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Ph. D. Dissertation in Engineering

Assessment of Environmental and Economic Impacts of Technological Change in the Manufacturing Sector Based on the Hybrid Model

산업부문 기술변화의 환경적 • 경제적 영향 평가를 위한
상하향 통합모형 연구

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Graduate School of Seoul National University
Technology Management, Economics, and Policy Program
Hwarang Lee

Assessment of Environmental and Economic Impacts of Technological Change in the Manufacturing Sector Based on the Hybrid Model

지도교수 구윤모

이 논문을 공학박사학위 논문으로 제출함

2020 년 **8** 월

서울대학교 대학원

협동과정 기술경영경제정책 전공

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2020 년 **8** 월

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Abstract

Assessment of Environmental and Economic Impacts of Technological Change in the Manufacturing Sector Based on the Hybrid Model

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Bottom-up and computable general equilibrium (CGE) models are representative approaches in environmental analysis. The bottom-up model is technology-based and determines the optimal technology mix of an energy system. Since it is a partial equilibrium model, it is inappropriate to observe macro-economic changes due to reduction options. In contrast, the CGE model finds the general equilibrium of an economy and explores the macro-economic effects of reduction options. Since it offers only a limited description of technology, analyzing technology-level changes is difficult. Because of these properties, previous studies developed a hybrid model that integrates both models and allows both technology-rich and macro-economic analysis. This study develops a hybrid model for the manufacturing sector of Korea and explains its advantages in environmental analysis.

The bottom-up model is developed using positive mathematical programming, which helps to maintain the data consistency of the hybrid model. The CGE model for environmental analysis is constructed based on the previous simple model. After developing the single models, this study integrates both models using the soft-link approach in which the models exchange information that they require. Based on the hybrid model, this study explores the environmental and economic impacts of technological change that arises from two sources. One source is new technology adoption, which increases the number of technology alternatives and sharply improves efficiency. The other is technology learning, which gradually improves efficiency based on technology capacity. The hybrid model integrates learning through the iterative approach. Although efficiency improvement has considerable emissions reduction effects, it also induces an unexpected rebound of emissions. This study assesses rebounding emissions due to technology efficiency improvement using the hybrid model.

This study provides a new framework for a comprehensive analysis of the environmental and economic impacts of technological change. Moreover, policymakers can employ this study's hybrid model to investigate the impacts of reduction options and policies before setting a reduction target.

Keywords: Hybrid model, bottom-up model, CGE model, technological change, technology learning, rebound effect

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Chapter 1. Introduction

1.1 Research background

The Paris Agreement calls for global efforts to control the rising global temperature and obliges countries to establish their own strategies to reduce greenhouse gas emissions (United Nations, 2015). Since the agreement, signatory countries are developing Long-term low greenhouse gas Emission Development Strategies (LEDS) to meet their reduction targets in 2050 (United Nations, 2020). Accordingly, it has become important to assess the environmental and economic impacts of reduction targets and options in advance.

Previous studies employ bottom-up and top-down models to analyze reduction targets and options. The bottom-up model finds the optimal technology mix that supplies energy services in an energy system with minimum costs (see Loulou et al., 2016). It usually analyzes the energy systems of energy-intensive sectors such as electricity generation, manufacturing and transport. The computable general equilibrium (CGE) model, which represents a top-down model, finds the optimal prices and quantities that clear all markets in the economy and satisfy all economic agents. It describes an economic phenomenon at a more aggregated level (Hourcade et al., 2006).

The bottom-up and CGE models have distinct advantages and disadvantages. The bottom-up model can explore technology-level changes because it explicitly describes technology (Hourcade et al., 2006). It can analyze energy consumption in a country beyond the sector level (Figure 1.1). By contrast, the CGE model is usually inappropriate for disaggregated representation of technology-level changes (Cai et al., 2015) and has limitations in explaining energy consumption at the energy service and technology levels. However, the CGE model can explore the macro-economic effects of reduction options (Sue Wing, 2008). It observes the environmental and economic impacts of reduction options in a certain sector on the rest of the economy. By contrast, the bottom-up model cannot explain these ripple effects because it is a partial equilibrium model (Helgesen et al., 2018).

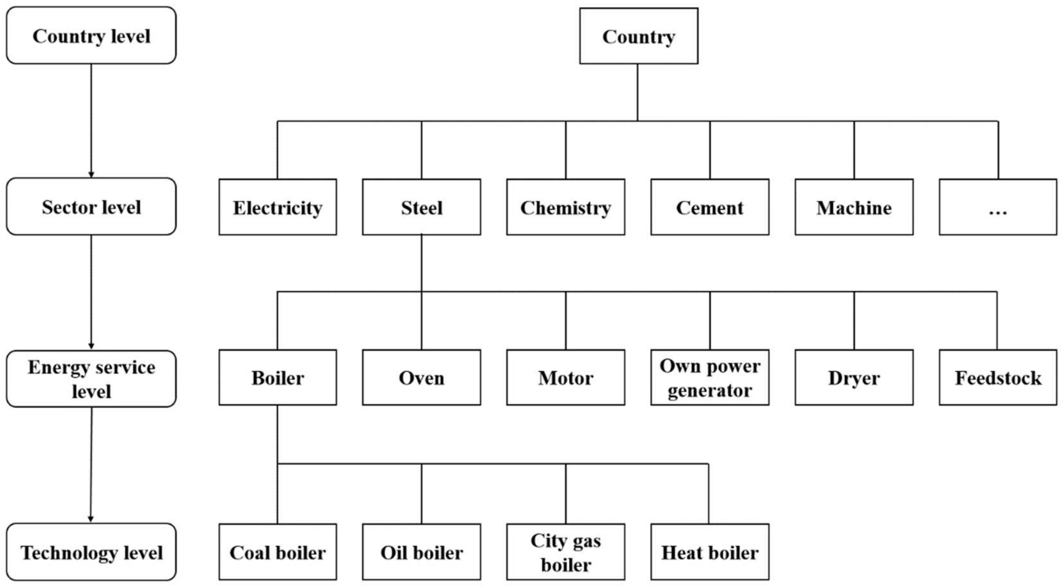

Figure 1.1. Energy consumption in the country

Due to the limitations of the single bottom-up and CGE models, previous studies attempted to employ only their advantages. The hybrid model integrates both models and enables both a technology-rich and macro-economic analysis (Andersen et al., 2019a). For example, when a reduction technology is introduced, the hybrid model enables the economy to find a new technology mix and move to a new general equilibrium based on technological change. It is also useful to observe feedback between technology-level changes and macro-economic effects. That is, the hybrid model is an advanced framework to assess the environmental and economic impacts of reduction targets and options.

1.2 Research purpose

This study develops a hybrid model for the manufacturing sector by integrating the industrial bottom-up and CGE models and assesses the environmental and economic impacts of technological change. The first purpose of this study is to construct a hybrid model of Korea's manufacturing sector and show the advantages of the hybrid model in assessing the impacts of technological change. Second, this study explores rebounding emissions due to technological change using the hybrid model. Third, this study incorporates endogenous technology learning in the hybrid model and investigates the environmental and economic impacts of learning.

This study focuses on ten emission-intensive industries in Korea [1] because the manufacturing sector is significant in achieving the national reduction target. In 2017, the

[1] Steel, chemistry, cement, machine, semiconductor & display, electronics, automobile, nonferrous metals, glass and textile industries (Korea Environment Institute [KEI], 2019).

manufacturing sector generated 43% of global emissions which include those from heat and electricity generation (International Energy Agency [IEA], 2019). Additionally, Korea’s manufacturing sector accounts for one-third of the 2050 business-as-usual (BAU) national emissions (Ministry of Environment, 2020). Although the manufacturing sector generates considerable emissions, previous studies generally focus on the electricity sector and are less concerned with a technology-level analysis of the manufacturing sector.

This study considers efficiency improvement as major technological change. Many countries are considering efficiency improvement as an option to achieve their reduction targets. For example, the United Kingdom planned to improve business and industrial efficiency through 162 million GBP of public R&D investments (UK government, 2017). Japan planned to adopt highly efficient process technologies to reduce emissions from the steel, chemistry and cement industries (The government of Japan, 2019). Korea is also expecting to meet 30–40% of the 2050 reduction target in the manufacturing sector through high-efficiency capacities and a smart energy management system (Ministry of Environment, 2020).

This study assumes two sources of efficiency improvements. One source is new technology adoption based on a government-managed technology database. The other is technology learning through experience using technology. Learning is endogenously incorporated in the bottom-up model using an iterative approach (Yang et al., 2016).

Although efficiency improvement contributes to emissions reduction, it also causes a rebound in emissions. Since efficiency improvement lowers energy demand and total costs, outputs in the economy rebound. Then, the economy demands more energy to produce the rebounding outputs, and emissions thus also rebound. The hybrid model contributes to exploring the rebound effects of technology efficiency improvement.

This study also simulates a carbon tax policy that allows the market to achieve the minimum abatement costs and find advanced reduction options (Marron et al., 2015). This simulation helps to determine the impacts of efficiency improvements on emissions and abatement costs. Efficiency improvements through new technology adoption and learning contribute to more emissions reduction with lower abatement costs.

1.3 Outline of the study

This study proceeds in seven chapters (Figure 1.2). Chapter 2 develops the bottom-up models for the ten emission-intensive industries in Korea based on positive mathematical programming (PMP). Chapter 3 constructs the recursive dynamic CGE model for Korea by modifying an existing CGE model. Chapter 4 integrates the bottom-up and CGE models based on a soft-link approach. It explains the integration process and investigates the environmental and economic impacts of efficiency improvement through new technology adoption. Chapter 5 assesses the rebounding outputs and emissions due to new technology adoption. Chapter 6 incorporates learning into the hybrid model and analyzes the environmental and economic impacts of learning. Chapter 7 concludes this study and explains implications and limitations of this study.

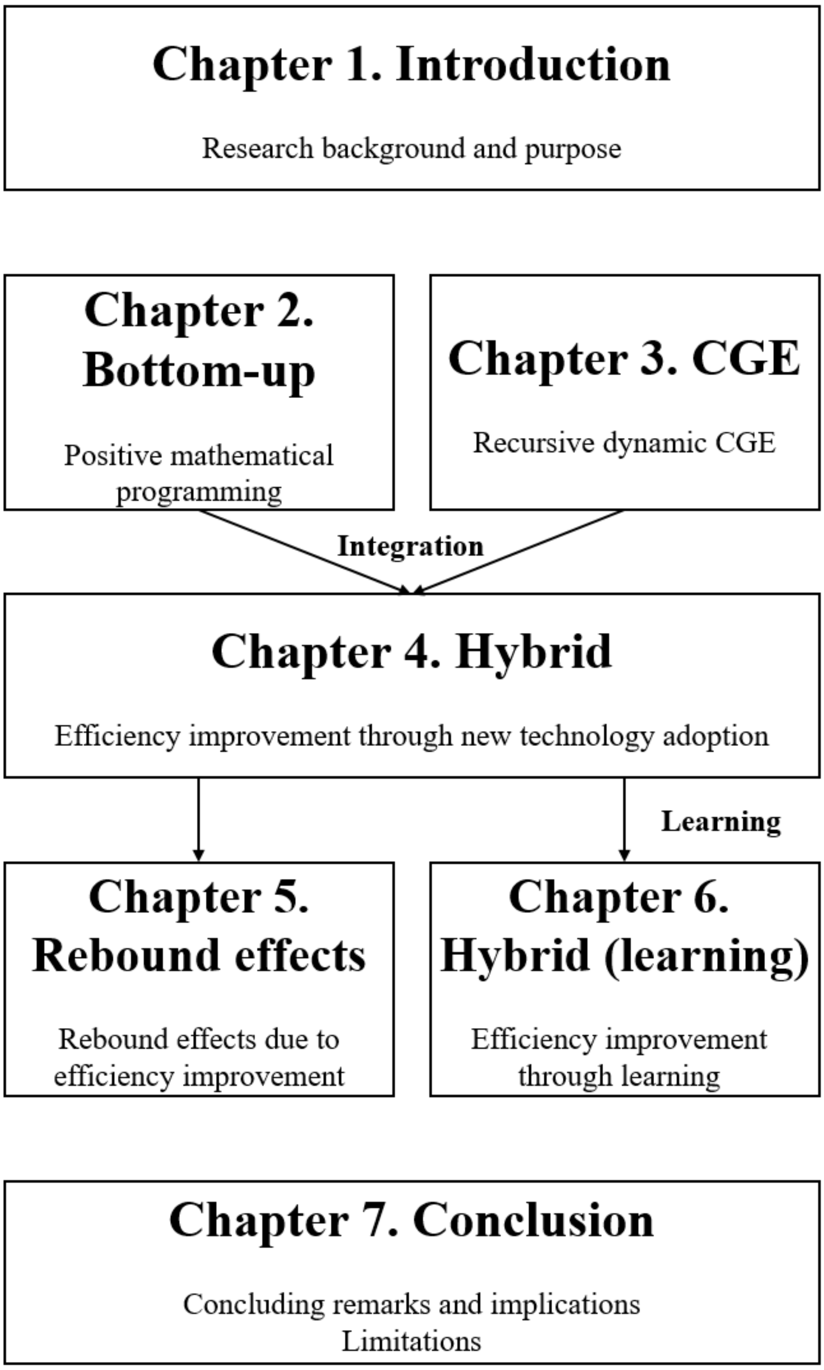

Figure 1.2. Outline of the study

Chapter 2. Industrial bottom-up model based on positive mathematical programming[2]

2.1 Introduction

2.1.1 Research background

Since their introduction in the 1970s (Herbst et al., 2012), bottom-up models were employed to analyze the energy systems of energy-consuming sectors, including the electricity, manufacturing, transport, residential and agriculture sectors. The bottom-up model is generally based on an optimization (Trutnevyte, 2016) that aims to minimize the total cost to provide a given energy demand in an energy system for certain periods. It determines the cost-minimizing technology mix that describes the optimal energy consumption and capacities of technologies. Since the bottom-up model explicitly represents technology, it is appropriate for a technology-rich analysis. It can describe the changes in technology competition due to the adoption of low-emission technologies and observe the emissions reduction from technology substitution.

Previous studies generally employ bottom-up models to analyze energy and environment policies. Loulou et al. (2016) stated that the detailed technology descriptions of the bottom-up model enable researchers to evaluate almost any policy. The bottom-up

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[2] Parts of this chapter were published in *Energy, 173*, Lee et al., A bottom-up model of industrial energy system with positive mathematical programming, 679-690, Copyright Elsevier (2019).

model has an advantage in analyzing technology-related policies in particular. For example, if the government plans to improve the efficiency of certain technologies or lower the investment costs of new technologies, then the bottom-up model is necessary because it explicitly describes technology characteristics. If the model is not technology-based, then it should explain the changes in technology characteristics at a more aggregated level.

Representative bottom-up models, such as the Model for Energy Supply System Alternatives and their General Environmental Impacts (MESSAGE), Market allocation (MARKAL), and the Integrated MARKAL-EFOM System (TIMES), usually solve their cost minimization using linear programming (LP).[3] LP involves several problems because it finds corner solutions. First, LP usually returns an overspecialized or winner-take-all technology mix if there are no constraints that prevent corner solutions (Heckelei and Britz, 2005). It adopts the most cost-efficient technology and excludes the remaining options. Second, LP observes radical technological change when an available technology set changes. The results may exclude the currently dominant technology from the technology mix when a more efficient technology is available, or currently uncompetitive technology suddenly becomes the dominant one (Röhm and Dabbert, 2003).

LP generally depends on supplementary constraints, which are upper and lower bounds for technology use, to avoid corner solutions. The number of supplementary constraints affects the number of effective technologies in LP (Petsakos and Rozakis, 2009). However, although supplementary constraints prevent overspecialization and radical technological

[3] See International Atomic Energy Agency (2016), Loulou et al. (2004) and Loulou et al. (2016).

change, they are difficult to justify (Garnache et al., 2017) because the upper and lower bounds induce a technology mix within a certain range. Moreover, LP calibrates the base-year technology mix using supplementary constraints. Since supplementary constraints, which are still included under simulated scenarios, affect policy simulation results (Heckelei and Britz, 2005), they disrupt the interpretation of the policy simulation results.

2.1.2 Research purpose

This study develops an industrial bottom-up model for the hybrid model. Since the hybrid model integrates independent bottom-up and CGE models, it is important to maintain consistency between the models. In particular, the capital, labor and energy inputs in the base year should be consistent. This study applies PMP (Howitt, 1995), which employs a quadratic objective function instead of a linear objective function, to achieve consistency. PMP calibrates the base-year technology mix of the industries without adding supplementary constraints and helps to maintain base-year consistency in the hybrid model. Moreover, PMP avoids an overspecialized technology mix, radical technological change, and simulation results bounded by the constraints.

There is no industrial bottom-up model based on PMP, although the agriculture sector has employed PMP for decades. This study develops industrial bottom-up models for the ten emission-intensive industries in Korea and explains the application of PMP to the manufacturing sector. This study derives equations to modify LP to PMP and suggests a method to determine the parameters in the equations. Moreover, this study shows the advantages of PMP empirically. Finally, this study describes technology substitution in the bottom-up model using a carbon tax simulation.

2.2 Literature review

2.2.1 Previous industrial bottom-up model

Previous studies usually construct industrial bottom-up models for energy-intensive industries such as steel and cement (Table 2.1). Although most industrial bottom-up models were based on MARKAL and TIMES models, several previous studies developed their own bottom-up models.

Industrial bottom-up models for one industry generally take a process-oriented approach, which describes energy consumption in the order of industrial processes and explains sector-specific technologies. Dutta and Mukherjee (2010) considered unique processes for three industries in India to investigate their future energy consumption. Chen et al. (2014) constructed a TIMES model for China to analyze the steel industry based on six steel processes. Li et al. (2017) considered 21 sector-specific reduction technologies in the cement industry and examined carbon tax effects.

By contrast, a service-oriented approach describes the energy consumption of the manufacturing sector based on common energy services such as boilers, ovens, and motors. This approach can describe the energy consumption of multiple industries using the same structure. Kannan et al. (2007) categorized industrial energy demand into five energy services. They assumed that the share of each energy service was fixed. Zhou et al. (2013)

explained industrial energy demand using six energy services with the assumption that an energy service does not replace the other energy services, but rather that the technology providing the energy service replaces other such technologies.

Table 2.1. Previous industrial bottom-up models

Author	Country	Industry	Model	Approach
Dutta and Mukherjee (2010)	India	Steel, aluminum and cement	MARKAL	Process
Chen et al. (2014)	China	Iron and steel	TIMES	Process
Karali et al. (2014)	U.S.	Iron and steel	ISEEM(Industry Sector Energy Efficiency Modeling)	Process
García-Gusano et al. (2015)	Spain	Cement	TIMES	Process
Li et al. (2017)	China	Cement	TIMES	Process
Tan et al. (2019)	China	Iron and steel	Cost-minimizing bottom-up	Process
Kannan et al. (2007)	UK	Five categorized industries	MARKAL	Service
Zhou et al. (2013)	China	Eleven industries	Service-oriented bottom-up	Service

Industrial bottom-up models in Korea also focus on energy-intensive industries (Table 2.2). These models were developed with a process-oriented approach using MARKAL. Korea Energy Economics Institute (KEEI, 2005; KEEI, 2006) developed industrial bottom-up models for the cement and oil refinery industries. Both studies investigated emission and energy reduction potential under reduction scenarios and evaluated the marginal abatement costs and cost-effectiveness of the reduction strategies. Ahn et al. (2009) examined the role of reduction technologies in the steel industry. They evaluated emissions reduction and abatement costs using seven reduction scenarios depending on the reduction technology mix.

Table 2.2. Industrial bottom-up models in Korea

Author	Country	Industry	Model	Approach
KEEI (2005)	Korea	Cement	MARKAL	Process
KEEI (2006)	Korea	Oil refining	MARKAL	Process
Ahn et al. (2009)	Korea	Steel	MARKAL	Process

2.3 Data

2.3.1 Technology characteristics

This study employs the database of the Korea Institute of Energy Technology Evaluation Planning (KETEP). The KETEP database (KETEP, 2016) provides detailed technology characteristics, including adoption year, lifetime, investment cost, operation and maintenance (O&M) cost, efficiency and availability. Descriptions for technology characteristics are shown in Table 2.3.

Table 2.3. Descriptions for technology characteristics

Technology characteristics	Description
Adoption year	The year when technology is available
Lifetime	The years during which the installed technology capacity is available
Investment cost	Unit investment cost to install technology capacity
Operation and maintenance cost	Unit operation and maintenance cost to manage technology capacity
Efficiency	The amount of energy output per a unit of energy input
Availability	The amount of available technology capacity per a unit of installed technology capacity

The KETEP database chose five representative common technologies, which were boilers, motors, kilns, furnaces and dryers, based on their energy consumption, expert opinions and importance in policies. KETEP calculated energy consumption of common technologies using Energy Consumption Survey (ECS) and identified a future trend by reviewing energy technology plans and government reports.

Since the KETEP database was not officially published, this study shows arbitrary values as technology characteristics (Table 2.4). Current technology is introduced in the base year.[4] New technology is introduced in a future time period. New technology generally has higher investment cost and efficiency than current technology. Efficiency and availability are a value between 0 and 1. In the model, costs and energy consumption have units of billion KRW and thousand ton of oil equivalent (TOE), respectively.

Table 2.4. Example of technology characteristics

	Adoption year	Lifetime	Investment cost	O&M cost	Efficiency	Availability
Current technology	2015	5	0.150	0.015	0.5	0.6
New technology	2020	5	0.200	0.020	0.8	0.6

Note: a unit of costs is billion KRW/thousand TOE.

4 The base year of the model is 2015. The model years are from 2015 to 2050.

2.3.2 Base-year energy consumption

A PMP-based bottom-up model requires base-year energy consumption of technology for calibration. ECS is published every three years and provides energy consumption of industries in Korea. Although the base year of this study is 2015, this study employs energy consumption in 2016 from 2017 ECS (KEEI, 2017a). ECS categorized the manufacturing sector into 37 industries based on Korean Standard Industrial Classification (KSIC) (Statistics Korea, 2020). This study allocates ECS industries into the ten emission-intensive industries (Table 2.5).

Table 2.5. Industry matching

This study	Energy Consumption Survey	KSIC
Steel	Basic iron and steel	241
Chemistry	Basic chemicals	201
	Plastics and synthetic rubber in primary forms	202
	Fertilizers, pesticides, germicides and insecticides	203
	Other chemical products	204
	Pharmaceuticals, medicinal chemical and botanical products	21
	Rubber and plastic products	22
Cement	Cement, lime, plaster and its products	233
Machine	Fabricated metal products, except machinery and furniture	25
	Other machinery and equipment	29

Semiconductor & display	Electronic components, computer; visual, sounding and communication equipment	26
Electronics	Medical, precision and optical instruments, watches and clocks	27
	Electrical equipment	28
Automobile	Motor vehicles, trailers and semitrailers	30
Nonferrous metals	Basic precious and non-ferrous metals	242
Glass	Glass and glass products	231
Textile	Textiles, except apparel	13
	Wearing apparel, clothing accessories and fur articles	14
	Leather, luggage and footwear	15
	Man-made fibers	205

Source: Author's work based on KEEI (2017a)

After the allocation, this study adds energy consumption of the allocated ECS industries to obtain energy consumption of the ten emission-intensive industries (Table 2.6). Each cell of Table 2.6 means base-year energy consumption of technology in the steel industry

Table 2.6. Energy Consumption of the steel industry (Unit: thousand TOE)

		Boiler	Oven	Motor	Own Power generator	Dryer	Feed stock	Total
Coal	Anthracite	0	197	0	0	0	673	870
	Bituminous coal (fuel)	16	89	0	0	0	0	105
	Bituminous coal (feedstock)	0	0	0	0	0	22,601	22,601
	Coal product	0	9	0	0	0	0	9
Oil	Gasoline	0	0	0	0	0	0	0
	Kerosene	0	0	0	0	0	0	0
	Diesel	0	3	0	0	0	0	3
	Heavy oil	0	42	0	0	0	0	42
	LPG	0	21	0	0	2	0	23
Others	City gas	268	1,613	0	313	27	0	2,222
	Heat	0	0	0	0	17	0	17
	Electricity	0	674	486	0	1,720	0	2,880
Total		284	2,647	486	313	1,765	23,274	28,770

Source: Author’s work based on KEEI (2017a)

2.3.3 Energy service demand and final energy demand

Technology produces an energy service by consuming fuel. Energy services consist of boilers, ovens, motors, own power generators and dryers, which are also common technologies. Although feedstock is not a common technology, it is also included in energy services.

Energy service demand is the sum of all energy consumption to produce each energy service. For example, the steel industry requires 284 thousand TOE to produce a boiler energy service (Table 2.6), which requires 16 thousand TOE bituminous coal and 268 thousand TOE city gas.

Final energy demand is the sum of all energy consumption to produce all energy services. The sum of all energy consumption of five energy services and feedstock is equal to 28,770 thousand TOE in the steel industry. Final energy demand is also the sum of all energy service demand. Shares of five energy service demand and feedstock in final energy demand are assumed to be unchanged, which implies that each energy service demand is not substitutable. These shares are calculated based on Table 2.6. This study assumes that energy service and final energy demand grow at an annual rate of 3%, considering economic growth.

Figure 2.1 shows final energy demand of the ten emission-intensive industries. The steel industry is the most energy-intensive industry in the manufacturing sector of Korea. Feedstock occupies about 80% of final energy demand of the steel industry because the steel industry requires a large amount of bituminous coal, which is highly emission-intensive, as feedstock (Figure 2.2). The cement, nonferrous metals and glass industries highly depends on their oven energy services, while a half of final energy demand of the semiconductor and display industries is a dryer energy service. Since there is high dependency on a motor energy service in the machine, electronics and automobile industries, these three industries require a substantial amount of electricity.

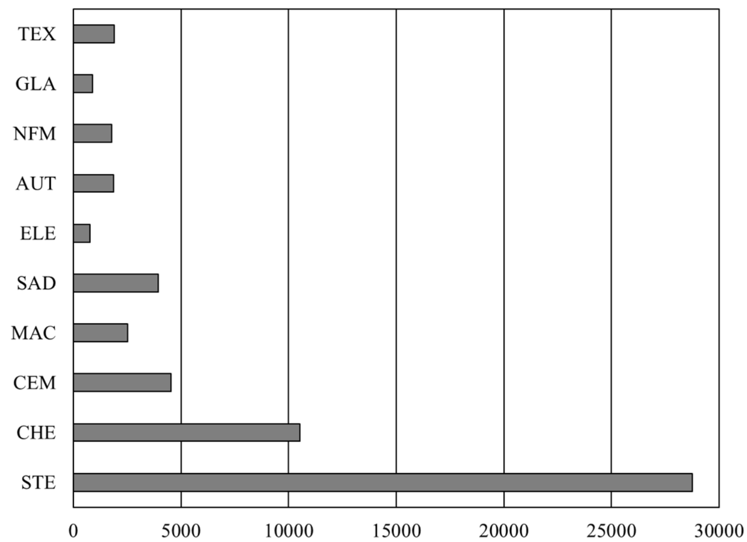

Figure 2.1. Final energy demand of ten emission-intensive industries

Source: Author’s work based on KEEI (2017a)

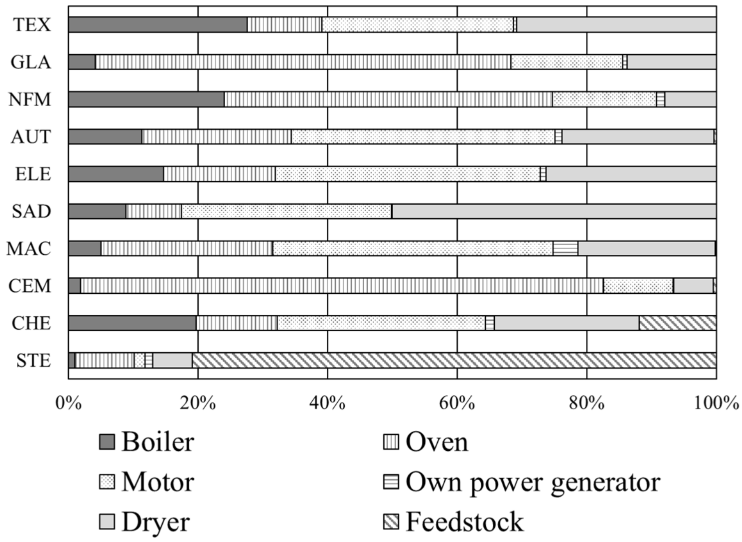

Figure 2.2. Energy service demand of ten emission-intensive industries

Source: Author's work based on KEEI (2017a)

That is, importance of each energy service demand in final energy demand is different among the industries. This implies that technological change has different impacts depending on the industries. For example, when efficiencies of oven technologies are improved, the cement, nonferrous metals and glass industries are more affected by efficiency improvement because oven energy services occupy more than half of final energy demand of these three industries.

2.3.4 Energy price

Although energy prices are not technology characteristics, they largely affect the industry's total cost. This study uses energy prices of KEI (2019). KEI (2019) calculated

2015 energy prices based on government reports and statistics (Table 2.7). The bottom-up model of this study assumes that energy prices do not change.

Table 2.7. 2015 energy prices (Unit: billion KRW/thousand TOE)

Fuel	2015 energy price	Fuel	2015 energy price
Anthracite	0.31	Diesel	0.63
Bituminous coal (fuel)	0.12	Heavy oil	0.50
Bituminous coal (feedstock)	0.10	LPG	0.55
Coal product	0.43	City gas	0.66
Gasoline	0.71	Heat	1.00
Kerosene	0.61	Electricity	0.50

Source: KEI (2019)

2.3.5 Emission coefficient

Emission coefficients of fuels are required to calculate emissions from energy consumption. Fossil fuels generate greenhouse gases during combustion. Heat and electricity indirectly contributes to an increase in emissions because fossil fuels are used to generate them. This study considers CO2, CH4 and N2O emissions and converts emission coefficients of CH4 and N2O into a unit of CO2 equivalent using Global Warming Potential of Intergovernmental Panel on Climate Change (IPCC, 2001).

As Figure 2.3 shows, coal (anthracite, bituminous coal and coal product) is the most emission-intensive fuel, and oil (gasoline, kerosene, diesel, heavy oil and LPG) follows coal. City gas, heat and electricity have lower CO2 emission coefficients than coal and oil.

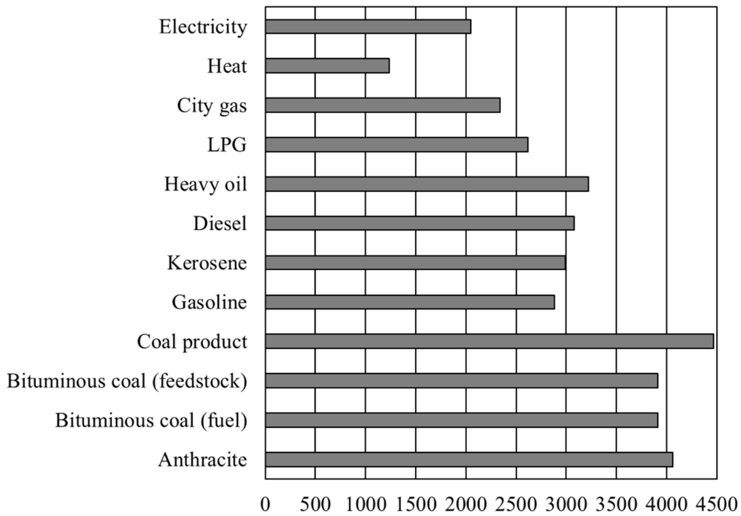

Figure 2.3. Emission coefficients

Source: Author's work based on KEEI (2020), Korea District Heating Corporation (2015), IPCC (2006), IPCC (2001) and Korea Power Exchange (2020)

2.3.6 Other data

A discount rate is used to calculate net present value of the total cost. This study assumes that a discount rate is 5%. The last year of technology means the year when technology is unavailable. This study assumes that technology is not expired in the model years and defines the last year as an arbitrary year out in the model years.

2.4 Model

2.4.1 Outline of the bottom-up model

The industrial bottom-up model of this study is based on Lee et al. (2019). The bottom-up model minimizes the net present value of the total cost under several constraints (Figure 2.4). It uses technology characteristics, energy prices, CO2 emission coefficients, and a discount rate as input data. A PMP-based bottom-up model obtains Lagrange multipliers by solving the static cost minimization problem for time period 0 and delivers the multipliers to the dynamic cost minimization problem for all periods. Then, the bottom-up model solves the dynamic problem and determines the energy consumption, new capacity, and total capacity of the technology. Based on the solutions, the bottom-up model calculates the energy demand, emissions, and cost information.

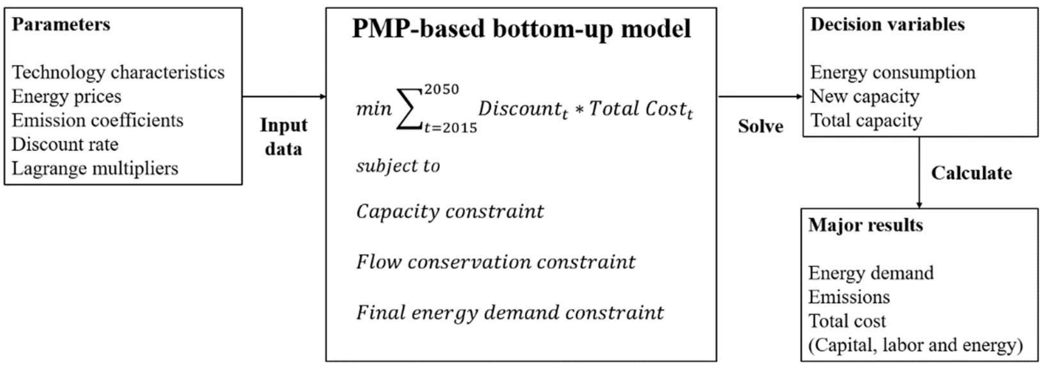

Figure 2.4. Outline of the bottom-up model

2.4.2 Reference energy system

A reference energy system (RES) describes energy flows in the bottom-up model (Figure 2.5). Technology, which is divided into process and demand technologies, uses energy input to produce energy output. Process technology converts fuel (energy input) into an energy service (energy output). Demand technology converts an energy service (energy input) into final energy demand (energy output). Since the bottom-up model of this study is service-oriented, the ten emission-intensive industries have identical RESs. Although this model is difficult to describe for sector-specific technologies, it is appropriate to describe multiple industries based on the use of an identical framework.

The industry satisfies five types of energy service and feedstock demand using process technologies and final energy demand using demand technology. The energy service and feedstock demand occupies fixed shares of final energy demand, which implies that this demand is aggregated by a Leontief function.

The technologies that produce an energy service compete with each other, while feedstock technologies cannot replace the others. Although only current technologies are available in the base year, industries adopt new technologies after their introduction. New oven technology is adopted in 2016. Boiler and dryer technologies are available in 2018. New own power generator technology is introduced in 2020. New motor technologies are introduced in 2020, 2025 and 2035. When both current and new technologies are available, they compete with each other. The share of a competing technology is determined based on technology characteristics such as efficiency and cost information.

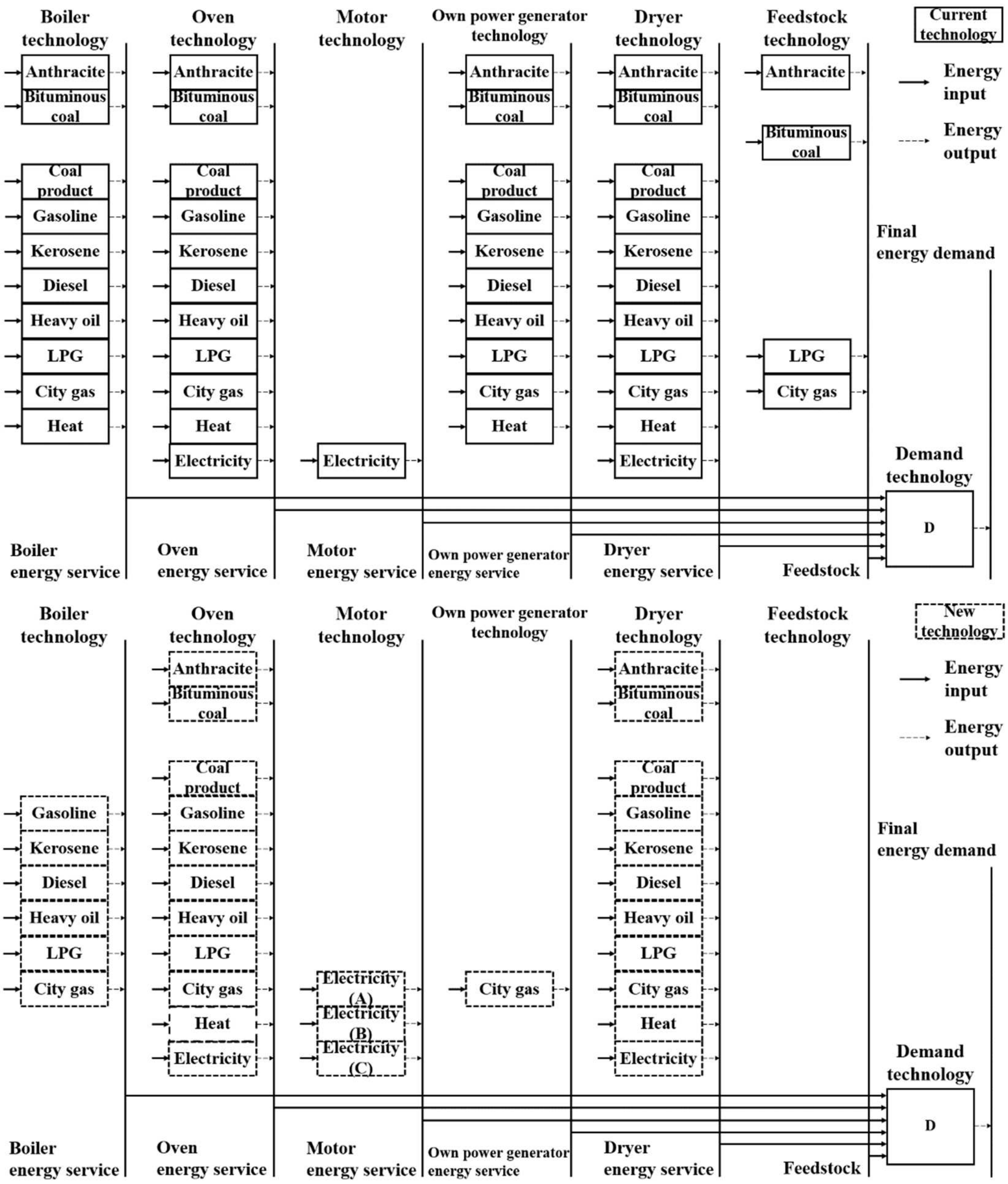

Figure 2.5. Reference energy system

2.4.3 Objective function

The net present value of the industry's total cost, which is Eq. (2.1), includes four costs. First, an industry pays annualized investment costs to install capacity. A capital recovery factor, which is calculated by Eq. (2.2), annualizes investment costs. Second, operation and maintenance costs are paid to manage installed capacity. Third, energy costs are required to purchase fuels to produce an energy service. Fourth, carbon taxes are levied based on emission coefficients of fuels if there is a carbon tax policy.

An objective function of a PMP-based bottom-up model is quadratic, whereas an LP-based bottom-up model employs a linear objective function. The last term of Eq. (2.1) is determined by the squares of energy consumption. The third and last terms of Eq. (2.1) indicates energy costs and carbon taxes of the industry. The values of these two terms depends on coefficients $a_{TECH,t}$ and $b_{TECH,t}$, which will be explained in Section 2.4.5 (see Eq. (2.18)).

$$\begin{aligned} \underset{x_{TECH,t}, Y_{TECH,t}}{Min} \sum_{t=0}^{35} Discount_t \sum_{TECH \in Process} [& INVEST_{TECH} * CRF_{TECH,t} * Y_{TECH,t} \\ & + OM_{TECH} * Y_{TECH,t} + (a_{TECH,t} * x_{TECH,t} \\ & + 0.5 * b_{TECH,t} * x_{TECH,t}^2)] \end{aligned} \qquad \text{Eq. (2.1)}$$

$$CRF_{TECH,t} = \frac{Discount_t * (1 + Discount_t)^{Lifetime_{TECH}}}{(1 + Discount_t)^{Lifetime_{TECH}} - 1} \qquad \text{Eq. (2.2)}$$

$TECH$: Technology

t: Time period

$x_{TECH,t}$: Energy consumption of technology $TECH$ at time period t

$Y_{TECH,t}$: Total capacity of technology $TECH$ at time period t

$Discount_t$: Discount rate at time period t

$Process$: Process technology set

$INVEST_{TECH}$: Unit investment cost of technology $TECH$

$CRF_{TECH,t}$: Capital recovery factor of technology $TECH$ at time period t

OM_{TECH}: Unit operation and maintenance cost of technology $TECH$

$a_{TECH,t}$: Intercept of presumed marginal cost of technology $TECH$ at time period t

$b_{TECH,t}$: Slope of presumed marginal cost of technology $TECH$ at time period t

$Lifetime_{TECH}$: Lifetime of technology $TECH$

2.4.4 Constraints

Three constraints are generally used in the bottom-up model. Capacity constraints in Eq. (2.3) mean that the industry should have available capacity more than energy service production. Although the industry installs capacity $Y_{TECH,t}$, it can use only part of capacity based on availability $AV_{TECH,t}$. Technology consumes fuel to produce an energy service. Energy service production is determined by efficiency $EFF_{TECH,t}$. Flow conservation constrains in Eq. (2.4) implies that technology should consume fuel more than energy service production. A final energy demand constraint in Eq. (2.5) indicates that the sum of energy service production should be greater than final energy demand.

$$EFF_{TECH,t} * x_{TECH,t} \leq AV_{TECH,t} * Y_{TECH,t}$$
$$for\ \ all\ \ process\ \ technologies\ \ and\ \ time\ \ periods \qquad \text{Eq. (2.3)}$$

$$\sum_{TECH\in P} EFF_{TECH,t} * x_{TECH,t} \leq \sum_{TECH\in C} x_{TECH,t}$$
$$for\ \ all\ \ time\ \ periods \qquad \text{Eq. (2.4)}$$

$$\sum_{TECH\in Process} EFF_{TECH,t} * x_{TECH,t} \geq D \qquad \text{Eq. (2.5)}$$

$EFF_{TECH,t}$: Efficiency of technology $TECH$ at time period t

$AV_{TECH,t}$: Availability of technology $TECH$ at time period t

P: Energy production technology set

C: Energy consumption technology set

D: Final energy demand

2.4.5 Static PMP-based bottom-up model

This section explains a process to obtain coefficients $a_{TECH,t}$ and $b_{TECH,t}$ in the quadratic objective function. To calculate two coefficients, this study assumes a static cost minimization problem, which is expressed by Eq. (2.6)–(2.9). Eq. (2.6) is a linear objective function that an LP-based bottom-up model uses. Eq. (2.7)–(2.9) are constraints for the static cost minimization problem.

$$\begin{aligned} \underset{x_{TECH,0},Y_{TECH,0}}{Min} \sum_{TECH \in Process} [&INVEST_{TECH} * CRF_{TECH,0} * Y_{TECH,0} \\ &+ OM_{TECH} * Y_{TECH,0} + EPRICE_{TECH} * x_{TECH,0} \\ &+ CTAX * COEF_{TECH} * x_{TECH,0}] \end{aligned} \quad \text{Eq. (2.6)}$$

$$\begin{aligned} &EFF_{TECH,0} * x_{TECH,0} \leq AV_{TECH,0} * Y_{TECH,0} \\ &for\ all\ process\ technologies \end{aligned} \quad \text{Eq. (2.7)}$$

$$\sum_{TECH \in P} EFF_{TECH,0} * x_{TECH,0} \leq \sum_{TECH \in C} x_{TECH,0} \quad \text{Eq. (2.8)}$$

$$\sum_{TECH \in Process} EFF_{TECH,0} * x_{TECH,0} \geq D \quad \text{Eq. (2.9)}$$

$EPRICE_{TECH}$: Unit fuel cost of technology $TECH$

$CTAX$: Unit carbon tax

$COEF_{TECH}$: CO_2 coefficient of technology $TECH$

At first, the constraint in Eq. (2.10) is added to limit upper bound of endogenous energy consumption of technology at time period 0. Because of this constraint, the endogenous energy consumption is almost equal to base-year energy consumption that is given from ECS. This study assumes that ε is 10^{-6}. If Eq. (2.10) is considered, the objective function is modified to Eq. (2.11).

$$x_{TECH,0} \leq (1+\varepsilon) * \overline{x_{TECH,0}} \qquad \text{Eq. (2.10)}$$

ε: Small constant

$\overline{x_{TECH,0}}$: Base-year energy consumption of technology $TECH$ (given from ECS)

$$\begin{aligned} \underset{x_{TECH,0},Y_{TECH,0}}{Min} \sum_{TECH \in Process} & [INVEST_{TECH} * CRF_{TECH,0} * Y_{TECH,0} \\ & + OM_{TECH} * Y_{TECH,0} + EPRICE_{TECH} * x_{TECH,0} \\ & + CTAX * COEF_{TECH} * x_{TECH,0} \\ & + \lambda_{TECH,0} * (x_{TECH,0} - (1+\varepsilon) * \overline{x_{TECH,0}})] \end{aligned} \qquad \text{Eq. (2.11)}$$

$\lambda_{TECH,t}$: Lagrange multiplier of technology $TECH$ at time period t

After adding the constraint, a quadratic objective function is presumed. In Eq. (2.12), coefficients $a_{TECH,0}$ and $b_{TECH,0}$ are intercept and slope of the first derivative function of the quadratic objective function. If coefficients $a_{TECH,0}$ and $b_{TECH,0}$ are determined to make solutions of Eq. (2.11) and Eq. (2.12) identical, solutions of Eq. (2.12) calibrate base-year energy consumption $\overline{x_{TECH,0}}$. Moreover, the solutions avoid overspecialization and radical technological change because the quadratic objective function is used.

$$\begin{aligned} \underset{x_{TECH,0},Y_{TECH,0}}{Min} \sum_{TECH\in Process} [&INVEST_{TECH} * CRF_{TECH,0} * Y_{TECH,0} \\ &+ OM_{TECH} * Y_{TECH,0} + (a_{TECH,0} * x_{TECH,0} \\ &+ 0.5 * b_{TECH,0} * x_{TECH,0}^2)] \end{aligned} \qquad \text{Eq. (2.12)}$$

If the marginal costs of two objective functions are equal, then solutions of those also equal. Eq. (2.14) and Eq. (2.16) are the first-order conditions with respect to total capacity, and two conditions are identical. Eq. (2.13) and Eq. (2.15) are the first-order conditions with respect to energy consumption. The number of combination of coefficients $a_{TECH,0}$ and $b_{TECH,0}$, which satisfies Eq. (2.17), is infinite.

$$EPRICE_{TECH} + CTAX * COEF_{TECH} + \lambda_{TECH,0} = 0 \quad \text{Eq. (2.13)}$$

$$INVEST_{TECH} * CRF_{TECH,0} + OM_{TECH} = 0 \quad \text{Eq. (2.14)}$$

$$a_{TECH,0} + b_{TECH,0} * x_{TECH,0} = 0 \quad \text{Eq. (2.15)}$$

$$INVEST_{TECH} * CRF_{TECH,0} + OM_{TECH} = 0 \quad \text{Eq. (2.16)}$$

$$\begin{aligned} &EPRICE_{TECH} + CTAX * COEF_{TECH} + \lambda_{TECH,0} \\ &\qquad = a_{TECH,0} + b_{TECH,0} * x_{TECH,0} \end{aligned} \quad \text{Eq. (2.17)}$$

This study considers identification methods (ID) of previous studies to determine the coefficients (Table 2.8). The identification method affects solutions and simulation results of the bottom-up model. In ID1, $b_{TECH,0}$ identifies all parameters excluding a carbon tax term. A carbon tax linearly increases depending on energy consumption of technology because $a_{TECH,0}$ identifies a carbon tax term. In ID2, all parameters are included in $b_{TECH,0}$. A carbon tax is proportional to squares of energy consumption of technology. In ID3, $b_{TECH,0}$ includes only the Lagrange multiplier. ID4 is similar to ID3, except that both $a_{TECH,0}$ and $b_{TECH,0}$ identifies the Lagrange multiplier. This study adopts ID1 as the identification method because it is appropriate for carbon tax simulation and calibration of base-year observations. That is, the quadratic objective function, which is shown as Eq. (2.1), is expressed as Eq. (2.18).

Table 2.8. Identification methods

	Intercept ($a_{TECH,0}$)	Slope ($b_{TECH,0}$)
ID 1	$CTAX * COEF_{TECH}$	$\frac{EPRICE_{TECH} + \lambda_{TECH,0}}{\overline{x_{TECH,0}}}$
ID 2	0	$\frac{EPRICE_{TECH} + \lambda_{TECH,0} + CTAX * COEF_{TECH}}{\overline{x_{TECH,0}}}$
ID 3	$EPRICE_{TECH} + CTAX * COEF_{TECH}$	$\frac{\lambda_{TECH,0}}{\overline{x_{TECH,0}}}$
ID 4	$EPRICE_{TECH} - \lambda_{TECH,0} + CTAX * COEF_{TECH}$	$\frac{2\lambda_{TECH,0}}{\overline{x_{TECH,0}}}$

Sources: ID1 (de Frahan et al., 2007), ID2 (Paris, 1988), ID3 (Paris, 1988), ID4 (Heckelei and Britz, 2000)

Note: The identification method affects solutions and simulation results of the bottom-up model because it changes the objective function. Lee et al. (2019) explained the dependence on the identification method.

$$\underset{x_{TECH,t},Y_{TECH,t}}{Min} \sum_{t=0}^{35} Discount_t \sum_{TECH \in Process} [INVEST_{TECH} * CRF_{TECH,t} * Y_{TECH,t} + OM_{TECH} * Y_{TECH,t} + (CTAX * COEF_{TECH} * x_{TECH,t} + 0.5 * \frac{EPRICE_{TECH} + \lambda_{TECH,0}}{\overline{x_{TECH,0}}} * x_{TECH,t}^2)] \quad \text{Eq. (2.18)}$$

Since Eq. (2.12) calibrates only base-year energy consumption, there are the Lagrange multipliers only for time period 0. The Lagrange multipliers for future time periods are unknown. This study assumes that the Lagrange multipliers do not change for all time periods.

Additionally, it is problematic that there is no Lagrange multiplier of new technology because the industry uses only current technology in time period 0. This study uses the Lagrange multiplier of current technology as that of new technology. For example, this study uses the Lagrange multiplier of current city gas boiler as that of new city gas boiler. Although the parameter of new technology is arbitrarily determined, new technology adoption is also affected by technology characteristics.

2.4.6 Decision variables

There are three major decision variables in the bottom-up model of this study. First, $x_{TECH,t}$ means technology's energy consumption, which minimizes the total cost and satisfies energy service demand and final energy demand. Second, new capacity of technology is the newly installed capacity in each time period to satisfy capacity constraints, although it is not expressed in the objective function and constraints. Third, total capacity of technology $Y_{TECH,t}$ is the sum of installed capacities in the current time period, but does not include expired capacities.

2.4.7 Scenario

In a business-as-usual (BAU) scenario, there is no reduction policy. Energy service and final energy demand annually increases at a rate of 3%. New technologies are introduced in their introduction years. In a carbon tax (CTAX) scenario, the industry should pay additional costs to use fuel based on energy demand and emission coefficients. This study assumes 30 thousand KRW/ton CO2eq carbon tax based on a price of emission permission in 2019 (Korea Exchange, 2020). Since the carbon tax affects technology mix and energy demand of the industry, emissions of the industry also change. This study identifies effects of the carbon tax with a focus on emissions, abatement costs and changes in energy demand.

2.4.8 Calculation of major results

Industry's energy demand for each fuel at time period t is the sum of energy consumption of technologies that use each fuel in Eq. (2.19). Moreover, industry's energy demand for each energy service at time period t is the sum of energy consumption of technologies that produce each energy service in Eq. (2.20). Additionally, industry's final energy demand at time period t is the sum of energy consumption of all technologies in Eq. (2.21).

$$\sum_{TECH \in Fuel} x_{TECH,t} \qquad \text{Eq. (2.19)}$$

$$for \;\; anthracite, \ldots, electricity \in Fuel$$

$$\sum_{TECH \in Energy \;\; service} x_{TECH,t} \qquad \text{Eq. (2.20)}$$

$$for \;\; boiler, \ldots, feedstock \in Energy \;\; service$$

$$\sum_{TECH \in Process} x_{TECH,t} \qquad \text{Eq. (2.21)}$$

Industry's total emissions are obtained based on Eq. (2.22). The total emissions are the sum of technology emissions, which are calculated by multiplying an emission coefficient and energy consumption of technology.

$$\sum_{TECH \in Process} COEF_{TECH} * x_{TECH,t} \qquad \text{Eq. (2.22)}$$

The total cost, including capital, labor, energy and carbon costs, of the industry is calculated using the objective function (see Eq. (2.1)). If the government implements a carbon tax policy, the industry chooses new technology mix, which minimizes an increase in costs due to a carbon tax. The share of low-emission and more efficient technologies in technology mix increases. The abatement cost is calculated according to Eq. (2.23). The total cost in calculating the abatement cost excludes the carbon tax.

$$Abatement\ \ cost = -\frac{\sum_{t=0}^{35} CTAX\ \ total\ \ cost_t - BAU\ \ total\ \ cost_t}{\sum_{t=0}^{35} CTAX\ \ emissions_t - BAU\ \ emissions_t} \qquad \text{Eq. (2.23)}$$

2.5 Results

2.5.1 Calibration of base-year energy consumption

PMP calibrates given base-year energy consumption of technology ($\overline{x_{TECH,0}}$) from the ECS database (Table 2.9). The steel industry uses 18 technologies to produce five energy service and feedstock demand. Calibration errors for the technologies are less than 10^{-6}, which is an upper bound of a calibration error (see Eq. (2.10)).

Although PMP temporarily adds calibration constraints in Eq. (2.10), the final objective function in Eq. (2.18) excludes those constraints. Calibration in PMP depends on the Lagrange multipliers, which are endogenously determined, instead of the calibration constraints. The calibration constraints do not directly affect the calibration results in Table 2.9. Thus, simulation results of PMP do not depend on the calibration constraints.

Table 2.9. Calibration of base-year energy consumption of the steel industry (Unit: thousand TOE)

Technology	Calibration error ($\left\|\frac{x_{TECH,0}-\overline{x_{TECH,0}}}{\overline{x_{TECH,0}}}\right\|$)	Technology	Calibration error ($\left\|\frac{x_{TECH,0}-\overline{x_{TECH,0}}}{\overline{x_{TECH,0}}}\right\|$)
Bituminous boiler	$< 10^{-9}$	Electric oven	$< 10^{-8}$
City gas boiler	$< 10^{-11}$	Electric motor	0
Anthracite oven	$< 10^{-8}$	City gas own power generator	0
Bituminous oven	$< 10^{-8}$	LPG dryer	0
Coal product oven	$< 10^{-8}$	City gas dryer	0
Diesel oven	$< 10^{-8}$	Heat dryer	0
Heavy oil oven	$< 10^{-8}$	Electric dryer	0
LPG oven	$< 10^{-8}$	Anthracite feedstock	0
City gas oven	$< 10^{-9}$	Bituminous feedstock	0

2.5.2 Simultaneous use of multiple technologies

PMP describes simultaneous use of multiple technologies without adding supplementary constraints. Figure 2.6 shows boiler technologies in the steel industry. In the base year, the steel industry uses current bituminous and city gas boiler technologies to produce a boiler energy service. More than 90% of the boiler energy service is provided by a current city gas technology, which implies that a current city gas boiler technology is more competitive. Although a current bituminous boiler is less competitive and provides a small amount of the boiler energy service, it is not excluded from an available boiler technology set. In 2018, a new city gas boiler technology is adopted. After the adoption of the new technology, the steel industry still uses the current boiler technologies.

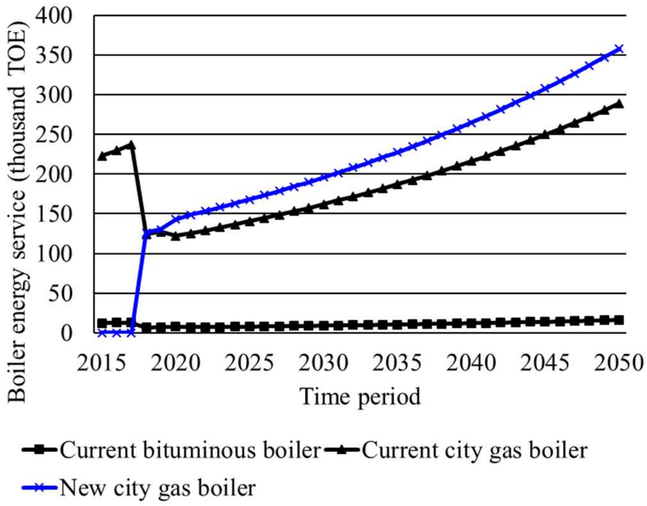

Figure 2.6. Boiler energy service production of boiler technologies in the steel industry (Unit: thousand TOE)

2.5.3 Gradual technological change

PMP shows gradual technological change without adding supplementary constraints. Figure 2.7 represents the most competitive current and new technologies in providing energy services. Although investment, operation and management costs of new technology are more expensive, new technology substitutes current one in its introduction year because it is more efficient and lowers energy costs.

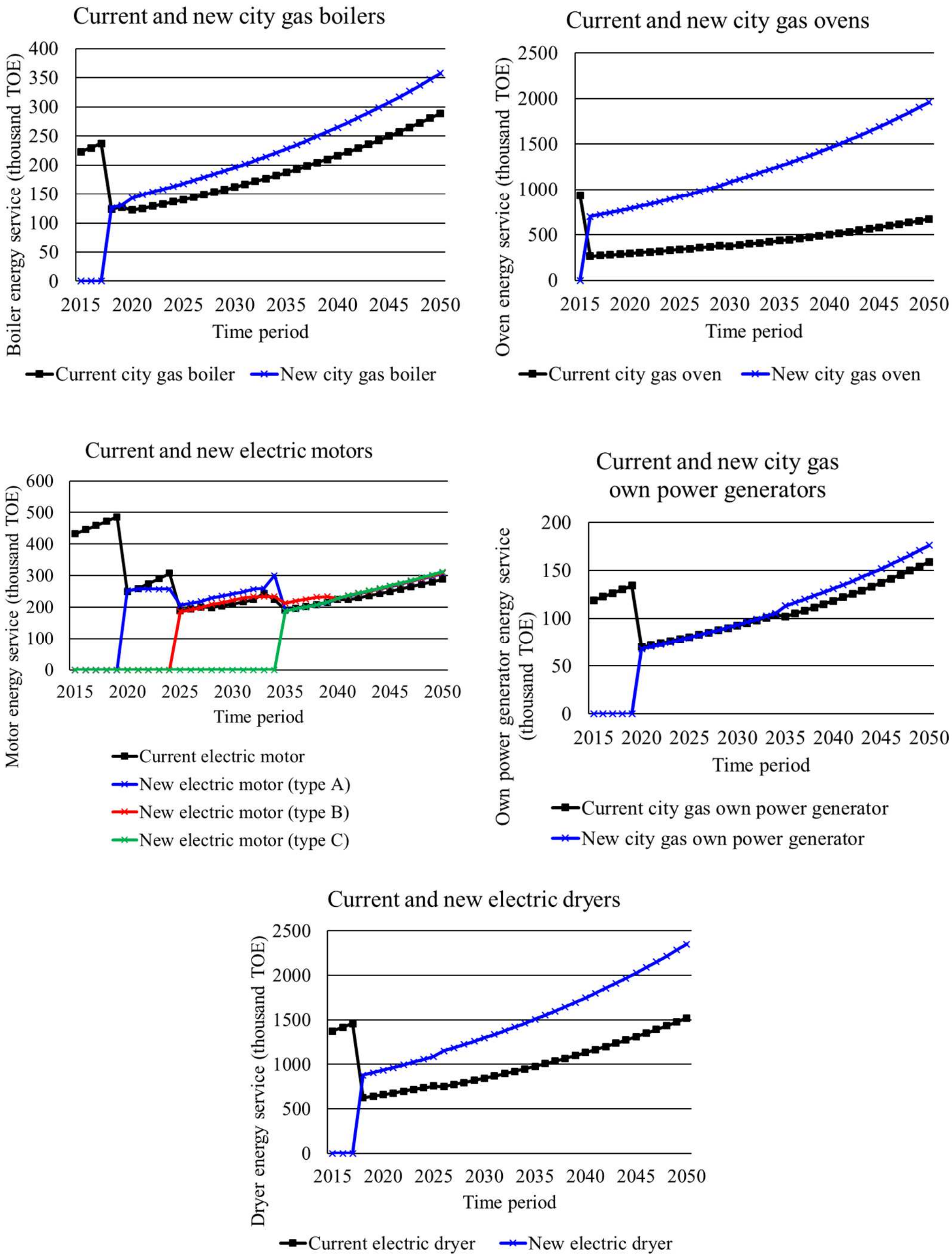

Figure 2.7. Energy service production in the steel industry (Unit: thousand TOE)

For example, a new electric dryer technology substitutes current dryer technologies in 2018. After the adoption of a new electric dryer technology, a current electric dryer technology is still operated. That is, PMP avoids complete elimination of current technology by new technology. Additionally, the difference between current and new electric dryer technologies gradually increases. This implies that technology substitution in PMP is gradual rather than radical.

2.5.4 Carbon tax simulation

The manufacturing sector in a BAU scenario generates 10,000 million ton CO2eq emissions from 2015 to 2050 (Figure 2.8). The steel industry accounts for 64% of emissions of the manufacturing sector. Although the chemistry and cement industries follow the steel industry, their emissions are much less than emissions of the steel industry. The three most emission-intensive industries generate 83% of emissions of the manufacturing sector.

When the government imposes a carbon tax, the manufacturing sector pays additional costs proportional to emission coefficients of technologies. Since the objective of the manufacturing sector is to minimize its total cost, the manufacturing sector replaces high-emission technologies to low-emission technologies and current technologies to new technologies. These technology mix changes reduce emissions of the manufacturing sector.

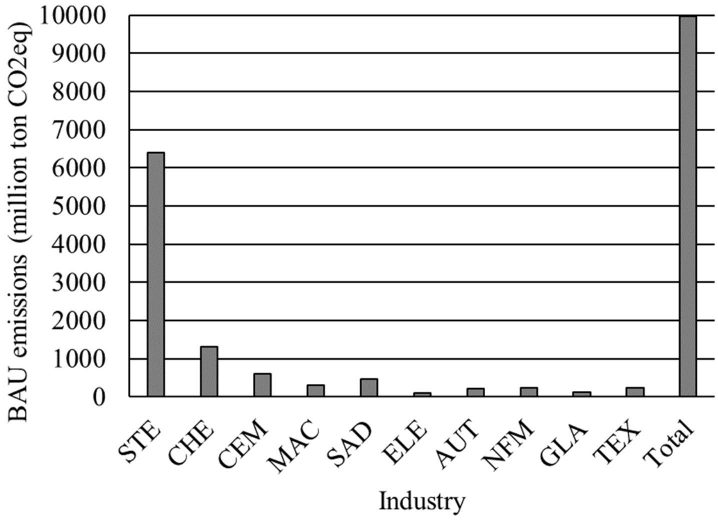

Figure 2.8. BAU emissions (2015–2050) of the manufacturing sector (Unit: million ton CO2eq)

Note: STE (steel), CHE (chemistry), CEM (cement), MAC (machine), SAD (semiconductor and display), ELE (electronics), AUT (automobile), NFM (nonferrous metals), GLA (glass), TEX (textile)

The carbon tax reduces 0.32% of BAU emissions of the manufacturing sector (Figure 2.9). Although emissions reduction effects on the cement, nonferrous metals and glass industries are much larger than the other industries, those effects on the manufacturing sector are small because the steel industry has small reduction capacities due to fixed demand for bituminous coal (feedstock).

By contrast, the cement industry is the most emission-reducing industry in the manufacturing sector. The cement industry uses kiln technologies, which occupy more than

80% of total energy consumption of the cement industry and experience significant efficiency improvement through new technology adoption. That is, shares of energy service demand and a level of technological change affect emissions reduction of the industry.

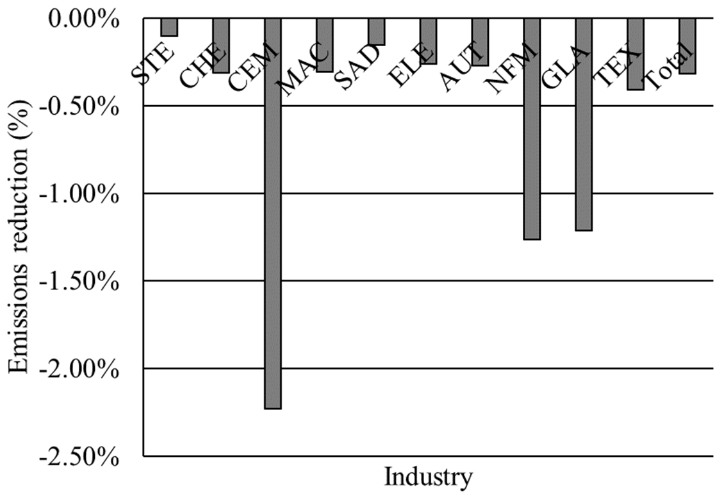

Figure 2.9. Emissions reduction effects of the carbon tax (2015–2050) (Unit: %)

The unit abatement cost excluding the carbon tax is calculated using Eq. (2.23). The unit abatement cost of the manufacturing sector is 7 thousand KRW/ton CO2eq (Figure 2.10). It is comparable between industries because the bottom-up model is service-oriented. All industries have an identical technology set, which implies that costs and efficiencies of available technologies are similar.

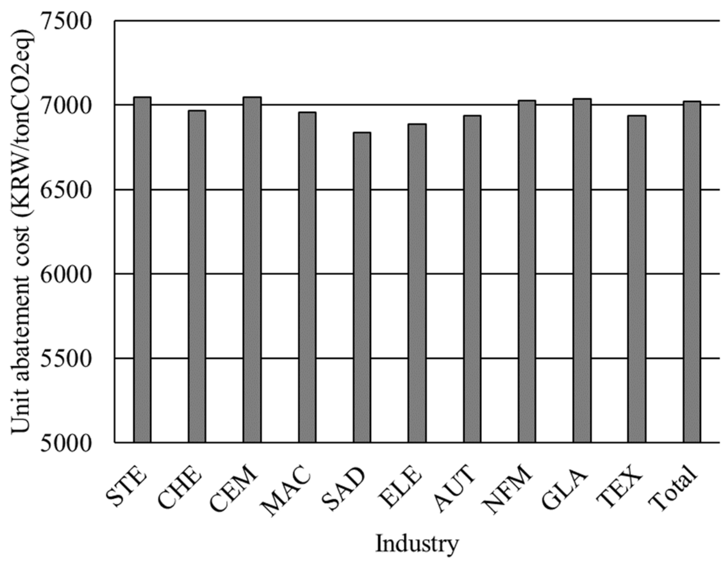

Figure 2.10. Unit abatement cost excluding the carbon tax (2015–2050) (Unit: KRW/ton CO2eq)

The manufacturing sector changes its technology mix in two ways to avoid the carbon tax burden. First, low-emission technologies replace high-emission technologies based on emission coefficients. Second, new technologies, which are more efficient, replace current technologies. The former effects increase energy demand for low-emission energy and decrease energy demand for high-emission energy. The latter effects reduce energy demand for all energy because new technologies produce energy services using less fuels.

Energy demand varies based on two technology substitution effects (Figure 2.11). Energy demand for coal decreases because both effects are negative. Since coal has the emission coefficient (see Figure 2.3), other technologies replace coal technologies. An increase in new coal technologies due to the carbon tax also induce a decrease in energy demand for coal. Energy demand for oil (excluding LPG) also drops for the same reasons.

Since LPG has a low emission coefficient, the share of LPG technologies rises. By contrast, the adoption of new LPG technologies reduces energy demand for LPG. Energy demand for LPG increases because the former effects are larger than the latter effects. Energy demand for heat also increases, similar to LPG.

Energy demand for city gas, which is low-emission energy, diminishes because the negative effects of new city gas technologies are larger than the positive effects of the low emission coefficient. Energy demand for electricity also diminishes for the same reasons.

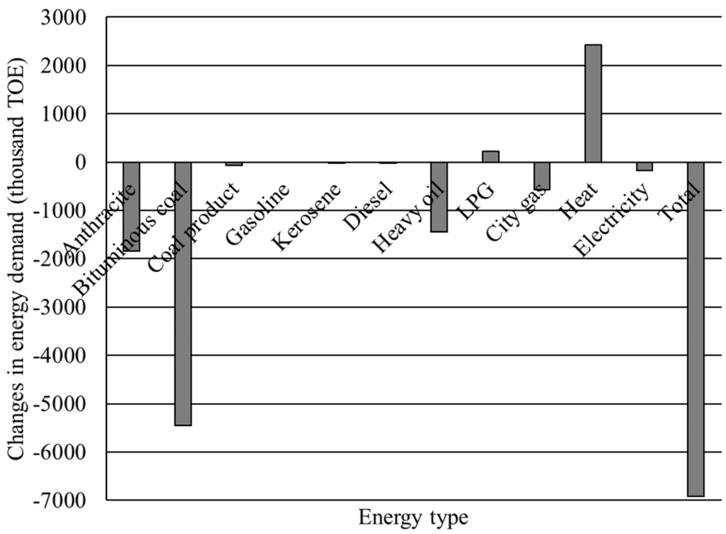

Figure 2.11. Changes in energy demand of the manufacturing sector (2015–2050) (Unit: thousand TOE)

Although energy demand for city gas and electricity decreases due to the carbon tax, the energy demand shares of city gas and electricity increase because their emission coefficients are low (Figure 2.12). Technology substitution due to the carbon tax causes the manufacturing sector to depend more on low-emission technologies.

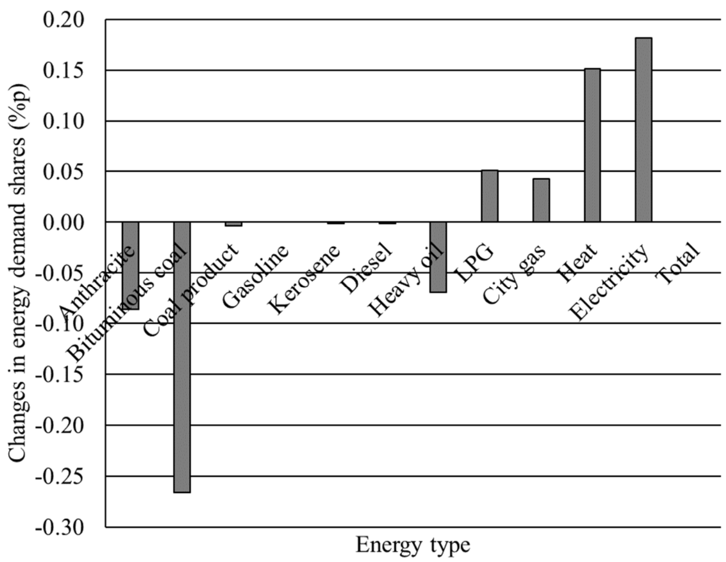

Figure 2.12. Changes in energy demand shares of the manufacturing sector (2015–2050) (Unit: %p)

Chapter 3. Computable general equilibrium model for environmental analysis

3.1 Introduction

3.1.1 Research background

The computable general equilibrium (CGE) model has its theoretical basis in research by Arrow and Debreu (1954) (Ross, 2007). Their Walrasian general equilibrium structure helps to find solutions that clear all markets (Sue Wing, 2009) and describe the optimal behavior of all economic agents. The CGE model's solutions satisfy the objectives of all economic agents.

The CGE model has been used as a tool to assess policy impacts. Although CGE models generally focus on tax and trade policies (Chisari and Miller, 2015), their applications were extended to environmental policies (RTI International, 2008). The environmental policies that the CGE models usually investigate include carbon tax, emissions reduction targets, and energy efficiency (Babatunde et al., 2017).

These environmental policies induce both environmental and macro-economic changes in the economy. Emissions are usually generated from energy consumption, which is a significant input in production activities. As policies affect energy consumption, production activities also changes. Since the CGE model easily captures these ripple effects, it is a useful tool for environmental policy analysis.

3.1.2 Research purpose

This study constructs a recursive dynamic CGE model based on Hosoe et al. (2010). Hosoe et al. (2010) developed the simple CGE model that includes a household and two producers. Each producer manufactures a product using capital and the labor supplied by the household. The household maximizes its utility by consuming products under its budget constraint. The producers maximize their profits by producing products under their production functions. Hosoe et al. (2010) extended the simple CGE model to the standard CGE model, which adds the behavior of other economic agents. Their standard CGE model includes intermediate inputs, the government, an investment agent, and international trade.

Although Hosoe et al.'s (2010) CGE model allows for a basic analysis, it has limitations in analyzing environmental policies. This study modifies the standard CGE model for environmental policy analysis and adds recursive equations to describe the dynamic changes in the economy. Additionally, this study introduces a more complicated production nesting structure and adds emission coefficients to investigate emissions from energy consumption and production activities. Finally, this study explores the effects of carbon tax policies on the emissions and abatement costs based on the CGE model.

3.2 Data

3.2.1 Social accounting matrix

The CGE model uses a Social Accounting Matrix (SAM), which is a table to describe the base-year transactions in the economy, as input data. This study constructs an SAM using the 2015 Input-Output (IO) Table of the Bank of Korea (2019). The Bank of Korea (2019) classifies production into 381 sectors at a basic level. This study reclassifies them into 41 sectors based on KEI (2015) (Table 3.1). For example, the coal sector in this study incorporates the anthracite (0611) and the bituminous coal sectors (0612) in the 2015 IO table. The energy sector includes 14 sectors (1–14) according to the energy classification of the bottom-up model. The manufacturing sector consists of 18 sectors (15–24 and 26–33). The service sector is divided into 6 sectors (34–35 and 37–40). This study does not disaggregate the agriculture, transport and other sectors because these sectors are small.

Table 3.1. Aggregation of the production sectors in the 2015 IO Table

This study		2015 IO Table
Energy	1 Coal	0611–0612
Energy	2 Coal product	1611–1612
Energy	3 Gasoline	1622
Energy	4 Kerosene	1624
Energy	5 Diesel	1625
Energy	6 Heavy oil	1626
Energy	7 LPG	1627
Energy	8 City gas	4610
Energy	9 Heat	4620
Energy	10 Electricity	4501–4505

Energy	11 Crude oil	0621
Energy	12 Natural gas	0622
Energy	13 Other Oil products	1621, 1628, 1631, 1639
Energy	14 Jet oil	1623
Manufacturing	15 Steel	2711–2799
Manufacturing	16 Chemistry	1711–1802, 2000–2499
Manufacturing	17 Cement	2620–2699
Manufacturing	18 Machine	3011–3099, 3810–3999
Manufacturing	19 Semiconductor& display	3101–3523
Manufacturing	20 Electronics	3611–3799
Manufacturing	21 Automobile	4011–4032
Manufacturing	22 Nonferrous metals	2811–2900
Manufacturing	23 Glass	2501–2509
Manufacturing	24 Textile	1111–1209, 1900
Agriculture	25 Agriculture	0111–0402
Manufacturing	26 Other mining	0711–0729
Manufacturing	27 Food & beverage	0811–1000
Manufacturing	28 Timber	1311–1329
Manufacturing	29 Paper & printing	1410–1500

Manufacturing	30 Ceramic	2611–2614
Manufacturing	31 Ship	4101–4103
Manufacturing	32 Other transport equipment	4210–4299
Manufacturing	33 Other manufacturing	4311–4402
Service	34 Waste	4801–4920
Service	35 Construction	5010–5190
Transport	36 Transport	5321–5720
Service	37 Commerce	0500, 5200–5310, 5811–6599, 6700, 6911–6920, 7002–7490, 7602–7603, 7702–7703, 7802, 7902–8229
Service	38 Insurance	6601–6603
Service	39 Domestic (Housing)	6800
Service	40 Public	4700, 7001, 7511–7601, 7701, 7801, 7901
Other	41 Other	8300

Sources: Bank of Korea (2019) and KEI (2015)

The shaded elements in the SAM comprises the IO table (Figure 3.1). Sector i receives money from sector j and provides products or factors to sector j. Sector j pays money to sector i and receives products or factors from sector i. The column sum is the total expenditure of sector j and includes the purchases of intermediate inputs, capital and labor, tax payments, and imports. The row sum is the total income of sector i and includes supplies for intermediate input demand, factor demand, final demand, and export demand. The column and row sums of the sector should be identical, which implies that the total expenditure is equal to the total income.

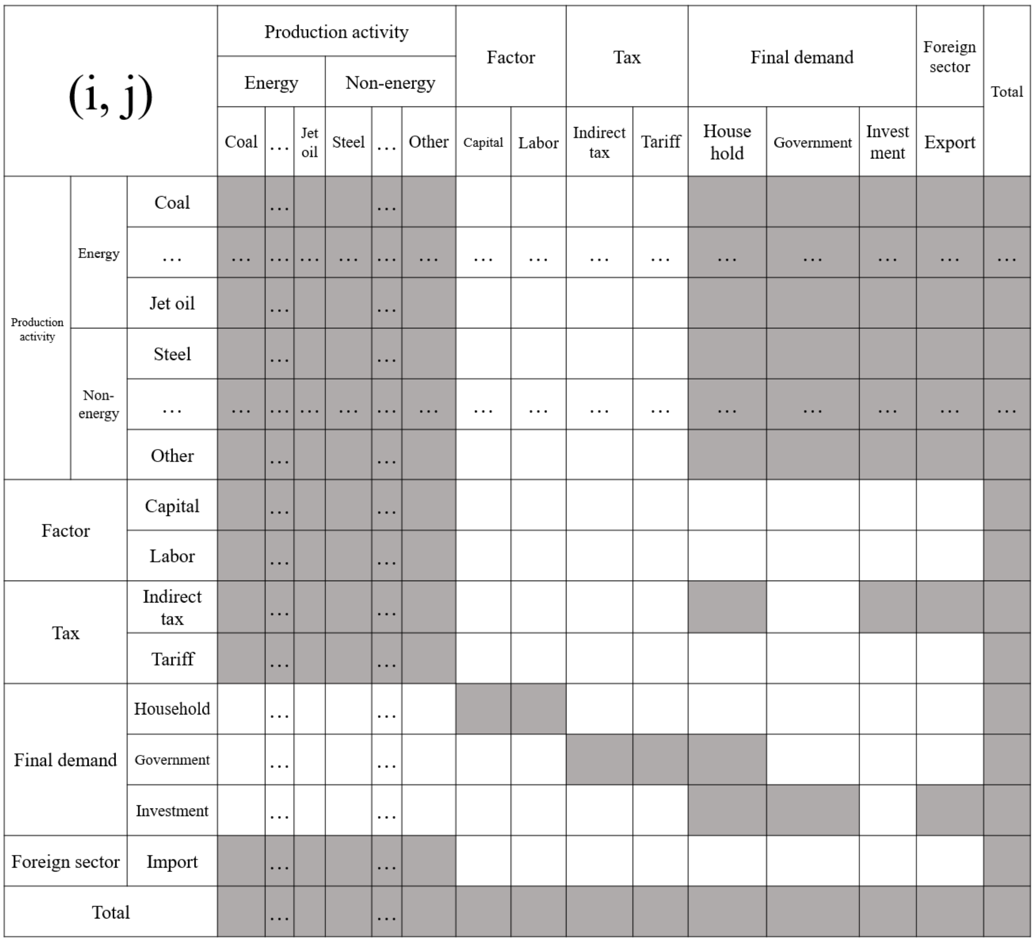

Figure 3.1. Social accounting matrix

3.2.2 Parameter

Although most of the parameters in the CGE model are calibrated base on the SAM, several parameters cannot be calibrated. Substitution elasticities, which have significant impacts on solutions, are usually obtained from the literature because they are difficult to estimate. This study also adopts the substitution elasticities in the literature (Table 3.2). Armington and transformation elasticities are assumed to be 2.0 in the range of the previous elasticities. Substitution elasticities between intermediate inputs are assumed to be 0.5.

Table 3.2. Elasticities

Elasticity	Value	References
Armington	2.0	Sue Wing (2003), Lim (2012), Hwang et al. (2014), Yeo (2019)
Transformation	2.0	Sue Wing (2003), Yeo (2019)
CapitalEnergy−Labor	0.5	Okagawa and Ban (2008), Ge and Lei (2017), Duarte et al. (2018)
Capital−Energy	0.5	
Heat−Electricity−Fossil fuels	0.5	Hwang et al. (2014), Oh et al. (2015)
Coal−Liquid fossil fuels	0.5	Kim et al. (2019)
Oil−Gas	0.5	Oh et al. (2015), Duarte et al. (2018)

A labor endowment growth rate is obtained from KEI (2019) (Table 3.3). KEI (2019) calculates the total employment for all time periods based on population prospects by age and the current employment rate by age. A labor endowment growth rate is equal to a total employment growth rate. The rate has a decreasing trend and is less than 0 after 2030 because total employment decreases due to a decline in the population.

Table 3.3. Labor endowment growth rate (Unit: %)

Time period	Growth rate	Time period	Growth rate
2015	0.9	2019	0.8
2016	1.2	2020–2029	0.1
2017	0.4	2030–2039	-0.4
2018	0.8	2040–2050	-0.6

Source: KEI (2019)

3.2.3 Emission coefficient

Emissions coefficients are calculated based on KEI (2015), which considers emissions from fuel combustion and production processes. The combustion emission coefficients as a unit of monetary value were calculated using the Energy Balance of Yearbook of Energy Statistics (KEEI, 2017b). The Yearbook of Energy Statistics provides a gross calorific value of primary energy supply in 2015. This study converts the gross calorific value into net calorific value using conversion coefficients (Table 3.4). Then, the total emissions from fuel combustion are calculated by multiplying the combustion emission coefficients in a unit of energy by the net calorific value of the primary energy supply. The combustion emission coefficients as a unit of monetary value are obtained by dividing the total emissions by the total demand, which includes intermediate input demand and household demand.

Table 3.4. Combustion emission coefficients

Fuel	(net calorific) Primary energy supply	IPCC emission coefficient	Total emissions	Total demand	Monetary emission coefficient
Coal	79,869	3,892	310,857,745	11,734	26,491
Coal product	2,393	4,437	10,616,734	707	15,013
Gasoline	8,801	2,871	25,268,981	6,396	3,951
Kerosene	2,116	2,977	6,299,346	1,963	3,209
Diesel	20,931	3,069	64,238,210	13,597	4,725
Heavy oil	5,682	3,208	18,228,496	10,028	1,818
LPG	8,545	2,614	22,338,890	6,010	3,717

City gas	38,996	2,336	91,081,447	27,688	3,290
Oil product	49,707	880	43,754,564	30,393	1,440
Jet oil	4,447	2,963	13,174,079	6,009	2,193

Sources: Author's work based on Yearbook of Energy Statistics (KEEI, 2017b), KEEI (2020) and IO Table (Bank of Korea, 2019)

Note: Primary energy supply (thousand TOE). IPCC emission coefficient (ton CO2eq/thousand TOE). Total emissions (ton CO2eq). Total demand (billion KRW). Monetary emission coefficient (ton CO2eq/billion KRW). Moreover, several oil products do not emit all of the carbon in themselves. The stored carbon is excluded from combustion emissions.

The process emission coefficients are obtained from the 2015 National Inventory Report (Greenhouse Gas Inventory and Research Center, 2015), which assumes that emissions in Korea are generated from energy, industrial processes, agriculture, LULUCF (Land Use, Land-Use Change and Forestry), or waste. It classifies each category more specifically depending on the emissions sources. This study allocates emissions from industrial processes, agriculture, and waste to the production sectors in the SAM consistent with the sector specification of National Inventory Report (Table 3.5). This study assumes that process emissions are proportional to output per base-year output.

Table 3.5. Process emission coefficients

Production sector		Emissions
This study	National Inventory Report	[ton CO2eq/billion KRW]
Steel	Steel production	2.2
Chemistry	Chemistry industry	4.7
Cement	Cement production	1800.4
Semiconductor & display	Semiconductor production	43.6
Electronics	Heavy electronic machine	32.2
Nonferrous metals	SF6 consumption of magnesium production	2.6
Agriculture	Agriculture	351.3
Waste	Waste	1110.0

Source: Author's work based on National Inventory Report (Greenhouse Gas Inventory and Research Center, 2015)

3.3 Model

3.3.1 Outline of the CGE model

This study adopts and modifies equations of Hosoe et al. (2010) to reflect Table 3.6. Although Hosoe et al. (2010) constructed a static CGE model, it did not allow dynamic changes in the economy. Capital stock is updated based on previous capital stock and investments. Labor endowment is also adjusted based on the labor endowment growth rate.

Moreover, the standard CGE model has a simple production nesting structure. This study adopts more complicated production nesting structure to describe the substitution between energy inputs. Additionally, this study considers combustion and process emissions of the production sectors.

Table 3.6. Comparison of the CGE models

	Hosoe et al. (2010)	This study
Model type	Static	Recursive dynamic
Production nesting	Two-stage	Six-stage
Capital	Exogenously given and fixed	Recursively updated
Labor	Exogenously given and fixed	Exogenously updated
Emissions	n/a	Emission coefficients

The CGE model describes behavior of economic agents in the economy. A household maximizes its utility by consuming products under limited income, which is obtained by providing capital and labor. Producers maximize its profits from sales of products, which are produced using capital, labor and intermediate inputs. The government levies taxes on the household and the producers and purchases products. An investment agent makes investment-saving decisions and consumes products using savings of the household, government, and foreign sector. Since the economy is open, the domestic economy exports domestic products and imports foreign products.

3.3.2 Household behavior

The household is assumed to maximize the Cobb-Douglas utility function under the budget constraint (Hosoe et al., 2010). Eq. (3.1) shows household consumption of the product i (HX_i). The household provides capital ($KS * RATE$) and labor ($\bar{L}$) to the economy and receives capital price (R) and labor price ($WAGE$). A part of household's factor income is saved (HS) or collected as a direct tax (DT). Household's budget is used to consume products, and the share of expenditure for the product i is shown as α_i. The household pays price ($(1 + HITR_i) * PQ_i$), which includes price of the Armington composite product and a household indirect tax, to purchase the product.

$$HX_i = \frac{\alpha_i * (R * KS * RATE + WAGE * \bar{L} - HS - DT)}{[(1 + HITR_i) * PQ_i]} \qquad \text{Eq. (3.1)}$$

HX_i: Household consumption of the product i

α_i: Household consumption share for the product i

R: Interest rate (capital price)

KS: Capital stock

$RATE$: Rate of return

$WAGE$: Wage (labor price)

$\bar{L}$: Labor endowment

HS: Household saving

DT: Direct tax

$HITR_i$: Household indirect tax rate on the product i

PQ_i: Price of the Armington composite product i

3.3.3 Producer behavior

The producer maximizes its profit, which is revenue minus the costs of purchasing inputs. The producer makes products by aggregating capital, labor and intermediate inputs based on the six-stage production nesting structure (Figure 3.2). This study employs the production nesting structure of KEI (2015) (see also Ge and Lei, 2017; Duarte et al., 2018; Huang et al., 2019).

In the first stage, the producer aggregates oil and gas, which include gasoline, kerosene, diesel, heavy oil, LPG, crude oil, oil product, jet oil, city gas and natural gas. Oil and gas are aggregated into liquid fossil fuel (LFF_j) based on the constant elasticity of substitution (CES) function in Eq. (3.2). The substitution between oil and gas is determined by the substitution parameter $OG\eta_j$, which is calculated using the substitution elasticity $OG\sigma_j$. Higher substitution elasticity means that inputs are easier to replace each other. The input share parameter $OG\delta_{i,j}$ indicates the share of the input i in the liquid fossil fuel. Demand for the input i ($X_{i,j}$) is determined by Eq. (3.3). It depends on parameters in the CES function and the relative price of oil or gas and the liquid fossil fuel.

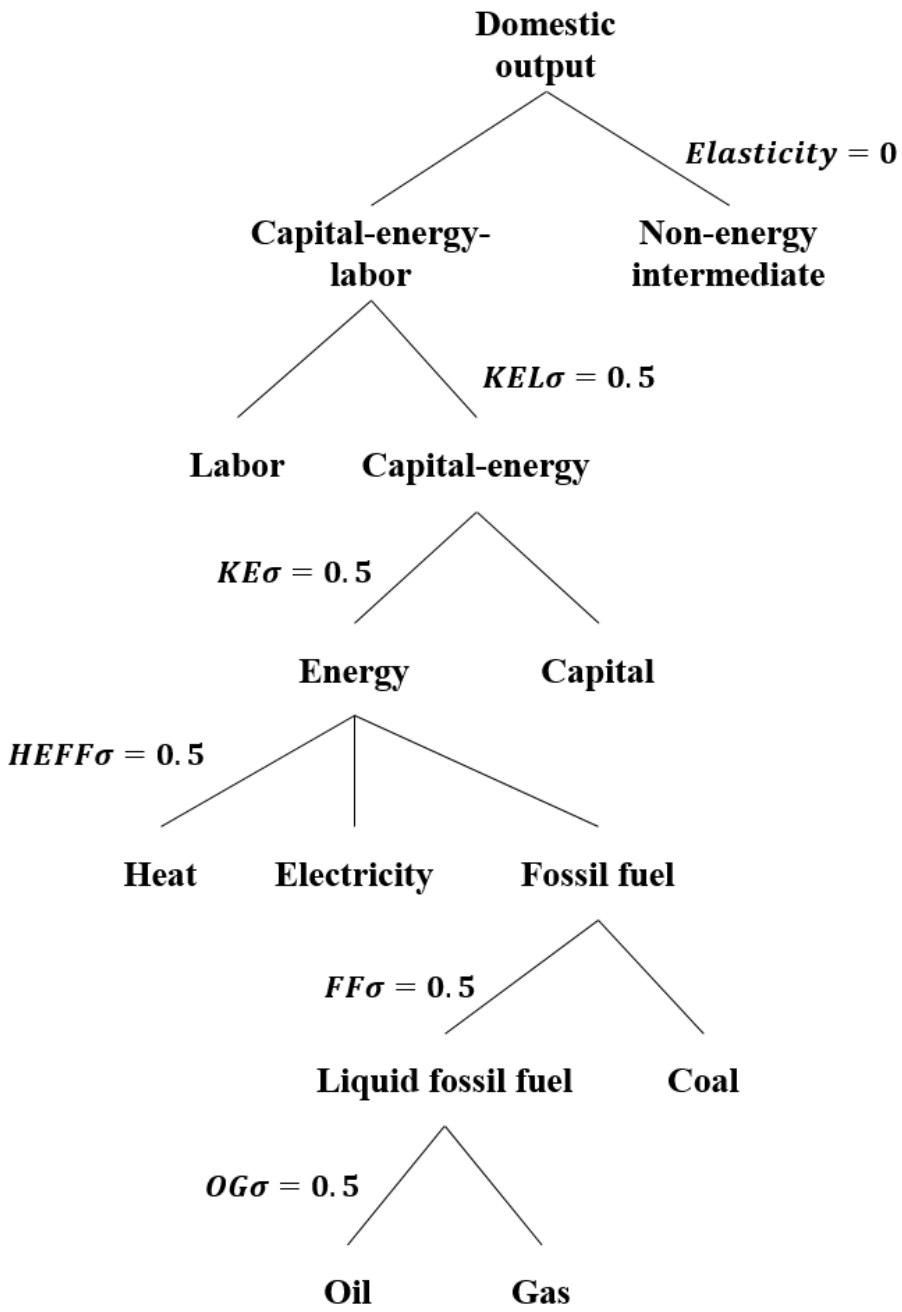

Figure 3.2. Production nesting structure

$$LFF_j = LFF\gamma_j * \left(\sum_{i \in oil\ \ or\ \ gas} OG\delta_{i,j} * X_{i,j}^{OG\eta_j}\right)^{\frac{1}{OG\eta_j}} \qquad \text{Eq. (3.2)}$$

$$X_{i,j} = \left[\frac{LFF\gamma_j^{OG\eta_j} * OG\delta_{i,j} * PLFF_j}{PQ_i}\right]^{\frac{1}{1-OG\eta_j}} * LFF_j \ \ for\ \ i \in oil\ \ or\ \ gas \qquad \text{Eq. (3.3)}$$

LFF_j: Liquid fossil fuel demand of the producer j

$LFF\gamma_j$: Scaling parameter in the liquid fossil fuel demand function of the producer j

$OG\delta_{i,j}$: Share parameter for the input i (oil or gas) in the liquid fossil fuel demand function of the producer j

$X_{i,j}$: Demand for the input i of the producer j

$OG\eta_j$: Oil-gas substitution parameter of the producer j $(OG\eta_j = (OG\sigma_j - 1)/OG\sigma_j)$

$PLFF_j$: Liquid fossil fuel price of the producer j

In the second stage, the producer aggregates liquid fossil fuel, coal and coal product. These are aggregated into fossil fuel (FF_j) in Eq. (3.4). The substitution between liquid fossil fuel, coal and coal product is also determined by the substitution elasticity $FF\sigma_j$.

$$FF_j = FF\gamma_J * \left(\left(\sum_{i \in coal\ \ or\ \ coal\ \ product} COAL\delta_{i,j} * X_{i,j}^{FF\eta_j} \right) + LFF\delta_j * LFF_j^{FF\eta_j} \right)^{\frac{1}{FF\eta_j}} \quad \text{Eq. (3.4)}$$

$$X_{i,j} = \left[\frac{FF\gamma_j^{FF\eta_j} * COAL\delta_{i,j} * PFF_j}{PQ_i} \right]^{\frac{1}{1-FF\eta_j}} * FF_j \quad \text{Eq. (3.5)}$$

$$for\ \ i \in coal\ \ or\ \ coal\ \ product$$

$$LFF_j = \left[\frac{FF\gamma_j^{FF\eta_j} * LFF\delta_j * PFF_j}{PLFF_j} \right]^{\frac{1}{1-FF\eta_J}} * FF_j \quad \text{Eq. (3.6)}$$

FF_j: Fossil fuel demand of the producer j

$FF\gamma_j$: Scaling parameter in the fossil fuel demand function of the producer j

$COAL\delta_{i,j}$: Share parameter for the input i (coal or coal product) in the fossil fuel demand function of the producer j

$LFF\delta_j$: Share parameter for the liquid fossil fuel in the fossil fuel demand function of the producer j

$FF\eta_j$: Coal-liquid fossil fuel substitution parameter of the producer j ($FF\eta_j = (FF\sigma_j - 1)/FF\sigma_j$)

PFF_j: Fossil fuel price of the producer j

In the third stage, the producer makes energy composite by combining heat, electricity and fossil fuel. Similar to the first and second stages, those inputs are combined by the CES function. The substitution between heat, electricity and fossil fuel is determined by the substitution elasticity $HEFF\sigma_j$.

$$ECOMP_j = ECOMP\gamma_j * \left(\left(\sum_{i \in heat\ or\ electricity} HE\delta_{i,j} * X_{i,j}^{HEFF\eta_j}\right) + FF\delta_j * FF_j^{HEFF\eta_j} \right)^{\frac{1}{HEFF\eta_j}} \quad \text{Eq. (3.7)}$$

$$X_{i,j} = \left[\frac{ECOMP\gamma_j^{HEFF\eta_j} * HE\delta_{i,j} * PECOMP_j}{PQ_i} \right]^{\frac{1}{1-HEFF\eta_j}} * ECOMP_j \quad \text{Eq. (3.8)}$$

$$for\ \ i \in heat\ \ or\ \ electricity$$

$$FF_j = \left[\frac{ECOMP\gamma_j^{HEFF\eta_j} * FF\delta_j * PECOMP_j}{PFF_j} \right]^{\frac{1}{1-HEFF\eta_j}} * ECOMP_j \quad \text{Eq. (3.9)}$$

$ECOMP_j$: Energy composite demand of the producer j

$ECOMP\gamma_j$: Scaling parameter in the energy composite demand function of the producer j

$HE\delta_{i,j}$: Share parameter for the input i (heat or electricity) in the energy composite demand function of the producer j

$FF\delta_j$: Share parameter for the fossil fuel in the energy composite demand function of the producer j

$HEFF\eta_j$: Heat-electricity-fossil fuel substitution parameter of the producer j ($\mathrm{HE}FF\eta_j = (HEFF\sigma_j - 1)/\mathrm{HE}FF\sigma_j$)

$PECOMP_j$: Energy composite price of the producer j

The fourth stage describes the aggregation of capital and energy composite. Although many CGE models combine capital with labor, this study emphasizes the substitution between capital and energy. In the hybrid model, the bottom-up model explains technological change, which induces changes in capital, labor and energy inputs. When new technology replaces current technology, in the bottom-up model, capital input increases and energy input decreases because new technology is more expensive to install and more efficient.

$$KE_j = KE\gamma_j * \left(ECOMP\delta_j * ECOMP_j^{KE\eta_j} + K\delta_j * K_j^{KE\eta_j}\right)^{\frac{1}{KE\eta_j}} \qquad \text{Eq. (3.10)}$$

$$ECOMP_j = \left[\frac{KE\gamma_j^{KE\eta_j} * ECOMP\delta_j * PKE_j}{PECOMP_j}\right]^{\frac{1}{1-KE\eta_j}} * KE_j \qquad \text{Eq. (3.11)}$$

$$K_j = \left[\frac{KE\gamma_j^{KE\eta_j} * K\delta_j * PKE_j}{R}\right]^{\frac{1}{1-KE\eta_j}} * KE_j \qquad \text{Eq. (3.12)}$$

KE_j: Capital-energy composite demand of the producer j

$KE\gamma_j$: Scaling parameter in the capital-energy composite demand function of the producer j

$ECOMP\delta_j$: Share parameter for the energy composite in the capital-energy composite demand function of the producer j

$K\delta_j$: Share parameter for the capital in the capital-energy composite demand function of the producer j

$KE\eta_j$: Capital-energy composite substitution parameter of the producer j ($KE\eta_j = (KE\sigma_j - 1)/KE\sigma_j$)

K_j: Capital demand of the producer j

PKE_j: Capital-energy composite price of the producer j

The fifth stage explains the aggregation of labor and capital-energy composite. In the sixth stage, the producer produces domestic output (Z_j) using non-energy inputs (Eq. (3.16)) and capital-energy-labor composite (Eq. (3.17)). Domestic output is a Leontief composite of non-energy inputs and capital-energy-labor composite. Since the share of each input in domestic output is fixed, the sum of share parameters is 1. Eq. (3.18) is the zero profit condition for the product j. The left-hand side is the marginal revenue to produce domestic output. The right-hand side is the marginal cost to produce domestic output.

$$KEL_j = KEL\gamma_j * \left(KE\delta_j * KE_j^{KEL\eta_j} + L\delta_j * L_j^{KEL\eta_j}\right)^{\frac{1}{KEL\eta_j}} \quad \text{Eq. (3.13)}$$

$$KE_j = \left[\frac{KEL\gamma_j^{KEL\eta_j} * KE\delta_j * PKEL_j}{PKE_j}\right]^{\frac{1}{1-KEL\eta_j}} * KEL_j \quad \text{Eq. (3.14)}$$

$$L_j = \left[\frac{KEL\gamma_j^{KEL\eta_j} * L\delta_j * PKEL_j}{WAGE}\right]^{\frac{1}{1-KEL\eta_j}} * KEL_j \quad \text{Eq. (3.15)}$$

KEL_j: Capital-energy-labor composite demand of the producer j

$KEL\gamma_j$: Scaling parameter in the capital-energy-labor composite demand function of the producer j

$KE\delta_j$: Share parameter for the capital-energy composite in the capital-energy-labor composite demand function of the producer j

$L\delta_j$: Share parameter for the labor in the capital-energy-labor composite demand function of the producer j

$KEL\eta_j$: Capital-energy-labor composite substitution parameter of the producer j ($KEL\eta_j = (KEL\sigma_j - 1)/KEL\sigma_j$)

L_j: Labor demand of the producer j

$PKEL_j$: Capital-energy-labor composite price of the producer j

$$X_{i,j} = A_{i,j} * Z_j \;\; for \;\; i \in non-energy \;\; inputs \qquad \text{Eq. (3.16)}$$

$$KEL_j = B_j * Z_j \qquad \text{Eq. (3.17)}$$

$$PZ_j = \sum_{i \in non-energy \;\; inputs} A_{i,j} * PQ_i + B_j * PKEL_j \qquad \text{Eq. (3.18)}$$

$A_{i,j}$: Share parameter for the non-energy input i in the domestic output function j

B_j: Share parameter for the capital-energy-labor composite in the domestic output function j

Z_j: Domestic output j

PZ_j: Domestic output price j

3.3.4 Government behavior

The government consumes products using levied taxes, which are collected from two sources. A direct tax (DT) is from household income. Indirect taxes include a production tax (PT_j), an import tariff (IT_j), a household indirect tax (HIT_j), an investment indirect tax (IIT_j) and an export indirect tax (EIT_j). Indirect taxes are paid at the production tax rate (PTR_i), the import tariff rate (ITR_i), the household indirect tax rate ($HITR_i$), the investment indirect tax rate ($IITR_i$) and the export indirect tax rate ($EITR_i$). The government purchases products (GX_i) using its tax revenue excluding the government saving (GS). The share of expenditure for the product i is shown as μ_i.

$$GX_i = \mu_i * (DT + \sum_j PT_j + \sum_j IT_j + \sum_j HIT_j + \sum_j IIT_j + \sum_j EIT_j - GS)/PQ_i \qquad \text{Eq. (3.19)}$$

$$DT = DTR * (WAGE * \bar{L} + R * KS * RATE) \qquad \text{Eq. (3.20)}$$

$$PT_i = PTR_i * PZ_i * Z_i \qquad \text{Eq. (3.21)}$$

$$IT_i = ITR_i * PM_i * M_i \qquad \text{Eq. (3.22)}$$

$$HIT_i = HITR_i * PQ_i * HX_i \qquad \text{Eq. (3.23)}$$

$$IIT_i = IITR_i * PQ_i * IX_i \qquad \text{Eq. (3.24)}$$

$$EIT_i = EITR_i * epsilon * PWE_i * E_i \qquad \text{Eq. (3.25)}$$

GX_i: Government consumption of the product i

μ_i: Government consumption share for the product i

PT_j: Production tax from the producer j

IT_j: Import tariff from the producer j

HIT_i: Household indirect tax for the product i

IIT_i: Investment indirect tax for the product i

EIT_i: Export indirect tax for the product i

GS: Government saving

DTR: Direct tax rate

PTR_j: Production tax rate for the producer j

PZ_j: Price of the product j

Z_j: Domestic output of the product j

ITR_j: Import tariff rate for the product j

PM_j: Import price in a local currency for the product j

M_j: Import of the product j

$IITR_i$: Investment indirect tax rate for the product i

IX_i: Investment demand for the product i

$EITR_i$: Export indirect tax rate for the product i

$epsilon$: Exchange rate

PWE_i: Export price in a foreign currency for the product i

E_i: Export of the product i

3.3.5 Investment behavior

The investment agent gathers savings of the household (HS), the government (GS) and the foreign sector (FS). As Eq. (3.26) indicates, total expenditure for investments is equal to total savings. The share of expenditure for the product i always maintains the base-year share based on Eq. (3.29) (KEI, 2015). The investment agent pays price ($(1 + IITR_i) * PQ_i$), which includes price of the Armington composite product and the investment indirect tax, to purchase the product. The household and the government save income and tax revenue at the rates of HSR and GSR, respectively. The foreign sector saves its export revenue excluding expenditure to import domestic products (see Eq. (3.32)).

$$\sum_i (1 + IITR_i) * PQ_i * IX_i = HS + GS + epsilon * FS \quad \text{Eq. (3.26)}$$

$$HS = HSR * (WAGE * \bar{L} + R * KS * RATE) \quad \text{Eq. (3.27)}$$

$$GS = GSR * (DT + \sum_j PT_j + \sum_j IT_j + \sum_j HIT_j + \sum_j IIT_j + \sum_j EIT_j) \quad \text{Eq. (3.28)}$$

$$IX_i = \overline{IX_i} * \lambda \quad \text{Eq. (3.29)}$$

FS: Foreign saving in a foreign currency

HSR: Average propensity for household saving

GSR: Average propensity for government saving

$\overline{IX_i}$: Base-year investment demand for the product i

λ: Investment adjustment variable

3.3.6 International trade

Although the CGE model of this study is a national model, international trade is described because the domestic economy exchanges with the foreign sector. World export price (PWE_i) and world import price (PWM_i) are excahnged to domestic export price (PE_i) and domestic import price (PM_i) using an exchange rate ($epsilon$). The domestic economy receives world export price excluding the export indirect tax (Eq. (3.30)) and pays world import price to purchase products of the foreign sector (Eq. (3.31)). The foreign sector generates income by selling the products and uses its income to purchase products of the domestic economy. The rest of the income is saved in Eq. (3.32).

Products in the domestic economy can be domestically produced or imported. The CGE model usually assumes that the domestic economy consumes the Armington composite product, which is an aggregation of domestic products and imports. The aggregation is done based on the CES function in Eq. (3.33). The substitution elasticity $A\sigma_i$ influences on the substitution between domestic products and imports.

The domestic economy can sell products to domestic or foreign consumers. Domestic demand and exports relies on the transformation function in Eq. (3.36). The transformations is done based on the transformation parameter ϕ_i.

$$PE_i = (1 - EIT_i) * epsilon * PWE_i \qquad \text{Eq. (3.30)}$$

$$PM_i = \; epsilon * PWM_i \qquad \text{Eq. (3.31)}$$

$$FS + \sum_i \; (1 + EIT_i) * PWE_i * E_i = \; \sum_i \; PWM_i * M_i \qquad \text{Eq. (3.32)}$$

$$Q_i = \; A\gamma_i * \left(M\delta_i * M_i^{A\eta_i} + D\delta_i * D_i^{A\eta_i}\right)^{\frac{1}{A\eta_i}} \qquad \text{Eq. (3.33)}$$

$$M_i = \left[\frac{A\gamma_i^{A\eta_i} * M\delta_i * PQ_i}{(1 + ITR_i) * PM_i}\right]^{\frac{1}{1 - A\eta_i}} * Q_i \qquad \text{Eq. (3.34)}$$

$$D_i = \left[\frac{A\gamma_i^{A\eta_i} * D\delta_i * PQ_i}{PD_i}\right]^{\frac{1}{1 - A\eta_i}} * Q_i \qquad \text{Eq. (3.35)}$$

$$Z_i = \; \theta_i * \left(E\psi_i * E_i^{\phi_i} + D\psi_i * D_i^{\phi_i}\right)^{\frac{1}{\phi_i}} \qquad \text{Eq. (3.36)}$$

$$E_i = \left[\frac{\theta_i^{\phi_i} * E\psi_i * (1 + PTR_i) * PZ_i}{PE_i/(1 - EITR_i)}\right]^{\frac{1}{1 - \phi_i}} * Z_i \qquad \text{Eq. (3.37)}$$

$$D_i = \left[\frac{\theta_i^{\phi_i} * D\psi_i * (1 + PTR_i) * PZ_i}{PD_i}\right]^{\frac{1}{1-\phi_i}} * Z_i \qquad \text{Eq. (3.38)}$$

PE_i: Export price in a local currency for the product i

PWM_i: Import price in a foreign currency for the product i

Q_i: Armington composite product i

$A\gamma_i$: Scaling parameter in the Armington composite function of the product i

$M\delta_i$: Import share parameter for the product i

$D\delta_i$: Domestic demand share parameter for the product i

D_i: Domestic demand for the product i

$A\eta_i$: Substitution parameter of the product i $(A\eta_i = (A\sigma_i - 1)/A\sigma_i)$

PD_i: Price of the domestic demand i

θ_i: Scaling parameter in the transformation function of the product i

$E\psi_i$: Export share parameter for the product i

$D\psi_i$: Domestic demand share parameter for the product i

ϕ_i: Transformation parameter of the product i $(\phi_i = (ED\sigma_i - 1)/ED\sigma_i)$

3.3.7 Market clearing

Eq. (3.39) is the market clearing condition for the Armington composite product. The producer supplies Q_i in the market. The household (HX_i), the government (GX_i) and the investment agent (IX_i) consumes the Armington composite product. Producers purchase the Armington composite product and employ it as intermediate input ($X_{i,j}$). Eq. (3.40) and Eq. (3.41) show the market clearing condition for the capital and labor markets. All capital should be employed by producers, and all labor should be hired by producers.

Eq. (3.39) excludes the market clearing condition for the *Other* sector. When there is n markets in the economy, the market clearing of the $n-1$ markets assures the market clearing of the nth market due to Walras's law. The CGE model generally excludes the market clearing condition for one market to test the model. If left-hand and right-hand sides of the market clearing condition for the *Other* sector is equal, the model is considered to be consistent.

$$Q_i = HX_i + GX_i + IX_i + \sum_j X_{i,j} \qquad \text{Eq. (3.39)}$$
$$for \;\; i \in all \;\; products \;\; excluding \;\; Other$$

$$\sum_j K_j = KS * RATE \qquad \text{Eq. (3.40)}$$

$$\sum_j L_j = \bar{L} \qquad \text{Eq. (3.41)}$$

$\bar{L}$: Labor endowment

3.3.8 Consumer price index

The CGE model adopts the relative price system. This study considers the consumer price index (CPI) as the numeraire price. The CPI is derived in Eq. (3.42). The CPI is the weighted price of the products that the household consumes. The CPI weight is the share of household consumption of the product i in total household consumption.

$$CPI = \sum_i CPIWEIGHT_i * PQ_i \qquad \text{Eq. (3.42)}$$

CPI: Consumer price index

$CPIWEIGHT$: Consumer price index weight

3.3.9 Recursive equation

There is no time subscript in the previous equations because the recursive dynamic CGE model iteratively solves static problems. This study assumes that capital stock is updated based on solutions of previous time period, and labor endowment is updated based on the exogenous growth rate (see Table 3.3). As Eq. (3.43) indicates, capital stock at time period $t+1$ (KS_{t+1}) is the sum of depreciated capital stock at time period t ($(1 - DEPR) * KS_t$) and all new investments ($\sum_i IX_{i,t}$). A depreciation rate and a rate of return is calculated based on KEI (2015). Labor endowment at time period $t+1$ ($\overline{L_{t+1}}$) grows depending on the labor endowment growth rate ($LGROWTH_{t+1}$) in Eq. (3.44).

$$KS_{t+1} = (1 - DEPR) * KS_t + \sum_i IX_{i,t} \qquad \text{Eq. (3.43)}$$

$$\overline{L_{t+1}} = (1 + LGROWTH_{t+1}) * \overline{L_t} \qquad \text{Eq. (3.44)}$$

KS_t: Capital stock at time period t

$DEPR$: Depreciation rate

$IX_{i,t}$: Investment demand for the product i at time period t

$\overline{L_t}$: Labor endowment at time period t

$LGROWTH_{t+1}$: Labor endowment growth rate at time period $t+1$

3.3.10 Adjustment of labor productivity and energy efficiency

Gross domestic product (GDP) represents the scale of the economy. Since emissions increase depending on the scale of the economy, it is necessary to calibrate future GDP in the CGE model. This study adopts the GDP outlook, which the Ministry of Environment employs to establish the LEDS (Ministry of Environment, 2020).

As Eq. (3.45) indicates, this study assumes that labor productivity improves for the calibration of GDP. Labor endowment at time period $t+1$ ($\overline{L_{t+1}}$) grows based on a labor endowment growth rate ($LGROWTH_{t+1}$) and labor productivity at time period $t+1$ ($LPROD_{t+1}$).[5] Labor productivity improvement induces an increase in labor endowment and GDP growth.

$$\overline{L_{t+1}} = LPROD_{t+1} * (1 + LGROWTH_{t+1}) * \overline{L_t} \qquad \text{Eq. (3.45)}$$

[5] Assuming that labor productivity grows at an annual rate of 1.65%, labor productivity in 2050 is 1.7 times greater than the base-year labor productivity. Additionally, the labor productivity of the manufacturing sector of Korea doubled from 2000 to 2019 (Korea Productivity Center, 2020).

$LPROD_{t+1}$: Labor productivity at time period $t + 1$

The LEDS predicted emissions in 2050 under the assumption that energy efficiency would improve. Due to improving energy efficiency, the estimated BAU national emissions in 2050 are 761.4 million ton CO2eq (Ministry of Environment, 2020), which is comparable with national emissions 692.3 million ton CO2eq in 2015 (Greenhouse Gas Inventory and Research Center, 2015). To prevent emissions in the CGE model from growing with a GDP growth path, this study assumes energy efficiencies of all sectors excluding the energy sector improves based on an Autonomous Energy Efficiency Improvement (AEEI) parameter in Eq. (3.46). The AEEI parameter does not improve energy efficiency of the energy sector because it may cause energy output of the energy sector to be inconsistent with the laws of thermodynamics (Sue Wing and Eckaus, 2007). Moreover, this study assumes that process emission coefficients annually decrease at a rate of 3%.

$$ECOMP\gamma_{j,t+1} = AEEI_{t+1} * ECOMP\gamma_{j,t}$$
$$for\ \ j \in all\ \ sectors\ \ excluding\ \ the\ \ energy\ \ sector \qquad \text{Eq. (3.46)}$$

3.3.11 Carbon tax

With the carbon tax, the household and the producers pay additional costs to consume energy and produce products. The producer pays $PQCTAX_i$, which includes the price of the Armington composite product and the carbon tax, to consume products of the energy sector. The carbon tax is proportional to a combustion emission coefficient in Eq. (3.47). Additionally, if there are process emissions, the producer pays the carbon tax, which is proportional to a process emission coefficient. As Eq. (3.48) indicates, this carbon tax is included in the producer's marginal cost. Moreover, the household pays the carbon tax to consume products of the energy sector. The equation to describe household consumption is modified as Eq. (3.49). This study assumes that all carbon taxes that the government collects are transferred to the household.

$$PQCTAX_i = PQ_i + CO2E_i * CTAX * CPI \quad for \;\; i \in Energy \;\; sector \qquad \text{Eq. (3.47)}$$

$PQCTAX_i$: Price of the Armington composite product i including a carbon tax

$CO2E_i$: Combustion emission coefficient for the energy product i

$CTAX$: Unit carbon tax

$$PZ_j = \sum_{i \in non-energy \;\; inputs} A_{i,j} * PQ_i + B_j * PKEL_j$$
$$+ CO2P_j * CTAX * CPI \qquad \text{Eq. (3.48)}$$
$$for \;\; j \in non-zero \;\; process \;\; emission \;\; sectors$$

$CO2P_j$: Process emission coefficient for the product j

$$HX_i = \frac{\alpha_i * (R * KS * RATE + WAGE * \bar{L} + TCTAX - HS - DT)}{[(1 + HITR_i) * PQ_i + (PQCTAX_i - PQ_i)]} \quad \text{Eq. (3.49)}$$

$$for \;\; i \in Energy \;\; sector$$

$TCTAX$: Total carbon tax

3.3.12 Scenario

This study adopts a carbon tax policy as a representative reduction policy and assess its impacts on emissions and abatement costs. The government is assumed to impose a 30 thousand KRW/ton CO2eq carbon tax in 2015. The carbon tax linearly and annually increases until 360 thousand KRW/ton CO2eq in 2050 (Figure 3.3).[6]

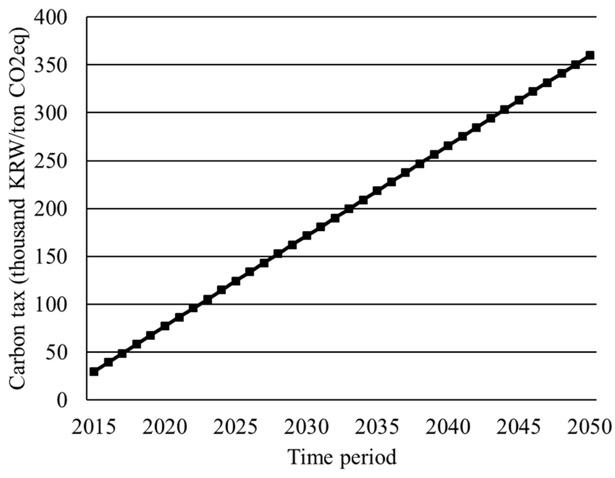

Figure 3.3. Carbon tax (Unit: thousand KRW/ton CO2eq)

[6] This carbon tax level achieves the lowest 2050 target (40% reduction) of the LEDS (Ministry of Environment, 2020).

Table 3.7 summarizes the scenarios in this chapter. CGEONLY_BAU is the BAU scenario without the carbon tax. CGEONLY_CTAX is the carbon tax scenario, which imposes the carbon tax in Figure 3.3.

Table 3.7. Scenario description

Scenario	Description
CGEONLY_BAU	CGE model No carbon tax
CGEONLY_CTAX	CGE model Carbon tax: 30–360 thousand KRW/ton CO2eq (2015–2050)

3.4 Results

3.4.1 BAU

The CGE model calibrates the 2050 BAU national emissions of the LEDS. As Figure 3.4 shows, national emissions slowly increase from 689 million ton CO2eq in 2015 to 776 million ton CO2eq in 2050. By contrast, GDP in 2050 is two times larger than the GDP in 2015 (Figure 3.5). Although the CGE model does not calibrate national emissions and GDP for all periods, it calibrates these LEDS values for 2050.

The base-year emissions in the CGE model calibrate the 2015 National Inventory Report (Figure 3.6). Since this study does not allocate the rest of industrial process emissions, the CGE model has smaller base-year industrial process emissions.

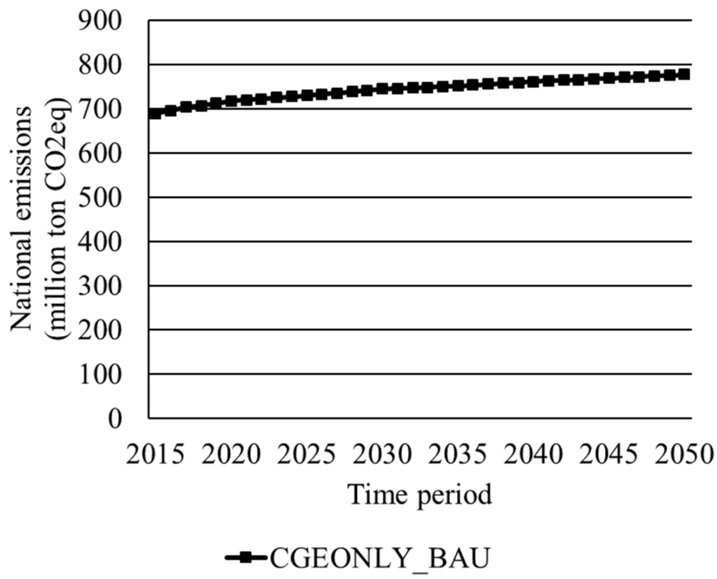

Figure 3.4. BAU national emissions (Unit: million ton CO2eq)

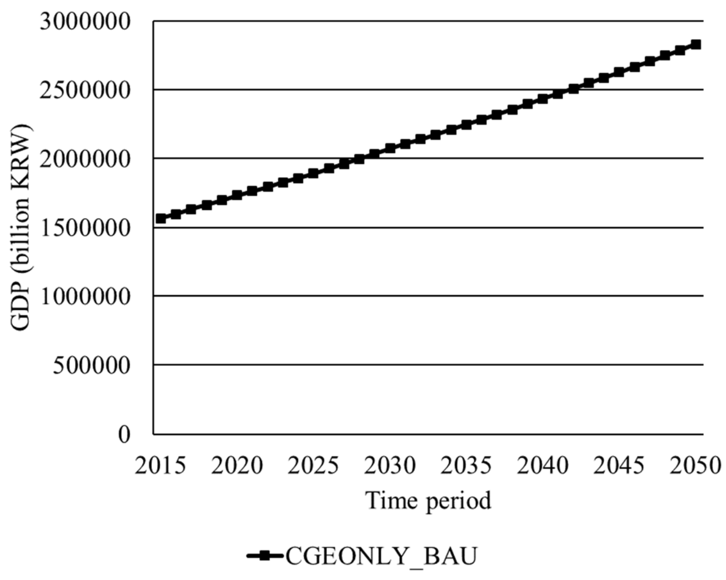

Figure 3.5. BAU GDP (Unit: billion KRW)

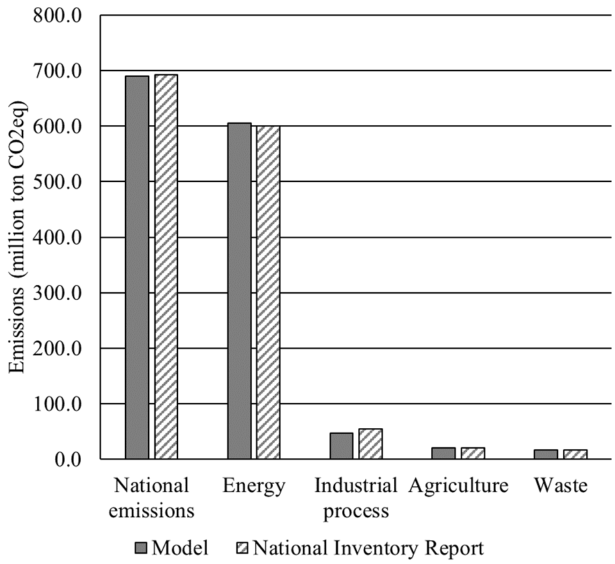

Figure 3.6. Comparison of 2015 emissions in the CGE model and National Inventory Report (Unit: million ton CO2eq)

Sources: The CGE model of this study and Greenhouse Gas Inventory and Research Center (2015)

If emissions from heat and electricity generation are allocated to each sector, then the ten emission-intensive industries are the largest emission sources (Figure 3.7). One-third of the base-year national emissions are generated by these industries. The service sector follows the emission-intensive industries and generates 23.7% of the base-year national emissions. The rest of the manufacturing sector excluding the emission-intensive industries is also a large emission source and generates 15.8% of the base-year national emissions. The transport, agriculture, energy, and other sectors accounts for small shares of the base-year national emissions. If the energy sector includes emissions from heat and electricity generation, then it would be a significant emission source. However, due to the allocation of indirect emissions, the energy sector generates only 3.0% of the base-year national emissions.

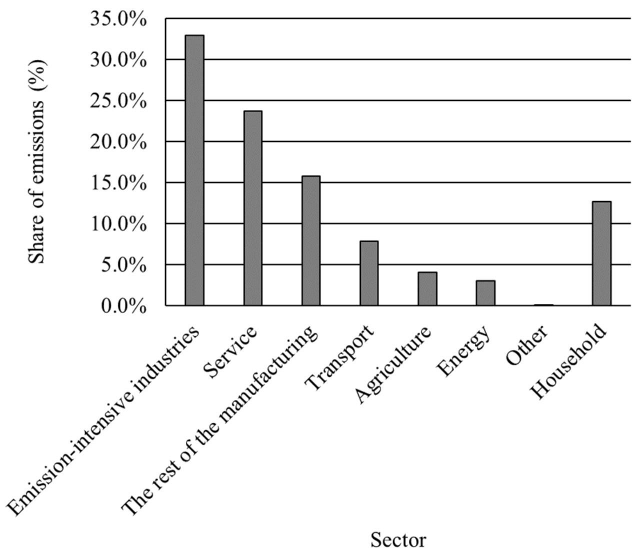

Figure 3.7. Share of emissions of each sector in 2015 (Unit: %)

3.4.2 Carbon tax simulation

With the carbon tax, capital input replaces energy inputs. When the price of energy increases because of the carbon tax, capital replaces energy because both inputs compete in the capital-energy composite nest. The substitution of energy by capital is determined by the substitution elasticity.

As Figure 3.8 shows, the energy input share decreases 1.5%p, but the shares of capital and labor inputs increase 1.2%p and 1.7%p, respectively. An increase in the labor input share is caused by a decrease in the shares of energy and non-energy inputs because labor endowment is fixed. Although non-energy inputs in the sector are fixed by the Leontief function, the non-energy input share can change because of the changes in the production structure.

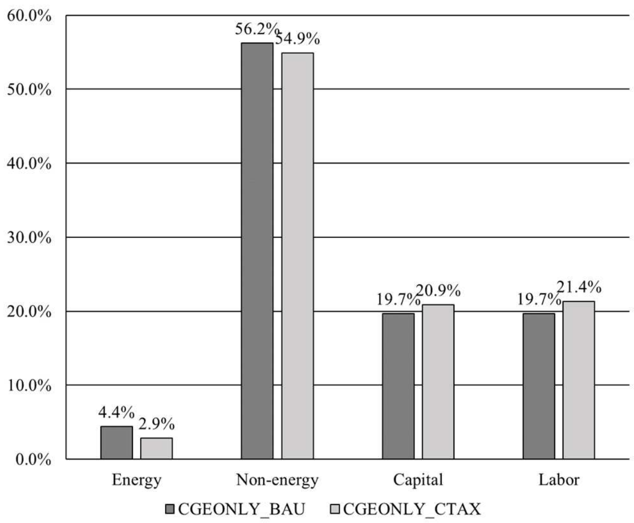

Figure 3.8. Changes in the input share in 2050 due to the carbon tax (Unit: %)

Moreover, the carbon tax leads to the substitution of high-emission energy with low-emission energy (Figure 3.9). Although all energy demand drops because of the rise in energy prices, they decreases at different levels. The energy demand for high-emission energy such as coal, coal product, and gasoline drop more steeply than do low-emission energy such as heavy oil and heat.

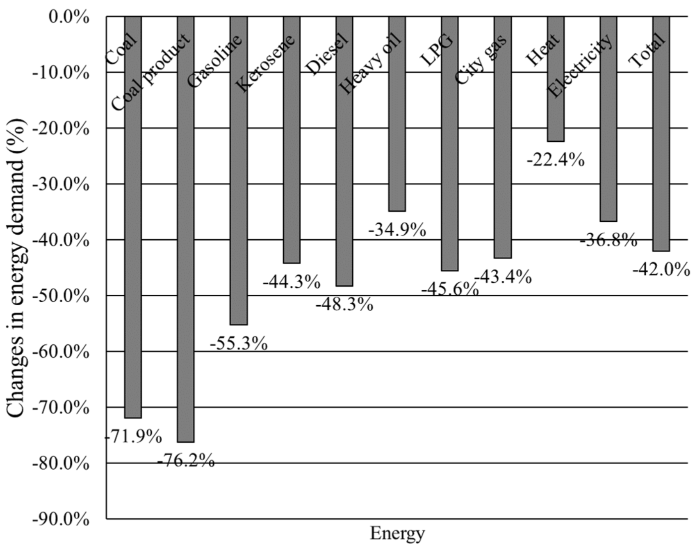

Figure 3.9. Changes in energy demand in 2050 due to the carbon tax (Unit: %)

Additionally, a decrease in domestic outputs due to the carbon tax also reduces emissions. Production of less domestic outputs by producers mitigates emissions because the producers consume less energy and generates less process emissions. Process emissions are generated from the steel, chemistry, cement, semiconductor & display, electronics, nonferrous metals, agriculture, and waste sectors. The domestic outputs of these eight sectors decreases with the carbon tax (Figure 3.10), and process emissions also decrease.

As the carbon tax rises, the gap between CGEONLY_BAU and CGEONLY_CTAX national emissions increases (Figure 3.11). In 2050, with a 360 thousand KRW/ton CO2eq carbon tax, the estimated reduction rate of national emissions is 54.2% (Figure 3.12). However, the slopes of the reduction rates are less steep, which implies that the reduction effects of an additional carbon tax decrease.

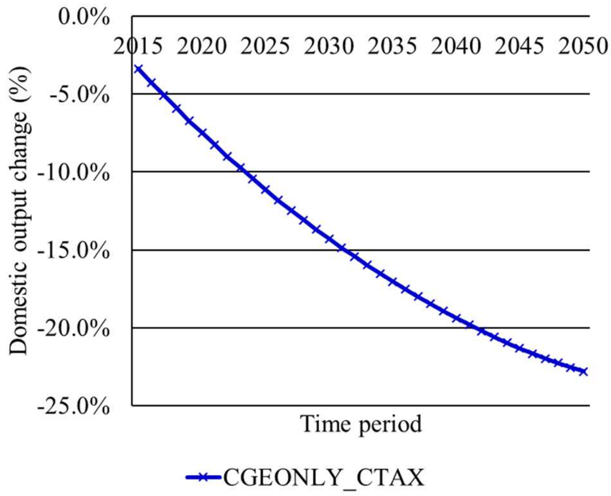

Figure 3.10. Domestic output change in the process emission sectors (Unit: %)

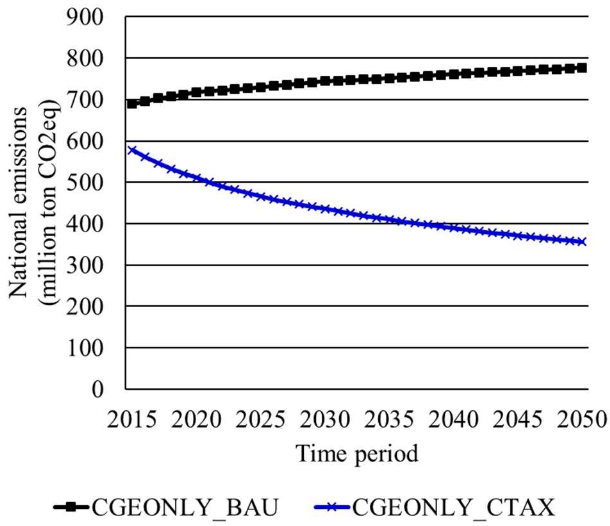

Figure 3.11. National emissions (Unit: million ton CO2eq)

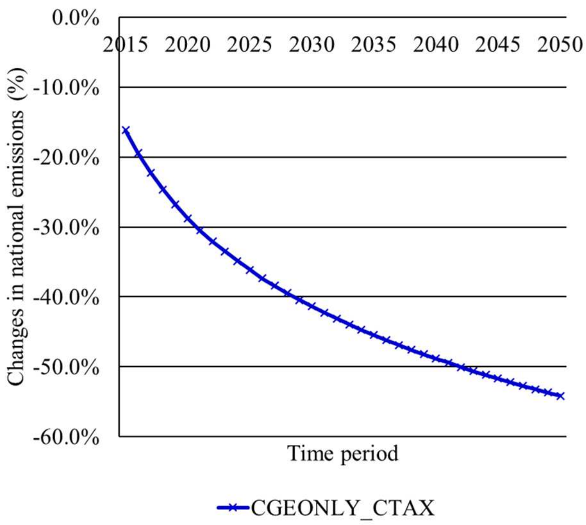

Figure 3.12. Emission change due to the carbon tax (Unit: %)

The government imposes the carbon tax and transfers it to the household. The household uses the carbon tax payment for its consumption and saving. Although this transfer does not incur social welfare losses, the carbon tax does affect GDP.

A low carbon tax does not have significant impacts on GDP (Figure 3.13). In 2026, the economy experiences 1% loss of GDP with a 133 thousand KRW/ton CO2eq carbon tax. As the carbon tax rises, GDP loss increases compared to the CGEONLY_BAU scenario. In 2050, with a 360 thousand KRW/ton CO2eq carbon tax, GDP decreases 2.4%.

The unit abatement cost is average GDP loss under the carbon tax to reduce a unit of emissions (Figure 3.14).[7] In 2015, the unit abatement cost is not large (19 thousand

[7] Abatement cost can be defined in the bottom-up and CGE models. This study calculates abatement cost using GDP and emissions in the CGE model. The value of abatement cost can be positive or negative depending on the use of the carbon tax. Moreover, unit abatement cost in this study means average abatement cost.

KRW/ton CO2eq), but it increases with the carbon tax. In 2050, the economy should accept 165 thousand KRW to mitigate one unit of emissions.

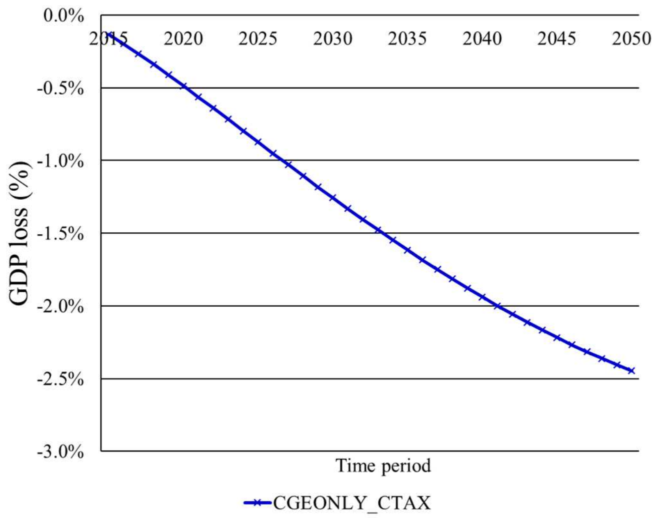

Figure 3.13. GDP loss due to the carbon tax (Unit: %)

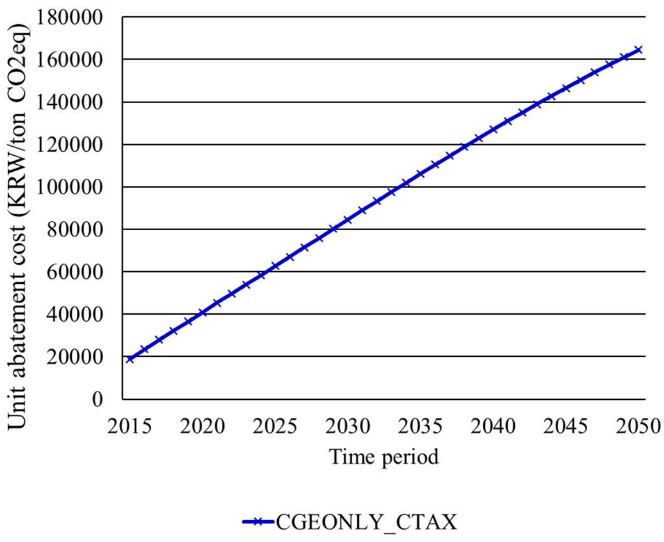

Figure 3.14. Unit abatement cost (Unit: KRW/ton CO2eq)

Chapter 4. A hybrid model to assess environmental and economic impacts of technological change in the manufacturing sector

4.1 Introduction

Chapter 1 briefly explains the advantages and disadvantages of the bottom-up and CGE models. This section describes these characteristics in more detail.

4.1.1 Research background

The bottom-up and CGE models are representative tools to explore the environmental and economic impacts of reduction options. Since the bottom-up model has the advantage of providing a detailed technology description (Hourcade et al., 2006), it is appropriate to describe new technology adoption. If technology characteristics and the price of the energy it uses are known, then the bottom-up model identifies the substitution of current technology by new technology and changes in the total cost, energy demand and emissions. By contrast, the CGE model has limitations in describing effects of new technology adoption because it depends on the substitution elasticity to explain energy substitution (Böhringer and Rutherford, 2008). The substitution elasticity is estimated using historical data (see Hourcade et al., 2006), which do not include information about the new technology. That is, the CGE model explains changes due to new technology based on the estimated elasticity before new technology adoption.

Moreover, the bottom-up model can describe the adoption of new technology using new energy that does not exist in the base year, if price of the new energy is known. However, the CGE model has difficulty in explaining new energy adoption. Since the CGE model calibrates parameters using base-year data, there is no information to calibrate the parameters of the new energy.

Additionally, the bottom-up model can investigate a wide range of technology-level reduction options (Loulou et al., 2016) such as efficiency improvements and a decrease in the investment costs of technology. By contrast, the CGE model reflects the technology-level reduction options at a more aggregated level.

Since the CGE model finds the optimal quantities and prices in the economy (Andersen et al., 2019a), it is appropriate to observe output changes due to relative price changes and the ripple effects of the output changes. By contrast, the bottom-up model cannot observe output changes because the output and final energy demand in the model are given, although the bottom-up model employs the new technology mix and observes the changes in production costs.

Moreover, the bottom-up model does not assure the equilibrium of the sectors besides the one under analysis (Helgesen et al., 2018). Additionally, the bottom-up model assumes that the energy prices are given, and overlooks changes in the energy prices due to the changes in energy demand, although a new technology mix induces such changes.

4.1.2 Research purpose

The hybrid model overcomes problems of the single models and employs the advantages of both models. It is an advanced framework that allows both technology-based and macro-economic analysis.

This study constructs a hybrid model for the manufacturing sector of Korea using the soft-link approach, which helps to exploit the full advantages of both models. This study explains a method to construct the hybrid SAM and to modify the single models for integration and information exchange. After constructing the hybrid model, this study investigates the impacts of new technology adoption. New technology induces technological change in the manufacturing sector and affects the whole economy. The effects of new technology on emissions and abatement costs under a carbon tax policy are also explored.

4.2 Literature review

4.2.1 Integration approach

There are three approaches to develop the hybrid model (see Böhringer and Rutherford, 2008). The reduced form approach simplifies one model and incorporates the simplified model into the other model. The hybrid model based on this approach has usually simplified the macro-economic model (Table 4.1). This approach is appropriate for global analysis rather than regional analysis (Krook-Riekkola et al., 2017) because several details of the models disappear. Moreover, it is not a complete approach for the hybrid model because one of two models is reduced.

Table 4.1. Previous hybrid models

Author	Country	Integration approach	Bottom-up model	Top-down model
Messner and Schrattenholzer (2000)	Global	Reduced form	MESSAGE-Macro (reduced top-down model)	
Strachan and Kannan (2008)	UK	Reduced form	MARKAL-Macro (reduced top-down model)	
Kypreos and Lehthila (2015)	Global	Reduced form	TIAM-Macro (reduced top-down model)	
Proença and Aubyn (2013)	Portugal	MCP		
Rasuch and Mowers (2014)	U.S.	MCP		
Fortes et al. (2014)	Portugal	Soft-link	TIMES	CGE (GEM-E3)
Krook-Riekkola et al. (2017)	Sweden	Soft-link	TIMES	CGE (EMEC)
Andersen et al. (2019a)	Denmark	Soft-link	TIMES	CGE

The mixed complementarity problem (MCP) and soft-link approaches integrate the bottom-up and CGE models without reducing one model. The MCP approach expresses two models using an MCP format to incorporate technology details in the CGE model (Böhringer and Löschel, 2006). This approach maintains coherence of the hybrid model, but the large number of equations in the model induces a dimensionality problem (Böhringer and Rutherford, 2009).

The soft-link approach relies on information exchange between the bottom-up and CGE models. In this approach, each model delivers information that the other model requires. These information exchanges continue until solutions of the hybrid model converge. Although this approach allows to employ characteristics of independent two models (Martinsen, 2011), it is difficult to maintain coherence of the hybrid model because two models are developed based on different assumptions (Böhringer and Rutherford, 2008).

4.2.2 Previous hybrid model

Several countries have developed the hybrid models to evaluate impacts of energy and environmental policies (see Table 4.1). Previous hybrid models generally focus on energy consumption (Messner and Schrattenholzer, 2000; Strachan and Kannan, 2008; Dai et al., 2016; Andersen et al., 2019a) and emissions (Strachan and Kannan, 2008; Rausch and Mowers, 2014; Krook-Riekkola et al., 2017; Helgesen et al., 2018). Technology details of the hybrid model allowed to analyze technology mix changes due to the policies (Proença and Aubyn, 2013; Rausch and Mowers, 2014; Helgesen et al., 2018). Moreover, macro-economic aspects of the hybrid model enabled to identify changes in macro-economic variables including GDP and welfare (Proença and Aubyn, 2013; Rausch and Mowers, 2014).

Fortes et al. (2014), Krook-Riekkola et al. (2017) and Andersen et al. (2019a) developed the hybrid model based on the soft-link approach. Although three studies adopted different CGE models, they integrated the CGE models with TIMES models. Fortes et al. (2014) employed General Equilibrium Model for Economy, Energy, Environment (GEM-E3), while Krook-Riekkola et al. (2017) used Environmental Medium term Economic model (EMEC).

Andersen et al. (2019a) points out that previous soft-linked hybrid models adopted the bottom-up and CGE models, which were already developed. Contrary to the previous models, they newly developed two models considering an integration. This study also adopts the soft-link approach and newly develops the bottom-up and CGE models for an integration.

4.3 Model

4.3.1 Outline of the hybrid model

Based on Böhringer and Rutherford (2009) and KEI (2018)[8], this study develops a hybrid model of ten emission intensive industries (Figure 4.1). The CGE model is

[8] KEI (2018) modified equations of the single bottom-up and CGE models, derived equations for information exchanges between the models and explained the integration process. This study adopts the equations and the integration process of KEI (2018).

recursively solved from 2015 to 2050. It saves and delivers the information that the bottom-up model requires. The bottom-up model recursively solves the cost minimization problems of the industries. It saves and delivers the information that the CGE model requires. These information exchanges finish when the differences in the linked variables in the previous and current iterations converge.

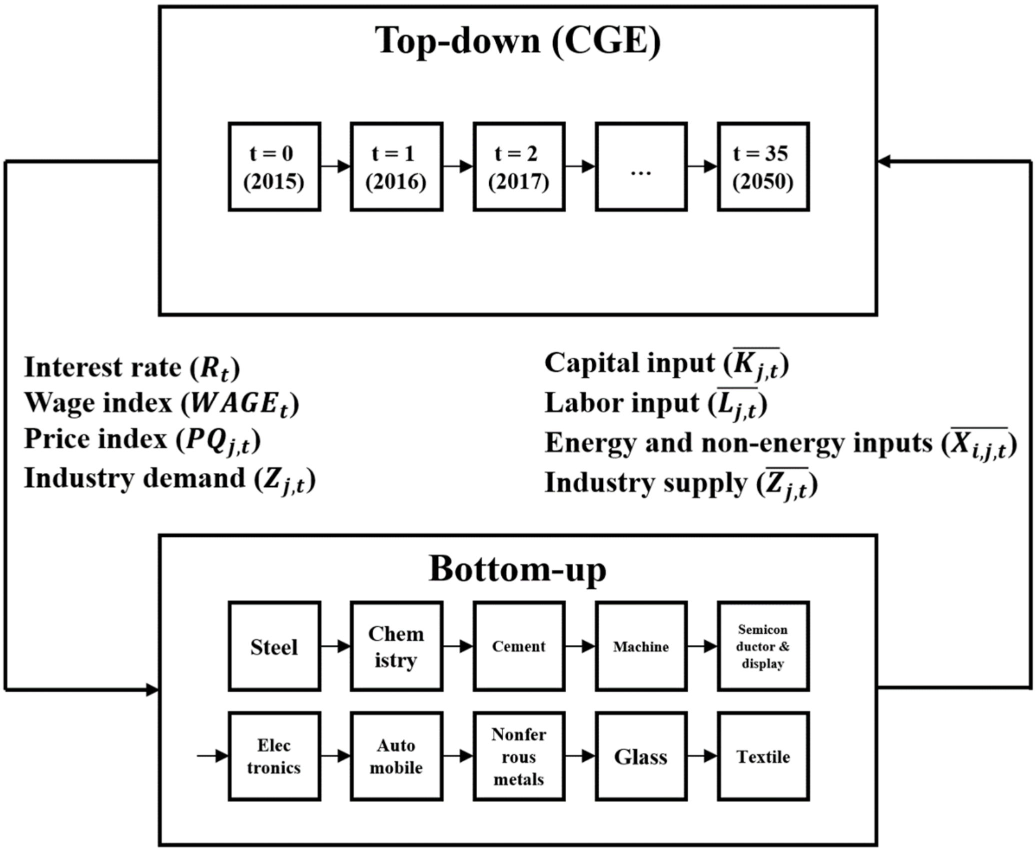

Figure 4.1. Outline of the hybrid model

Source: Author’s work based on KEI (2018)

4.3.2 Hybrid social accounting matrix

The base-year energy, capital and labor inputs of the manufacturing sector in the bottom-up and CGE models are inconsistent because each model uses different data sources. However, these inputs in the hybrid model should be consistent at least for the base year. A hybrid SAM is an adjusted SAM that helps to maintain the base-year consistency. This study develops a hybrid SAM based on KEI (2017).

This study describes the construction of the hybrid SAM for the steel industry as an example (Figure 4.2). As the first step, the industry column in the SAM is divided into two parts. The linked column includes the CGE inputs explained by the bottom-up model. The unlinked column records the rest of the CGE inputs that the bottom-up model does not explain.

As the second step, the energy, capital and labor inputs in the SAM are allocated in the hybrid SAM. Before the allocation, the bottom-up and CGE inputs in the base year are compared (Table 4.2). If the CGE input is larger, then bottom-up input is recorded in the linked column, and the difference between the CGE and bottom-up inputs is recorded in the unlinked column (see coal in Figure 4.2). If the bottom-up input is larger, then the linked column is equal to the bottom-up input, and the unlinked column is 0 (see city gas in Figure 4.2). If the CGE input is not 0, but the bottom-up input is 0, then the linked column is equal to the CGE input, and the unlinked column is 0 (see gasoline in Figure 4.2).

SAM

		Steel
Energy input	Coal	3624
	Coal product	327
	Gasoline	10
	Kerosene	9
	Diesel	23
	Heavy oil	47
	LPG	36
	City gas	639
	Heat	0
	Electricity	4728
Non-energy input	Other intermediate 1	0
	…	…
	Steel	26884
	…	…
	Other intermediate 30	67
	Capital	11631
	Labor	6041
	Indirect tax	200
	Household	0
	Government	0
	Investment	0
	Import	19890

Step 1

Step 2

Step 3

Step 2

Step 4

Hybrid SAM

	Steel (linked)	Steel (unlinked)
Coal	2536	1088
Coal product	4	323
Gasoline	10	0
Kerosene	9	0
Diesel	2	21
Heavy oil	21	26
LPG	12	24
City gas	1466	0
Heat	17	0
Electricity	1452	3276
Other intermediate 1	0	0
…	…	…
Steel	26884	0
…	…	…
Other intermediate 30	67	0
Capital	114	11517
Labor	65	5976
Indirect tax	147	52
Household	0	0
Government	0	0
Investment	0	0
Import	14661	5229

	…	Steel (linked)	Steel (unlinked)	…	Household	Government	Investment	Export
Steel	…	26884	0	…	0	0	-4132	26277

Step 5

Step 6

	…	Steel (linked)	Steel (unlinked)	…	Household	Government	Investment	Export
Steel (linked)	…	19816	0	…	0	0	-3046	19369
Steel (unlinked)	…	7068	0	…	0	0	-1086	6908

Figure 4.2. Hybrid SAM construction (Unit: billion KRW)

Table 4.2. Energy, capital and labor inputs of the steel industry in the base year (Unit: billion KRW)

Input	CGE	Bottom-up	Comparison
Coal	3624	2536	CGE > BU
Coal product	327	4	CGE > BU
Gasoline	10	0	CGE > 0 and BU = 0
Kerosene	9	0	CGE > 0 and BU = 0
Diesel	23	2	CGE > BU
Heavy oil	47	21	CGE > BU
LPG	36	12	CGE > BU
City gas	639	1466	BU > CGE
Heat	0	17	BU > CGE
Electricity	4728	1452	CGE > BU
Capital	11631	114	CGE > BU
Labor	6041	65	CGE > BU

Source: Author's work based on the SAM and bottom-up model output

In the third step, the non-energy inputs in the SAM are allocated. This study assumes that only the linked column uses non-energy inputs, which means that the unlinked column does not use non-energy inputs. In the fourth step, the indirect tax and imports in the SAM are allocated based on the weights of the linked and unlinked columns. The weight is the sum of energy, capital, labor, and non-energy inputs in the hybrid SAM. The ratio between the two weights is about 2.80 for the steel industry. In the fifth step, the industry row in the SAM is also divided into the linked and unlinked rows. Finally, the row in the SAM is allocated to the linked and unlinked rows in the hybrid SAM by weight.

This adjustment processes are identical for the other nine linked industries. However, the column and row sums in the hybrid SAM are not identical after the adjustment. This study adjusts the differences between the column and row sums in the intermediate inputs to maintain consistency in the hybrid SAM.

4.3.3 Modification of the bottom-up model

At first, the objective function of the bottom-up model is modified. Eq. (4.1) shows the modified objective function based on Böhringer and Rutherford (2009). Whereas the previous objective function aims to minimize the total cost, the modified objective function aims to maximize the sum of consumer and producer surplus.

$$\max_{q_t, x_{TECH,t}, Y_{TECH,t}} \sum_{t=0}^{35} \overline{Discount_t} * Surplus_t \qquad \text{Eq. (4.1)}$$

q_t: Industry supply at time period t
$x_{TECH,t}$: Energy consumption of technology $TECH$ at time period t
$Y_{TECH,t}$: Total capacity of technology $TECH$ at time period t
$\overline{Discount_t}$: Discount rate at time period t (given from the CGE model)
$Surplus_t$: Consumer and producer surplus at time period t

The surplus at a certain quantity is defined as the height of the consumer's inverse demand function minus the producer's total cost in Eq. (4.2). As Eq. (4.3) indicates, this is represented as given price, given demand, price elasticity of demand, endogenous supply, capital cost, labor cost and energy cost. Although the single bottom-up model, which is not developed for the hybrid model, assumes that quantity of product is given, industry supply (q_t) is an endogenous variable in the bottom-up model for the integration.

$$Surplus_t = \int PZ_t(q_t)dq_t - Total\ \ cost_t \qquad \text{Eq. (4.2)}$$

$PZ_t(q_t)$: Inverse demand function at time period t
$Total\ \ cost_t$: Total cost of the industry at time period t

$$Surplus_t = \overline{PZ_t} * q_t * \left(1 - \frac{q_t - 2 * \overline{q_t}}{2 * ELAS_t * \overline{q_t}}\right) - (Capital\ \ cost_t + Labor\ \ cost_t + Energy\ \ cost_t) \qquad \text{Eq. (4.3)}$$

$\overline{PZ_t}$: Price of the industrial product at time period t (given from the CGE model)
$\overline{q_t}$: Industry demand at time period t (given from the CGE model)
$ELAS_t$: Price elasticity of the industrial product demand at time period t[9]
$Capital\ \ cost_t$: Capital cost of the industry at time period t
$Labor\ \ cost_t$: Labor cost of the industry at time period t
$Energy\ \ cost_t$: Energy cost of the industry at time period t

[9] This elasticity is a step size to find solutions of the hybrid model and affects convergence speed. Elasticities of all linked industries excluding the cement industry are assumed to be 1. The elasticity of the cement industry is assumed to be 0.5 for the convergence of the cement industry.

$$\max_{q_t, x_{TECH,t}, Y_{TECH,t}} \sum_{t=0}^{35} \overline{Discount_t} * [\overline{PZ_t} * q_t * \left(1 - \frac{q_t - 2 * \overline{q_t}}{2 * ELAS_t * \overline{q_t}}\right) - (Capital\ \ cost_t + Labor\ \ cost_t + Energy\ \ cost_t)] \qquad \text{Eq. (4.4)}$$

The industrial bottom-up model endogenously finds industry supply, energy consumption and total capacity based on delivered CGE information such as industry demand, price indices, an interest rate and a wage index. Capital, labor, energy and non-energy inputs of the linked industries are obtained after finding solutions of the bottom-up model. The bottom-up model delivers input information to the CGE model.

Eq. (4.5) explains capital cost of the industry in the bottom-up model. Similar to the single bottom-up model, capital cost is determined by total capacity. However, unlike the single bottom-up model, a capital recovery factor depends on an interest rate from the CGE model. Eq. (4.6) describes labor cost of the industry in the bottom-up model. Labor cost is also dependent on total capacity. A wage index from the CGE model also affects labor cost.

$$Capital\ \ cost_t = \sum_{TECH \in Process} INVEST_{TECH} * CRF_{TECH,t} * Y_{TECH,t} \qquad \text{Eq. (4.5)}$$

$INVEST_{TECH}$: Unit investment cost of technology $TECH$
$CRF_{TECH,t}$: Capital recovery factor of technology $TECH$ at time period

$$Labor\ \ cost_t = \sum_{TECH \in Process} \overline{w_t} * OM_{TECH} * Y_{TECH,t} \qquad \text{Eq. (4.6)}$$

$\overline{w_t}$: Wage index at time period t (given from the CGE model)
OM_{TECH}: Unit operation and maintenance cost of technology $TECH$

Eq. (4.7) shows energy cost of the industry in the bottom-up model. Energy cost is determined by fuel price index, which is also from the CGE model. The single bottom-up model employs given predictive values for an interest rate, a wage index and fuel price indices. By contrast, in the hybrid model, price indices are endogenously determined in the CGE model and delivered to the bottom-up model.

$$\begin{aligned} Energy\ \ cost_t &= \sum\nolimits_{TECH \in Process} 0.5 * b_{TECH,t} * x_{TECH,t}^2 \\ &= \sum\nolimits_{TECH \in Process} 0.5 * \frac{\overline{PI_{TECH,t}} * EPRICE_{TECH} + \lambda_{TECH,t}}{\overline{x_{TECH,0}}} * x_{TECH,t}^2 \end{aligned} \qquad \text{Eq. (4.7)}$$

$b_{TECH,t}$: Slope of presumed marginal cost of technology $TECH$ at time period t
$\overline{PI_{TECH,t}}$: Fuel price index of technology $TECH$ at time period t (given from the CGE model)
$EPRICE_{TECH}$: Unit fuel price of technology $TECH$
$\lambda_{TECH,t}$: Lagrange multiplier of technology $TECH$ at time period t
$\overline{x_{TECH,0}}$: Base-year energy consumption of technology $TECH$

The CGE model explains non-energy inputs and taxes as well as the capital, labor and energy inputs. By contrast, the bottom-up model explains linked industries' capital, labor and energy inputs based on the optimal technology mix, and there is no information about non-energy inputs and taxes in the bottom-up model. That is, the bottom-up model explains industry supply using only parts of industry demand, which does not include non-energy inputs and taxes that occupy large parts of industry demand.

This study solves this problem based on KEI (2019). KEI (2019) added dummy technologies to describe CGE inputs that are not explained with the bottom-up model. Table 4.3 shows linked industry's inputs in each model. The linked industry in the bottom-up model pays capital, labor and energy costs to provide final energy demand (a thousand TOE). The linked industry in the CGE model pays $A+B+C+D$ billion KRW to produce domestic output. From the second row in Table 4.3, the ratio between energy consumption and money is derived. The ratio is a/A thousand TOE/billion KRW.

Table 4.4 shows decisions on energy consumption of dummy technologies. Unknown information in Table 4.3 is calculated using the ratio. Dummy technology for unknown energy inputs consumes $B*\frac{a}{A}$ thousand TOE. Since the share of tax in linked industry's demand is small, tax is incorporated with non-energy inputs. Dummy technology for non-energy inputs and tax in the bottom-up model consumes $(C+D)*\frac{a}{A}$ thousand TOE. As the ratios for all inputs are equivalent, final energy demand of the bottom-up model increases from a thousand TOE to $(A+B+C+D)*\frac{a}{A}$ thousand TOE.

While the CGE model uses multiple non-energy inputs, the bottom-up model explains the non-energy inputs using one dummy technology. Although the bottom-up model calculates cost information of one dummy technology, it divides the information depending on the share of non-energy inputs in the CGE model.

Table 4.3. Linked industry's inputs in each model

	Bottom-up (Unit: thousand TOE)	CGE (Unit: billion KRW)
Capital, labor and energy inputs	a	A
Energy inputs (unknown in the bottom-up model)	Unknown	B
Non-energy inputs	Unknown	C
Tax	Unknown	D
Total	a	$A + B + C + D$

Table 4.4. Decisions on energy consumption of dummy technologies

	Bottom-up (Unit: thousand TOE)	CGE (Unit: billion KRW)
Capital, labor and energy inputs	a	A
Energy inputs (unknown in the bottom-up model)	$B * \frac{a}{A}$	B
Non-energy inputs and tax	$(C + D) * \frac{a}{A}$	$C + D$
Total	$(A + B + C + D) * \frac{a}{A}$	$A + B + C + D$

4.3.4 Modification of the CGE model

The CGE model is modified as follows. First, linked industries' inputs and domestic outputs, which are endogenous variables in the CGE model, are parameterized, and the production nests of the linked industries are eliminated in the hybrid model. The bottom-up model endogenously determines linked industries' inputs and domestic outputs and delivers them to the CGE model as parameters. Second, additional profits of the linked industries are transferred to the household. The profits of the linked industries may be larger than 0 because the bottom-up model, which does not consider zero profit conditions, determines linked industries' inputs and domestic outputs. Since the CGE model assumes that producers' profits are equal to 0, the additional profits are inconsistent with the assumption of the CGE model. To handle this problem, KEI (2015) assumed that the household used the additional profits.

Eq. (4.8) shows linked industries' capital inputs. In the CGE model, capital input is determined in the capital-energy composite nest. However, in the hybrid model, the bottom-up model determines capital input depending on technology mix. Linked industries' capital inputs are $\overline{K_{J,t}}$.

$$K_{j,t} = \overline{K_{J,t}} \ \ for \ \ j \in Linked \ \ industries \qquad \text{Eq. (4.8)}$$

Eq. (4.9) shows linked industries' labor inputs. Although labor input is determined in the energy-value added composite nest of the CGE model, the hybrid model obtains labor input based on technology mix of the bottom-up model. Linked industries' labor inputs are $\overline{L_{J,t}}$.

$$L_{j,t} = \overline{L_{J,t}} \ \ for \ \ j \in Linked \ \ industries \qquad \text{Eq. (4.9)}$$

Eq. (4.10) explains linked industries' energy inputs. The CGE model employs energy inputs to produce energy composite. However, in the hybrid model, technology mix of the bottom-up model determines energy inputs. Linked industries' production nest structures are not employed in the hybrid model. Linked industries' energy inputs are $\overline{X_{\iota,J,t}}$.

$$X_{i,j,t} = \overline{X_{\iota,J,t}} \ \ for \ \ i \in Energy \ \ sector \ \ and \ \ j \in Linked \ \ industries \qquad \text{Eq. (4.10)}$$

Eq. (4.11) describes linked industries' non-energy inputs. The producer in the CGE model uses more non-energy inputs to produce more domestic output. In the hybrid model, the bottom-up model determines non-energy inputs, which are proportional to industry supply. Linked industries' non-energy inputs are $\overline{X_{\iota,J,t}}$.

$$\begin{aligned} X_{i.j,t} = \overline{X_{\iota,J,t}} \ \ & for \ \ i \in Non-energy \ \ sector \\ & and \ \ j \in Linked \ \ industries \end{aligned} \qquad \text{Eq. (4.11)}$$

Eq. (4.12) shows linked industries' domestic outputs (industry demand). The CGE model determines domestic output depending on its price and the zero profit condition. The producer produces more domestic output when its price is higher. In the hybrid model, the bottom-up model determines industry supply and delivers this information to the CGE model as industry demand. This study eliminates the zero profit condition and assumes that linked industries' domestic outputs are $\overline{Z_{J,t}}$.

$$Z_{j,t} = \overline{Z_{J,t}} \qquad \text{Eq. (4.12)}$$

Eq. (4.13) shows the additional profits of the linked industries. The producer earns PZ_j for a unit of domestic output. The producer uses capital, labor, energy and non-energy inputs to produce domestic output and pays R, $WAGE$, $PQCTAX_i$ and PQ_i for a unit of input, respectively. Eq. (4.14) is modified household consumption. In the hybrid model, the additional profits ($ADDPROFIT$) of the linked industries are transferred to the household.

$$\begin{aligned} ADDPROFITS = \sum\nolimits_{j \in Linked\ \ industries} & [PZ_j * Z_j - R * K_j - WAGE * L_j \\ & - \sum\nolimits_{i \in Energy\ \ sector} PQCTAX_i * X_{i.j} \qquad \text{Eq. (4.13)} \\ & - \sum\nolimits_{i \in Non-energy\ \ sector} PQ_i * X_{i,j} - CO2P_j * CTAX * CPI * Z_j] \end{aligned}$$

$$HX_i = \frac{\alpha_i * (R * KS * RATE + WAGE * \bar{L} + TCTAX + ADDPROFITS + -HS - DT)}{[(1 + HITR_i) * PQ_i + (PQCTAX_i - PQ_i)]} \qquad \text{Eq. (4.14)}$$

4.3.5 Information delivery from the bottom-up model to the CGE model

The bottom-up model endogenously determines energy consumption of technology, total capacity of technology and industry supply. Capital, labor, energy intermediate and non-energy inputs are calculated based on energy consumption and total capacity of technology.

Eq. (4.15) explains the calculation of capital inputs. The producer pays capital costs, which are the annualized investment costs to install capacity of technology. The bottom-up model calculates capital inputs by dividing capital costs with an interest rate.

$$\overline{K_{J,t}} = \frac{Capital\ \ cost_{j,t}}{R_t} = \frac{\sum_{TECH \in Process}[INVEST_{j,TECH} * CRF_{j,TECH,t} * Y_{j,TECH,t}]}{R_t} \qquad \text{Eq. (4.15)}$$

Labor inputs are calculated as per Eq. (4.16). The producer pays labor costs, which are costs to operate and manage capacity of technology. The bottom-up model calculates labor inputs by dividing labor costs with a wage index.

$$\overline{L_{J,t}} = \frac{Labor\ \ cost_{j,t}}{WAGE_t} = \frac{\sum_{TECH \in Process}[\overline{w_t} * OM_{j,TECH} * Y_{j,TECH,t}]}{WAGE_t} \qquad \text{Eq. (4.16)}$$

Eq. (4.17) calculates energy inputs. Energy costs are determined depending on the energy consumption of the producer and scaled using the scale coefficient $ENSCALE_{i,j}$ for consistency. The scale coefficient is calculated by dividing initial energy input at time period 0 with initial energy cost at time period 0 in Eq. (4.18). It is based on the assumption that initial ratio between two variables at time period 0 is maintained over time and iteration.

$$\begin{aligned} \overline{X_{\iota,J,t}} &= ENSCALE_{i,j} * Energy\ \ cost_{i,j,t} \\ &= ENSCALE_{i,j} * \sum\nolimits_{TECH \in i} \overline{PI_{TECH,t}} * EPRICE_{TECH} \\ &* x_{j,TECH,t}\ \ for\ \ i \in Energy\ \ sector \end{aligned} \qquad \text{Eq. (4.17)}$$

$$ENSCALE_{i,j} = \frac{X0_{i,j,0}}{Energy\ \ cost0_{i,j,0}} \qquad \text{Eq. (4.18)}$$

$ENSCALE_{i,j}$: Scale coefficient for the energy input i of the linked industry j

$X0_{i,j,0}$: Demand for the energy input i of the linked industry j at time period 0 (initial iteration)

$Energy\ \ cost0_{i,j,0}$: Energy cost for the energy input i of the linked industry j at time period 0 (initial iteration)

Non-energy inputs are calculated based on Eq. (4.19). The producer determines consumption of non-energy dummy technology in the bottom-up model. Non-energy costs are adjusted with the scale coefficient $NENSCALE_{i,j}$ and distributed to each non-energy input depending on $NENSHARE_{i,j}$. The share and the scale coefficient are calculated using Eq. (4.20) and Eq. (4.21). They are determined depending on initial non-energy input at time period 0.

$$\begin{aligned}\overline{X_{\iota,J,t}} &= NENSHARE_{i,j} * NENSCALE_{i,j} * NEnergy\ \ cost_{i,j,t} \\ &= NENSHARE_{i,j} * NENSCALE_{i,j} \\ &\quad * \sum_{TECH\in i} \overline{PI_{TECH,t}} * EPRICE_{TECH} * x_{j,TECH,t}\end{aligned} \qquad \text{Eq. (4.19)}$$

$$for\ \ i \in Non-energy\ \ sector$$

$$NENSHARE_{i,j} = \frac{X0_{i,j,0}}{\sum_{i\in Non-energy\ \ sector} X0_{i,j,0}} \qquad \text{Eq. (4.20)}$$

$$for\ \ i \in Non-energy\ \ sector$$

$$NENSCALE_{i.j} = \frac{X0_{i,j,0}}{NENSHARE_{i,j} * NEnergy\ \ cost_{i,j,0}} \qquad \text{Eq. (4.21)}$$

$$for\ \ i \in Non-energy\ \ sector$$

$NENSHARE_{i,j}$: Share of the non-energy input i of the linked industry j

$NENSCALE_{i,j}$: Scale coefficient for the non-energy input i of the linked industry j

$NEnergy\ \ cost_{i,j,t}$: Non-energy cost of the non-energy input i of the linked industry j at time period t

$X0_{i,j,0}$: Demand for the non-energy input i of the linked industry j at time period 0 (initial iteration)

$NEnergy\ \ cost0_{i,j,0}$: Non-energy cost for the non-energy input i of the linked industry j at time period 0 (initial iteration)

According to Eq. (4.1), industry supply is endogenously determined in the bottom-up model. Eq. (4.22) explains delivery of industry supply to the CGE model. The CGE model uses industry supply from the bottom-up model as domestic output.

$$\overline{Z_{J,t}} = q_t \quad \text{Eq. (4.22)}$$

4.3.6 Information delivery from the CGE model to the bottom-up model

The CGE model endogenously determines an interest rate, a wage index, price indices and industry demand. The bottom-up model requires this information to solve its optimization problem. The bottom-up model updates parameters based on delivered information.

Eq. (4.23) shows the discount rates, which is calculated using the interest rates. In the single bottom-up model, an interest rate is a constant value, which does not change depending on capital stock, savings and investments, and cannot reflect the impacts of economic changes on the interest rate. In the hybrid model, the CGE model gives the endogenously determined interest rate to the bottom-up model.

$$\overline{Discount_t} = \frac{1}{(1 + R_t)^t} \qquad \text{Eq. (4.23)}$$

The bottom-up model requires a wage index to calculate labor costs and inputs. When technology mix in the bottom-up model changes, labor demand also changes because operation and management costs depend on technology mix. Although the wage index is affected by labor demand and supply, it is generally given in the bottom-up model. As Eq. (4.24) indicates, in the hybrid model, the bottom-up model uses the wage index from the CGE model.

$$\overline{w_t} = WAGE_t \qquad \text{Eq. (4.24)}$$

Similar to the interest rate and the wage index, the bottom-up model cannot reflect endogenous changes in energy prices. Endogenously determined energy prices in the CGE model are delivered to the bottom-up model according to Eq. (4.25). The bottom-up model updates technology mix and the slope of the marginal cost function based on energy price indices.

$$\overline{PI_{TECH,t}} = PQCTAX_{i.t} \ \ for \ \ TECH \in i \qquad \text{Eq. (4.25)}$$

The bottom-up model solves its surplus maximization problem and obtains industry supply. The bottom-up model determines new quantity (q_t) based on previous quantity ($\overline{q_t}$) from the CGE model. Eq. (4.26) describes the delivery of industry demand to the bottom-up model.

$$\overline{q_{J,t}} = Z_{j,t} \qquad \text{Eq. (4.26)}$$

4.3.7 Convergence test

At the end of each iteration, the hybrid model tests whether the linked variables are at a convergence level. If the difference of the linked variables in the previous and current iterations are less than 0.1%, then the hybrid model ends the information exchange process. That is, the values of the linked variables in the last iteration are the solutions of the hybrid model.

$$\max_{j,t}\left[\frac{LV_{j,t,iter} - LV_{j,t,iter-1}}{LV_{j,t,iter-1}} * 100\right] < 0.1\% \qquad \text{Eq. (4.27)}$$

$$for \ \ all \ \ linked \ \ variables$$

$LV_{j,t,iter}$: Linked variables of the linked industry j at time period t and iteration $iter$

4.3.8 Calibration of domestic output

It is necessary to set appropriate BAU domestic output in the hybrid model because emissions largely depend on production scale. This study employs the calibration method of KEI (2019), which calibrates linked industries' domestic outputs in the single CGE model.

This study uses PMP to calibrate the BAU domestic outputs of the linked industries. Whereas the single bottom-up model calibrates energy consumption in time period 0, the hybrid model reproduces energy consumption in all time periods. Since only base-year energy consumption is observable, energy consumption in other time periods is projected using the domestic output of the single CGE model. This study assumes that energy consumption in future time periods increases based on an increase in the domestic output of the single CGE model. Eq. (4.28) shows the projection of energy consumption of technology in future time periods.

$$\overline{x_{J,TECH,t}} = \overline{x_{J,TECH,0}} * \frac{\overline{Z_{J,t}}}{\overline{Z_{J,0}}} \qquad \text{Eq. (4.28)}$$

Eq. (4.29) is the constraint that forces the bottom-up model to calibrate $\overline{x_{J,TECH,t}}$. The bottom-up model solves its surplus maximization problem and obtains solutions around $\overline{x_{J,TECH,t}}$. Then, industry supply calibrates the domestic output of the single CGE model because the sum of energy consumption of each technology is equal to final energy demand. After solving the surplus maximization problem under Eq. (4.29), the Lagrange multipliers for all periods are obtained.

$$x_{j,TECH,t} \leq (1+\varepsilon) * \overline{x_{J,TECH,t}} \qquad \text{Eq. (4.29)}$$

4.3.9 Scenario

Table 4.5 summarizes the scenarios in this chapter. LINK_BAU is the BAU scenario, which excludes new technology and the carbon tax. This scenario compulsorily prevents the adoption of new technology that should be adopted in the future. In the LINK_NEW scenario, the linked industries adopts new technology based on the KETEP database without the carbon tax. The LINK_BAU_CTAX and LINK_NEW_CTAX scenarios introduces the carbon tax in Chapter 3 to investigate impacts of new technology adoption on emissions and abatement costs.

Table 4.5. Scenario description

Scenario	Description
LINK_BAU	Hybrid model Only current technology No carbon tax
LINK_NEW	Hybrid model New technology adoption (Linked industries) No carbon tax

LINK_BAU_CTAX	Hybrid model Only current technology Carbon tax: 30–360 thousand KRW/ton CO2eq (2015–2050)
LINK_NEW_CTAX	Hybrid model New technology adoption (Linked industries) Carbon tax: 30–360 thousand KRW/ton CO2eq (2015–2050)

4.4 Results

4.4.1 BAU

Table 4.6 shows the deviations of the linked variables between the previous and current iterations and explains the convergence process in the BAU scenario. The deviations in the first and second iterations are almost equal, which implies that information exchange until the second iteration does not narrow the deviations. In the third and fourth iteration, the deviations sharply decrease. An interest rate and a wage index already satisfy the convergence condition. As the deviations decrease, all linked variables excluding an output price index converge in the seventh iteration. An output price index, which has the slowest convergence speed, converges in the tenth iteration. Solutions of the other scenarios also converge based on a similar process of convergence of the BAU scenario.

Table 4.6. Convergence process of the hybrid model (BAU) (Unit: %)

Iteration number	Energy input	Non-energy input	Capital input	Labor input	Interest rate	Wage index	Domestic output	Output price index
1	3.22	2.96	3.11	2.54	2.91	5.60	2.96	20.55
2	3.22	2.96	3.11	2.54	2.91	5.60	2.96	20.55
3	1.45	1.38	1.15	1.13	0.06	0.16	1.37	9.91
4	0.70	0.66	0.45	0.44	0.03	0.07	0.66	4.93
5	0.34	0.32	0.19	0.19	0.01	0.02	0.31	2.29
6	0.17	0.15	0.09	0.09	0.00	0.01	0.15	1.11
7	0.08	0.07	0.04	0.04	0.00	0.00	0.07	0.53
8	0.04	0.03	0.02	0.02	0.00	0.00	0.03	0.25
9	0.03	0.02	0.01	0.01	0.00	0.00	0.02	0.12
10	0.01	0.03	0.00	0.00	0.00	0.00	0.01	0.06

National emissions are higher in the hybrid model (Figure 4.3). Since there is no production nests of the linked industries in the hybrid model, the energy efficiency of the linked industries does not improve based on the AEEI. Thus, the 2050 national emissions in the hybrid model are 33% higher than those in the CGE model. Assuming that technology efficiency in the bottom-up model improves, national emissions in the hybrid model can be lower. However, it is less meaningful to use an explicit technology database if bottom-up technology efficiency is adjusted.

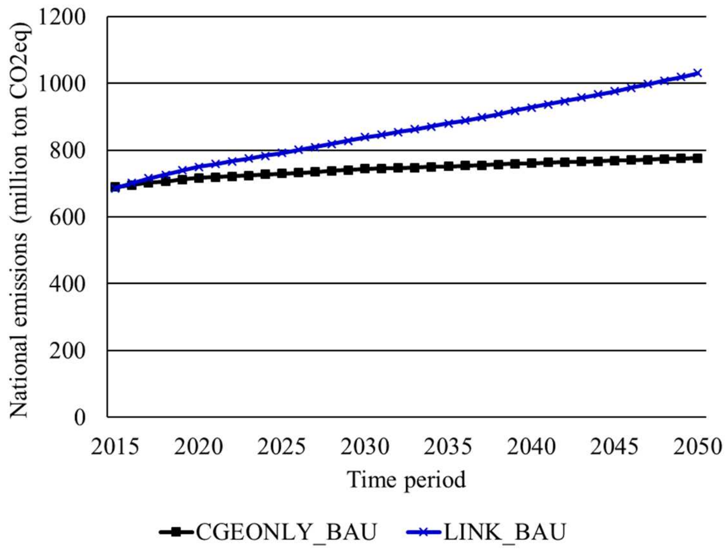

Figure 4.3. National emissions in the CGEONLY_BAU and LINK_BAU scenarios (Unit: million ton CO2eq)

Contrary to national emissions, GDP is lower in the hybrid model (Figure 4.4). The AEEI induces a domestic output increase because it contributes to a more efficient production of the energy composite. This change in domestic output leads to GDP growth. Since the AEEI of the linked industries in the hybrid model does not improve, they have a higher domestic output in the CGE model. Thus, GDP is larger in the CGE model.

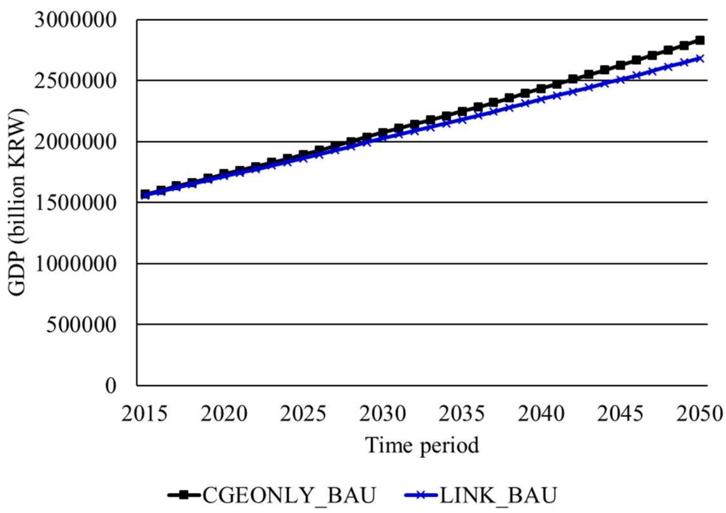

Figure 4.4. GDP in the CGEONLY_BAU and LINK_BAU scenarios (Unit: billion KRW)

4.4.2 Impacts of new technology adoption

The liked industries adopt new technology in future periods. New technology adoption induces efficiency improvement in energy service technology (Figure 4.5). The relative efficiency is derived based on the reference efficiency, which is the initial efficiency of the energy service technology in LINK_BAU.

In LINK_BAU, the relative efficiency is almost unchanged because only the current technologies are employed.[10] By contrast, in LINK_NEW, the relative efficiency improves in the year that the new technology is introduced. Moreover, it improves when the current technology expires and is replaced by the new technology.

[10] This study uses the steel industry as an example to explain technology-level results.

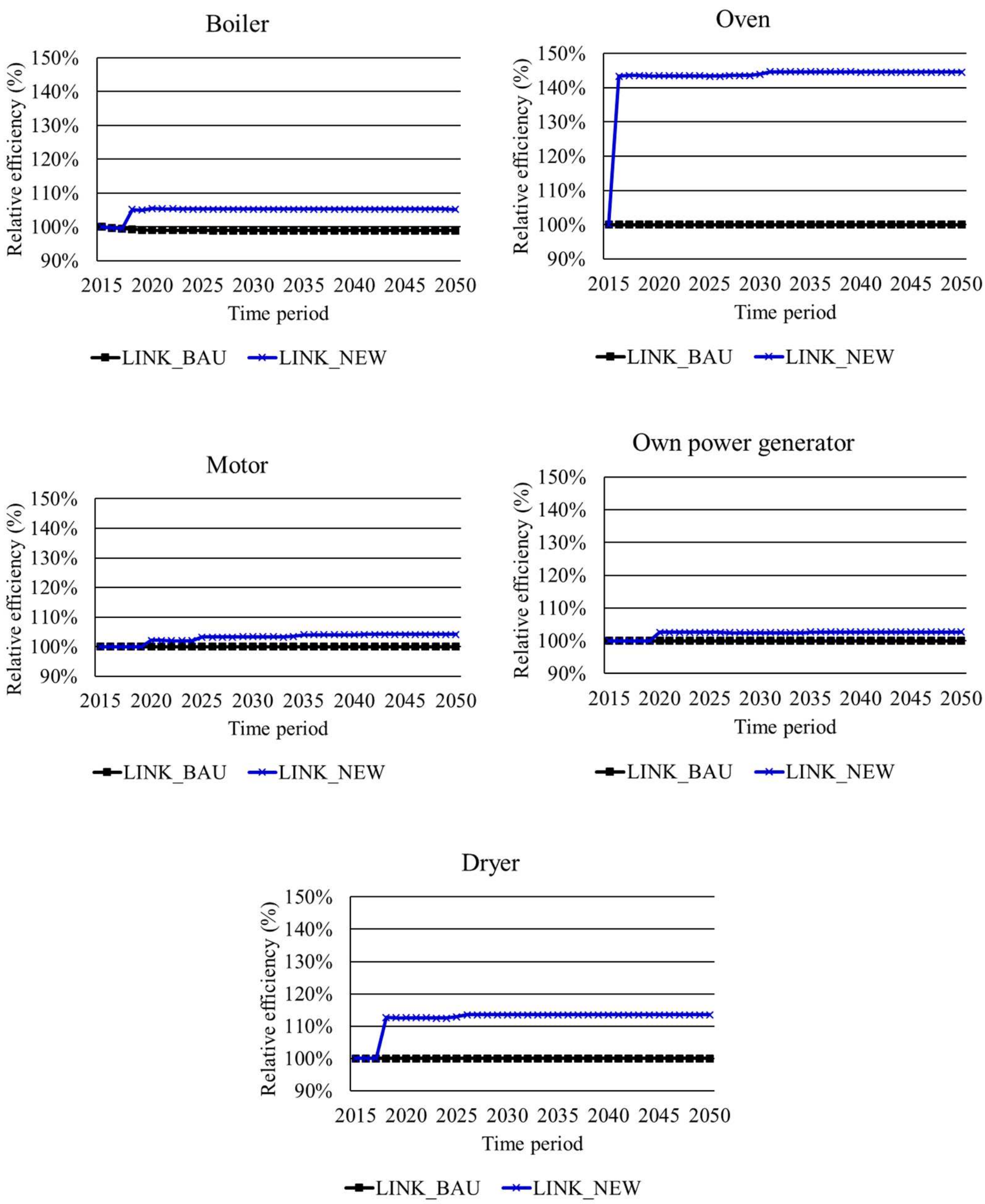

Figure 4.5. Relative efficiency of energy service technology in the steel industry (Unit: %)

The linked industries produce more energy services per energy consumption through new technology adoption. The efficiency improvement of oven technology is the most significant, while the boiler, motor, and own power generator technologies experience efficiency improvements of less than 10%.

When the steel industry does not adopt new technology, the share of new technology is 0% (Figure 4.6). By contrast, in LINK_NEW, the share increases and is kinked in several time periods. In 2016, the new oven technology is introduced, and the share increases from 0% to 30%. Since the new oven technology has significantly higher efficiency than the current technology, the share steeply rises. In 2018, new boiler and dryer technologies are introduced, and the share steeply rises as well. That is, the technology mix sharply changes when industries adopt new technology. The degree of change depends on a level of efficiency improvement.

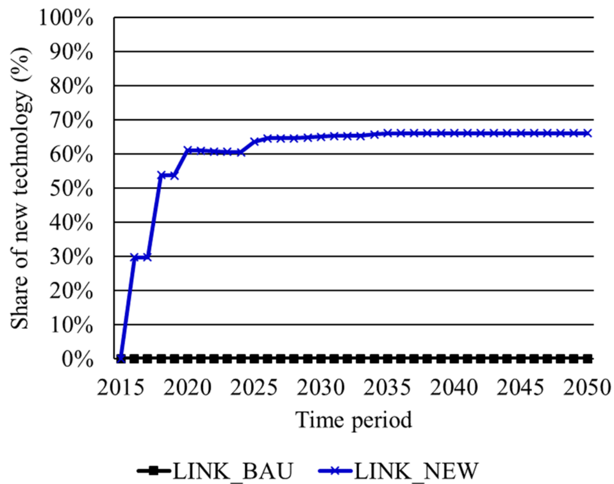

Figure 4.6. Share of new technology in the steel industry (Unit: %)

Efficiency improvement due to new technology contributes to domestic output increases as well as emissions reduction. Since the marginal costs of the linked industries decrease due to efficiency improvement, the linked industries expand their production (Figure 4.7 and Figure 4.8). Additionally, due to decreases in the marginal costs, the prices of the domestic outputs of the linked industries also decrease (Figure 4.9 and Figure 4.10).[11] Since the unlinked sectors employ the products of the linked industries as intermediate inputs, they experience indirect effects.

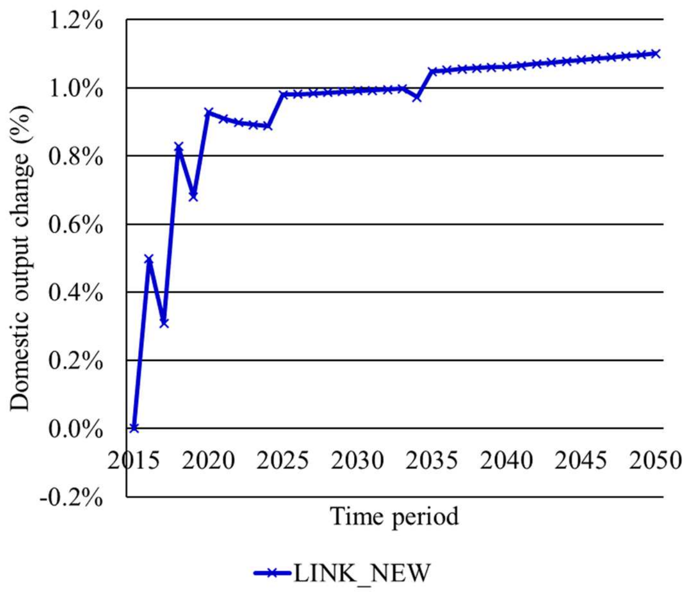

Figure 4.7. Domestic output change in the linked industries (compared to LINK_BAU) (Unit: %)

[11] $Weighted\ domestic\ output\ price = \frac{\sum_{i \in Linked\ industries} Z_i * PZ_i}{\sum_{i \in Linked\ industries} Z_i}$

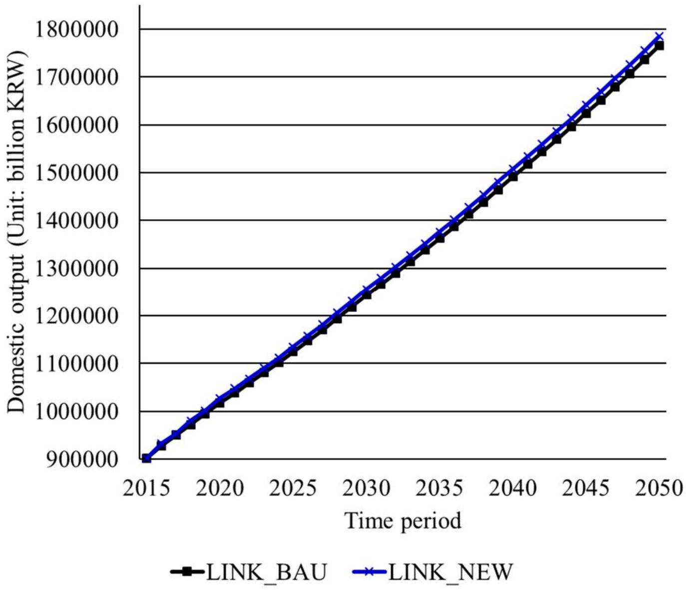

Figure 4.8. Domestic output of the linked industries (Unit: billion KRW)

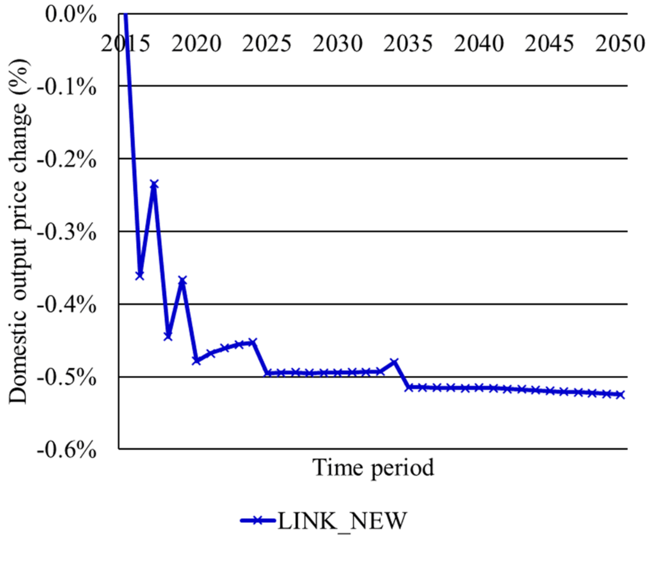

Figure 4.9. Changes in weighted domestic output price of the linked industries (compared to LINK_BAU) (Unit: %)

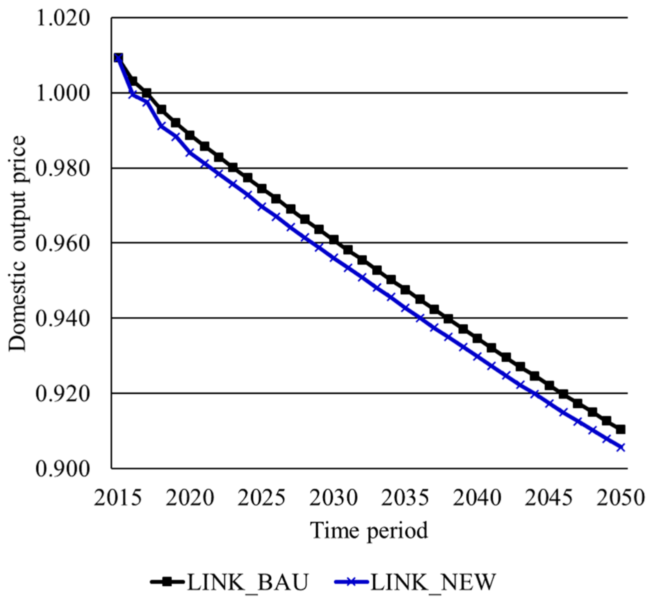

Figure 4.10. Weighted domestic output price of the linked industries

New technology reduces energy consumption in the linked industries. A decrease in the energy demand of the linked industries reduces total energy demand (Figure 4.11). Due to adoption of new oven technologies in 2016, the total energy demand for the linked fuels[12] decreases 1.3%p. As the linked industries introduce other new technologies, the total energy demand for the linked fuels decreases. Since energy prices rely on energy demand, the weighted energy price for the linked fuels also drops (Figure 4.12). The unlinked sectors experience indirect effects of new technology adoption in the linked industries through changes in energy prices.

[12] Coal, coal product, gasoline, kerosene, diesel, heavy oil, LPG, city gas, heat and electricity.

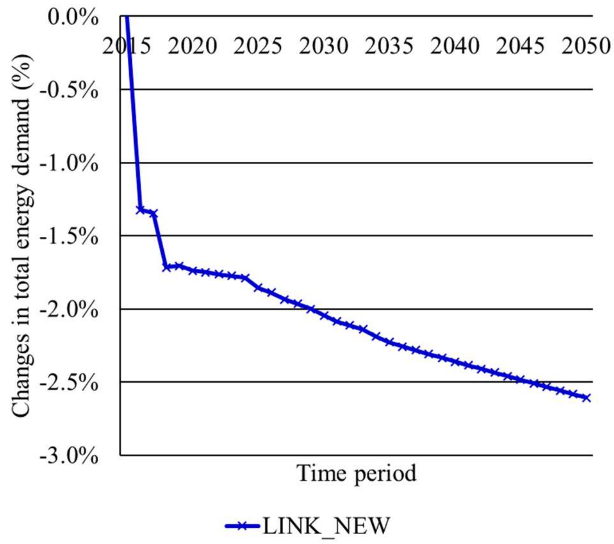

Figure 4.11. Changes in total energy demand for the linked fuels (compared to LINK_BAU) (Unit: %)

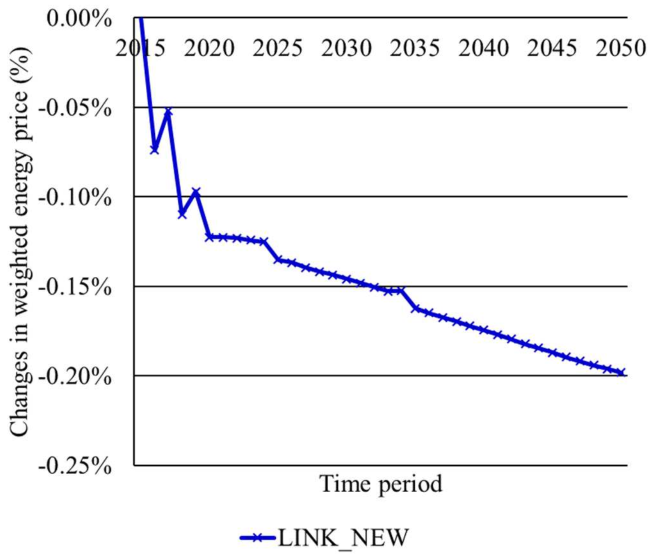

Figure 4.12. Changes in weighted energy price of the linked fuels (compared to LINK_BAU) (Unit: %)

4.4.3 Carbon tax simulation

When the government imposes a carbon tax, the production sectors replace their energy inputs with capital input and reduces their production activities. The household also decreases its energy consumption. These changes in the production sectors and the household decreases energy consumption and emissions in the economy.

Without new technology, the emissions of the linked industries in 2015 decrease by 4.3% (Figure 4.13). As the government imposes more carbon tax, its reduction effects are more significant. In 2050, the linked industries that use only current technologies reduces 21.2% of their BAU emissions, although the effects of additional carbon taxes gradually diminish.

In LINK_NEW_CTAX, the emissions of the linked industries in 2015 are equivalent to the emissions of LINK_BAU_CTAX. However, the linked industries have more potential to mitigate their emissions after 2016 due to the introduction of new technology. In 2016, the linked industries that adopt new oven technologies achieve 50% more emissions reductions compared to LINK_BAU_CTAX. In 2050, the efficiency improvement in the linked industries induces a 1.2%p increase in the reduction rate.

Although new technology helps to reduce more emissions, its impacts decline due to the rebound effect. Efficiency improvement reduces the production costs of the linked industries. Then, their outputs and emissions rebound. Rebounding emissions decrease the reduction effects of new technology. Chapter 5 will investigate the rebound effect in detail.

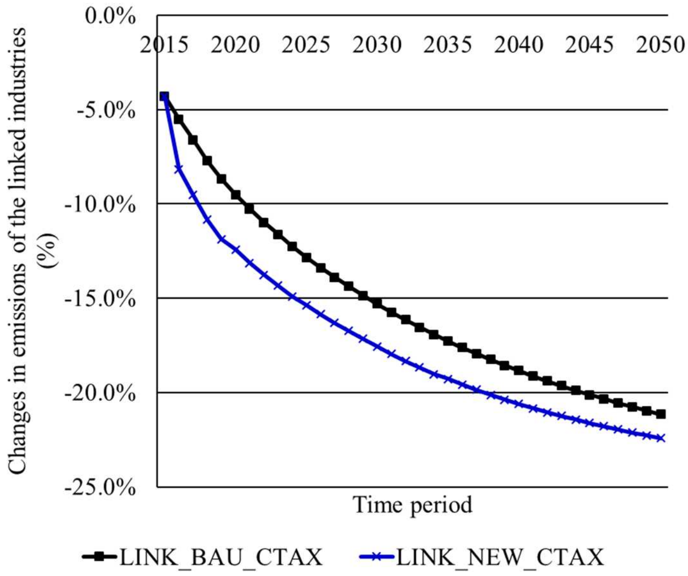

Figure 4.13. Changes in emissions of the linked industries (compared to LINK_BAU) (Unit: %)

The adoption of new technology by the linked industries also affects national emissions (Figure 4.14). Since the linked industries generate about 30% of national emissions, new technology directly decreases national emissions. Moreover, the production sectors excluding the linked industries change their production activities because the prices of the products of the linked industries drop. Changes in the production activities of the unlinked sectors indirectly affect national emissions.

With new technology and the carbon tax, 40.7% of the 2050 national emissions are mitigated, which implies that the linked industries have less potential for emissions reduction. Since the linked industries are integrated, the technology mix in the bottom-up model determines their emissions. For example, the steel industry uses a large and fixed amount of bituminous coal as raw material. Although the price of bituminous coal rises due to the carbon tax, the steel industry cannot reduce its use of bituminous coal. That is, the linked industries may reduce emissions to a lesser extent because of constrains in the bottom-up model.

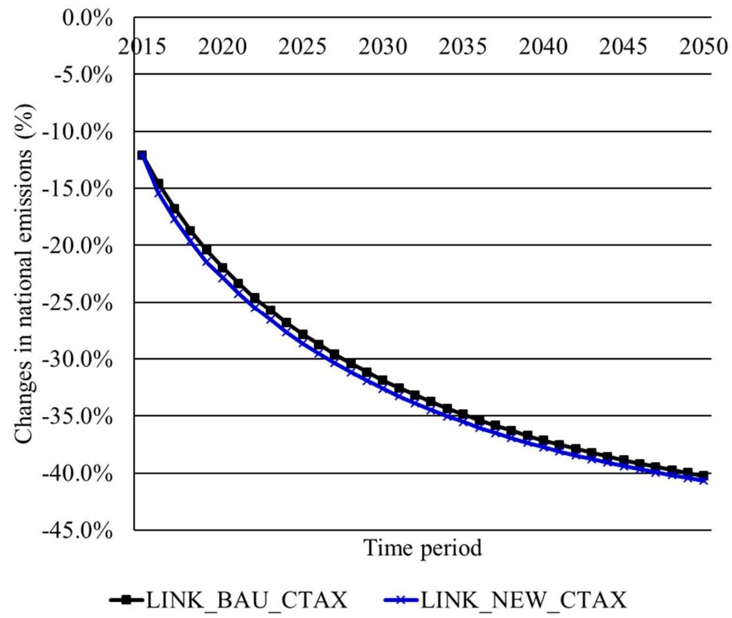

Figure 4.14. Changes in national emissions (compared to LINK_BAU) (Unit: %)

Although the government collects the carbon tax and transfers it to the household, GDP decreases because it restricts production activities (Figure 4.15). In LINK_BAU_CTAX, the GDP loss constantly decreases, and the carbon tax reduces 1.4% of GDP in 2050.

New technology mitigates GDP loss because domestic outputs of the linked industries increase (see Figure 4.7). Moreover, decreases in the prices of the products of the linked industries and energy prices due to new technology also help the production activities of the unlinked sectors. That is, the impacts of new technology adoption in Section 4.4.2 reduce a carbon tax shock.

In 2016, the GDP loss in LINK_NEW_CTAX is kinked because the efficiency of new oven technologies significantly improves, which implies that the positive effects of the new oven technologies on GDP mitigate GDP losses due to the carbon tax. In 2050, the new technologies in the linked industries contribute to a 0.3%p decrease in GDP loss.

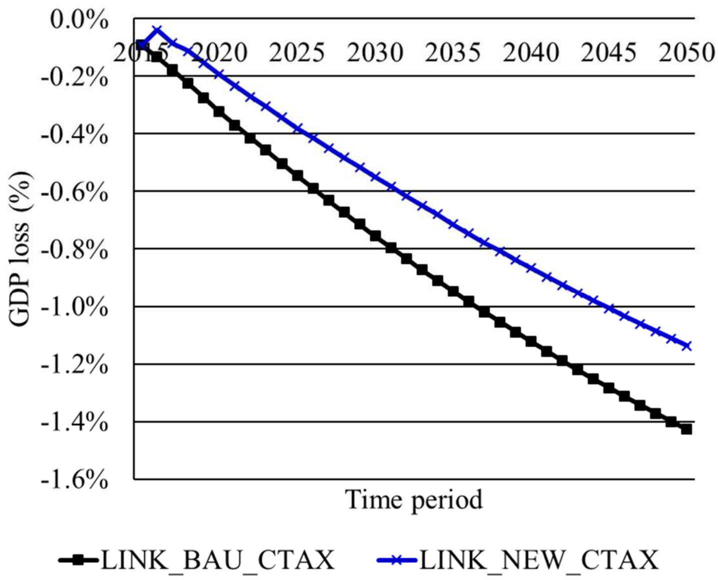

Figure 4.15. GDP loss due to the carbon tax (compared to LINK_BAU) (Unit: %)

The economy accepts the GDP loss to reduce emissions under a carbon tax policy. The unit abatement cost shows GDP loss to mitigate a unit of emissions (Figure 4.16). With new technology, the economy has lower costs compared to LINK_BAU_CTAX. The unit abatement cost is kinked in 2016 for the same reason that GDP loss is kinked in 2016. Due to efficiency improvement based on new technology adoption in the linked industries, the unit abatement cost of the economy decreases from 92 thousand KRW/ton CO2eq to 73 thousand KRW/ton CO2eq.

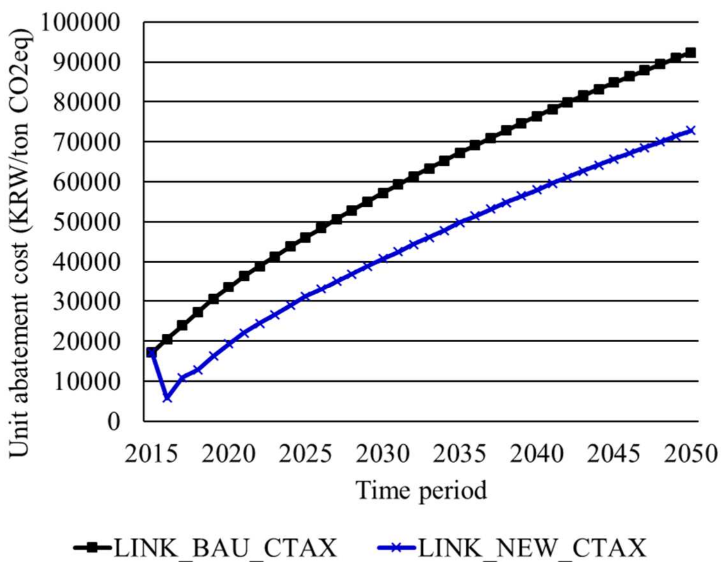

Figure 4.16. Unit abatement cost (compared to LINK_BAU) (Unit: KRW/ton CO2eq)

Chapter 5. Assessment of the rebound effect of efficiency improvement in the manufacturing sector based on the hybrid model

5.1 Introduction

5.1.1 Research background

The manufacturing sector reportedly emitted one-third of all 2017 global emissions if the calculation includes indirect emissions from heat and electricity (IEA, 2019). Since the manufacturing sector is a major emission source, managing its emissions are receiving increasing attention.

Efficiency improvement is one of the most promising reduction options for the manufacturing sector (de Pee et al., 2018). After the Paris Agreement, the UK and Japan designed efficiency improvement plans for their manufacturing sectors (UK government, 2017; The government of Japan, 2019). The Korean government also selected efficiency improvement plans to achieve about one-third of the manufacturing sector's reduction target in 2050 (Ministry of Environment, 2020).

Efficiency improvement mitigates emissions by reducing the energy consumed to provide energy services. However, efficiency improvement involves an unexpected increase in energy consumption. Efficiency improvement reduces producers' energy demand, implying that their total costs decrease. Then, energy service prices drop, which leads to an increase in energy service demand (Greening et al., 2000). The rebound effect indicates the unexpected rebound of energy consumption, which partially cancels out the effects of efficiency improvement (Berkhout et al., 2000). Assessing the rebound effect is important because it can be a potential obstacle to implementing efficiency improvement policies (Sorrell and Dimitropoulos, 2008).

Although the bottom-up and CGE models are representative models to investigate environmental policies, they are insufficient to assess the rebound effects of technology efficiency improvement. The bottom-up model explains technology efficiency improvement, but it does not describe the rebound of energy demand. The CGE model explores the changes in energy demand and ripple effects of efficiency improvement, but reflects technology efficiency improvement at a more aggregated level.

5.1.2 Research purpose

The hybrid model allows researchers to assess the rebound effect more precisely by adopting the advantages of the bottom-up and CGE models. It explicitly represents technological change in the manufacturing sector and explains the supply and demand changes in the economy.

This study assesses the rebounding emissions due to technology efficiency improvement in the manufacturing sector. Efficiency improves through new technology adoption. Since new technology is more efficient, it reduces energy consumption and affects the total costs in the manufacturing sector. The manufacturing sector changes its output, which in turn affects the rest of the economy. This study considers the rebound effects from the efficiency-improving sector and those outside of the efficiency-improving sector. Moreover, this study explores the factors that cause rebound effects and shows the impacts of the rebound effects on the reduction target. Finally, this study tests the impacts of the substitution elasticities in the CGE model on the rebound effects to identify the extent to which the results depend on the assumption of the CGE model.

5.2 Literature review

5.2.1 Classification of the rebound effect

As Turner (2013) mentioned an insufficient consensus regarding the rebound effect, previous studies have employed their own definition and classification of the rebound effect. The classification of Greening et al. (2000) has been adopted by many previous studies (see Sorrell and Dimitropoulos, 2008; Barker et al., 2009; Turner, 2013; Broberg et al., 2015; Lu et al., 2017) and included four rebound effects. A direct effect means that falling energy service prices induce more energy service demand. A secondary effect indicates that the price changes help to save expenditure for energy services and energy service demand changes based on the savings. An economy-wide effect measures the rebound effect because of the adjustment of the equilibrium in the economy. A transformational effect is the rebound effect from varying characteristics of consumers and institutions.

Böhringer and Rivers (2018) classified the rebound effect into partial and general equilibrium effects. Direct and indirect rebound effects are sorted as the partial equilibrium effect. An economy-wide rebound effect is classified as the general equilibrium effect. They reported that two-thirds of the rebound effects of efficiency improvement in the manufacturing sector were the partial equilibrium effect, whereas one-third of the rebound effects was the general equilibrium effect.

5.2.2 Approaches to assess the rebound effect

Jin and Kim (2019) explained approaches to assess the rebound effects. The CGE model reflects efficiency improvement by reducing energy consumption or prices and has an advantage in evaluating the general equilibrium effect. Panel and time-series analysis is also used to assess the rebound effects. In these analysis, energy prices are used as independent variables, which measure efficiency improvement that is difficult to observe. A macro-economic growth approach evaluates the rebound effects by calculating potential and actual energy savings. The rebound effects are represented as the differences between potential and actual energy savings. In this approach, efficiency is measured through changes in energy intensity.

Although these approaches are general in the literature, they have limitations in discussing technology efficiency improvement and exploring energy consumption at a technology level. If the approach cannot describe technologies in the manufacturing sector, it has difficulty in precisely assessing the rebound effects of technology efficiency improvement.

5.2.3 Previous studies on the rebound effect

There is no specific range for the rebound effects in the manufacturing sector (Table 5.1). Barker et al. (2007) employed an econometric model to investigate the rebound effects in the UK industries. They divided the UK industries into the energy-intensive industries and the other industry. They showed that the rebound effects were larger in the energy-intensive industries (27.0%) than the other industry (14.0%) in 2010. Lin and Li (2014) and Lin and Tian (2016) employed the dynamic ordinary least squares approach to estimate the rebound effects in Chinese heavy and light industries, respectively. According to their estimation, the rebound effects in the heavy industry (74.3%) were two times larger than the light industry (37.7%). Li et al. (2016) explored the rebound effects of the Chinese industrial sectors using the output distance function. They considered 36 industrial sectors and estimated the rebound effects as 88.4%.

There are several studies that tried to employ advantages of the bottom-up and top-down models. Barker et al. (2007) explored the rebound effects in the UK economy by partially combining both models. However, their efforts are insufficient to fully employ advantages of both models because their model less specifically describes bottom-up aspects. Howells et al. (2010) adopted the approach to deliver economic feedbacks to the bottom-up model to explore the Korean electricity sector. Their model employed input-output multipliers for the integration of economic feedbacks in the bottom-up model. Although Lehr et al. (2011) explored the rebound effects in Germany based on macro-econometric model as well as the bottom-up model, two models were not fully integrated.

Giraudet et al. (2012) investigated the rebound effects from French households by recursively solving two models. However, their model considered limited feedbacks of household and energy. Andersen et al. (2019b) developed the Danish hybrid model based on the soft-link approach and investigated impacts of energy efficiency policies. They considered a subsidy for investments in energy savings and a decrease in the barrier for the investments as the energy efficiency policies. According to their results, the rebound effect of the policies was 12.5%.

Table 5.1. Previous studies on the rebound effect in the manufacturing sector

Author	Country and sector	Period	Rebound effect
Bentzen (2004)	US manufacturing	1949-1999	24.0%
Barker et al. (2007)	UK industries	2000-2010	15.0–30.0% (2005) 14.0–27.0% (2010)
Lin and Li (2014)	Chinese heavy industry	1980-2011	74.3%
Lin and Tian (2016)	Chinese light industry	1980-2012	37.7%
Li et al. (2016)	Chinese industrial sectors	1998-2011	88.4%
Lin and Zhao (2016)	Chinese textile industry	1990-2012	20.9%

5.3 Rebound effect

5.3.1 Scenario

This study examines the scenarios in Chapter 4 to assess the rebound effects of technology efficiency improvement (Table 5.2). In the BAU scenario, the linked industries employs only the current technology and do not adopt new technology. In the LINK_NEW scenario, the linked industries introduce new technology based on its introduction year in the KETEP database. In the LINK_NEWNR scenario, the rebound effects are not considered and emissions are calculated based on the LINK_BAU and LINK_NEW scenarios.

Table 5.2. Scenario description

Scenario	Description
LINK_BAU	Hybrid model Only current technology
LINK_NEW	Hybrid model New technology adoption (Linked industries) With rebound effects
LINK_NEWNR	Hybrid model New technology adoption (Linked industries) Without rebound effects

5.3.2 Calculation of the rebound effect

This study considers two rebound effects based on their sources. A direct rebound effect is the rebounding emissions of the linked industries (efficiency-improving sectors) due to linked industries' efficiency improvement. An indirect rebound effect is the rebounding emissions of the unlinked sectors and the household energy consumption (the rest of the economy) due to linked industries' efficiency improvement.

Emission intensity is defined as emissions to produce a unit of output. When the linked industry j adopts new technology, emissions and output of the linked industry j also change. Eq. (5.1) shows emission intensity of the linked industry j in LINK_NEW. Emission intensity decreases if emissions are reduced or output increases.

$$EI_j^{NEW} = e_j^{NEW}/Z_j^{NEW} \qquad \text{Eq. (5.1)}$$

EI_j^{NEW}: Emission intensity of the linked industry j in LINK_NEW
e_j^{NEW}: Emissions of the linked industry j in LINK_NEW
Z_j^{NEW}: Output of the linked industry j in LINK_NEW

If there are no rebound effects, which means that output of the linked industry j does not rebound, emissions of the linked industry j is calculated by Eq. (5.2). Since output does not change, it maintains output in LINK_BAU. That is, emissions of the linked industry j drop based on a decrease in emission intensity.

$$e_j^{NR} = Z_j^{BAU} * EI_j^{NEW} \quad \text{Eq. (5.2)}$$

e_j^{NR}: Emissions of the linked industry j in LINK_NEWNR (without rebound effects)
Z_j^{BAU}: Output of the linked industry j in LINK_BAU

If there are rebound effects, which means that output of the linked industry j rebounds, a direct rebound effect is calculated by Eq. (5.3). The linked industry produces more output when the marginal cost drops due to new technology. Although new technology reduces emissions of the linked industry, its reduction effects are offset because of output expansion. A direct rebound ratio is calculated based on Eq. (5.4) and means the share of rebounding emissions in potential reduction.

$$Direct\ \ rebound\ \ effect$$
$$= \sum_j [\left(Z_j^{NEW} - Z_j^{BAU}\right) * EI_j^{NEW}] = \sum_j [\Delta Z_j * EI_j^{NEW}] \quad \text{Eq. (5.3)}$$

$$Direct\ \ rebound\ \ ratio = \frac{e_j^{NEW} - e_j^{NR}}{e_j^{BAU} - e_j^{NR}} \quad \text{Eq. (5.4)}$$

Eq. (5.5) calculates the indirect rebound effect. Changes in the linked industries also affects emission of the unlinked sectors and the household energy consumption. The indirect rebound effects are emission differences between LINK_BAU and LINK_NEW. The first and second terms indicates the indirect rebound effects from the unlinked sector and the household energy consumption, respectively.

$$Indirect\ rebound\ effect = \sum_j (e_j^{NEW} - e_j^{BAU}) + (e_H^{NEW} - e_H^{BAU}) \qquad \text{Eq. (5.5)}$$

e_j^{NEW}: Emissions of the unlinked sector j in LINK_NEW

e_j^{BAU}: Emissions of the unlinked sector j in LINK_BAU

e_H^{NEW}: Emissions of the household energy consumption in LINK_NEW

e_H^{BAU}: Emissions of the household energy consumption in LINK_BAU

5.4 Results

5.4.1 Impacts of efficiency improvement

In Section 4.4.2, this study investigated the impacts of new technology adoption. When the linked industries introduces new technology (Figure 4.6), their efficiency improves (Figure 4.5). Efficiency improvement causes the marginal costs and domestic output prices in the linked industries to drop (Figure 4.9). Due to decreasing prices, the linked industries expand their outputs (Figure 4.7). Moreover, new technology reduces energy demand (Figure 4.11) and energy prices (Figure 4.12).

Since the domestic outputs of the linked industries rebound, their emissions also rebound. Moreover, the domestic outputs and emissions of the unlinked sectors rebound because their costs drop based on the lower prices of intermediate inputs. Furthermore, decreasing energy prices cause the household to use more energy.

5.4.2 Direct rebound effect

In LINK_BAU, the 2050 emissions of the linked industries are 470.4 million ton CO2eq (Figure 5.1). In LINK_NEW, new technology adoption reduces 4.2% (19.8 million ton CO2eq) of the emissions from the linked industries. Although the outputs of the linked industries rebound, emissions decreases because the energy efficiency improvement reduces energy consumption.

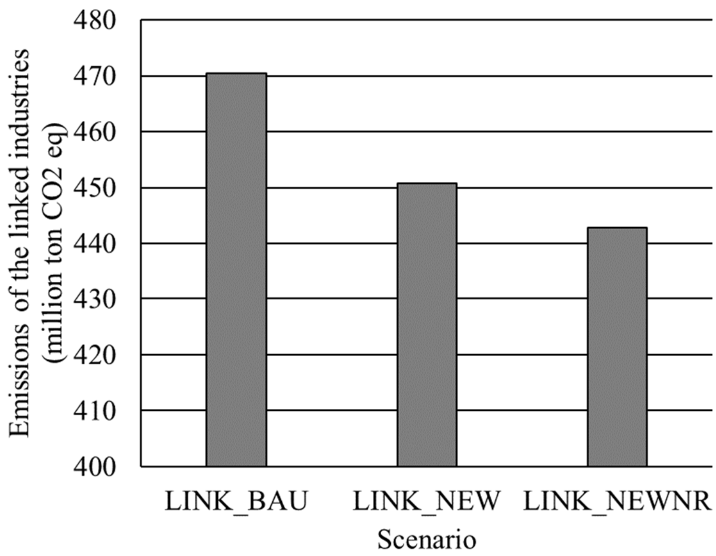

Figure 5.1. Emissions of the linked industries in 2050 (Unit: million ton CO2eq)

Emission intensity and output rebound are the two main factors that determine the extent of mitigation. More efficient new technology decreases emission intensity and contributes positively to mitigation, while the output rebound contributes negatively to mitigation. If there is no direct rebound effect (LINK_NEWNR), which implies that only the positive impact is considered, then the linked industries reduce 5.9% (27.6 million ton CO2eq) of their emissions. However, because of the direct rebound effects, 7.8 million ton CO2eq rebound, and there is a reduction of only 19.8 million ton CO2eq. That is, about 28% of the expected reduction is offset by output rebound.

Direct rebound effects tend to be large in emission-intensive industries (Table 5.3). The steel and chemistry industries, which occupy 77% of the emissions of the linked industries in LINK_BAU, generate 88% of the total direct rebound effect. Direct rebound effects in the other linked industries are not large because their emissions are low.

As Eq. (5.3) indicates, the direct rebound effects depend on the output rebound ($Z_j^{NEW} - Z_j^{BAU}$) and new emission intensity (EI_j^{NEW}). The direct rebound effect in the chemistry industry is the largest because it experiences the largest output rebound (Table 5.4). Although new emission intensity in the chemistry industry is around the average new emission intensity of the linked industries (253 ton CO2eq/billion KRW), its output rebound is almost three times larger than that of the steel industry. The direct rebound effect in the steel industry is also large because it has the largest new emission intensity due to its use of bituminous coal as raw material.

The cement industry has the second largest new emission intensity, but its direct rebound effect is small because its output rebound is much smaller than that of the steel and chemistry industries. That is, both the output rebound and new emission intensity are significant in determining the direct rebound effect.

Table 5.3. Direct rebound effects in 2050 (Unit: million ton CO2eq)

Industry	Emissions			Direct rebound effect	Direct rebound effect ratio
	LINK_BAU	LINK_NEW	LINK_NEWNR		
Steel	152.81	150.44	146.99	3.44	59%
Chemistry	210.16	206.84	203.37	3.47	51%
Cement	53.26	45.09	44.57	0.52	6%
Machine	10.64	9.51	9.46	0.05	4%
Semiconductor & display	11.96	11.11	11.03	0.08	9%
Electronics	5.13	4.80	4.79	0.01	4%
Automobile	7.84	7.08	7.05	0.03	3%
Nonferrous metals	9.21	7.46	7.36	0.10	5%
Glass	2.77	2.36	2.27	0.10	19%
Textile	6.69	5.99	5.94	0.05	7%
Total	470.47	450.68	442.84	7.84	28%

Table 5.4. Changes in the linked industries in 2050 (Unit: billion KRW, ton CO2eq/billion KRW)

Industry	Z_j^{BAU}	Z_j^{NEW}	ΔZ_j	EI_j^{BAU}	EI_j^{NEW}
Steel	116,568	119,300	2,732 (2.3%)	1,311	1,261
Chemistry	603,820	614,115	10,295 (1.7%)	348	337
Cement	38,078	38,522	444 (1.2%)	1,399	1,170
Machine	260,941	262,190	1,250 (0.5%)	41	36
Semiconductor & display	181,830	183,156	1,326 (0.7%)	66	61
Electronics	137,999	138,390	391 (0.3%)	37	35
Automobile	252,973	253,948	975 (0.4%)	31	28
Nonferrous metals	54,895	55,623	728 (1.3%)	168	134
Glass	8,506	8,865	359 (4.2%)	325	267
Textile	109,791	110,723	932 (0.8%)	61	54
Total	1,765,401	1,784,833	19,432 (1.1%)	266	253

Output rebound largely depends on the energy input share because new technology affects the energy costs of the industry. Since the marginal cost of the energy-intensive industry fluctuates more after new technology adoption, the output price reduction in such industries is more significant (Figure 5.2).[13] Energy-intensive industries such as the cement and glass industries experience large output price changes.

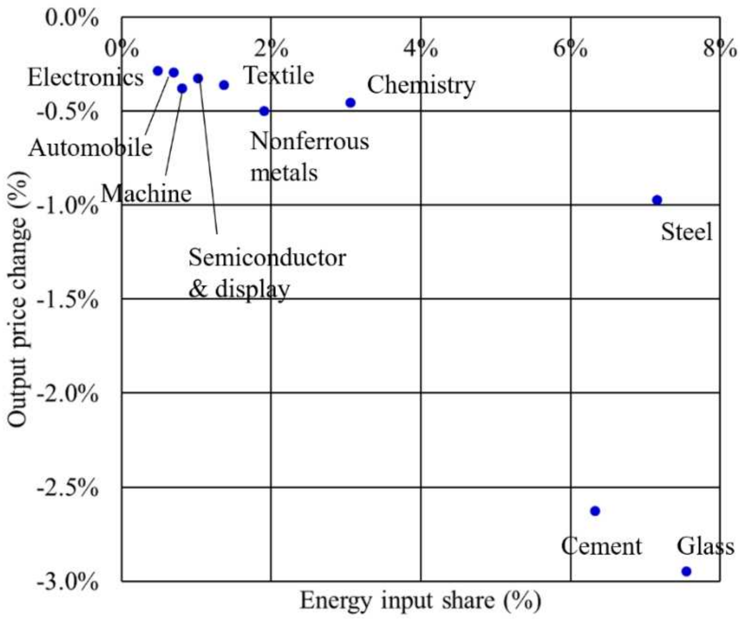

Figure 5.2. Energy input share and output price change (Unit: %)

When the output price drops, output rebounds due to the higher demand for this output. Output rebound tends to be proportional to output price change (Figure 5.3). For example, the glass industry, the most energy-intensive industry, experiences the largest output price change, and its output rebound is also the largest.

13 The energy input share considers only linked fuels.

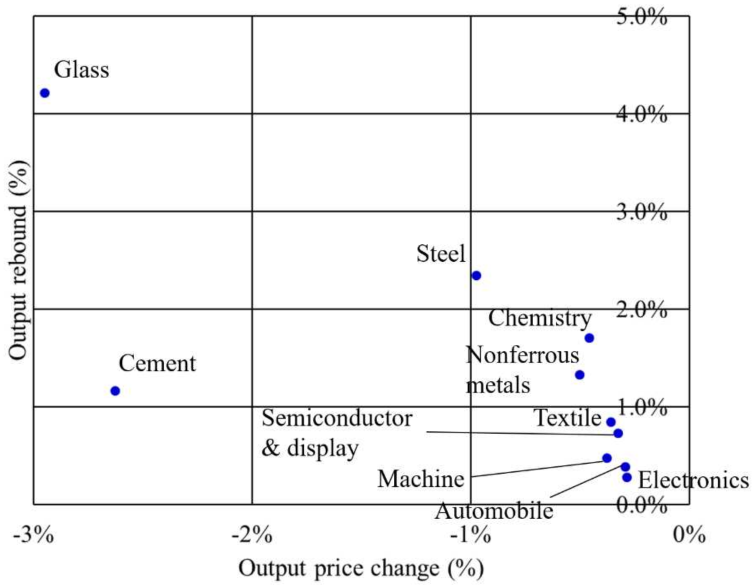

Figure 5.3. Output price change and output rebound (Unit: %)

The black line in Figure 5.4 shows the emissions differences between LINK_BAU and LINK_NEW. Since new technology reduces the steel industry's emissions, several points of the line are kinked in the introduction years. The blue line in Figure 5.4 shows the emissions differences between LINK_BAU and LINK_NEWNR. If there is no rebound effect, then the steel industry can reduce more of its emissions. Rebounding emissions are measured as the differences between the two lines.

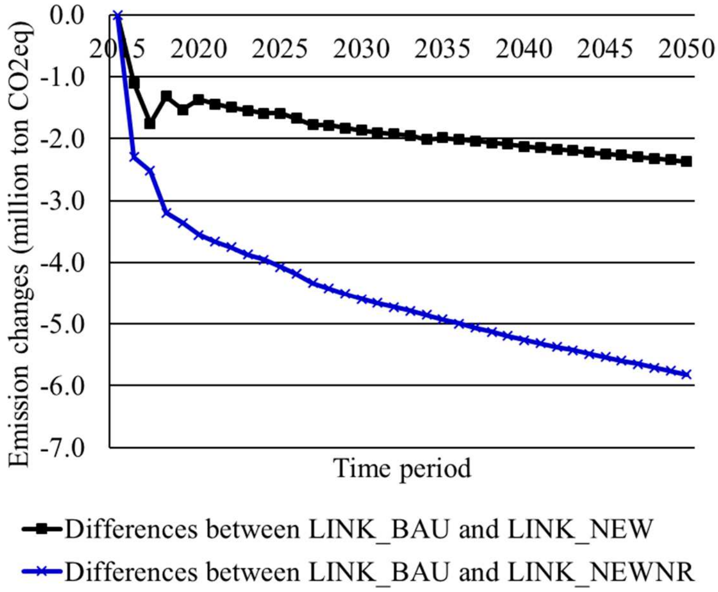

Figure 5.4. Emission changes in the steel industry (Unit: million ton CO2eq)

5.4.3 Indirect rebound effect

The indirect rebound effect occurs in the unlinked sectors and household energy consumption (Figure 5.5). Since new technology adoption in the linked industries leads to lower prices in the linked industries and energy products, the unlinked sectors and household can save their expenditures and increase their outputs or energy consumption (Figure 5.6).

The service sector, which includes the waste, construction, commercial, insurance, domestic and public sectors, occupies 33% of the indirect rebound effects because of its large output rebound. After new technology adoption, more than half of the rebounding emissions in the service sector arise from the commercial sector (0.4 million ton CO2eq), which accounts for about 70% of service sector output.

The indirect rebound effects in the manufacturing sector (excluding the linked industries) are comparable to those in the service sector, although its output does not change much. Output rebound in the energy sector is also small, but its rebounding emissions are considerable because its new emission intensity (185 ton CO2eq/billion KRW) is twice the average new emission intensity of the unlinked sectors (88 ton CO2eq/billion KRW). The transport, agriculture, and other sectors do not contribute much to the indirect rebound effects, although the emissions of these sectors rebound.

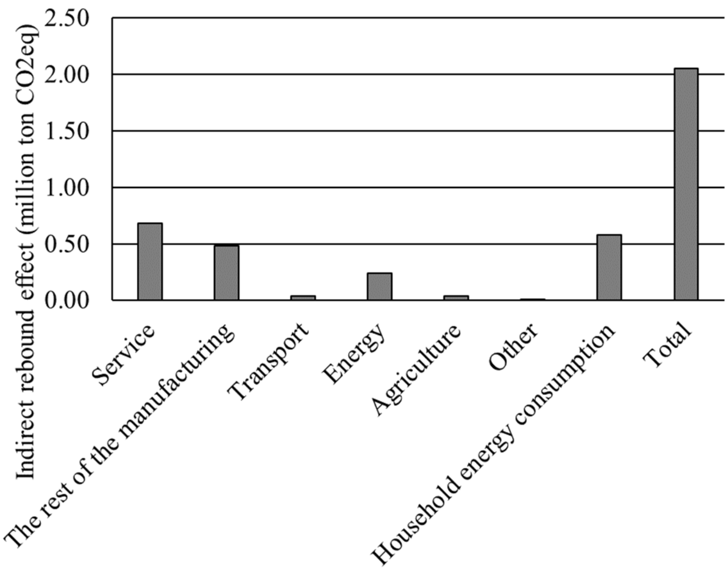

Figure 5.5. Indirect rebound effects in 2050 (Unit: million ton CO2eq)

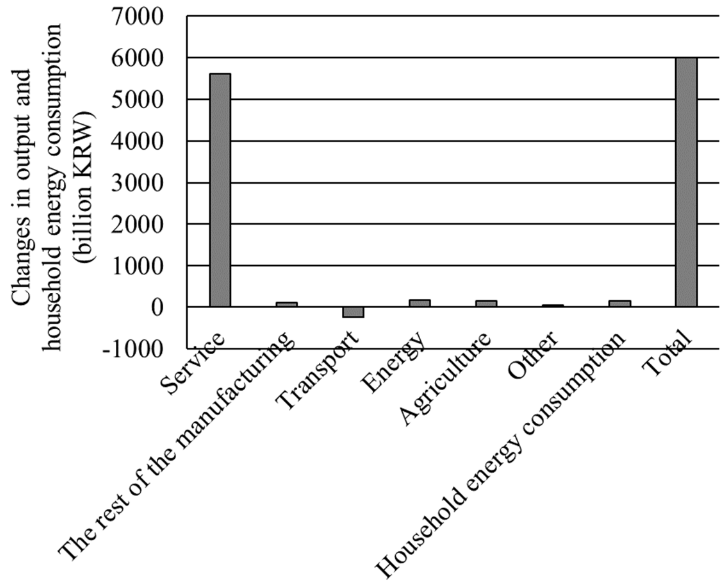

Figure 5.6. Changes in output and household energy consumption in 2050 (Unit: billion KRW)

5.4.4 Total rebound effect

The total rebound effect, which is a sum of direct and indirect rebound effects, is 9.9 million ton CO2eq (Figure 5.7). About 80% of the total rebound effect occurs from the linked industries. As outputs of the linked industries expand, their emissions are also rebounded. About 20% of the total rebound effect arises from the unlinked sectors and the household energy consumption. As changes in the linked industries induce economy-wide changes, the unlinked sectors and the household find new equilibrium and generate additional emissions.

Without the rebound effects, new technology adoption reduces 27.6 million ton CO2eq in the linked industries (see Figure 5.1). However, with the rebound effects, 9.9 million ton CO2eq is rebounded, and the net reduction effects are 17.7 million ton CO2eq. Thus, the reduction effects of new technology adoption is overestimated if the rebound effects are not considered.

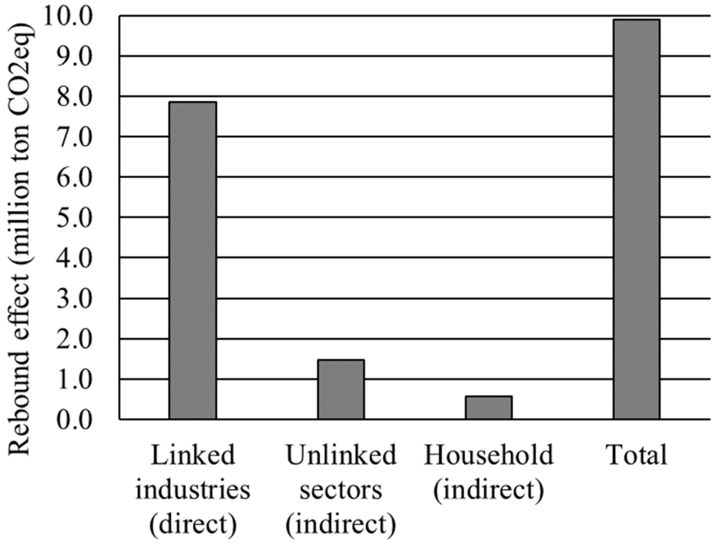

Figure 5.7. Total rebound effect in 2050 (Unit: million ton CO2eq)

5.4.5 Sensitivity test

Substitution elasticities in the production nest of the CGE model can influence the rebound effects. When the linked industries introduce new technology, energy prices drop because they demand less energy. After this price reduction, the unlinked sectors tend to use more energy inputs. Since the substitution between inputs depends on substitution elasticities, this study tests the effects of substitution elasticities on the rebound effects.

Although previous sections assume substitution elasticities of 0.5, this section assumes substitution elasticities of 30% lower (0.35) and higher (0.65) than this original benchmark.

As the substitution elasticities increase, the economy tends to expand its domestic output and generate more emissions. Since higher substitution elasticities enable the production sectors to more easily replace inputs, their outputs increase. National emissions in 2050 also rise with outputs (Figure 5.8).

As Figure 5.9 shows, there is an increasing trend in the direct and indirect rebound effects with the substitution elasticities, but the sizes of two effects are not reversed. That is, although the sizes of the rebound effects can differ based on the substitution elasticities, the implications regarding the rebound effects from the previous sections do not change.

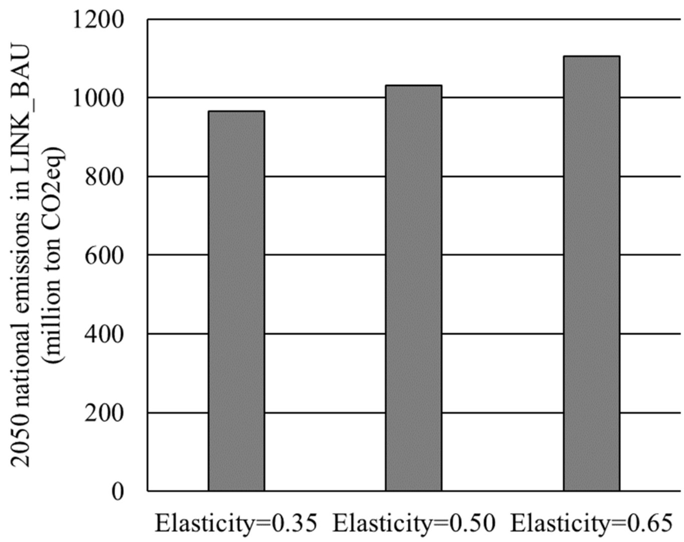

Figure 5.8. Effects of the substitution elasticities on the 2050 national emissions (Unit: million ton CO2eq)

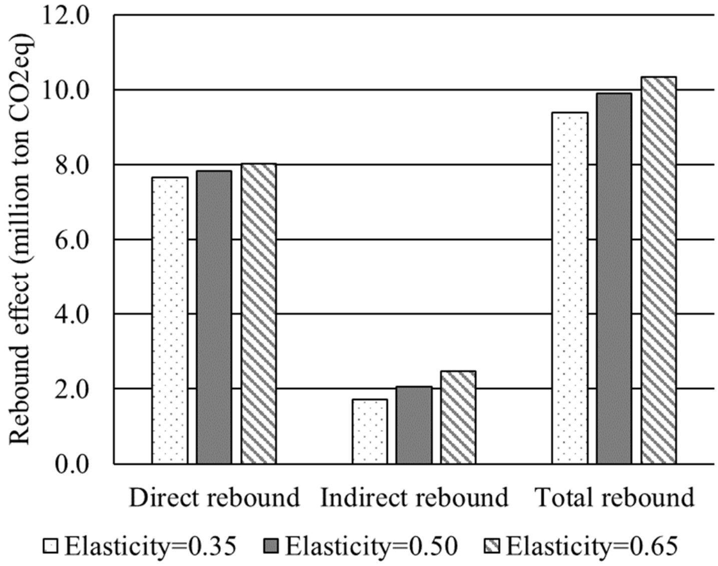

Figure 5.9. Effects of the substitution elasticities on the rebound effects (Unit: million ton CO2eq)

Chapter 6. Assessment of environmental and economic impacts of endogenous technology learning in the manufacturing sector based on the hybrid model

6.1 Introduction

6.1.1 Research background

Technological change is a significant issue in designing sustainable environmental policies (Popp, 2005). The introduction of new technology and changes in the characteristics of technology affect the amount of both combustion and process emissions. Additionally, technological change contributes to reducing abatement costs (see Dowlatabadi, 1998; Carlson et al., 2000; Jaccard et al., 2004). Thus, it is important to appropriately reflect technological change in environmental analysis.

In reflecting technological change, it is also significant to adopt an appropriate method because the method largely affects the results of an environmental analysis (Gillingham et al., 2008). The bottom-up and CGE models are representative models that incorporate technological change (Löschel, 2002). Since the bottom-up model is technology-based, it can handle technological change at the technology level. It easily describes the changes in technology characteristics and the emergence of new technology. That is, it explains both gradual and radical technological changes that Grübler et al. (1999) mentioned.

However, the bottom-up model cannot examine ripple effects of technological change on the economy. When there is technological change, the bottom-up model finds a new technology mix, which leads to changes in output and energy demand. These changes affect the rest of the economy through price changes, but the bottom-up model assures only partial equilibrium. Because of this disadvantage, the bottom-up model has limitations in identifying the impacts of technological change on national emissions and abatement costs.

The CGE model can clarify the macro-economic impacts of technological change because it describes the relationship between the sectors in the economy. However, the CGE model handles technological change at a more aggregated level. As mentioned in Chapter 4, it has limitations in representing radical technological change such as the adoption of new technology using new fuel. Moreover, although technological change affects energy substitution, the CGE model explains this substitution using previously estimated substitution elasticities.

6.1.2 Research purpose

The hybrid model helps researchers use the advantages of the bottom-up and CGE models in exploring the impacts of technological change. The bottom-up model helps to describe technological change at the technology level. The CGE model receives information about technological change from the bottom-up model and identifies the ripple effects of technological change.

This study incorporates technological change through endogenous learning in the hybrid model. With learning, technology performance improves based on the accumulation of experience. This study assumes that technology efficiency improves based on the technology capacity of the bottom-up model. Learning is incorporated using the iterative approach (Yang et al., 2016), which updates the technology characteristics based on the solutions of the bottom-up model.

After reflecting endogenous learning, this study investigates the changes in national emissions and abatement costs due to learning. Additionally, this study identifies the impacts of speed of learning on national emissions and abatement costs.

6.2 Literature review

6.2.1 Technological change in the bottom-up model

New technology has significant impacts on emissions and abatement costs because it usually reduces energy consumption to provide an energy service. Since new technology requires more investment, operation and management costs, it tends to be less attractive than expected in its introduction year. New technology can be more competitive in the future if its costs are reduced based on an increase of its adoption rate (see Söderholm and Sundqvist, 2007).

The bottom-up model has analyzed cost reduction of new technology using learning, which means that accumulated knowledge from technology use experience induces the cost reduction (Viguier et al., 2006). Although technology use experience is diversely measured based on characteristics of learning (see Samadi, 2018), the bottom-up model usually considers cumulative capacity of technology to measure technology use experience.

Although the total cost of the bottom-up model includes investment, operation, management and energy costs, previous studies generally assumed that the investment cost was affected by learning (Messner, 1997; Kypreos and Bahn, 2003; Kim et al., 2012; Huang et al., 2017). If the share of the investment cost in the total cost is high, reduced investment cost largely affects new technology adoption, emissions and abatement costs. For example, in cases of photovoltaic and wind power technologies, most of their total costs are investment costs, whereas energy costs are zero. Learning promotes the adoption of both technologies because their total costs are largely affected by learning.

By contrast, technology used in the manufacturing sector consumes energy to produce an energy service. If the share of the energy costs in the total cost is high, an adoption rate of new technology does not change much through reduction of the investment cost because the energy costs are more dominant in determining technology mix.

Several previous studies stated that learning also affected efficiency of technology (Barreto and Klaassen, 2004; Loulou et al., 2004; Junginger et al., 2008). As technology capacity is accumulated, energy consumption can be reduced through efficiency improvement. Previous studies generally described energy consumption reduction, instead of efficiency improvement, depending on cumulative capacity (Ramírez and Worrell, 2006; Weiss et al., 2008; Weiss et al., 2010).

A learning curve shows the relationship between technology use experience and a performance indicator of learning. This relationship is differently formulated based on characteristics of learning (see Grosse et al., 2015). Technology performance was usually assumed to be exponentially proportional to cumulative capacity or production (Ibenholt, 2002; Kypreos and Bahn, 2003; Wand and Leuthold, 2011; Lin and He, 2016). Some previous studies assumed that the performance improved based on cumulative capacity over initially installed capacity (Kim et al., 2012; Moser et al., 2016; Huang et al., 2017).

6.2.2 Technological change in the CGE model

The CGE model generally adopts an AEEI parameter to reflect technological change. The AEEI is exogenously determined and reduces energy consumption. The AEEI is either estimated or assumed to remain over time (Löschel, 2002). However, the AEEI overlooks the factors that induce technological change (Gillingham et al., 2008) and neglects the processes and costs to improve efficiency. Moreover, the AEEI is not affected by changes in the economy because it is a parameter (see Jaccard et al., 2004).

Backstop technology is also employed to model exogenous technological change in the CGE model. Backstop technology is generally adopted after depletion of current technology (Nordhaus et al., 1973). Although backstop technology is less competitive in its initial stage, it provides energy infinitely after cost reduction (Löschel, 2002). However, since the cost reduction of backstop technology is usually assumed to depend on time (Gillingham et al., 2008), it also has limitations in explaining complicated technological change.

Several CGE models adopts the endogenous methods to reflect technological change instead of exogenous methods. Wang et al. (2009) considered knowledge capital input in the CGE model and explained that accumulated knowledge capital based on R&D induced technological change. Jin (2012) also adopted knowledge and R&D concepts to represent technological change in the CGE model endogenously. Kemfert and Troung (2007) assumed that R&D induced efficiency improvement and explored the environmental and economic impacts of endogenous technological change. Although the CGE model reflects technological change endogenously, it is difficult to explain technological change at the technology level.

6.2.3 Technological change in the hybrid model

Martinsen (2011) investigated the impacts of learning on the electricity sector using a hybrid model that integrates national bottom-up and macro-economic models and a global bottom-up model. The model contributed to overcoming the limitations of the bottom-up and macro-economic models by reflecting technological change, and was used to explore the environmental impacts of technological change.

Learning was assumed to diffuse from the global bottom-up model to the national bottom-up model. Although the national bottom-up model exchanges information with the macro-economic model, its solutions do not affect learning. That is, learning occurred regardless of the domestic technology mix and energy consumption.

6.3 Model

6.3.1 Outline of the hybrid model with learning

As Figure 6.1 shows, the hybrid model is modified to include learning. Although the overall structure is maintained, the bottom-up model now includes convergence processes.

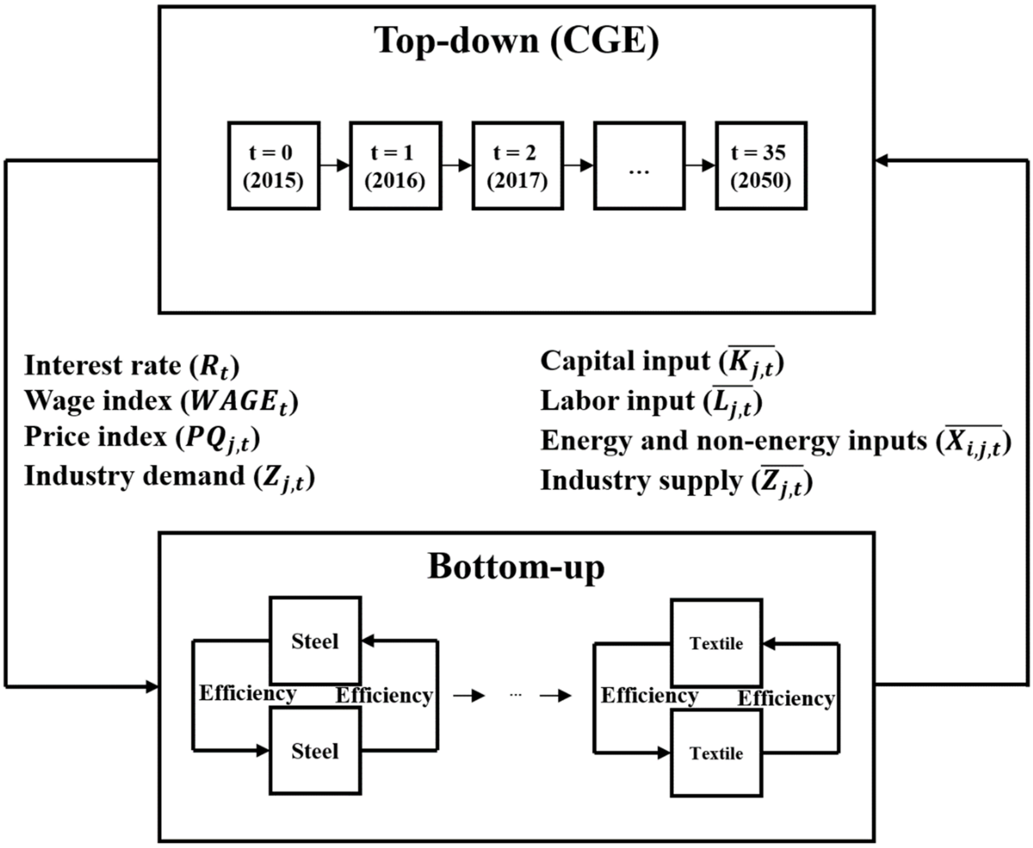

Figure 6.1. Outline of the hybrid model with learning

The CGE model obtains its solutions and delivers the information required by the bottom-up model. Each bottom-up model solves its cost minimization problem using the

CGE information and updates the efficiencies of new technologies based on the cumulative capacities of the technologies. The bottom-up model again solves its cost minimization problem using the updated efficiencies. The bottom-up model repeats this process until its solutions converge at the level of 0.1%. After convergence, the bottom-up model delivers the information that the CGE model requires. The hybrid model repeats the information exchanges until all linked variables converge.

6.3.2 Learning in the bottom-up model

A learning domain is various depending on technology characteristics. Learning basically occurs in individual technology in the industry. Moreover, learning occasionally occurs in common technologies. For example, boiler technologies can share technology use experience because these technologies belong to the same common technology. Additionally, effects of learning can be diffused between industries. For example, since industries in a service-oriented bottom-up model use the same technologies, the technologies in different industries can share technology use experience. This study considers learning of individual technology and excludes spillovers between common technologies and industries.

As Eq. (6.1) indicates, this study assumes that efficiency of only new technology improves based on its cumulative capacity.[14] Efficiency increases as a power function of cumulative capacity over initially installed capacity. If initially installed capacity of new

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[14] More precisely, learning reduces new technology's energy consumption to produce a unit of energy service.

technology is small, its efficiency improvement may be excessively large. This study avoids this problem because new technology in the KETEP database is sufficiently competitive in its introduction year. A rate of efficiency improvement depends on a learning parameter β, which is determined based on Eq. (6.2) and Eq. (6.3).

Although there is no learning, current technology is replaced by new technology. Leaning intensifies this technology substitution because new technology is more competitive due to learning.

$$EFF_{TECH,t} = EFF_{TECH,\bar{t}} * \left(\frac{CC_{TECH,t}}{CC_{TECH,\bar{t}}}\right)^{\beta} \quad \text{Eq. (6.1)}$$

$$LR = 1 - PR \quad \text{Eq. (6.2)}$$

$$PR = 2^{-\beta} \quad \text{Eq. (6.3)}$$

$EFF_{TECH,\bar{t}}$: Efficiency of technology $TECH$ in its introduction year

$CC_{TECH,\bar{t}}$: Capacity of technology $TECH$ in its introduction year

$CC_{TECH,t}$: Cumulative capacity of technology $TECH$ at time period t

β: Learning parameter

LR: Learning rate

PR: Progress rate

6.3.3 Iterative approach

The hybrid model of this study is complicated because the objective function of the bottom-up model is quadratic and there is a convergence process. Thus, this study adopts the iterative approach, which helps to avoid computation burden in endogenizing learning (Karali et al., 2017).[15]

There are two approaches to iteratively reflect learning in the model. Karali et al. (2017) recursively solved their cost minimization problem and updated technology's unit cost in the following period using cumulative activity in the current period. The unit costs in the future periods were iteratively updated based on this process until the end of the period. Yang et al. (2016) modeled learning in a forward-looking optimization problem. They obtained cumulative capacities in all periods by solving the problem and updated the unit investment costs in all periods using the cumulative capacities. The investment costs were iteratively updated until all investment costs were in a convergence level. This study adopts Yang et al. (2016) and updates efficiency of new technology until solutions of the bottom-up model are in a convergence level.

6.3.4 Learning rate

To estimate the learning rate, capacity and efficiency data are required. However, it is difficult to obtain these data for the manufacturing sector and find already estimated learning rate in the literature. Thus, this study considers the learning rate as a scenario

[15] See Kim et al. (2020) for more explanation of the iterative approach.

parameter.

According to Kahouli-Brahmi (2008), an average learning rate of conventional technology is 4%, which is lower than new renewable technology. This study determines 5% as a mid-level learning rate. To identify the role of the learning rate, this study determines 1% and 10% as low-level and high-level learning rates, respectively.

6.3.5 Scenario

Table 6.1 summarizes the scenarios in this chapter. In LINK_NEWLR5, the linked industries adopt new technologies whose efficiencies improve at a rate of 5%. This study considers 1% (LINK_NEWLR1) and 10% (LINK_NEWLR10) learning rates for the sensitivity test.

Moreover, this study imposes the carbon tax in Chapter 3 to investigate the impacts of learning on emissions and abatement costs. LINK_BAU_ADDCTAX and LINK_NEW_ADDCTAX determine the carbon tax levels to achieve the 2050 national emissions with learning when there is no learning. Additionally, LINK_NEWLR5NR is the scenario to calculate the rebound effects with learning.

Table 6.1. Scenario description

Scenario	Description
LINK_NEWLR1 LINK_NEWLR5 LINK_NEWLR10	Hybrid model New technology adoption with learning (1, 5, 10%) (Linked industries) No carbon tax
LINK_NEWLR1_CTAX LINK_NEWLR5_CTAX LINK_NEWLR10_CTAX	Hybrid model New technology adoption with learning (1, 5, 10%) (Linked industries) Carbon tax: 30–360 thousand KRW/ton CO2eq (2015–2050)
LINK_BAU_ADDCTAX	Hybrid model Only current technology Carbon tax: 30–386 thousand KRW/ton CO2eq (2015–2050)
LINK_NEW_ADDCTAX	Hybrid model New technology adoption (Linked industries) Carbon tax: 30–376 thousand KRW/ton CO2eq (2015–2050)
LINK_NEWLR5NR	Hybrid model New technology adoption with learning (1, 5, 10%) (Linked industries) No carbon tax Without rebound effects

6.4 Results

6.4.1 Impacts of technological change through learning

The efficiency of new technology is constant without learning. By contrast, with learning, efficiency improves based on the cumulative capacity of the technology (Figure 6.2). The reference of relative efficiency is the initial efficiency of LINK_BAU.

Although LINK_NEW introduces new technology, it does not consider learning. The relative efficiencies of all energy service technologies (excluding motor technology) are almost constant after their introduction. The relative efficiency of the motor technology improves because three types of new motors are adopted in different years.

In LINK_NEWLR5, there is an increasing trend in the relative efficiency because the cumulative capacity of the new technology continuously increases. Moreover, a stepwise increase in the relative efficiency is observed. Since the lifetime of already installed capacity is finite, a large amount of capacity is installed periodically, and the relative efficiency also improves cyclically. For example, the relative efficiency of boiler technology rises steeply every seven years.

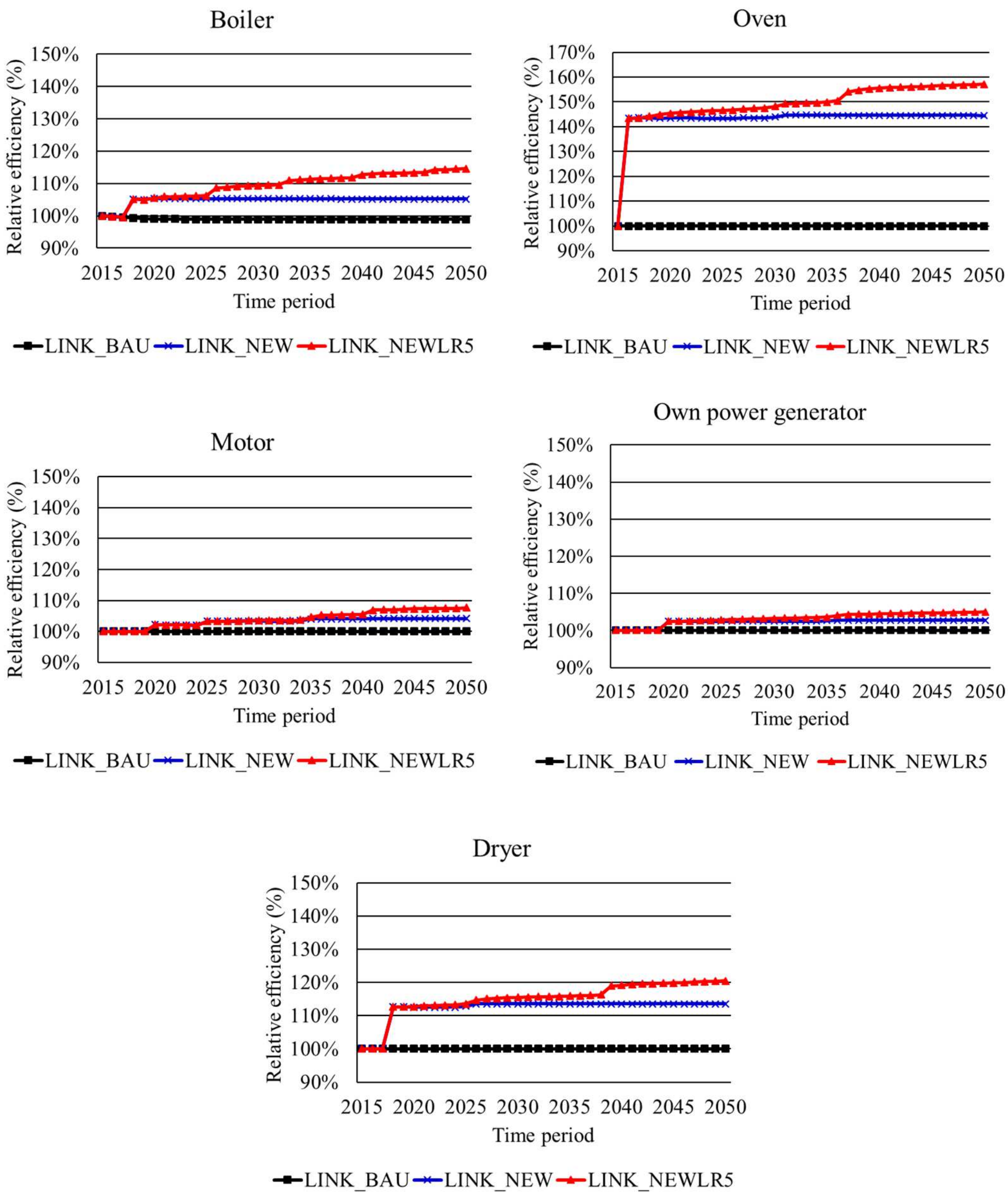

Figure 6.2. Relative efficiency of energy service technology in the steel industry

(Unit: %)

Learning also affects the share of new technology (Figure 6.3). For the first ten years, since the cumulative capacity of new technology is insufficient to induce significant efficiency improvement, the share of new technology is almost unchanged. However, learning causes the gap between LINK_NEW and LINK_NEWLR5 to grow after 2026.

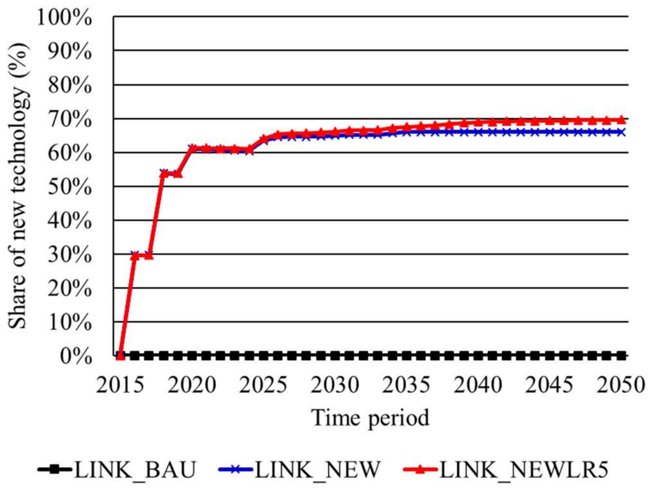

Figure 6.3. Share of new technology in the steel industry (Unit: %)

The linked industries expand their production with learning because the additional efficiency improvement allows an additional reduction in the marginal costs (Figure 6.4). Furthermore, since domestic output expands, the weighted domestic output price in the linked industries drops further in LINK_NEWLR5 (Figure 6.5). Since the unlinked sectors purchase the products of the linked industries, they also save costs and tend to expand their production. Changes in the linked industries due to learning affect GDP loss due to the carbon tax through two sources. First, the increase in the domestic outputs of the linked industries mitigates the GDP loss. Second, the increase in the domestic outputs of the unlinked sectors mitigates the GDP loss.

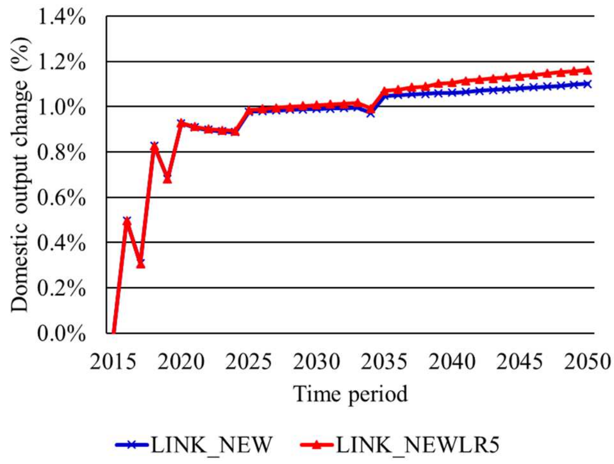

Figure 6.4. Domestic output change in the linked industries (compared to LINK_BAU) (Unit: %)

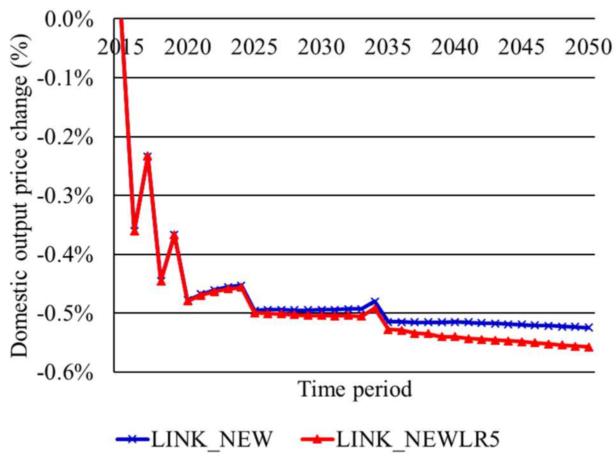

Figure 6.5. Changes in weighted domestic output price of the linked industries (compared to LINK_BAU) (Unit: %)

Efficiency improvement enables the linked industries to produce their outputs while consuming less energy. With learning, both the energy demand of the linked industries and the total energy demand decreases (Figure 6.6). Energy prices also drop because of a decrease in total energy demand (Figure 6.7).

Since lower energy prices decrease costs in the unlinked sectors and helps to expand their production, these changes also mitigate GDP loss due to the carbon tax. That is, although learning occurs in the linked industries, it affects the rest of the economy indirectly. These macro-economic effects of learning can be observed using the hybrid model.

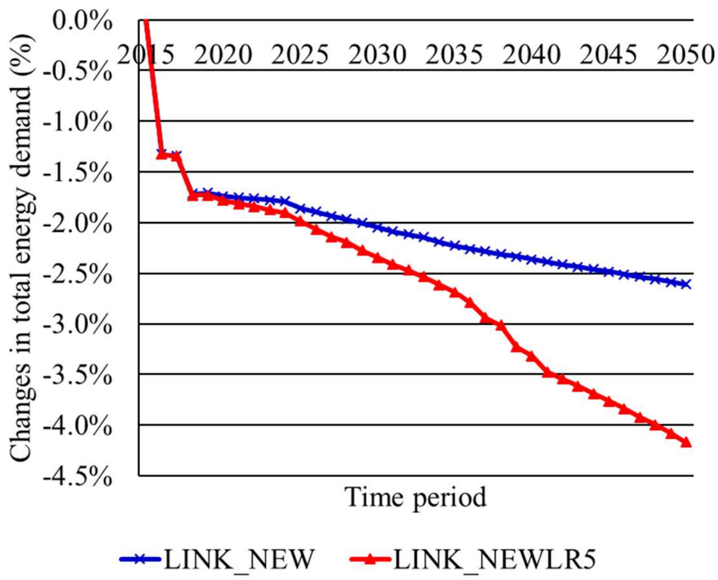

Figure 6.6. Changes in total energy demand for the linked fuels (compared to LINK_BAU) (Unit: %)

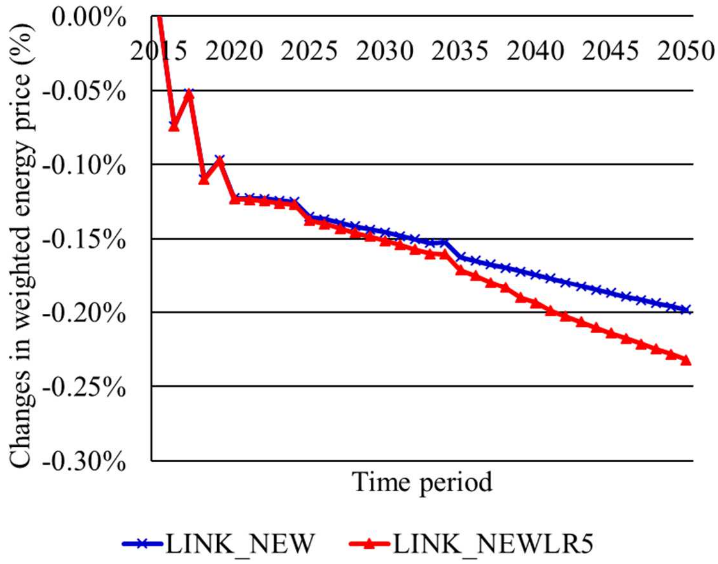

Figure 6.7. Changes in weighted energy price of the linked fuels (compared to LINK_BAU) (Unit: %)

6.4.2 Carbon tax simulation

The emissions of the linked industries in LINK_NEWLR5_CTAX until 2026 are similar to those in LINK_NEW_CTAX (Figure 6.8). As learning effects are enhanced after 2026, the reduction rate in the linked industries gradually increases. In 2050, the additional efficiency improvement reduces 1.2%p of emissions in the linked industries compared to LINK_NEW_CTAX.

Moreover, learning mitigates the rebound effects of new technology adoption. In LINK_NEW_CTAX, the slope of the reduction rate considerably decreases due to the rebound effects. By contrast, with learning, the decreasing trend in the slope is less remarkable.

Learning in the linked industries also affects national emissions, although its effects are not large (Figure 6.9). Since the emissions of the linked industries are mitigated, national emissions are also mitigated. Additionally, the macro-economic effects of learning affect the production and emissions of the linked sectors.

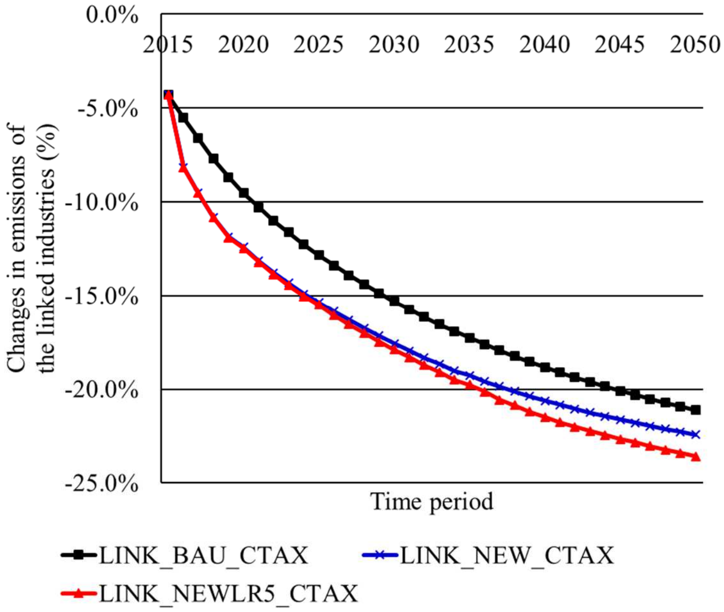

Figure 6.8. Changes in emissions of the linked industries (Unit: %)

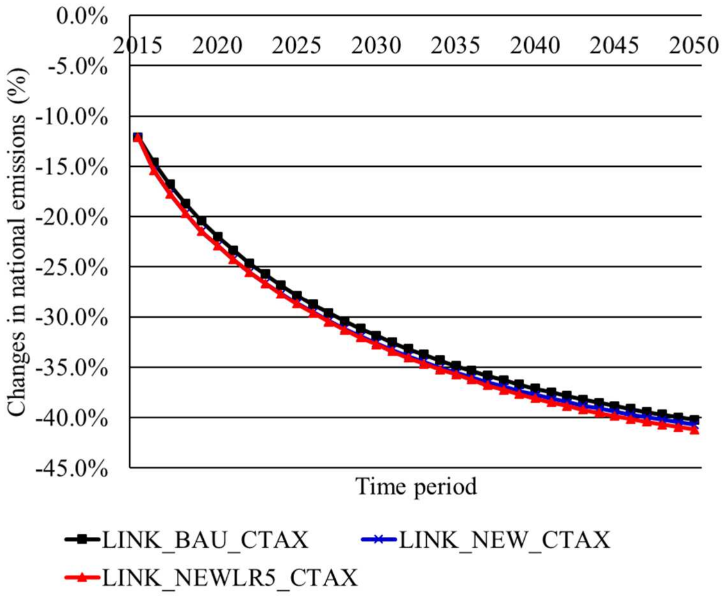

Figure 6.9. Changes in national emissions (Unit: %)

Since the carbon tax raises energy prices, it increases the production costs in the production sectors and interrupts their production. These carbon tax effects reduce the domestic outputs of the production sectors and induces a further GDP loss.

Without learning (LINK_NEW_CTAX), the economy experiences a 1.14% GDP loss compared to LINK_BAU (Figure 6.10). With learning, (LINK_NEWLR5_CTAX), the estimated GDP loss for the economy is 1.04% compared to LINK_BAU. That is, learning helps to reduce negative economic effects of the carbon tax. Since the hybrid model observes both macro-economic effects and technology-level changes, it can explain the output changes in the production sectors, including the unlinked sectors. Thus, the hybrid model helps to more precisely assess economic impacts of learning.

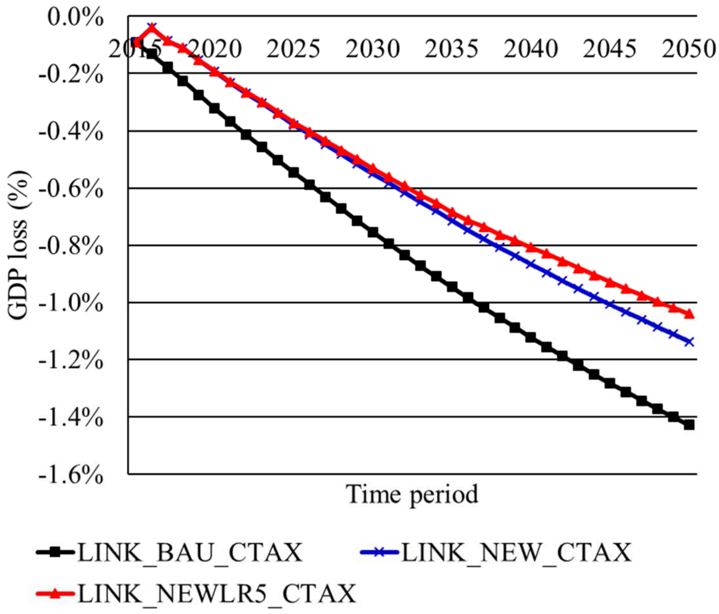

Figure 6.10. GDP loss due to the carbon tax (Unit: %)

Figure 6.11 shows the unit abatement cost to mitigate one unit of emissions. As the government imposes more carbon tax, the unit abatement cost also rises in the three scenarios. Moreover, the differences between LINK_NEW_CTAX and LINK_NEWLR5_CTAX gradually increase because the effects of learning on efficiency improvement increase over time. In 2050, the unit abatement costs without and with learning are 73 thousand KRW/ton CO2eq and 66 thousand KRW/ton CO2eq, respectively. That is, the unit abatement cost with learning is 10% lower (7 thousand KRW/ton CO2eq). The economy pays about 3,000 billion KRW more to reduce 424 million ton CO2eq in 2050 if there is no learning.

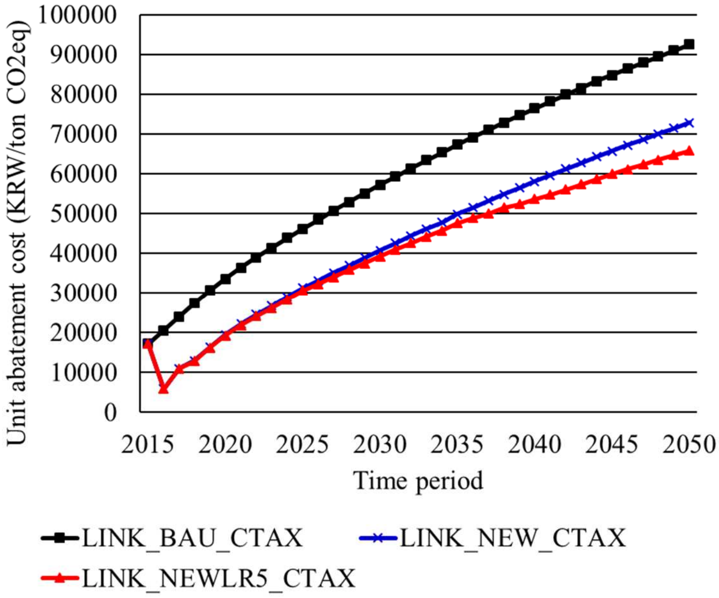

Figure 6.11. Unit abatement cost (Unit: KRW/ton CO2eq)

6.4.3 Sensitivity test

This section tests the robustness of learning effects on emissions and unit abatement cost by adjusting the learning rate. A higher learning rate means more efficiency improvement of new technology. As the linked industries are more efficient, they can contributes to reducing the national emissions and mitigating the negative economic effects of the carbon tax to a greater extent (Figure 6.12 and Figure 6.13).

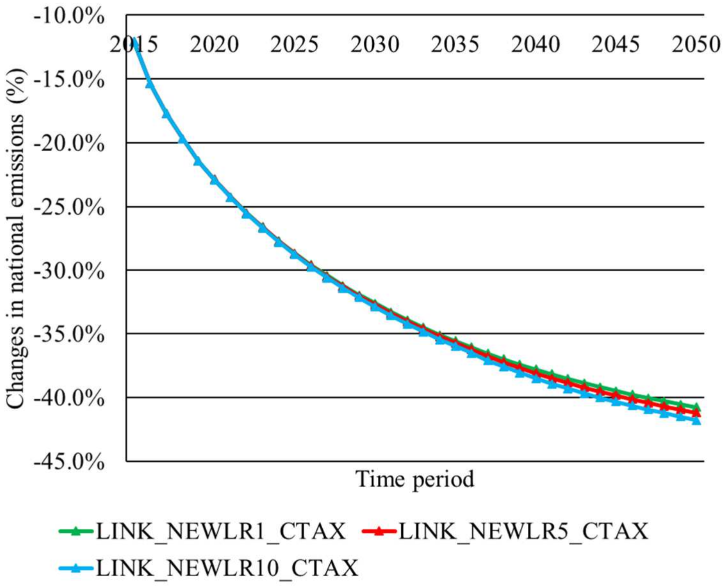

Figure 6.12. Changes in national emissions at 1%, 5% and 10% learning rates (Unit: %)

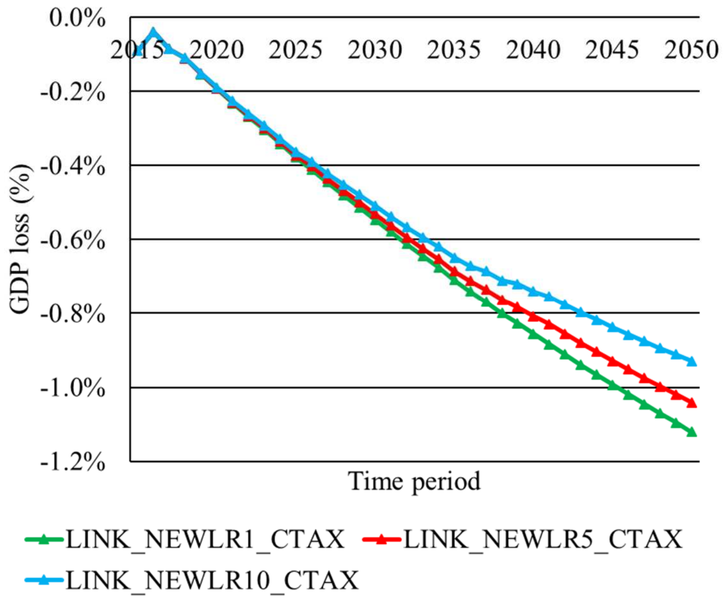

Figure 6.13. GDP losses due to the carbon tax at 1%, 5% and 10% learning rates (Unit: %)

The learning rate also affects the unit abatement cost due to its environmental and economic effects (Figure 6.14). The unit abatement costs in 2050 are 72 thousand KRW/ton CO2eq and 58 thousand KRW/ton CO2eq at 1% and 10% learning rates, respectively. For every 4–5% increase in the learning rate, the unit abatement cost in 2050 decreases as much as approximately 70 thousand KRW/ton CO2eq, which implies a consistent pattern depending on a learning rate.

In the range of the considered learning rates, the unit abatement cost difference is 14 thousand KRW/ton CO2eq. This means that the economy pays about 6,000 billion KRW more to reduce 424 million ton CO2eq in 2050 if the learning rate is low.

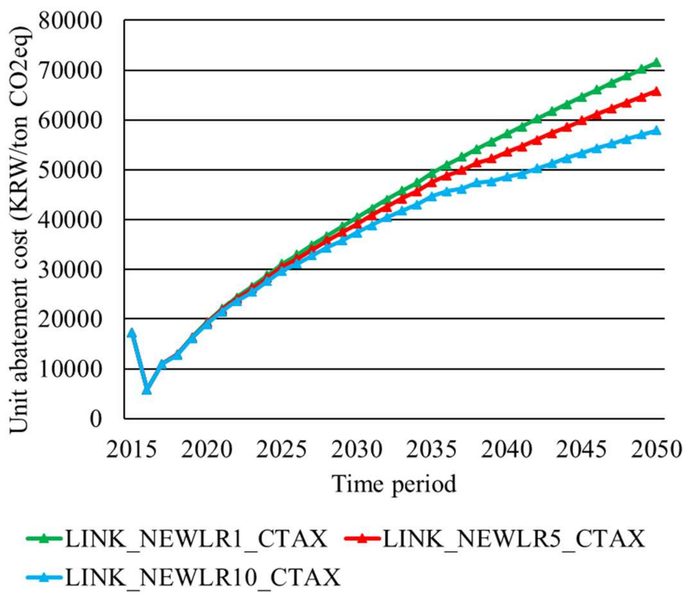

Figure 6.14. Unit abatement costs at 1%, 5% and 10% learning rates (Unit: KRW/ton CO2eq)

6.4.4 Additional carbon tax simulation

Without learning, the government should impose additional carbon taxes to meet the national emissions level it would achieve with learning. This section determines carbon tax levels to achieve the 2050 national emissions in LINK_NEWLR5_CTAX when there is no learning.

In LINK_BAU_CTAX and LINK_NEW_CTAX, the government should impose additional 26 thousand KRW/ton CO2eq and 16 thousand KRW/ton CO2eq of carbon taxes, respectively, in 2050 to achieve the national emissions level with learning. Although national emissions under the additional carbon taxes until 2040 are slightly different with those of LINK_NEWLR5_CTAX, the 2050 national emissions are well-fitted (Figure 6.15).

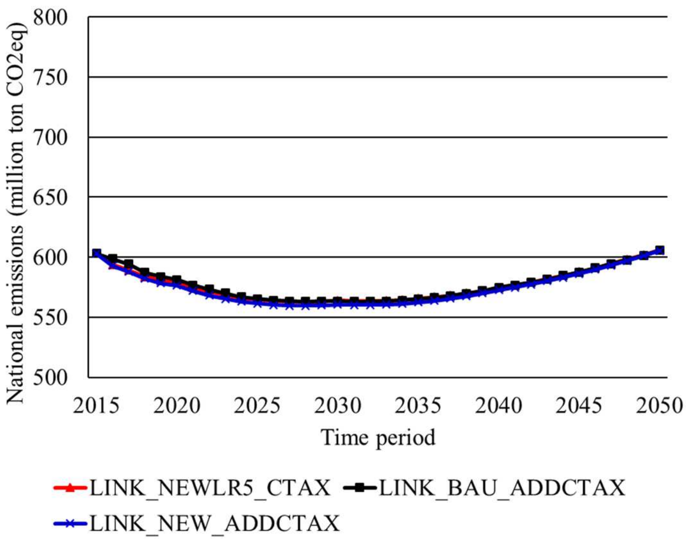

Figure 6.15. National emissions with additional carbon taxes (Unit: million ton CO2eq)

In every time period, the economy experiences additional GDP losses due to the carbon taxes (Figure 6.16 and Figure 6.17). In LINK_BAU_ADDCTAX and LINK_NEW_ADDCTAX, the economy should accept 0.10%p and 0.06%p GDP losses in 2050, respectively, to meet the national emissions level it would achieve with learning. The additional GDP losses from higher carbon taxes are not large because learning occurs only in the linked industries. However, the additional carbon tax burden on the economic agents who generate emissions increases considerably (Figure 6.18). Without new technology and learning, the additional burden increases by about 16,000 billion KRW in 2050.

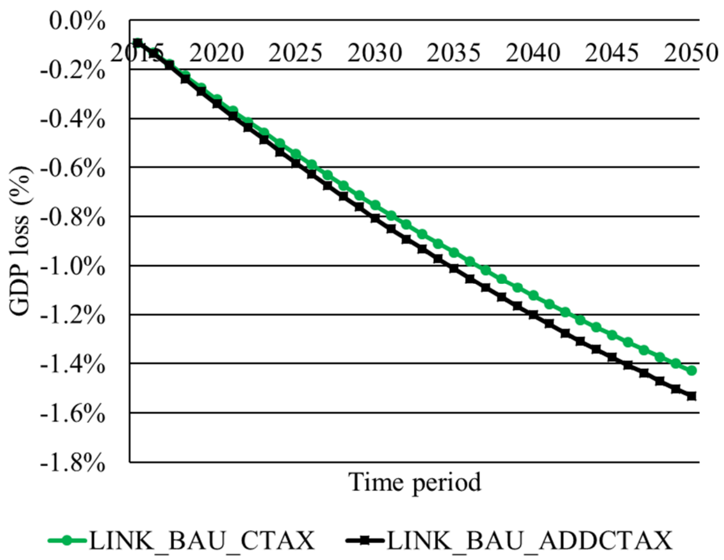

Figure 6.16. GDP loss due to additional carbon tax (LINK_BAU_CTAX) (Unit: %)

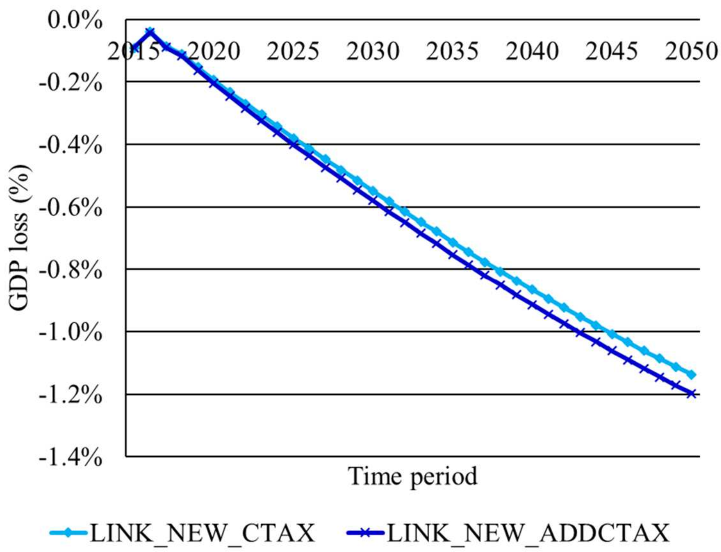

Figure 6.17. GDP loss due to additional carbon tax (LINK_NEW_CTAX) (Unit: %)

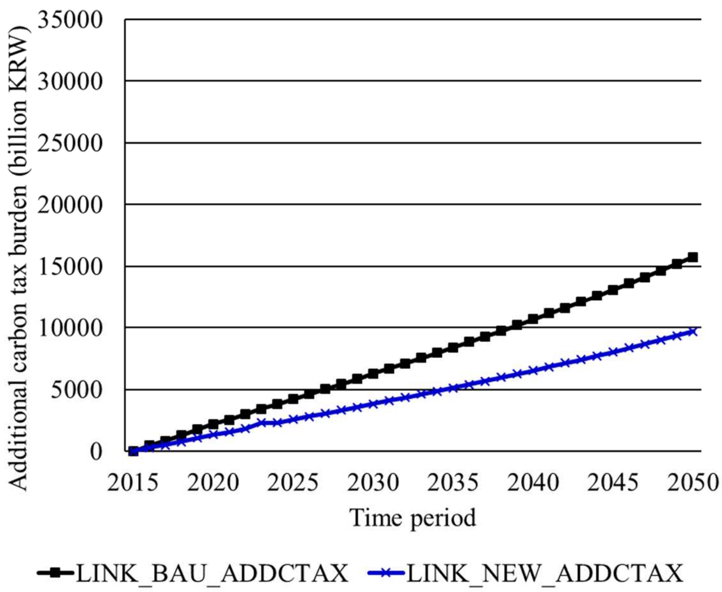

Figure 6.18. Additional carbon tax burden (Unit: billion KRW)

6.4.5 The rebound effect of learning

As Figure 6.19 shows, both the direct and indirect rebound effects increase with learning. Since the efficiency of the linked industries additionally improve, learning intensifies their output and emission rebound. Moreover, the additional price reduction in the linked industries and energy products stimulates indirect rebound effects in the unlinked sectors and household energy consumption.

The total rebound effect in 2050 increases by 6.7% (0.6 million ton CO2eq) due to the effect of learning on efficiency improvements. Half of additional total rebound effect arises from the linked industries (0.3 million ton CO2eq). Furthermore, the rebound effect from the household increases 0.2 million ton CO2eq, which is larger than the additional rebound effect from the unlinked sectors (0.1 million ton CO2eq).

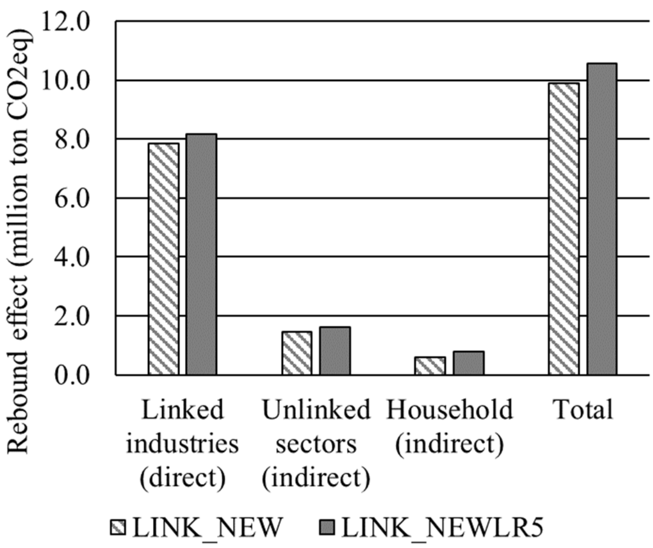

Figure 6.19. Comparison of total rebound effect in 2050 (Unit: million ton CO2eq)

Chapter 7. Conclusion

7.1 Concluding remarks and implications

This study developed a hybrid model for ten emission-intensive industries in Korea. The bottom-up model was developed based on PMP, which maintains base-year consistency in the hybrid model and avoids an overspecialized technology mix and radical technological change. The recursive dynamic CGE model was developed to analyze the reduction options and carbon tax effects. The bottom-up and CGE models were integrated based on the soft-link approach. Advantages of the hybrid model were explained, and practical problems in the integration process were also addressed. Moreover, both the direct and indirect rebounding emissions due to technology efficiency improvement were measured using the hybrid model, and the causes of rebound effects were described. This study also incorporated learning into the hybrid model with an iterative approach. The effects of learning on efficiency improvement, national emissions, and abatement costs were explored.

This study offers several contributions to the literature. First, this study shows the advantages of the hybrid model in environmental analysis. The hybrid model can investigate technology-level changes and macro-economic effects, including ripple effects due to changes in the analyzed sectors. Moreover, the hybrid model allows for feedback between technology-level changes and macro-economic effects, whereas the single models have difficulty observing feedback effects.

Second, this study assesses the rebound effects due to efficiency improvement using the hybrid model. Since the hybrid model allows for technology efficiency improvement, it can overcome methodological limitations of previous studies. Additionally, this study measures the rebound effects within and beyond the efficiency-improving sectors and explains the process by which emissions rebound.

Third, this study incorporates technological change in the hybrid model endogenously. Although single bottom-up and CGE models reflect technological change, they are inappropriate for a comprehensive analysis of technological change due to their limitations as the single models. In the hybrid model, the bottom-up model enables researchers to endogenize technological change at a technology level, and the CGE model helps to explore the macro-economic effects of technological change. Moreover, this study shows that the soft-linked hybrid model can converge despite including the additional convergence process for endogenous learning.

The government can apply the hybrid model of this study as a new framework to investigate emissions reduction options and policies. The government should predict the environmental and economic impacts of reduction options and policies before establishing a reduction target. The hybrid model helps to evaluate these impacts at the technology- and macro-economic levels. Additionally, the hybrid model with learning can provide the government with opportunities to explain technological change in the future and predict its environmental and economic impacts. Since technological change is a promising reduction option, the need for a method to assess technological change will be higher.

Moreover, the government can assess unexpected rebound effects using the hybrid model before implementing efficiency improvement policies. As Sorrell and Dimitropoulos (2008) mentioned, rebound effects may be a barrier to the government's reduction target. If the government ignores rebound effects, then actual reduction effects of efficiency improvement will be below expectations. The government should understand that the reduction effects of efficiency improvement may be overestimated and aim to determine the precise reduction effects. Additionally, the government should comprehend that the reduction options for one sector can cause an increase in the emissions of other sectors. Although the government may successfully achieve the reduction target of the manufacturing sector, it may fail to achieve the national reduction target because of indirect rebound effects. Thus, the government should prepare options to handle rebounding emissions.

Furthermore, the iterative approach can be applied to hybrid models of the other sectors, although this study employs the iterative approach for the manufacturing sector. For example, the electricity sector can apply the iterative approach to explain changes in the characteristics of renewable energy technologies. Since the investment costs of these technologies are high, the adoption rate and reduction effects of such technologies may be less than expected. A hybrid model for the electricity sector with the iterative approach can explain the reduction in the investment costs and assess the macro-economic effects of the diffusion of the renewable energy.

7.2 Limitations and future research

This section discusses the limitations of this study and suggests future research directions. First, this study includes the bottom-up model for the manufacturing sector only. The hybrid model can incorporate the bottom-up models for other sectors such as the electricity, transport and residential sectors. Considering the technological change in these sectors can change the national emissions and abatement cost estimates. Future research should integrate the CGE model with bottom-up models for multiple sectors.

Second, the learning rate in this study is a scenario parameter. Although this study shows that learning contributes to reducing national emissions and abatement costs, the learning rate is not an estimated value. Estimating the learning rates of common technologies in the manufacturing sector will provide a more precise estimate of the effects of learning.

Third, this study does not consider spillovers of learning. Technology use experience can diffused from one industry to other industries because all industries use common technologies in the service-oriented bottom-up model. These spillovers enable additional efficiency improvement for less competitive technologies. Including the spillovers of learning between industries in future research can reveal more significant effects of learning.

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Abstract (Korean)

상향식 모형과 CGE 모형은 온실가스 감축수단과 감축정책의 효과를 분석하는 대표적인 모형이다. 상향식 모형은 기술을 명시적으로 표현할 수 있다는 장점을 가지고 있으며, 에너지시스템의 최적 기술조합을 찾아낸다. 그러나 상향식 모형은 부분균형모형이기 때문에 감축수단의 거시경제적 효과 분석에 어려움을 가진다. 반면, CGE 모형은 경제의 일반균형을 찾는 모형으로 감축수단의 파급효과 분석에 이용되어 왔다. 그러나 CGE 모형은 기술에 대한 설명이 제한적이기 때문에 기술 레벨 변화의 분석에 한계가 있다.

두 모형이 가지는 장점과 단점으로 인해 기존연구들은 두 모형을 결합하는 통합모형을 구축하기 위해 노력해왔다. 이러한 통합모형은 기술 레벨 효과와 거시경제적 효과를 모두 분석할 수 있다는 장점을 가진다. 본 연구는 국내 제조업 부문에 대해 통합모형을 구축하고 감축수단 분석에 있어 통합모형이 가지는 장점을 설명하고자 한다.

상향식 모형은 두 모형 간 기준연도 자료의 일치성을 확보하는 데에 유리한 positive mathematical programming 방법을 이용하여 구축되었다. 이 방법에 기반한 상향식 모형은 다중 기술선택과 점진적인 기술변화를 설명하는 데에 유리하다. CGE 모형은 이미 구축되어 있는 단순한 형태의 CGE 모형을 변형하여 배출량과 탄소세 효과를 분석할 수 있도록 구축되었다. 단독 모형을 구축한 후에는 두 모형 간 필요한 정보를 교환하는 연성 결합 방법을 이용하여 통합모형을 구축하였다.

본 연구는 구축된 통합모형을 이용하여 기술변화의 환경적·경제적 영향을 평가하였다. 먼저 기술변화는 신기술 도입으로 인해 발생할 수 있는데, 신기술 도입은 제조업 내 기술대안의 수를 증가시키고 급격하게 기술의 효율을 향상시킨다. 그리고 기술이용 경험이 축적됨에 따라 효율이 점진적으로 개선되는 기술학습의 형태로 기술변화가 발생할 수도 있다. 본 연구에서는 통합모형 내에 기술학습을 반영하기 위해서 모형의 해에 따라 기술특성치를 반복적으로 갱신하는 방법을 이용하였다.

효율 개선은 동일한 에너지서비스를 산출하기 위한 에너지소비량을 줄이기 때문에 국가 배출량을 줄이는 데에 기여하지만, 경제 내 산출 증가를 유도하여 배출량을 반등시키기도 한다. 본 연구는 기술 효율 개선으로 발생하는 배출량 반등을 통합모형을 이용하여 평가하였다.

본 연구는 기술변화의 환경적·경제적 영향을 종합적으로 분석하는 새로운 모형을 제시하였다. 통합모형은 기존 단독 모형의 단점을 극복하고, 감축수단과 기술변화의 효과를 방법론적인 제한 없이 분석할 수 있도록 한다. 따라서 본 연구가 제시하는 통합모형은 정부의 감축목표 달성을 위한 감축수단과 감축정책의 선제적 평가에 기여할 것으로 기대된다.

주요어 : 통합모형, 상향식 모형, 하향식 모형, 기술변화, 기술학습, 반등효과
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