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A Comprehensive Approach to the Effect of Technology Diffusion Induced by Consumer Choice

- Transition to Green Mobility -

소비자 선택 기반의 기술 확산의 영향에 대한 통합적 접근
: 친환경차를 중심으로

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Abstract

A Comprehensive Approach to the Effect of Technology Diffusion Induced by Consumer Choice

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The neoclassical-induced innovation approach views the speed and direction of innovation as being determined by changes in demand and relative factor prices and emphasizes the role of demand in technological innovation. In other words, innovation spreads from consumer demand with the introduction of new technologies into the market. However, the diffusion on a socially optimal level may not fully occur solely based on the decision-making of consumers due to the relative superiority of existing technologies, high entry costs and uncertainty. Consequently, the government intervenes in the diffusion of innovation and acts as a mediator in the market by designing specific policies to address the shortfalls.

This study explored how the government's intervention affects consumer choices and

markets, as well as the consequences thereof. This study examined green mobility and focused on market-inducing (regulatory) measures. The automobile industry is a representative business-to-consumer market, and therefore, it is possible to predict the spread of new technologies by understanding consumer preferences. In anticipation of positive externalities (environmental improvement and economic growth through new industry creation), the government supports the diffusion of green mobility through various policy instruments. This study analyzed the ripple effects of regulation and growth, policy effectiveness and equity on tax and subsidy as well as investment in infrastructure as representative of green mobility dissemination policy measures.

The discrete choice (DC) model is a representative methodology that can predict demand for products and technologies according to individual preferences However, it is difficult to grasp the cascading effect between other industries and the economy because it focuses on the substitution effect between products and technologies. On the contrary, the computable general equilibrium (CGE) model broadly analyzes changes in economic variables such as price and demand through considering the relationship between economic agents; however, the CGE model has a limited explanation of technology and market changes, depending on the price and quantity of goods. Through an integration of both models, it can be noted that the DC model captures more elastic changes in the attribute level by endogenously reflecting the results of the CGE model, whilst the CGE model implements a substitution relationship reflecting the specific technical specifications of the DC model. Therefore, using the integrated model, this study

investigated the effect of demand fluctuations according to individual consumer preferences on the diffusion of new technologies within the whole country.

Consequently, the proliferation of electric vehicles and hydrogen cars has led to economic growth. From an environmental point of view, the transport sector's CO2 emissions decreased significantly because of the shift in demand for electric and hydrogen vehicles. However, emissions from other industries increased owing to the increase in production output, resulting in a rebound effect that offset the emission reduction effect in the transport sector. In addition, if green mobility surges in the early stages, emissions will increase because of coal-fired power generation and hydrogen production centered on liquefied natural gas reforming. Therefore, an environmental benefit will only be observed when a clean power mix is a prerequisite before the demand for green mobility spreads.

The impact of policy measures on green mobility dissemination is as follows. Firstly, the imposition of a tax may cause the cost of production for many companies to increase; however, depending on a learning rate, innovation may offset this cost rapidly. In other words, more effective results can be obtained when environmental policies such as taxation and technological policies that increase corporate productivity are implemented simultaneously. Secondly, investment in the complementary goods (infrastructure) market to improve the future market environment has proven to have a longer-term beneficial effect on the national economy than direct economic incentives (subsidies) for consumers. Finally, the differential payment of subsidies has a positive effect on the income

improvement of the low-income class in the short-term; however, it is less beneficial to household income growth and national economic growth in the long-term as it slows the adoption of new technologies.

By combining the two models in this study, it was possible to observe the innovation process from individual technology adoption to technology diffusion, targeting the entire economy. In addition to the above, the current framework that integrates the two models can more accurately predict the impact of government policies and provide a clear rationale for government decision-making than when testing policies using only an independent model.

Keywords: Computable General Equilibrium Model, Discrete Choice Model, Green Mobility, Technology Diffusion, Economic Instruments, CO2 Emissions

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Chapter 1. Introduction

1.1 Research Background

The neoclassical-induced innovation approach has a profound impact on macroeconomic and microeconomic literature, stating that the speed and direction of innovation are determined by changes in demand and relative factor prices and emphasizes the role of demand in technological innovation (Löschel, 2002). This is in accordance with the demand-pull theory, which highlights with the importance of technological innovation driven by demand. Demand-pull theory emphasizes that changes in market demand determine the supply of knowledge and technology (Griliches, 1957; Schmookler, 1966).

In other words, when a new technology is introduced into the market, innovation spreads to consumer demand. Currently, the initial rate of diffusion is crucial to avoid falling into a chasm wherein new technologies cannot reach the mainstream market. Rogers (1962) argues that the diffusion of new technologies (innovations) might fail because of the relative superiority of existing technologies in the market, high entry costs, and uncertainty. In addition, it can be attributed to the cause of the typical market failure in economics due to monopoly, incomplete information, and externalities (Stoneman and Diederen, 1994). Therefore, the spread of new technology to the socially optimal level may not occur solely as a result of the voluntary decision-making of consumers.

The equilibrium approach assumes that government policies are necessary to resolve market failures and achieve market equilibrium. Market failure has become the basis for

government intervention, which has led to the design of specific policy measures. The instrumentalist paradigm presents general policy measures that can correct market failures (Chun and Lee, 2010). In the instrumentalist paradigm, the concept of policy measures is goal oriented and refers to techniques used by governments to influence social change (Vedung, 1998), specifically, policy interventions that act as a major driver of significant changes in the speed of technology diffusion, as shown by Figure 1. The government acts as a moderator by intervening in the dissemination of innovative technologies. Certain technology policies can provide new commercial opportunities for companies and respond to rapidly growing markets characterized by high rates of innovation (Lundvall and Borrás, 2009).

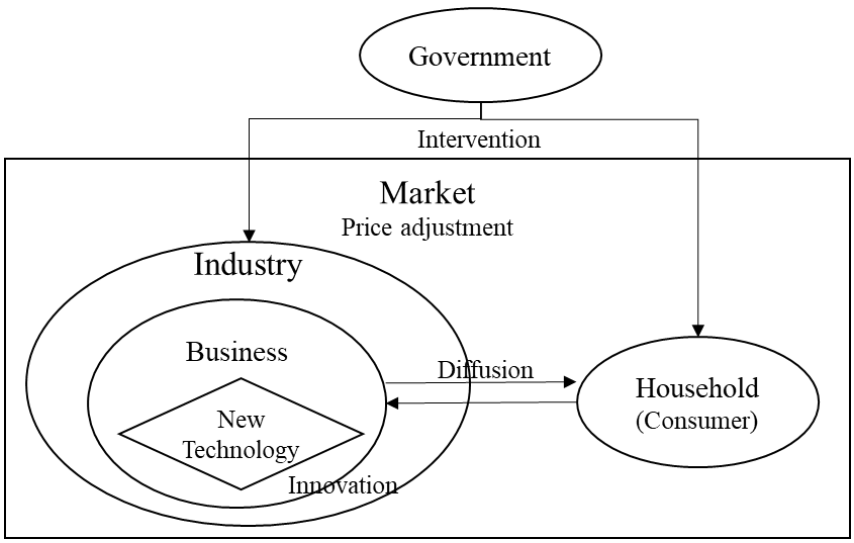

Figure 1. Relationship between economic agents in technology diffusion

Representatively, these technology policies include means for market formation, taxation and subsidies, regulation for establishing rules, and supplying public goods through non-market mechanisms. This study focuses on market-inducing indirect (regulatory) means among the various policy measures. One such policy measure is taxation, which is a representative policy that supports the diffusion of new technologies through the regulation of existing technologies, and induces cost-effectiveness with the use of a market-based approach (Jaffe and Stavins, 1995). The tax imposition policy begins with internalizing externalities (Baumol et al., 1988). An effective way to reduce regulatory compliance costs is through imposing taxation measures proportionate to the amount of non-compliance by introducing a price function to government regulations (e.g., Pigou tax) (Kim, 2009).

Taxation can induce the diffusion of new technologies without government spending; however, it can result in negative economic impacts (Acemoglu et al., 2012). A tax imposition generally increases the production cost of a firm and causes an increase in the price of goods. Additionally, economic growth decline may occur because of a decrease in consumer demand and overall consumption. However, Porter and Van Der Linde (1995) argued that well-designed environmental regulations bring about technological innovation and offset the implementation cost, contrary to the conventional idea. In other words, the results of extant studies on the effectiveness of taxation as a regulatory policy are diverse and do not converge with one opinion.

Governments prefer to implement an amalgamation of different measures to create

one integrated policy and will simultaneously implement various measures such as subsidies, regulations, and price mechanisms to transition to a low-carbon society. However, in order for governments to design a proper integrated policy, it is necessary to evaluate whether policies aim to achieve the same goal and generate greater synergy or rather to focus on individual policies (Axsen et al., 2020). Simultaneously implementing reckless policy measures is inefficient, and can result in excessive administrative costs. Therefore, it is important to properly evaluate the impact of a policy (e.g., cost-effectiveness, equity, efficiency) to prioritize it in a policy mix.

Policy instruments can be evaluated by understanding how government interventions affect consumer choices and the market as well as the consequences thereof. Previous studies have examined how technology diffusion occurs based on consumers' technology choices, how government intervention affects the diffusion rate, and the effect of diffusion on the national economy.

Since this study focuses on technological innovation and dissemination in terms of consumer demand, it starts by forecasting demand, based on consumer preferences. Discrete choice (DC) is a representative method of demand forecasting. DC analyzes consumer utility for products through consumer choice behavior analysis, which can predict future demand changes. Due to the market share of new technology being relatively low during the early stages of diffusion, the use of discrete choice experiments (DCE) based on explicit consumer preferences is an appropriate method to analyze consumer preferences (Kim et al., 2020).

DCE can accurately represent the competition between technologies in terms of demand, but only a partial equilibrium result is obtained, excluding the ripple effect on other industrial sectors (Choi and Koo, 2019; Wolinetz and Axsen, 2017). In other words, it is difficult to grasp the linkage effect (macroeconomic effect) with other products and industries. The DCE model is based on consumer preferences derived through a hypothetical set of choices resulting in real-life patterns and constraints, such as restrictions on consumer income not being taken into consideration. When the DCE model makes decisions, the outcomes can be biased (Wolinetz and Axsen, 2017) in that they tend to provide high estimates of alternative new commodity valuations and market share (Tran et al., 2013). Moreover, they are an unreliable source of data unless combined with actual published preferences or markets (Axsen et al., 2009). In addition, the supply side is generally not expressed in the individual choice model, so it is difficult to see the effects of the policy.

In summary, the prediction based on the DC model is straightforward. For example, when simulating a policy instrument, consumers receive the resulting change exogenously. In other words, the simulation of the choice model is based on the assumption that there is no feedback from related industries or changes in other economic factors due to changes in demand for those goods.

Contrastly, CGE is a macroeconomic model that can determine the impact of changes in demand and specific factors on the entire country, including industries and households. The CGE model can analyze a broader economic framework by considering the feedback

effect between different economic actors in the context of policy changes (Yun et al., 2016). Therefore, the CGE model can test government intervention in the diffusion of new technologies and measure their ramifications.

However, CGE is a top-down model that cannot reflect technical details, which makes it challenging to capture technological advances (Andersen et al., 2019; Dai et al., 2016; Fortes et al., 2014). Studies of top-down models also assume an exogenous parameter, i.e., the existence of a backstop technology that becomes economical at an exogenously specified threshold (Rip and Kemp, 1998). It is difficult to reflect on the technical factors affecting the diffusion of new technologies in the CGE model as changes in consumer demand only depend on the relative prices of the goods.

In other words, the CGE model is suitable for estimating the impact of policy changes on the overall industry but has limitations in realizing sophisticated technological progress or competition (Li et al., 2017; Osawa and Nakano, 2015). Specifically, in the context of the proliferation of new technologies, it may be necessary to accurately represent the competitive situation between future technologies in terms of demand; however, when using the CGE model alone it is difficult to adequately reflect this. Therefore, to identify the impact of the diffusion of consumer-inducing new technology on the national economy and environment exactly, it is difficult to see through a single model, and an integrated approach between models is required.

This study focused on green mobility. Following the Paris Agreement, pledged to set carbon-neutral targets and strategies for achieving close to net-zero emissions in the long

term. CO2 emissions from the transport sector account for one quarter of global greenhouse gas emissions, mostly from road transport (72%) (Axsen et al., 2020). In this vein, the importance of alternative fuel vehicles (AFVs), including electric and hydrogen fuel cell vehicles, as a primary means of reducing global greenhouse gas emissions in the transportation sector has become prioritized.

The transition to green mobility is occurring with innovations in the automobile industry. Due to technological changes in the transport sector and increasing environmental problems, technological innovation has occurred within the transportation environment, including but not limited to new driving practices, charging routines, and energy storage (V2G). Environmental (eco) innovation in the transport sector emphasizes air quality, CO2 emissions reduction, and decreased oil dependency. The need for the introduction of environmental innovations to replace the fossil-fuel-based transport sector in an attempt to decrease the effects of global warming has become mandatory (Figenbaum, 2017). With technological and environmental innovations, the paradigm of the global automobile market is shifting from an existing internal combustion engine vehicle to a next-generation alternative fuel vehicle. As new technology in the automobile sector spreads, the intention to develop new technology, i.e., innovation will be created and the ripple effect thereof must be measured.

The automobile industry is a representative business-to-consumer (B2C) market, and consumer behavior is essential for spreading new technologies. Additionally, the automobile industry has a chain effect as multiple industries are inter-connected, from

manufacturing of steel, semiconductors, and glass used in automobile production to the fuel required for driving, roads, and gas stations. It shows a sociotechnical landscape comprising steel and plastic, road concrete, traffic rules, and culture, rather than just one artifact (Rip and Kemp, 1998). The energy demand structure is straightforward, because the fuel used for each vehicle is different. The introduction of green mobility can significantly transition the energy industry, including electrification and hydrogenation of automobiles. Therefore, in order to measure the impact of green mobility, it is necessary to identify the substitution effect between vehicles and the entire industry and, it is crucial to confirm how companies and industries respond to demand changes.

Therefore, this study analyzed the environmental and economic effects of various policy instruments in transportation by linking the CGE model to the DC model, as shown in Figure 2. The CGE model provides a macro-perspective assessment of changes in industrial structures, whereas the DC model investigates consumption behavior from a micro-perspective. By integrating the two models, the DC model captures more elastic changes in the level of attributes (e.g., price) by endogenously reflecting CGE results. CGE reaches equilibrium at the point where supply and demand meet, and it tries to find a new equilibrium according to changes in consumer demand by receiving the choice probability of the DC model. Additionally, the CGE model reflects the technological specifications (e.g., changes in vehicle type and infrastructure improvements) in the DC models. Consequently, through the use of the integrated model, the effect of the diffusion of green mobility can be identified in detail, thus replicating the technical information in

the CGE model where the market share prediction calculated in the model ultimately leads to more reasonable results.

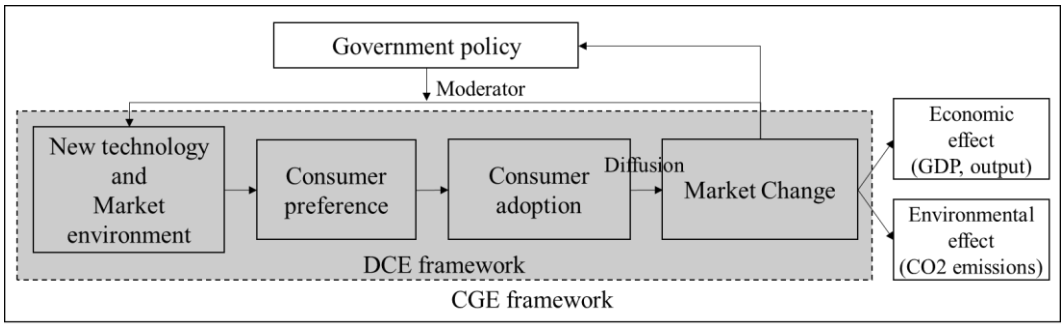

Figure 2. Research framework

1.2 Research Objectives

For the purpose of improving economic and environmental spheres, the government aims to accelerate the supply of green mobility. As a result, various policies have been developed and implemented. Government and policy designers may be interested in the following issues regarding the spread of green mobility in the automobile market.

Firstly, environmental regulations becoming stricter due to the international demand for carbon neutrality under the Paris Agreement. Among these, a carbon tax has already been implemented as a representative regulatory tool in several European countries. Korea is also considering a carbon tax to achieve its national goal of carbon neutrality. Generally, carbon taxes encourage the development of clean technologies; however, simultaneously reducing production in current day-carbon heavy technologies stifle

innovation in these sectors, and thereby reduces overall current production and consumption. This means that additional means of driving innovation for clean technologies must be used concurrently, as carbon prices alone can hinder economic growth, making it an expensive policy scenario (Acemoglu et al., 2012). In other words, effective results can be obtained when technology policies are implemented simultaneously (Buonanno et al., 2003; Goulder and Mathai, 2000; Popp, 2006). In this respect, this study intends to examine the effect of carbon tax imposition by adding carbon price to the fuel tax in the transport sector, as shown in Figure 3.

(Research Question 1) Tax imposition policies help spread new technologies but have a negative impact on economic growth; however, if the pace of technological progress increases, how will taxation policies affect economic growth?

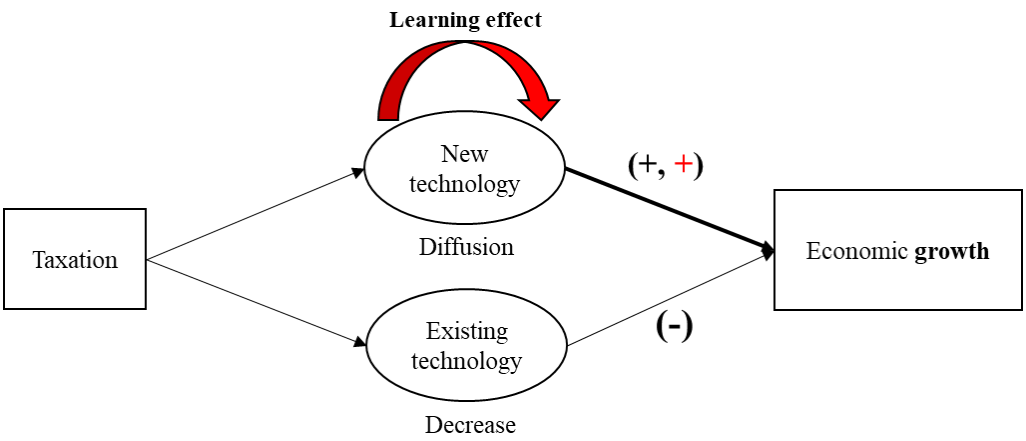

Figure 3. Research Question 1

Secondly, representative policy measures aimed at supporting the dissemination of green mobility include subsidies for the purchase and installation of a charging infrastructure, which serve as an inducement to go green. While taxation is a market-inducing instrument that supports the diffusion of new technologies through the regulation of existing technologies, subsidies directly support the consumption of new technologies. In addition, installation cost support for the charging infrastructure, which is a complementary good, improves the accessibility of the infrastructure, leading to consumers' purchase of green mobility. Opinions vary on the effectiveness of purchase subsidies and charging infrastructure investments as economic incentives. Some argue that subsidies increase the rate of diffusion of the initial market by lowering barriers to entry (Kumar et al., 2021; Miele et al., 2020; Schwartz and Clements, 1999), while others argue that charging infrastructure leads to the possibility of structural change, making it a natural choice for consumers to induce diffusion (Hardman et al., 2017; Lieven, 2015; Sæther, 2022; Sierzchula et al., 2014).

(Research Question 2) Which approach will have a greater effect on the diffusion of technology and economic growth, a direct government price subsidy policy for consumers, and indirect support for the complementary goods market?

Lastly, the evaluation of subsidy policy raises the issues of equity and cost-effectiveness. Subsidies can be an effective tool for promoting industrial development and

economic growth and can improve the welfare of society. However, subsidy policies can also have unintended distributive effects (Kwon and Park, 2009). For example, when subsidies are allocated to electric and hydrogen cars, they are more likely to be purchased by high-income groups because they are relatively expensive, and the benefits of subsidies are therefore only enjoyed by high-income groups. If so, should more subsidies be given to the low-income class for equality of income distribution or should the same subsidies be given regardless of income to spread green mobility?

(Research Question 3) Although the differential payment of subsidies to support the low-income class has a positive effect on income distribution in the short term, will it negatively affect national economic growth in the long term?

This study aims to answer the above research questions for the automobile industry, specifically for passenger cars. To solve this problem, an integrated model that links DC to the CGE model was developed. An integration model is appropriate to determine the impact of consumer-induced technology diffusion because changes in the economic system caused by technology diffusion due to consumer choices ultimately affects consumers past, present and future choices. The DC method investigates consumption behavior from a micro perspective. When using a DC model, economic factors, such as vehicle price, and noneconomic factors, including car type and charging infrastructure, are considered. The CGE model provides a macro perspective assessment of changes in

industrial structure. It is possible to determine general equilibrium at the national level by reflecting individual consumer choices.

Table 1 shows the advantages of model integration, for example, environmental aspects can also be identified in an integrated model. If ICEVs are converted to green mobility vehicles, such as electric vehicles and hydrogen vehicles, emissions at the driving stage can be reduced. However, what are the actual emissions during the production of producing electric vehicles and hydrogen cars? The intensity of emissions from the production of one ICEV may differ from the intensity of emissions from the production of one electric vehicle/hydrogen vehicle. ICEVs have a high engine input share, but electric vehicles and hydrogen cars have other components, such as batteries and hydrogen tanks. The CGE model allows industry structures to identify emission changes in automobile manufacturing as well as emissions from the fuel production stage. Electricity and hydrogen are secondary energy sources, and therefore, electric and hydrogen powered vehicles have no CO2 emissions during driving. However, in Korea's current power generation structure, most of the electricity comes from thermal power generation, and hydrogen is generated from LNG gas reforming and by-product gas (brown hydrogen). In other words, changes in emissions from fuel production, automobile manufacturing, and driving owing to the spread of green mobility can be observed in an integrated manner.

Even in the case of government policy testing, certain advantages can be obtained through model integration. For example, when the DC model subsidy policy is used,

subsidies are given exogenously but their origin is unknown; however, when the DC model and the CGE model are combined into one integrated model, it is possible to identify where the subsidy or tax is derived from and how the tax revenue is collected.

Table 1. Advantages of model integration

	DC model	CGE model	Integrated model
Technology substitution	○	X	○
Industrial change	X	○	○
Net effects on economy and environment	X	○	○

If a consumer's demand for transport services changes according to an exogenously given situation, industrial production and fuel prices adjust, affecting consumers' choice of transport services. To consider these interactions, an integrated model proposed in this study is required. Changes in the transport market structure and energy (fuel) demand are expected owing to the changes in the future transport sector. This study uses an integrated model to predict future transportation sector changes through consumer behavior analysis and analyzes the national economic and environmental ripple effects. In other words, in stark comparison to the use of a single model, the use of an established integrated evaluation model allows for the comprehensive analysis of the ripple effect of the diffusion of new technologies in the transport sector and policy intervention.

1.3 Research Outline

This dissertation comprises five chapters. Figure 4 shows the structure and outline of this study.

Chapter 1 introduces the research background, objectives and outline. Chapter 2 describes the theoretical and methodological background of the research and summarizes the extant studies. Previous studies on the environmental and economic effects of the spread of green mobility have been introduced, especially when the choice model is linked based on the examined equilibrium model. A literature review is used to identify the shortcomings of existing studies and shows how this study significantly contributes to this field of research.

Chapter 3 introduces the methodologies used in this dissertation: I.e., the DC, CGE, and integrated models. A hierarchical Bayesian mixed logit model was used for DC analysis to consider individual heterogeneity and household income deciles. The results by income quintile indicate targets likely to be purchased from the company's point of view. According to the characteristics of the study, the CGE model was transformed from a reconstruction of social accounting matrix to separating the vehicle service sector from households, adding the hydrogen industry, and subdividing the power structure.

An integrated model that uses the strengths of each model by linking two models with contrasting benefits was required, and therefore, in this study, DC was merged into the CGE model as a reduced hard-linked form. In the CGE model, the input was a logit-type function representing consumers' indirect utility. Households choose a combination that

maximizes utility in the passenger car sector and based on this, the probability of choosing a car is calculated. This choice probability data eventually leads to the calculation of household demand and in the CGE model, price and production are determined, which ultimately reflects the market. At this time, the price obtained from the CGE model is transferred back to the DC model to change the attribute value. In addition, the integrated model allowed household passenger car stock to affect charging infrastructure and automobile productivity.

Chapter 4 includes an empirical analysis and discussion of the various scenarios. The results of the DC single model and the link model integrated with the CGE model were compared, whereafter the results of the baseline scenario reflecting the government plan were summarized. Each scenario was used to test the research question. Scenario 1 shows the effect of fuel taxation as a means of promoting the spread of green mobility, depending on the learning rate. Scenario 2 compares the effect of representative green mobility proliferation policies on purchase subsidies and investment in charging infrastructure. Finally, Scenario 3 tests the trade-off between equity and the effectiveness of subsidy policies by comparing a differential subsidy payment case.

Lastly, Chapter 5 concludes the paper with remarks, implications, and contributions of this study. Additionally, based on the limitations of this study, suggestions are made for future research directions.

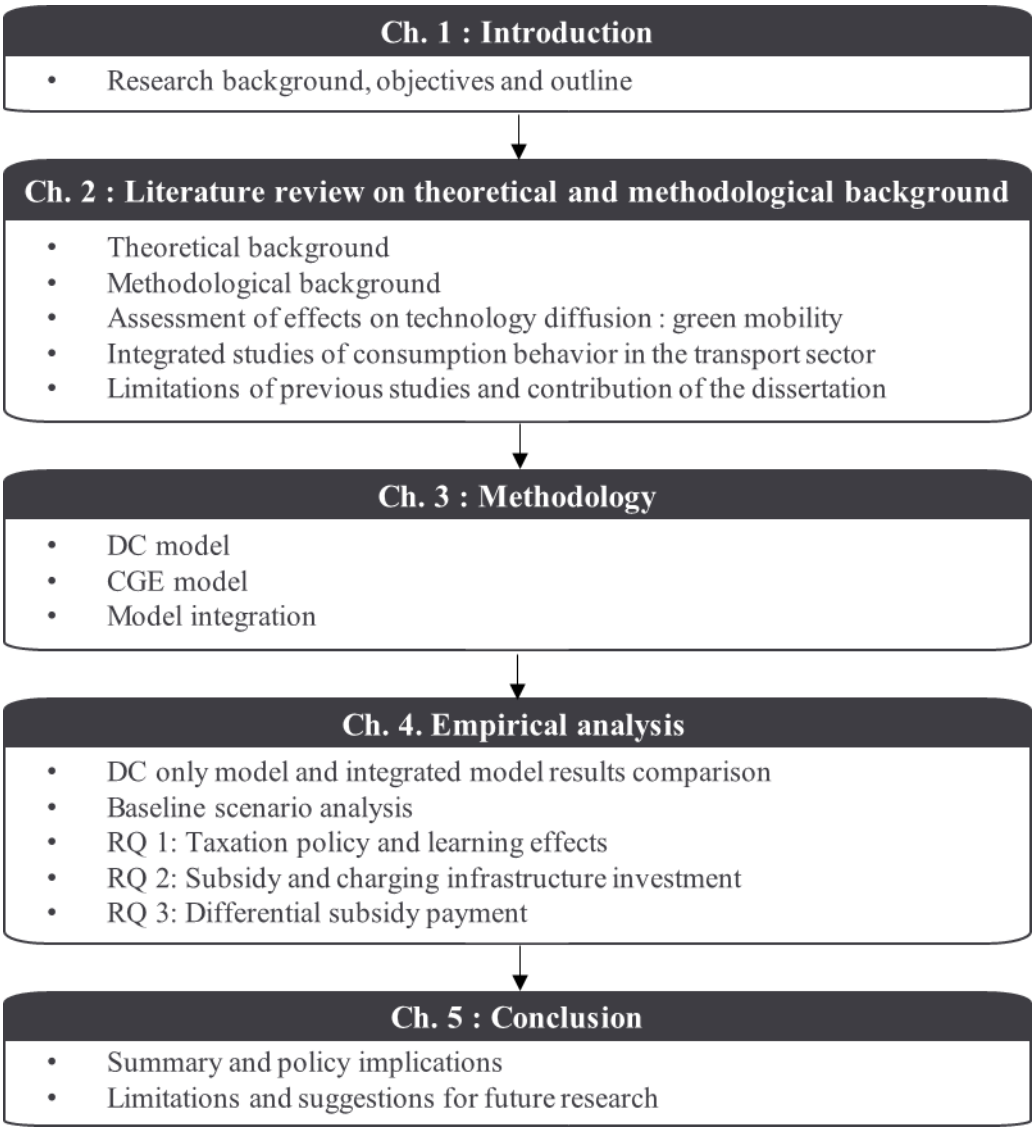

Figure 4. Research outline

Chapter 2. Literature Review and Theoretical and Methodological Background

2.1 Theoretical Background

2.1.1 Debates on Environmental Regulation and Innovation

"Properly designed environmental standards can trigger innovation that may partially or more than fully offset the costs of complying with them." (Porter and Van Der Linde, 1995)

Generally, environmental regulation incurs additional private costs in a firm's production. Porter and Van Der Linde (1995) acknowledged that regulation could appear as an economic burden because it increases production costs in a static world where firms are already making cost-minimizing production. However, they argued that the so-called "innovation offsets" appear, in which environmental regulations reduce production costs and contribute to productivity improvement in the long run in a dynamic situation where companies have the ability to pursue innovation continuously.

Moreover, what they call "properly designed environmental standards" can serve six purposes. ① Regulations draw attention to resource inefficiency and technological innovation that companies are unaware of. ② Regulations for information collection can lead to profits by allowing companies to recognize the situation and improve themselves. ③ Regulation diminishes the uncertainty of environmental investment. ④ Regulation forces businesses to inspire innovation and progress. ⑤ Regulation buffers the

transitional market. ⑥ If innovation does not entirely offset the cost of implementing a policy, regulation is necessary.

Even before Porter and Van Der Linde (1995), there were discussions about regulation and innovation. Ashford argued that "environmental regulation of production activities has a substitution effect for current or new products, and can sometimes induce significant levels of innovation in the production process" (Rothwell, 1992).

Porter and Van Der Linde (1995) proved this hypothesis through various examples. However, those opposing this hypothesis argued that these were only specific cases. Palmer et al. (1995) insisted that there is no relationship between environmental regulations and competitiveness. They said that it is only in some firms that innovation enhances competitiveness, and the "innovation offsets" that Porter assert is not a typical situation, especially when considering opportunity cost. They expressed doubts about whether cost reduction through innovation is truly a win-win strategy.

On the other hand, the integration position shows that the Porter hypothesis depends on the circumstances in which a company is located and that the environment and the economy are not necessarily in conflict but can be maintained in harmony if well managed (Jaffe et al., 1995; Jaffe and Palmer, 1997; Jaffe and Stavins, 1995). Jaffe et al. (1995) showed what types of regulation can induce innovation under what conditions and how such innovation improves competitiveness. Jaffe and Palmer (1997) also saw that only well-designed policies could induce innovation.

In other aspects, Porter's hypothesis is also expanded to research on diffusion in terms

of environmental regulations fostering the adoption and spread of new technologies. Strict environmental regulations may induce companies to choose clean technologies rather than undertake their innovation activities (Gray and Shadbegian, 1998) or promote the dissemination of new technologies along with corporate R&D activities (Perino and Requate, 2012). Based on various research results, Shao et al. (2020) emphasized innovation through diffusion because environmental regulations have more influence on diffusion than technological innovation, but the spread of technology from a macroeconomics perspective helps improve the overall competitiveness of the industry.

Various studies have shown that environmental and technological policies can lead to effective results when implemented simultaneously (Buonanno et al., 2003; Goulder and Mathai, 2000; Popp, 2006). The study of Goulder and Mathai (2000) found that the optimal carbon tax pathway decreased when considering R&D-based and learning-by-doing-based knowledge accumulation, suggesting that the knowledge growth effect offsets the shadow cost effect. Popp (2006) also found that combining a carbon tax and R&D subsidy could yield the most significant welfare benefit. Meanwhile, Goulder and Schneider (1999) argued that the increase in fuel prices due to carbon tax increases the market for low-carbon technologies, leading to incentives for increased R&D and bringing about technological change. Azar and Dowlatabadi (1999) also confirmed that the carbon tax accelerated the diffusion of new technologies and lowered their costs. In all, taxation policies such as carbon taxes can help economic growth when the technology has high growth rates but can burden the national economy when it is not.

2.1.2 Transport Policy for the Diffusion of Green Mobility

Previous studies emphasized the need for policy intervention in the diffusion of technology. New technologies have relatively low price competitiveness compared to existing technologies. Therefore, the government supports securing market competitiveness of new technologies through various policies. The role of the government is to control the speed of diffusion as a moderator. For example, there are regulations to curb congestion in existing markets or multiple pushes to promote the diffusion of new technologies targeting consumers or suppliers.

Transport policy is primarily separated into the supply side and demand side. In particular, in the B2C market, when a technology appears, the demand side policy that induces consumers to purchase for diffusion prevails. Demand-side policies provide direct subsidies to consumers or target factors influencing direct consumer purchases, such as building charging infrastructure and fuel tax. On the other hand, supply-side policies change the company's supply by improving productivity through R&D investment or more directly with the ZEV mandate (phase-out of ICEVs sale).

In the case of automobiles, green mobility is a new type of product with a different fuel, fuel charging method, and driving mode. Unlike conventional ICEVs, there are uncertainties about the market because factors influencing consumer choices are diversified. In this case, a demand-based policy that directly pushes the entry and spread of new products into the market is implemented to reduce market uncertainty. If the diffusion rate is not fast at the beginning, it may face a chasm and fail to enter the

mainstream market (Rogers, 1962).

Many studies have shown that the government's active intervention had a significantly positive effect on the spread of green mobility (Figenbaum, 2017; Kester et al., 2018; Lieven, 2015; Wolinetz and Axsen, 2017). For instance, Norway offers favorable conditions for using electric vehicles, including generous incentives such as tax exemption on registration and installing charging facilities at home. It can also be charged with electricity generated from hydroelectric power plants, which have low CO2 emissions and are inexpensive. As a result, Norway's BEV market share is high (Figenbaum, 2017).

2.1.2.1 Debates on the Effectiveness of Green Mobility Support Policies

Controversial opinions exist on subsidies and infrastructure investments as representative policies for the transition to green mobility. As an economic incentive, subsidies can speed up the diffusion of early markets by lowering the barriers to entry for new technologies. In particular, purchase subsidies enable consumers to purchase goods and services at lower prices than those offered in a perfectly competitive market and increase producer income (Schwartz and Clements, 1999). In other words, purchase subsidies increase consumer convenience by inducing direct consumer purchases. Kumar et al. (2021) found that providing EV subsidies to consumers increases the number of EVs sold, maximizing social welfare rather than directly investing in charging infrastructure under a limited budget by the government. In addition, Miele et al. (2020) noted that other strong

policies and subsidies are needed to promote ZEV sales since the effect of dissemination of charging infrastructure is limited.

On the other hand, charging infrastructure is a representative complement to automobiles, which causes systematic change. If a charging facility base is formed by investing in infrastructure, the network effect induces technology diffusion as a natural choice for consumers. The inability to use a proper charging facility is a significant constraint on EV penetration (Kumar and Alok, 2020). The relationship between charging stations and green mobility can be explained as the chicken-egg problem. The charging infrastructure takes on the character of a vehicle's complement, and an indirect network effect appears. If either green mobility or charging stations are insufficient, a vicious cycle can be formed that acts as a factor hindering mutual supply and diffusion. For this reason, the government is actively constructing charging stations using public funds in the early stages.

Several studies have shown that the charging infrastructure effect is greater than the financial incentive effect in EV penetration (Lieven, 2015; Sæther, 2022; Sierzchula et al., 2014). Sæther (2022) found that charging infrastructure was a significant and vital factor in increasing PEV market share and was more important than personal incentives. Personal incentives – subsidies, tax exemptions, and taxes on traditional fossil fuels – show a gradual increase in the PEV market share. However, the gradual increase does not necessarily cause structural changes, while charging infrastructure, on the other hand, can lead to structural changes. Meanwhile, Hardman et al. (2017) argued that financial

incentives for BEV and PHEV promotions were insufficient to increase PEV adoption significantly. In particular, Lieven (2015) emphasized the combination of low consumer subsidies and high investment in charging infrastructure.

Subsidies are currently oriented, but investments in charging infrastructure are future-oriented. In the early stage of the spread of green mobility, it is essential to increase the speed of distribution by using both means. However, it is also necessary to prioritize in consideration of the effectiveness of the policy in a situation where the government's budget is limited.

2.1.2.2 Debates on the Equity of the Subsidy

Subsidies and tax policies are often accompanied by equity issues in terms of the income distribution. The subsidy system on AFVs may also result in more payments to high-income earners who are more willing to purchase them. According to Kester et al. (2018), Denmark was exempt from VAT for electric vehicles, which resulted in relatively higher discounts on relatively more expensive cars. Although the government encouraged people to buy more electric vehicles (emphasis on the quantitative aspect), they ended up buying more expensive cars, leading to tax cuts on luxury cars. As a result, the Danish government phased out tax exemption due to the image of the rich and financial regulations. Lévay et al. (2017) also showed that flat tax exemptions in Norway and the Netherlands lead to a preference for expensive electric vehicles. The subsidies were given to the wealthy members of society by subsidizing the purchase of large electric vehicles

through subsidy policies in Norway and the Netherlands. Since electric vehicle purchases are high among high-income groups, subsidies will likely be transferred to high-income groups. In other words, electric vehicle subsidy is an effective instrument for diffusion but can cause inequity problems.

2.2 Methodological Background

2.2.1 Demand Forecasting on Individual Level

Demand forecasting can be broadly classified into diffusion and behavioral models. As a representative diffusion model, the bass model predicts future sales of new technologies using initial sales data according to a growth curve, for example, an S-curve (Bass, 1969). This approach has been widely used because it is easy to apply and can directly estimate new sales and inventory by period. However, since this model assumes exogenous market potential, it is difficult to reflect changes in diffusion patterns caused by competition between technologies or policy intervention. Also, evaluating how individual consumers make purchases and spread the technology is impossible.

For a new technology to successfully enter the market, it is crucial to understand consumer preferences accurately. It is possible to predict the spread of technology according to policy and market environment changes by identifying consumers' preferences for technology attributes and building a utility function. The discrete choice method is used to analyze consumers' acceptance and benefits of products and services in the early stage of the market (Train, 2009). The discrete choice model shows the diffusion

of technology on the demand side based on the consumer's stated preference data. Consumer utility is expressed by including several attributes in the choice model. This method serves as a valuable tool to elicit specific attribute preferences for alternatives, thus helping to predict the market potential of new technologies and provide policy support (Miess et al., 2015). The discrete choice model was derived from an economic agent utility maximization assumption, random utility theory (McFadden, 1974).

Based on the probabilistic utility theory, indirect utility (U_{nj}) obtained by the consumer *n* from the alternatives *j* in the choice set is divided into deterministic utility and stochastic utility in equation (1).

$$U_{nj} = V_{nj} + \varepsilon_{nj} \quad \cdots\cdots \text{Eq. (1)}$$

(V_{nj} : deterministic utility, ε_{nj} : stochastic utility)

Deterministic utility (V_{nj}) means an explainable part and stochastic utility(ε_{nj}) means an unexplainable part, such as individual respondents' preference characteristics. V_{nj} can be expressed as the multiplication of the vector of observed attributes X_{nj} and the vector of preference parameter estimates β. Each respondent chooses the option that gives the highest utility among several alternatives, and the probability that the respondent chooses the alternative is defined as the following equation (2).

$$
\begin{aligned}
P_{n,j} &= \Pr(U_{n,j} > U_{n,k} \ \ \forall k \neq j) \\
&= \Pr(\varepsilon_{n,k} - \varepsilon_{n,j} < V_{n,j} - V_{n,k} \ \ \forall k \neq j)
\end{aligned}
\quad \cdots\cdots \text{Eq. (2)}
$$

There are various models according to the distribution of error terms and the parameter estimation method. The (multinomial) logit model is the most straightforward and widely used assuming that the error term is independent and identically distributed (iid) extreme value. Therefore, the density of each error term is given in equation (3), and the cumulative distribution is in equation (4).

$$
f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}} \quad \cdots\cdots \text{Eq. (3)}
$$

$$
F(\varepsilon_{nj}) = e^{-e^{-\varepsilon_{nj}}} \quad \cdots\cdots \text{Eq. (4)}
$$

Using the distribution, choice probability can be represented in closed form as equation (5).

$$
\begin{aligned}
P_{nj} &= \int \left(\prod_{i \neq j} e^{-e^{-(\varepsilon_{nj} + V_{nj} - V_{ni})}} \right) e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}} d\varepsilon_{nj} \\
P_{nj} &= \frac{e^{V_{nj}}}{\sum_i e^{V_{ni}}} = \frac{e^{\beta' X_{nj}}}{\sum_i e^{\beta' X_{ni}}}
\end{aligned}
\quad \cdots\cdots \text{Eq. (5)}
$$

The likelihood that respondent *n* will choose alternative *j* can be easily estimated through the maximum likelihood estimation (MLE) method in the logit model. Deriving

the likelihood function to apply the MLE method is as follows:

$$L = \prod_{n=1}^{N} P_n = \prod_{n=1}^{N} \prod_{j} P_{nj}^{\ y_{nj}} \quad \cdots\cdots \text{Eq. (6)}$$

where y_{ni} is 1 if consumer *n* chooses alternative j, and otherwise 0.

The assumption of the main characteristics of the logit model- preference homogeneity and the property of independence of irrelevant alternatives (IIA)- makes model estimation simple but has limitations. IIA means that the ratio between the choice probability of alternatives depends only on the attributes of the alternatives and is not affected by other alternatives (Train, 2009). This may be an unreasonable assumption in reality.

In this vein, various methods have been suggested to overcome limitations of the logit model. For example, the mixed logit model can reflect the heterogeneity of individual consumer preferences by assuming that the marginal utility (β) of the attribute has a stochastic distribution (Train, 2009). When estimating the coefficient of an attribute, it can be assumed that a probability distribution is assumed for each coefficient; that is, it follows a normal distribution. Since coefficients are extracted for each individual from the normal distribution, each individual can have different estimation coefficients, and the IIA constraint can be relaxed by allowing correlation between coefficients in the covariance matrix. It is assumed that the coefficient vector (β_n) follows a normal

distribution with mean (b) and variance (W) for this population. Accordingly, the utility of respondents *n* choosing an alternative *j* may be expressed as follows.

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta_n^{'} X_j + \varepsilon_{nj},\ \beta_n \sim N(b,W) \quad \cdots\cdots \text{Eq. (7)}$$

In the coefficient vector (β_n) is given, the probability that the respondent *n* will choose the alternative *j* is the same as the choice probability equation of the general multinomial logit model, but β_n is also a parameter to be estimated. Therefore, choice probability equation of the mixed logit model is as below:

$$P_{nj} = \int L_{nj}(\beta) f(\beta_n | b,W) d\beta_n \quad \cdots\cdots \text{Eq. (8)}$$

where $L_{nj}(\beta) = \dfrac{e^{V_{nj}}}{\sum_i e^{V_{ni}}} = \dfrac{e^{\beta_n^{'} X_{nj}}}{\sum_i e^{\beta_n^{'} X_{ni}}}$

Then, the likelihood function of consumer *n* also can be transformed as equation (9).

$$L = \prod_{n=1}^{N} P_n = \int \prod_{n=1}^{N} \prod_j \{L_{nj}(\beta)\}^{y_{nj}} f(\beta_n | b,W) d\beta_n \quad \cdots\cdots \text{Eq. (9)}$$

To estimate parameters in mixed logit model, simulated MLE or Bayesian estimation should be used instead of MLE method.

2.2.2 General Equilibrium Theory

General Equilibrium theory originated from Leon Walras, who proved that the interaction of supply and demand results in general equilibrium. Walras formulated the state of an economic system as a solution to simultaneous equations that demonstrate equilibrium conditions in which supply and demand are equal. Arrow and Debreu (1954) proved the existence and stability of solutions of competitive equilibrium based on Walras' law. The CGE model is a macroeconomic model created based on the theoretical background of the general equilibrium theory and is designed to establish a numerical framework (Hosoe et al., 2010). Figure 5 represents the economic structure and the transaction flow between economic agents in the CGE model. In the CGE model, households determine consumption bundles to maximize consumption utility according to budget constraints. And firms try to maximize profits by managing inputs and outputs according to production technology. The results obtained through the optimization actions of economic agents must satisfy the market clearing conditions. The CGE model finds a state of equilibrium even when an external shock occurs. Due to these characteristics, the policy can be empirically analyzed and evaluated using the CGE model.

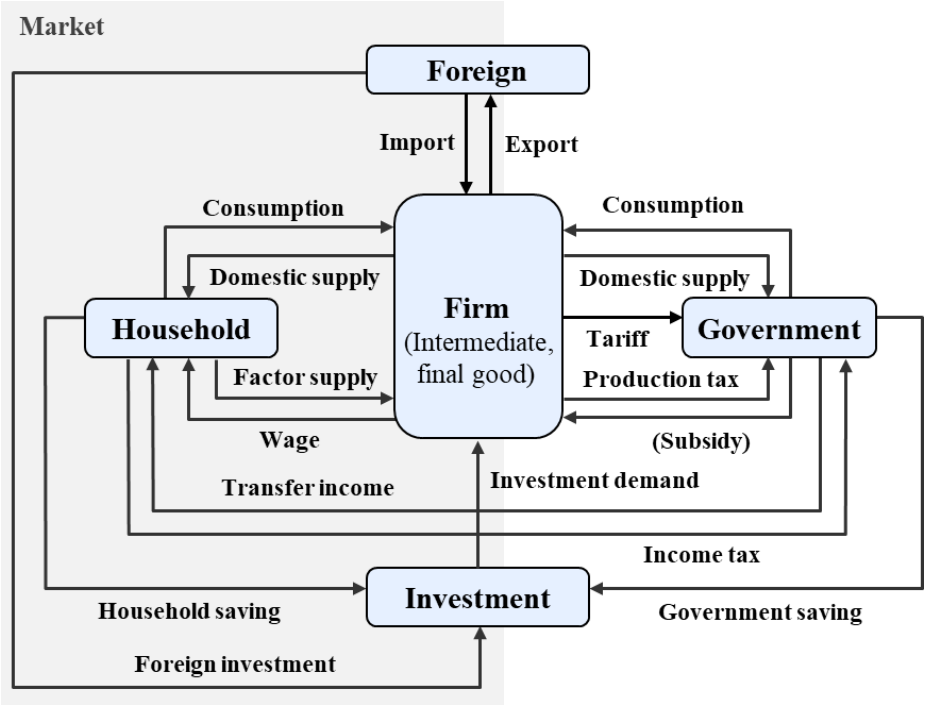

Figure 5. Economy structure in CGE model

Source: Korea Environment Institute (KEI) (2021)

2.3 Assessment of the Effects of Technology Diffusion: Green Mobility

2.3.1 Environmental Effects

The environmental effect of green mobility dissemination is not always positive. Table 2 shows the environmental results according to the diffusion of EVs. Requia et al. (2018) quantitatively evaluated the impact of EVs on the environment and human health through meta-analysis. They consistently showed a reduction in GHG emissions and some air pollutants. In contrast, the increase or decrease in PM and SO2 is highly dependent on the

source of energy generation, driving conditions, and charging patterns. Vilchez et al. (2019) modeled the air quality impact of the EV development policy following the EU Directive 2014/94/EU. The predictions for emissions on tailpipe and urban concentrations showed that EVs reduced CO2, NOx, and PM2.5 emissions by approximately 3%, 6%, and 4%, respectively. However, the changes in concentration were based solely on transport policy and did not consider emissions from other areas.

Unlike other studies that focused only on the emission stage, Hawkins et al. (2013) utilized a life cycle assessment from the power generation to the consumption stage to evaluate the environmental effects of EVs. They calculated a 10–24% reduction in GHG emissions from EVs in comparison with ICEVs. In addition, Kim (2017) compared the emissions of GHG and PM10 (per km) between gasoline and EVs with the LCA method. Based on the power mix in the case of Korea 2016, electric cars emit about 53% of GHG and 92.7% of PM10 compared to gasoline cars.

Meanwhile, Manjunath and Gross (2017) estimated the CO_2 emissions from electricity production to consumption stage through an EV emission index (EVEI). EVs showed higher emissions than GVs in the case of fossil fuel-intensive generation mixes. In a survey by Tessum et al. (2014), air pollution and health effects were estimated when EVs replaced 10% of vehicles by 2020. They showed environmental benefits when charging electricity consisted of clean energy, although the number of deaths increased from 230 to 3,200 under the existing coal power generation. Weis et al. (2016) also showed that plug-in EVs (PEVs) could be more environmentally damaging than hybrid

EVs (HEVs) as the share of coal power generation increases. Wu and Zhang (2017) showed that EVs mitigate CO_2 emissions significantly, but their effects on air pollution vary depending on the country's power structure using the well-to-wheel (WTW) approach. Several studies pointed out higher emissions in EVs than in gasoline vehicles and adverse effects on the environment in a fossil-fuel-intensive power mix (Hawkins et al., 2013; Kim et al., 2020; Kim, 2017; Manjunath and Gross, 2017; Tessum et al., 2014; Weis et al., 2016; Woo et al., 2017). In summary, most studies assess the environmental benefits of EVs by considering both power generation production stages and emphasize that EVs can be a measure to reduce air pollution in the transport sector using clean energy sources.

Table 2. Environmental effects of EV diffusion

Authors	Main results
Requia et al. (2018)	Reduction in greenhouse gas emissions and some air pollutants, and the increase or decrease in PM and SO2
Gómez Vilchez et al. (2019)	EVs reduced about 3% CO2, 6% NOx, and 4% PM2.5 emissions
Hawkins et al. (2013)	10–24% reduction in GHG emissions from EVs
Kim (2017)	Electric cars emit about 53% of GHG and 92.7% of PM10 compared to gasoline cars
Manjunath and Gross	EVs showed higher emissions than GVs in the case of fossil fuel-

(2017)	intensive generation mixes
Weis et al. (2016)	Plug-in EVs (PEVs) could be more environmentally damaging than hybrid EVs (HEVs) as the share of coal power generation increase
Wu and Zhang (2017)	EVs significantly mitigate CO2 emissions, but their effects on SO2, PM10, and NOx emissions vary

2.3.2 Economic Effects

The CGE model can observe the economic effects of policies and new technologies, as represented in Table 3. Li et al. (2017) estimated the change in GHG emissions due to the expansion of EVs and carbon capture and storage (CCS) technology in China by 2050 using the dynamic CGE model. Based on the market share of EVs and simulation through the change of substitution elasticity in the energy sector and the parameters in the production and demand function of the land transportation industry, EV and CCS would reduce CO2 by 9.33% compared to the business-as-usual (BAU) scenario in 2050 but would cause economic loss.

Several studies established a new input-output (IO) table that separated the EV sector, which assumed that EVs could replace whole ICEVs (Leurent and Windisch, 2015; Miyata et al., 2014; Osawa and Nakano, 2015). Miyata et al. (2014) analyzed the impact of introducing EVs on the Japanese urban economy through the CGE model. The results showed that the total industrial output and city gross domestic product (GDP) increased slightly, and CO2 emissions increased. Osawa and Nakano (2015) estimated the

production and employment inducement coefficients of the Japanese automobile industry. They confirmed that the introduction of eco-friendly vehicles would result in a drop in the production of 1.5 trillion yen (JPY) in 2030. Leurent and Windisch (2015) also investigated the socioeconomic effect of the spread of EVs based on the cost structure of ICEVs and EVs through inter-industry analysis. This study showed that the supply of EVs varied depending on the production and export structure of the country, which is financially neutral for domestic manufacturing and uses but causes losses in imported cases.

Han et al. (2019) evaluated the effects of EVs and HFCVs on the GDP and CO2 emissions using the CGE model. This study integrated the Bass model for combining EVs and HFCVs into the CGE model as a shock and showed that EVs have a negative impact on CO2 emissions, whereas HFCVs mitigate CO2 emissions and increase GDP. The study was conducted by simulating exogenous market shock to the input coefficient without creating a new IO table. Moreover, they applied Bass diffusion model predictions for electric and hydrogen vehicles to the CGE model to analyze the environmental and economic impacts but showed no competition between car types.

Most studies on the spread of green mobility using the CGE model have confirmed their impact on the national economy and environment. In order to reflect the technology diffusion in the model, the Bass diffusion model is incorporated, or exogenous parameters are simply adjusted. However, in this case, it is difficult to confirm the change in demand from the transformation in technology characteristics because the change in cost is not

reflected endogenously.

Table 3. Economic effects of EV diffusion

Authors	Main results
Li et al. (2017)	EV would reduce CO2 by 9.33% compared to the BAU scenario in 2050 but would cause economic loss
Miyata et al. (2014)	The total industrial output and city gross domestic product (GDP) increased slightly and CO2 emissions increased
Osawa and Nakano (2015)	A drop in the production of 1.5 trillion yen (JPY) in 2030
Han et al. (2019)	EVs have a negative impact on CO2 emissions but increase GDP

2.4 Integrated Studies of Consumption Behavior in the Transport Sector

Various studies were conducted to model the consumption behavior in the transportation sector, as shown in Table 4. The unified climate options nexus (UNICON) was developed as a hybrid model integrating the bottom-up (BU) model that describes the demand sectors such as industry, buildings, and transportation in the general equilibrium model (KEI, 2021). Household demand related to transportation services was divided into independent nests, showing a substitution function in the transport sector. In the BU model, the utility of each alternative was estimated by a mixed logit model considering the consumer's preference through a conjoint survey; still, it could not be linked to the

CGE model. In addition, non-cost factors were calibrated based on the base year value, but the EV sector was not classified in the top-down IO table.

Ou et al. (2020) simulated how the properties of the charging infrastructure affect the PEV market share using the new energy and oil consumption credits (NEOCC) optimization model. Using the DC method, the probability of vehicle purchase was determined according to the consumer utility incorporating the total value of charging activities in the NEOCC model. Finally, the market share of vehicles was predicted based on consumer preference for public charging opportunities and vehicle attributes. The results showed the market share of each vehicle for maximizing the profit under the policy restraints in the automotive industry but did not explain the effect on society. Lee et al.(2013) linked the market allocation (MARKAL) optimization model with the Bass diffusion model and identified the impact of green mobility technology on mitigating GHG emissions. MARKAL seeks to minimize the total system costs without considering noneconomic factors such as design and functionality. Therefore, adding the results of the DC model as the constraints for the MARKAL prevents excessive cost bias and allows non-cost attributes when selecting technology. The study estimated energy mix and CO2 emissions in the transport sector based on the market share prediction of green cars, though it did not observe the impact on the whole economy.

Not many studies deal with consumer behavior, including the discrete choice model, from a macroeconomic perspective; however, most utilize the CGE model. Initially, the behavioral variables were estimated using DCE, which were then used as exogenous

variable inputs to CGE (Bataille et al., 2006; Jaccard et al., 2004; Magnani and Mercenier, 2009; Rivers et al., 2003; Rivers and Jaccard, 2005). In others, a discrete choice model was applied to the CGE model, but the integration method is one-way (Miess et al., 2015, 2022; Truong and Hensher, 2012, 2014). Rivers and Jaccard (2005) presented vehicle selection as a bottom-up model for cost minimization and linked it with a top-down model related to energy supply. It has the advantage of enabling observations of endogenous technological changes.

Venturini et al. (2019) summarized behavior studies in the energy and transport model. Most studies have linked the DC (logit) to the BU model, only referring to the top-down model (Karplus et al., 2013). Karplus et al. (2013) developed a new method for predicting physical demand for passenger vehicle services in the CGE model. The income elasticity of households for vehicle transport services was calibrated by identifying how the number of cars owned and the proportion of household vehicle expenditure vary over time. Using the physical unit of vehicle miles traveled (VMT), they showed the relationship between the expenditure and quantity of VMT. The predicted VMT was calculated by dividing the sector output value into the cost per mile and relative cost in production. This study, however, did not reflect the consumer preference for the change of physical demand in vehicle transport service and only considered the cost of adopting EVs.

Truong and Hensher (2012) linked the DC to the continuous demand (CD) method in the CGE model to test a project for the rail network. The CD model estimated the total demand by reflecting the aggregate price index from the DC components connected with

the demand quantity. The Development of an Evaluation Framework for the Introduction of Electromobility (EU DEFINE) project by Schmelzer and Miess (2015) analyzed the environmental and economic effects of the supply of EVs in Austria by linking the DC model to the continuous demand from the CGE model, which applied the methodology in Truong and Hensher (2012). Several policy instrument scenarios demonstrated that EVs reduce CO2 emissions but negatively affect the GDP. However, these studies have limitations in that the linking method is a one-way coupling, so the DC model cannot capture the results of the CGE model.

Table 4. Integrated model in regard to vehicle consumption

Authors	Methodology
KEI (2021)	Hybrid model (BU model and CGE model)
Ou et al. (2020)	Optimization model (NEOCC) using discrete choice method
Lee et al. (2013)	Optimization model(MARKAL) using discrete choice method and Bass diffusion model
Han et al. (2019)	CGE with Bass diffusion model
Karplus et al. (2013)	Discrete choice model in CGE model
Truong and Hensher (2012)	Discrete choice with continuous demand in CGE model (DC+CD+CGE model)
Schmelzer and Miess (2015)	Discrete choice with continuous demand CGE model (DC+CD+CGE)

2.5 Limitations of Previous Studies and Contribution of the Dissertation

This study intends to examine the effect on the country when technological innovation in the transport sector called green mobility is spread through consumer choice. DC model can predict demand at the micro level based on individual preference for alternatives. CGE model can find the solution which balances supply and demand at the macro level and test the results of various policies. Previous studies have been conducted on integrating models to include consumer behavior in the top-down model. However, they just predicted market share or did not take into account consumer preference for the change of physical demand in vehicle transport.

Han et al. (2019) applied the Bass diffusion model prediction results for hydrogen and electric vehicles to the CGE model to analyze the environmental and economic impacts. But there are limitations because they do not represent the competitive situation between transportation technologies.

Several studies also utilized DC model results from other studies to calibrate parameters or integrate DC into the CGE model. But they were not a bidirectional link as it was only one-way information transfer. Consequently, they did not capture changes in the technical details or power generation structure to confirm the net environmental effects of green mobility.

In this study, I integrated the DC model into the CGE model to capture changes in technical specifications and endogenously determine the market share of private cars. The

price variable in the DC model, which influences consumer preference, is updated from the result of the equilibrium model. Therefore, the results of the DC model reflect the macro-economy. Moreover, the economic impact arising from technology and cost factors can be determined by reflecting the consumer's preference in the CGE model. This is achieved by implementing a logit function based on the discrete choice method rather than simply changing the share parameter in the constant elasticity of substitution (CES) structure. Additionally, our results are more useful than exogenous policy shock because we reflect consumer preferences directly in the CGE model and analyze individual choices from a general equilibrium perspective. This framework allows confirmation of the net effect on the economy and the environment from the spread of green mobility, covering the transport sector and other surrounding industries. Table 5 summarizes the model difference from previous studies.

Table 5. Comparison with other studies

Authors	Bottom-up Diffusion	Top-down	Integrated method	Subjects	Environmental effect
KEI (2021)	Accounting	CGE	Bidirectional	EV, FCEV	CO2
Ou et al. (2020)	Optimization	-	Bidirectional	EV	-
Lee et al. (2013)	DC, BASS diffusion model	Optimization	One-way	EV, FCEV	CO2
Han et al. (2019)	BASS diffusion model	CGE	One-way	EV, FCEV	CO2
Karplus et al. (2013)	DC	CGE	One-way	EV	CO2
Schmelzer and Miess (2015)	DC	CGE	One-way	EV	CO2
This study	DC	CGE	Bidirectional	EV, FCEV	CO2

Chapter 3. Methodology

3.1 Discrete Choice Model

3.1.1 Conceptual Background

In order to predict the demand for new products and services, it is necessary to understand consumers' preferences in the market. The DC method is mainly used to analyze consumers' acceptance and benefits of products and services that have not yet been launched or are still in the early stage of the market (Train, 2009). The value of attributes comprising alternatives can be measured by recording the ranking preferred or choosing a specific one among a set of alternatives consisting of the product's main attributes through a questionnaire. This method serves as a valuable tool to elicit specific attribute preferences for alternative fuel vehicles, thus helping to predict the market potential of new technologies and provide policy support (DEFINE Consortium, 2015). This section aims to identify the technological and economic factors that affect consumer choice in the passenger car market and to derive an accurate consumer utility function based on this.

Existing studies have shown demand forecasting of green mobility and environmental effect on CO2 emissions and air pollution in various policies and market environments through analysis of choice behavior. Studies that analyzed consumer preference for green mobility emphasized consumers' heterogeneous lifestyles and preferences (Axsen et al., 2015), estimated the WTP for EVs (Hidrue et al., 2011), and predicted vehicle choice and

usage patterns (Shin et al., 2012). Using the mixed logit model, Choi et al. (2018) identified how the power generation mix affected EV adoption.

Recent studies analyzed purchasing behaviors, including hydrogen cars (Moon et al., 2021), predicted dynamic market share (Byun et al., 2018), showed the environmental improvement effect of green mobility dissemination policy (Shin et al., 2019), and confirmed CO2 emission change according to consumer preference and power mix for electricity through WTW analysis (Kim et al., 2020).

Critical attributes in vehicle selection can be derived based on the research of factors and obstacles in adopting green mobility. Javid and Nejat (2017) studied the effect of household income level on PEV adoption and showed that household income (+) and fuel price (-), including gasoline price, affect PEV sales adoption. Berkeley et al. (2018) investigated why 26,000 ICEV drivers did not purchase electric vehicles According to the survey results, high purchase cost and availability of charging facilities were reported as the highest barriers to EV purchase. As a short-term solution for electric vehicle dissemination, metropolitan, high-income earners, and young people should be the priority purchase targets. On the other hand, Chu et al. (2019) analyzed the psychological/behavioral factors that affect the distribution of electric vehicles by early adopters in Korea and China. They showed that interest in the environment (China), low fuel cost, and government subsidies (Korea) were related to electric vehicle purchases. In addition to these, the vehicle properties used in the study are summarized in Table 6.

Table 6. Vehicle attributes in previous studies

	Fuel type	Vehicle price	Fuel cost	Charging infrastructure	Vehicle type	Driving range	Charging time	Others
Axsen et al. (2015)	√	√	√	√		√	√	
Byun et al. (2018)	√	√	√	√			√	CO2 emissions
Choi et al. (2018)	√	√	√	√				Power mix
Choi and Koo (2019)	√	√	√	√	√			
Kim et al. (2020)	√	√	√	√	√	√	√	
Moon et al. (2021)	√	√	√	√	√			brand
Oryani et al (2022)	√	√	√	√				Public policies
Shin et al. (2015)	√	√	√	√	√			Smart car option
Shin et al. (2019)	√	√	√	√				PM emissions

3.1.2 Method

3.1.2.1 Conjoint Survey

A conjoint survey is a technique to collect choice pattern data by providing a virtual

situation to respondents for new technology or products that have not yet been active in the market, such as EVs and FCEVs. The conjoint survey was conducted to collect data for choice model analysis. The survey was conducted online in December 2020 for 516 vehicle owners, including 63 electric vehicle owners. Respondents, except for EV owners, were selected through probability sampling using quotas based on proportions by demographic characteristics such as age, gender, and region. The quota sampling method was chosen because it is cheaper than random sampling and can guarantee sample representativeness. Respondent's demographics are shown in Appendix 1.

The vehicle attributes that have a significant impact on consumer preference were determined by referring to the results of previous studies (Axsen et al., 2015, 2016; Byun et al., 2018; Choi et al., 2018; Choi and Koo, 2019, 2021; Kim et al., 2020; Moon et al., 2021; Oryani et al., 2022; Shin et al., 2019, 2015). For the properties of each vehicle, the fuel type (gasoline, diesel, electricity, hydrogen)[1], vehicle type (sedan and SUV), accessibility to charging facilities, fuel cost and purchase price were considered.

Fuel type consists of gasoline, diesel, electricity, and hydrogen fuel cell depending on the type of passenger car currently available for purchase2. Because our focus is on the ripple effect of the spread of green mobility, factors that impede green mobility purchases, such as high purchase costs and low charging station availability, were considered in the model (Berkeley et al., 2018; Kumar and Alok, 2020). Accessibility to charging facilities

1 It is assumed that the charging time and the maximum driving range are information already included in the fuel type.

2 LPG vehicles were excluded due to purchase specificity and vehicle model limitations.

applies to EVs and FCEVs and represents the relative accessibility of charging stations compared to gas stations; the levels are 100%, 50%, and 10%. Vehicle types were divided into sedan and SUV in consideration of the model of green mobility. Lastly, each vehicle's average purchase price and fuel costs are considered. Fuel cost refers to the cost of driving 1km, which reflects the fuel efficiency of each fuel type. Table 7 represents the attributes and levels in the conjoint survey questionnaire.

Table 7. Attributes and levels for the choice experiment

Attributes	Attributes level
Fuel type	Gasoline, diesel, electricity, hydrogen fuel cell
Accessibility of charging facility (%)	10, 50, 100
Vehicle type	Sedan, SUV
Fuel cost (KRW/km)	50, 100, 150
Vehicle cost (10 Thousand KRW)	2,000, 3,000, 4,000, 5,000

Based on these attributes, virtual choice alternatives were created. Thirty-two alternatives were selected utilizing an orthogonal test with a fractional factorial design. Eight choices, with four alternatives each, were formed to cover each fuel type for respondents to choose. A sample of the conjoint cards is in Table 8. In addition, demographic characteristics of individuals, such as income, education, etc., were asked as follow-up questions.

A total of 32 alternative sets were generated using an orthogonal test considering the main attributes of car selection. Because unrealizable cards were not removed, there exist cases where hydrogen filling station accessibility is 100% in the set of alternatives. Also, there are cases where access to gas stations is reduced compared to the present (the accessibility of gas stations is 50%). This reflects the future situation of installing electric vehicle charging stations instead of gas stations.

In other words, to identify the trade-off between the main properties in a virtual situation, even if there is a discrepancy from a real-life situation, an alternative was selected so that the properties could be well distinguished. Alternatives derived through orthogonality analysis were appropriately assigned to each selection set, so that was no single superior alternative.

Table 8. A choice sample set in the conjoint survey

	Type A	Type B	Type C	Type D
Fuel type	Gasoline	Diesel	Electricity	Hydrogen
Accessibility of charging facility (%)	100%	100%	50%	10%
Vehicle type	Sedan	Sedan	SUV	SUV
Fuel cost (KRW/km)	100	150	50	100
Vehicle purchase price (10 Thousand KRW)	2,000	3,000	4,000	5,000
Choice (most preferred)				√

3.1.2.2 Estimation Model

This study utilized a mixed logit model to estimate consumer preferences for a private car to reflect individual heterogeneity. Even though the mixed logit model overcomes the constraints of the IIA property, the calculation is complicated, and it may not be able to obtain a unique maximum likelihood estimate (Allenby and Rossi, 1998; Train, 2001; Train, 2009). To solve this problem, the Bayesian method is generally used the prior distribution of the parametric distribution and the posterior distribution of the likelihood function.

In the Hierarchical Bayesian (HB) method, the parameter representing the partial value of each attribute β_{nj} is set differently for each respondent, which reflects the heterogeneity of consumers. The coefficient vector β_n is expressed as the following equation (10), unlike equation (8) which follows a normal distribution with mean (b) and variance (W):

$$\beta_n = \Gamma \mathbf{z}_n + \zeta_n,\ \zeta_n \sim N\left(0, \Sigma\right) \quad \text{Eq. (10)}$$

where z_n denotes the vector representing the individual characteristics of the respondent n, Γ is the matrix of parameter z_n, ζ_n defines a stochastic term about the heterogeneity of unobserved consumers, and Σ refers to a matrix the covariance between each partial value (Allenby and Rossi, 1998). In general, Bayesian analysis estimates the posterior distribution of each parameter by combining it with the likelihood

determined by the data based on the prior distribution for each parameter. To complete the hierarchical Bayesian model, prior distributions for Γ and Σ must also be established. HB estimation method can also analyze β by adding explanatory variables, and it has a hierarchical structure ($U-\beta-\Gamma$) in equation (11) where Γ follows the normal distribution and Σ follows the inverse-Wishart distribution.

$$\begin{aligned} &\Gamma \mid \Sigma, \beta_n \\ &\Sigma \mid \beta_n, \Gamma \quad \text{where } \Gamma \sim N(a, A) \text{ and } \Sigma \sim W(w, W) \\ &\beta_n \mid \Gamma, \Sigma \end{aligned} \quad \cdots\cdots\text{Eq. (11)}$$

In the model, utility functions for the purchase of vehicles are as follows:

$$\begin{aligned} U_{nj} &= V_{nj} + \varepsilon_{nj} = \beta_n^{'} X_{nj} \\ &= \beta_{n,gasoline} X_{j,gasoline} + \beta_{n,diesel} X_{j,diesel} + \beta_{n,electricity} X_{j,electricity} \\ &\quad + \beta_{n,sedan} X_{j,sedan} + \beta_{n,\inf ra} X_{j,\inf ra} \\ &\quad + \beta_{n,fuel\cos t} X_{j,fuel\cos t} + \beta_{n,carprice} X_{j,carprice} + \varepsilon_{nj} \end{aligned} \quad \cdots\cdots\text{Eq. (12)}$$

It is possible to obtain information about consumer n's preference for each attribute *j* by estimating β_{nj}. Hydrogen is the baseline in the fuel type attribute. Therefore $\beta_{gasoline}$, β_{diesel}, and $\beta_{electricity}$ indicate preferences for each fuel type compared to hydrogen fuel cell vehicles. In terms of vehicle type, SUV is the baseline, and β_{sedan}

also represents relative preference compared to SUV. β for accessibility of charging facility, fuel cost and vehicle purchase price represent a change in preference with an increase of one unit for each attribute.

In this study, by linking the variation of the variable z_n representing individual characteristics and the individual parameter β_n through the HB mixed logit model, it is possible to estimate individual characteristics, that is, preference distribution according to income class, and to classify consumption patterns.[3] Each individual parameter β_{nj} is expressed as the following equation (13).

$$\beta_{nj} = \alpha + \Gamma_{income,j} z_{income,n} + \zeta_n \quad \cdots\cdots \text{Eq. (13)}$$

Based on this, the choice probability can be expressed simply as in equation (14) below. This model is analyzed using Sawtooth Software CBC/HB Module (Ver. 5.6).

$$\Pr_j = \frac{\exp(V_j)}{\sum_i \exp(V_i)}, j = 1, ..., J \quad \cdots\cdots \text{Eq. (14)}$$

[3] Income is only sued as the demographic variable to account for β_i. It is assumed that respondents were divided by income only, and the influence of other variables such as age and gender was already included in the income information.

3.2 CGE Model

CGE model divides economic agents into households and firms and determines the optimal behavior of individual economic agents in a perfectly competitive market. The model can estimate how the economy will change according to policies using actual economic data.

3.2.1 Social Accounting Matrix

The underlying data of the CGE model are structured in a social accounting matrix (SAM), which describes the flow of transactions between economic agents in the country. Entries in a SAM represent the flow of goods and services from an economic agent listed in a row to a counterpart agent listed in a column (Hosoe et al., 2010). The row indicates the income structure, and the column shows the expenditure structure. Cell $X(i, j)$ in row *i* and column *j* means that account *i* received income from account *j*, or account *j* spent on account *i*. The account consists of commodities, production activities, factors and institutions. Production activity records transactions between goods, and the production factor shows transactions such as labor and capital input to production activities. The institutional sector indicates transactions between economic entities such as households, industries, government, and foreign trade. Sum of each row and each column are equal. In this study, the SAM was organized based on the 2015 input-output (IO) table and basic prices published by the Bank of Korea (2019). Data from the IO table

fill the gray shaded cell in Figure 6. For the industry classification required for this study, 381 commodities were aggregated into 64 products and industries in Appendix 2.

			Production activity			Factor		Tax		Final demand				ROW	Total
			Industry	Vehicle service	Energy	Capital	Labor	Indirect tax	Tariff	Household 1 … 10			Government	Investment	Export	
Production activity	Industry		X(i,j)							XP(i)			Xg(i)	Xv(i)	E(i)	
	Vehicle service															
	Energy															
Factor	Capital		K(j)													
	Labor		L(j)													
Tax	Indirect tax		Tz(j)							Tih				Tii	Tie	
	Tariff		Tm(j)													
Final demand	Household	1														
		…														
		10														
	Government									Td						
	Investment									Sp			Sg		Sf	
ROW	Import		M(j)													
Total																

Figure 6. Structure of social accounting matrix

SAM was constructed by disaggregating the vehicle sector to reflect new technologies in the transportation market (KEI, 2021; Leurent and Windisch, 2015; Miyata et al., 2014). The characteristics of ICEVs and AFVs adjusted input data in the vehicle manufacturing sector. I adjusted SAM to indicate households purchase total private transport services, including fuel and vehicles, rather than consuming them separately for smooth linkage to the DC model. Transportation services were allocated to independent nests in the household-utility function to investigate possible alternatives (KEI, 2021; Miyata et al., 2014). Vehicle services were calculated using the number of new and cumulative car registrations by fuel type (Korea Energy Agency, 2016; Korea Transportation Safety

Authority, 2016), the average price of domestic cars, fuel consumption (Korea Energy Economics Institute (KEEI), 2017), and average fuel prices.

Since electricity and hydrogen are highly related energies to other industries, they are separated into individual sectors to increase the model's resolution. The electricity was divided into hydropower, thermal power, nuclear power, private self-power, and renewable energy power according to the power generation source. In addition, one representative household agent was divided into ten income class groups by income decile to understand the ripple effect of purchasing green mobility by income.

3.2.1.1 Vehicle Manufacturing Sector

In order to understand household private vehicle services, the passenger car manufacturing industry was classified by fuel type. Internal combustion locomotives allocated input according to the production ratio. For example, EVs and FCEVs do not have an internal combustion engine, but EVs have batteries, and FCEVs have tanks (stacks) to drive motors. The input and output of green mobility manufacturing were constructed by reflecting these characteristics. The production rate of batteries in EVs has adopted the value of Leurent and Windisch (2015). For hydrogen cars, the fuel cell stack accounts for 40% of the cost of an FCEV, followed by 20% of the cost of a hydrogen storage device, as shown in Table 9 (MOTIE, 2019). The input of other equipment was distributed according to the production ratio in the same way as for ICEVs. In addition, the battery manufacturing of electric equipment and the automobile engine manufacturing

in the transportation equipment sector were separately classified.

Table 9. FCEV production cost ratio

	Stack	Driving gear	Hydrogen storage device	Electric device	Body
Cost ratio(%)	40	15	20	10	15

Source: MOTIE (2019)

3.2.1.2 Private Car Service

Figure 7 shows that household demand for passenger cars is separated into the individual virtual sector. The passenger car service sector consists of automobiles and fuel consumption. First, for automobile demand, private consumption expenditure-passenger cars were separated according to the new passenger car consumption ratio (car sales multiplied by average car price). In the case of fuel, the fuel value of private consumption expenditure was directly transferred to the car service sector. Gasoline and diesel were assumed to be 100% for transportation in household consumption. LPG was classified according to the amount of propane and butane used data from the energy balance (Korea Energy Economics Institute (KEEI), 2017). Demand for electricity and hydrogen was estimated by considering the number of car stock multiplied by the annual average charge amount per vehicle and average price. At this time, stocks for each vehicle were adjusted,

assuming the same mileage.[4]

		Industry		Final demand		
		Non-energy	Energy	Household	Government	Investment
Production activity	Non-energy (Vehicle)	X		Xp	Xg	Xv
	Energy (Fuel)					
Tax	Indirect tax	Tz		Tih		Tii

(a) A standard SAM

		Industry			Final demand		
		Non-energy	Energy	Vehicle service	Household	Government	Investment
Production activity	Non-energy (Vehicle)	X		①	Xp vehicle	Xg	Xv
	Energy (Fuel)			②	Xp fuel		
	Vehicle service			④			
Tax	Indirect tax	Tz		③	Tih Subsidy or tax		Tii

(b) New SAM with virtual vehicle service

Figure 7. New SAM structure in vehicle service

[4] It is assumed that each vehicle's mileage is the same to see the substitution relationship between vehicles in the model.

3.2.1.3 Electricity Sector

Since the future power mix is different from the current power generation structure, it is necessary to reflect the national energy mix forecast. In addition, since electricity is an energy that has an extensive relationship with other industries, the model needs a high resolution. The power sector is classified by five power generation sources: hydropower, thermal power, nuclear power, private self-power, and renewable power. Based on the power source, it composes an electricity composite (ELEC) with the characteristics of final goods. The electricity composite from the power source will be consumed in other industries, households, and investments.

3.2.1.4 Hydrogen Sector

The virtual hydrogen sector was built based on extant literature since it is not separated as an independent product in the IO table. The input of the hydrogen sector includes by-product gas from the petrochemical manufacturing industry, reformed LNG from the natural gas sector, water electrolysis from the renewable energy sector, and imports. For the hydrogen production ratio, the value of ‘the hydrogen activation roadmap’ (MOTIE, 2019) was used in Table 10. The hydrogen production cost was calculated by applying the weighted average value to the production unit price for each technology as a weight. In addition, it was assumed that the hydrogen produced in the model was produced only as much as used in fuel cells for hydrogen vehicles and power generation.

Table 10. Hydrogen production cost and ratio

Technology	min	max	median	Production ratio
Petrochemical byproduct gas	1,500	2,000	1,750	98%
LNG reforming	2,700	5,100	3,900	1%
Electrolysis	9,000	10,000	9,500	1%

Unit : KRW/kg

Source: MOTIE (2019)

3.2.1.5 Household Income Class

In the existing general equilibrium model, a household that can reflect the average consumption behavior of consumers is introduced into the model. Therefore, a single utility function that reflects the characteristics of the average consumer is used. However, this model, including only representative consumers, is weak in not analyzing the gap in the ripple effect on mutually heterogeneous households (Korea Environment Institute (KEI), 2021). Therefore, in this study, consumers were classified according to income. Also, the utility functions of representative consumers representing each group were constructed.

In order to consider the consumption heterogeneity by income class, one representative household agent was composed of the income decile group. Each income class consists of one representative consumer, and the principle of utility maximization determines consumption under the budget constraint over periods. I used Korean

Household Income & Expenditure Trends (Statistics Korea, 2016a) data to describe a distribution of income and consumption by household income class in the base year.

The Household Trend Survey (Statistics Korea, 2016a) divides household income into wage and salary, business, property, and transfer income. In this model, the proportion of each income decile was calculated using wage income as labor income and business and property income as capital income. In the case of household consumption, the work was performed to match consumption expenditure information by household decile with goods in the SAM. First, the remainder (the surplus) after deducting consumption expenditure from disposable income was classified as savings. Then, the government transfer expenditure was the value obtained by subtracting transfer income from the non-consumption expenditure. In the case of indirect tax, the same value as the consumption expenditure ratio was used. For the demand for passenger car service, the financial panel data (Korea Institute of Public Finance, 2020) was used to apply the car purchase rate and stock rate by vehicle fuel type.

In this case, the sum of income and expenditure distributed by the income decile does not match, so adjustment is necessary. The RAS method was used as the matrix adjustment work. The RAS iterative adjustment procedure creates a new matrix through iterative bi-proportional adjustments to the existing matrix (Stone, 1985). Income was recalculated based on the sum of the consumption of households. The R program was used for this work, and household income was corrected by convergence at iteration less than 500. The income of the low-income group decreased, and the revenue of the high-

income group increased compared to before the RAS method.

3.2.2 Model Structure

The CGE model in the study was constructed based on the standard model suggested by Hosoe et al. (2010). However, the CES production function, which divided the energy and value-added composite into separate nesting, was used to more precisely describe the production structure related to energy use. In addition, there is a difference in the part that the SAM was modified to classify household consumption behavior by income quintile for EVs and FCEVs. Several equations of economic activity related to the private car service sector have been modified. The model is one country and a recursive dynamic model.

3.2.2.1 Firms

Firms use intermediate inputs and production factors (capital and labor) to maximize profits under the constraints of production technology. The production process of factor composites can be viewed as the action of a hypothetical company that maximizes profits by selecting production levels and inputs according to the relative prices targeted by technology. Various production functions can be used depending on how production factors and intermediate inputs are combined. In this study, each firm's production function is a nested structure of constant elasticity of substitution (CES) function. The nesting structure for production is shown in Figure 8. Due to the CES structure, capital,

labor, and energy can be replaced.

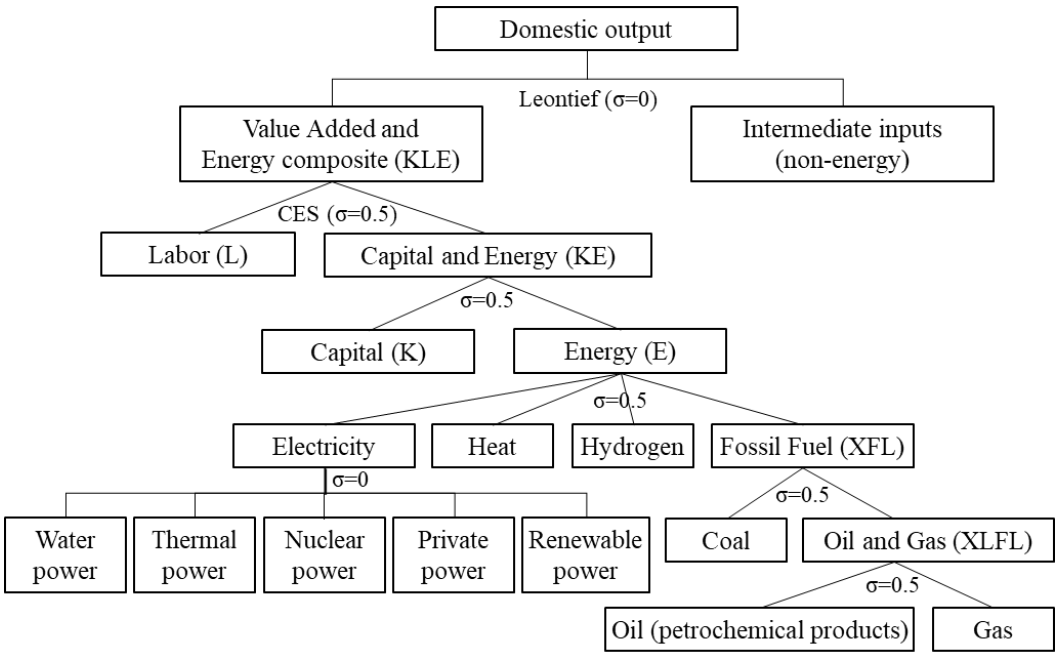

Figure 8. Nesting structure in production

At the top nest, the output is a function of capital, labor, energy, and non-energy materials. (KLEM). Equations (15) and (16) determine the domestic production (Z) by combining non-energy intermediate input composite and energy-capital-labor composites (KLE) in a specific ratio assuming the Leontief function. Using the Leontief production function, the input ratio is supposed to be kept constant even between non-energy intermediate input composites. In short, non-energy intermediate goods are irreplaceable, and non-energy intermediate goods and value-added cannot substitute. In a condition of zero profit in a competitive market, the marginal revenue in production equals the

marginal cost of production in equation (17).

$$X_{ij} = ax_{ij} Z_j \quad (\mathrm{i} \in \text{non-energy}) \cdots\cdots \text{Eq. (15)}$$

$$KLE_j = ay_j Z_j \cdots\cdots \text{Eq. (16)}$$

$$p_j^z = ay_j p_j^{KLE} + \sum_{i \in non-energy} ax_{ij} p_i^q \cdots\cdots \text{Eq. (17)}$$

X_{ij} : Intermediate input of commodity *i* in industry *j*

ax_{ij} : Share parameter for non-energy input *i* for output of *j*

Z_j : Domestic output of *j*

KLE_j : Capital-Labor-Energy composite factor demand of *j*

ay_j : Share parameter for Capital-Labor-Energy composite factor for output of *j*

p_j^Z : Domestic output price of *j*

p_j^{KLE} : Capital-Labor-Energy composite factor price of *j*

p_j^q : Commodity price of *j*

At the second nest, capital-labor-energy composites (KLE) are divided into labor and capital-energy composites (KE) with substitution elasticity 0.5 as part of the CES

function in equations (18) ~ (20).

$$KLE_j = \gamma_j^{KLE} (\delta_j^{KE} KE_j^{\eta_j} + \delta_j^L L_j^{\eta_j})^{\frac{1}{\eta_j}} \quad \text{Eq. (18)}$$

$$KE_j = KLE_j \left[\frac{(\gamma_j^{KLE})^{\eta_j} \delta_j^{KE} p_j^{KLE}}{p_j^{KE}} \right]^{\frac{1}{1-\eta_j}} \quad \text{Eq. (19)}$$

$$L_j = KLE_j \left[\frac{(\gamma_j^{KLE})^{\eta_j} \delta_j^{L} p_j^{KLE}}{p^{L}} \right]^{\frac{1}{1-\eta_j}} \quad \text{Eq. (20)}$$

γ_j^{KLE} : Scaling parameter for Capital-Labor-Energy composite factor for output of *j*

δ_j^{KE} : Share parameter for Capital-Energy composite factor for output of *j*

KE_j : Capital-energy composite factor demand of *j*

δ_j^L : Share parameter for labor for output of *j*

L_j : Labor demand of *j*

η_j : Substitution elasticity parameter of *j* $(\eta_j = (\sigma_j - 1)/\sigma_j)$

p_j^{KE} : Capital-energy composite factor price of *j*

p_j^L : Labor price of *j*

At the third nest, capital-energy composites (KE) consist of capital and energy composite in the form of CES production function as shown in equation (21) ~ (23).

$$KE_j = \gamma_j^{KE} (\delta_j^{XEP} XEP_j^{\eta_j} + \delta_j^K K_j^{\eta_j})^{\frac{1}{\eta_j}} \quad \text{Eq. (21)}$$

$$XEP_j = KE_j \left[\frac{(\gamma_j^{KE})^{\eta_j} \delta_j^{XEP} p_j^{KE}}{p_j^{XEP}} \right]^{\frac{1}{1-\eta_j}} \quad \text{Eq. (22)}$$

$$K_j = KE_j \left[\frac{(\gamma_j^{KE})^{\eta_j} \delta_j^K p_j^{KE}}{p^K} \right]^{\frac{1}{1-\eta_j}} \quad \text{Eq. (23)}$$

γ_j^{KE} : Scaling parameter for Capital-Energy composite factor for output of *j*

δ_j^{XEP} : Share parameter for Energy composite factor for output of *j*

XEP_j : Energy composite factor demand of *j*

δ_j^K : Share parameter for capital for output of *j*

K_j : Capital demand of *j*

p_j^{XEP} : Energy composite factor price of *j*

p_j^K : Capital price of *j*

Energy composite comprises fossil fuel composite (XFL), electricity composite (ELEC), heat, and hydrogen. CES form was used in which the energy composite was divided into a separate nesting for the production function to elaborate the production energy utilization structure in equation (24) ~ (27).

$$XEP_j = \gamma_j^{XEP}(\delta_j^{XFL} XFL_j^{\eta_j} + \delta_j^{ELEC} ELEC_j^{\eta_j} + \sum_{i \in \text{hydrogen,heat}} \delta_{ij}^{HH} X_{ij}^{\eta_j})^{\frac{1}{\eta_j}} \quad \cdots\cdots\cdots \text{Eq. (24)}$$

$$XFL_j = XEP_j \left[\frac{(\gamma_j^{XEP})^{\eta_j} \delta_j^{XFL} p_j^{XEP}}{p_j^{XFL}} \right]^{\frac{1}{1-\eta_j}} \quad \cdots\cdots\cdots \text{Eq. (25)}$$

$$ELEC_j = XEP_j \left[\frac{(\gamma_j^{XEP})^{\eta_j} \delta_j^{ELEC} p_j^{XEP}}{p^{ELEC}} \right]^{\frac{1}{1-\eta_j}} \quad \cdots\cdots\cdots \text{Eq. (26)}$$

$$X_{ij} = XEP_j \left[\frac{(\gamma_j^{XEP})^{\eta_j} \delta_{ij}^{HH} p_j^{XEP}}{p_i^q} \right]^{\frac{1}{1-\eta_j}} \quad (i \in \text{hydrogen or heat}) \quad \cdots\cdots\cdots \text{Eq. (27)}$$

γ_j^{XEP} : Scaling parameter for Energy composite factor for output of *j*

δ_j^{XFL} : Share parameter for fossil fuel composite for output of *j*

XFL_j : Fossil fuel composite factor demand of *j*

δ_j^{ELEC} : Share parameter for electricity composite for output of *j*

$ELEC_j$: Electricity composite demand of *j*

δ_{ij}^{HH} : Share parameter for input *i* (hydrogen or heat) for output of *j*

p_j^{XFL} : Fossil fuel composite factor price of *j*

p_j^{ELEC} : Electricity composite price of *j*

At the fifth nest, fossil fuel composites (XFL) are divided into coal and liquid-type fossil fuel, which combine oil and gas in equation (28) ~ (30). Meanwhile, equations (31) and (32) represent that the electricity composite (ELEC) assumes a Leontief production function with a fixed share of zero elasticity.

$$XFL_j = \gamma_j^{XFL}(\delta_j^{XLFL} XLFL_j^{\eta_j} + \sum_{i \in \text{coal or coal product}} \delta_{ij}^{Coal} X_{ij}^{\eta_j})^{\frac{1}{\eta_j}} \quad \cdots\cdots \text{Eq. (28)}$$

$$XLFL_j = XFL_j \left[\frac{(\gamma_j^{XFL})^{\eta_j} \delta_j^{XLFL} p_j^{XFL}}{p_j^{XLFL}} \right]^{\frac{1}{1-\eta_j}} \quad \cdots\cdots \text{Eq. (29)}$$

$$X_{ij} = XFL_j \left[\frac{(\gamma_j^{XFL})^{\eta_j} \delta_{ij}^{Coal} p_j^{XFL}}{p_i^q} \right]^{\frac{1}{1-\eta_j}} \quad (i \in \text{coal or coal product}) \quad \cdots\cdots \text{Eq. (30)}$$

$$X_{ij} = axelec_{ij} ELEC_j \quad (i \in power) \quad \cdots\cdots \text{Eq. (31)}$$

$$p_j^{ELEC} = \sum_{i \in power} axelec_{ij} p_i^q \quad \cdots\cdots \text{Eq. (32)}$$

γ_j^{XFL} : Scaling parameter for fossil fuel composite factor for output of *j*

δ_j^{XLFL} : Share parameter for liquid fossil fuel composite for output of *j*

$XLFL_j$: Liquid fossil fuel composite factor demand of *j*

δ_{ij}^{Coal} : Share parameter for input *i* (coal or coal product) for output of *j*

p_j^{XLFL} : Liquid fossil fuel composite factor price of *j*

$axelec_{ij}$: Share parameter for electricity production of commodity *i*

Finally, at the bottom nest, liquid fossil fuel composite (XLFL) divides into oil and gas, as shown in equations (33) and (34). Oil includes gasoline, kerosene, diesel, BC, jet oil, LPG, crude oil, and oil product such as naphtha. Gas includes city gas and LNG.

$$XLFL_j = \gamma_j^{XLFL} \left(\sum_{i \in \text{oil or gas}} \delta_{ij}^{OG} X_{ij}^{\eta_j} \right)^{\frac{1}{\eta_j}} \quad \cdots\cdots \text{Eq. (33)}$$

$$X_{ij} = XLFL_j \left[\frac{(\gamma_j^{XLFL})^{\eta_j} \delta_{ij}^{OG} p_j^{XLFL}}{p_i^q} \right]^{\frac{1}{1-\eta_j}} \quad (i \in \text{oil or gas}) \quad \cdots\cdots \text{Eq. (34)}$$

γ_j^{XLFL} : Scaling parameter for liquid fossil fuel composite factor for output of *j*

δ_{ij}^{OG} : Share parameter for input *i* (oil or gas) for output of *j*

3.2.2.2 Household

The household consumption function assumes that one representative household has a Cobb–Douglas utility function and consumption behavior that maximizes utility under budget constraints in equation (35).

$$\text{maximize } UU = \prod_i X_i^{p^{\alpha i}} \quad \cdots\cdots \text{Eq. (35)}$$

$$subject\ to \sum_i p_i^q X_i^p = DHI - S^p$$

X_i^p : Household consumption of commodity *i*

α_i : Share parameter of household consumption *i*

DHI : Direct household income

S^p : Household savings

The first-order optimal condition is obtained employing the Lagrange multiplier method in equation (36). Households consume (X_i^p) each commodity with the Leontief's ratio (α_i) of disposable income (DHI) minus savings (S^p) divided by indirect tax (τ_i^{ih}) and the price of goods (p_j^q). Household disposable income is net of a household income except for income tax rate (τ^d) in equation (37). A household's income is calculated by adding the stock of capital (KS) multiplied by the interest rate (the price of capital p^K)

and the rate of return (ror) with labor (LE) multiplied by wages (the price of labor p^L).

$$X_i^p = \frac{\alpha_i (1 - ss^p) DHI}{(1 + \tau_i^{ih}) p_i^q} \quad \text{Eq. (36)}$$

$$DHI = (1 - \tau^d)(p^K \times KS \times ror + p^L \times LE) \quad \text{Eq. (37)}$$

ss^p : Saving parameter in household

τ_i^{ih} : Household indirect tax rate on consumption i

τ^d : Household direct tax rate

p^K : Capital price

KS : Capital stock

ror : Rate of return

p^L : Labor price

LE : Labor endowment

3.2.2.3 Government

The government prepares a budget by collecting taxes from economic agents and consumes goods or subsidizes or transfers to households in the same proportion as in the base year. Equation (44) shows that government spending on goods and services is determined by fixed proportions (μ_i). Government revenue comes from capital and labor

tax (T^d), sales tax (T_j^z), import tariff (T_i^m), and indirect tax on household consumption (T_i^{ih}), investment (T_i^{iv}) and export (T_i^{ie}) in equation (38) ~(43).

$$T^d = \tau^d (p^K \times KS \times ror + p^L \times LE) \quad \text{Eq. (38)}$$

$$T_j^z = \tau_j^z p_j^z Z_j \quad \text{Eq. (39)}$$

$$T_i^m = \tau_i^m p_i^m M_i \quad \text{Eq. (40)}$$

$$T_i^{ih} = \tau_i^{ih} p_i^q X_i^p \quad \text{Eq. (41)}$$

$$T_i^{iv} = \tau_i^{iv} p_i^q X_i^v \quad \text{Eq. (42)}$$

$$T_i^{ie} = \tau_i^{ie} \varepsilon p_i^{WE} E_i \quad \text{Eq. (43)}$$

$$X_i^g = \frac{\mu_i}{p_i^q}\left(T^d + \sum_j T_j^Z + \sum_j T_j^m + \sum_{j,uh} T_{j,uh}^{ih} + \sum_j T_j^{iv} + \sum_j T_j^{ie} - S^g \right) \quad \text{Eq. (44)}$$

T^d : Household direct tax

T_j^z : Production tax of industry *j*

τ_j^z : Production tax rate of industry *j*

T_i^m : Import tax of commodity *i*

τ_i^m : Import tax rate of commodity *i*

p_i^m : Import price of commodity *i*

M_i : Import demand of commodity *i*

T_i^{ih} : Household indirect tax of commodity *i*

T_i^{iv} : Investment indirect tax of commodity *i*

τ_i^{iv} : Investment indirect tax rate of commodity *i*

X_i^{iv} : Investment demand of commodity *i*

T_i^{ie} : Export indirect tax of commodity *i*

τ_i^{ie} : Export indirect tax rate of commodity *i*

ε : Exchange rate

p_i^{WE} : Export price in a foreign currency of commodity *i*

E_i : Export demand of commodity *i*

X_i^g : Government consumption of commodity *i*

μ_i : Government consumption rate of commodity *i*

S^g : Government saving

3.2.2.4 Savings and Investment

Savings consists of the amount households save (S^p) from their disposable income minus consumption from equation (46) and a certain portion (ss^g) of government tax

revenues from equation (47). Within the limit of the sum of savings and foreign investment (S^f), a certain percentage of each sector (λ_i) leads to investment. Although households and the government may decide to invest and save respectively, this study assumes that the hypothetical agent absorbs all savings and uses a certain percentage (λ_i) to purchase goods. The investment demand function is as follows in equation (45) and is similar to the government's product demand function. Households and governments depend on external sector savings. Since the share parameter is constant, total savings equals total investment.

$$X_i^v = \frac{\lambda_i}{(1+\tau_i^{iv})p_i^q}(S^p + S^g + \varepsilon S^f) \quad \cdots\cdots \text{Eq. (45)}$$

$$S^p = DHI - \sum_i (p_i^q X_i^p + T_i^{ih}) \quad \cdots\cdots \text{Eq. (46)}$$

$$S^g = ss^g \left(T^d + \sum_j T_j^Z + \sum_j T_j^m + \sum_{j,uh} T_{j,uh}^{ih} + \sum_j T_j^{iv} + \sum_j T_j^{ie} \right) \quad \cdots\cdots \text{Eq. (47)}$$

λ_i : Investment share of commodity *i*

S^f : Foreign saving in a foreign currency

ss^g : Government saving rate

3.2.2.5 Import and Export

Because countries buy goods and sell goods in other countries, the CGE model must

consider exports and imports. World prices (p_i^{WM} and p_i^{WE}) are calculated by applying exchange rates (ε) to domestic export (p_i^e) and import prices (p_i^m), as shown in equations (48) and (49). This model assumes an incomplete substitution relationship in the form of an Armington (1969) function in consumption between imported and domestic products. Armington goods are supplied by the input of imported and domestic products through the CES structure. Firms consume Armington goods as intermediate goods, and households and governments demand final goods. The production function for the Armington good is in equation (51) ~ (53).

$$p_i^e = (1-\tau_i^{ie})\varepsilon p_i^{We} \quad \text{Eq. (48)}$$

$$p_i^m = \varepsilon p_i^{Wm} \quad \text{Eq. (49)}$$

$$\sum_i (1+\tau_i^{ie}) p_i^{We} E_i + S^f = \sum_i (p_i^{Wm} M_i) \quad \text{Eq. (50)}$$

$$Q_i = \gamma_i (\delta_i^m M_i^{\eta_i} + \delta_i^d D_i^{\eta_i})^{\frac{1}{\eta_i}} \quad \text{Eq. (51)}$$

$$M_i = Q_i \left[\frac{\gamma_i^{\eta_i} \delta_i^m p_i^q}{(1+\tau_i^m) p_i^m} \right]^{\frac{1}{1-\eta_i}} \quad \text{Eq. (52)}$$

$$D_i = Q_i \left[\frac{\gamma_i^{\eta_i} \delta_i^d p_i^q}{p_i^d} \right]^{\frac{1}{1-\eta_i}} \quad \text{Eq. (53)}$$

p_i^e : Export price in domestic currency of commodity *i*

p_i^{WM} : Import price in foreign currency of commodity *i*

Q_i : Armington composite *i*

γ_i : Scaling parameter in the Armington composite *i*

δ_i^m : Share parameter in the Armington composite import *i*

δ_i^d : Share parameter in the Armington composite domestic demand *i*

D_i : Domestic demand of commodity *i*

p_i^d : Domestic demand price of commodity *i*

Assuming a Constant Elasticity of Transformation (CET) function in export, firms choose the product configuration that maximizes the total revenue from composite production (for domestic sales and export). Among domestic sales and export goods, the composition of products is shifted toward goods whose prices have risen more than the average growth rate of composites. In the case of automobiles, the Leontief function was assumed to control the sharp increase in production and exports due to a decrease in prices due to the green mobility support policy in equation (54) ~ (56).

$$E_i = \xi_i^e (1+\tau_i^Z) Z_i \quad \cdots\cdots \text{Eq. (54)}$$

$$D_i = \xi_i^d (1+\tau_i^Z) Z_i \quad \cdots\cdots \text{Eq. (55)}$$

$$p_i^z = \frac{\xi_i^e p_i^e}{(1-\tau_i^e)} + \xi_i^d p_i^d \quad \cdots\cdots \text{Eq. (56)}$$

ξ_i^e : Export share parameter of commodity *i*

ξ_i^d : Domestic demand share parameter of commodity *i*

3.2.2.6 Market Clearing Condition

Market clearing conditions should be set so that supply and demand match in the market. The conditions for market clearing of Armington composites are as follow in equation (57). Armington composites (Q_i) are consumed in production of firms, household, government, and investment. The equation is specified for the n-1 number of *i* in which one element is missing by Walras law.

$$Q_i = X_i^P + X_i^G + X_i^V + \sum_j X_{ij} \quad (i \in \text{all products except others}) \quad \cdots\cdots\cdots\cdots \text{Eq. (57)}$$

This model is a recursive dynamic model, and the conditions for clearing the factor market (income balance conditions) are as follows:

$$\sum_i K_i = ror \times KS \quad \cdots\cdots\cdots\cdots \text{Eq. (58)}$$

$$\sum_i L_i = LE \quad \cdots\cdots\cdots\cdots \text{Eq. (59)}$$

Lastly, since this model has the characteristic of a zero-order homogeneity function, it is necessary to fix one price index as the reference price. Accordingly, in equation 60, the

consumer price index, which is a weighted average of consumer prices for each industry by the proportion of household consumption, was set as numeraire with a fixed base price of 1.

$$CPI = \sum_i cpi\_weight_i p_i^q \quad \cdots\cdots \text{Eq. (60)}$$

3.2.2.7 Law of Motion

The CGE model used in the study is a recursive dynamic model and requires a motion equation that adjusts some parameter values every time. First, capital accumulation and labor are updated over time. Capital stock reflects the process of changing capital supply in the following year due to investment and depreciation rate (dep) in equation (61). Labor supply is determined by the population growth rate ($poprate_t$) exogenously. Population growth rate is adopted from Statistics Korea (2016b). At this time, since the GDP calculated by the population forecast in the model and the actual GDP forecast are different, this was calibrated as an improvement in labor productivity ($lprod_t$) in equation (62).

$$KS_{t+1} = (1 - dep)KS_t + \sum_i X_{it}^v \quad \cdots\cdots \text{Eq. (61)}$$

$$LE_{t+1} = (1 + poprate_{t+1})(1 + lprod_{t+1})LE_t \quad \cdots\cdots \text{Eq. (62)}$$

dep : Depreciation rate

$poprate_t$: Population growth rate in time t

$lprod_t$: Labor productivity improvement in time t

Private vehicle stock was predicted using a linear logarithmic function (Ahn, 2017). Vehicle stock can be calculated by the relationship of GDP and population in equation (63).

$$\ln(pop/carstock - \overline{pop/carstock}) = a + b\ln(GDP/pop) \quad \cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (63)}$$

Coefficients (a and b) are estimated using historical data from 1970 to 2015. The convergence of the number of population per vehicle registration number ($\overline{pop/carstock}$) was 1.45 from Ahn (2017). Based on this, the predicted car stock will reach saturation around 2040 and gradually decrease in Figure 9. By reflecting the stock of previously registered automobiles and the lifespan of the automobiles, it is possible to calculate the stock trend of previously registered automobiles. The difference between the projected number of registered cars in the future and the stock trend of existing registered cars is the demand for new cars to be purchased in the future (sales). I assumed that the vehicle lifespan was 15 years. Future sales were estimated using stocks and vehicle registration data for the past 15 years. The number of new car purchases in 2016 (sales) was obtained by subtracting the 2015 stock from the 2016 stock forecast value and adding the number of car purchases in 2001 that were demolished according to the life cycle.

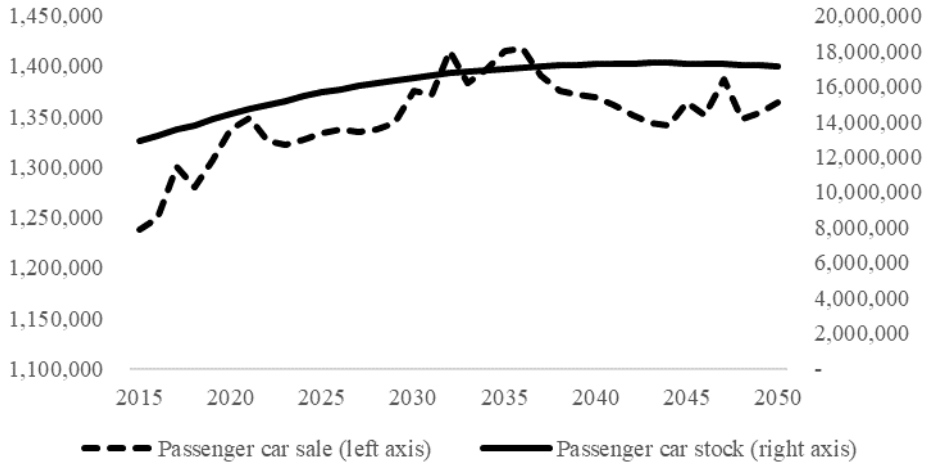

Figure 9. Forecasting on vehicle sale and stock

3.2.2.8 CO2 Emission

This study only considers CO2 emissions from energy consumption except process emissions. Total CO_2 emissions were derived based on the energy balance (Korea Energy Economics Institute (KEEI), 2018) and the CO_2 emission coefficient for each energy source. CO2 emissions of each industry were allocated according to the energy input of the industry and the composition of the final energy demand. To avoid redundant calculations of energy in the conversion sector, it was assumed that CO2 is not generated when using electricity and heat energy.

CO2 emissions increase in proportion to GDP. Since the emission becomes too significant in this case, this study adjusts the emission by using the AEEI (Autonomous Energy Efficiency Improvement) parameter. The AEEI parameter was applied to all

industries except the energy sector in equation (64). This is because it can violate the laws of thermodynamics, which increase output versus input (Wing and Eckaus, 2007). The AEEI parameter is calibrated using this emission forecasting in Ministry of Environment (2020).

$$\gamma_{j,t+1}^{XEP} = AEEI_t \gamma_{j,t}^{XEP} \quad (j \notin \text{energy sector}) \quad \cdots\cdots \text{Eq. (64)}$$

3.3 Model Linkage

There are two main methods (hard-linked and soft-linked approaches) for linking the bottom-up and the top-down models. First, the hard-linked process refers to a single unified, integrated form and is a single framework that obtains a solution through simultaneous optimization of models. While this method transmits information without the user's arbitrary judgment, the problem arises with obtaining a solution as the model becomes more complex (Wene, 1996). Representative examples include ETA-MACRO, MARKAL-MACRO, and WITCH models (Böhringer and Rutherford, 2009; Bosetti et al., 2006; Helgesen et al., 2018; Strachan and Kannan, 2008). The hard-linked approach includes a reduced form model and a fully integrated model. The reduced form model is a method of constructing an integrated model by designing either a bottom-up or top-down model in a simplified form (WITCH model (Bosetti et al., 2006)). Reduced form models may be less useful and complicated because they omit sectoral or technical details (Andersen et al., 2019). On the other hand, the fully integrated model directly integrates

the bottom-up and top-down models into the Mixed Complementarity Problem (MCP) (Böhringer and Rutherford, 2009). Fully integrated models are more likely to introduce errors in the model specification as the MCP format usually doubles the number of equations (Andersen et al., 2019).

The soft-linked approach refers to the coupling between two independent models, where the models are linked through an iterative computation algorithm. Representative examples include MESSAGE-MACRO and CGE-TIMES models (Andersen et al., 2019; Fortes et al., 2014; Lee et al., 2020, 2022; Martinsen et al., 2007). The independent model solves the optimization problem and exchanges necessary information, enabling information delivery under the user's control (Wene, 1996). Transmission is iteratively performed through the decomposition method until an optimal solution is found. It can be viewed as a transparent process because complex calculations and time can be managed (Fortes et al., 2014). On the other hand, there is no consistency between the bottom-up and top-down models, and convergence cannot be guaranteed, which means that the solution is only the best approximation from the hard link. Nevertheless, as the model becomes more complex, the soft-link approach is more often used than the hard-linked approach.

This study follows the hard-linked approach where the indirect utility function from the discrete choice model and the choice probability are used as inputs to the CGE model in a reduced form method. This is because the expression expressed through the DC model is not a complicated technology (substitution relationship between vehicles).

3.3.1 Choice Probability

DC model is linked in a reduced form in the CGE model. The DC model receives the price variable that is the result of the CGE model and calculates the choice probability again. It can also reflect the subsidy received by households and the technological level (charging infrastructure) due to changes in vehicle stock. The consumer's utility for vehicle service in DC is revised in equation (66).

The income variable ($z_{income,uh}$) reflects the increase compared to the base year for each income decile and the distribution of β_j changes over time in equation (65). For example, if income overall increases over time, the distribution of β_j shifts to the right.

$$z^t_{income,uh} = z^0_{income,uh} DHI^t_{uh} / DHI^0_{uh} \quad \cdots\cdots \text{Eq. (65)}$$

$$\begin{aligned} V_{i,uh} &= \sum_j \beta_j X_{j,uh} = \sum_j (\alpha + \Gamma_{income} z_{income,uh}) X_{j,uh} \\ &= \alpha_{fueltype} X_{fueltype,i} + \alpha_{sedan} X_{sedan,i} + \alpha_{\inf ra} X_{\inf ra,i} \\ &\quad + \alpha_{fuel\cos t} X_{fuel\cos t,i} p^q_{fuel} + \alpha_{carprice} (X_{carprice,i} - sub_{i,uh}) p^q_{car} \\ &\quad + z_{income,uh} (\Gamma_{fueltype} X_{fueltype,i} + \Gamma_{sedan} X_{sedan,i} + \Gamma_{\inf ra} X_{\inf ra,i} \\ &\quad + \Gamma_{fuel\cos t} X_{fuel\cos t,i} p^q_{fuel} + \Gamma_{carprice} (X_{carprice,i} - sub_{i,uh}) p^q_{car}) \end{aligned} \quad \cdots\cdots \text{Eq. (66)}$$

$$\Pr_{i,uh} = \frac{\exp(V_{i,uh})}{\sum_i \exp(V_{i,uh})} \quad \cdots\cdots \text{Eq. (67)}$$

The substitution relationship between ICEVs and AFVs is considered in the CGE

model to adjust the proportion of household demand while maintaining the total quantity of vehicles. By inserting the choice probability equation in the DC model into the CGE model, the effects of non-cost attributes can be confirmed (Lee et al., 2013).

DC results can predict vehicle demand (relative ratio) over time. The vehicle sale obtained from the choice probability leads to stock and is input to the CGE model. When household demand for a vehicle is solved from the choice probability of the DC model, the price also changes. At this time, the adjusted price (fuel and vehicle prices) again leads to a change in the DC model's attribute values and affects the choice probability. In addition, changes in car stock will affect the diffusion of charging infrastructure, and the level of charging infrastructure will also change. Therefore, the price variable and the level of charging facility in CGE are endogenously input into the DC model. Thus, price and demand reach equilibrium values through the link between the two models. Therefore, technology combination information in the DC model and the economic variables in the CGE model can be generated within a consistent analysis framework (Korea Environment Institute (KEI), 2021). Through this process, more realistic demand forecasting is possible.

Consumer behavior affects production, and the equilibrium price in the market derived from supply and demand, in turn, influences consumer choice. Consumer choice (t-1) → Vehicle stock change (t-1) → green mobility productivity change due to learning effect (t) → green mobility production cost reduction (t) → Price change (t) → Consumer choice (t). DC model and CGE model solutions are computed together in

one model (hard-linked approach). The linked variables and the integrated framework between the two models are displayed in Figure 10.

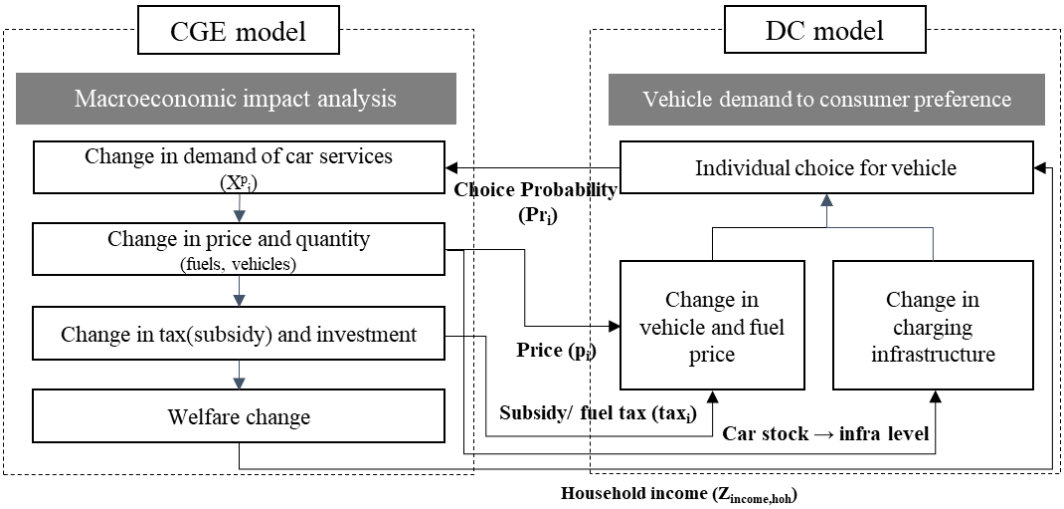

Figure 10. Integration framework between CGE and DC models

3.3.2 Household Sector

The household consumption function assumes that a representative household has a Cobb–Douglas utility function and consumption behavior that maximizes utility under budget constraints. Household consumption of commodity *i* (X_i^p) is determined by multiplying the share parameter (α_i) with household disposable income (DHI) excluding savings (S^p) and dividing it by price (p_i) in Equation (36). The Cobb–Douglas utility function causes homothetic preferences; therefore, the relative price determines demand (Karplus et al., 2013). However, Figure 11 displays that the private car service consumption structure differs from other commodities. The service consumption function

does not calculate the fixed share of the household consumption budget but fixes the quantity by reflecting the choice probability in the DC model. Because our study focuses on consumer vehicle purchases influenced by price and other technical attributes, the DC model is used in a CGE framework. Therefore, household consumption of vehicle services ($X^{p}_{\text{vehicle service}}$) is calculated by multiplying the choice probability (Pr_i, share of vehicle service *i*) obtained from the mixed logit model by the fixed total vehicle quantity ($totalcarsale_{i,uh}$) in Equation (68). The vehicle's stock is acquired by reflecting the new sales quantity and the life of the vehicle (15 years) from the previous stock $carstay_{i,uh}$ in equation (69).

$$carsale_{i,uh} = \Pr_i \, totalcarsale_{uh} \quad \cdots\cdots \text{Eq. (68)}$$

$$carstock_{i,uh} = carsale_{i,uh} + carstay_{i,uh} \quad \cdots\cdots \text{Eq. (69)}$$

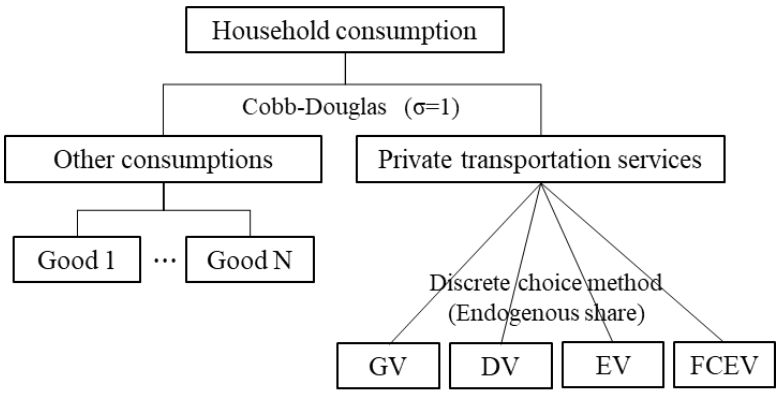

Figure 11. Consumption structure of household

Household consumption of vehicle service is divided into vehicles X_i^{pv} and fuels X_i^{pvf}. Household demand (quantity) for vehicles is obtained by multiplying car sales by a parameter (pv_i *and* pvf_i) calibrated for each vehicle's price in the base year. In the CGE model, prices appear relative to the base year. However, AFVs are relatively more expensive than ICEVs of the same model (European Parliament, 2019)[5]. To reflect the relative price difference between passenger cars, I used a parameter pv_i calibrated by dividing household demand in SAM (value) by the number of vehicles (quantity) in the base year. Since the price of green mobility purchased by households can be changed by giving subsidies, this is adjusted in a relative ratio $\tau_{i,uh}^{z\_sub}$ as shown in equation (70). Meanwhile, household consumption quantity of vehicle fuel is determined by vehicle stock multiplied by fuel parameter pvf_i and fuel-stock usage ratio ($sfratio_{i,uh}$) in equation (71). The household consumption of passenger car service is given by Equation (72).

$$X_i^{pv} = carsale_{i,uh} \times pv_i \times (1+\tau_{i,uh}^{z\_sub}) \ (i \in carservice) \quad \cdots\cdots \text{Eq. (70)}$$

$$X_i^{pvf} = carstock_{i,uh} \times pvf_i \times sfratio_{i,uh} \ \ (i \in carservice) \quad \cdots\cdots \text{Eq. (71)}$$

$$X_i^{p} = X_i^{pv} + X_i^{pvf} \ \ (i \in carservice) \quad \cdots\cdots \text{Eq. (72)}$$

5 According to the EU (European Commission, 2019), average EV prices exceed similar ICEV prices by at least 40%.

As the probability of green mobility increases, household consumption of vehicles may increase compared to the base year. The difference is adjusted to household savings (Sp_{uh})[6]. Household saving is determined endogenously by subtracting household consumption from household disposable income instead of the way households save a certain amount in proportion to their factor income using an exogenous ratio. If an AFV is more expensive than an ICEV, savings will decrease as S-a+b+Δincome (shaded area) in Figure 12. On the other hand, if an AFV is cheaper than an ICEV, savings will increase as S+a+b+Δincome.

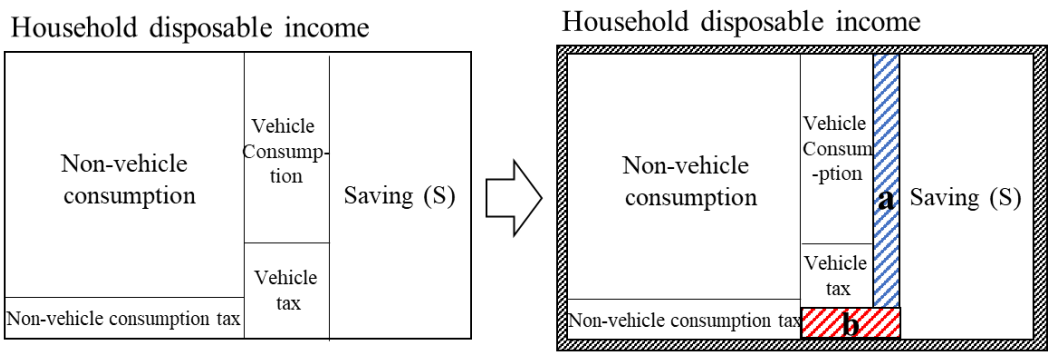

Figure 12. Household expenditure structure in link model

Not only household savings but also indirect taxes from consumption are different.

6 Households save in proportion to their factor income using exogenous ratios and consume commodities, except vehicle services, endogenously (model closure rule). However, household vehicle consumption is given exogenously in the DC model; therefore, the remaining savings are determined by the difference between vehicle consumption values and those in the base year.

Household indirect tax revenue $Tih_{i,uh}$ is also divided into fuel and vehicle purchase tax. In the Leontief consumption function, each product's indirect tax rate is the same. However, in reality, the tax rate for each fuel is different, and applying the same tax rate for green mobility is difficult due to the tax reduction policy Therefore, the indirect tax on automobile services is applied separately to see the change in the fuel tax and automobile tax on changes in demand.

First, the difference between the purchase price list and the basic price list in the IO table was applied in the case of fuel tax. Gasoline was calculated to be taxed at about 65% based on the buyer's price, and diesel at 54%. On the other hand, electricity and hydrogen were assumed to be tax-free. The automobile tax was calculated based on the difference in private consumption expenditure between the purchase price and the basic price of the IO table. When purchasing a vehicle, individual consumption tax, education tax, and value-added tax (VAT) must be paid, as well as acquisition tax and public bond purchase fee when registering a vehicle. However, as a tax reduction policy for EVs and FCEVs, individual consumption and education tax are excluded, and acquisition tax is also reduced to a certain level. In other words, AFVs pay a part of VAT and acquisition tax. Reflecting this, the vehicle tax and fuel tax rates are adjusted. The indirect tax on car service was distributed by households by reflecting the ratio of car purchase and fuel by households in equation (73).

$$T_i^{ih} = \tau_{vehicle}^{ih} p_i^q X_i^{pv} + \tau_{fuel}^{ih} p_i^q X_i^{pvf} \ (i \in car\ service) \quad \cdots\cdots \text{Eq. (73)}$$

3.3.3 Industry (Private Car Service) Sector

As household demand for vehicles changes, the private car service sector also changes. The production of the private car service sector is modified since the demand for vehicles and vehicle fuel in households directly leads to the car service sector. The input of private car service consists of fuel and vehicle. Therefore vehicle demand goes to non-energy intermediate input X_{ij} in equations (74), and fuel demand goes to factor composite Y_i in equation (75). According to the change of production function, production tax or subsidy (Tz_i) is also revised in equations (77) and (78).

$$X_{ij} = \sum_{uh} pv_i carsale_{i,uh} \quad (i \in transport,\ j \in carservice) \quad \cdots\cdots \text{Eq. (74)}$$

$$Y_j = \sum_{uh} pvf_i sfratio_{i,uh} carstock_{i,uh} \quad (j \in carservice) \quad \cdots\cdots \text{Eq. (75)}$$

$$p_j^z Z_j = p_j^{KLE} KLE_j + \sum_{i \in non-energy} p_i^q X_{ij} \quad (j \in carservice) \quad \cdots\cdots \text{Eq. (76)}$$

$$\tau_{i,uh}^{z\_sub} = \frac{sub_{i,uh} \tau_i^z}{X_{carprice,i} - X_{carprice,GV}} \quad \cdots\cdots \text{Eq. (77)}$$

$$T_i^z = \sum_{uh} \tau_{i,uh}^{z\_sub} pv_i carsale_{i,uh} p_i^q (i \in carservice) \quad \cdots\cdots \text{Eq. (78)}$$

$\tau_{i,uh}^{z\_sub}$: vehicle *i* purchase subsidy rate by household income class

3.3.3.1 Learning Effect in Production Function

Bass (1980) considered the industry's learning curve in the diffusion of new technology products. Metcalfe (1981) also considered growth in production capacity as well as growth in demand in the diffusion of new technology products. When the market share of technology increases, the cost of production decreases due to economies of scale with an accumulation of knowledge, experience, and learning effect, and the price goes down. Large-scale (fixed) capital investment is usually needed in industries requiring large-scale production equipment, such as automobiles and fuel cells. Economies of scale (i.e., increasing returns of scale) tend to occur in large-scale equipment industries with such a large fixed capital scale. In the context of economies of scale, firms can gain price competitiveness through large-scale production (i.e., mass production) to lower the average cost of production per unit (i.e., production cost).

The learning effect is reflected as a change in the scale parameter (ax_{ij}, ay_j) of the production function; the input to produce one unit of output decreases. It is more suitable for the scale parameter of the production function to change with time than to be fixed. As the stock of green mobility increases, productivity improves due to the learning effect in equation (79). This reduces the cost of vehicle production, leading to lower green mobility prices.

For example, the price of electric vehicle battery packs plummeted from $1183/kWh in 2010 to $381/kWh in 2015 and $132/kWh in 2021 (BloombergNEF, 2020). On the other hand, the price of a stack, which accounts for more than half of hydrogen cars, was

about 40 million KRW, and the price of hydrogen cars of the same model decreased by about 1.25 million KRW (1.5%) from 2018 to 2022. The rate of improvement in the production cost of hydrogen vehicles is slow.

$$ax_{i,GEV,t} \text{ (or } ay_{GEV,t}) = ax_{i,GEV,0} \text{ (or } ay_{GEV,0}) \left(\frac{carstock_{GEV,t}}{carstock_{GEV,0}} \right)^{\beta} \quad \cdots\cdots\cdots\cdots\cdots \text{Eq. (79)}$$

where $LR = 1 - PR$ and $PR = 2^{-\beta}$ in which β is a learning parameter.

3.3.3.2 Installation Cost of Charging Infrastructure

If the stock of electric vehicles and hydrogen cars increases, the installation of charging infrastructure also increases. Depending on the stock of green mobility, the initial speed of infrastructure installation is fast but gradually slows down over time. In this case, the cost of installing and maintaining the charging infrastructure is linked to the government investment expenditure in the CGE model. Ruffini and Wei (2018) argue that both BEVs and FCEVs require large new investments in charging infrastructure. The government supports the installation of chargers by investing in electrical equipment and the hydrogen sector.

The number of new chargers installed in period t ($Infra_{AFV,t}$) is derived by multiplying the increase in vehicle stock by the ratio of chargers installed per vehicle stock. Total installation cost is calculated by multiplying the number of newly installed chargers by the unit installation cost (Infracost_{AFV}). For the installation cost of the

charger, I referred to the details of support for the installation of slow/high-speed chargers for electric vehicles and hydrogen charging stations in the Ministry of Environment's revenue and expenditure budget statement (Ministry of Environment. (2015-2022). It is assumed that hydrogen charging stations are 3 billion KRW per unit and electric vehicle chargers are 6 million KRW per unit considering the installation rates of slow/rapid chargers. In addition, a depreciation rate of 5% was applied to the maintenance cost of the charger, which was assumed to be 4% of the installation cost in equation (80). Each of equations (44) and (45) is modified as equations (81) and (82) each.

$$S^{g}_{\text{infra,t}} = \text{Infracost}_{AFV}\text{infra}_{AFV,t} + \sum_{t=0}^{t-1} 0.04\text{Infracost}_{AFV}\text{infra}_{AFV,t}(1-dep)^{t} \quad \text{Eq. (80)}$$

$$X_i^{g} = \frac{\mu_i}{p_i^q}\left(T^d + \sum_j T_j^Z + \sum_j T_j^m + \sum_{j,uh} T_{j,uh}^{ih} + \sum_j T_j^{iv} + \sum_j T_j^{ie} - S^g - S^g_{\text{infra}} \right) \quad \text{Eq. (81)}$$

$$X_i^{v} = \frac{\lambda_i}{(1+\tau_i^{iv})p_i^q}(S^p + S^g + \varepsilon S^f) + \text{S}^g_{\text{infra}} \quad \cdots\cdots \text{Eq. (82)}$$

$(i \in \text{electrical equipment and hydrogen})$

Chapter 4. Empirical Analysis

4.1 DC and Integrated Model Results

4.1.1 DC Estimation Results

It is possible to grasp the consumer preference for each attribute of purchasing a private car through the empirical model set above. In particular, the preference distribution by income class was subdivided to confirm the structure of passenger car consumption by income decile. The parameter is estimated through iteration of probability extraction by setting a conditional distribution according to the Monte-Carlo Markov Chain technique. Among 20,000 iterations, the first 10,000 trials were excluded as a burn-in process for convergence, and the average and significance were derived with the remaining 10,000 results. Table 11 shows the estimated results in the DC model.

Mean beta (b) shows the individual partial value, the marginal utility for one unit change. The variance indicates the heterogeneity in respondents' attributes; the larger the variance, the more heterogeneous the responses. The mean beta values of all variables are statistically significant at a 95% confidence level. The coefficient for the fuel type represents the preference for each type compared to FCEVs. It is confirmed that the mean value of the GV and EV attribute is positive and preferred over FCEV. In contrast, diesel cars present negative values, indicating they are preferred less than hydrogen cars. Since FCEVs were most recently commercialized, a degree of lock-in effect is not quiet. In other words, the preference of vehicles by fuel type appears in the order of EV > GV >

FCEV > DV. According to this result, it can be predicted that the stock of EVs and FCEVs is currently at a very low level but will increase in the future, and diesel cars will become less preferred. By vehicle class, a sedan is less preferred than SUV. As expected, more charging stations and lower price factors increased vehicle preferences.

The characteristic of the hierarchical Bayesian procedure is that it can be estimated by subdividing the beta distribution into a preference distribution according to individual characteristics. The estimated coefficient results for each income decile differ slightly from the mean beta. In the case of vehicle class, SUVs are generally preferred, but as income increases, they tend to prefer sedans more. The estimation coefficient of the price factor considering the income decile showed a positive value rather than a negative value. It can be seen that as income increases, it responds less sensitively to price. Estimates of vehicle fuel type considering income also showed the highest value for EVs. In other words, as income increases, they prefer EVs and GVs. On the other hand, DVs become less preferred as income increases. This is consistent with the higher preference for EVs among the higher-income earners who own multiple vehicles, as the characteristics of "early adopters" described in the Diffusion of Innovation Theory (Rogers, 1962).

However, the effect of income on the preference parameters of GV, DV, accessibility of charging infrastructure, and fuel cost are insignificant statistically, which means that the household preference for them remains constant regardless of how much they earn.

Table 11. Parameter estimates results

Parameter	Mean (b)		Variance (W)
	$\alpha_{intercept}$	Γ_{income}	
β_{GV}	0.2026** (base : FCEV)		9.0046***
	0.0842	0.0002	
β_{DV}	-0.9100*** (base : FCEV)		11.6297***
	-0.7263*	-0.0003	
β_{EV}	1.1667*** (base : FCEV)		7.2198***
	0.5421*	0.0011*	
β_{sedan}	-0.3042*** (base : SUV)		1.6566***
	-0.7390***	0.0008***	
$\beta_{Infrastructure}$ [a]	3.5731***		8.7015***
	3.4508***	0.0002	
$\beta_{fuel\,cost}$ [b]	-0.9509***		3.2046***
	-0.9290***	-0.0004	
$\beta_{vehicleprice}$ [c]	-0.7038***		1.2896***
	-1.1032***	0.0007**	

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level; a unit: %; b unit: KRW/km; c unit: 10 Million KRW

Mean β is statistically significant for all attributes; however, there are attributes with insignificant α and Γ. However, although α and Γ are insignificant, they are used to identify the trend of vehicle preference by income[7].

4.1.2 Comparison of DC Model and Integrated Model

Based on the estimated mean value (β), it is possible to calculate the vehicle choice probability by the attribute level in each scenario. DC model is a partial equilibrium model that seeks to maximize utility under exogenously given conditions. In this case, the model focus only on consumer choice, which reacts to the given value in a particular situation and does not lead to the next phase. In other words, my choices in the previous period do not affect the next period. However, the attribute level may differ if it is linked with a macroeconomic model. This is because, in the CGE model, a new equilibrium point is found, and prices are affected when household demand is determined based on the choice result. Due to economic variables in CGE, the attribute values of DC are endogenously updated. By linking the two models, it is possible to observe how the consumer's choice probability changes. Attribute levels in the base year reflect the current automotive technology levels and market environments. Attribute levels in the base year

7 The utility formula was modified to use mean β (b) for attributes with insignificant Γ, the regression coefficient of income, which is also an explanatory variable for β, instead of α and Γ. Compared with the current model, the preference for green mobility was similar, suggesting the validity of using the existing estimation formula. This tendency was revealed as the Γ value of statistically insignificant attribute was relatively small.

are shown in Table 12.

Table 12. Attributes level in the base year

Attributes	GV	DV	EV	FCEV
Accessibility of charging facility	100%	100%	2%	1%
Vehicle type	Sedan, SUV	Sedan, SUV	Sedan	SUV
Fuel cost (KRW/km)	112.4	89.4	40.6	83.2
Vehicle price (Million KRW)	30	32	50	70

The vehicle choice probability of the base year was calculated based on the parameter estimates. Table 13 shows the choice probability on a passenger car in DC and the link model in the base year scenario. In the DC-only model, the attribute level does not change, so the probability of consumer choice is constant regardless of time. In the case of gasoline vehicles, the choice probability is the highest irrespective of income and is almost constant (70~74%). People with low incomes prefer diesel cars more than people with high incomes, and there is a difference of about 8% between the highest and the lowest income deciles. Electric vehicles, on the other hand, show the opposite trend. People with higher incomes prefer EVs, and the difference in the probability of choosing between the highest and lowest incomes is up to 3%. In the case of hydrogen cars, the choice probability is the lowest in all income groups and relatively high in the high-income groups (0.1%), similar to the results of EVs.

Table 13. Choice probability results of DC model and integrated model

Household income class	DC model				Integrated model			
	GV	DV	EV	FCEV	GV	DV	EV	FCEV
HOH 1	70%	30%	0.3%	0.01%	68%	31%	0.3%	0.01%
HOH 2	71%	29%	0.4%	0.01%	69%	30%	0.5%	0.01%
HOH 3	71%	27%	0.5%	0.01%	70%	30%	0.6%	0.01%
HOH 4	72%	28%	0.7%	0.01%	70%	29%	0.7%	0.01%
HOH 5	72%	27%	0.8%	0.02%	71%	28%	0.9%	0.02%
HOH 6	72%	27%	0.9%	0.02%	71%	28%	1.0%	0.02%
HOH 7	73%	26%	1.2%	0.03%	72%	27%	1.3%	0.03%
HOH 8	73%	25%	1.5%	0.04%	72%	26%	1.6%	0.04%
HOH 9	74%	24%	2.2%	0.06%	73%	25%	2.3%	0.06%
HOH 10	74%	22%	3.9%	0.12%	73%	22%	4.1%	0.12%

The result that high-income people prefer green mobility is similar to the explanations of "innovators" and "early adopters" in Rogers' (1962) “theory of diffusion of innovation.” In theory, Rogers explained innovators and early adopters as having higher incomes, higher social standing, and greater willingness to take risks than the rest of society. In addition, a recent study in Norway supported the theory by showing that most EV owners are high-educated with above-average income living in metropolitan areas

(Lévay et al., 2017). In other words, due to the relatively high entry cost of new technologies, it can be seen that the high-income class is more rapidly adopting it than the low-income class.

On the other hand, the results are slightly different in the model linking DC and CGE. The trend of vehicle preference by income decile is the same, but the degree is slightly different between the two models. Compared to the DC model, the choice probability of GVs decreased in the link model. On the other hand, the probability of choice between DVs and EVs increased. Although the exogenously given attribute levels are the same, the price index obtained as a solution in the CGE model is reflected in the LINK model. That is, the results of the link model are different because the relative prices between fuel and automobiles have changed over time.

In addition, ICEVs have the same input ratio but different import and export ratios. Although the production price index of the gasoline and diesel vehicles is the same, the domestic demand price is different (Gasoline > Diesel). This is because the import price fixed according to the exchange rate is relatively lower than the production price. At this time, diesel cars with a hefty import share parameter are imported more than gasoline cars. As a result, the domestic sales price is relatively lower than gasoline cars due to the increase in the import volume of diesel cars. Therefore, the result of the choice probability is different due to the price change in the CGE model. In addition, the difference in the choice probability between the two models was more significant in the low-income group because of the high price sensitivity.

4.2 Baseline Scenario Analysis

4.2.1 Scenario Description

This study aims to analyze and evaluate the effect of changes in technological environments and government policies by linking the CGE model, which can analyze macroeconomic influences, and the DC model, which can reflect consumer preferences in vehicle demand. The baseline scenario was set by considering the government's policy rather than the current standard.

4.2.1.1 Power Generation Mix

Several studies confirmed that the precondition for the environmental benefit of green mobility dissemination is a clean power generation mix. When the proportion of coal-fired power generation is high, the amount of CO2 reduction when replacing ICEVs with EVs in the driving phase can be smaller than the CO2 increase in the electricity production phase.

Korean government implemented an energy transition policy to expand renewable energy by establishing a power supply and demand plan in consideration of economic feasibility, environmental, and safety. This study applied the proportion of renewable energy generation targeted by the "9th Basic Plan for Power Supply and Demand." The ratio of renewable energy generation is 7.4% in 2020 and 25.8% by 2034, which will continuously increase to 30% in 2040. In this scenario, it is set that renewable energy generation will increase linearly even after 2034, reaching 40% in 2050. It is also

assumed that the share of thermal power generation decreases as the amount of renewables increases.

4.2.1.2 Hydrogen Production Mix and Cost

Currently, the demand for hydrogen is very small. Hydrogen used in FCEVs can be fully supplied with by-product gas in the petrochemical industry in the base year. However, the demand for hydrogen as a new energy source is expected to surge. It is challenging to reflect the current hydrogen production structure as it is.

The Korean government has announced a 'Hydrogen Economy Roadmap' to accelerate the use of hydrogen in transportation and energy sectors (MOTIE, 2019). According to this roadmap, hydrogen was mainly supplied as a by-product gas in the petrochemical industry and a reforming gas from LNG in the base year. However, as the demand for hydrogen increases and emphasizes its role as a cleaner energy source, the government announced that it would increase the proportion of water electrolysis and imported hydrogen. Therefore, I reflected hydrogen production mix plan. Moreover, hydrogen production costs will decrease with the development of technology and economies of scale. Thus, hydrogen supply price projections that reflect changes in hydrogen production costs according to the hydrogen mix were used.

4.2.1.3 Subsidy for Green Mobility

The government has provided purchasing subsidies equal to the price difference with

ICEVs to induce consumers to purchase EVs and FCEVs. However, since vehicle subsidies are decreasing over time, it is assumed that there will be no vehicle subsidies after 2035.

4.2.1.4 Vehicle Price Changes from Increased Productivity

Green mobility prices are on the decline based on the same model. In addition, as the cost of producing batteries becomes lower and lower, the cost of producing EVs will also decrease. EVs are currently more expensive than conventional passenger cars but may become cheaper due to technological learning or economies of scale. A learning curve represents the technology's cost dynamics (Ruffini and Wei, 2018; Weiss et al., 2012). Based on the empirically observed phenomenon, the unit cost tends to decrease at a constant rate whenever the cumulative output is doubled. Therefore, in this study, I assumed that productivity increases as a power function of vehicle stock over base year vehicle stock in equation (79), where LR (learning rate) is 1-PR (progress rate). It is assumed that EVs will be similar in price to average GVs after 2030, while the price of hydrogen vehicles cannot reach as of GVs. Considering this, the learning parameter of electric vehicles was assumed to be 2% and hydrogen cars to be 1%.[8]

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8 In general, the learning rate is reflected in the production cost. However, instead of directly lowering the cost, the learning rate is different from the general learning rate because it is carried out in the direction of lowering costs by improving productivity. For example, (Ruffini and Wei, 2018) used 8% as the learning rate for the battery and 15% as the learning rate for the hydrogen tank.

4.2.1.5 Charging Infrastructure Improvement

The charging infrastructure is increasing exponentially with the active investment of the government. It is assumed that as the cumulative number of green mobility compared to ICEVs increases, more charging stations are installed to reach gas station accessibility. When EVs reach the stock level of ICEVs (about 10 million units), it is assumed that the level of charging stations for EVs will be the same as that of gas stations. On the other hand, since hydrogen cars have a faster-charging speed than EVs and are charged similarly to ICEVs, it is assumed that charging stations will be installed at the level of about 1 million units, similar to gas stations.

Table 14 shows the assumption of the baseline scenario. The level of key attributes that reflect the baseline scenario is shown in Figure 13 (vehicle price), Figure 14 (fuel cost), and Figure 15 (access to charging facility). Because of the improvement in productivity reflecting the learning effect, the price of EVs will become similar to GVs after 2035. The price of hydrogen cars will fall by half compared to the base year. Although the price of AFVs is higher than that of ICEVs, EVs appear at a similar level to them when subsidies are taken into account, while hydrogen vehicles are about 10 million won more expensive. The hydrogen fuel price will also reach about KRW 4,000/kg, half of the base year in 2040, considering the hydrogen outlook. With the spread of EVs and FCEVs, access to charging stations will improve, reaching the level of gas stations after 2041 and 2035.

Table 14. Forecasting of the main parameters in the baseline scenario

Parameter		2015 (baseyear)	2030	2040	2050
Power mix	Thermal power	68.2%	54.6%	45%	35%
	Renewable power	6.7%	20.3%	30%	40%
Hydrogen mix	LNG reforming	90%	50%	30%	30%
	Electrolysis	10%	50%	70%	70%
Hydrogen price (KRW/kg)		8,000	4,500	3,500	3,500
Subsidy (Million KRW)	EV	20	5	0	0
	FCEV	40	15	0	0
Productivity (Relative to 2015)	EV	-	7~10%	12~16%	16~22%
	FCEV	-	7~9%	12~14%	16~19%
Charging infrastructure (Relative to gas station)	EV	2%	55%	99%	100%
	FCEV	1%	61%	100%	100%

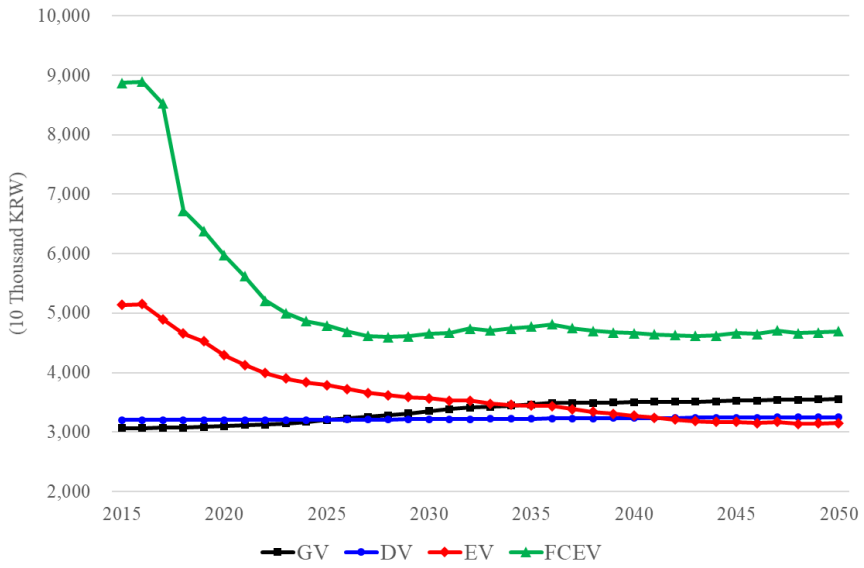

Figure 13. Vehicle price in the baseline scenario

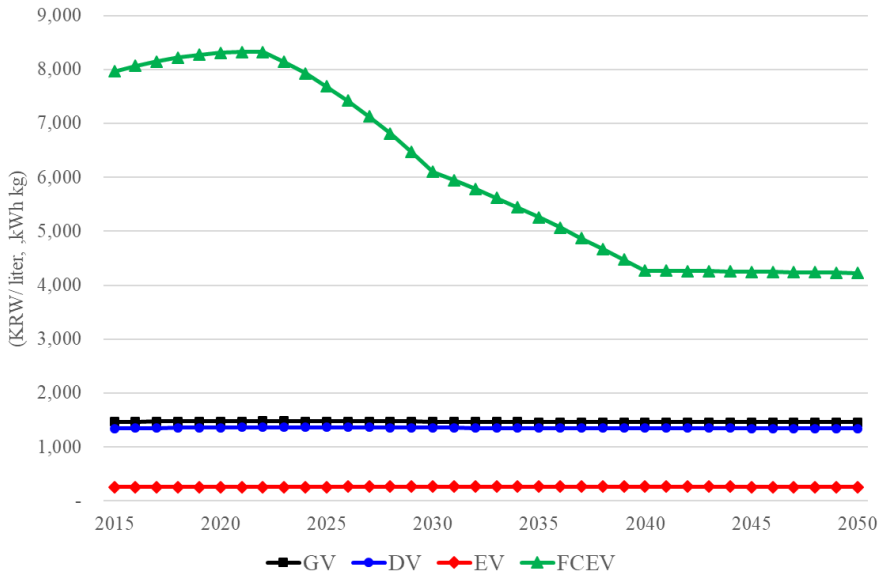

Figure 14. Vehicle fuel cost in the baseline scenario

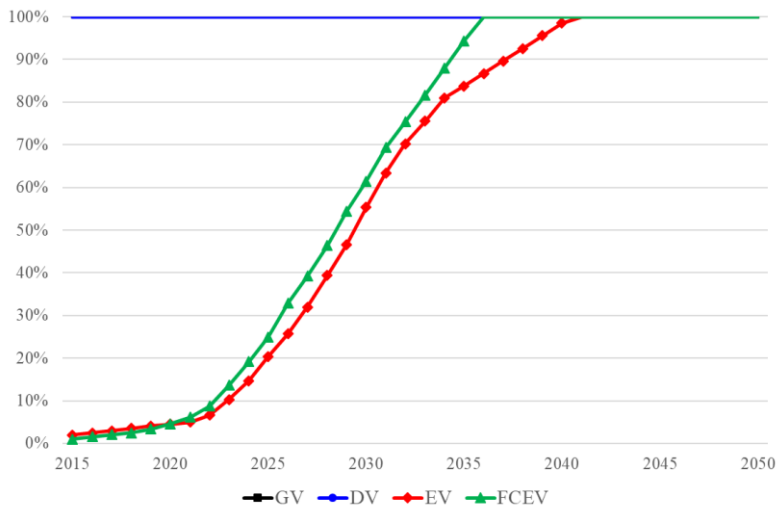

Figure 15. Accessibility of charging infrastructure in the baseline scenario

Figure 16 shows that the value of the preferred parameter beta for electric vehicles by household gradually increases as income increases over time.

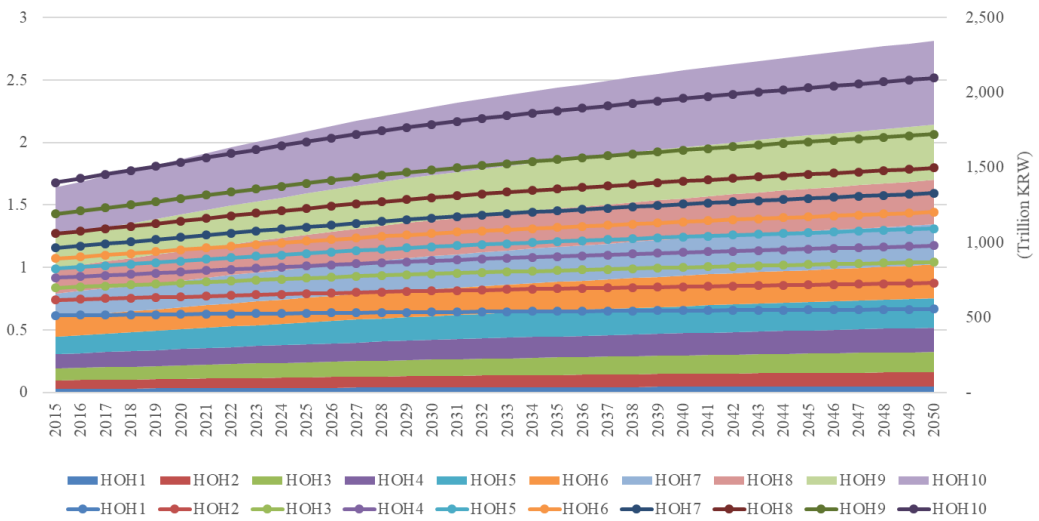

Figure 16. β_{EV} distribution and household income by class

4.2.2 Validation

The CGE model is a representative methodology that can confirm the impact of a policy through a comparative analysis between the reference scenario and policy scenarios. Nonetheless, discussion about the suitability of the CGE model in real-life problems is still an issue; therefore, it is necessary to validate how well it reflects real-life situations. The CGE model has been criticized for insufficient validation in terms of reliability of results (Beckman et al., 2011; Dixon and Rimmer, 2010, 2013; Hong et al., 2014; Valenzuela et al., 2007; Van Dijk et al., 2016). In particular, studies on the suitability of the CGE model mainly appear in the early stages of model studies (Johansen, 1974). The input data, SAM, only use the base year value; not requiring historical data may cause a discrepancy from reality.

Therefore, in most studies, thorough data work and restoration are performed to improve the predictive power and validity of the CGE model, mainly by adjusting the elasticity parameters. Valenzuela et al. (2007) confirmed that the results are enhanced when the model's estimated price elasticity using actual data is reflected. Beckman et al. (2011) estimated realistic price volatility using up-to-date quantitative estimates of energy demand and supply elasticity.

The proposed integration model was validated before testing the policy simulations. The initial situation of the model reflected past data (2015-2021) to validate the baseline scenario as the CGE model is dependent on exogenous parameters. Previous studies conducted historical and predictive simulations to fit the model to reality, as the past

observation data can be used to predict the future (Dixon and Rimmer, 2010). Accordingly, the total amount of subsidies for purchasing green mobility and charging infrastructure investment costs derived from the model are adjusted to be similar to the actual government budget in Table 15. Also, the model used the actual number of charger installations for charging infrastructure. The price of vehicles and fuels were matched to the data of the base year. For example, the price of hydrogen cars reached around 70 million KRW in 2018 from about 85 million KRW in 2015. In addition, EVs appeared in the market first as sedans and expanded to SUVs, and hydrogen cars appeared as SUVs, reflecting the limitations of green mobility types in Korea.

Table 15. Historical data and model results on installed chargers and government subsidy budget

	Charging infrastructure		Subsidy (Billion KRW)			
	Historical data (stock)		Historical data		Model results	
	BEV	FCEV	BEV	FCEV	BEV	FCEV
2015	3,040	10	44	2	41	2
2016	11,090	13	95	2	86	2
2017	21,135	23	196	4	165	4
2018	34,205	33	240	4	203	13
2019	47,405	53	378	90	512	97
2020	56,905	80	520	227	526	206
2021	66,505	115	525	338	555	337
2022	104,705	172	987	622	731	519

Source: Author’s work based on Ministry of Environment (2015-2022)

For validation of the built model, actual data and initial forecast results in the baseline scenario are compared. Mean absolute percentage error (MAPE) was used as an indicator to measure the goodness-of-fit between the model and the real world. MAPE indicates the degree of deviation by year in equation (83); the smaller the value, the closer to the actual data.

$$\text{MAPE: } \frac{1}{T}\sum_{t=1}^{T}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100 \quad \text{.....Eq. (83)}$$

where Y_t is a real value of a variable (GDP) and $\hat{Y}_t$ is an estimated (forecasted) value of a variable from the CGE model. MAPE in GDP from 2015 to 2021 is 5%, and the value from 2015 to 2050 is 4%. In addition, MAPE in CO2 emissions from 2015 to 2021 is 1%. As a result of a comparison using historical data and forecasts, it was found that the initial estimates are similar. The verification result can also be checked through the slope in Figure 17~19. The baseline scenario results of the model were verified.

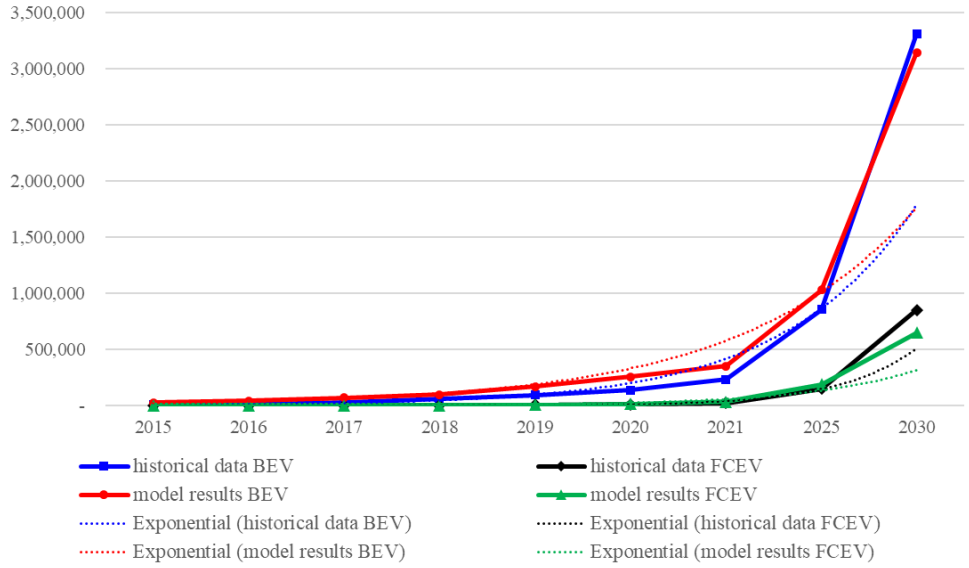

Figure 17. Comparison of historical data and forecasting on green mobility stocks

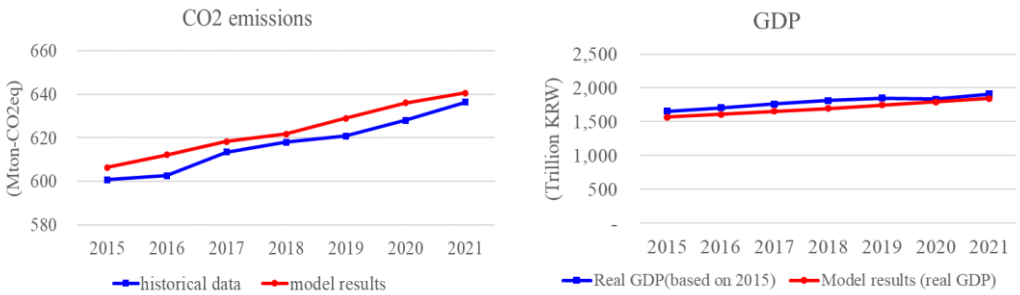

Figure 18. Comparison of historical data and model results (left: CO2 emissions, right: GDP)

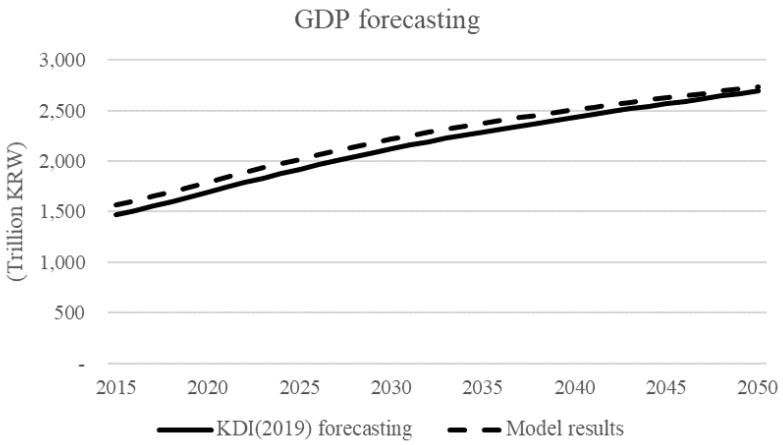

Figure 19. Comparison of institution data and model results on GDP projections

4.2.3 Scenario Results

4.2.3.1 Vehicle Sale and Stock

Figure 20 shows the choice probability results in the baseline scenario in 2050. Compared to the base year, EVs and FCEVs are more likely to be selected than ICEVs in 2050. EVs are the highest choice probability in all income groups (72%-85%), followed by GVs (6-14%), FCEVs (7%-9%), and DVs (1-10%). This suggests that EVs could become mainstream enough in the market when they reach the technological and cost level ICEVs. The choice probability of hydrogen cars increases from 0.1% in the base year to 7%-9% in 2050. Still, compared to other vehicles, the choice probability by income decile is almost the same having a smaller deviation. This is because the low-income class is sensitive to price, and the preference for hydrogen cars has surged due to increased income. This result could be observed because the beta distribution was estimated in the

discrete choice model, which is an advantage of the HB estimation method. On the other hand, the choice probability of electric vehicles has the highest variance by income quintile. This is because the preference for electric vehicles by income quintile is different from other cars; the preference for EVs increases as income increases.

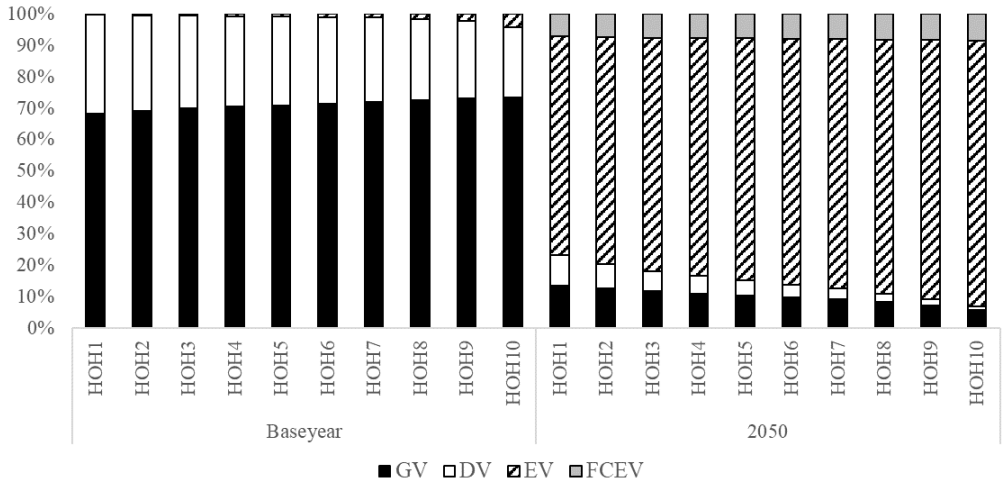

Figure 20. Choice probability results in the baseline scenario in 2050

In terms of income quintile, ICEVs are preferred by low-income groups. In the case of gasoline cars, there is a positive preference value for the income variable. Still, the result is different due to the influence of the infrastructure, sedan, and vehicle price variables (preferred as the income is higher). The higher the income quintile, the more the electric car is preferred. As the price of hydrogen cars decreases, the low-income class prefers hydrogen cars rather than the high-income class. It appears that the preference of the low-income class is increasing due to improved productivity and lower fuel prices for

hydrogen cars.

Table 16 represents the vehicle choice probability in the base year, 2030 and 2050. It can be predicted that half of the new cars will be purchased with electric vehicles and hydrogen cars after 2030. A change in the choice probability eventually leads to a change in the vehicle stock. Figure 21 shows the difference in vehicle stock by household. As time goes by, the demand for ICEVs decreases, and the demand for green mobility increases. By 2040, the stock of green mobility is expected to exceed that of ICEVs. After 2040, EV supply is expected to reach 10 million units. If the properties of EVs are not improved, the stock of EVs as of 2050 in the DC-only model is about 1 million, resulting in a difference of about ten times from the baseline scenario.

In the case of electric vehicles, compared to hydrogen vehicles, the diffusion rate is faster because of the high accessibility of charging facilities and the low initial purchase price and fuel. However, in the second half, the diffusion rate of hydrogen vehicles will be slow because the price will continue to be higher than ICEVs, about 10 million KRW.

Table 16. Choice probability in the baseline scenario

	GV			DV			EV			FCEV		
	2015	2030	2050	2015	2030	2050	2015	2030	2050	2015	2030	2050
HOH1	68%	37%	14%	31%	22%	6%	0.3%	30%	70%	0.01%	10%	7%
HOH2	69%	37%	13%	30%	20%	10%	0.5%	33%	72%	0.01%	10%	7%
HOH3	70%	36%	12%	30%	18%	8%	0.6%	36%	74%	0.01%	10%	8%
HOH4	70%	36%	11%	29%	17%	6%	0.7%	38%	76%	0.01%	9%	8%
HOH5	71%	35%	10%	28%	16%	6%	0.9%	40%	77%	0.02%	9%	8%
HOH6	71%	34%	10%	28%	14%	5%	1.0%	42%	78%	0.02%	9%	8%
HOH7	72%	33%	9%	27%	13%	4%	1.3%	45%	79%	0.03%	9%	8%
HOH8	72%	32%	8%	26%	12%	3%	1.6%	48%	81%	0.04%	8%	8%
HOH9	73%	30%	7%	25%	10%	3%	2.3%	52%	82%	0.06%	8%	8%
HOH10	73%	27%	6%	22%	7%	2%	4.1%	59%	85%	0.12%	7%	9%

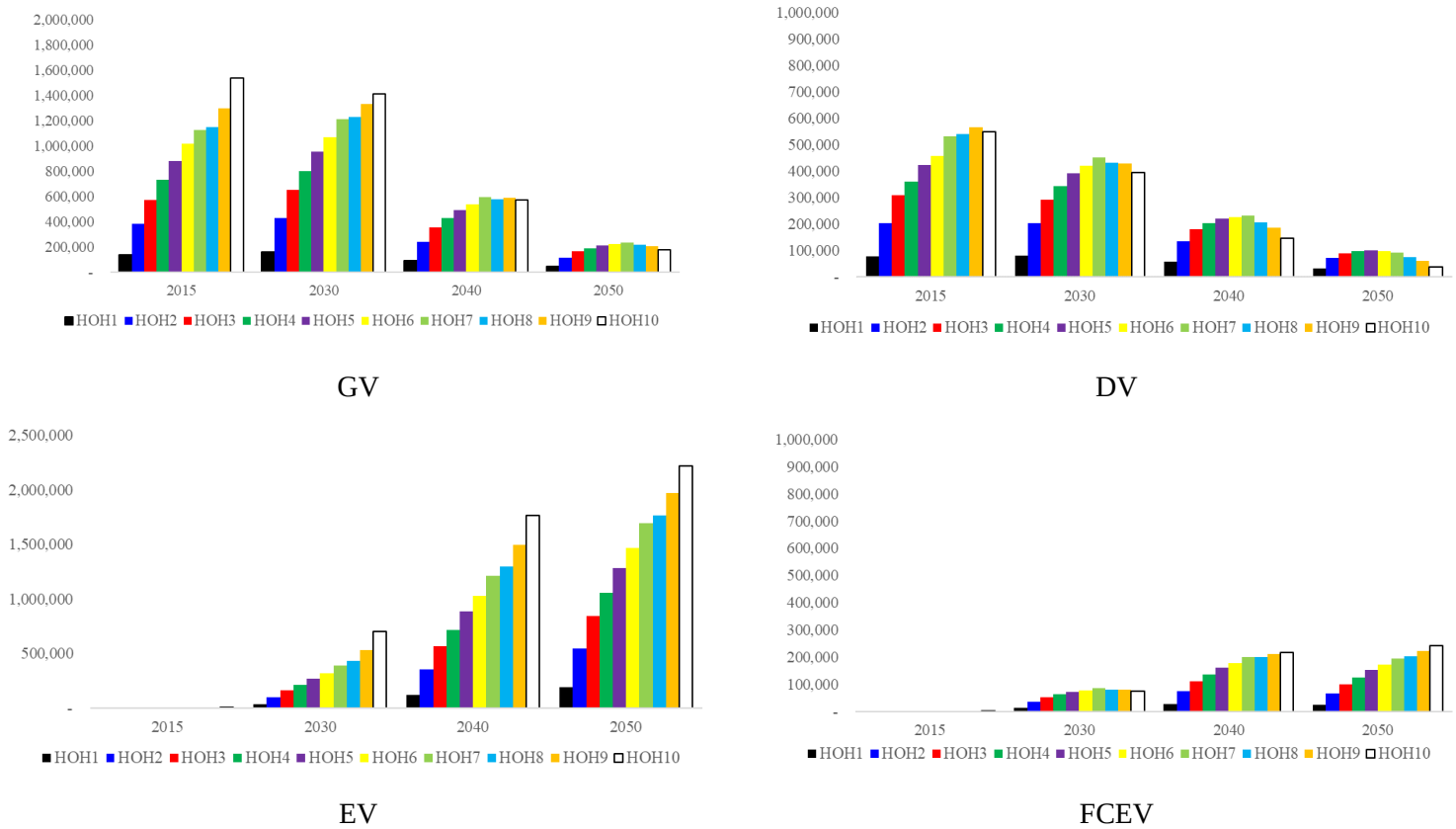

Figure 21. Vehicle stock by household and vehicle type in the baseline scenario

4.2.3.2 Economic Effects

Various economic indicators were used to analyze the effect of the diffusion of green mobility on the national economy. The baseline scenario results are compared to the base year level of the link model. First, GDP is the real GDP valued at the base year price and is calculated based on expenditure. Figure 22 shows GDP increasing over time and reaching around 2,735 Trillion KRW in 2050. Also, the average annual GDP growth rate is 1.6%. As the spread of AFVs increases rapidly by 2030, the GDP growth rate appears to be 2.34% per year, while after that, as the spread rate gradually stabilizes, the annual average GDP growth rate decreases by half to 1.06%.

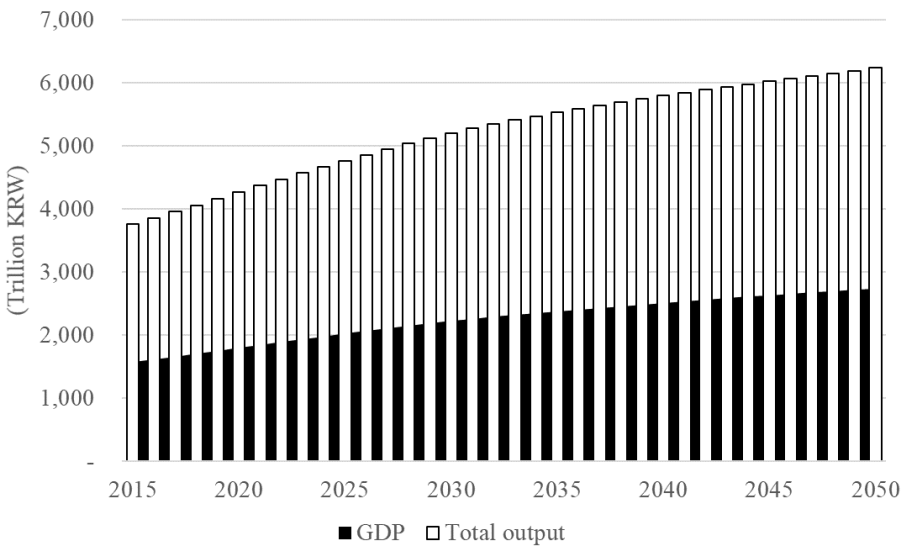

Figure 22. GDP and total output in baseline scenario

Total output is measured as GDP plus input from industry. Total output in the baseline scenario increases annually by about 1.45% by 2050. The automobile industry has a high chain effect, and changes in products used in automobile manufacturing may be induced. Table 17 represents the change in production by sector in the baseline scenario. As the demand for AFVs increases, the production of electricity and hydrogen, batteries, and non-ferrous metals, including the AFVs manufacturing industry, increases. On the other hand, a decline in demand for ICEVs leads to a decrease in the production of petroleum products, including gasoline and diesel, and a reduction in output in automotive engine manufacturing. In other words, the proliferation of AFVs changes the ecosystem of the automobile industry.

Since the increment in output due to the demand for green mobility exceeds the effect of the decrease in the production of ICEVs manufacturing, the total output increases when expanded to the whole economy. As a result, industries that are not closely related to automobiles, such as construction, also increase production.

As green mobility becomes more widespread, the price of capital increases, and wage decreases, leading to an increment in household income. Household consumption does not show an increase in spending due to green mobility subsidies at the beginning but gradually increases over time. On the other hand, household indirect tax (consumption tax) is decreasing because ICEVs and fuel account for a large proportion of consumption tax. As household income increases, consumption does not increase significantly, and consumption tax is paid less, household saving increases, as shown in Figure 23.

Table 17. Changes in production and growth rate by industries in the baseline scenario

	2015	2050	CAGR(%)
GV manufacturing	72	39	-1.71
DV manufacturing	11	11	0.05
EV manufacturing	2.2	123	12.13
FCEV manufacturing	0.2	34	16.29
Gasoline production	12	5	-2.28
Diesel production	26	21	-0.57
Thermal power generation	38	23	-1.38
Renewable energy generation	3	20	5.62
Hydrogen production	0.003	1.4	120%
Transport engine	22	20	-0.35
Battery	12	95	6.55
Non-ferrous primary metal	41	76	1.81
Construction	205	418	2.05
Total	3,603	5,978	1.46

Unit: Trillion KRW

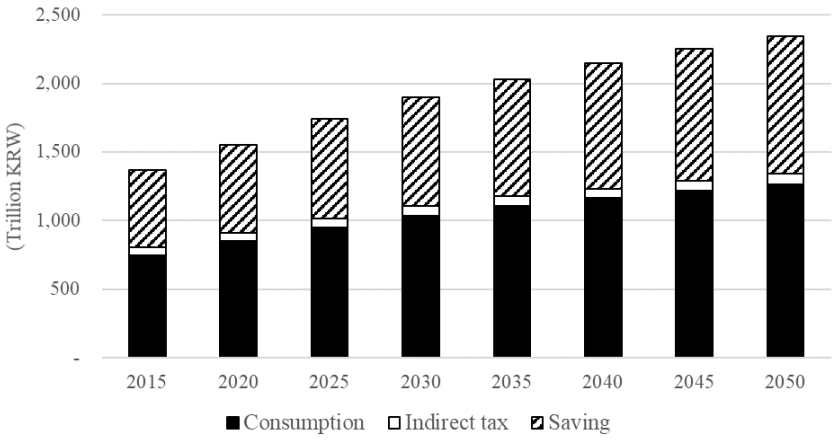

Figure 23. Household expenditure change in the baseline scenario

In the baseline scenario, green mobility purchasing subsidies are assumed to decrease gradually until 2035, which is different from base year results assuming no subsidy exists. The subsidy is paid at a specific rate when purchasing a vehicle, regardless of income quintile. Since the pool of subsidies is not limited, it is supposed that all buyers can receive subsidies. By 2034, the amount of subsidy support will be 18 trillion won, equivalent to 1 trillion won per year.[9]

The bottom 10% household income class (the lowest income quintile) receives a total of 287 billion won and 14 billion won per year. On the other hand, the highest income decile (top 10%) households will receive a total of 3,240 billion won or 162 billion won per year. Since the high-income class has a high probability of choosing green mobility,

9 According to the Ministry of Environment (2022), the subsidy for the purchase of passenger cars in the budget for purchasing electric and hydrogen vehicles is about 900 billion won in 2021.

more subsidies are provided in Figure 24.

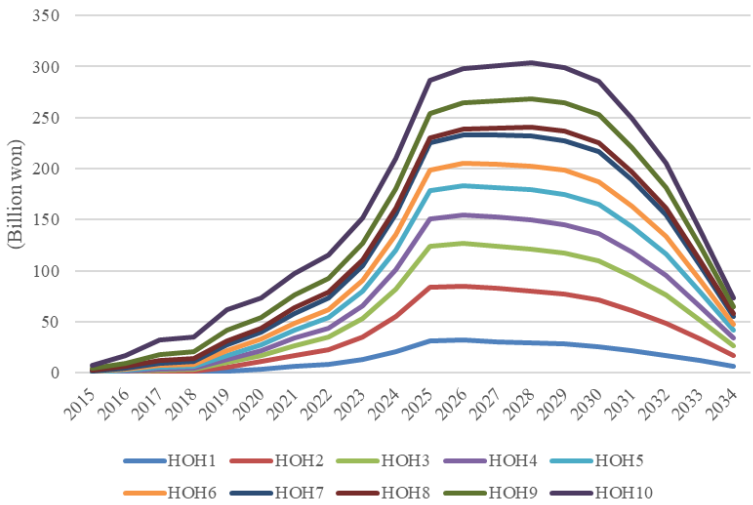

Figure 24. Subsidy by households in the baseline scenario

Figure 25 represents the proportion of subsidies to household incomes. Households with low incomes are less likely to choose green mobility, receiving fewer subsidies but a high share of total revenue. As the income quintile increases, green mobility is more purchased, and the subsidy increases, increasing the proportion of expenditures. However, even if the high-income class buys a lot of cars and receives subsidies, their consumption of other goods is also high, so the proportion of total income decreases again. In other words, the low-middle class has the highest subsidy receipt as a share of income, showing an inverted U-shaped curve in Figure 26. As their income increases, they receive more subsidies, but high-income earners have so much income that even if they receive

subsidies, they do not contribute to the rise in income. In other words, the green mobility subsidy policy does not have a significant regressive effect but instead increases the income of the low-middle class. However, since the proportion of subsidies to income (about 0.1%) is not high, it is expected that the distribution effect by income class will be insignificant compared to the amount of tax support[10].

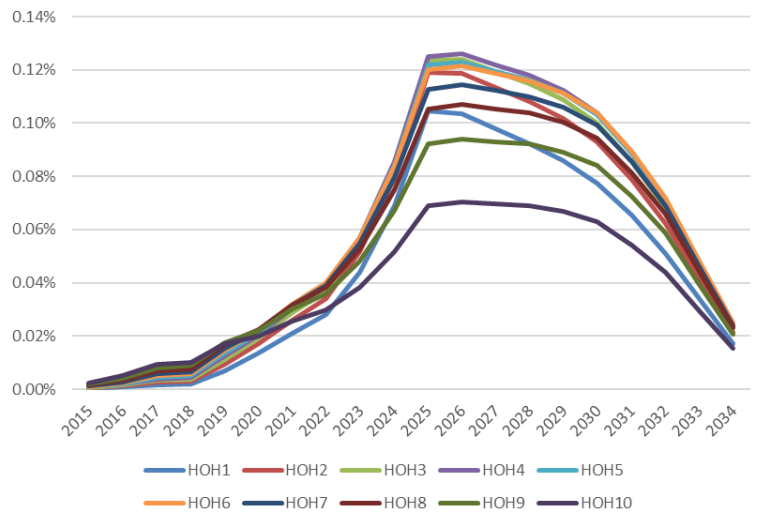

Figure 25. Subsidy ratio to household incomes in the baseline scenario

10 As a result of estimation using the Gini coefficient, which is an index of income inequality, there is little change from the value of the base year.

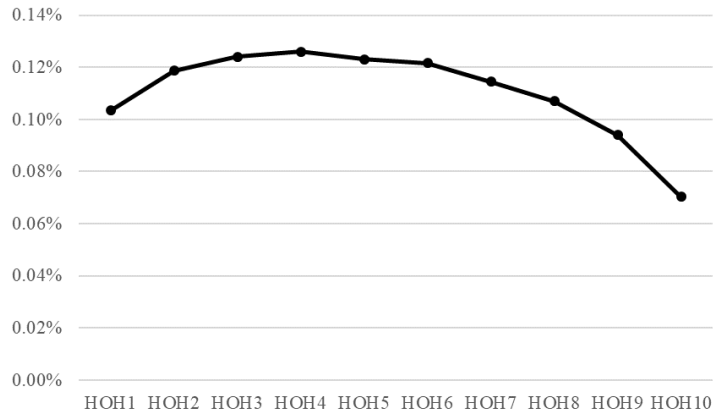

Figure 26. Subsidy ratio to household income

Government tax revenue does not rise as much as GDP increases. As of 2050, GDP increased by 75% compared to 2015, but government tax revenue increased by 65%, which is 0.15% lower than the annual growth rate of GDP. Income tax accounts for the largest share of government tax revenue, followed by production, indirect household, investment, and export and import tariffs. In the baseline scenario, government tax revenue will decrease due to the spread of green mobility. First, the total output increases, but the cost of production decreases, resulting in a reduction of the total production tax. Secondly, in the case of households, income tax increases due to an increase in income, but indirect tax decreases significantly as consumption of ICEVs decreases. AFVs have lower taxes than ICEVs of the same price due to individual consumption tax and education tax exemption, and acquisition tax reduction as a tax reduction benefit. Fuel tax is also high for gasoline and diesel, but there is no fuel tax for electricity and hydrogen for charging. Taxes related to automobiles account for a large portion of households.

Therefore, the total consumption tax will decrease even if the demand for green mobility increases and household consumption increases.

4.2.3.3 Environmental Effects

In the baseline scenario, total CO2 emissions in 2050 will be about 540 Mtons-CO2, which is about an 11% decrease compared to the base year in Figure 27. This results from changes in the power generation mix, hydrogen mix, and automobile demand. The share of renewable energy in generation grows 30%p in 2050 than in 2015. Coal emissions decreased by about 14% by fuel, reducing 47 Mton-CO2 in 2050. Due to the decrease in demand for ICEVs, gasoline emissions decreased by 56% (about 15 Mtons-CO2) and diesel by about 19% by 12 Mtons-CO2. However, due to the increase in the country's overall production, starting from the demand for electric and hydrogen vehicles, the emissions of LNG and LPG increased. In addition, primary metal, gas, and nonmetal manufacturing emissions will increase from a linkage effect by industry.

In the base year, a FCEV is the highest vehicle emissions per unit, followed by GV and DV, and EVs have the lowest. This is because most of the hydrogen was produced in the LNG reforming at the beginning. However, due to the hydrogen outlook, the proportion of water electrolysis production will increase, resulting in lower emissions per unit than EVs in 2050. On the other hand, even if hydrogen is produced by electrolysis, CO2 emissions may increase when electricity produced based on the current electricity mix is used (Yoo et al., 2018).

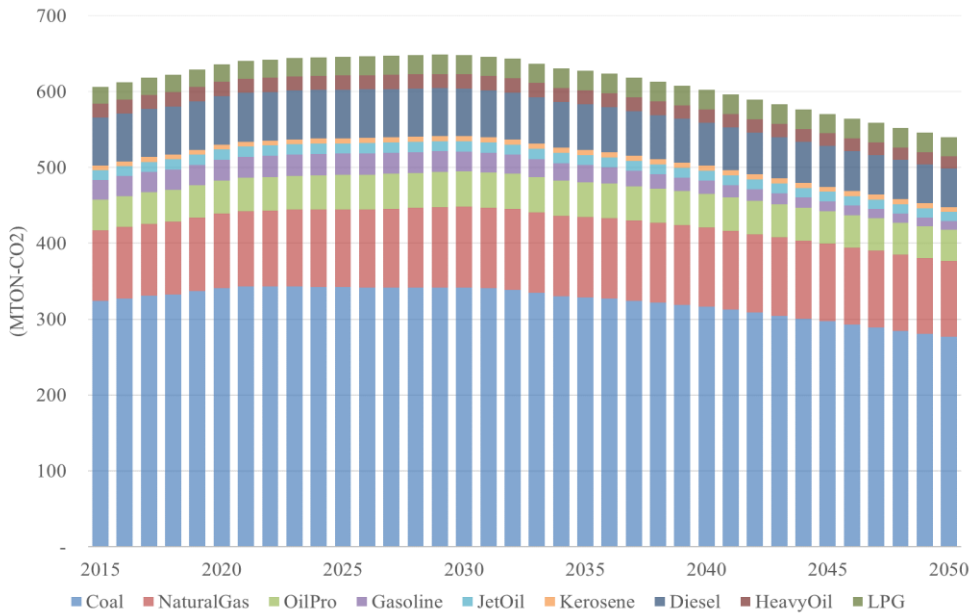

Figure 27. National CO2 emissions in the baseline scenario

In other words, the increase in demand for EVs and FCEVs in the state where the electricity mix and hydrogen mix is not improved causes more emissions. Figure 28 displays changes in passenger car emissions as the power generation and hydrogen production mix changes. By 2050, passenger car emissions will increase to 30 Mtons-CO2, an increase of 7 Mtons-CO2 compared to the base year. On the other hand, in the case of clean power generation, the supply of EVs and FCEVs makes the passenger car emissions about 14 Mton-CO2, which is about 41% lower than a base year, approximately 9.6 Mton-CO2. Although the reduction of automobile emissions is 15% of the total reduction, the emission of automobiles is insignificant at about 3% of the total emission.

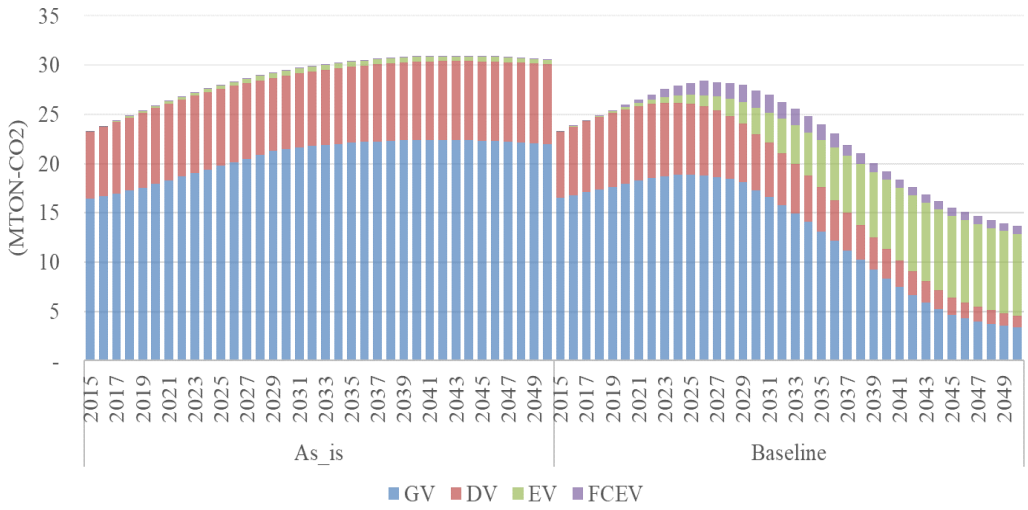

Figure 28. CO2 emissions in passenger cars in the baseline scenario

4.3 Scenario Analysis 1: Fuel Tax and Learning Effects

4.3.1 Scenario Description

In this section, scenario 1 refers to the situation where fuel taxes were additionally imposed on gasoline and diesel as a concept of a carbon tax to test research question 1[11].

(Research Question 1) Tax imposition policies help spread new technologies but have a negative impact on economic growth; however, if the pace of technological progress increases, how will taxation policies affect economic growth?

11 The fuel tax is not limited to passenger cars but is reflected in all fuel demand, since the effect of imposing a fuel tax on the passenger car sector is not significant and the fuel tax is reflected in the fuel price.

In the case of an increase in fuel tax in the form of a carbon tax, endogenously, it tries to select a fuel with low emission in the model, and the price of gasoline and diesel increases, which may increase the demand for green mobility. The tax rate is assumed that reaches 200,000 KRW/tonCO2eq by 2050; there is a linear annual increase. The fuel tax was estimated considering the carbon emission coefficients of gasoline and diesel; an increase of 436 KRW/l and 520 KRW/l in gasoline and diesel, respectively, in 2050. Fuel tax revenue is returned to consumers lump-sum due to government transfer expenditure, which is constant regardless of income.

According to Porter's hypothesis, when new technologies enter the market, and transitional competition occurs, regulation acts as a buffer until the new technologies reduce production costs through the learning effect. He also insisted that learning could reduce the innovation costs caused by regulation. In this vein, sensitivity analysis was performed to confirm the production reduction effect due to the fuel tax appearing to depend on the learning rate. In the baseline scenario, learning parameters were assumed to be 2% in EV production and 1% in FCEV production. Several cases in which this learning parameter increases or decreases by 0.1%p~0.5%p was additionally tested to examine how the fuel tax effect changes according to the speed of technological progress.

In addition, the CGE model has been criticized for not being able to prove the robustness of the parameter estimation results because a calibration method based on the base year data is used for estimation instead of the econometric approach (Hosoe et al., 2010). In order to examine the robustness of the scenario results, it is necessary to analyze

the sensitivity of the exogenously assumed key parameters of the model. Therefore, since the learning rate that affects production activities is a key parameter, different learning rates were used to observe and compare the results.

4.3.2 Scenario Results

4.3.2.1 Vehicle Sale and Stock

The fuel tax induces the diffusion of green mobility due to the increase in fuel costs, increasing their choice probability by 8% compared to the baseline in 2050. Figure 29 describes the household vehicle choice probability in 2050 by scenario. As the price increased due to the addition of fuel tax to gasoline and diesel, the choice probability of gasoline and diesel vehicles decreased by 5% and 2%, respectively, compared to the baseline scenario. In particular, the change in the low-income group was relatively huge because the low-income group is more sensitive to prices. In the case of green mobility, the choice probability of electric vehicles increased significantly more than hydrogen cars.

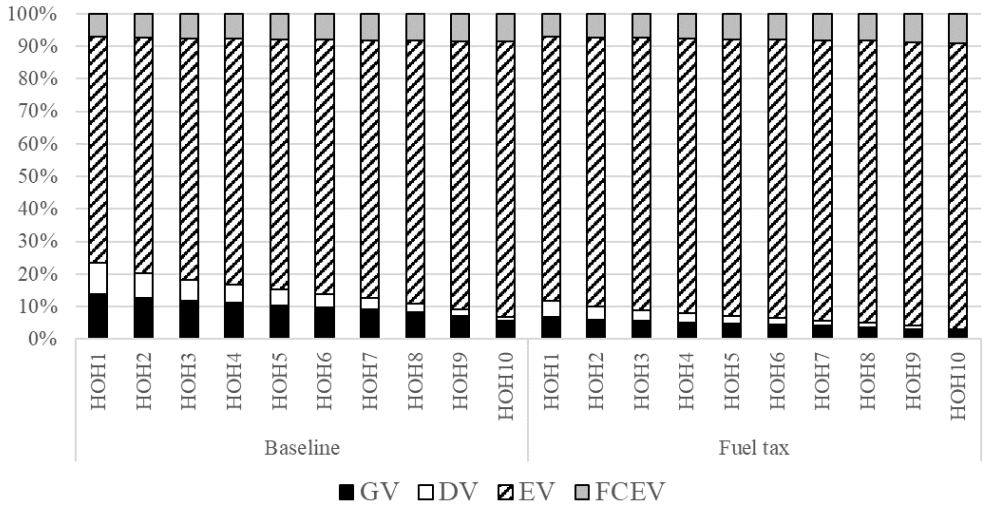

Figure 29. Choice probability of automobiles in 2050 by scenario

The choice probability of green mobility increases the cumulative number by 8% compared to the baseline in 2050. On the other hand, the stock of ICEVs will decrease by about 1.2 million units by 2050. In the baseline situation, where the learning rate of EVs is greater than that of FCEVs, the imposition of the fuel tax further stimulates the spread of EVs.

Figure 30 represents the effect of a tax imposition policy on the technological process rate (i.e., the learning rate) through vehicle stock changes. Depending on the learning rate, the pace of productivity improvement changes and directly impacts the cost and price of vehicle production. Vehicle price will influence consumer choices, resulting in changes in demand and car accumulation. As the learning rate increased, the demand for hydrogen cars increased, while the demand for electric vehicles decreased. The hydrogen car

responds more sensitively to the learning rate, which has greater fluctuation. Because the car price of FCEVs in the base year is much higher than those of other cars, it is more sensitive to the learning effect due to the base effect.

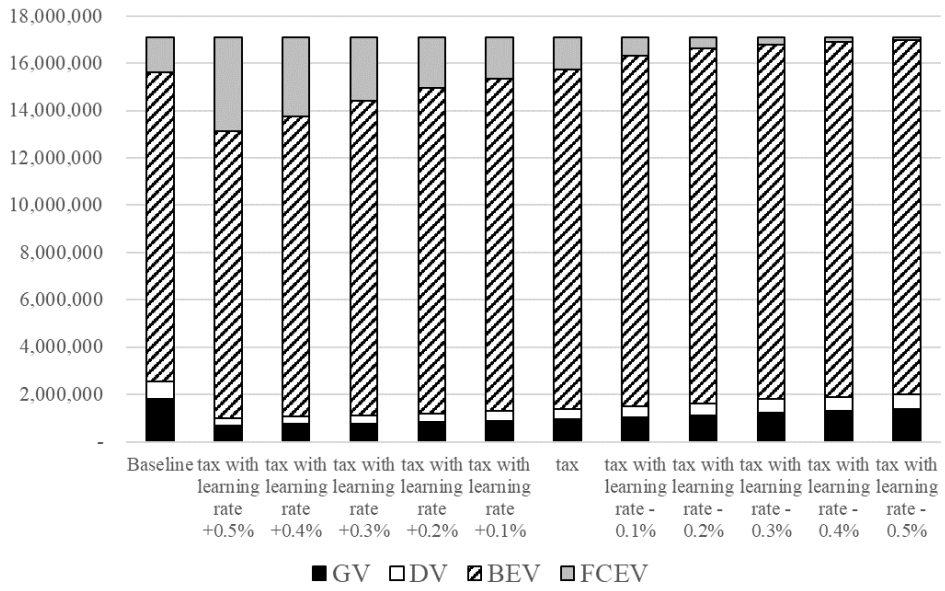

Figure 30. Share of automobile stocks in 2050 by learning rate in tax imposition policy

4.3.2.2 Economic Effects

Gasoline demand mostly comes from gasoline vehicles (64%). On the other hand, demand for diesel is greater not only in passenger cars (11 percent), but also for different modes of transportation, including buses and trucks (40 percent). Therefore, the fuel tax increases the price of gasoline and diesel, which further reduces the consumption of ICEVs, especially gasoline vehicles. This leads to a decline in vehicle manufacturing and

crude oil production.

The production reduction effect from the fuel tax is offset by the learning effect on green mobility production. Figure 31 shows the changes in GDP depending on the learning rate compared to the baseline scenario. Even if a fuel tax is imposed, the learning rate of green mobility influences GDP; a higher learning rate leads to an increase in GDP, and a lower learning rate leads to a decrease in GDP. The learning effect when fuel tax is imposed in the baseline scenario is greater than the GDP increase from the fuel tax effect. This is because the rise in green mobility demand and production is greater than a decrease in production in ICEVs and other transportation sectors.

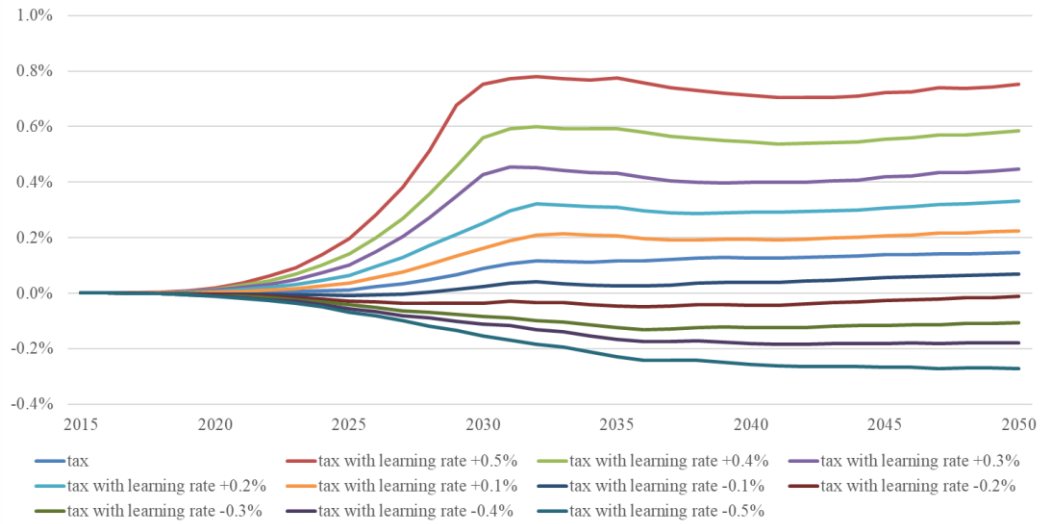

Figure 31. Changes in GDP over baseline scenario

As the learning rate for green mobility decreased, a decrease in production was

observed due to the fuel tax. If the learning rate for green mobility decreases by 0.2%p compared to the baseline, the relative GDP compared to the baseline scenario is less than zero. This is because reducing production due to the fuel tax is more remarkable than increasing production due to the learning effect of green mobility. At this time, the hydrogen charging infrastructure did not reach 100%. When the learning rate is lowered in the fuel tax scenario (-0.5%p), the demand for ICEVs increases, resulting in a 6.8% increase in gasoline vehicle production and a 3.1% increase in diesel vehicle production. On the other hand, the demand for FCEVs declined sharply, resulting in a 78% decrease in FCEV demand and a 67% decrease in hydrogen production.

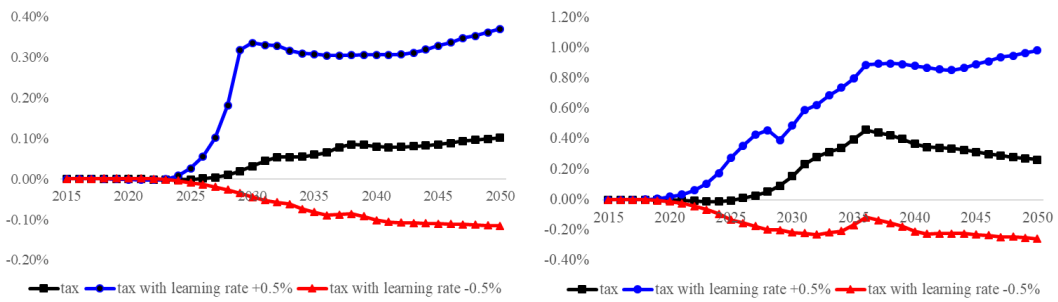

Figure 32. Changes in household income (left) and savings (right) compared to the baseline scenario

Household income also shows a similar trend to changes in GDP. Figure 32 depicts the change in household income and savings compared to the baseline. Given the learning rate of green mobility to a certain extent, the imposition of fuel tax increases household

income, and when the learning rate decreases, income decreases. Moreover, household savings increase further as the learning rate increases, and thus the price of green mobility decreases, which reduces spending on passenger cars.

Changes in welfare due to the spread of green mobility can be confirmed through Hicksian equivalent variation. Hicksian equivalent variation is calculated utility using the expenditure function. However, in this case, the share parameter value of green mobility in the base year is fixed and too low, and the utility decreases as purchases increase. However, since vehicle attribute levels on the base year and the scenario are different, vehicles cannot be regarded as goods at the same level. Therefore, I measured social welfare change except for the consumption of passenger cars.

Figure 33 shows the household welfare changes depending on the learning rate of green mobility. As the learning rate increases, household income increases, so households can increase consumption. As a result, the welfare of the households will increase. In addition, when the price of AFVs decreases due to the learning effect, vehicle expenditure decreases, which in turn relatively increases the expenditure on other goods, increasing welfare.

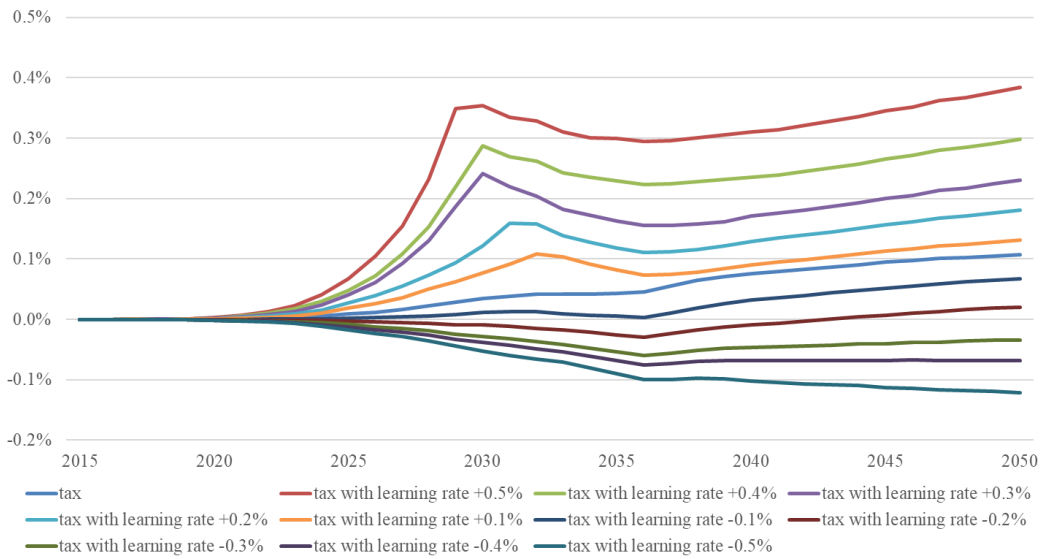

Figure 33. Changes in household welfare compared to the baseline scenario

Figure 34 shows the proportion of fuel tax to income by household in 2021, the first year of additional fuel tax, and 2050, the model's final year. As the fuel tax increases, the burden of the fuel tax relative to the income of the low-income class gradually increases. When the fuel tax is low, it shows an inverted U-shaped curve, but the regression is remarkable when the fuel tax increases. Although the additional fuel tax that households bear is insignificant compared to their income, the government should take this into account when designing policies because the degree to which households experience a different increase in fuel tax increases.

Some argue that it is not fair to strengthen the regressive consumption tax in the case of enhancing the function of the energy tax system as an environmental tax (Kim, 2011; Yi and Kim, 2016). Kim (2011) showed that the proportion of consumption of petroleum

products, which is transportation fuel, tends to increase significantly as the higher-income class goes up. Yi and Kim (2016) represented that the tax burden on transportation oil has an inverted U-shape, showing low-income-progressiveness, middle-proportionality, and high-income-weak regression. This study confirmed that when the tax rate is low, the tax rate to income shows an inverted u-shape depending on household income, but the higher the tax rate, the more burdensome it can be for the low-income group.

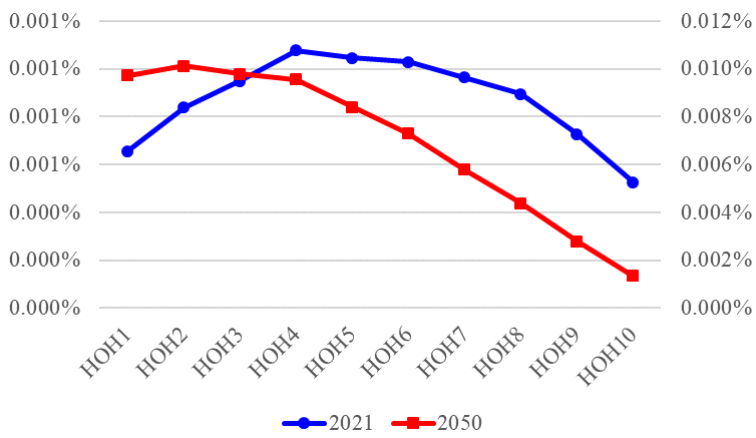

Figure 34. Ratio of fuel tax to income by household

On the other hand, the government's tax revenue shows a different trend from the above results. Figure 35 represents the change in government tax revenue compared to the baseline scenario. The imposition of a fuel tax increases the government's tax revenue in the short run, but in the long run, production decreases, leading to a decrease in government tax revenue. This is more pronounced when the learning effect is low. On the

other hand, if the learning effect is high, the government's tax revenue decreases in the short term because the spread of green mobility is fast. This shows that the tax revenue from the acquisition and registration tax decreases because the fuel consumption and vehicle purchases of ICEVs decrease rather than the increase in the fuel tax on gasoline and diesel. However, over time, the total production increased due to the learning effect of green mobility rather than the impact of the fuel tax, so the government's tax revenue increased because of an increase in production tax from corporate.

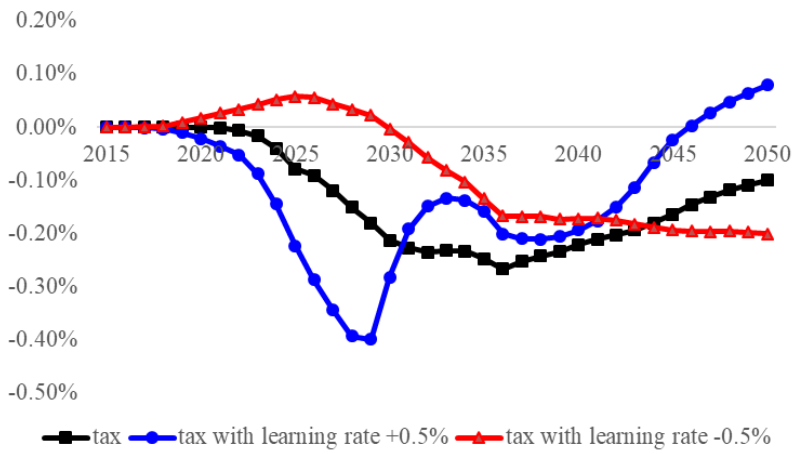

Figure 35. Changes in government tax revenue compared to the baseline scenario

4.3.2.3 Environmental Effects

Figure 36 shows the change in CO2 emissions in passenger cars. Emissions from the passenger car decreased by about 10% due to the imposition of the fuel tax compared to the baseline. An increase in the fuel tax relative to the baseline reduces the demand for

ICEVs, resulting in reduced emissions from the transport sector. Also, the reduction effect becomes more prominent as the learning rate increases. On the other hand, when the learning rate increases by 0.5%p, the emission from the hydrogen car at the beginning is relatively enormous because the hydrogen production mix is mainly LNG in the beginning, and the proportion of water electrolysis increases over time which becomes a cleaner fuel. In other words, since the emission reduction effect from hydrogen vehicles depends on the hydrogen mix, production from a cleaner source should be prioritized before increasing the demand for hydrogen vehicles.

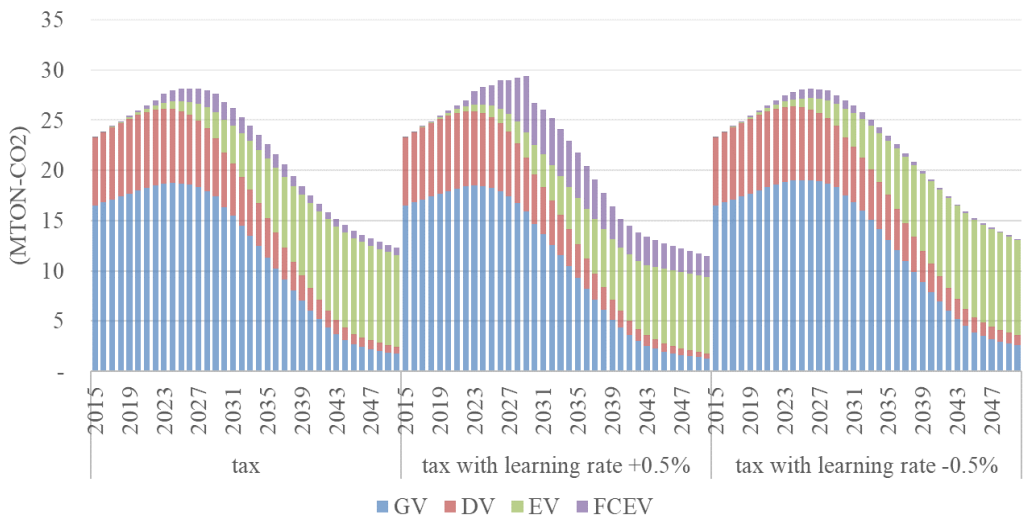

Figure 36. Passenger cars emissions changes

However, an increase in national GDP increased emissions of the entire industry, offsetting the emission reductions in the passenger car sector in Figure 37. Due to the fuel

tax, gasoline emissions in 2050 decreased by about 16%, and diesel by about 3.5%, compared to the baseline. Since gasoline consumption is mostly from passenger cars, the emission reduction rate compared to diesel is large. As demand for AFVs increased, emissions from battery manufacturing (5.9%) and electric vehicle manufacturing (6.5%).

In other words, the rebound effect in which the total output increases and the emission increases is more eminent than the emission decreases due to the decline in demand due to fuel substitution. However, when the learning rate is lower than the baseline, reducing emissions from passenger cars offsets the effect of rebounding from increased production.

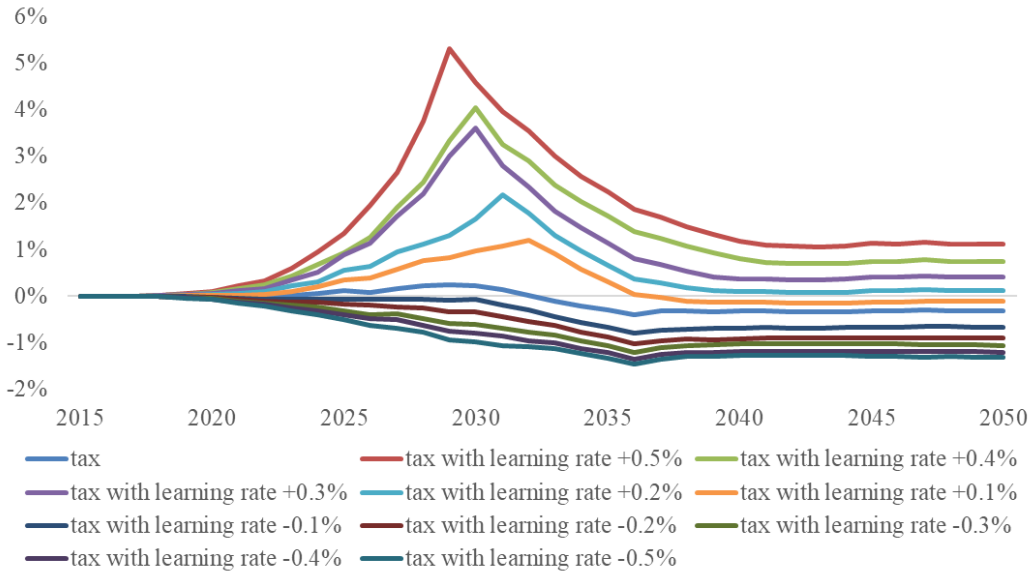

Figure 37. Changes in total emissions compared to the baseline scenario

In summary, taxation can be applied as a beneficial policy when the green mobility production growth rate is high, but as a burden or damage to society when the production growth rate is low. I identified the threshold value at which the learning rate that taxation policy negatively affects society (-0.2%p) compared to the baseline scenario. In other words, results prove that levying tax positively affects economic growth only if supported by a certain pace of technological progress.

Table 18 represents the difference in results between the single model and the linked model, highlighting the strengths of the linked model. In the fuel tax scenario, the linkage model can capture both the CO2 reduction effect due to fuel substitution and the rebound effect in which the CO2 emission increases due to the increase in production through the learning effect.

Table 18. Main results of scenario 1 by model

	DC model	CGE model	Link model
Demand of green mobility	P	P	P
GDP growth	X	N	↑ (Learning effect)
CO2 emissions reduction	P (Only in transport sector)	P	- (Fuel substitution: P Production increase: N)

※ P: positive effect, N: negative effect, X: cannot be identified in the model, -: offsets

4.4 Scenario Analysis 2: Subsidy and Charging Infrastructure Investment

4.4.1 Scenario Description

In order to establish an early market for green mobility, the government is encouraging consumers to purchase through aggressive purchase subsidies and charger installations. The total budget for subsidy support for purchasing electric vehicles and hydrogen cars in Korea has nearly doubled from 862 billion KRW in 2021 to 1.6 trillion KRW (57%) in 2022. Support for charger installation has also increased from 173 billion KRW in 2021 to 430 billion KRW (15%) in 2022 (Ministry of Environment, 2022). Most of the budget for the supply of green mobility is allocated to purchase subsidies.

Nevertheless, various opinions are being debated about the effectiveness of the green mobility supply policy, as indicated by research question 2. Of course, both subsidy policies and charging infrastructure installation support policies are necessary to spread green mobility. However, since the government's budget is limited, an increase in one has no choice but to decrease the other. In other words, priorities should be set in the implementation of policy instruments.

(Research Question 2) Which approach will have a greater effect on the diffusion of technology and economic growth, a direct government price subsidy policy for consumers, and indirect support for the complementary goods market?

In this situation, to answer research question 2, two scenarios were constructed in which investment in charging infrastructure changes as much as the government budget changes by increasing or decreasing subsidies for purchasing green mobility. This means a modification in the proportion of subsidies and charging infrastructure investment in the government's budget. The 'subsidy more & infra less' scenario refers to a case where investment in charging infrastructure is reduced by 1 trillion won instead of executing an additional 1 trillion won in total purchase subsidy. Conversely, the 'subsidy less & infra more' scenario assumes an additional 1 trillion won in investment in charging infrastructure instead of 1 trillion won less in total purchase subsidy.

Figures 38 and 39 show the charging station accessibility and vehicle price forecasts by scenario. If the total investment in charging infrastructure increases by an additional 1 trillion won, electric vehicle chargers will reach the level of gas stations seven years earlier and hydrogen charging stations five years earlier. However, if infrastructure investment is reduced by more budgeting for subsidies, both EV chargers and hydrogen charging stations will reach the level of gas stations after 2045, which will delay five years for EVs and ten years for FCEVs than baseline. In the case of vehicle prices, when the subsidy is higher, the price of the vehicle during that period is slightly lower than the baseline scenario. Conversely, when the subsidy is less, the price increases slightly. However, the price of EVs and FCEVs will remain the same in all scenarios after 2040.

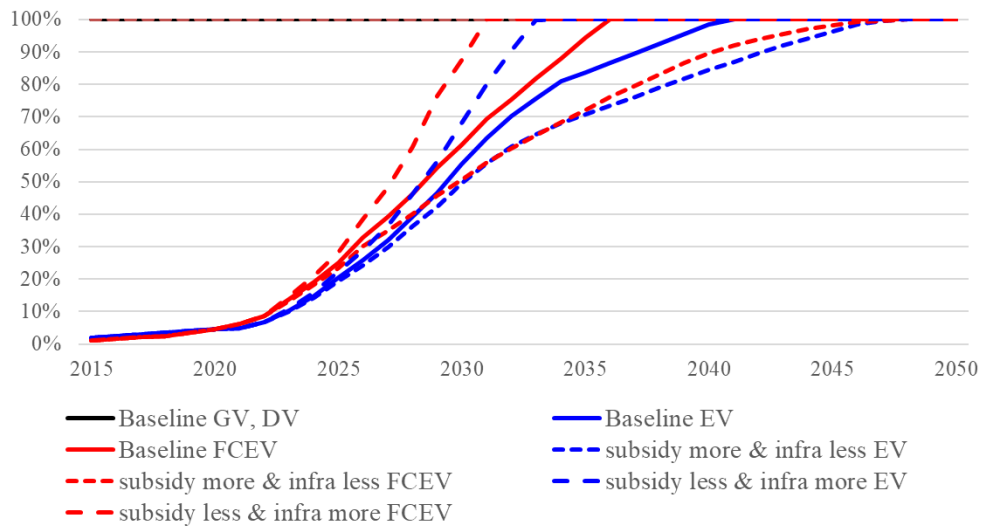

Figure 38. Accessibility of charging stations by scenario

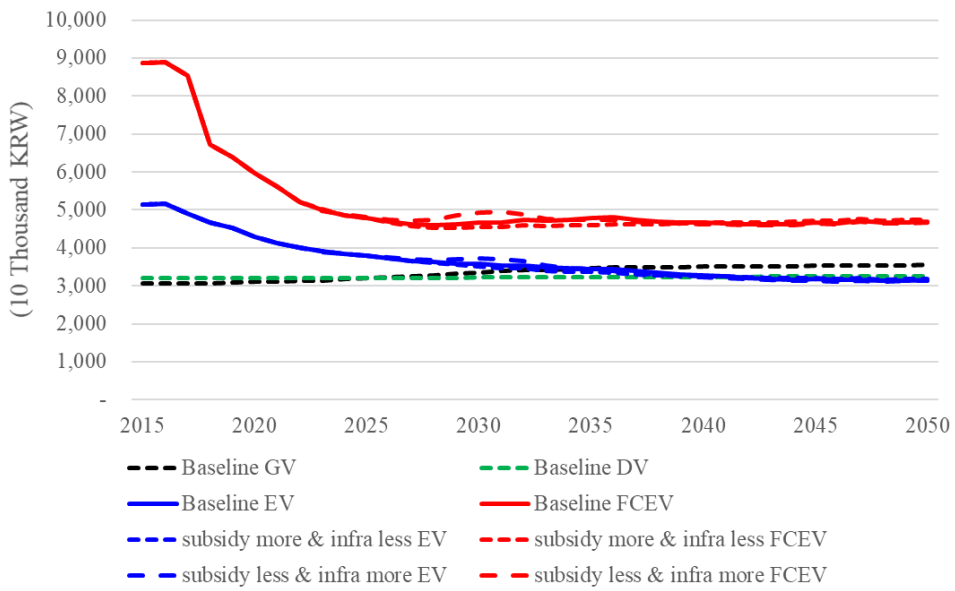

Figure 39. Vehicle price forecasting by scenario

4.4.2 Scenario Results

4.4.2.1 Vehicle Sale and Stock

If the speed of charging infrastructure construction slows down by distributing a total subsidy of 1 trillion KRW more, green mobility diffusion speed will slow. With more subsidies, the spread of EVs and FCEVs is relatively fast in the beginning. However, when the subsidy no more exists, the spread rate of green mobility decreased because the infrastructure level was relatively low compared to gas stations. According to Figure 40, it can be seen that there is a considerable difference in the rate of green mobility penetration from 2025 to 2045.

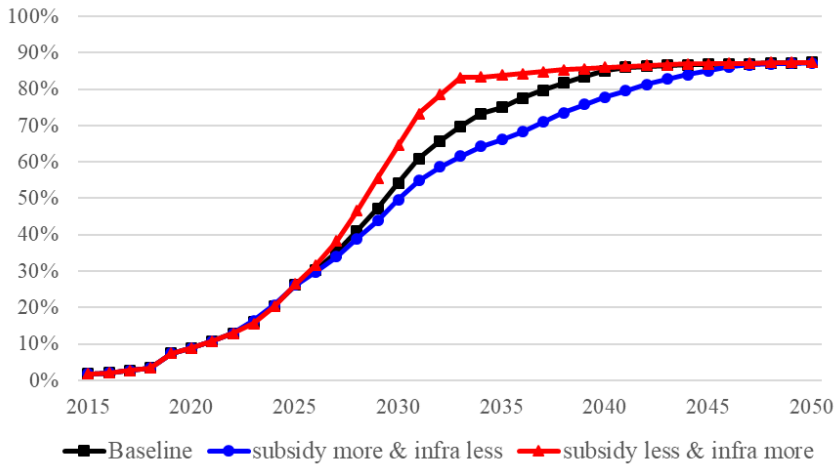

Figure 40. Green mobility sale ratio by scenario

Figure 41 shows the accumulation of vehicles by scenario. The stock ratio by vehicles

in 2030 and 2050 looks similar, but the result in 2040 differs. In the 2040 'subsidy less & infra more' scenario, in particular, the proportion of EVs increased significantly compared to other scenarios. This indicates that the spread of EVs increases when the supply of chargers increases. On the other hand, in the 'subsidy more & infra less' scenario, it can be confirmed that the electric vehicle stock in 2040 and 2050 is smaller than in the baseline. Since the level of EV charging stations did not reach the level of gas stations before 2045, the cumulative number of registered EVs in 2050 decreased by 4% compared to the baseline. In other words, if the speed of charging infrastructure construction increases by reducing the subsidy, the spread of green mobility will accelerate.

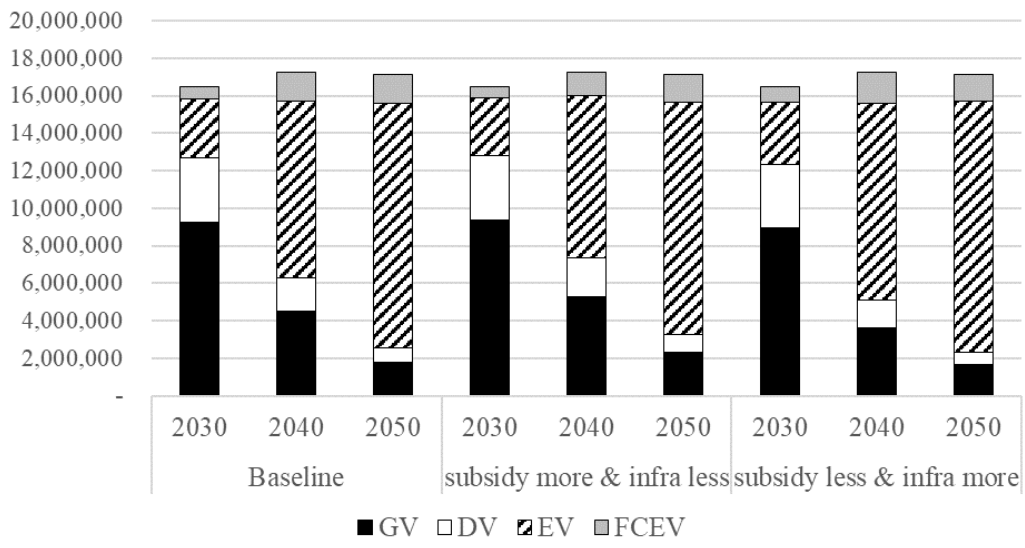

Figure 41. Share of automobile stocks in 2050 by subsidy and infrastructure budget

Figure 42 shows the number of vehicles by household in 2050. In all scenarios, it can be seen that electric vehicles have become the mainstream passenger cars. However, looking at each household, it can be seen that the middle class has a high probability of choosing ICEVs in the 'subsidy more & infra less' scenario. This is because the accessibility of AFVs charging stations varies in each scenario. In the scenario of giving more subsidies, the low accessibility of AFVs charging stations was applied as a barrier for the middle class to purchase AFVs. Meanwhile, vehicle prices are almost the same in all scenarios after 2040, indicating that the low-income class, who is relatively sensitive to price, has a similar will to purchase AFVs regardless of the scenario.

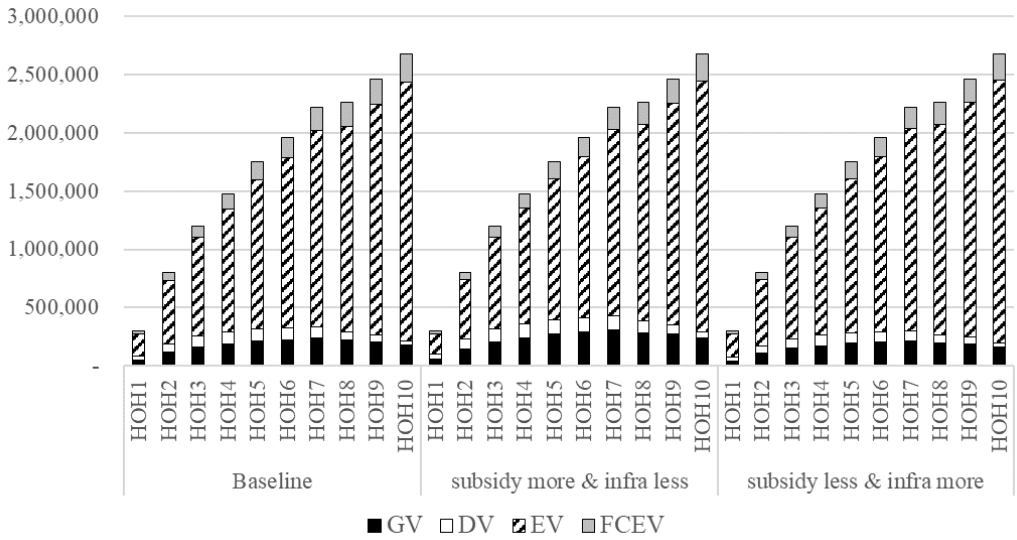

Figure 42. Share of automobile stocks in 2050 by household

4.4.2.2 Economic Effects

The scenario with increased investment in charging infrastructure yielded a more notable increase in GDP than the scenario with more subsidies at the level of 1.8 trillion KRW (0.1%) per year in Figure 43. In 2050, the scenario with more subsidies compared to the baseline scenario led to a decrease in the stock of electric vehicles by -1.8%p and hydrogen vehicles by -2.0%p. On the other hand, in the scenario where infrastructure investment increased, EV stock increased by 0.2%p and FCEVs by 0.1%p compared to the baseline. Especially, investment in charging infrastructure leads to an increase in electric equipment manufacturing (1%p) and hydrogen production (17%p), which are highly related to the installation of charging stations as well as EVs (11%p) and FCEVs (14%p) manufacturing.

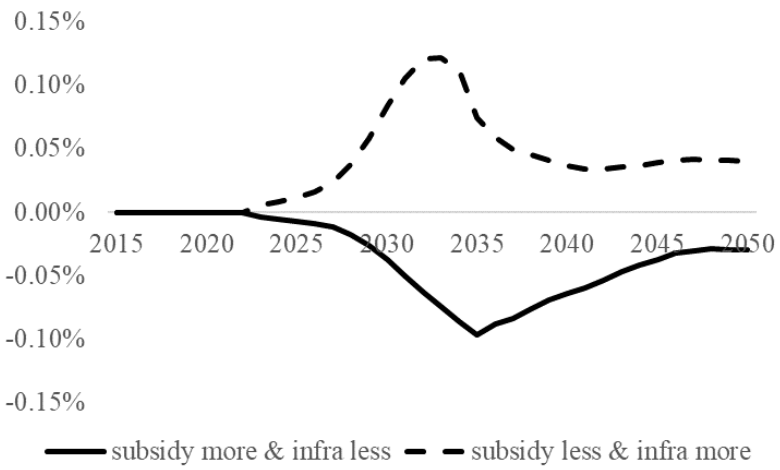

Figure 43. Changes in GDP over baseline scenario

In the ‘subsidy more & infra less’ scenario, as the spread of green mobility was delayed compared to the Baseline scenario, GDP and total output decreased, leading to a decrease in household income in Figure 44. However, household savings in the early stages increase slightly because more subsidies are being paid to spend less on car purchases. After the subsidy ceases, income decreases with GDP, and so does savings. Conversely, in the ‘subsidy less & infra more’ scenario, household savings reduce at the initial stage as subsidies are diminished, which makes household spending on vehicle consumption relatively more. However, after the subsidy ceases, household savings will increase due to improved access to charging station infrastructure and productivity resulting from the stock of green mobility.

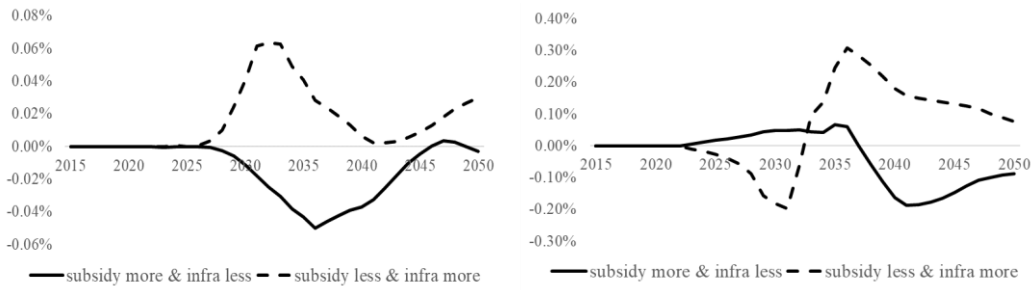

Figure 44. Changes in household income (left) and savings (right) compared to the baseline scenario

Figure 45 shows the household welfare changes depending on the government budget allocation between subsidy and investment of charging infrastructure. In the ‘subsidy less

& infra more' scenario, household income increases, so households can increase consumption. As a result, the welfare of the household will increase. In the scenario with increased investment in infrastructure installation, household welfare increased relative to the baseline around 2032 (0.05%), and as time passed, it became similar to the baseline. Otherwise, household welfare decreased the most in 2035 (-0.07%) in the scenario with more subsidies and became identical to the baseline over time (-0.03% in 2050).

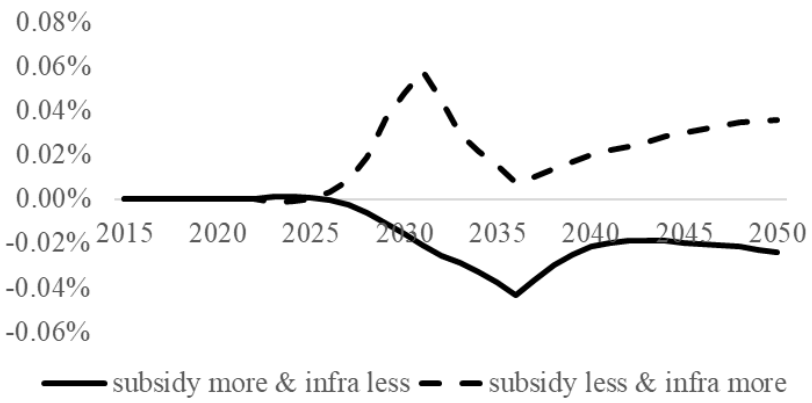

Figure 45. Changes in household welfare compared to the baseline scenario

4.4.2.3 Environmental Effects

Figure 46 shows the change in CO2 emissions in passenger cars. Emissions from passenger cars were reduced more in scenarios with high investment in charging infrastructure, about 1 million tons of CO2 per year, than in the subsidy more scenario. Nevertheless, total emissions increased slightly to approximately 1.3 million tons of CO2 annually due to the rebound effect as production of the economy as a whole increased in

Figure 47. Total national emissions in the ‘subsidy more & infra less’ scenario were reduced by about 1 million tons per year compared to the baseline scenario. Consequently, in the ‘subsidy less & infra more’ scenario, where the spread of green mobility is faster, the emissions of passenger cars have decreased relatively. However, as the production cost is reduced due to the learning effect of green mobility, the overall production of the industry increases, resulting in a rebound effect in which the total national emissions increase.

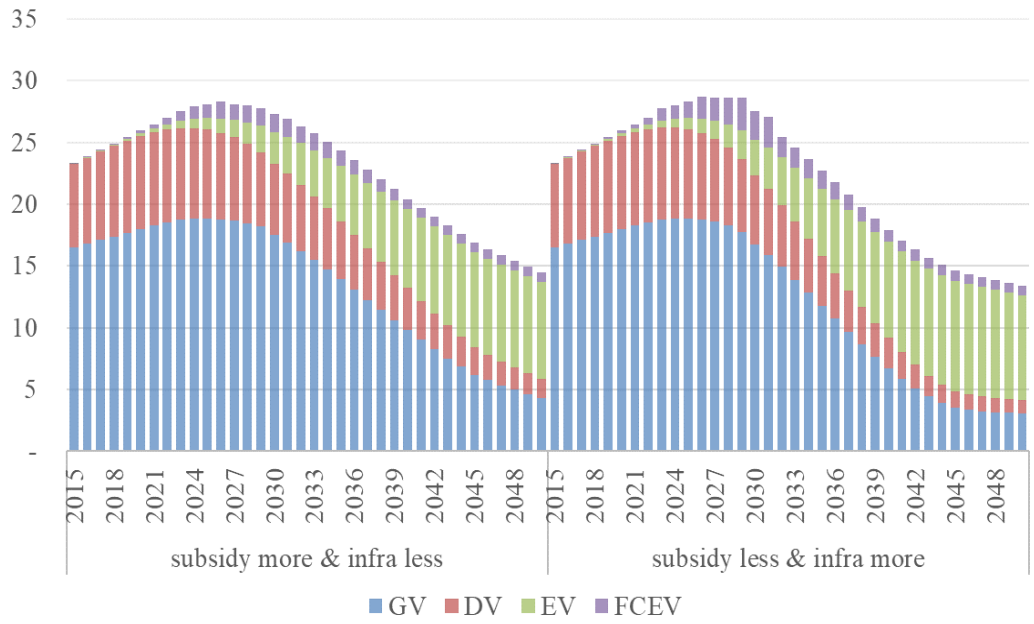

Figure 46. Passenger cars emissions changes

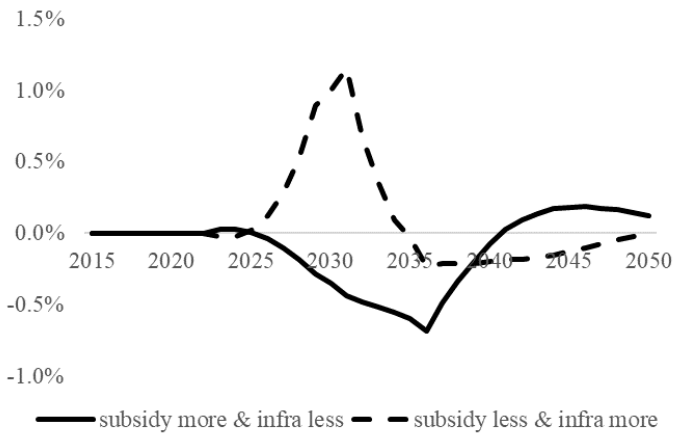

Figure 47. Changes in total emissions compared to the baseline scenario

To sum up, research question 2 was answered as investing in charging infrastructure, a complementary market for automotive, was more helpful in terms of the speed of vehicle proliferation and economic growth than direct purchase subsidies to consumers. However, regarding CO2 emission mitigation, investment in charging infrastructure will likely raise gross national product, resulting in a slight increase in emissions across the industry.

4.5 Scenario Analysis 3: Differential Subsidy Payment

4.5.1 Scenario Description

In the domestic green mobility supply policy budget, subsidies for purchasing electric and hydrogen cars are about 1.6 trillion KRW, accounting for 57% of the budget in 2022 (Ministry of Environment, 2022). The subsidy budget is growing, but individual vehicle subsidies decrease as more consumers buy AFVs. Many studies have emphasized

economic incentives as the main factor in adopting green mobility. As confirmed in the DC model results, vehicle price is the most critical attribute for vehicle purchase, and purchase subsidy is a support policy tool. However, in the case of purchase subsidies, there may be more high-income groups than low-income groups that can be targeted. In fact, due to the vehicle preference by income decile, it can be confirmed that the high-income class has an increased probability of choosing an electric car, and they want to purchase more.

There have been a lot of discussions abroad regarding the cessation of EVs subsidies for large vehicles, especially luxury vehicles (Kester et al., 2018; Lévay et al., 2017). Also, differentiated subsidy support based on vehicle price exists in Korea. For example, there is a difference in subsidy portion support between domestic and imported cars. However, it is difficult to see the effect of subsidies by dividing large/small vehicles because the SAM of the CGE model is not classified by vehicle size. Instead of separating vehicle sizes to subsidize differentially, this study sets up a scenario that provides more subsidies to the low-income class, named as the 'subsidy-low' scenario. Comparing the cases where subsidies are paid uniformly regardless of income and when subsidies are given more to the low-income class can prove the effectiveness and equity of the subsidy policy as in research question 2.

(Research Question 3) Although the differential payment of subsidies to support the low-income class has a positive effect on income distribution in the short term, will it negatively affect national economic growth in the long term?

It is suggested that the differential payment of subsidies reflects the higher possibility of high-income groups purchasing luxury vehicles. In the Baseline scenario, identical subsidies are given regardless of income. However, to answer research question 3, the subsidy differential payment scenario assumes that the subsidy increases by 10% as the income quintile goes down; there is a 45% increase in subsidies for the first quintile compared to the baseline.

4.5.2 Scenario Results

4.5.2.1 Vehicle Sale and Stock

Depending on the subsidy for each income decile, the household's choice of probability changes, resulting in different vehicle sale prospects for green mobility. Since the low-income class is sensitive to vehicle prices and has a slightly higher preference for hydrogen cars, providing more subsidies to the low-income class amplifies the demand for hydrogen cars. Because of this, the stock of FCEVs increases faster, resulting in a better charging infrastructure environment, while the level of EV charging facilities is relatively low in Figure 48. Therefore, differential payment causes an increase in

hydrogen car sales than paying at the same rate for each income decile; if the subsidy is equally paid, the spread of electric vehicles is the fastest in Figure 49.

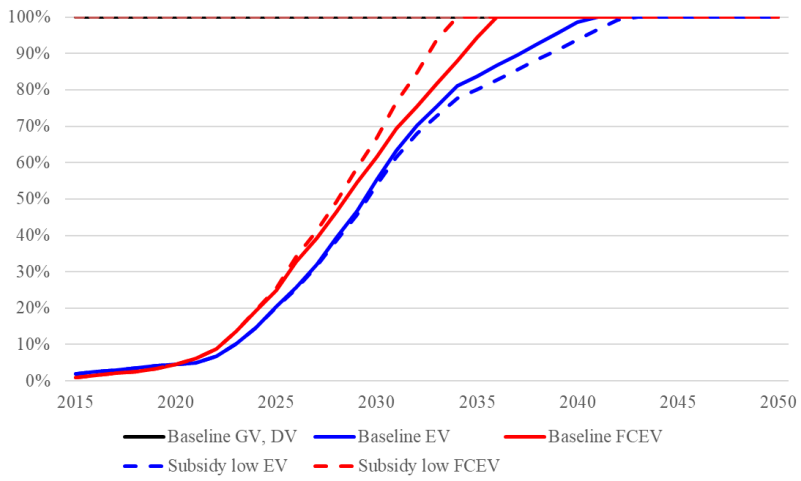

Figure 48. Accessibility of charging stations by scenario

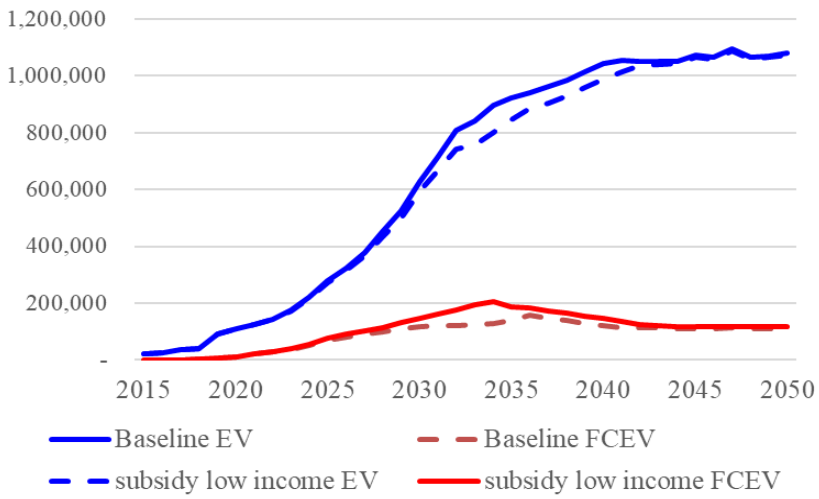

Figure 49. Green mobility sales by scenario

In the 'subsidy low' scenario, more subsidies are paid to the low-income group, so the low-income group's probability of choosing green mobility increases. However, the subsidy will cease in 2035, and the charging infrastructure and vehicle price will be determined according to the number of green mobility purchases during that time. As EVs stocks are less than in the baseline scenario, the indirect effect of subsidy payments to low-income families is somewhat negative as of 2040 in Figure 50. As the vehicle properties of green mobility are less improved, the choice probability decreases rather than the baseline in the case of electric vehicles. On the other hand, in the case of hydrogen cars, more vehicles are purchased than baseline due to differential subsidies; so as the properties of hydrogen cars are improved, the choice probability in 2040 will increase slightly. In other words, if more subsidies are given to the low-income class, the overall probability of choosing a hydrogen car increases.

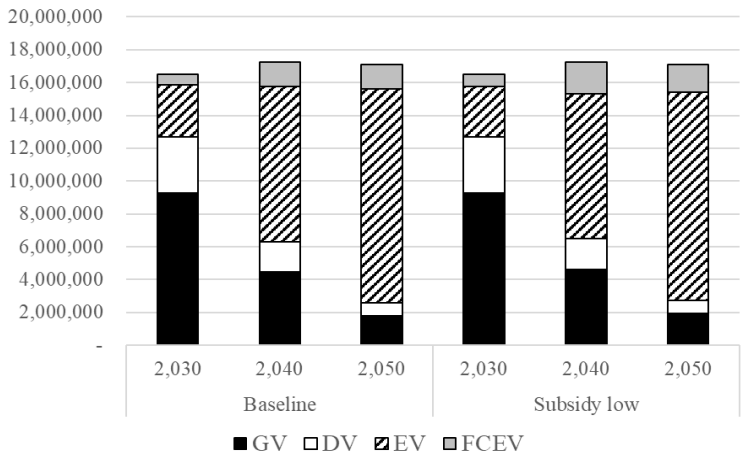

Figure 50. Share of automobile stocks

4.5.2.2 Economic Effects

A negative economic impact was observed as the spread of green mobility was delayed. GDP slightly increased compared to the baseline during the subsidy period but decreased afterward; GDP decreased by 400 billion KRW per year in Figure 51.

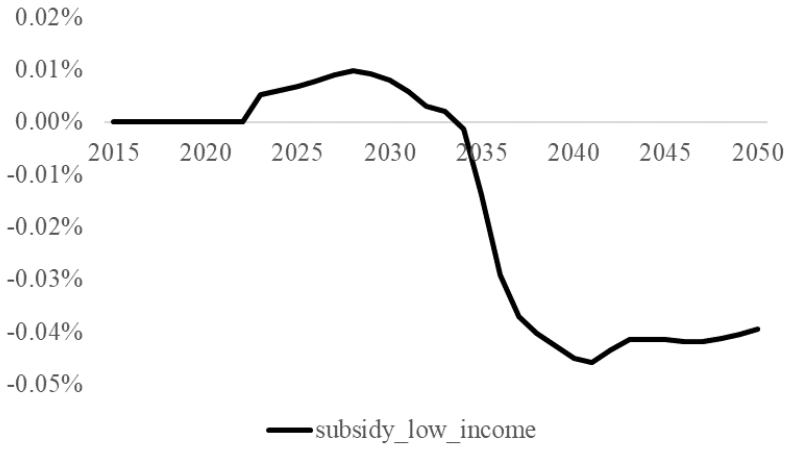

Figure 51. Changes in GDP over baseline scenario

As high-income groups with a relatively high willingness to buy AFVs earn fewer subsidies in the 'subsidy low' scenario, the government subsidy budget was reduced by about 900 billion KRW compared to the baseline. Still, the total accumulated decrease in GDP and household income by 2050 due to the slowdown in the spread of green mobility was about 14.6 trillion KRW, which is about 19 times the subsidy amount in Table 19. In other words, a decrease in subsidies led to more economic damage.

Table 19. Changes in the total subsidy budget, household income, and GDP compared to the baseline scenario

Changes in total subsidy	Changes in household income	GDP change
-864	-12,600 (16 times of the total subsidy)	-14,620 (19 times of the total subsidy)

Unit: Billion KRW

However, the differential payment of subsidies alleviates the regressiveness of existing subsidies. In the baseline scenario, the total subsidy increases significantly as the income quintile increases, so the total subsidy difference between the upper and lower classes is about ten times or more, as shown in Figure 52. However, in the case of differential subsidies, the total subsidy paid by income appears as an inversed U-shaped curve for the middle class with the highest level, and the difference between the first and the tenth decile decreases by about three times.

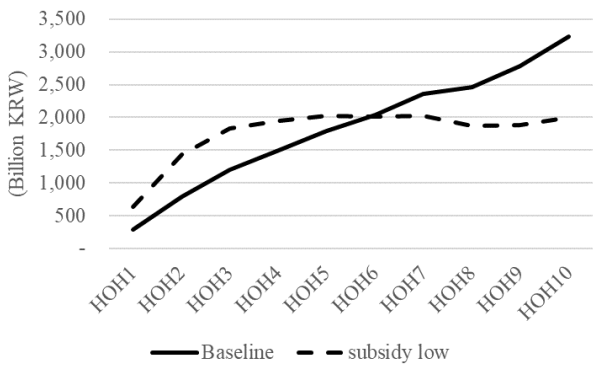

Figure 52. Total subsidy by household

Figure 53 shows the income change by decile compared to the baseline scenario. As the government subsidy decreased, the total household income with subsidy decreased. Looking at the cumulative amount of income growth by 2050, the differential payment of subsidies led to income growth for the 1st to 5th decile. When the subsidy is given (2015-2034), the income of the low-income class increases and the revenue of the high-income class decreases, which is to the subsidy effect. The income growth tendency of the 2nd and 3rd decile is greater than that of the lowest income class (1st decile) as the choice probability of green mobility is higher. On the other hand, the lower the subsidy, the income reduction effect was more remarkable for a higher-income group. After the subsidy suspension (2035-2050), the income level of the low-income and the high-income groups was reduced, which is attributable to the production effect of the slow diffusion rate of AFVs.

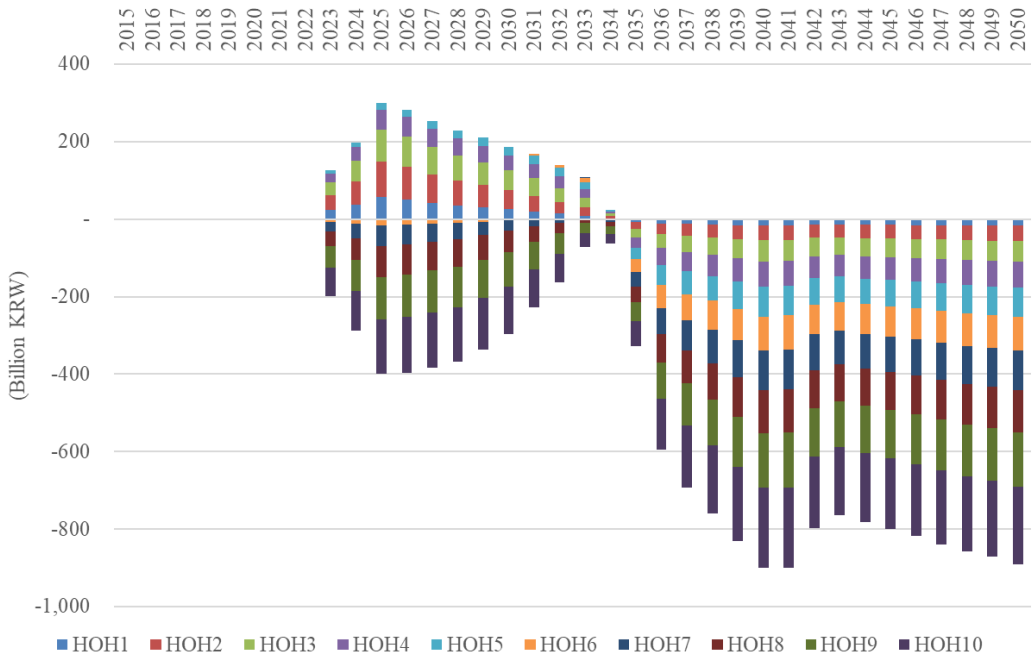

Figure 53. Income change by decile compared to the baseline scenario

Household welfare by income decile in 2034, when subsidies are provided last, is the highest in the first decile (0.013%) and the lowest in the 10th decile (0.008%) compared to the baseline scenario in Figure 54. However, the household welfare in 2050 after subsidy suspension ranges from -0.047% (1st decile) to -0.037% (10th decile) compared to the baseline scenario. The change after the subsidy suspension indirectly affected the accumulating green mobility during subsidy, with a delay in the supply of EVs reducing social welfare. In other words, when subsidies are provided, more subsidies to the low-income group will help increase the income of the low-income group. However, after the subsidy ceases, the economic growth slows down, and as household income declines, the

decline in revenue for the low-income class is more remarkable.

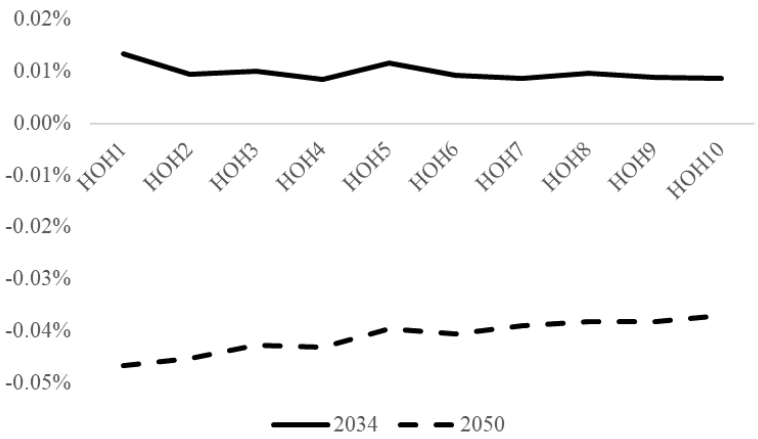

Figure 54. Social welfare changes by household compared to the baseline

Providing more subsidies to the low-income class increased their propensity to purchase FCEVs. As of 2050, FCEVs supply increased slightly (0.4%p) compared to the Baseline scenario, resulting in growth in production of hydrogen car manufacturing (9%), hydrogen production (8%), electrical equipment (including stack) (0.7%), and metal (including hydrogen storage devices) (0.3%). On the other hand, as the penetration of electric vehicles decreased relatively slightly (0.6%p), the production of the battery manufacturing industry decreased compared to the baseline scenario (about 1%).

4.5.2.3 Environmental Effects

Emissions in passenger cars are almost identical to the baseline scenario. However, by

2035, the overall emissions in the subsidized differential scenario are slightly higher (0.5% as of 2034), which stems from a proliferation in demand for hydrogen cars in Figure 55. As shown in Figure 49, the consumption of hydrogen cars increases if more subsidies are given to the low-income class. However, most hydrogen is produced from the reforming of LNG in the base year, and the proportion of water electrolysis in the hydrogen mix increases over time. In other words, when hydrogen is a relatively dirty fuel, the rapid increase in hydrogen use leads to an increase in emissions. However, as the subsidy ceases and the demand for hydrogen declines, emissions become close to the baseline scenario.

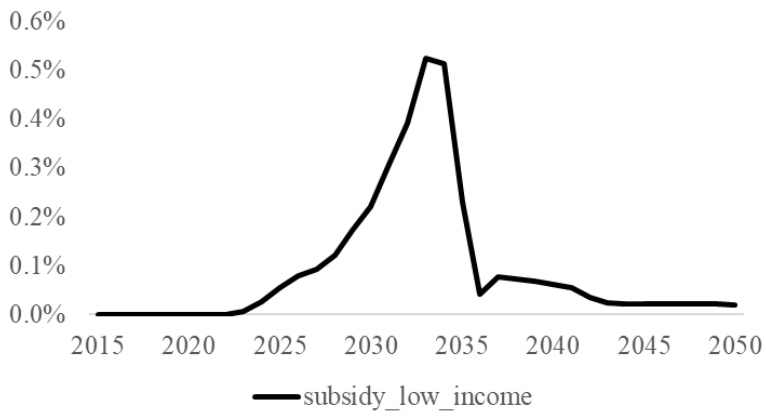

Figure 55. Changes in total emissions compared to the baseline scenario

To sum up, there is a trade-off between equity and effectiveness in subsidy policies. In terms of the income distribution, differential subsidy payments amplify the increasing

income tendency of low-income groups. In contrast, in terms of technology diffusion, the equalization of subsidies increases the distribution rate of AFVs, which helps increase economic growth and income. Differential payment of subsidies by income is not very helpful for economic growth and CO2 reduction. Moreover, in terms of income distribution, the income of the low-income class increases relatively when the subsidy is paid; but it leads to an enormous income decrease after the subsidy is stopped. Therefore, it can be seen that the current subsidy execution method, which pays priority to buyers, is more beneficial to the national economy from a long-term perspective. Table 20 captures the difference in results between the DC single model and the linked model. The link model has the advantage of confirming the income difference of the low-income class over time that cannot be observed with the DC single model.

Table 20. Main results of differential subsidy scenario by model

	DC model	Link model
Demand of green mobility	N	N
GDP growth	X	N
Low class income	X	P→N
CO2 emissions reduction	N (Only in transport sector)	N (Vehicle substitution: N Production decrease: P)

※ P: positive effect, N: negative effect, X: cannot be identified in the model

Chapter 5. Conclusion

5.1 Concluding Remarks and Contributions of This Study

This study describes the impact of various economic decision-makers (consumers and government) related to technological innovation, the process of diffusion of innovation, and its ripple effects. To identify this, the impact of the spread of green mobility from the individual level to the national level was analyzed by integrating the consumer-based choice model and the general equilibrium model.

Recent studies have emphasized the need for an integrated model to improve the problems of the single model, particularly to evaluate greenhouse gas reduction policies. The integrated model was mainly developed based on the optimization model. In addition, research has been conducted focusing on the structure of energy or the industrial sector. In particular, integrated models are not studied much in the case of transportation, and existing studies have limitations in that they are accounting methods. Since demand in the passenger car sector has a direct relationship with consumers, it is necessary to build a bottom-up model centered on demand forecasting that reflects consumer preferences rather than optimization.

The DC model allows for analyzing consumer preferences and utility and predicting future demand changes in the passenger car sector. In the study, household consumption was changed by linking the car utility function for each income decile derived by the DC model to the CGE model as a hard-linked approach. When household demand for

passenger cars is determined, a new equilibrium is found in the model, and prices and supply change. At this time, the price variable again influences the consumer's choice and interacts within the model. In addition, household demand for green mobility will accumulate, which will affect the installation of charging infrastructure and improvement of productivity. In other words, the level of factors affecting the consumer's car consumption is changed, and all these factors are reflected to find a choice probability and an equilibrium simultaneously.

By integrating two models, the DC model captures price and technology change in the market from past choices, while the CGE model catches changes in demand through technical factors and price changes. Combining the two models allows us to observe the innovation process from individual technology adoption to technology diffusion across society, from the micro level of a household to the macro level of society. Whereas a one-way relationship was seen in the existing integrated model, this study has a difference in modeling a two-way relationship.

The current framework that integrates the two models can more accurately predict the impact of government policies and provide a rationale for decision-making than when only the discrete choice model or the CGE model is used to test various policies. Using the proposed model, the government and policy designers can check the answers to research questions for the case of the spread of green mobility in the automobile market, which is the subject of empirical analysis of this study.

Based on the constructed model, three research questions were tested and answered.

First of all, this study supports Porter's hypothesis through the framework which linked the CGE and DC models in terms of the regulation of ICEVs for the spread of green mobility on passenger cars.

Tax imposition policy as a market-based regulatory instrument leads to the proliferation of new technologies and economic growth depending on the learning rate. When new technology enters the market, and transitional competition appears, regulation acts as a buffer until the new technology reduces production costs due to the learning effect, and learning reduces the innovation costs caused by regulation (Porter and Van Der Linde, 1995). The results of this study show that the imposition of taxes has a positive effect on economic growth only when a certain rate of technological progress is supported. As a tax is imposed, a firm's production cost may increase, but depending on the learning rate, the likelihood that innovation will offset this cost may rise rapidly. The model identifies the boundary value of the learning rate at which taxation policy negatively affects society. In other words, more effective results can be obtained when environmental policies such as taxation and technological policies that increase corporate productivity are implemented simultaneously.

Second, I confirmed that investment in the complementary goods market has a more beneficial effect on disseminating new technologies and economic growth than direct economic incentives (subsidies) targeting consumers. The difference between the direct benefits consumers receive from purchasing green mobility (e.g., cost reduction through subsidies) and indirect benefits (e.g., installing charging infrastructure) makes a different

impact on the spread of green mobility and the economy as a whole. The result proves that investing in charging infrastructure to improve the future market environment will benefit the national economy in the long run rather than expanding the current market by providing more subsidies.

Finally, I verified that the differential payment of subsidies has a positive effect on the income distribution of the low-income class in the short term but has a negative impact on the national economic growth in the long term. Differential payment of subsidies does not increase household income in the long run, as it ultimately slows the diffusion of new technologies.

The economy can be reflected in the DC model by integrating the two models, and the ripple effect on the whole country can be observed. Changes in the industry and economy as an entire due to consumer choices make it possible to observe a net effect that the existing single model did not see. For example, regarding consumer choice, preference for AFVs increases as household income increases over time. This study uses income as an explanatory variable, and the income change according to the CGE model results is also applied to the DC model. As the economy grows, the household income level improves, leading to more AFV purchases even with the same attribute level of the car.

In addition, in terms of the economic aspect, the economy grows because the production increase through demand growth for AFVs is greater than the demand decline for ICEVs. On the other hand, reducing emissions in the transport sector due to the proliferation of green mobility is less than increasing emissions (rebound effect) due to

the increase in industrial production, so it may have a slightly negative impact on CO2 emission mitigation. Therefore, the trade-off between the economy and the environment is observed due to the spread of green mobility.

Furthermore, this study tested various policies that promote the spread of green mobility to analyze the economic and environmental impacts. First of all, in the case of technological change, charging infrastructure and productivity improvement, the two factors interlocked and caused a greater spread than expected. When the charging infrastructure is improved, household consumption of green mobility increases, resulting in decreased production costs according to the accumulated supply. Conversely, if productivity improves, the green mobility price cut also causes household consumption to increase, and as the stock increases, the recharging infrastructure also enhances. As a result, the faster the spread of green mobility, the greater the country's GDP and total output.

As the economy grows, household income increases, which leads to increased consumption and savings. In addition, lower AFVs prices and vehicle registration and fuel taxes could reduce car spending, further increasing household savings. On the other hand, the government's tax revenue will decrease as ICEVs are replaced by AFVs. Therefore, it is expected that the government will gradually reduce the tax reduction benefits of green mobility in consideration of the decline in tax revenue caused by the spread of green mobility.

Second, from an environmental point of view, reducing emissions in the passenger car

sector can be intuitively confirmed. Still, the results may be different when looking at the country. The reduction in production cost due to the proliferation of green mobility eventually causes an increase in the country's total production, which in turn increases the emissions of other industries. In addition, if the number of electric vehicles increases rapidly in the absence of clean power generation and renewable energy, the demand for coal increases, negatively affecting emissions. In the case of hydrogen, as most of the supply source is from LNG on a base year, an increase in green mobility without a clean production structure can rather increase CO2 emissions. Therefore, clean power mix and hydrogen mix are prerequisites for green mobility to be economically and environmentally beneficial.

In the future, by using the framework of this study, the policy effect can be tested by changing the research subject, such as using it in other industrial fields.

5.2 Limitations and Suggestions for Future Research

Even though this study developed a new framework integrating DC and CGE models to investigate the effect of technology diffusion induced by consumer choice, there are some issues it did not reflect. Therefore, this section suggests several points for future research development considering the limitations of this study.

First, in terms of the DC model, the non-realizable card of the conjoint question was not removed. Even though the choice sets are extracted through the orthogonal test, it cannot assure to exclude unrealistic choice situations (Rose and Bliemer, 2009).

Therefore, to solve this problem, a D-efficient design using the predicted average attribute level as a reference alternative in a choice set can be considered rather than using a randomly drawn orthogonal design (Rose et al., 2008; Rose and Bliemer, 2009).

Second, the CGE model in this study mimics a closed economy that does not represent an open economy. In other words, the structure of imports and exports does not change over time and has certain limitations. In particular, the model can not reproduce the import or export structure of AFVs. The base year of the model is 2015, when the number of imports and exports of EVs was meager and assumed that imports or exports were zero in FCEVs.

In addition, energy price does not consider the international oil price forecast, which is used only as a relative price due to supply and demand compared to the base year. The production cost is also not reflected in the power generation and hydrogen production sector. That is, the power generation mix and the hydrogen production mix are given exogenously regardless of cost; a Leontief function. In the case of electricity, generation costs and electricity prices may increase as the proportion of renewable energy increases. For hydrogen, an increase in the proportion of water electrolysis can lead to price hikes. Changes in electricity and hydrogen prices should be taken into account as they eventually affect consumer vehicle choices. Therefore, BU optimization model can be an option for integrating with this model by allocating energy production costs in detail, including the electricity generation mix.

In this study, charging infrastructure and productivity improvement depend on the

stock of AFVs. Charging infrastructure and productivity improvement interlocked and caused a greater spread than expected. In addition, this study has limitations in assuming the learning rate exogenously. The learning rate is just selected with reference to the prediction that the price of electric and hydrogen cars will decrease to some extent in the future. In the current model, it is supposed that productivity increases with vehicle stock and cost/investment aspects are not considered; that is, how changes in R&D cost affect productivity were not captured.

Third, the results failed to measure the utility that considers all household consumption. Household consumption in the CGE model is calculated as a combination of utility maximization in the Cobb-Douglas function. The Hicksian Equivalent Variation is calculated to measure consumer welfare based on the expenditure function. When using Hicksian Equivalent Variation, it depends on the base year's share parameter to obtain the expenditure function to measure welfare. However, the consumption of EVs and FCEVs is very small in the base year, and the value of the share parameter that measures utility is very low. As a result, the more households purchase electric and hydrogen cars, the lower their welfare. The base year's green mobility attribute level is different from that of 2050, so it is difficult to see it as the same commodity. Also, in the case of vehicle consumption, the choice probability expression of the DC model is derived by maximizing the indirect utility. In other words, since the utility formula between passenger cars and other goods is different, there is a limit to observing only the relative welfare change in consumption of the rest, excluding vehicles, when measuring the household's welfare.

Finally, in terms of the results of the study, the effect on the country is negligible because the subject of the study is a domestic passenger car. From the point of environment, CO2 emissions in passenger cars are relatively minor than in other industries, just 5% of national emissions in the base year. Therefore, changes in emissions by scenarios appear smaller than expected. Also, the absolute emission and GDP changes derived from each scenario are not significant. In particular, due to the structure and SAM characteristics of the CGE model, there is a limitation in dealing with the used car market because it targets new cars. Consequently, it is necessary to expand the scope of the study to test more policies.

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Appendix 1: Respondent's Demographics in Conjoint Survey

		Number of samples	Ratio(%)
Gender	Male	354	68.6
	Female	162	31.4
Age	20s	46	8.9
	30s	185	35.9
	40s	206	39.9
	50s	79	15.3
Region	Seoul	147	28.5
	Metropolitan city	129	25.0
	Gyeonggi	129	25.0
	Other provinces	111	21.5
Household Income*	1 (0~1.3)	7	1.4
	2 (1.3~2.2)	12	2.3
	3 (2.2~3)	53	10.3
	4 (3~3.6)	63	12.2
	5 (3.6~4.3)	57	11.0
	6 (4.3~5)	64	12.4
	7 (5~5.8)	74	14.3
	8 (5.8~7)	56	10.9
	9 (7~8.6)	54	10.5
	10 (8.6~)	76	14.7
Total		516	100.0

*Unit: Million KRW/month

Appendix 2: Classification of Industry in the CGE Model

No.	Sector	No.	Sector	No.	Sector
1	Agriculture	22	Computer/electronics	43	Water/waste
2	Coal	23	Electrical equipment	44	Construction
3	Oil	24	Battery	45	Wholesale/retail
4	Natural gas	25	Machine	46	Transport service – except road
5	Mining	26	Transport equipment	47	Transport road service
6	Food/drink	27	Gasoline vehicle	48	Gasoline car service
7	Fiber/leather	28	Diesel vehicle	49	Diesel car service
8	Wood/paper	29	LPG vehicle	50	LPG car service
9	Coal products	30	Electric vehicle	51	Electric car service
10	Oil products	31	Hydrogen FCEV	52	FCEV car service
11	Gasoline	32	Transport engine	53	Accommodation/ restaurant service
12	Jet-oil	33	Other manufacturing	54	IT service
13	Kerosene	34	Industry equipment	55	Finance service
14	Diesel	35	Hydropower	56	Estate service
15	Heavy oil(BC)	36	Thermal power	57	Science service
16	LPG	37	Nuclear power	58	Business service
17	Chemical products	38	Private power	59	Administration
18	Nonmetal products	39	Renewable power	60	Education service
19	Primary metal products	40	Gas	61	Social service
20	Primary metal products - nonferrous	41	Steam	62	Culture service
21	Metal products	42	Hydrogen	63	Other service
				64	Others

Abstract (Korean)

신고전파의 유인된 혁신 접근법은 혁신이 수요와 상대요소가격 변화에 따라 그 속도와 방향이 결정된다고 보았으며, 기술 혁신에 있어서 수요의 역할을 강조하였다. 즉, 신기술이 도입되면 소비자의 수요로 혁신이 확산된다. 그러나 시장에서의 기존 기술의 상대적 우위, 높은 진입 비용 및 불확실성 등으로 인해 소비자의 의사결정 만으로는 사회적으로 최적의 수준까지 확산이 일어나지 않을 수 있다. 이로 인해 정부는 시장의 중재자로서 혁신의 확산을 위해 개입을 하게 되며 구체적인 정책 수단을 설계한다.

그렇다면 이러한 정부 개입이 소비자 선택과 시장에 어떤 영향을 미치며 어떤 결과를 초래하는가? 본 연구에서는 그린 모빌리티를 연구 대상으로 하여 시장유인적 (규제) 수단에 집중하였다. 자동차 산업은 대표적인 B2C 시장으로 소비자의 선호를 파악하여 신기술의 확산을 예측할 수 있으며, 연쇄 효과가 크기 때문에 산업 및 경제에 미치는 영향이 크다. 정부는 그린 모빌리티로 인해 야기되는 긍정적 외부효과 (환경 개선 및 신 산업 창출을 통한 경제 성장 등)를 기대하며 다양한 정책수단으로 신기술의 확산을 지원하고 있다. 본 연구에서는 친환경차 보급 정책수단 중 대표적으로 조세 및 보조금, 충전 인프라 설치 투자에 대하여 규제와 성장, 정책 효과성 그리고 형평성 측면에서 파급 효과를 분석하였다.

이산선택모형은 개인의 선호에 따라 제품 및 기술의 수요를 예측할 수 있는 대표적인 방법론이다. 그러나 제품 및 기술 간 대체효과에 치중하여 다른

산업과 경제 간의 연쇄효과를 파악하기 어렵다. 한편 계산가능한 일반균형모형은 경제 주체 간의 관계를 고려하여 경제 변수(가격 및 수요 등)의 변화를 광범위하게 분석한다. 그러나 일반균형모형은 기술에 대한 설명이 제한적이며, 시장 변화가 재화의 가격 및 수량에만 의존한다. 두 모형을 통합함으로써 이산선택모형은 일반균형모형의 결과를 내생적으로 반영하여 속성 수준의 보다 탄력적인 변화를 포착하고, 일반균형모형은 이산선택모형의 구체적인 기술 사양을 반영한 대체 관계를 구현할 수 있다. 따라서 본 연구에서는 구축된 통합모형을 바탕으로 개인 단위의 소비자 선호에 따른 수요 변동이 신기술의 확산과 국가 전체에 미치는 영향을 규명하고자 하였다.

결과적으로 전기차와 수소차의 확산은 경제 성장으로 이어졌다. 환경적인 측면에서 전기차 및 수소차로의 수요 전환에 따라 수송 부문의 배출량이 크게 감소하였다. 그러나 전 산업의 배출량은 총 생산 증가로 인해 오히려 증가하여, 수송 부문의 배출 저감 효과를 상쇄하는 반등 효과가 나타났다. 게다가 그린 모빌리티가 초기에 급증하는 경우 석탄 화력 발전 및 LNG 개질 위주의 수소 생산으로 인해 오히려 배출량이 증가하게 된다. 따라서 그린 모빌리티의 급진적인 수요 확산 이전에 친환경 발전이 전제 되어야 바람직한 환경 개선 효과를 관찰할 수 있다.

그린 모빌리티 보급을 위한 정책 수단의 주요 결과는 다음과 같다. 첫째, 조세가 부과됨에 따라 기업의 생산 비용은 증가할 수 있으나, 학습률에 따라 혁신이 이 비용을 상쇄하는 가능성은 훨씬 더 빠르게 증가할 수 있다. 즉, 조세와 같은 환경정책과 기업의 생산성을 높이는 기술정책을 동시에 시행할 때

보다 효과적인 결과를 얻을 수 있다. 둘째, 소비자를 대상으로 한 직접적인 경제적 인센티브인 보조금 정책 보다 보완재 시장으로서 인프라에 대한 투자가 신기술 확산 및 경제 성장에 더 긍정적인 영향을 준다. 즉, 보조금을 더 많이 주어 현재 시장을 확대하기 보다는 충전 인프라에 투자하여 미래 시장 환경을 개선하는 것이 장기적으로 국가 경제에 도움이 될 것으로 보인다. 마지막으로 보조금의 차등 지급은 단기적으로 저소득층의 소득 향상에 긍정적인 영향을 주지만, 장기적으로는 국가 경제 성장에 부정적인 영향을 초래한다. 보조금의 차등 지급은 궁극적으로 신기술의 보급을 늦추기 때문에 장기적으로 가계 소득 증가에 덜 도움이 되기 때문이다.

본 연구에서는 두 모형을 결합함으로써 개인의 기술 채택(technology adoption)에서부터 사회 전체를 대상으로 한 기술 확산(technology diffusion)의 혁신 과정을 관찰할 수 있었다. 게다가 이산선택모형 혹은 일반균형모형만 사용하여 정책을 테스트하는 경우 보다 두 모형을 통합한 현재의 프레임워크가 정부 정책의 영향을 더 정확하게 예측할 수 있으며, 정부의 의사결정에서 명확한 근거를 제시할 수 있을 것으로 보인다.

주요어 : 연산가능일반균형모형, 이산선택모형, 친환경 차, 기술 확산, 경제적 유인수단, 이산화탄소 배출량
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