slow the shift to the aged population and ease the burden on the economy theoretically. In Korea, immigration, including temporary foreign workers, would take require a large increase from the current level and would need to last for at least 30 years in order to achieve a sufficient replacement rate. Immigration, however, can bring with it social burdens and unrest if it goes beyond a certain point, and Korean society is already struggling to find a balance between the need for labor and social cohesion. We think that replacement immigration as a policy for population aging may not be feasible in practice.

B. *The labor market for older workers*

1. The Quality of Employment

A labor policy that increases the LFP of the working-age population seems reasonable, but due to the severe imbalance in the population structure, it is not

[7]In order to make up for the slowdown of growth, Korea needs to maintain the high LFP rates for the elderly (65+) at the current level and must follow Japan's LFP for men and Sweden's LFP for women. See Lee (2019).

[8]There are caveats: when interpreting the simulation results, the impact of the reduced labor supply is based on a static analysis under the assumption that there are no changes in other variables.

TABLE 2—ECONOMIC ACTIVITY STATUS OF THE ELDERLY IN KOREA

(Unit: %)

Economic activity status of the elderly		Employed		
		(55-79)	55-64	65-79
Employment rate		58.1	69.9	43.9
Distribution of the employed by industry	Agriculture and fisheries	13.8	8.4	24.0
	Wholesale, retail and lodging	17.1	19.3	12.8
	Individual Service	38.0	35.2	43.2
	Manufacturing	11.8	14.8	6.0
Distribution the employed by job type	Farmers & fishermen	13.1	7.8	23.3
	Simple worker	24.6	19.4	34.4
	Manager	10.3	12.9	5.3

Note: The category of distribution is selected by the author and is not exhaustive.

Source: Statistics Korea, "Economically Active Population Survey," May 2022.

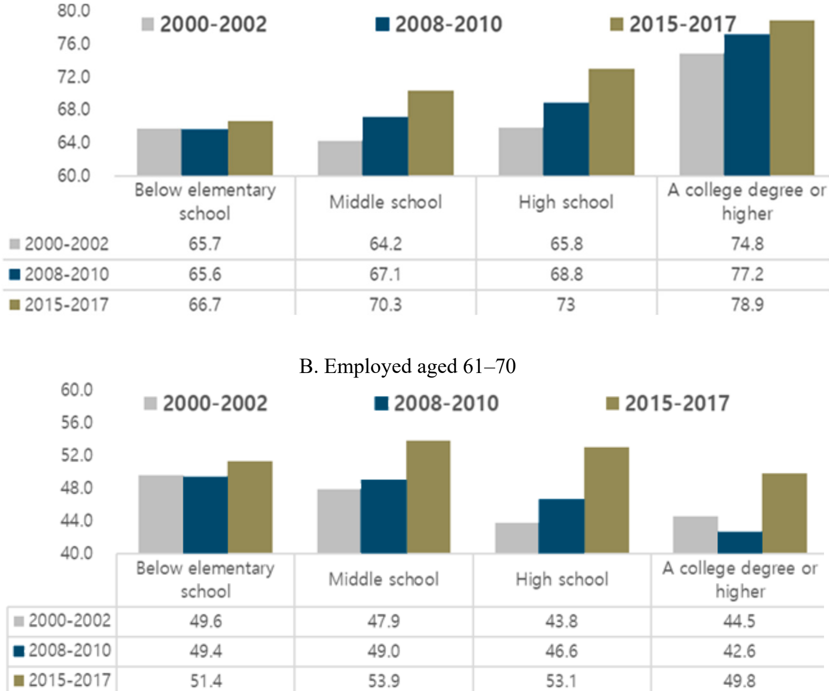
sufficient to recover the growth trend, as discussed in the previous section. Thus, an effective alternative in terms of the labor supply is that older generations must participate longer in production activities. The problem is that the current participation rate of the elderly in Korea is relatively high, meaning that it is unclear as to whether there is enough room for a further increase.

Table 2 shows some of the characteristics of older workers by industry and occupation, reflecting the dismal aspects of the labor market for older workers in Korea. The employment rate of the elderly aged 65+, 43.9%, is higher than that of any other developed country. These workers are mainly engaged in low-value-added industries, such as agriculture, fisheries, and traditional service sectors such as wholesale, retail and lodging. Looking at job types, the share for 'simple worker' is highest (34.4%), and that of 'manager' is relatively low at 5.3%. In sum, the labor market for older workers in Korea shows seemingly good performance in terms of quantity, but it is in an impoverished condition in terms of quality.

One of factors for this low level of quality is related to a peculiar practice in the Korean labor market. The majority of workers in Korea tend to retain their jobs only up to their early 50s. When retiring early, many become self-employed or take low-paying jobs in low-value-added industries, at which point they maintain a second career for a decade or two to support their livelihoods. This tends to continue before they stop working in their early 70s. These retirement dynamics are mainly driven by a certain pay scheme, known as the seniority-based wage system. Under this wage system, as the gap between older workers' wages and productivity rises, many face dismissals from their main job with limited opportunities for re-employment.

2. A condition for improving older workers' employment

We examine the characteristics of the labor market for older workers in Korea, focusing on their relevance to education. Figure 6 shows the employment rates of older workers by education level. They are divided into two cohorts at the age of 60, the usual retirement age in Korea, because we focus on the nature of the labor market



A. Employed aged 51–60

	Below elementary school	Middle school	High school	A college degree or higher
2000-2002	65.7	64.2	65.8	74.8
2008-2010	65.6	67.1	68.8	77.2
2015-2017	66.7	70.3	73	78.9

B. Employed aged 61–70

	Below elementary school	Middle school	High school	A college degree or higher
2000-2002	49.6	47.9	43.8	44.5
2008-2010	49.4	49.0	46.6	42.6
2015-2017	51.4	53.9	53.1	49.8

FIGURE 6. EMPLOYMENT RATE BY EDUCATIONAL LEVEL

Source: Author's calculations based on the Economically Active Population Survey of Statistics Korea.

for this cohort as a secondary market.

For workers aged 51-60, as shown in Panel A of Figure 6, we find that the employment rate rises with educational attainment, tending to rise over time, except for the 'Below elementary school' group. The gains are relatively large for workers with a 'high-school' education, rising from 65.8% in 2000-02 to 73.0% in 2015-17. In contrast, a relationship between education level and the employment rate is not observed in the group aged 61-70 (Panel B). This phenomenon may be related to the fact that, as mentioned above, most of the job opportunities offered to older workers mainly involved simple types of work and/or were in the low-value-added sector where the level of education is not a deterministic factor when hiring.

Here we must examine the flip side of this phenomenon. In Korea, there is a relatively large generation gap in the educational attainment of the elderly. In particular, the education level of the baby boomers is significantly different from those of the previous generations. Because they were on the verge of their retirement age in 2015, we compare them at that point in Figure 7. Among those in their 60s, 38.9% had an elementary school or lower level of education, 22.9% had a middle-school education, 27.3% had a high school diploma, and only 10.9% attended college or had higher education. Considering that Korea's economic and social environments were precarious in the early 1950s due to the Korean War, it is inevitable that the fundamentals of the labor force, i.e., education and health, for those aged 60+ were very poor. On the other hand, for those who were in their 50s in 2015 — mostly baby boomers — the proportion who record 'below elementary school' drops to 13.7%,

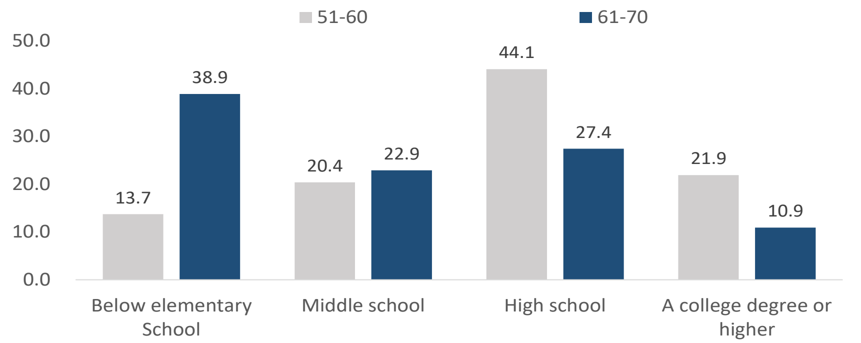


FIGURE 7. EDUCATIONAL ATTAINMENT BY GENERATION

Source: Author's calculations based on data from the Economically Active Population Survey of Statistics Korea.

while the proportion of those with a college degree rises significantly to 21.9%. In the past, most of the potential suppliers in the elderly labor market were mainly under-educated, and this weakness of the supply side was one of the reasons for the poor condition of the labor market of the elderly. In the near future, potential entrants into the elderly labor market have significantly enhanced educational attainment levels compared to those of previous generations, causing the fundamentals of the labor market for the elderly to improve.

3. Education and Employability

We implement a quantitative analysis in order to determine whether educational attainment is significantly related to employment and whether the link differs with age.[9] In the equation,

$$Empr_t^i = c + a^i + \beta^i Edu_t^i + \gamma Gr_t + \varepsilon_t^i,$$

$Empr_t^i$ is the employment rate of cohort $i = 1, 2, \cdots, M$ (5-year age group from 20~24 to 70~74) at time $t = 1, 2, \cdots, T$ (1988~2017) and Edu_t^i is the variable for their educational attainment. We use the proportion of people who have education higher than a college degree as a proxy. Gr_t is the GDP growth rate to control for common macroeconomic shocks to the labor market.[10] The disturbance ε_t^i in the equation above has an (MT*MT) covariance matrix in a stacked model. We conjecture some features of the error structure.

First, the errors may be heteroskedastic across the equations because the labor market for different cohort has its own characteristics. Second, the errors in each equation may be correlated because employment conditions are affected by common economic shocks. In this case, Zellner's SUR (seemingly unrelated regression)

[9]This data analysis is not for the determinants of the employment rate but is rather to determine whether the relationship between employment and educational attainment differs by age, which may present partial evidence to support policy implications for the elderly labor market.

[10]The data descriptions are in the Appendix.

estimator is appropriate given that the errors are contemporaneously correlated and the regressors, the educational attainment and GDP growth rate, can be assumed to be exogenous.

The SUR estimation results are in the second column of Table 3. The coefficients of interest are significant, but the Durbin-Watson test strongly suggests serial correlations in the error terms, which means that the estimates may be biased. To handle this with serially correlated errors, we add an auto-regressive (AR) term in the errors, and these results are in the third column, SUR with AR error. Furthermore, we checked the stationarity of the dependent variables, and the test could not reject the null of the unit root for most age groups. Also, some of the education variables could not reject the unit root. If these two variables have a unit root, the estimation is likely to be a spurious regression. Thus, we estimate the SUR system with first-differenced variables.

Depending on the estimation method, the estimates of the coefficient change considerably. For the SUR estimation, all coefficients appear significant, but if the autocorrelation is taken into account, the magnitude of the coefficient estimates generally decreases and the level of significance deteriorates. We pay attention to the relative

TABLE 3—ESTIMATES FOR $\hat{\beta}^i$ BY AGE GROUP

		SUR	SUR with AR Error	SUR for Difference
Constant		Fixed Effect	Fixed Effect	-0.91*** (0.318)
Education attainment by age group	20~24	0.26*** (0.042)	-0.04 (0.026)	-0.01 (0.024)
	25~29	0.19*** (0.011)	0.14*** (0.024)	0.01 (0.055)
	30~34	0.05*** (0.011)	0.06** (0.027)	0.05 (0.054)
	35~39	-0.03*** (0.009)	-0.04** (0.020)	0.001 (0.049)
	40~44	0.04*** (0.013)	0.01 (0.034)	0.07 (0.055)
	45~49	0.15*** (0.011)	0.13*** (0.017)	0.16** (0.069)
	50~54	0.28*** (0.024)	0.22*** (0.041)	0.19*** (0.073)
	55~59	0.46*** (0.050)	0.33*** (0.100)	0.46*** (0.125)
	60~64	0.79*** (0.070)	0.59*** (0.175)	0.74*** (0.186)
	65~69	1.17*** (0.077)	0.91*** (0.099)	0.71*** (0.238)
	70~74	1.90*** (0.141)	0.005 (0.495)	0.001 (0.433)
GDP		0.16*** (0.046)	0.14*** (0.037)	0.18*** (0.047)
$Adj. R^2$		0.997	0.998	0.105
Durbin-Watson		1.202	2.024	1.861
Sample period		1988~2017	1989~2017	1989~2017
# observations		330	319	319

Note: 1) *, **, and *** indicate significance at p < 0.10, p < 0.05 and p < 0.01, respectively; 2) Standard errors are in parentheses.

variations across age groups. In Table 3, we compare the estimated coefficients, $\hat{\beta}^i$ to find age-specific relationships between education and employment.[11]

The magnitude of the estimate is generally small or insignificant for those in their 20s and 30s, after which it becomes positive and significant for those past their 40s. Interestingly, these values are significant after the late 40s, and the magnitude continues to rise, remaining until this cohort reaches their 60s in all three estimations. In other words, although the estimation results are quite different according to the estimation method, it is common that the influence of education on employment increases in the elderly labor market, which means that workers who tend to work longer have better educational credentials.

Considering the employability gain for greater educational achievements for young adults, workers with potentially higher abilities tend to invest more in human capital and to remain out of the labor force. In their 30s most workers — the prime working-age group — tend to maintain their employment status. The employability gain gradually increases over the age profile after the middle age levels, which is consistent with the fact that retirement in Korea begins at the age of 50. Thus, the higher the educational background, the higher the possibility of remaining in the labor market or being re-employed after retirement. This result implies that employment benefits by educational attainment increase in the labor market for older workers.

In the past, working by the elderly seemed mostly poverty driven and related to their livelihoods, and it was common for this cohort to work in unstable and low-value-added sectors. It is not desirable for the increasing number of the elderly to engage in economic activities under such unfavorable conditions. We note that in the past, the low educational attainment of those aged 60+ underlay the low quality of the elderly labor market in Korea. However, the baby boomers in Korea, who have recently approached their retirement age, have higher education levels than previous generations, as well as experience in economic development. The supply of this workforce with enhanced human capital can be a fundamental basis to improve the elderly labor market in the near future.

C. *Policy Recommendations*

It is more likely that those with higher skills and education will be engaged in professional jobs with longer tenures. Hence, the level of education or human capital has a significant causal effect on the economic participation of older people. Therefore, policy measures should focus on improving human capital for older citizens. There are some prerequisites for this action.

Most of all, the perception of the elderly above a certain age as dependent should be jettisoned, and accordingly the social practices and institutions based on the presumption that those aged 65+ are "old" should be changed.[12] We must utilize the positive factors during the on-going population aging trend, such as improving health and increasing longevity. The older generations should have the opportunity to enter

[11]The magnitude of the estimate $\hat{\beta}^i$ indicates the %p change in the employment rate related to a 1%p increase in college educated workers in that age group.

[12]A recent study, Lee et al. (2020), discusses this issue.

a new, productive stage in their life cycles so that they may continue to contribute to society. Social reforms must be promoted for this purpose.

Mandatory retirement, which forces workers to leave the labor market at a certain age, should become an obsolete system. We must reform the retirement rule and have a more flexible system so that people can decide whether or not to retire based on their abilities and willingness to work. In this regard, it is crucial to ensure that aging does not reduce overall productivity. More resources should be invested in the improvement of human capital, especially to improve the human capacity for older workers. The current education system, which utilizes both time and resources for higher education for those in their early years of adulthood, is unlikely to be a reasonable approach given the pace of future technological change and social development. The education system must adjust to life expectancy reaching the 80s, in particular, in order to be of practical help to middle-aged individuals who attempt to build another career.

Finally, labor market conditions must be improved to become more age-friendly. Age discrimination should be prohibited in all workplaces. Accordingly, reforming the seniority-based wage system entrenched in most sectors in Korea will be the first step towards flexibility, enabling longer retention that could benefit both workers and employers. In the longer run, Korea's entire human resources sector will need to move towards more performance-based jobs and away from the focus on stability.

IV. Conclusion

Population aging is taking place in nearly every country with considerable variations. A distinctive feature of the Korean case is that its magnitude and speed are enormous such that the dependency ratio will quadruple only in the next three decades, even without sufficient per capita income, as shown in Figure 2. This study showed, through an analysis of growth accounting, that policies that seek substitutes for retired labor will not easily realize any recover from the decline in economic growth caused by population aging.

An effective measure to prevent the decline in the labor supply due to population aging is to utilize labor from the older generations. Participation in the labor market by older generations would be effective because it can boost economic growth and reduce the fiscal burden. To this end, it is necessary to improve the conditions of the labor market for elderly workers. In particular, we pay attention to the fact that Korea's baby boomers, who just recently reached retirement age, have much higher levels of education than those of the previous generations, which will act as the driving force from the supply side of the elderly labor market.

Population aging affects most economic decisions and consequently transforms many parts of the economy. The rapid aging process in Korea gives policymakers a very narrow window of opportunity to prepare for the changes. We note that economic agents will most likely respond to these changes rationally. Policymakers must pay more attention to the behavioral responses of economic agents and build more flexible institutions for the aged society.

APPENDIX

A. *Simulation for Economic Growth*

To examine the magnitude of the consequences of population aging, we project the long-run GDP growth rate based on population projections, assuming that the LFPs of ages remain in the same shape. Our long-term growth projections are based on a growth accounting frame. Some features are described below. We assume the production process in a simple form because the gains of a parsimonious model would be greater than those of a complicated model. Doing this reduces the sources of uncertainty. We use the standard Cobb-Douglas production function,

$$Y_t = A_t L_t^{\alpha} K_t^{1-\alpha}$$

where Y denotes GDP, A: total factor productivity, L denotes the number of workers, K is capital stock and, α is the labor share. The measurement of the labor supply is the number of employees and the labor force participation rates are projected from an estimated model (see Kwon, 2014). The population is based on

TABLE A1—LABOR FORCE PARTICIPATION RATE BY AGE IN MAJOR COUNTRIES

		15-24	25-34	35-44	45-54	55-64	65+	15-64
Korea	Men	26.1	84.0	94.8	93.1	82.7	41.5	79.3
	Women	34.3	69.0	61.7	69.4	55.9	24.1	59.0
	All	30.3	76.9	78.6	81.3	69.1	31.5	69.2
Japan	Men	44.1	94.8	96.1	95.5	87.5	32.5	85.5
	Women	44.9	78.5	75.3	78.8	63.3	16.5	69.4
	All	44.5	86.8	85.9	87.2	75.3	23.5	77.5
Germany	Men	51.3	89.2	93.8	92.8	77.9	9.8	82.4
	Women	48.3	79.1	82.5	85.3	67.5	4.8	74.0
	All	49.9	84.3	88.2	89.1	72.6	7.0	78.2
Sweden	Men	53.8	91.0	95.7	94.3	83.3	21.5	84.3
	Women	55.1	85.4	90.5	90.4	77.9	13.3	80.6
	All	54.4	88.3	93.2	92.4	80.6	17.5	82.5
U.S.	Men	56.7	88.8	91.7	86.4	70.6	23.9	79.0
	Women	54.3	75.5	75.0	74.5	58.9	15.7	67.9
	All	55.5	82.1	82.7	80.3	64.5	19.3	73.3
OECD	Men	51.0	90.6	93.5	90.1	72.3	20.2	80.2
	Women	43.5	72.3	73.4	73.3	54.3	10.5	64.0
	All	47.3	81.5	83.3	81.6	63.0	14.8	72.1
G7	Men	51.8	90.0	92.8	90.1	73.0	20.0	80.4
	Women	49.3	76.8	77.0	77.6	59.1	11.4	68.7
	All	50.6	83.4	84.8	83.7	65.9	15.2	74.5

Source: OECD Statistics.

the estimated future population from Statistics Korea. The data for capital stock are based on the BOK's Korean National Balance Sheet. For future investments, we estimate the savings rates on the dependency ratios and then convert these values to investments under the assumption of long-run equilibrium between them. There is considerable uncertainty in forecasting future productivity in the aging economy. Hence, total factor productivity (TFP), including the quality of labor, is presumed to grow at a steady rate (i.e., 1.2%) based on qualitative judgements of technologies and institutions (see Shin *et al.*, 2013). The forecast horizon is set to 30 years because population aging is predicted to accelerate by 2050 and then stabilize gradually (see Lee, 2019).

B. *Estimation for the employability of education*

TABLE A2—DATA OF THE VARIABLES

	Data
$Empr_t^i$	$(The\ employment\ of\ the\ age\ i\ /\ The\ populations\ of\ the\ age\ \ i) * 100$
Edu_t^i	$(The\ number\ of\ college\ graduate\ of\ the\ age\ i\ /\ The\ populations\ of\ the\ age\ i\ ) * 100$
$\mathrm{Gr_t}$	$[(Real\ GDP(t)/Real\ GDP(t-1)-1\ )] * 100$

Note: 1) The subscript *i* refers to age, and *t* denotes the year; 2) The employment rate is calculated using the total number of people surveyed and employed.

Source: Economically Active Population Survey of Statistics Korea (1986-2017).

REFERENCES

Acemoglu Daron and Pascual Restrepo. 2017. "Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation," *American Economic Review*, 107(5), pp.174-179.

Bloom, David E., David Canning, and Pia Malaney. 2000. "Demographic Change and Economic Growth in Asia," *Population and Development Review*, 26 (supplement), pp.257–90.

Bloom, David E., David Canning, Guenther Fink, and Jocelyn Finlay. 2007. "Demographic Change, Institutional Settings, and Labor Supply," PGDA Working Paper 42, Harvard University, Cambridge, MA.

Bank of Korea. 2017. "The Effects of Population Aging and Policy Issues" (in Korean).

Burtless, G. 2013. "The Impact of Population Aging and Delayed Retirement on Workforce Productivity," Center for Retirement Research at Boston College Working Paper.

Clark, Robert, Rikiya Matsukura, and Naohiro Ogawa. 2013. "Low Fertility, Human Capital, and Economic Growth: The Importance of Financial Education and Job Retraining," *Demographic Research*, 29: 865-884.

Gordon, Robert J. 2016. *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*, REV-Revised. Princeton University Press.

Hwang, Sookyeong. 2012. *Impact of Baby Boomers' Transition on Labor Markets in Korea*, *KDI* Policy Study 2012-15, KDI (in Korean).

IMF. 2015. "The Fiscal Consequences of Shrinking Population," IMF Staff Discussion Notes No.15/21.

Kelley, A. and R. Schmidt. 1995. "Aggregate population and economic growth correlations: The role of the components of demographic change," *Demography*, 32(4): 543-555.

Kelley, A. and R. Schmidt. 2007. "A century of demographic change and economic growth: The Asian experience in regional and temporal perspective," in A. Mason and M. Yamaguchi (eds.), *Population change, labor markets and sustainable growth: Towards a new economic paradigm*, Amsterdam: Elsevier.

Kwon, Kyooho. 2014. "Saving Rate, Investment Rate, and Current Account: Focusing on Changes in Population Structure," in Dongchul Cho (eds.), *Economic Dynamism of Korea: With a Focus on the Comparison with Japan*, Chapter 2, *KDI Research Monograph*, 2014-03, KDI (in Korean).

Lee, Jaejoon. 2019. "Population Aging and Economic Growth: Impact and Policy Implications," *KDI Policy Forum*, No.273 (2019-02), KDI (in Korean).

Lee, Ronald. 2016. "Macroeconomics, aging, and growth," *Handbook of the economics of population aging*, North-Holland, 1: 59-118.

Lee, Tae Suk, *et al*. 2020. *Structural Reforms in Response to Demographic Changes in Korea*, KDI Research Monograph 2020-08, KDI. (in Korean)

OECD. 2018. "Working better with age: Korea."

Shin, Sukha, *et al*. 2013. *Long-term Projection of Potential Growth in Korean Economy*, KDI (in Korean).

Statistics Korea. 2015. "Economically Active Population Survey" (in Korean).

Statistics Korea. 2021. "Population Projections for Korea (2020~2070)" (in Korean).

Statistics Korea. 2022. "Economically Active Population Survey," May (in Korean).

LITERATURE IN KOREAN

권규호. 2014. 「저축률과 투자율, 경상수지: 인구구조의 변화를 중심으로」, 조동철 편, 『우리 경제의 역동성: 일본과의 비교를 중심으로』, 제2장, KDI 연구보고서, 2014-03, 한국개발연구원.

신석하 외. 2013. 『한국의 장기 거시경제변수 전망』, KDI 기타보고서, 한국개발연구원.

이재준. 2019. 「고령화 사회, 경제성장 전망과 대응방향」, KDI 정책포럼, 제273호(2019-02), 한국개발연구원.
이태석 외. 2020. 『인구구조 변화에 대응한 구조개혁 방안』, KDI 연구보고서, 2020-08, 한국개발연구원.
통계청. 2015. 「경제활동인구조사」.
통계청. 2021. 「장래인구추계: 2020~2070년」.
통계청. 2022. 「경제활동인구조사」. 5월.
한국은행. 2017. 「인구구조 고령화의 영향과 정책과제」.
황수경. 2012. 『베이비붐 세대 이행기의 노동시장 변화』, KDI 정책연구시리즈, 2012-15, 한국개발연구원.

KDI Book Membership Information

Exclusive Offer (Members-Only)

- All KDI publications, with the exception of those classified as confidential or limited, are to be mailed to members
- Preferential invitations to special events hosted by KDI including seminars, policy discussion forums, public hearings, etc., are to be mailed.
- A 10% discount on the online purchases of additional copies of the published research monographs (printed-only) from the KDI homepage.

KDI Publications

- Publications include books, research monographs, policy studies, KDI policy forums, KDI FOCUS, research papers and policy-information materials.
- Three types of periodicals are available:
  - Monthly: KDI Monthly Economic Trends, KDI Review of the North Korean Economy, Economic Bulletin, Narakyungje
  - Quarterly: KDI Journal of Economic Policy, KDI Analysis on Real Estate Market Trends
  - Biannual: KDI Economic Outlook

Annual Fees

- Individual Purchase: 100,000 KRW
- Institutional Purchase: 300,000 KRW

Sign-Up

- You may sign up for membership via KDI homepage. Please register on the homepage by completing and submitting the registration form. Possible payment methods are as follows:
  - Bank-Transfer: Woori Bank, 254-012362-13-145 (account holder name: Korea Development Institute)
  - GIRO System: No. 6961017 (Credit Card and Mobile Payments available)
  - Direct Payment to the Research Outcome Dissemination Unit of KDI Division of External Affairs.

Contact

- Publication personnel in charge: Research Outcome Dissemination Unit, Division of External Affairs, KDI.
  - Tel: 82-44-550-4346 / Fax: 82-44-550-4950 / E-mail: book@kdi.re.kr
- Sales Distributors
  - Kyobo Bookstore (Gwanghwamun Branch: Government Publications Section)
    Tel: 82-2-397-3628
  - Yongpoong Bookstore (Jongno Branch: Policy & Economy Section)
    Tel: 82-2-399-5632

KDI Journal of
Economic Policy
韓國開發研究

Registration Number 세종 바00002호
Printed on May, 26, 2023
Published on May, 31, 2023
Published by Dongchul Cho, President of KDI
Printed by Good Idea Good Peoples

Price : 3,000 KRW

Registered on March, 13, 1979

KDI
Korea Development Institute
263, Namsejongro, Sejong-Si, Korea I **TEL** 82-44-550-4114
FAX 82-44-550-4310 I www.kdi.re.kr

ISSN 2586-2995