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# Consumers' Intertemporal Choice for New Products considering Product Line Extension

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**Graduate School of Seoul National University**

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# Abstract

# Consumers' Intertemporal Choice for New Products considering Product Line Extension

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New technology products diffuse gradually while competing with conventional products. The government may use various policy options to alter the speed of such diffusion, and long-term policies with different levels over time may affect consumers' choice of product purchase timing. Moreover, different choice situations caused by different product supplies may also affect consumer choice. For example, in their early stage of diffusion, new technology products are likely to have limited a product line, but new products will be introduced over time through product line extension. Therefore, in this dissertation, I propose a model that can incorporate consumers' intertemporal choice for new products, taking into account product-line extension. Moreover, I apply the proposed model to the case of electric vehicle diffusion in South Korea. The proposed model consists of two parts. One is the intertemporal consumer choice model and the other is the

product-line extension model. In the proposed model, consumers decide their purchase timing from a choice set with extended timeframe. The product-line extension model derives a revenue-maximizing product-line extension plan considering cannibalization between products. The empirical analysis consists of three main parts. In the first part, I focus on analyzing consumers' intertemporal choice behavior under policy intervention while fixing product-line extension. In the second part, I analyze the impact of a product-line extension (change in product supply) on consumers' intertemporal choice. Finally, in the third part, I analyze the impact of a new entrant on product supply and consumer choice. The results of the empirical analysis suggest that consumers in the proposed model show significantly different behavior compared to myopic consumers. Moreover, consideration of varying the product-line extension from changing policy situation had a significant impact on the forecasted diffusion of new technologies.

**Keywords:** demand forecasting; discrete choice model; intertemporal choice; product line design; product supply; technology diffusion

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# Chapter 1. Introduction

## 1.1 Research Background

When do consumers purchase new products, and under which circumstances? Such a research question has been of interest to numerous researchers and can be especially interesting in the diffusion phase of new technology (Anderson & Ortinau, 1988; Bass, Gordon, Ferguson, & Githens, 2003; Norton & Bass, 1987). First, as regards when consumers purchase new products, the possibility of an intertemporal choice exists in the different phases of a new technology diffusion. This is because new technologies diffuse fast compared to conventional technologies, and thus the performance of new technology products is also rapidly improving. Moreover, other social and organizational changes accompany the process of new technology diffusion, which makes new technology products more attractive as time passes. Therefore, some early adopters may purchase the new products in the early diffusion stage, but the majority of consumers are likely to wait until the new product appears sufficiently attractive to them (Rogers, 1962).

New technologies may not be very attractive in their early stage due to factors such as high cost, insufficient performance, insufficient infrastructure, and the socio-technical inertia of market agents (Briggs, Webb, & Wilson, 2015; Steinhilber, Wells, & Thankappan, 2013). However, governments may desire to accelerate the diffusion of new technology by using policy interventions, in the case of a transition to more sustainable new technology, for example. Therefore, understanding the mechanism of consumers'

purchase timing decision for new products is an important research question to be investigated, so that better promotion policies can be designed. Moreover, most high-technology goods are durable goods used for a long time and new purchases occur mainly due to obsolescence of existing goods rather than complete usage or breakdown (Lee & Lee, 1998; Prince, 2008; Stacchetti & Stolyarov, 2015). Therefore, consumers may naturally adjust their technology adoption timing for a better deal, which leads to a strategic intertemporal choice.

On the other hand, as regards under which circumstances consumers make their purchase decisions, various factors have been previously considered in the literature. For example, supply capability (Bass, 1980; Metcalfe, 1981), infrastructure for the new technology (Hong, Koo, Jeong, & Lee, 2012; Moon, Park, Jeong, & Lee, 2018), and policy interventions (Byun, Shin, & Lee, 2018; Choi, Shin, & Woo, 2018) have been considered. Another important point concerning consumers' purchase in the diffusion phase of new technology is the supply of appropriate product models. For example, Lin and Greene (2010) incorporated the expansion in product model variety followed by an increase in sales amount, and Kieckhäfer, Wachter, and Spengler (2017) analyzed the impact of different product model supply scenarios on the diffusion of new technology. Moreover, some studies included the level of model variety or availability as a key attribute that affects the adoption of a new technology product (Hoen & Koetse, 2014; Wolinetz & Axsen, 2017). However, considering heterogeneous preference of consumers for new technology products, suppliers deciding which specific product models to

introduce given the existing product line (product line extension), can also have a significant impact on new technology adoption.

Therefore, in this dissertation, I propose an intertemporal consumer choice model that considers the product line extension for new technology products across time. Then, using the proposed model, I empirically analyze how consideration of model supply may affect the diffusion of new technology and offset or leverage the impact of policy interventions.

## 1.2 Research Objectives

The research in this dissertation has two main objectives. The first is to develop an intertemporal consumer choice model for new products, which can analyze the impact of product line extension (supply of a new product model) on the diffusion of new technology. The other is to apply the proposed model to the diffusion of electric vehicles in South Korea, to empirically analyze the impact of consumers' intertemporal choice and of a product line extension on the diffusion of the new technology under various policy situations. By using the proposed model, policymakers may gain valuable insights to design better policies to promote new technology products in the market.

The proposed model consists of two main parts. The first is the intertemporal consumer choice model, and the other is the product line extension model. First, the intertemporal consumer choice model utilizes data collected from multiple choice experiments to model consumers' intertemporal choice for new products at the individual

level. On the other hand, the product line extension model uses the consumer model to evaluate the performance of its new product model supply and to find the optimal product line extension plan that maximizes the total revenue for the entire analysis period. The point is that, as consumers' choice changes by a policy intervention, the optimal product line extension plan (supply of a new product model) considering the consumers' choice also changes. Therefore, a more reasonable market situation (compared to simply fixing a certain market situation regardless of the policy intervention) where consumers make their choice can be derived from the model.

I start by explaining the objectives of consumers' intertemporal choice model. Since high technology durables like vehicles or home appliances are usually used for a long time, one of the largest competitors of new products is the consumers' current alternative (status quo, SQ). Therefore, I also include consumers' SQ in the consumers' current choice set (Koo, 2012). By doing so, consumers' choice problem for a high-technology durable good can be seen as a replacement decision problem. To summarize, to derive consumers' optimal purchase timing, I include not only alternatives currently available in the market but also past alternative (SQ) and future alternatives to the consumers' current choice set. By using a replacement viewpoint and identifying consumers' optimal purchase timing of consumers, the model can identify the new product buyers at each time period, and derive actual sales and stock share estimates for each technology product.

Moreover, for high-technology durables, most new purchases (or replacements)

occur because of the obsolescence created by the introduction of a new generation of models or the desire to use products with a better performance, rather than physical breakdown or complete usage of the product (Lee & Lee, 1998; Prince, 2008; Stacchetti & Stolyarov, 2015). Therefore, depending on future market/policy situations, strategic consumers may delay or advance their purchase to take advantage of or avoid disadvantage in their purchase. To model such behavior, I included future alternatives into the consumers' current choice set to represent the behavior of strategically postponing one's purchase, by enabling consumers to compare current and future alternatives.

Next, the product line extension model determines the new product model supply considering the cannibalization among different product models. In many cases, firms will already have other product models with conventional technologies, which currently generate the most revenue since it requires some time for new technology products to become the main products in the market. Therefore, cannibalization between existing product models and new product models should be properly considered when introducing new products (product line extension). In other words, firms should determine a positioning of new technology products that reduces such cannibalization and maximizes their total revenue from both existing and new products.

However, the aforementioned cannibalization is not the only type of cannibalization that occurs when introducing new technology products. Since it requires some time for new technology products to be the mainstream products in the market, new-technology product models are introduced gradually, rather than simultaneously.

Therefore, cannibalization among newly introduced products should also be considered. For example, new products introduced now may cannibalize the revenue of a new product introduced the following year. Therefore, many business practices indicate that businesses usually introduce expensive high-end products first, and then introduce cheaper low-end products because the latter are likely to cannibalize the demand for the more profitable high-end products if they are introduced first or simultaneously with them (Moorthy & Png, 1992). Moreover, such cannibalization can be stronger when consumers make a strategic intertemporal choice, as in the proposed consumer model.

Using the proposed consumer model, I conduct a market simulation for the entire analysis period for a given supply situation (product line extension), from a replacement viewpoint. Therefore, within the timeframe of the analysis, the above-mentioned cannibalizations are all considered when evaluating the product line extension plan. To reduce cannibalization, most profitable product models should be introduced at intervals. However, this makes the revenue for some profitable models arrive later. Although reducing cannibalization is important, firms prefer early realization of revenue. Therefore, I apply some discount rate to future revenue when calculating the total revenue for a given product line extension plan.

Finally, the second objective of the current research is to apply the proposed model to the case of the diffusion of electric vehicles in South Korea. Using the model, I aim to empirically analyze how consumers' intertemporal choice and the consideration of a product line extension affect the diffusion of electric vehicles. The empirical analysis

consists of three main parts. In the first part, I focus on the proposed consumer choice model to show how consumers' strategic intertemporal choice behavior can be analyzed, by comparing its results with those of comparable models with different consumer choice sets and behavioral specifications for various policy scenarios. Moreover, a policy analysis to analyze consumers' strategic behavior on drastic change of policy situation is conducted. This part aims to investigate questions such as the following: 1) Do consumers delay or advance their purchase in response to different policy/market situations at different times? 2) How does policy intervention affect the shrink or expansion of the market? Next, the second part of the empirical analysis considers the impact of varying supply responses (product line extensions) for various policy scenarios. In this part, I aim to examine questions points such as the following: 1) How does a product line extension (new product model supply) change in different policy situations? 2) How does such a supply response affect the diffusion of new technology? Finally, in the third part of the empirical analysis, I add a new entrant, which can only introduce new-technology product models (pure battery electric vehicles in this case) to the market, and observe its impact on the vehicle market. The questions I aim to investigate by adding this competition to the supply side are the following: 1) How much will a new entrant contribute to the diffusion of new technology? 2) How will product line extension of the incumbent change with the new entrant?

## 1.3 Research Outline

This dissertation consists of five chapters. In the Chapter 2, I start by reviewing studies that have considered the impact of supply factors on the diffusion of new technology. Then, I review the literature on consumer choice models, focusing on individual-level choices and intertemporal choices. Then, I move on to the literature on optimal product line design considering consumer preference. Finally, I summarize the limitations of previous studies and provide the motivation for and the contributions of the research in this dissertation.

In Chapter 3, an intertemporal consumer-choice model that can forecast the diffusion of high-technology durables, incorporating product line extension, is presented. First, I introduce the overall framework of the proposed model. Then, the intertemporal consumer-choice model, which can analyze consumers' strategic intertemporal decision-making in response to market/policy situation, is explained. Next, a product-line extension model, which can determine the revenue-maximizing product-line extension plan (new product model supply) in response to a policy intervention, and its extension to incorporate competition, are explained. It should be noted that the proposed product-line extension model uses the proposed consumer-choice model to evaluate the new product line extension plan from the former model. This is where linkage between the two models is achieved, and thus the product line extension model can respond to changes in consumer behavior from a policy intervention.

Chapter 4 presents empirical applications of the model proposed in Chapter 3.

The proposed model is applied to the case of electric vehicle diffusion in South Korea. The analysis consists of three main parts. In the first part (Analysis 1), I focus on the intertemporal consumer-choice model (while fixing the product line extension) to show how consumers' strategic behavior can be analyzed using the proposed model. I compare the results with those of comparable choice models with different choice sets and behavioral specifications, and conduct a simulation analysis for various policy situations. In the second part (Analysis 2), to observe the impact of a product line extension on new technology adoption, the intertemporal consumer-choice model considering product line extension is analyzed for various policy situations. Finally, in the third part (Analysis 3), I add a new entrant to the market, and observe its impact on the diffusion of new technology. Specifically, I analyze the impact of the entrant's new product introduction itself, and its impact on the incumbent's product line extension plan.

The last chapter, Chapter 5, summarizes this dissertation and presents its key contributions. Moreover, limitations of the current research are presented, along with directions for possible future research topics.

# Chapter 2. Literature Review

This section first starts by reviewing studies concerning the impact of supply factors on technology diffusion. Second, attempts to model individual-level choices and intertemporal choices using discrete choice models are examined. Third, the literature on optimal product-line design considering consumer preference is reviewed. Finally, I present the limitations of the existing literature and the contribution of the research in this dissertation.

## 2.1 Impact of Supply Factors on New Technology Diffusion

Rogers (1962) defined diffusion of innovation as a new idea being communicated among the members of a social system over time. Early approaches on studying the diffusion of new technology used the epidemic model, which had little (or no) consideration of adopters' choice of technology (Mansfield, 1968). Then, the milestone work of Bass (1969) suggested an aggregated technology-diffusion model (the Bass model) that can analyze the adoption timing of new products by fitting early adoption data to an s-curve with knowledge of the product's timing of peak sales and market potential. Since then, the model has been widely applied in various fields and extended in various directions (Bass, 1980; Jiang & Jain, 2012; Norton & Bass, 1987). In terms of considering supply factors, Bass (1980) incorporated the theory of experience-curve to the Bass model. Specifically, the model includes the inverse relationship between the unit cost of the

product and the accumulated output (experience). On the other hand, Metcalfe (1981) indicated that existing diffusion studies almost entirely neglected the role of supply factors, and proposed a diffusion model that can incorporate the growth of productive potential in addition to the growth in demand. On the other hand, although these studies considered only a monopolized supply sector, Stoneman and Ireland (1983) also considered an oligopolized supply sector considering the learning-by-doing effect of the supply side. Frambach (1993) also indicated that studies concerning the individual-level adoption decision of innovation considered only the adopter-side perspective and failed to consider the impact of supplier innovation, and proposed an integrated model that can analyze both organizational adoption and diffusion of innovations. The study integrates the research findings of innovation diffusion theory and innovation management to create a conceptual model for the diffusion of innovation.

## 2.2 Individual-Level New Technology Adoption using a Choice Model

Since analyzing new technology adoption of the demand side in *ex-ante* fashion can provide significant insights in terms of marketing and policy perspectives, numerous researchers have conducted such an analysis using various methodologies. As regards the analysis unit, some models forecast new technology adoption in an aggregated unit, whereas some studies model the individual-level decision-making process and then aggregate individual results to forecast market-level changes. For example, aggregate

stock models such as the Bass model (Bass, 1969) fit early sales data to some form of curve (typically an S-curve) to forecast the future sales of the new technology. The strength of such an approach is its easy application and ability to directly estimate the new sales and stock per period. Although the model has been used to forecast the demand for some new technologies (Lavasani, Jin, & Du, 2016), the model by itself is not appropriate as an *ex-ante* analysis tool for analyzing the impact of a policy or marketing intervention (Wolinetz & Axsen, 2017). This is because it is hard for these models to incorporate the competition between competing technologies or changes in the diffusion pattern due to policy or marketing interventions, since these models exogenously assume the timing of peak sales and market potential. Moreover, such aggregate models cannot be used to understand individuals' motivation and decision making process in the adoption of new technology to provide insights for designing marketing strategies for companies or policy for governments.

Therefore, discrete choice models, which utilize consumer-choice pattern data collected from structured surveys, are widely used to model the demand side in new technology diffusion (Choi et al., 2018; H. Lee, Choi, & Koo, 2018; Lin & Greene, 2010; Moon, Choi, Lee, & Lee, 2017; Wolinetz & Axsen, 2017). This is because market data on new technologies are limited, and thus data collection through consumer surveys can be useful. Choice models directly include key attributes into the consumers' utility function to model consumer decision and use some form of logit model to estimate parameters and calculate the choice probabilities for different alternatives (Train, 2009). Using the choice

probabilities for different technology alternatives, the researcher can analyze technology competition and new technology diffusion for various market and policy scenarios.

Moreover, since the researcher can decide which attributes to include in the consumers' utility function, the impact of new technological characteristics on consumer choice can be analyzed. For example, one can analyze the impact of: a new powertrain and the related infrastructure on vehicle choices (Choi et al., 2018; Hong et al., 2012; Moon et al., 2018), renewable energy and environmental impact of power sources on the choice of residential electricity services (Huh, Woo, Lim, Lee, & Kim, 2015), and more convenient functions on the choice of mobile telecommunications services (H. Lee et al., 2018).

Among the various types of discrete choice models, the multinomial logit model is the most basic and popular (Train, 2009). Discrete choice models, including the multinomial logit model, are based on the random utility maximization framework (McFadden, 1974). In a multinomial logit model, the utility that consumer *n* obtains from alternative *j* in choice situation *t* can be defined as equation (1) below.

$$U_{njt} = V_{njt} + \varepsilon_{njt} = \beta' X_{njt} + \varepsilon_{njt} \quad \cdots\cdots \text{Eq. (1)}$$

In the equation above, a consumer's utility can be divided into a deterministic part $V_{njt}$ and a stochastic part $\varepsilon_{njt}$. The deterministic part $V_{njt}$ can be represented as the

multiplication of the vector of observable attributes $X_{njt}$ and the vector of corresponding preference parameter estimates $\beta$.

In the model, the consumer chooses the alternative that generates the maximum utility. Then, the choice probability that a consumer may choose alternative *i* over *j* can be represented by equation (2) (where $\forall j \neq i$).

$$\begin{aligned} P_{nit} &= P\left(U_{nit} > U_{njt}\right) \\ &= P\left(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt}\right) \\ &= P\left(\varepsilon_{njt} < \varepsilon_{nit} + V_{nit} - V_{njt}\right) \end{aligned} \quad \cdots\cdots \text{Eq. (2)}$$

In a multinomial logit model, it is assumed that stochastic part $\varepsilon_{njt}$ follow independently and identically distributed type I extreme value distributions. The density of these distributions is given in equation (3).

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

Using equation (3), equation (2) can be written as equation (4) below, and equation (4) can be expressed in closed form as equation (5) below.

$$P_{nit} = \int \left( \prod_{j \neq i} e^{-e^{-(\varepsilon_{nit} + V_{nit} - V_{njt})}} \right) e^{-\varepsilon_{nit}} e^{-e^{-\varepsilon_{nit}}} d\varepsilon_{nit} \quad \cdots\cdots \text{Eq. (4)}$$

$$P_{nit} = \frac{e^{V_{nit}}}{\sum_j e^{V_{njt}}} = \frac{e^{\beta' X_{nit}}}{\sum_j e^{\beta' X_{njt}}} \quad \cdots\cdots \text{Eq. (5)}$$

Next, the likelihood of consumer *n* choosing alternative *i* in various choice situations based on actual observations can be written as equation (6).

$$P_n = \prod_t \prod_i (P_{nit})^{y_{nit}} \quad \cdots\cdots \text{Eq. (6)}$$

Here, $y_{nit}$ has a value of 1 if consumer *n* chooses alternative *i* in choice situation *t*, and 0 otherwise. Given that consumers' choices are independent, the likelihood function of the entire sample *N* can be written as the following product:

$$Likelihood = \prod_{n=1}^{N} P_n = \prod_{n=1}^{N} \prod_t \prod_i (P_{nit})^{y_{nit}} \quad \cdots\cdots \text{Eq. (7)}$$

The advantage of a multinomial logit model is that it can be easily estimated through the method of maximum likelihood, due to its closed-form choice probability. However, the model has some important limitations, namely, the assumption of preference homogeneity and the property of independence from irrelevant alternatives

(IIA) (Train, 2009). Preference homogeneity means that the model assumes the entire sample has the same form of preferences; the IIA property implies that the ratio of the choice probabilities of two alternatives does not change, regardless of whether any changes occur in the other remaining alternatives. Intuitively, these assumptions are unrealistic in most cases (Train, 2009).

In this context, various models exist to avoid these limitations. In terms of preference heterogeneity, two main models are widely used in the literature: the latent class logit model and the mixed logit model (Greene & Hensher, 2003; Train, 2009). The key difference between these models is that, while the latent class logit model represents consumer preference heterogeneity in a discrete style (by segment), the mixed logit model represents this heterogeneity in a continuous style (by individual). The latent class logit model has the advantage of segmenting the consumers' preferences and utilizing segment membership model to identify the characteristics of each segment (Greene & Hensher, 2003; M. Lee, Choi, & Koo, 2017; Wolinetz & Axsen, 2017). However, in this section, I focus on the mixed-logit model since it can provide individual-level preference estimates, which can be used to model individual-level choices.

The mixed logit model accommodates consumers' preference heterogeneity at the individual level. Usually, the model assumes that the vector of parameters for the population follows a normal distribution with mean $b$ and variance $W$ ($N(b,W)$), and estimate $b$ and $W$. Therefore, in a mixed logit model, the utility that consumer $n$ gains from choosing alternative $j$ in choice situation $t$ can be expressed as:

$$U_{njt} = V_{njt} + \varepsilon_{njt} = \beta_n{}' X_{njt} + \varepsilon_{njt} \quad \cdots\cdots \text{Eq. (8)}$$
$$\beta_n \sim N(b, W)$$

In a nixed logit model, the choice probability $P_{nit}$ can be expressed as the integrals of the multinomial logit probabilities evaluated at parameter $\beta$ over $f(\beta_n \mid b, W)$, as in equation (9) below.

$$P_{nit} = \int L_{ni}(\beta) f(\beta_n \mid b, W) d\beta_n \quad \cdots\cdots \text{Eq. (9)}$$

where

$$L_{ni}(\beta) = \frac{e^{V_{nit}}}{\sum_j e^{V_{njt}}} = \frac{e^{\beta_n' X_{nit}}}{\sum_j e^{\beta_n' X_{njt}}}$$

Then, the likelihood of consumer *n* and the entire sample can be written as equations (10) and (11), respectively.

$$P_n = \int \prod_t \prod_i \{L_{ni}(\beta)\}^{y_{nit}} f(\beta_n \mid b, W) d\beta_n \quad \cdots\cdots \text{Eq. (10)}$$

$$Likelihood = \prod_{n=1}^{N} P_n = \int \prod_{n=1}^{N} \prod_t \prod_i \{L_{ni}(\beta)\}^{y_{nit}} f(\beta_n \mid b, W) d\beta_n \quad \cdots\cdots \text{Eq. (11)}$$

However, unlike in the multinomial logit case, the choice probability of a mixed

logit model is not closed form, and hence the traditional maximum likelihood estimation method cannot be used. Therefore, other estimation methods, such as simulated maximum likelihood estimation or Bayesian estimation, must be used to estimate the parameters (Train, 2009).

## 2.3 Consumers' Intertemporal Choice

Since discrete choice models usually use survey data collected in a specific time period, the model is static in nature. However, some products of interest are durable goods, which means that, once chosen, the product will be used for a rather long time. In this case, considering the utility the product will generate throughout its lifetime may be more appropriate in modelling consumer choice. However, since consumers tend to prefer utility generated now or in the near future than utility generated in the far future, appropriate discounting should be applied to future utilities. For example, hyperbolic discounting of future utility is the most widely used approach (Lobel, Patel, Vulcano, & Zhang, 2016; Rust, 1987; Song & Chintagunta, 2003). As a representative example, Rust (1987) maximizes the utility for a given period with discounting according to equation (12) below.

$$\sum_{j=0}^{T} \beta^{j} U\left(a_{i,t+j}, s_{i,t+j}\right) \cdots\cdots \text{Eq. (12)}$$

Here, $\beta$ is the discount factor and $j$ is the time lag from the current time period

*t*. $a_{i,t}$ and $s_{i,t}$ represent the action and state of agent *i* in period *t*. In other words, to calculate the current utility, the action and state for each time period are summed up with future discounts. However, previous literature suggests that estimating the discount rate $\beta$ is computationally intractable (Rust, 1987; Song & Chintagunta, 2003). Therefore, these studies usually simply assume a specific value for the discount rate (e.g. 0.9 or 0.95) and compare the results of different discount rates.

On the other hand, some studies include "no-choice" or past alternatives (SQ) options in discrete choice models to identify the purchase timing of new products. Haaijer, Kamakura, and Wedel (2001) claim that a "no-choice" option should be included in conjoint choice experiments to enhance the model's predictive fit and to provide respondents with a more realistic choice situation. On the other hand, Dhar (1997) argues that if a "no-choice" option is included in the choice set, respondents are likely to choose the "no-choice" option, since it is likely to stand out among other alternatives. Finally, Koo (2012) included SQ in consumers' current choice set, while considering the obsolescence and usage level of the SQ.

## 2.4 Optimal Product Line Design and Product Line Extension

There exists a rich body of literature for solving the optimal product line design problem (Jiao, Simpson, & Siddique, 2007; Krishnan & Ulrich, 2003). Various optimization methods and tools have been used to this problem (Green & Krieger, 1985) and various objectives have been pursued. In this section, however, I would like to focus on product

design studies that consider consumer preferences. For example, Luo et al. (2005) use consumer preference information derived from a choice model to find the optimal design for a single product with a multi-objective genetic algorithm. The key contribution of the study is that it considered multiple objectives—not only the performance of the design but also its robustness. The approach was extended to a product line design problem by Luo (2011). Here, the objective was 1) to ensure the feasibility and robustness of the products and 2) to maximize the cost synergy across products in the product line. Kwong, Luo, and Tang (2011) also proposed a one-step multi-objective optimization for product line design, aiming to 1) maximize the product market share, 2) minimize the total product development cost, and 3) minimize the total development cycle time. On the other hand, Michalek, Feinberg, and Papalambros (2005) used analytic target cascading to link consumer preferences and product design. The approach was also extended to a product line design problem in Michalek, Ebbes, Adigüzel, Feinberg, and Papalambros (2011). Deng, Aydin, Kwong, and Huang (2014) proposed a multi-objective product line optimization model that can explicitly define specific market positions for different product variants. When considering consumer preferences in product (line) design, taking into account consumers' preference heterogeneity is a key issue, as previous studies suggest that a model with simpler heterogeneity may lead to suboptimal product line design (Michalek et al., 2011).

Furthermore, product line extension is a widely accepted term, which has also been introduced in marketing textbooks (Kotler & Armstrong, 2017; Lamb, Hair, &

McDaniel, 2012). Product line extension can be explained as adding depth to an existing product line by introducing new products in the same product category. For example, Lamb et al. (2012) provide an example of product line extension using the case of the automotive manufacturer Ford adding alternative fuel vehicles (electric vehicles, hybrid vehicles, etc.) to its existing product line of conventional internal combustion engine vehicles. Product line extension can be seen as an intertemporal product line optimization problem, while fixing the existing products in the product line and adding new products. Therefore, the problem can be seen as an optimal new model introduction problem, considering the existing product line.

The primary trade-off in deciding the optimal model introduction order is between reducing cannibalization and early accrual of revenue. Moorthy and Png (1992) is one of the first studies to address this problem. The study shows that, considering the cannibalization among products, it is advisable to introduce high-end products first and then to introduce low-end products, since low-end products may cannibalize the revenue of high-end models significantly if they are introduced beforehand. On the other hand, Bhattacharya, Krishnan, and Mahajan (1998) suggest that, in the presence of technological advancement, introducing models starting from the low-end models to the high-end models and providing consumers with the choice to upgrade their product may be more optimal for the producer. Moreover, Padmanabhan and Srinivasan (1997) suggest that, if there exist network externality and information asymmetry between the consumer and the producer, starting from low-end models may be more optimal. Wilson and Norton

(1989) analyze the optimal entry timing for a product line extension. The study emphasizes the importance of the interrelationship between the existing and new product due to substitution and diffusion, relative margin, and length of the firm's planning horizon. The results of the study show that, if the relative margin of a new product is small, a firm should conduct a product line extension early on or not conduct a product line extension at all. A more recent study by Lobel et al. (2016) analyzed a producer's optimal model introduction plan in the presence of strategic consumers and previous product models. The product to be considered was a multi-generation product (e.g., iPhone 6 → 6S → 7), and consumers maximized their discounted consumer surplus. The results show that, with appropriate adjustments in the introduction interval and commitment to a model introduction plan, the producer may achieve additional profit.

## 2.5 Limitations of Previous Literature and Contribution of the Current Dissertation

This section aims to summarize limitations of previous studies and present the key contributions of the present research. First, as seen in Section 2.1, previous studies considered the supply factor as one of the important determinants of new technology diffusion. However, these studies usually focused on incorporating some factors that may affect the diffusion rate in aggregated diffusion models. The advantages of aggregated diffusion models are their ease of application and good fit in actual new product diffusion cases. However, as regards policy analysis and examining the competition among various

technology products, the use of aggregate diffusion models is limited. This is because the method fits early sales data to a specific form of curve and has an exogenous assumption on peak sales timing and market potential (Wolinetz & Axsen, 2017). Moreover, the model cannot analyze the motivation and behavioral mechanisms for choosing new technology products. Therefore, discrete choice models are widely used for policy analysis, since the researcher can define a utility function with desired explanatory variables and design a structured survey to collect consumer choice data for hypothetical situations (Train, 2009).

However, although choice models can elaborately represent demand, they have constraints on incorporating actual limitations on the choice of new technology products. For example, since the model uses data generated from hypothetical choice situations, the effect of model availability cannot usually be considered. The model availability of products can have a significant impact on consumer choice, especially for new technology products, since these products may not be introduced to the market at all or have only few model choices. Considering this aspect, Hoen and Koetse (2014) considered model variety as one of the key attributes in the choice experiment but, considering that a researcher can include only a small number of attributes in the choice experiment, such an approach is quite costly.

On the other hand, Lin and Greene (2010) incorporated the impact of supply factors in a simulation framework. Their model assumes that more new technology product models are introduced as sales of new technology product models increase.

Specifically, the demand for specific technology product models in period $\tau$ directly affects the number of these product models in period $\tau+1$. However, this approach assumes a passive response of the supply, whereas a supplier may adjust its product line extension plan to induce consumer behavior in a certain direction and accomplish its managerial objectives.

The more recent work of Kieckhäfer et al. (2017) focused on the introduction of a new technology product itself. The study linked a consumer model (an agent based model) with a manufacturer model (a system dynamics model) to analyze the impact of changes in product supply in new technology (electric vehicles) diffusion. In the study, the authors analyzed 6 product portfolio scenarios, including early introduction of specific technology models (plug-in hybrid vehicles or fuel-cell electric vehicles), sequential introduction of new technology models (hybrid electric → plug-in hybrid → pure battery electric), and discontinuance of some gasoline fuel vehicle models. The results show that a future product supply plan has a significant impact on new technology diffusion. However, the model could not determine the supply response within it. As some previous literature suggests (Al-Alawi & Bradley, 2013; Wolinetz & Axsen, 2017), this may be because it is hard to acquire or reasonably assume data that can empirically model the supply of a new product.

Moreover, the studies introduced above do not consider product heterogeneity in the new product supply. For example, previous studies considered only the number of models available (Hoen & Koetse, 2014; Lin & Greene, 2010), or considered a single

model for each technology (Kieckhäfer et al., 2017). However, considering the preference heterogeneity for new technology products, *which* product is introduced is important. In this aspect, of key contribution of the research herein is that it constructs a module that can derive a supplier's optimal product line extension (new model introduction) for a given policy situation (product line extension model), to provide choice situations that consumers will face. Then, using this information, consumers' intertemporal choices for new products are simulated to analyze the diffusion of the new technology product by policy intervention.

Next, I provide specific contribution for the intertemporal consumer choice model proposed in this dissertation. Although the market share estimate provided by general consumer choice models has its implications, the analysis of the actual sales quantities or the stock composition of the market is also important. For markets that show stable sales (e.g., the automotive industry), some studies exogenously assume the sales quantity and multiply it by the choice probability for the new technology alternative derived from the choice model to calculate the actual sales of new technology products (Byun et al., 2018; DeShazo, Sheldon, & Carson, 2017). Moreover, some advanced models included elaborate modelling for estimating the stock composition of the market. This is because for some products that continuously consume energy (e.g., vehicles and home appliances) or work as a platform (e.g. smart mobile devices), information about the stock share of the market can have important implications. In this section, I focus on introducing models analyzing the vehicle market. For example, the Market Acceptance of

Advanced Automotive Technologies model uses a nested multinomial logit model to estimate the sales market share of each vehicle technology, and multiplies this value with exogenously given sales quantities to calculate the actual sales. Consequently, using this actual sales value and the retirement rate of stock by age, stock turnover is derived for the market (Lin & Greene, 2010; McCollum et al., 2017; Xie & Lin, 2017). Similarly, the Alternative Automobiles Diffusion and Infrastructure model estimates the sales market share for each vehicle technology by making consumers choose a vehicle that minimizes one's total cost of ownership, and uses exogenously given new registration volumes and the survival probability of stock to derive stock turnover (Gnann, Plötz, Kühn, & Wietschel, 2015). On the other hand, the Canadian Integrated Modelling System model estimates the sales market share of each vehicle technology by using the relative lifecycle cost of each technology, and assumes a certain level of own-price elasticity to determine new demand (Fox, Axsen, & Jaccard, 2017; Sykes & Axsen, 2017).

To summarize, these models use their own method to elicit the sales market share, multiply it with sales amounts, and combine it with the stock (with retirement considered) to derive the stock turnover of the market. However, such an approach implicitly assumes that the same or similar new-product buyers exist in all the time periods. In reality, new-product buyers may vary over time, especially when a strong policy intervention starts or ends. For example, if a high purchase subsidy for EVs ends next year, would not some consumers that would have purchased an EV in the following year (if the subsidy was sustained) strategically *advance* their purchase? Moreover,

previous studies lack attempts to include consumers' heterogeneous SQ in individual-level choice of product adoption (Koo, 2012).

Therefore, the main contribution of the current choice model is that it analyzes an important but unexplored aspect: identifying the timing of product choice. Specifically, the research in this dissertation extends consumers' choice set for product adoption to a longer timeframe (including SQ and future alternatives) to identify new product buyers and stock turnover[1]. To my knowledge, this approach is new in the literature, and the analysis of such strategic consumer behavior can provide valuable insights for policymakers. Moreover, by incorporating SQ and future alternatives into the current choice set, I can model consumers' strategic decisions in various policy circumstances. Moreover, to link the results of the consumer model to the product-line extension model, this study suggests a deterministic simulation framework using the suggested consumer choice model.

Finally, for the proposed product-line extension model, there already are various studies incorporating consumer preference to product (line) design considering consumers' heterogeneous preferences (Camm, Cochran, Curry, & Kannan, 2006; Luo, 2011; Luo et al., 2005; Michalek et al., 2011; Wang, 2015). The product-line extension in this study involves deciding which new product to introduce for each time period. Specifically, new product models to be introduced are selected from a pre-defined pool of candidate models. Previous studies have usually focused on a theoretical analysis in

[1] Because my study takes the replacement point of view, the choice of a new vehicle over one's SQ means sales of that new product and retirement of the old SQ.

limited settings or relationships on this issue, but the current study aims to derive the optimal product line extension considering various forms of cannibalization simultaneously. Moreover, the model considers individual-level consumer heterogeneity, noting the argument in previous literature that simpler heterogeneity may lead to suboptimal product line design in preference-based product line design (Michalek et al., 2011).

# Chapter 3. Methodology

This chapter aims to propose a model that can analyze intertemporal choice of consumers considering product-line extension. Here, intertemporal choice means that the current choice of a consumer is modelled from considering one's current status and present and future market situations. On the other hand, product-line extension refers to new product models being supplied to the market considering existing product lines and consumer demand. First, Section 3.1 introduces the overall framework of the proposed model. Then, Section 3.2 introduces the intertemporal consumer choice model and Section 3.3 introduces the product-line extension model. Although the proposed model can generally be used for various new product adoption cases (especially for high-technology durables), in Chapter 4, I apply this model to the case of diffusion of EVs in South Korea. Therefore, I will use generalizable explanations for most parts in Chapter 3 but will explain the model using the case of consumer vehicle adoption as an example, especially when I explain the design of choice experiments in Section 3.2.2.

## 3.1 Methodological Framework

This section provides an overall framework of the proposed model that can analyze consumers' intertemporal choice for new products considering product-line extension. Since consumer choice (purchase) is directly related to a product's attractiveness, product-line extension (product model supply) varies by changes in consumer choice.

Figure 1 illustrates the framework of the model proposed in this dissertation. The model consists of two main parts. First is the consumers' intertemporal choice model, and the other is the product-line extension model. First, the proposed consumer choice model is different from conventional choice models in that it incorporates wider choices, set in terms of timeframe, to the model consumers' intertemporal choice decision. To be specific, included in the consumer's current choice sets are not only new products that are currently available in the market, but also one's currently owned products (status quo, SQ) and future products that are expected to be introduced in the near future. In the model, a consumer may choose a product being sold in the market and purchase that product (and replace one's SQ), but may also prefer one's SQ and remain with it or choose one of the future products and strategically postpone one's purchase (in both these cases, the purchase will not occur now).

For the consumer model, two types of choice experiments were conducted to model consumers' intertemporal choice decision at the individual level. The first choice experiment (Choice Experiment 1) analyzed consumer preferences between new products, and between one's status quo (SQ) and new products. In the second choice experiment (Choice Experiment 2), consumer's inconvenience of waiting for future products was calculated. Using the individual level estimates and calculations, consumers' intertemporal product choice decision was modelled at the individual level and considered the effect of SQ and future products.

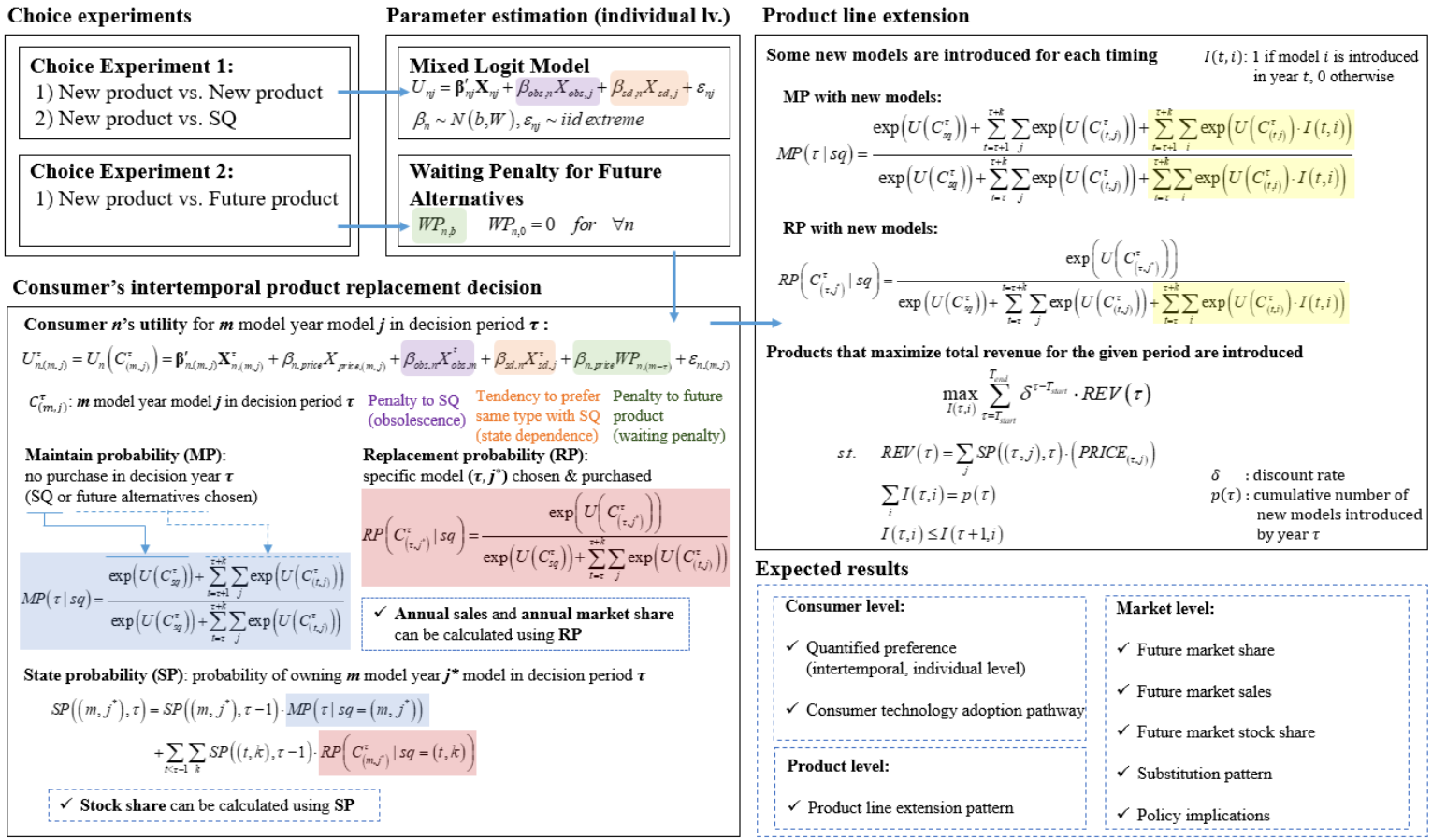



**Figure 1.** Methodological framework of the proposed model

Since choosing the SQ, or any future alternative results in the same action of not purchasing a new product (and remaining with the current SQ) for the corresponding time period, the probability that a consumer may maintain one's SQ (maintain probability, MP) can be calculated as the sum of the choice probability of SQ and future alternatives among the whole choice set. On the other hand, if one of the new products currently available in the market is chosen, this study assumes that the consumer replaces one's SQ with that product. The probability of replacing one's product to a specific model is defined as replacement probability (RP). One important point about RP is that it can be used to analyze annual sales of the market for each time period. Unlike conventional choice models that can analyze only market share[2], the suggested consumer model can analyze market sales, since it can identify "product buyers" from the whole sample for each time period by identifying product adoption timing of consumers.

Note that MP and SP are both conditional on one's current SQ. This is because the consumer's SQ is directly included in the consumer's current choice set, and thus influences the choice probability of other alternatives. Therefore, modelling changes in SQ by time is important in long-term forecasts that use MP and SP. In order to extend the model for long-term analysis, I define the concept of state probability (SP), which is the probability of owning a specific product model as the SQ after a choice decision is finished for the specific time period. Using SP, the stock share of the market can be easily

[2] In order to analyze annual sales, the total annual sales of the market should be exogenously given for these models. Moreover, most of these models assume the same new product buyers exist for every time period which is unrealistic, especially when market and policy situations fluctuate in new technology diffusion phases.

analyzed for each time period, since the SP of products in a specific period $\tau$ is directly the stock share of the period $\tau$. Moreover, the SP for new models (model year = decision year) is the same as market sales in this model, since the model assumes past models are not available for purchase.

Next, the proposed product-line extension model determines the new product model supply (when and which models are newly introduced within a pre-defined pool of candidate models) considering the market situation and consumer demand (which may change by the government's policy intervention). Thus, the model uses the consumer model to evaluate its plan. Since an extension in product line (introduction of new product models) directly influences consumers' choice set, change in product line induces change in consumer choice. One of the key objectives of the proposed model in this dissertation is to observe the influence of such supply changes on the consumer's new technology adoption and new technology diffusion.

The objective of the product-line extension model is to maximize its total revenue for the whole analysis period, by deciding which model to introduce in which time, given some exogenous constraints. When calculating the revenue for a given period, future revenues are discounted with fixed rate. The revenue for year $\tau$ is calculated by multiplying sales of new product models by their market price. The number of models to be introduced in each time period are exogenously given, and there is no discontinuance of models once introduced.

Various useful results can be expected from the proposed model. First, from the

consumer level, time-varying quantified preference can be elicited at the individual level. Moreover, by using changes in SP of consumers by time, one can analyze the technology adoption pathway of consumers in response to policy intervention and product-line extension. Next, at the product level, a product-line extension pattern can be derived in response to policy intervention. Finally, at the market level, future market shares, market sales, and stock shares between different products can all be analyzed, considering intertemporal choice of consumers and product-line extension. Most importantly, the proposed model aims to support the decision making of the government and policy makers. Through simulation analysis using various policy scenarios, useful policy implications can be derived to design better policies.

A more simplified and intuitive illustration of the methodology is provided in Figure 2. The figure focuses on the optimization process between model parts. First, policy intervention is exogenously given to the proposed model. Next, the product-line extension model passes its extension plan to the consumer model, and the consumer model simulates consumer choice and calculates the expected revenue of the corresponding plan. Then, the product model gives the expected revenue of the plan and adjusts its plan until an optimal plan is derived.

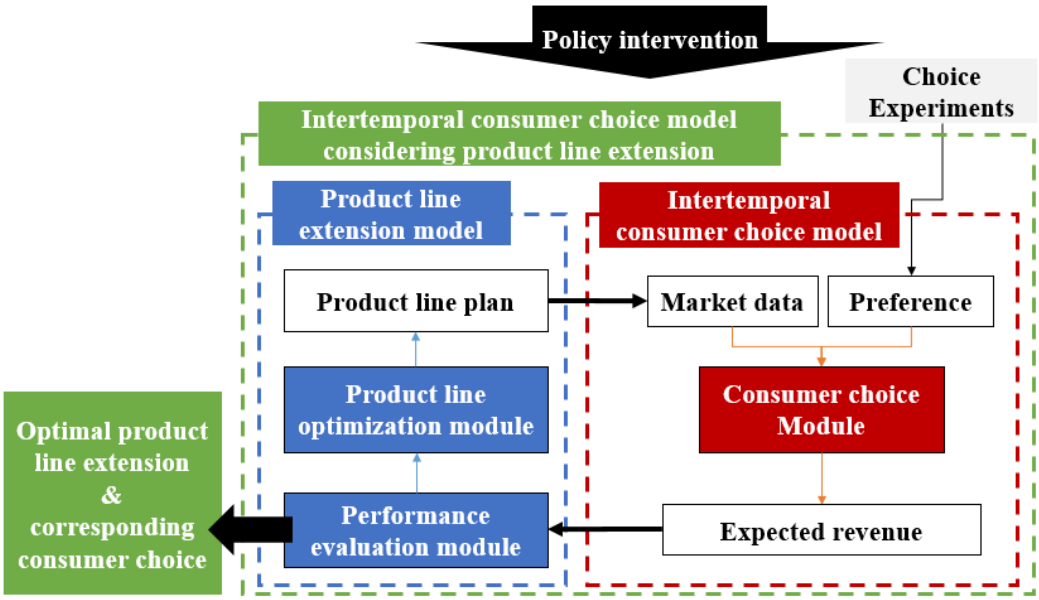



**Figure 2.** Optimization process between model parts

## 3.2 Intertemporal Consumer Choice Model

A key feature of the proposed intertemporal consumer choice model in this dissertation is that the model includes not only products that currently exist in the market, but also the consumer's current options (status quo, SQ), and products that will be introduced in the near future. In other words, the model considers an extended choice set in terms of timeframe to model strategic intertemporal choices of consumers. Therefore, consumers may purchase new products and *replace* their current SQ by selecting products that are currently available in the market, but may not purchase any new products *now* by selecting SQ or future products. Since the model adopts such replacement views, it can be seen as an intertemporal product *replacement* model. Moreover, it can identify product

buyers for each time period, since it can incorporate the decision of *not buying now*. Such a choice model can make the best use of itself in modelling consumer choice for high-technology durables like automobiles or high-cost consumer electronics.

Including SQ and future alternatives in the consumer's current choice set significantly enhances the analytic capability of the model when compared to conventional choice models. For example, the inclusion of SQ enables analysis of actual sales and stock shares of the market by taking the replacement viewpoint. Moreover, the inclusion of future alternatives enables the analysis of consumers' strategic choices of advancing or delaying their purchase in response to fluctuating future market and policy situations in the phase of new technology diffusion. The difference between the conventional choice model and the proposed intertemporal consumer choice model is summarized in Table 1.

**Table 1.** Difference between conventional choice model and proposed intertemporal consumer choice model

| | Conventional choice model | Proposed intertemporal choice model |
|---|---|---|
| Consumer's current choice set | Products now in the market (current alternatives) | Products now in the market (current alternatives) + Currently owned product (past alternative, SQ) + Products to be introduced in the near future (future alternatives) |
| Additional factors considered | - | Obsolescence of SQ<br>State dependence by the type of SQ<br>Waiting penalty for future alternatives |
| Future sales share | Can be analyzed | Can be analyzed |
| Future sales | Cannot be analyzed | |
| Future stock share | | |
| Strategic advancing/delaying of purchase | | |

The explanation for the intertemporal consumer choice model is divided into three parts. In Section 3.2.1, I provide the conceptual background of the proposed consumer choice model. Then, Section 3.2.2 explains how the choice experiments were conducted, key parameters estimated, and penalties calculated. Finally, Section 3.2.3 illustrates how the consumer's intertemporal new product choice decisions are modelled using individual-level values derived in Section 3.2.2.

### 3.2.1 Conceptual Background

In this section, I describe the characteristics of the SQ and future alternatives that are considered when they are included in consumers' current new product choices, and provide an explanation and conceptual background for key terminologies. This study mainly focuses on three factors from these extended alternatives. Specifically, for the SQ I consider the *obsolescence* of the SQ, and the *state dependence* according to the type of SQ (Dubé, Hitsch, & Rossi, 2010; Keane, 1997; Koo, 2012; Stacchetti & Stolyarov, 2015). For future alternatives, I consider consumers' *forward-looking behavior* for future alternatives, and *waiting penalty* for postponing one's purchase.

#### 3.2.1.1 Obsolescence of Status Quo by Length of Ownership

One of the biggest competitors of high-technology durable products in the market is the consumer's currently owned product (SQ). Therefore, an analysis that neglects the SQ may bias the market response to policy intervention (Prince, 2008, 2009). For example, consider a case of the government starting an EV promotion policy. If a strong EV promotion policy is enacted, a consumer may prefer those EV models over others, among current models being sold on the market. If only new vehicles are considered in the analysis, the policy will be considered a success in promoting EVs. However, in reality, consumers may not purchase the most preferred vehicle in the market after comparing it with their SQ. In other words, the existence of a good alternative (triggered by policy

intervention) does not ensure *immediate* purchase by consumers because of their SQ[3]. Therefore, the impact of promotion policies or technological advances may be quite different depending on whether the SQ is considered. Moreover, not considering the SQ requires the assumption that all consumers have the same outside option (outcome for not purchasing) for their purchase, which is unreasonable because consumers have heterogeneous SQs (Prince, 2008).

However, durable goods are generally used for a long time, and as the length of ownership increases, the utility one feels about one's SQ may decrease for various reasons, for example, by physical depreciation from usage or the obsolescence one feels from the introduction of a new line of products (Lee & Lee, 1998; Prince, 2008; Stacchetti & Stolyarov, 2015). In this study, I define such decreases in consumers' perceived utility for their SQ by the increase of *length of ownership* as *obsolescence* of the SQ, and empirically analyze its marginal effect.

Previous literatures categorize the concept of obsolescence into sub-categories. For example, Levinthal and Purohit (1989) categorize obsolescence to functional obsolescence, which results from the functional difference between past products and newly introduced products; and style obsolescence, which results from the style difference between past products and newly introduced products. Similarly, Granberg (1997) categorized obsolescence into functional obsolescence that occurs from

[3] Some studies included no choice option in the choice set of their choice experiment to extract the consumer decision of not purchasing (Tanaka, Ida, Murakami, & Friedman, 2014). However, such an approach can only provide limited behavioral implications about not buying.

differences in objective criteria (e.g., performance change), and psychological obsolescence that occurs from differences in subjective criteria (e.g., aesthetic style). Since the impact of difference in key functional aspects between old and new models will be captured by difference in the level of key attributes, as defined in the consumer's utility function, the obsolescence effect considered in this dissertation can be explained as the sum of psychological obsolescence and functional obsolescence that is not captured by key attributes.

#### 3.2.1.2 State Dependence by Status Quo Type and Lock-in Effect

In a repeated purchase, consumers are more likely to purchase a similar product to their previous purchase (Dubé et al., 2010; Koo, 2012). In this study, I define such a tendency as consumers' state dependence, which is also known as status quo bias (Heckman & Navarro, 2007; Keane, 1997; Masatlioglu & Ok, 2005; Samuelson & Zeckhauser, 1988). Many previous studies have analyzed this tendency (Dubé et al., 2010; Hortaçsu, Madanizadeh, & Puller, 2017; Shcherbakov, 2016), but intensive analysis for the high-technology durable market has not yet been thoroughly conducted, perhaps because of the difficulties that are inherent in acquiring relevant data[4]. In my empirical analysis in this dissertation (diffusion of EVs in South Korea), I define *state dependence* for vehicle

[4] These studies typically require individual-level repeat purchase data (panel) for the analysis. However, such data are unavailable in most cases and only exist for some special product categories. For example, in frequently purchased consumer goods, such as margarine or orange juice (Dubé et al., 2010), or subscription services such as residential electricity (Hortaçsu et al., 2017) or TV services (Shcherbakov, 2016). Therefore, many studies neglect the existence of state dependence due to a lack of appropriate data (Smith, 2005). For high technology durables, tracking individual level purchases are particularly difficult because of the long length of ownership, especially when new technology products are of main concern.

purchases as how much consumers prefer vehicles from the *same* class, or that use the *same* operating method (powertrain) as their SQ.

If the effect of state dependence is positively significant, it implies that there exists an additional utility loss when changing one's product type, and the existence of such utility loss may induce consumers to become locked-in to the type of their current SQ (Klemperer, 1995; Lee et al., 2018). In terms of new technology diffusion, the existence of such a *lock-in effect* can be both an obstacle and an opportunity. It would be hard to initially make consumers to adopt new technology products, but once adopted, the lock-in effect to the new technology may have a positive impact on consumers' future purchases.

#### 3.2.1.3 Forward-Looking Behavior for Future Alternatives and Waiting Penalty

Future high-technology products that are not yet available but will be introduced in the near future, with improved performance and under different market/policy situations, comprise of another group of alternatives that consumers consider with respect to their current purchase decision. In other words, consumers may compare their SQ and the currently available alternatives with future alternatives, thus strategically delaying their purchase for a better deal in the future, or advancing their purchase to avoid a worse deal in the future. In this study, I define such behavior of consumers as *forward-looking behavior*. However, even when future alternatives may be attractive, they have a serious

shortcoming: they are not available now, and require a certain amount of waiting until the actual purchase. Therefore, this study assumes that future options are penalized according to the length of waiting time required for purchase, and defines this penalty as *waiting penalty*. The inclusion of future alternatives makes consumers' decision-making more complex and strategic. For example, future alternatives will have better performance due to ongoing technological innovation, but policy circumstances may be better or worse, depending on when the product is introduced. Moreover, future alternatives are penalized according to the waiting time required for purchase.

### 3.2.2 Choice Experiments

Data for the proposed intertemporal consumer choice model were collected using a survey-based choice experiment. As mentioned before, empirical application using the proposed model will be conducted for the diffusion of EVs in South Korea; therefore, the survey was conducted accordingly. The survey was conducted by a professional survey company with 800 respondents in South Korea from February 5 to 14, 2018. The sample was collected considering the age, gender, and residential area of the population. Among 800 respondents, 333 who owned their own vehicle were considered for the analysis, since I focused on the vehicle replacement behavior of respondents (and thus, SQ information is needed). Therefore, the study can only incorporate replacement demand and cannot incorporate the new demand of first buyers. However, as the market for durables becomes saturated, most demand can be explained with replacement demand.

For example, in the Unites States, 70-90% of the total demand for consumer durables, such as refrigerators, washers, and vacuum cleaners, were from replacement demand in 1985 (Bayus & Gupta, 1992). Moreover, more than 60% of vehicle demand in the United States was replacement demand, even in 1936 (George, 1939). For the South Korean vehicle market, which is the scope of the empirical application of this dissertation, replacement demand exceeded new demand in 1995 and the proportion of replacement demand in 2017 reached 88%[5] (Consumer Insight, 2018).

Before responding to choice experiments, respondents provided information about their SQ. They were then required to respond to two types of choice experiments. One was a choice-based conjoint analysis with a follow-up question, which was carefully designed to estimate the consumer's general preferences toward vehicle adoption, along with consumer attitude toward the obsolescence of SQ and the tendency of state dependence. The other was an adaptive choice experiment (Cairns & van der Pol, 2004; Gensler, Hinz, Skiera, & Theysohn, 2012; Lim, Jonker, Oppe, Donkers, & Stolk, 2018), in which the respondent's current choice situation was dependent on the respondent's previous responses, and was designed to estimate consumer attitudes toward postponing one's purchase timing in favor of a better deal (forward-looking behavior).

#### 3.2.2.1 Choice Experiment 1

Choice Experiment 1 can be divided into two parts. The first part was a widely used

[5] The proportion of replacement demand in the South Korean vehicle market was 84% in 2012, 85% in 2014, 86% in 2015, and 88% in 2017.

choice based conjoint analysis, and the second part was a follow-up question that asked respondents whether they were willing to exchange their current vehicle (SQ) with their most-preferred vehicle for each choice situation in the conjoint analysis.

In the conjoint analysis, key attributes that characterized alternatives were selected, and these attributes were combined to construct multiple hypothetical choice alternatives. The constructed hypothetical alternatives were then grouped with others to construct multiple choice situations (Louviere, 1988). Finally, respondents were asked to answer the most preferred alternative for each choice situation. In this study, five key attributes were selected to represent various types of vehicles. Table 2 shows the attributes and attribute levels used for the conjoint analysis.

**Table 2.** Attribute and attribute levels for the Choice Experiment 1

| Attributes | Description and attribute levels | |
|---|---|---|
| **1. Operating method (fuel type)** | **Description** | 1) Gasoline engine (gasoline)<br>2) Diesel engine (diesel)<br>3) Hybrid engine (gasoline)<br>4) Electric motor (electric) |
| | **Levels (4)** | ① Gasoline ② Diesel<br>③ Hybrid ④ Electric |
| **2. Availability of charging facilities** | **Description** | Percentage of charging facilities assuming the current level of availability for gasoline fuel charging facility as 100% |
| | **Levels (3)** | ①100% ②60% ③20% |
| **3. Vehicle class** | **Description** | 1) Economy car<br>2) Compact/mid-size car<br>3) Full-size car<br>4) Compact/mid-size SUV |
| | **Levels (4)** | ① Economy<br>② Compact/mid-size<br>③ Full-size<br>④ SUV |
| **4. Fuel cost** | **Description** | Monetary expenditure needed to drive a kilometer |
| | **Levels (3)** | ① 150 KRW/km (0.13 USD/km) [a, b]<br>② 100 KRW/km (0.09 USD/km)<br>③ 50 KRW/km (0.04 USD/km) |
| **5. Purchase Price** | **Description** | Purchasing price of the vehicle |
| | **Levels (3)** | ① High (30% more expensive than normal)<br>② Normal<br>③ Low (30% less expensive than normal) |

[a] KRW and USD denote South Korean won and United States dollar, respectively

[b] 1 USD = 1130.61 KRW (2017 average, source: Bank of Korea; www.bok.or.kr).

The first attribute was the operating method of the vehicle. This explained which powertrain and fuel was used to operate the vehicle. Four attribute levels were assumed: gasoline, diesel, hybrid, and electric. Gasoline and diesel each represent traditional internal combustion engine vehicles (ICEVs), using each as its fuel. Hybrid represents hybrid electric vehicles (HEVs), which use both fossil fuel and electricity for driving. Specifically, HEVs represent gasoline hybrid electric vehicles (GHEVs) throughout this dissertation, which require only gasoline refueling, and electricity that is generated while driving is used to assist the powertrain to enhance fuel efficiency (e.g., Toyota Prius). Other types of HEVs exist, such as plug-in hybrid electric vehicles (PHEV) or diesel hybrid electric vehicles (DHEV). However, these vehicles have an extremely small market share (PHEV)[6], or no sales at all (DHEV), in the South Korean market due to low financial incentives (PHEV), or lack of available models in the market (DHEV). Therefore, I excluded them from my analysis and only considered GHEVs as HEVs. For the rest of this dissertation, all HEVs mentioned in this study are GHEVs. Finally, electric refers to the pure battery electric vehicles (BEVs), which only use electricity for driving.

Next, the availability of charging infrastructure was the second key attribute. To improve respondents' readability and understandability, attribute levels were defined in relative percentages by setting the availability of the current gasoline fuel charging station at 100% (Choi et al., 2018; Hong et al., 2012). The attribute could be used to observe

[6] Less than 1000 PHEVs were sold in 2018, while more than 73,000 GHEVs and 26,000 pure battery electric vehicles (BEVs) were sold.

changes in vehicle adoption behavior as the charging infrastructure for BEVs are expanded. Three attribute levels were assumed with the minimum value of 20%, referring to the current number of EV charging stations compared to the number of gas stations (Korea Environment Corporation, 2018; Korea Oil Station Association, 2016), the maximum value of 100%, and the median value of 60%.

The third key attribute was the class of the vehicle. Previous studies usually focused only on the operating method of vehicles, and did not consider the various vehicle classes (Byun et al., 2018; Choi et al., 2018). However, considering the class of a vehicle is important as it significantly effects the consumer's vehicle adoption behavior (Higgins, Mohamed, & Ferguson, 2017). Moreover, vehicles with different classes have different fuel economies and in turn, have different GHG emissions. This implies that the consideration of vehicle class can be especially important for environmental analysis for the road transport sector. However, I could not consider all classes that exist in the real market as attributes in my choice experiment. Therefore, I defined four class groups that are distinctly differentiated and set each as an attribute level. The first group was the economy car class. Economy cars are small hatchback vehicles with low displacement. Although they enjoy policy incentives such as designated parking spaces or toll-free discounts, regulations on size and engine displacement are strict for these vehicles[7]. This distinguishes this class from the other classes, and it was therefore considered separately in my analysis. The second group was the compact/mid-size class. This class represents

[7] In South Korea, the economy class has strict regulations: displacement 1000 cc, length 3600 mm, width 1600 mm, and height 2000 mm.

the popular intermediate sedan vehicles that have been a flagship product of the Korean auto market for many years. The compact and mid-size classes were combined since I assumed that these two classes were perceived similarly by consumers. The third group was the full-size class, which has a similar appearance to the compact/mid-size class but is larger and more luxurious. I separated this class since it is perceived significantly differently from the intermediate class (Higgins et al., 2017). The final group was the SUV; specifically, I referred to small and mid-sized SUVs. This class is attracting increasing attention and is clearly differentiated by its appearance.

The fourth key attribute was the fuel cost of the vehicle. To compare different fuel economy units of vehicles with different operating methods (km/L, km/kWh), I used the fuel cost unit (KRW/km) for the analysis[8]. I considered three attribute levels, taking into account that the current fuel cost of high-performance BEVs is approximately 50 KRW/km, and that of low-performance gasoline vehicles is approximately 150 KRW/km. I defined each value as a minimum and maximum attribute level and defined the median level as 100 KRW/km.

Finally, the fifth attribute was the vehicle purchase price. I assumed three attribute levels for vehicle purchase price: high, normal, and low. First, I used these three levels to construct hypothetical alternatives in the choice experiment. Then, I used the baseline price for each vehicle type based on its operating method and vehicle class (16 types according to four operating methods and four vehicle classes), to provide specific

[8] The 2018 average price was used for gasoline (1,581 KRW/L), diesel (1,392 KRW/L) and electricity (313.1 KRW/kWh).

values for each hypothetical alternative in the choice experiment. I derived the baseline price for each vehicle type by conducting a simple regression analysis using vehicle characteristics (operating method, class) and the market price of vehicle models being sold on the market. Table 3 shows the specific values used.

**Table 3.** Base price used for each vehicle type in Choice Experiment 1 (unit: million KRW)

| | Gasoline | Diesel | Hybrid | Electric |
|---|---|---|---|---|
| Economy | 15 | 17 | 20 | 38 |
| Compact/mid-size | 20 | 22 | 25 | 44 |
| Full-size | 30 | 36 | 39 | 60 |
| SUV | 23 | 25 | 27 | 50 |

For the high (low) attribute level, the price was set to be 30% higher (lower) than the baseline price. For the normal attribute level, the baseline price was applied. I used this design because I did not want to provide extremely unrealistic alternatives to respondents. For example, the cheapest vehicle type considered in this study was the gasoline economy car with a market price of approximately KRW 15 million. On the other hand, the most expensive vehicle type considered was the electric full-size vehicle with a market price that is expected to be over three to four times that of the gasoline economy car. In this situation, if I used a fixed price attribute level, the alternatives would

have been too unrealistic (for example, an electric full-size vehicle priced at KRW 15 million, or a gasoline economy vehicle priced at KRW 60 million).

Finally, when constructing choice alternatives using these attributes, the second attribute (the availability of charging infrastructure) only applied to BEVs, since gasoline and hybrid vehicles use gasoline fuel and almost all gas stations in South Korea also sell diesel fuel. Therefore, although the constructed alternatives were hypothetical, providing gasoline, hybrid, or diesel vehicles with a 20% or 60% infrastructure is unrealistic and may have confused respondents. Therefore, in this study, I combined the first and second attributes (operating method and availability of charging facilities) and considered a single attribute with six attribute levels[9] when conducting an orthogonality test to construct independent choice alternatives. I used SPSS 23 for the orthogonality test and derived 32 independent alternatives. These alternatives were grouped by four to construct 16 choice sets, with two alternatives for gasoline, hybrid, or diesel operating methods and two for the electric operating method. The 16 choice sets were divided into two types of questionnaire with eight choice sets each (type A and B), and these questionnaires were randomly distributed to the respondents.

Figure 3 shows an example of a choice situation that respondents encountered in Choice Experiment 1. In the actual survey, the parts shown in green italics in Figure 3 were not shown to respondents. These parts are related to the state dependence of respondents. Although state dependence was not explicitly incorporated in the choice set,

[9] Gasoline, diesel, hybrid, and electric with 20% availability, electric with 60% availability, and electric with 100% availability.

I assumed that consumers implicitly considered whether the operating method or class of the suggested vehicle alternative was the same as their SQ.

**Q1-1. Please choose the most preferred vehicle from among the four hypothetical options provided below.** Note: Assume that all the other attributes, besides the five proposed here, remain the same

| Vehicle attributes | Vehicle A | Vehicle B | Vehicle C | Vehicle D | *SQ* |
|---|---|---|---|---|---|
| 1. Operating method (fuel type) | Gasoline G | Diesel D | Electric | Electric | *Gasoline G* |
| 2. Availability of charging facility | 100% ■■■■■ | 100% ■■■■■ | 60% ■■■□□ | 20% ■□□□□ | *100% ■■■■■* |
| 3. Vehicle class | Economy | Compact/ mid-sized | SUV | Economy | *Compact/ mid-sized* |
| 4. Fuel cost (KRW/km) | 150 | 150 | 100 | 150 | *136* |
| 5. Purchase price (million KRW) | 19.5 | 28.6 | 65 | 49.4 | *0* |
| *State dependence (operating method)* | *Same (1)* | *Different (0)* | *Different (0)* | *Different (0)* | |
| *State dependence (class)* | *Different (0)* | *Same (1)* | *Different (0)* | *Different (0)* | |
| Choose the most preferred option | | | O | | |

**Figure 3**. Example of a choice situation in Choice Experiment 1

*Note*: the information shown in green italics was not explicitly provided to respondents but was assumed to be implicitly considered by them

However, the conjoint analysis suggested in Figure 3 was a choice situation concerning new vehicles only and such analysis cannot measure the effect of the SQ's obsolescence, which depends on the length of ownership. Therefore, I added a follow-up question after respondents chose the most preferred alternative for each choice situation in the conjoint analysis: "Are you willing to replace your current main vehicle[10] for the

[10] The main vehicle refers to the most used vehicle among one's vehicles if one has multiple vehicles.

vehicle you just selected within a year?" Figure 4 shows that the follow-up question can also be seen as a choice experiment as the selection was between two alternatives. The use of a follow-up question enabled us to analyze the effect of *obsolescence* by observing the choice pattern between vehicle alternatives with a different length of ownership (new cars versus the SQ; new cars have a zero length of ownership by definition). In Choice Experiment 1, each respondent answered 16 choice situations, eight of which were from the conjoint analysis, as well as the follow-up question[11].

[11] However, use of status quo option (reference alternative) and follow-up question may incur problems in efficiency of stated choice experiments (Rose, Bliemer, Hensher, & Collins, 2008). When including reference alternatives in choice experiment, trade-off between efficiency and realistic choice situation should be considered.

**Q1-2. Are you willing to replace your current vehicle with the hypothetical vehicle you've just chosen within 1 year? Yes / No**

| Vehicle attributes | Vehicle C | *SQ* |
|---|---|---|
| **1. Operating method (fuel type)** | Electric | *Gasoline* G |
| **2. Availability of charging facility** | 60% ■■■□□ | *100%* ■■■■■ |
| **3. Vehicle class** | SUV | *Compact/ mid-sized* |
| **4. Fuel cost (KRW/km)** | 100 | *136* |
| **5. Purchase price (million KRW)** | 65 | *0* |
| ***State dependence (fuel)*** | *Different (0)* | *Same (1)* |
| ***State dependence (class)*** | *Different (0)* | *Same (1)* |
| ***Length of ownership (year)*** | *0* | *5* |
| ***Choose the most preferred option*** | | |

**Figure 4.** Illustration of the follow-up question in Choice Experiment 1

*Note*: the information shown in green italics was not explicitly provided to respondents but was assumed to be implicitly considered by them

I used a mixed logit model to analyze consumers' general preferences toward vehicles, along with the tendency of obsolescence and state dependence using respondent responses in Choice Experiment 1. I used a mixed logit model because it incorporates the preference heterogeneity of different respondents (Train, 2009). This study aims to model individual-level vehicle replacement behavior, and thus, individual-level preference parameter estimates, as provided by the model, are essential for the analysis. Incorporating preference heterogeneity is significant because respondents with different

preference structures make different choices in similar choice situations (Fiebig, Keane, Louviere, & Wasi, 2009; Hess & Rose, 2012). I used the Bayesian estimation method for the parameter estimation of the mixed logit model (Train, 2009). The utility gain of respondent *n* from choosing model *j* can be represented as equation (13).

$$
\begin{aligned}
U_{nj} &= \mathbf{V}_{nj} + \varepsilon_{nj} \\
&= \boldsymbol{\beta}'_n \mathbf{X}_{nj} \\
&= \beta_{n,gasoline} X_{j,gasoline} + \beta_{n,diesel} X_{j,diesel} + \beta_{n,electric} X_{j,electric} \\
&\quad + \beta_{n,mid} X_{j,mid} + \beta_{n,big} X_{j,big} + \beta_{n,SUV} X_{j,SUV} \\
&\quad + \beta_{n,infra} \ln\left(X_{j,infra}\right) + b_{n,fuel\_cost} X_{j,fuel\_cost} + b_{n,buy\_cost} X_{j,buy\_cost} \\
&\quad + \beta_{n,obsol} \ln\left(X_{j,obsol} + 1\right) + \beta_{n,sd\_op} X_{j,sd\_op} + \beta_{n,sd\_cls} X_{j,sd\_cls} + \varepsilon_{nj}
\end{aligned}
\qquad \because \text{Eq. (13)}
$$

The utility function is composed of the deterministic part $\mathbf{V}_{nj}$, and probabilistic part $\varepsilon_{nj}$ (error term). I obtained knowledge of the consumer *n*'s preference structure by estimating $\boldsymbol{\beta}_{nj}$, which constitutes $\mathbf{V}_{nj}$. The first line after the third equality refers to the vehicle operating method, with hybrid vehicles as the baseline. Therefore, $\beta_{gasoline}$, $\beta_{diesel}$, and $\beta_{electric}$ represent preferences for each operating method when *compared to* hybrid vehicles. The second line refers to vehicle class, with economy cars as the baseline. Therefore, the estimated parameters refer to consumer preferences for each vehicle class when *compared to* economy class. The third line refers to charging infrastructure, fuel cost and vehicle purchase price. Assuming that consumer utility from an infrastructure

expansion of 20% to 60% is different from that of an infrastructure expansion of 60% to 100%, I used the log percentage value for the charging infrastructure (ln(%)). The last line represents the vehicle's characteristics as a durable good; the obsolescence and state dependence. $X_{j,obsol}$ represents vehicle *j*'s length of ownership, and the log value is used as the vehicle's depreciation is more likely to occur immediately after purchase. Finally, $X_{j,sd\_op}$ and $X_{j,sd\_class}$ are dummy variables that take the value of 1 if model *j*'s operating method or class is the same as the respondent's SQ, and zero otherwise. Therefore, $\beta_{sd\_op}$ and $\beta_{sd\_class}$ represent the additional utility that a consumer gains for vehicles with the same operating method or class as their SQ. After estimating the individual-level parameter estimate $\boldsymbol{\beta}_n$, I can calculate the choice probability of consumer *n* choosing model $j^*$ among *J* choice alternatives as equation (14). (Train, 2009).

$$P_{nj^*} = \frac{V_{nj^*}}{\sum_j \exp\left(V_{nj}\right)}, \quad j = 1, 2, \ldots, J \qquad \text{Eq. (14)}$$

#### 3.2.2.2 Choice Experiment 2

Choice Experiment 2 analyzed consumers' forward-looking behavior for future products. In general, future alternatives have better technological performance than past alternatives,

and new technology options may also benefit from better infrastructure and model availability (by product-line extension). However, these alternatives are not available yet and require some waiting time until actual purchase. Consumers' inconvenience for such waiting will increase as the required waiting time increases, and the degree of such inconvenience may be heterogeneous across individuals. Therefore, to compare future alternatives with the SQ and the alternatives currently available in the market, an additional choice experiment, Choice Experiment 2, was designed to determine the extent that consumers penalize future alternatives due to the waiting time required (which I refer to as *waiting penalty*). To be specific, the objective of Choice Experiment 2 was to calculate the trade-off for consumers when postponing their purchase in terms of purchase price. Then, I penalized the future alternatives faced by each individual using this trade-off (how much each consumer perceives future alternatives to be more expensive).

The experiment was a type of adaptive choice experiment, and the respondent's choice situation was dependent on the respondent's previous responses (Cairns & van der Pol, 2004; Gensler et al., 2012; Lim et al., 2018). Figure 5 shows an example of Choice Experiment 2.

**The following questionnaire is provided to obtain knowledge of your attitude toward postponing your vehicle purchase for a better deal. The questionnaire will be provided consecutively, depending on your previous response.**

**Q. Please choose the preferred vehicle among two options below (attributes other than purchase price and available purchase timing remain the same)**

| Vehicle attributes | Vehicle Now | Vehicle Future |
|---|---|---|
| 1. Operating method (fuel type) | Gasoline G | Gasoline G |
| 2. Availability of charging facility | 100% ■■■■■ | 100% ■■■■■ |
| 3. Vehicle class | Compact/ mid-sized | Compact/ mid-sized |
| 4. Fuel cost (KRW/km) | 75 | 75 |
| 5. Purchase price (million KRW) | 20 | 18 (10% discount) |
| 6. Available purchase timing | NOW | 1 year later |
| Choose the preferred option | O | |

**Figure 5.** Example of a choice situation in Choice Experiment 2

*Note*: the information shown in red changes as choice experiment proceeds

Before starting Choice Experiment 2, each respondent provided a response that concerned the expected specifications of their future product purchase. Specifically, in this example of consumer vehicle adoption, the operating method, class, fuel cost, and purchase price of the expected future vehicle was collected. The main experiment asked the respondent to choose one preferred option among two alternatives; “vehicle now” and “vehicle future.” The frame is similar to that of Choice Experiment 1 but with an additional attribute “6. Available purchase timing”. Throughout the experiment, the values for attributes 1 to 4 were fixed, based on each respondent’s previous response concerning their expected specification for future purchases, and only the values for attributes 5 and 6 for “vehicle future” changed. For the alternative “vehicle now,” a

vehicle can be purchased immediately without waiting. The attribute level for “vehicle now” was NOW, which meant zero years of waiting. On the other hand, the alternative “vehicle future” provided a discount of $a$% but required $b$ years of waiting before purchase.

In Choice Experiment 2, a respondent’s previous responses affected their future responses. Initially, a respondent responded to a choice situation with $a$ = 10 and $b$ = 1. If “vehicle now” was chosen, $a$ increased by 10. On the other hand, if “vehicle future” was chosen, $b$ increased by 2. Respondents continued responding until the increased value of $a$ was more than 90, or the increased value of $b$ was more than 5. Accordingly, each respondent responded to the choice experiment three to eleven times depending on their response. The survey algorithm for Choice Experiment 2 is shown in Figure 6.

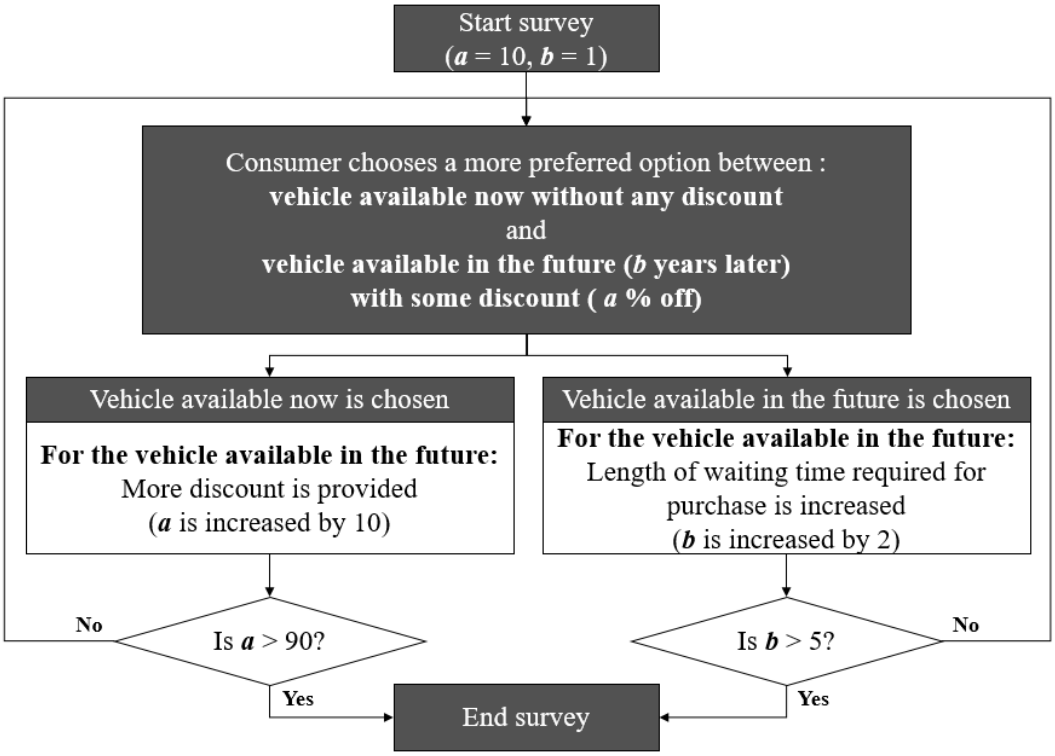



**Figure 6.** Survey algorithm for Choice Experiment 2

The results of Choice Experiment 2 reveal the amount of discount consumers expected from one, three, and five years of waiting. For example, if a respondent was not willing to wait one year for a 10% discount (they chose "vehicle now" when $a$ = 10, $b$ = 1) but was willing to wait a year for a 20% discount (they chose "vehicle future" when $a$ = 20, $b$ = 1), I can conclude that this respondent expected a 10–20% discount for one year of waiting. Let $\delta_{n,b}$ be the expected discount the consumer $n$ expected from $b$ years of waiting. Then, I naively assumed that the value was the median value of the expected discount interval (15% for the above example, $\delta_{n,1} = 0.15$). I then calculated the

magnitude of penalizing future alternatives using $\delta_{n,b}$. If the expected discount $\delta_{n,1}$ was 0.15 for respondent *n*, this can also be interpreted as a situation whereby the respondent perceived that vehicles that are available one year later are approximately 17.6% more costly (1/(1-0.15) = 1.176).

Finally, to represent waiting penalty, this dissertation calculates this additional perceived cost in monetized units using the expected price for future vehicles used in Choice Experiment 2, and converts this additional cost to utility loss using the parameter estimate for the purchase price of the vehicle. The utility loss of the consumer *n* from *b* years of waiting can be calculated as equation (15) below. For example, if the expected price for the future vehicle used in Choice Experiment 2 for the consumer $n$ was KRW 20 million, and the consumer's $\delta_{n,1}$ was 0.15, the additional cost induced from waiting a year would be KRW 3.53 million. In other words, the consumer perceived the one year later alternative as KRW 3.53 million more expensive ($WP_{n,b}$). Then, if the parameter estimate for purchase price for the consumer $n$ was -1.5 per KRW 10 million ($\beta_{n,buy\_cost}$), utility loss induced from the KRW 3.53 million is 0.53.

$$WP_{n,b} \cdot \beta_{n,buy\_cost} \quad \cdots\cdots \text{Eq. (15)}$$

where

$$WP_{n,b} = expected\_price_n \cdot \left( \frac{1}{1-\delta_{n,b}} \right)$$

For the expected discount rate of two, four, and five years of waiting, I used the linear interpolated value between $\delta_{n,1}$, $\delta_{n,3}$, and $\delta_{n,5}$ to calculate waiting penalty. By using waiting penalty, future alternatives and current alternatives (SQ and alternatives now available in the market) could be compared for the specific decision-making period. The deterministic part of the utility that the consumer *n* anticipates for $m$ model year *j* model in decision-making period $\tau$ is represented as equation (16). It should be noted that $WP_{n,(m-\tau)}$ was *calculated*, not *estimated*, for each individual from the results of Choice Experiment 2.

$$\begin{aligned} V^{\tau}_{n,(m,j)} &= \boldsymbol{\beta}'_n \mathbf{X}^{\tau}_{(m,j)} + \beta_{n,buy\_cost} X^{\tau}_{buy\_cost,(m,j)} + \beta_{n,buy\_cost} WP_{n,(m-\tau)} \\ &= \boldsymbol{\beta}'_n \mathbf{X}^{\tau}_{(m,j)} + \beta_{n,buy\_cost} \left( X^{\tau}_{buy\_cost,(m,j)} + WP_{n,(m-\tau)} \right) \end{aligned} \quad \cdots\cdots\cdots\cdots \text{Eq. (16)}$$

### 3.2.3 Modelling Intertemporal Product Adoption Behavior

In this section, I explain how the consumer's intertemporal product adoption behavior is modelled using results derived in Section 3.2.2. I suppress the subscript *n* in this section for a more concise illustration. First, the deterministic part of the utility that the consumer feels for *m* model year *j* model in decision period $\tau$ ($C^{\tau}_{(m,j)}$) can be described as in

equation (17).

$$
\begin{aligned}
V^{\tau}_{(m,j)} &= U\left(C^{\tau}_{(m,j)}\right) \\
&= \beta_{gas} X_{gas,(m,j)} + \beta_{die} X_{die,(m,j)} + \beta_{ele} X_{ele,(m,j)} \\
&\quad + \beta_{mid} X_{mid,(m,j)} + \beta_{big} X_{big,(m,j)} + \beta_{SUV} X_{SUV,(m,j)} \\
&\quad + \beta_{\inf} \ln(X_{\inf,j,\tau}) + \beta_{fuel\_cost} X_{fuel\_cost,(m,j)} + \beta_{buy\_cost} X_{buy\_cost,(m,j)} \\
&\quad + \beta_{obsol} \ln(X_{obsol,(m,j),\tau} + 1) + \beta_{sd\_op} X_{sd\_op,(m,j)} + \beta_{sd\_cls} X_{sd\_cls,(m,j)} \\
&\quad + \beta_{buy\_cost} WP_{(m-\tau)}
\end{aligned}
\quad \cdot \text{Eq. (17)}
$$

Then, replacement probability (RP) in which a new purchase (replacement) would occur to replace any product in decision period $\tau$ is given by equation (18).

$$
RP(\tau \mid sq) = \frac{\sum_{j} \exp\left(U\left(C^{\tau}_{(\tau,j)}\right)\right)}{\exp\left(U\left(C^{\tau}_{sq}\right)\right) + \sum_{t=\tau}^{\tau+k} \sum_{j} \exp\left(U\left(C^{\tau}_{(t,j)}\right)\right)} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (18)}
$$

Moreover, specific RP of replacement to a specific model $C^{\tau}_{(\tau,j^*)}$ can be described as in equation (19).

$$
RP\left(C^{\tau}_{(\tau,j^*)} \mid sq\right) = \frac{\exp\left(U\left(C^{\tau}_{(\tau,j^*)}\right)\right)}{\exp\left(U\left(C^{\tau}_{sq}\right)\right) + \sum_{t=\tau}^{t=\tau+k} \sum_{j} \exp\left(U\left(C^{\tau}_{(t,j)}\right)\right)} \quad \cdots\cdots\cdots\cdots\cdots \text{Eq. (19)}
$$

On the other hand, the maintain probability (MP) that the consumer's SQ would be maintained either by consumers choosing SQ or future alternatives can be described as in equation (20). Note that MP is the probability of choosing SQ or future alternatives among one's current choice set.

$$MP(\tau \mid sq) = \frac{\exp\left(U\left(C_{sq}^{\tau}\right)\right) + \sum_{t=\tau+1}^{\tau+k}\sum_{j}\exp\left(U\left(C_{(t,j)}^{\tau}\right)\right)}{\exp\left(U\left(C_{sq}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_{j}\exp\left(U\left(C_{(t,j)}^{\tau}\right)\right)} \quad \cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (20)}$$

It should be noted that both RP and MP are conditional for the current SQ, since SQ is directly included in one's choice set. Therefore, SQ for each decision period should be specified to simulate the future market. If only the consumer choice model is used, the agent-based model (ABM) that uses RP and MP to probabilistically decide the agent's decision can be used to determine SQ for each consumer segment. However, such an approach would not make simulation results fixed for a given market situation. Increasing the number of agents would stabilize the results, but they would still not be fixed. Thus, using the consumer model to evaluate the plan of the product-line extension model (to be introduced in Section 3.3) could be an issue.

Therefore, in this dissertation, I consider *all possible states that consumers may belong to for each time period* and calculate the probability of each state conditionally to the state probability of the previous period. The term *state* in this dissertation is identical

to the consumer's SQ in a specific time period after all purchase decisions are made. A simple example in Figure 7 can be used to explain the procedure. Consider decision making in two periods, 2018 and 2019. Let there be two new product models in 2018 and three new product models in 2019 (one newly introduced model). Initially, a consumer starts from his original SQ (initial state). Then, in 2018, a consumer may end up in three different states. One may remain with one's SQ or may purchase a new product and replace one's SQ with model (2018, A) or (2018, B). The probability for each state can be calculated using MP (remain with SQ) and RP (change one's SQ) presented in equations (19) and (20). For example, in Figure 7, a consumer may remain with his SQ with an 80% probability, replace SQ with model (2018, A) with a 15% probability, and replace SQ with model (2018, B) with a 5% probability in 2018. Then, for the forecast of the next decision period in 2019, the choice that is conditional to each possible state (SQ) in 2018 should be separately calculated. In other words, the simulation when the SQ is the original SQ, the model (2018, A), and the model (2018, B), should all be separately conducted (Figure 7 (b) to (d)). The final probability for states in 2019 should be calculated conditionally to the previous state that is now being considered. For example, if state probability for the original SQ in 2018 is 0.8, and MP is 0.7, the inherited probability to state probability for original SQ in 2019 is not 0.7, but $0.8 \times 0.7 = 0.56$. Such an approach using state probability can also be used to analyze the probability of the *adoption pathway*. That is, the probability that the consumer will retain their original SQ in 2018 but adopt vehicle (2019, A), displayed as 0.064 in Figure 7 (b).

In this dissertation, I assume that the purchase of old models are impossible (one cannot purchase 2018's model products in 2019). This means that old models can only inherit state probability from the state probability of the corresponding model in the previous decision period. On the other hand, new models now in the market can inherit probability from *all* possible states in the previous decision period. Therefore, state probability for new vehicles cannot be determined until the simulation of all possible states for the previous period are complete (Figure 7 (b) to (d)), and the RP from all previous states are condensed.

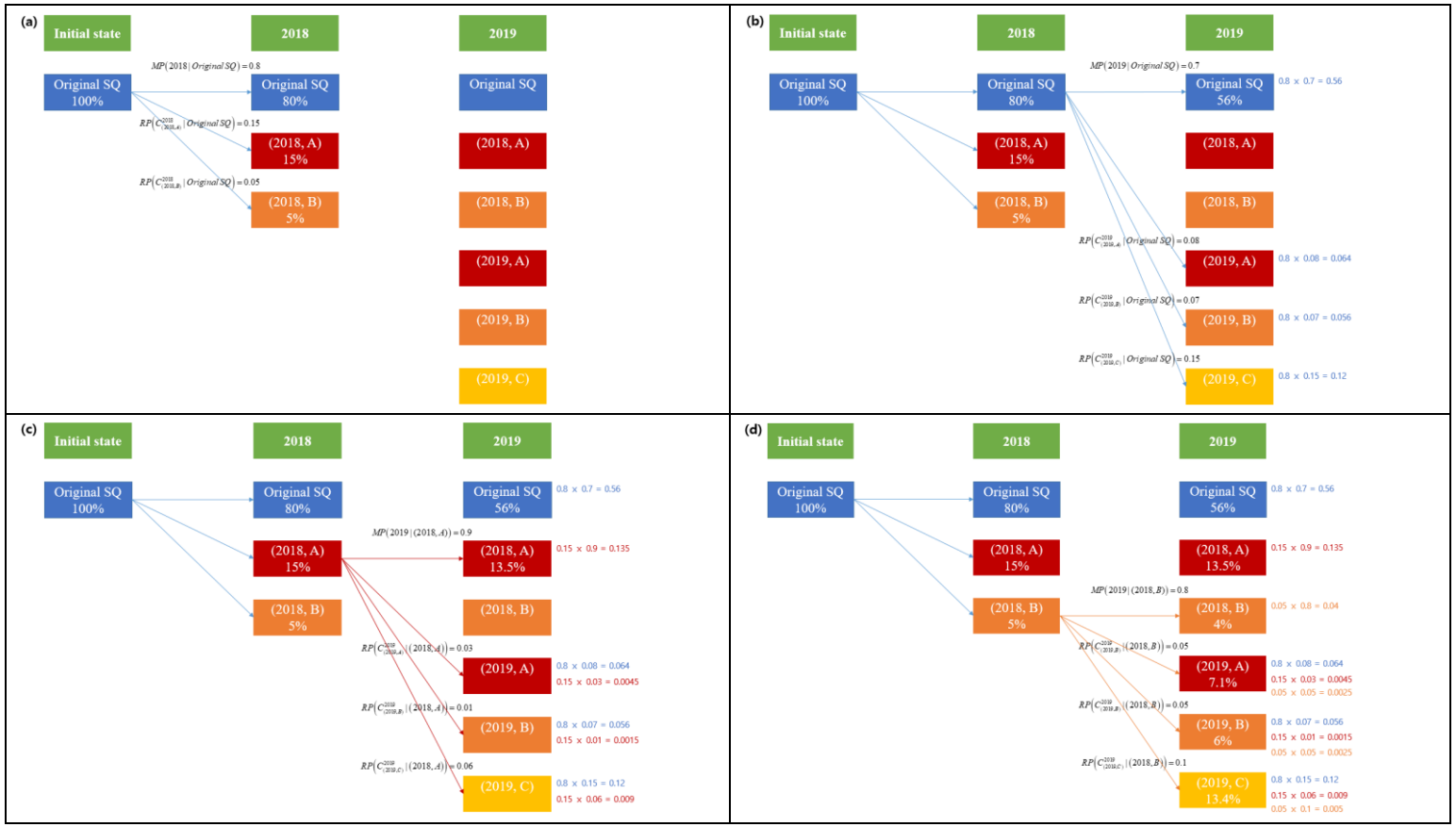



**Figure 7.** Illustration of deterministic market simulation using state probability

The method to calculate state probability can be summarized as equation (21) below. $SP\left(\left(m, j^{*}\right), \tau\right)$ refers to state probability of owning model $\left(m, j^{*}\right)$ after all decisions are taken in decision period $\tau$ (SQ is model $\left(m, j^{*}\right)$ in decision period $\tau$). The first term at the right-hand side of the equation refers to probability inherited from previous decision period ($\tau-1$) for the same model. Therefore, the state probability of owning model $\left(m, j^{*}\right)$ in $\tau-1$ ($SP\left(\left(m, j^{*}\right), \tau-1\right)$) is multiplied by the maintain probability (MP) in $\tau$ when SQ is $\left(m, j^{*}\right)$ ($MP\left(\tau \mid sq=\left(m, j^{*}\right)\right)$). If model $\left(m, j^{*}\right)$ is the newly introduced model in this period ($m=\tau$), the first term is 0 since it cannot have any state probability in previous period, which means $SP\left(\left(m, j^{*}\right), \tau-1\right)$ is 0. Next, the second term at the right-hand side of the equation refers to state probability inherited from other model states in the previous decision period by replacement. As explained in Figure 7, the probability of replacement from all previous states should be examined to determine the state probability of new models. Therefore, for all previous states (model year earlier than $\tau$), replacement probability (RP) to the specific model $\left(m, j^{*}\right)$ should be calculated and added from the previous period ($\tau-1$). If the model $\left(m, j^{*}\right)$ is not a newly introduced model in the current decision period ($m \neq \tau$), the second term at the right-hand side of the equation is 0, since I assume the purchase of old models are impossible, which means that $RP\left(C_{(m, j)}^{\tau} \mid sq=(t, k)\right)$ is 0.

$$SP\left(\left(m, j^{*}\right), \tau\right) = SP\left(\left(m, j^{*}\right), \tau - 1\right) \cdot MP\left(\tau \mid sq = \left(m, j^{*}\right)\right) + \sum_{t<\tau} \sum_{k} SP\left(\left(t, k\right), \tau - 1\right) RP\left(C^{\tau}_{(m,j)} \mid sq = \left(t, k\right)\right) \quad \cdots\cdots \text{Eq. (21)}$$

Such an approach has strength in its deterministic output and capability to analyze the consumer's *technology adoption pathway* throughout the analysis period. For example, in Figure 7, the possibility that a consumer would retain their original SQ in 2018 and purchase model (2019, C) in 2019 is 12%. However, it can be inferred that as the number of models increase and the analysis period gets longer, the computational burden would be massive. For example, if there are 50 models in the market (with no new model introductions) and the analysis period is from 2018 to 2030, then the number of possible states to be covered throughout the timeline is 3,913. Moreover, such calculations should be conducted for each respondent[12]. Therefore, the efficiency of the calculation should always be in consideration when using such method.

## 3.3 Product Line Extension Model

A key feature of the product-line extension model proposed in this dissertation is that it determines the long-term product-line extension plan that maximizes total revenue for the whole analysis period. The product-line extension model determines which models to

[12] In my empirical application, 333 consumers are considered, so the total simulation needed is 1,303,029 times (3,913 * 333).

introduce within a pre-defined pool of candidate products, and uses the consumer choice model described in Section 3.2 to evaluate the performance (total revenue for the whole analysis period) of its product-line extension plan. When the product line extension model sends its plan (future market situation) to the consumer model, the consumer model simulates consumers' intertemporal choice and then calculates the expected total revenue for the corresponding plan. The proposed model can provide model supply information, which may vary by the government's policy intervention to consumers. However, why is such information needed? It is because the product lines that consumers face have a significant impact on consumer choice and diffusion of new technology. For example, in a radical situation of no new technology products being introduced at all, new technology products cannot be diffused either. Therefore, policy makers should consider the impact of product-line extensions when designing promotion policies for new technology products. The proposed model in this dissertation can help policy makers design better policies by identifying the extent of such impact.

The proposed product-line extension model considers two aspects. The first is the consideration of cannibalization between products, and the second is the consideration of future revenue. First, the products in the same category have some level of substitutional relationship between them, so cannibalization can occur when more than one product is being sold in the same category. Therefore, cannibalization between existing models and newly introduced models should be properly considered when introducing new technology models in order to maximize the total revenue.

However, when new models are being introduced continuously, cannibalism between new models should also be considered. For example, this year's line extension may cannibalize revenue from next year's line extension. Therefore, product-line extension should not only consider "what" products will be introduced, but also consider "in what order" these products should be introduced.

Moreover, since the proposed model considers a long timeframe, the future revenue of current model introduction should be considered. For example, due to the fluctuating market situation in new technology diffusion phases, a model that is seen as attractive now could be seen as less attractive in the future, and vice versa. However, when calculating the total revenue, future revenue should be discounted with some fixed rate since early realization of revenue is preferred.

To summarize, when deriving a future model introduction plan, the product-line extension model considers the cannibalization between existing products and new products; cannibalization between new products; the future revenue of newly introduced models; and the timing of revenue realization. The product-line extension model in this dissertation can incorporate all these points by considering the total revenue for the whole analysis period as its determinant. Therefore, a more reasonable market situation where consumers make their choice could be derived (compared to simply fixing a certain market situation, regardless of policy intervention).

Think about a comparable greedy method of product-line extension, where the product line is extended by maximizing the expected revenue for each time period

sequentially. In this case, the cannibalization between existing products and new products being introduced for the corresponding period can be considered. However, cannibalization between new products being introduced in a different time period cannot be considered. Moreover, future revenue and the timing of revenue realization also cannot be considered because the determinant of decision is the only revenue of the corresponding period. The difference between the greedy method and the proposed method is summarized in Table 4.

**Table 4.** Comparison of greedy and proposed product line extension

<table>
<tr><th></th><th>Greedy<br>product line extension<br>method</th><th>Proposed<br>product line extension<br>method</th></tr>
<tr><td>Overview</td><td>Plan for each time period is decided sequentially for the whole analysis period</td><td>Plan for the whole analysis period is decided at once</td></tr>
<tr><td>Determinant of planning</td><td>Revenue for the corresponding time period</td><td>Total revenue for the whole analysis period</td></tr>
<tr><td>Cannibalization between existing models and new models</td><td colspan="2">Considered</td></tr>
<tr><td>Cannibalization between new models</td><td rowspan="2">Not considered</td><td rowspan="3">Considered</td></tr>
<tr><td>Change in future policy/market situation</td></tr>
<tr><td>Computational effort required</td><td>Low</td><td>High<br>(require optimization)</td></tr>
</table>

However, the proposed method will typically have too many cases to consider them all, as the number of candidate models and length of periods in which to consider model introduction increases. Therefore, I use a widely adopted discrete simulation optimization method (nested partitions (NP) method) to efficiently derive the global optimum among numerous possible cases. The application of the NP method will be explained in detail in Section 3.3.2.

### 3.3.1 Introduction of New Models

In the product-line extension model, some new models are introduced for some part of the whole analysis period from a pre-defined candidate pool that maximizes the total revenue for the whole analysis period. In the optimization process, the number of models to be introduced for each period and the pool of candidate product models are exogenously given. Therefore, the decision to be made is which model to introduce in what time period among the candidate models in order to maximize the total revenue for the whole analysis period.

The product-line extension model uses the consumer model explained in Section 3.2 to evaluate its plan. The decision of product-line extension directly influences consumers' intertemporal choice in the market. To be specific, it influences the choice set that consumers face in each time period. Therefore, RP and MP derived in Section 3.2.3 can be redefined as follows. First, when the product line is extended, RP in period $\tau$ can

be redefined as equation (22).

$$RP(\tau \mid sq) = \frac{\sum_j \exp\left(U\left(C^{\tau}_{(\tau,j)}\right)\right) + \sum_i \exp\left(U\left(C^{\tau}_{(\tau,i)}\right) \cdot I(\tau,i)\right)}{\exp\left(U\left(C^{\tau}_{sq}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_j \exp\left(U\left(C^{\tau}_{(t,j)}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_i \exp\left(U\left(C^{\tau}_{(t,i)}\right) \cdot I(t,i)\right)} \quad \cdot \text{Eq. (22)}$$

The difference between equation (22) and equation (18) is that one more term is added to both the numerator and denominator. Here, *j* is the index for existing products, and *i* is the index for candidate products that may be newly introduced. $I(t,i)$ is an indicator that takes the value of 1 if model *i* is introduced in period *t*, and 0 otherwise. Therefore, only the models that are actually introduced are included in the consumer's choice sets among the candidate products. Next, RP for the specific model $C^{\tau}_{(\tau,j^*)}$ is as equation (23). In the equation, $j^*$ can either be the existing product *j* or the newly introduced product *i*.

$$RP\left(C^{\tau}_{(\tau,j)} \mid sq\right) = \frac{\exp\left(U\left(C^{\tau}_{(\tau,j^*)}\right)\right)}{\exp\left(U\left(C^{\tau}_{sq}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_j \exp\left(U\left(C^{\tau}_{(t,j)}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_i \exp\left(U\left(C^{\tau}_{(t,i)}\right) \cdot I(t,i)\right)} \quad \cdot \text{Eq. (23)}$$

Finally, MP in decision period $\tau$ with a new model introduction can be explained as equation (24).

$$MP(\tau \mid sq) = \frac{\exp\left(U\left(C_{sq}^{\tau}\right)\right) + \sum_{t=\tau+1}^{\tau+k}\sum_{j}\exp\left(U\left(C_{(t,j)}^{\tau}\right)\right) + \sum_{t=\tau+1}^{\tau+k}\sum_{i}\exp\left(U\left(C_{(t,i)}^{\tau}\right)\cdot I(t,i)\right)}{\exp\left(U\left(C_{sq}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_{j}\exp\left(U\left(C_{(t,j)}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_{i}\exp\left(U\left(C_{(t,i)}^{\tau}\right)\cdot I(t,i)\right)} \quad \cdot\cdot \text{Eq. (24)}$$

Using the new RP and MP, the objective of product-line extension is to maximize total revenue for the whole analysis period. For this, the revenue for each time period should be first defined. The revenue for period $\tau$ can be calculated by multiplying the sales probability of each new model in period $\tau$ (products with model year $\tau$) with its market price ($PPRICE_{(\tau,j)}$). The sales probability in period $\tau$ should be basically summed up after calculating all possible states from the previous period. However, as explained in Section 3.2.3, since new products cannot be sold in the previous period (since they are not introduced yet) and thus cannot inherit SP from the previous self, SP for new products (model year = decision period = $\tau$) is directly the sales probability of new products in decision period $\tau$. Therefore, the revenue for the specific period $\tau$ can be written as equation (25).

$$REV(\tau) = \sum_{j} SP\left((\tau, j), \tau\right)\cdot\left(PPRICE_{(\tau,j)}\right) \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (25)}$$

However, USD 100 of revenue this year and USD 100 of revenue next year have different meanings. Therefore, this dissertation assumes that future revenue is discounted with a discount factor $\delta$ [13] when calculating the total revenue. Therefore, the total revenue that should be maximized for the whole analysis period can be expressed as equation (26).

$$TOTAL\_REVENUE = \sum_{\tau=T_{start}}^{T_{end}} \delta^{\tau-T_{start}} REV(\tau) \quad \cdots\cdots \text{Eq. (26)}$$

Finally, objective functions and constraints for the optimization are summarized in equation (27). The first to fourth constraints are revenue, SP, MP, and RP as defined in equations (21) to (25) to derive total revenue. $\sum_i I(t,i) = p(\tau)$ is the constraint of the cumulative number of models that should be introduced in period $\tau$. Finally, $I(\tau,i) \le I(\tau+1,i)$ means that the model, once introduced to the market, should be continuously introduced in the market with the new model year. In other words, there is no discontinuance of once introduced models.

[13] In the empirical application of this dissertation, I assumed $\delta = 0.95$.

$$\max_{I(i,t)} \sum_{\tau=T_{start}}^{T_{end}} \delta^{\tau-T_{start}} REV(\tau) \quad \cdots\cdots \text{Eq. (27)}$$

$$s.t.\ \ REV(\tau) = \sum_j SP((\tau, j), \tau) \cdot \left(PPRICE_{(\tau,j)}\right)$$

$$SP\left(\left(m, j^*\right), \tau\right) = SP\left(\left(m, j^*\right), \tau - 1\right) \cdot MP\left(\tau \mid sq = \left(m, j^*\right)\right)$$

$$+ \sum_{t<\tau} \sum_k SP((t,k), \tau - 1) RP\left(C^{\tau}_{(m,j)} \mid sq = (t,k)\right)$$

$$MP(\tau \mid sq) = \frac{\exp\left(U\left(C^{\tau}_{sq}\right)\right) + \sum_{t=\tau+1}^{\tau+k} \sum_j \exp\left(U\left(C^{\tau}_{(t,j)}\right)\right) + \sum_{t=\tau+1}^{\tau+k} \sum_i \exp\left(U\left(C^{\tau}_{(t,i)}\right) \cdot I(t,i)\right)}{\exp\left(U\left(C^{\tau}_{sq}\right)\right) + \sum_{t=\tau}^{\tau+k} \sum_j \exp\left(U\left(C^{\tau}_{(t,j)}\right)\right) + \sum_{t=\tau}^{\tau+k} \sum_i \exp\left(U\left(C^{\tau}_{(t,i)}\right) \cdot I(t,i)\right)}$$

$$RP\left(C^{\tau}_{(\tau,j)} \mid sq\right) = \frac{\exp\left(U\left(C^{\tau}_{(\tau,j^*)}\right)\right)}{\exp\left(U\left(C^{\tau}_{sq}\right)\right) + \sum_{t=\tau}^{t=\tau+k} \sum_j \exp\left(U\left(C^{\tau}_{(t,j)}\right)\right) + \sum_{t=\tau}^{\tau+k} \sum_i \exp\left(U\left(C^{\tau}_{(t,i)}\right) \cdot I(t,i)\right)}$$

$$\sum_i I(\tau, i) = p(\tau)$$

$$I(\tau, i) \le I(\tau + 1, i)$$

### 3.3.2 Nested Partitions Algorithm

The possible number of cases in the product-line extension problem can grow exponentially as the number of candidate models and number of models to be introduced in each period change. For example, when 42 candidate models exist and two models should be introduced annually for seven years (which is the case for the empirical analysis in this dissertation), the possible number of cases is ${}_{42}C_2 \times {}_{40}C_2 \times \ldots \times {}_{30}C_2 = 3.6 \times 10^{19}$. Moreover, the proposed consumer model used to

analyze performance of the product-line extension plan has a massive computational burden, since it should simulate consumer decisions for all possible states for the whole analysis period for each individual. In this situation, in order to derive an optimal solution within a reasonable time, this dissertation uses a discrete simulation optimization method (nested partitions (NP) method). The NP method can resolve problems that are hard to solve with traditional mathematical programming methods by using simulation approaches. The key feature of this method is to use more computational efforts to more promising parts in the solution space, where global optimum is likely to exist (Shi & Olafsson, 2009).

The NP algorithm divides the feasible solution space into some small number of promising regions where the algorithm suspects the optimal solution may be, and a single complementary region which represents parts other than promising regions. The algorithm finds the optimal solution by narrowing down the promising region until it is a singleton (only one feasible solution). The NP algorithm theoretically converges to the global optimum, as the algorithm keeps sampling solution from the complementary region and backtracks to the past state when the algorithm is malfunctioning. Therefore, the NP algorithm is widely applied in various discrete optimization problems such as facility location (Choi & Koo, 2018; Xia et al., 2010), resource allocation (Liu, Xiao, & Tian, 2016; Wu, Wei, Guan, & Shi, 2012), and job shop scheduling (Yau & Shi, 2009).

The pure NP algorithm consists of four main parts: partitioning, random sampling, calculating the promising index, and move. In partitioning, the structure of how

the promising region is divided as the algorithm proceeds is defined. In random sampling, a pre-defined number of solutions are randomly drawn from each region and the performance value of each solution is computed. In calculating the promising index, the promising index for each region is determined by the maximum performance value of solutions for each region. Finally, for move, the action (whether to narrow down the promising region or to backtrack) is chosen according to the promising index of each region. A detailed description of the pure NP algorithm can be found in Shi & Olafsson (2009).

In each step of the NP algorithm, the partitioning component is most frequently modified to enhance the performance of the algorithm, as the partitioning defines which types of feasible solutions are *close together*. The sampling component is also usually modified to enhance performance by adopting various types of biased sampling methods. In this dissertation, two strategies were applied to enhance the performance of the algorithm. The first was to order models by expected revenue from a single model extension case, and partition solution space by whether the model was included from the higher-ranking models. The second was to use biased probability to decide whether the model was included in the product-line extension plan by the rank of model in the single introduction case. An illustration of the NP algorithm used in this dissertation is provided in Figure 8 and Figure 9.

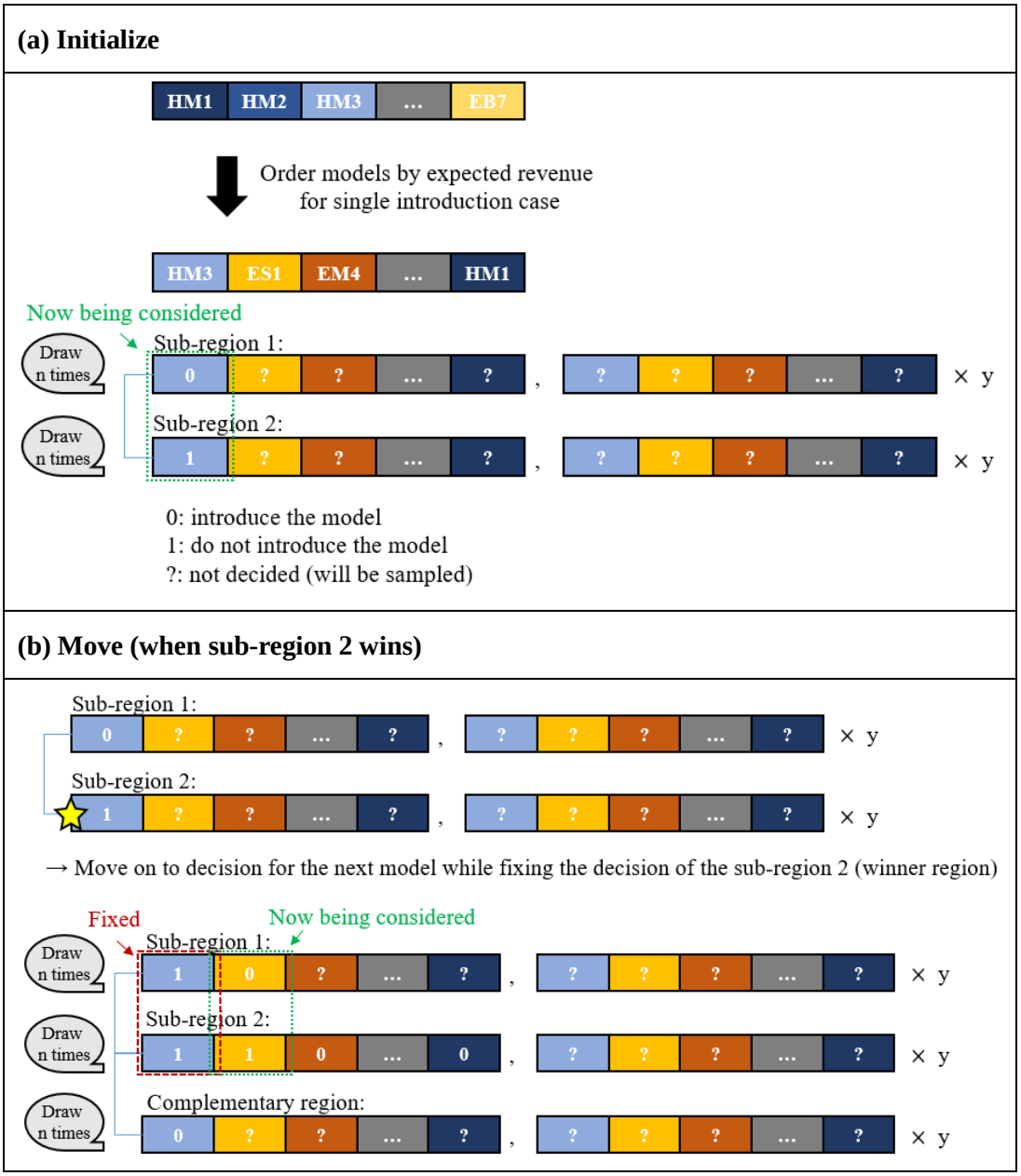



**Figure 8.** NP algorithm for the product line extension model: initialize and move

In Figure 8, each box represents the product model, and each bar that consists of

boxes represents the model introduction for each time period. First, candidate models were ordered by the expected revenue for the single introduction case. Then, starting from higher-ranking models, regions were divided by introducing (1) or not introducing (0) the corresponding model. Next, *n* solutions were sampled from each region. Sampling solutions is filling [?] boxes in Figure 8 with 1 (introduce) or 0 (not introduced), given constraints about the number of models to be introduced for each year. When deciding which model to be introduced (which box to have, 1), I used biased sampling probability based on the rank of the model. The probability is inversely proportional to the rank of the model. To be specific, the probability that the q-th model is drawn among the total Q models is $(Q-q+1)/\sum_{r=1}^{Q} r$. The reason behind such partitioning and biased sampling is because models with a higher expected revenue in the single introduction case are likely to be included in the whole product-line extension plan.

After the sampling solutions and the calculating of the promising index of each region was done, the next promising region was determined as the region with the highest promising index. Then, the decision of the corresponding model was fixed (whether to introduce the corresponding model), and the same process was repeated for the next rank model. Such processes were continued until the required number of models were introduced for the corresponding year. For example, Figure 8 (b) shows that when the sub-region 2 (introduced first model) was selected as the next promising region, the decision of introducing the first model was fixed and the former sub-region 2 is now the new promising region which is again divided by the introduction of the second model.

One point to be noticed here is that except for the initial case where the whole solution space is the promising region, there is another region, the complementary region, where *n* solutions are also drawn. The complementary region is defined as the mutually exclusive space from other promising sub-regions. Since the complementary region should be mutually exclusive with promising regions, the decision for the fixed models should be different with those of the promising region. For example, since the fixed model is to introduce the first model, the complementary region should only include plans that do not introduce the first model.

However, the proposed product-line extension problem at hand is a multi-period problem and the model introduction of different time periods affect the other's revenue. Therefore, not only should the models be introduced in the corresponding period (now being considered), but those to be introduced in the future periods should also be drawn. In this dissertation, introduction plan for future time periods was also sampled with biased probability by rank, while model introduction for the previous time period is fixed.

How, then, does the algorithm proceed after the model introduction plan for the corresponding period is done? Figure 9 can help explain the procedure. If the required number of models were introduced, the algorithm fixes the decision for the corresponding period and the optimization process proceeds to the next period. However, when the model introduction is fixed for the previous time period, the fixed models may significantly influence the expected revenue of the remaining models by cannibalization. Therefore, the suggested algorithm re-orders the candidate models by recalculating the

expected revenue, while fixing the model introduction of the previous period (Figure 9 (c)). With this new order, the previous optimization process is repeated until the final solution is derived.

Finally, if the performance index of the complementary region turns out to be the highest in the optimization process, the algorithm will backtrack to its initial state. Such backtracking is an important aspect in the NP algorithm, which can derive the global optimum and the correct malfunctioning of the algorithm.

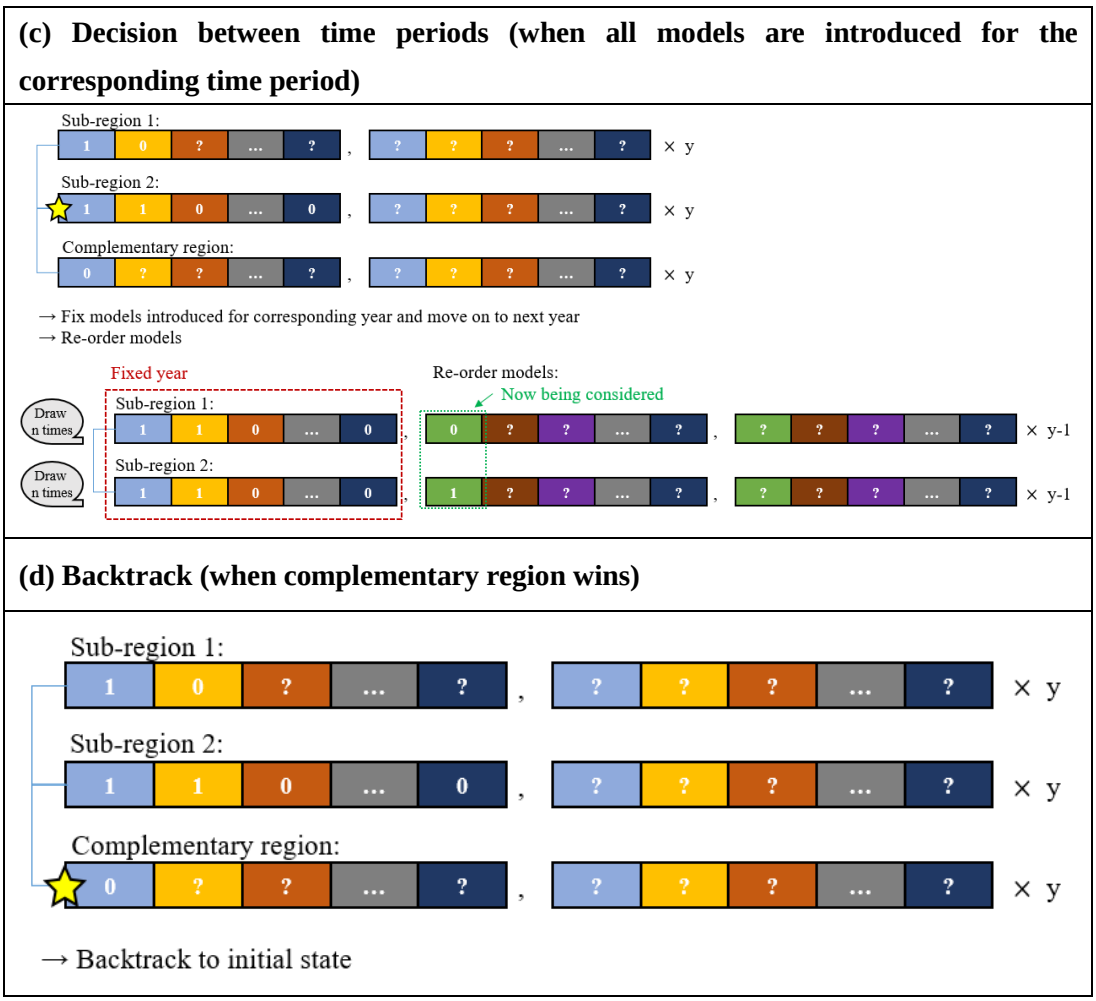



**Figure 9.** NP algorithm for the product line extension model: decision between time periods and backtrack

An explanation of the algorithm is now presented mathematically. The notations for this description follows those of Shi & Olafsson (2009). In this algorithm, *k* represents the promising region that is divided according to whether the k-th ranked model is in the

optimal model introduction set for the corresponding year. Therefore, if the current promising region is $\sigma(k)$, the inclusion decision of model 1 to k-1 is already determined. However, this can change by the process of backtracking. The initial value of k is 1.

1. Partitioning: the candidate models are aligned according to their rank in expected revenue for the single introduction problem, and the current promising region $\sigma(k)$ is divided into two sub-regions $\sigma_1(k)$ and $\sigma_2(k)$ by whether to include the k-th model in the product-line extension plan. All other regions that are not a promising region are defined as a complementary region $\sigma_3(k)$.

   A. In the first iteration, since the whole feasible solution is the promising region, the complementary region $\sigma_3(k)$ does not exist.

2. Weighted sampling: for each region *j*, $N$ number of product-line extension plans are drawn as:

$$x_1^j, x_x^j, \ldots, x_N^j, \quad j = 1, 2, 3$$

   where $x$ can be interpreted as a set of $I(t,i)$ in equation (27). Here, the sampling is not random and the weighted sampling method is used. The

probability that each model is drawn for the location set is proportional to the reciprocal of the model's ranking for the single introduction problem. For example, if there are 10 candidate models in total, the drawing probability for the first rank model in the single introduction problem is 10/55. This weighted probability makes sense, since the model with the highest performance for the single introduction problem is also likely to be included in the whole product-line extension plan.

Next, the performance evaluation function $f(\cdot)$ is used to calculate the performance value of each draw (introduction plan). $f(\cdot)$ here can be interpreted as total revenue in equation (27).

$$f\left(x_1^j\right), f\left(x_2^j\right), \ldots, f\left(x_N^j\right), \quad j = 1, 2, 3$$

The results are saved in the bank of draws and thus, if a duplicate draw occurs, that draw is not calculated.

3. Calculating promising index: defining the highest performance value of each region as its promising index $PI\left(\sigma_j\right)$.

$$PI\left(\sigma_j\right) = \max_{i=1,2,\ldots,N_j} f\left(x_i^j\right), \quad j = 1, 2, 3$$

4. Move: compare the promising index of each region and determine which region has the best promising index in the current iteration.

$$\hat{j}_k \in \arg\max_{j=1,2,3} PI\left(\sigma_j\right), \quad j=1,2,3$$

Next, compare the best performance value of the current iteration and the best performance value of the results stored in the bank.

A. If the best performance value in the bank is not better than the best performance value in the current iteration.

   i. If $\hat{j}_k = 1 \; or \; 2$ , change the current promising region considering $\hat{j}_k$.

$$\sigma\left(k+1\right) = \sigma_{\hat{j}_k}\left(k\right)$$

   ii. If $\hat{j}_k = 3$, backtrack to the initial promising region.

$$\sigma\left(k+1\right) = \sigma\left(1\right)$$

B. If the best performance value in the bank is better than the best performance value in the current iteration.

   iii. If the best case in the bank belongs to one of the promising sub-regions, change the current promising region considering the best case in the bank.

$$\sigma\left(k+1\right) = \sigma_{\hat{j}_{bank}}\left(k\right)$$

$\hat{j}_{bank} = 1$ if the best case in the bank belongs to $\sigma_1(k)$, and

$\hat{j}_{bank} = 2$ if the best case in the bank belongs to $\sigma_2(k)$.

C. If the best case belongs to the complementary region, the algorithm backtracks to the initial state (the whole solution space is the promising region).

$$\sigma(k+1) = \sigma(1)$$

5. Repeat stages (2) to (4) until the required number of models are introduced for the corresponding time period.
6. Repeat stages (1) to (5) until the promising region is a singleton.

### 3.3.3 Extensions on Duopoly Market

This section explains the extension of the product-line extension model when competition exists in the market. To be specific, I add a new entrant that introduces product models to the market to maximize its revenue. The biggest difference between the new entrant and the incumbent is that the latter should consider massive cannibalization between new technology products and existing products, but the former does not have to consider such cannibalization. The objective of this extension is to observe the response of the incumbent by the entrance of the new entrant, and how the model introduction plan between the two players are determined. When the new entrant enters the market, the RP

and MP are changed as follows. As the basic monopolistic product-line extension model was introduced in Section 3.3.1, the key difference now is that the newly introduced product model, by the new entrant, is also included in the consumer's choice set. First, the RP can be written as equation (28).

$$RP(\tau \mid sq) = \frac{RPS}{CS} \quad \cdots\cdots \text{Eq. (28)}$$

where

$$RPS = \sum_{t=\tau}^{\tau}\sum_{j}\exp\left(U\left(C_{(t,j)}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau}\sum_{i}\exp\left(U\left(C_{(t,i)}^{\tau}\right)\cdot I(t,i)\right)$$
$$+\sum_{t=\tau}^{\tau}\sum_{l}\exp\left(U\left(C_{(t,l)}^{\tau}\right)\cdot I(t,l)\right)$$
$$CS = \exp\left(U\left(C_{sq}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_{j}\exp\left(U\left(C_{(t,j)}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_{i}\exp\left(U\left(C_{(t,i)}^{\tau}\right)\cdot I(t,i)\right)$$
$$+\sum_{t=\tau}^{\tau+k}\sum_{l}\exp\left(U\left(C_{(t,l)}^{\tau}\right)\cdot I(t,l)\right)$$

Here, $l$ refers to the candidate models that the new entrant can introduce, and $I(t,l)$ is an indicator that takes the value of 1 if model $l$ is introduced in period $t$, and 0 otherwise. Likewise, the RP for the specific model $C_{(\tau,j)}^{\tau}$ can be calculated as equation (29). Here, $j^*$ can either be one of the existing models $j$, the incumbent's new model $i$, or the new entrant's new model $l$.

$$RP\left(C_{(\tau,j)}^{\tau} \mid sq\right) = \frac{\exp\left(U\left(C_{(\tau,j^*)}^{\tau}\right)\right)}{CS} \quad \cdots\cdots \text{Eq. (29)}$$

where

$$CS = \exp\left(U\left(C_{sq}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_{j}\exp\left(U\left(C_{(t,j)}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_{i}\exp\left(U\left(C_{(t,i)}^{\tau}\right)\cdot I\left(t,i\right)\right)$$
$$+\sum_{t=\tau}^{\tau+k}\sum_{l}\exp\left(U\left(C_{(t,l)}^{\tau}\right)\cdot I\left(t,l\right)\right)$$

Finally, the MP can be written as equation (30).

$$MP\left(\tau \mid sq\right) = \frac{MPS}{CS} \quad \cdots\cdots \text{Eq. (30)}$$

where

$$MPS = \exp\left(U\left(C_{sq}^{\tau}\right)\right) + \sum_{t=\tau+1}^{\tau+k}\sum_{j}\exp\left(U\left(C_{(t,j)}^{\tau}\right)\right) + \sum_{t=\tau+1}^{\tau+k}\sum_{i}\exp\left(U\left(C_{(t,i)}^{\tau}\right)\cdot I\left(t,i\right)\right)$$
$$+\sum_{t=\tau+1}^{\tau+k}\sum_{l}\exp\left(U\left(C_{(t,l)}^{\tau}\right)\cdot I\left(t,l\right)\right)$$
$$CS = \exp\left(U\left(C_{sq}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_{j}\exp\left(U\left(C_{(t,j)}^{\tau}\right)\right) + \sum_{t=\tau}^{\tau+k}\sum_{i}\exp\left(U\left(C_{(t,i)}^{\tau}\right)\cdot I\left(t,i\right)\right)$$
$$+\sum_{t=\tau}^{\tau+k}\sum_{l}\exp\left(U\left(C_{(t,l)}^{\tau}\right)\cdot I\left(t,l\right)\right)$$

Next, as the product line of both the incumbent and new entrant is different, their revenue calculation is also different. In other words, the revenue of the incumbent comes from existing models (*j*) and the newly introduced model by itself (*i*), but the revenue of the new entrant only comes from the newly introduced model by itself (*l*). Mathematically,

the revenue of the incumbent for year $\tau$ can be expressed as equation (31).

$$REV\_INC(\tau) = \sum_j SP((\tau, j), \tau) \cdot \left(PPRICE_{(\tau, j)}\right) + \sum_i SP((\tau, i), \tau) \cdot \left(PPRICE_{(\tau, i)}\right) \quad \cdots\cdots \text{Eq. (31)}$$

Note that the introduction of *i* is not explicitly expressed in equation (31). This is because the SP for models not introduced is 0. Likewise, the revenue of the new entrant for year $\tau$ can be expressed as equation (32).

$$REV\_NE(\tau) = \sum_l SP((\tau, l), \tau) \cdot \left(PPRICE_{(\tau, l)}\right) \quad \cdots\cdots \text{Eq. (32)}$$

In other words, the revenue of the incumbent and new entrant is mutually exclusive, and each decision directly influences the revenue of the other. In this dissertation, I find the final product-line extension plan of these players by repeating the optimization for each player, while fixing the optimal plan of the other player. The process can be summarized below:

1) While fixing the model introduction plan of the *incumbent*, the *new entrant* determines an optimal model introduction plan that maximize its revenue.
2) While fixing the model introduction plan of the *new entrant*, the *incumbent*

cancels its previous model introduction plan and determines a new optimal model introduction plan to maximize its revenue.

3) While fixing the new model introduction plan of the *incumbent*, the *new entrant* cancels its previous model introduction plan and determines a new optimal model introduction plan to maximize its revenue.

4) Repeat stage (2) and (3) until one of the player's optimal plans does not change in response to the other player.

# Chapter 4. Empirical Analysis
# : Diffusion of Electric Vehicles in South Korea

## 4.1 Background for Empirical Analysis

In this section, the empirical applications of the model proposed in Chapter 3 are conducted. To be specific, I apply the model to the case of diffusion of EVs; hybrid HEVs and BEVs in South Korea. The case of EV diffusion is appropriate for empirical applications of the proposed model, since vehicles are high-technology durable goods with long duration and high cost, which implies that consumers are likely to act strategically when purchasing. Moreover, considering heterogeneous preference in the consumer's vehicle choice, supplying appropriate product models can have a significant impact on new technology diffusion (Choi et al., 2018; Higgins et al., 2017). Finally, analyzing the impact of government policy intervention in the vehicle market is of great interest for various stakeholders due to the automotive industry's massive impact on the national/regional economy, energy use, and environment.

Since the proposed model aims to simulate consumers' intertemporal choice considering product-line extension over a long time period, appropriate settings for long-term analysis should be constructed. For example, the points that should be assumed are how each of the vehicle's technology may develop over time, how charging infrastructure for EVs may expand, and which vehicle models exist in the market. Section 4.1 provides information about such settings.

In Section 4.1.1, I explain the vehicle technologies to be considered in this empirical analysis, and provide assumptions about specific vehicle models in my simulation framework. Section 4.1.2 presents information regarding how technological advancements for each vehicle's technology is assumed, and how charging infrastructure for EVs expands by time. Section 4.1.3 provides information about policy scenarios that will be analyzed throughout my empirical analysis. Finally, Section 4.1.4 provides an outline for the empirical analysis to be conducted throughout Chapter 4.

### 4.1.1 Vehicle Technologies and Models Considered

In my empirical analysis for the diffusion of EVs in South Korea, four vehicle technologies are considered:

- ✓ *Gasoline internal combustion engine vehicles (gasoline ICEVs)*, which use gasoline internal combustion engines as their powertrain and requires refueling with gasoline.
- ✓ *Diesel internal combustion engine vehicles (diesel ICEVs)*, which use diesel internal combustion engines as their powertrain and requires refueling with diesel.
- ✓ *Hybrid electric vehicles (HEVs)*, which use both a gasoline internal combustion engine and electric motor as their powertrain but requires refueling only with gasoline. An electric motor uses the electricity charge from driving to improve

fuel efficiency, and no exogenous recharging is required.

- ✓ *Battery electric vehicles (BEVs)*, which use electric motors as their powertrain and requires recharging of electricity.

In some parts of the world, PHEVs have a significant market share in the vehicle market. However, PHEVs are excluded from my analysis after considering the current market situation and government policy of South Korea (see Section 3.2.2.1 for a more detailed explanation).

In the following, I explain vehicle models that are assumed to exist in my simulation framework. Previous studies usually define a single representative vehicle by vehicle type of interest (Byun et al., 2018; Choi et al., 2018; Qian & Soopramanien, 2015), or choose a specific representative model for each vehicle type of interest (Helveston et al., 2015). However, such an approach is valid only if the availability of each vehicle type is the same, or at least similar (Wolinetz & Axsen, 2017). However, the model availabilities of BEVs and HEVs are currently limited in comparison to ICEVs, and some vehicle classes do not have any BEV or HEV models at all. In this case, consumers may not buy (or are less likely to buy) BEV or HEV models because of the limited choice. Thus, the market share of these vehicles may be overestimated if such aspects are not considered. Hoen & Koetse (2014) considered that the number of brands/models is one of the key attributes. However, because the number of key attributes that can be assumed in choice experiments are limited, such an approach is quite costly.

Moreover, by only considering the number of models themselves cannot incorporate the complex impact of preference heterogeneity and heterogeneous models in new product adoption.

Therefore, in this study, I incorporate multiple vehicle models available for purchase for each vehicle type based on the current market situation of South Korea (Woo, 2016). However, since there are too many vehicle models in the market, I have selected 50 of the top selling domestic vehicle models in 2018[14]. The operating method and vehicle class that these 50 vehicles belong to are illustrated in Table 5. As one can observe, the model availability between the different vehicle types is quite different. Gasoline ICEVs consist of more than half of the total number of models (28), followed by diesel ICEVs (13). HEVs and BEVs had only a small number of models (6 and 3 each) compared to ICEVs. Moreover, there were no full-size BEVs in the market.

**Table 5.** Operating method and class of existing vehicle models considered for the simulation analysis

| | Economy | Compact/ mid-size | Full-size | SUV | Total |
|---|---|---|---|---|---|
| Gasoline | 3 | 12 | 5 | 8 | 28 |
| Diesel | 0 | 2 | 1 | 10 | 13 |
| Hybrid | 0 | 3 | 2 | 1 | 6 |
| Electric | 0 | 1 | 0 | 2 | 3 |
| Total | 3 | 18 | 8 | 21 | 50 |

[14] These vehicles are sold more than 2,900 units in 2018

However, the number of models for HEVs and BEVs are expected to increase as leading global auto manufacturers announced that they will expand the number of such models (CNBC, 2017; Volkswagen AG, 2018) to cope with strict environmental regulations and the fluctuating market situation. In my model, the product line for HEVs and BEVs is extended considering present and future market/policy situations and consumer demand. Therefore, I constructed a candidate pool of EVs (both HEVs and BEVs) using current market data. To be specific, I constructed a pool of 42 vehicles, with seven models each for six vehicle types[15]. The seven models differ by their price and fuel economy, with the more expensive, high-end vehicle models having better fuel efficiency within vehicle type.

The mean price and fuel economy of each vehicle type was assumed using price and fuel economy differences between the same or similar models with a gasoline operating method[16], and the range of model variation was assumed using the standard deviation of gasoline fuel vehicles for each vehicle class within a reasonable range. By using a mean and standard deviation value for each vehicle type, I calculated the mean, minimum, and maximum value ($\pm 1\sigma$) for each vehicle type. For the labeling of each of the vehicle models, I use the first word's character to represent the operating method of the vehicle (H: hybrid, E: electric), and the second character to represent the vehicle class

[15] Two operating methods (hybrid, electric) and three vehicle classes (compact/mid-size, full-size, and SUV). Economy class is excluded since it is hard to cope with strict regulations in its size if a hybrid or electric operating method is used.

[16] For example, the price difference between Hyundai Kona Electric and Kona Gasoline was used to get the price difference between electric SUVs and gasoline SUVs.

(M: compact/mid-size, F: full-size, S: SUV), and the final number to represent the position of the vehicle, with (1) as the most expensive and fuel efficient high-end model, and (7) as the cheapest and fuel-inefficient low-end model. For example, “HM4” represents the average vehicle within the hybrid compact/mid-size vehicle, and “ES7” represents the cheapest and most fuel-inefficient low-end vehicle within battery electric SUVs. The specifications of vehicles with the numbers (2), (3), (5), and (6) are determined by their linear interpolation between the mean of (4), the most high-end (1), and the most low-end (7) models. The specifications of these candidate vehicles are summarized in Table 6.

**Table 6.** Summary of specifications of candidate vehicles

| | | Price (million KRW) | Fuel economy [a] | Fuel cost (KRW/km) |
|---|---|---|---|---|
| HEVs | Compact/mid-size | 30.27 (37.54, 23.01) [b] | 18.01 (19.81, 16.21) | 87.79 (79.81, 97.54) |
| | Full-size | 50.39 (70.07, 37.73) | 13.69 (15.06, 12.32) | 115.5 (105.00, 128.33) |
| | SUV | 28.13 (32.34, 23.91) | 16.12 (17.73, 14.51) | 98.12 (89.20, 109.02) |
| BEVs | Compact/mid-size | 49.27 (57.16, 41.39) | 5.85 (6.43, 5.26) | 53.54 (48.67, 59.48) |
| | Full-size | 72.9 (87.48, 58.32) | 4.45 (4.89, 4.00) | 70.43 (64.03, 78.26) |
| | SUV | 51.13 (56.24, 46.01) | 5.23 (5.76, 4.71) | 59.83 (54.39, 66.48) |

[a] unit is km/L for hybrid electric vehicles (HEVs), and km/kWh for battery electric vehicles (BEVs)

[b] the first and second element inside the parenthesis are the minimum and maximum value among heterogeneous models, respectively

### 4.1.2 Technological Advances and Infrastructure

Although I have assumed the specifications of models that (may) exist in the market in Section 4.1.1, the fuel cost and purchase price data suggested are only for the base year (2018). However, vehicle fuel economy and purchase prices are expected to change in the future due to ongoing technological innovation. In this study, I used the projection of the Energy Information Administration (EIA, 2015) to determine future vehicles' fuel economy and purchase price change by vehicle operating method. First, the fuel economy

of ICEVs (gasoline, diesel), HEVs, and BEVs is assumed to improve by 35%, 25%, and 10%, respectively, in 10 years (compounded annual growth rate (CAGR) of 3.39%, 2.51%, and 1.06%, respectively). For the purchase price of vehicles, only the purchase price of BEVs is assumed to decrease, due to the decrease in battery cost[17]. In my assumption, the price of BEVs will decrease by KRW 9 million by 2025, and KRW 12.4 million by 2030, as compared to 2018. The purchase price of vehicles with other operating methods is fixed for the whole timeline. Table 7 summarizes the assumptions of the technological advancements mentioned above.

**Table 7.** Outline of technology advancements assumed for the simulation analysis

| | **Fuel economy** | **Purchase price** |
|---|---|---|
| **Gasoline** | 35% improvement for 10 years (CAGR 3.39%) | Fixed |
| **Diesel** | | |
| **Hybrid** | 25% improvement for 10 years (CAGR 2.51%) | |
| **Electric** | 10% improvement for 10 years (CAGR 1.06%) | 10% decrease in battery cost each year |

Finally, the level of charging infrastructure for BEVs compared to that of the current gasoline refueling infrastructure is assumed to be 15% in 2018, according to a comparison of the number of EV quick charging stations in 2018 with the number of gas stations (Korea Environment Corporation, 2018; Korea Oil Station Association, 2016).

[17] I assume a 64kWh battery capacity for all vehicles, and a 10% decrease in battery cost each year.

Following the government's expansion plan for EV charging infrastructure, I assume that the value will reach 100% by 2024. Table 8 shows the annual value of the assumed level.

**Table 8.** Expansion of EV charging infrastructure assumed for simulation analysis

| | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024~ |
|---|---|---|---|---|---|---|---|
| EV charging Infrastructure level | 15% | 33% | 43% | 56% | 68% | 83% | 100% |

Note: % values indicate relative percentage compared to current gasoline refueling infrastructure level

### 4.1.3 Policy Scenarios

Finally, using the market situations assumed in Section 4.1.1 and 4.1.2, I assume six separate policy scenarios which have differing financial incentives for HEVs and BEVs. In most parts of the world, HEVs and BEVs receive various financial incentives such as purchase subsidies or tax exemptions. This is same for the scope of my empirical analysis of South Korea. Financial incentives for HEVs and BEVs are summarized in Table 9 and Table 10 respectively. In South Korea, purchase subsidies for HEVs were abolished after 2018. However, tax incentives will be provided until 2021, with a rate of reduction. To be specific, a purchase subsidy of KRW 500,000 was provided for the purchase of HEVs until 2018, but no subsidy is provided afterwards. Tax incentives for HEVs are also scheduled to diminish and eventually end. In 2018, a maximum of KRW 3.2 million of tax incentives were provided, but this will diminish by KRW 0.5 million each year until

2021 (maximum KRW 1.7 million by 2021)[18], with all incentives being abolished after 2021.

**Table 9.** Financial incentives for hybrid electric vehicles (unit: million KRW)

| | Purchase subsidies | Tax incentives (maximum) |
|---|---|---|
| 2018 | 0.5 | 3.2 |
| 2019 | 0 | 2.7 |
| 2020 | 0 | 2.2 |
| 2021 | 0 | 1.7 |
| 2022~ | 0 | 0 |

In the case of BEVs, two types of purchase subsidies exist; national and regional. In 2018, 12 million national purchase subsidies and KRW 4.4~11 million regional purchase subsidies (mostly around KRW 5~6 million) were provided. Moreover, tax incentives of a maximum of KRW 5.9 million were provided[19]. This constitutes a financial incentive of more than KRW 20 million, which is almost half the price of compact/mid-sized BEVs. However, such heavy incentives will not last forever. In this study, I assume a 10% decrease in total financial incentives each year for most scenarios. However, along with the price reduction of BEVs due to technological advancement as explained in Section 4.1.3, the purchase price of BEVs does not see much fluctuation throughout the timeline.

[18] National tax of 1.3 million KRW until 2021, plus regional tax of 1.9 million KRW (with 0.5 million KRW reduction each year until 2021).
[19] National tax of 3 million KRW plus regional tax of 2.9 million KRW.

**Table 10.** Financial incentives for battery electric vehicles (unit: million KRW)

| | Purchase subsidies | | Tax incentives |
|---|---|---|---|
| | National | Regional | (maximum) |
| 2018 | 12 | 4.4~11 | 5.9 |

Considering the policy situations explained, I define six policy scenarios that will be used throughout the empirical analysis in this dissertation. These scenarios are summarized in Table 11. They differ by the strength and length of financial incentives for HEVs and BEVs. First, Scenario (1) can be called a “baseline” scenario, where no financial incentives exist for the whole timeline for both HEVs and BEVs. Next, Scenario (2), (3), and (4) differ only by when the financial incentives end for BEVs (until 2021, 2025, and 2033 respectively), while incentives for HEVs last until 2021 as shown in Table 9. Finally, Scenario (5) and (6) are variations of scenario (4) for additional analysis. Compared to Scenario (4), Scenario (5) does not provide any financial incentives to HEVs. On the other hand, Scenario (6) has a higher rate of annual decrease in financial incentives compared to Scenario (4), with 20% versus 10%. Using a combination of these scenarios, I define some cases to analyze the desired objective for each analysis.

**Table 11.** Summary of six policy scenarios assumed for the simulation analysis

| | HEV | BEV | |
|---|---|---|---|
| | Incentives until | Incentives until | Annual decrease |
| Scenario (1) | **None** | **None** | - |
| Scenario (2) | 2021 | 2021 | 10% |
| Scenario (3) | 2021 | 2025 | 10% |
| Scenario (4) | 2021 | 2033 | 10% |
| Scenario (5) | **None** | 2033 | 10% |
| Scenario (6) | 2021 | 2033 | **20%** |

### 4.1.4 Analysis Outline

Three main analysis will be conducted in the remaining part of Section 4. The outline of each analysis is provided in Table 12. We summarize each analysis using two key points: the analyzed model, and the main concern of the analysis. For more detailed information about these analysis, one may refer to Section 4.2-4.4.

**Table 12.** Outline of Analysis 1, 2, and 3 in Section 4

| | Analysis 1 | Analysis 2 | Analysis 3 |
|---|---|---|---|
| Focused model | Intertemporal consumer choice model | Intertemporal consumer choice model considering product line extension | Intertemporal consumer choice model considering product line extension |
| Main concern | Consumer's strategic intertemporal choice to policy interventions | Impact of product line extension on consumer choice | Market entrance of new entrant |

## 4.2 Analysis 1: Consumers' Intertemporal Choice for New Products

In this section, I focus on my intertemporal consumer choice model as explained in Section 3.2, while fixing the product-line extension for various policy scenarios. Key points to be analyzed in this section are:

1. Do consumers *delay or advance* their purchase in response to different policy situations in different times?
2. How do policy interventions affect *shrinkage or expansion* of the vehicle market?

Section 4.2.1.1 will first present parameter estimates of the intertemporal consumer choice model to observe the overall preference structure of the sample. Then, Section 4.2.1.2 will present models that can be compared with my intertemporal consumer choice model. This is to highlight the analytic capability of the proposed intertemporal consumer choice model. Comparable models have different assumptions about the consumer's current choice set, and behavioral aspects considered. Finally, in Section 4.2.2, I will conduct a simulation analysis for policy scenarios introduced in Section 4.1.3 to analyze the strategic decision making of consumers.

### 4.2.1 Background

#### 4.2.1.1 Key Parameter Estimates

Using the results of Choice Experiment 1 in Section 3.2.2.1, I estimated consumer preferences regarding the general characteristics of vehicles and tendencies of obsolescence and state dependence using a Bayesian procedure. A Monte-Carlo Markov Chain (MCMC) was iterated 50,000 times, and I used the last 10,000 iterations to estimate the parameters. Table 13 shows the estimation results.

**Table 13.** Estimation results of the suggested consumer choice model

| | | **Mean estimate** | **95% conf. int.** | |
|---|---|---|---|---|
| Operating method (base: hybrid) | Gasoline | -1.237*** | -1.481 | -0.941 |
| | Diesel | -1.310*** | -1.536 | -1.114 |
| | Electric | -0.909*** | -1.222 | -0.597 |
| Vehicle class (base: economy) | Compact/mid-size | 2.180*** | 1.951 | 2.454 |
| | Full-size | 2.239*** | 2.009 | 2.502 |
| | SUV | 2.258*** | 1.995 | 2.498 |
| Infrastructure (ln(%)) | | 0.937*** | 1.248 | 0.66 |
| Fuel cost (100 KRW/km) | | -0.360*** | -0.226 | -0.498 |
| Purchase price (10 million KRW) | | -1.011*** | -0.920 | -1.114 |
| Obsolescence (ln(years of ownership+1)) | | -2.156*** | -1.910 | -2.413 |
| State dependence | Operating method | 0.759*** | 0.981 | 0.571 |
| | Vehicle class | 0.437*** | 0.638 | 0.234 |

***: significant in 99% confidence level

The results show that all parameters are significant with a 99% confidence level. For the operating method of vehicles, consumers preferred hybrid, followed by electric, gasoline, and diesel. In general, consumers preferred new powertrain technologies compared to traditional technologies. Moreover, such results imply that if issues such as lack of charging infrastructure and high purchase cost can be solved in the future, electric powertrain technologies may have competitive advantages against traditional technologies. One point to be noted here is that in the alternative model (using the same input data) that did not separate the state dependence effect, the order of preference was hybrid, gasoline, electric, and diesel[20]. This implies that if state dependence is not separated, the preference for the new entrant with a small current stock share (which is usually new technology) may be undervalued. Regarding the vehicle class, SUVs were generally the most preferred, followed by full-size, compact/mid-size, and economy. The order of preference for vehicle class did not change by the consideration of state dependence effect. For other general attributes, consumers preferred vehicles with sufficient charging infrastructure, cheaper fuel, and lower purchase price.

Next, I interpret the results for the tendencies of obsolescence and state dependence, which are key aspects of my vehicle replacement model. First, obsolescence had significant effect on consumer utility. As I used log-scale data for obsolescence, the marginal loss of consumer utility per year decreased as the years of ownership increased.

[20] The results are presented in Appendix 1-2.

For example, if the length of ownership for the SQ increased from two to three years, the consumer's perceived utility loss for the current year was approximately 0.62. On the other hand, if the length of ownership for the SQ increased from three to four years, the marginal loss for the current year was approximately 0.48. Finally, for state dependence, a significant effect on consumer utility was observed for whether vehicles have the same operating method or class as the SQ, which may imply a lock-in effect for the SQ's vehicle type. In general, consumers had a stronger state dependence for the operating method rather than for class of vehicles.

Next, Table 14 shows waiting penalty for future alternatives, which is derived from Choice Experiment 2. It should be noted that a high level of heterogeneity lies in the consumer's forward-looking behavior. To be specific, for one year of waiting, the mean waiting penalty was -6.703, but more than 56% of respondents had a waiting penalty between 0 and -1, and more than 74% of respondents had waiting penalty between 0 and -2. However, around 13% of respondents had a severe waiting penalty of less than -10. This implies the polarized attitude for waiting for future alternatives. Since vehicles are a semi-durable good with a long length of ownership with replacements usually happening due to obsolescence rather than physical breakdown, some patient consumers could wait for future options with a tolerable utility loss, while some consumers could not wait for future options to consider them in current decision making situations. Such heterogeneity emphasizes the importance of considering consumer heterogeneity at the individual-level when forecasting the future of the vehicle market.

**Table 14.** Utility loss of future alternatives for a median consumer (waiting penalty)

| Year | Waiting penalty ( $\beta_{buy\_cost} \cdot WP_b$ ) |
|---|---|
| **1** | -0.809 |
| **2** | -1.316 |
| **3** | -2.266 |
| **4** | -3.467 |
| **5** | -6.178 |

#### 4.2.1.2 Settings

In Analysis 1, I consider the timeframe from 2018 to 2030 (13 years total). I consider three years of forward-looking for consumers, and thus, market data is prepared until 2033. In the simulation analysis, product-line extension is fixed to focus on observing strategic intertemporal consumer choice behavior, and the choice of 333 consumer agents are aggregated to forecast the future market.

#### 4.2.1.3 Comparable Models

The suggested vehicle replacement model can forecast the future vehicle market by using the parameter estimates in Section 4.2.1.1 and market assumptions in Section 4.1. However, since the model has multiple changes when compared to traditional choice models, I define three additional comparable models to observe how the inclusion of SQ and future alternatives in the consumer's current choice set, and consideration of related behavioral factors could affect the future market forecast. By doing so, I can highlight how the proposed model can simulate the strategic behavior of consumers. Table 15

shows the specifications of the four models to be compared. In the simulation analysis, all models were used to predict the future vehicle market for the same policy scenario. Among the four models, the last model (Model (4)) is the full model finally proposed in this study.

**Table 15.** Models considered for comparison to analyze strategic consumer behavior

| | | Simple ←——————————→ Comprehensive | | | |
|---|---|---|---|---|---|
| | | Model (1) | Model (2) | Model (3) | Model (4) (full model) |
| Choice set | Status quo (past alternative) | Not included | Not included | **Included** | **Included** |
| | Vehicles now in the market (current alternatives) | Included | Included | Included | Included |
| | Vehicles to be introduced in the future (future alternatives) | Not included | **Included** | **Included** | **Included** |
| Additional aspects | Obsolescence (vehicle age) | Not considered | Not considered | **Considered** | **Considered** |
| | State dependence (preference for SQ type) | Not considered | Not considered | Not considered | **Considered** |
| | Waiting penalty | Not considered | **Considered** | **Considered** | **Considered** |

As indicated in Table 15, the models with larger numbers are progressively more

comprehensive with wider choice sets (1 < 2 < 3 = 4), and have more aspects considered (1 < 2 < 3 < 4). The four models can be divided into two groups according to whether they consider consumers' SQ. (Group 1 = Models (1) and (2), versus Group 2 = Models (3) and (4)). This is because consideration of the SQ significantly changes the market forecast mechanism. If the SQ is considered (Group 2), consumers' replacement behavior and a comparison of their SQ (considering obsolescence) with new vehicles can be incorporated into the model, which enables the replacement rate (stock turnover) to be derived. However, if the SQ is not considered (Group 1), the competition is only among new vehicles and the stock turnover is obtained exogenously. By comparing the results of these two groups, I analyzed how consideration of the SQ affects the future market forecast.

In Group 1, Model (1) does not consider both the SQ and future alternatives, while Model (2) does not consider the SQ but considers future alternatives. By comparing these two models, I analyzed how incorporating consumers' forward-looking behavior into the model affects the future market forecast. Meanwhile, among Group 2, the model proposed in this study is Model (4), while Model (3) does not distinguish the effect of preference for SQ from Model (4). By comparing these two models, we analyzed how the separation of state dependence affects the model's future market forecast.

Section 4.2.1.1 already provided the parameter estimates for the proposed model, Model (4). For the other models, parameters were estimated separately with different model specifications. For Model (3), the preference for SQ terms were excluded from

equation (13). For Models (1) and (2), the preference for SQ and vehicle age terms were excluded from equation (13)[21]. The parameter estimation results for these models have been provided in Appendix 1.

However, since the four models defined in Table 15 have different specifications and capabilities, each model has different market forecast mechanisms. Notably, Models (1) and (2) require strong assumptions to forecast future the annual sales and stock shares. This is because if the SQ is not considered in the model, it is difficult to explain the link between the consumer's preference and the timing of the actual purchase. However, some previous studies calculate the market share only by consumers' choice probability for new vehicles in the market, and assume that they buy the most preferred vehicle at each decision point which can be quite unrealistic (Choi et al., 2018). Some studies, such as DeShazo et al. (2017), limited their sample to new car buyers to avoid such problems. However, such an approach may limit long-term market forecast capabilities when the characteristics of future new car buyers significantly differ from those at the point of data collection. In order to obtain long-term forecasts comparable with other models, we follow an approach similar to that in these studies for the annual sales share forecasts of Models (1) and (2). Specifically, for Model (1), we derive the annual sales share of year $\tau$ by calculating the mean choice probability of respondents for each vehicle type in year $\tau$. On the other hand, for Model (2), with future alternatives in the choice set, we

[21] Models (1) and (2) use the same parameter estimates as they use the same utility function specifications. This is because consumers' forward-looking behavior is not considered in the consumer utility function, but is incorporated in the model as a direct penalizing factor for future alternatives in an individual's decision-making process.

derive the annual sales share of year $\tau$ by calculating the mean choice probability of respondents for each new vehicle alternative from year $\tau$ to $\tau+3$ (where future alternatives are penalized), and take the adjusted probability for alternatives in year $\tau$ [22].

However, the more challenging part for Models (1) and (2) is to derive the stock share of vehicles for each year $\tau$. It is difficult to reasonably derive the long-term stock share without considering the SQ. However, to obtain comparable forecasts with the other models, we calculated the stock share of Models (1) and (2), assuming that 25%[23] of stock vehicles were *proportionally* replaced with new vehicles using their annual sales share forecast. Specifically, if we let $SS_j^{\tau-1}$ be model *j*'s stock share in year $\tau-1$, $AS_j^{\tau}$ be model *j*'s annual share in year $\tau$, and $RR$ be the replacement rate (0.25 in this case), then the stock share of model *j* in year $\tau$ is calculated as equation (28).

$$SS_j^{\tau} = SS_j^{\tau-1} \cdot (1-RR) + AS_j^{\tau} \cdot RR \quad \cdots\cdots \text{Eq. (28)}$$

## 4.2.2 Simulation Analysis

### 4.2.2.1 Intertemporal Choice of Consumers

In this section, I provide the market forecast results for the four models introduced in 4.2.1.3 for the policy scenarios introduced in Section 4.1.3. To be specific, I examine the

[22] For example, if the choice probability of gasoline mid-sized vehicles in year $\tau$ is 6% and the sum of choice probability for alternatives in year $\tau$ is 60%, the annual sales share of gasoline mid-sized vehicles in year $\tau$ is adjusted to 10% (6% × 100/60).

[23] The value is similar to the replacement rate derived from Models (3) and (4) in the simulation analysis.

two cases illustrated in Table 16.

**Table 16.** Cases to be considered in Analysis 1

| Case | Scenarios considered | Objective |
|---|---|---|
| Case1-A | Scenario (1) | Compare the results of the proposed intertemporal choice model and comparable models for the baseline Scenario (1), where financial incentives for HEVs and BEVs both do not exist for the whole timeline.<br>This case aims to analyze how my suggested vehicle replacement model differs from existing models. |
| Case1-B | Scenario (4) | Compare the results of Scenario (2), where financial incentives for BEVs continue until 2021, with Scenario (4), where financial incentives for BEVs continue until the end of timeline.<br>This case aims to analyze how consumers strategically respond to discontinuance of BEV promotion policies, and how such discontinuance affect the market. |
| | Scenario (2) | |

The objective of Case 1-A is to compare the suggested consumer choice model (vehicle replacement model) with comparable models to analyze the consideration of the main features of the suggested model, for example, how consideration of SQ, future alternatives, and state dependence by the type of SQ affect future market forecast. Next, the objective of Case 1-B is to analyze strategic behavior of consumers. To be specific, I focus on analyzing consumer's strategic decision of purchase timing and the corresponding fluctuation in market size by change in policy situation.

Throughout Analysis 1 (Section 4.2), I fix product-line extension (future model introduction) in all the analysis to focus on analyzing the strategic behavior of consumers. The change in product-line extension by the change in policy scenarios will be thoroughly investigated in Analysis 2 and 3. Here, I fix the product-line extension plan in response to Scenario 1, which is a baseline scenario where financial incentives for BEVs and HEVs do not exist[24]. An assumed product-line extension for Analysis 1 is provided in Table 17. Twenty-one models are introduced throughout the timeline, 15 of which are BEVs and 11 are battery electric SUVs. HEVs are introduced rather early (~2020) and are high-end models.

**Table 17.** Product line extension assumed for Analysis 1

| year | Newly introduced vehicle models | |
|---|---|---|
| | Incumbent | New entrant |
| 2019 | HS2, HS3 | EM7 |
| 2020 | HM2, HM1 | ES7 |
| 2021 | ES6, HS1 | EM6 |
| 2022 | ES2, HM3 | ES6 |
| 2023 | ES7, ES5 | ES5 |
| 2024 | ES4, ES3 | ES4 |
| 2025 | ES1, EM1 | EM5 |

First, I investigate Case 1-A, which compares the results of the four models introduced in Section 4.2.1.3 in Scenario 1. Figure 10 shows the market share projection

[24] This result is derived from Section 4.4.

of the four models by operating method.

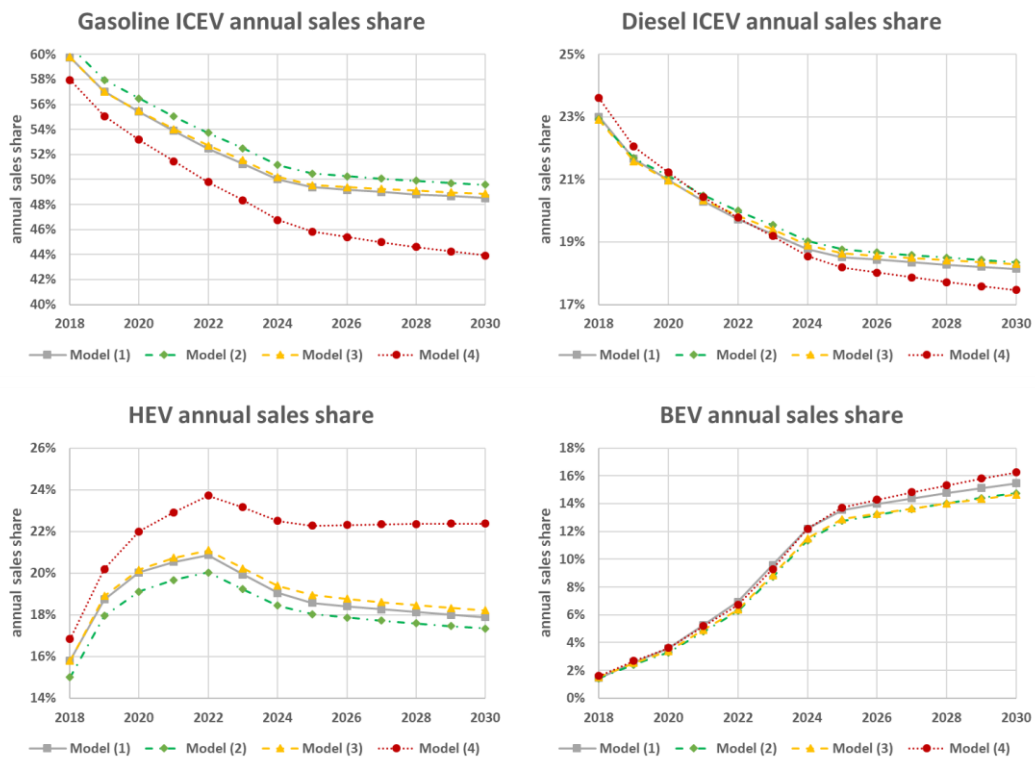



**Figure 10.** Annual sales share forecasts for Case 1-A by operating method (Scenario (1))

The results show that quite a significant difference in the market projection results are observed between the models. The largest difference was seen in the market share of HEVs. In general, the forecasts show great difference when SQ is considered. This is because Group 1 (Models (1) and (2)) can identify new car buyers from the whole sample for each time period, while Group 2 (Models (3) and (4)) assumes that the whole sample is the new car buyers throughout the timeline. In other words, the difference

between the two models stems from different assumptions regarding new car buyers for each time period.

First, I compare the results of Models (1) and (2), which only differ by the inclusion of future alternatives in the consumer's current choice set. The differences between the results of these two models are not very big in general, but Model (2), with future alternatives in the consumer's current choice set, displayed a lower market share forecast for HEVs and BEVs and a higher market share forecast for gasoline and diesel ICEVs when compared to Model (1). This implies that the inclusion of future alternatives makes market forecasts for HEVs and BEVs more pessimistic. This is because the market situation for HEVs and BEVs improves faster than for that of ICEVs. To be specific, the model availability improves for both HEVs and BEVs, and BEVs benefit from an expansion in charging infrastructure. Therefore, the choices for BEVs and HEVs are more biased toward the future alternatives when compared to ICEVs. Although market circumstances may vary by region, it is generalizable that EVs, rather than ICEVs, are the vehicle technology with more potential to improve over time (especially in terms of related infrastructure and model availability). Therefore, my argument of consumers' choice in new technology options (EVs) may be overestimated when myopic decision-making is assumed, can be generalized in most cases.

Finally, Models (3) and (4) differ only by the separation of the state dependence effect in the model specification. The initial forecast of these two models were similar, but the differences became significant over time. The biggest difference was observed for

HEVs. In Model (3), the market share of HEVs decreases after 2020, but in Model (4), it is sustained, even after 2020. This is because the two models show different responses to change in consumers' SQ. For example, consider a consumer whose SQ is a gasoline fuel vehicle and one's stated preference data indicates that the consumer prefers the gasoline operating method. Model (3) interprets that the consumer preference toward the gasoline operating method is solely because the consumer "prefers the gasoline operating method." However Model (4), which is the suggested model in this study, explains the reason in two parts: firstly, that the consumer prefers the gasoline operating method itself; and secondly, that the consumer prefers the gasoline operating method because it is the operating method of its SQ.

Therefore, in Model (3), even after the SQ of the consumer changes to a different operating method by a strong promotion policy, the consumer continues to prefer the gasoline operating method to the same extent. However, in Model (4) for the same case, the preference for the gasoline operating method due to it having the same operating method as the SQ disappears, and the operating method of the new SQ now takes advantage of being the same operating method as the SQ. Such a lock-in to the newly purchased vehicle type has important implications for EV promotion policies. The existence of a lock-in effect implies that encouraging consumers to change their SQ to the EV once through strong promotion policies can have the additional impact of enhancing the probability that consumers will buy an EV model for their next purchase.

Although the forecasts of annual sales shares have significant implications

(especially for businesses), the market stock shares also have important implications for policy makers designing environmental policy. The stock shares forecast for each model by the operating methods are shown in Figure 11. The results show that the difference between the models was not as big as those of the annual market share, but the patterns were similar. Specifically, Model (4) displayed a significant difference in the stock shares of HEVs with Model (3), since consumers were locked-in to the hybrid operating method.

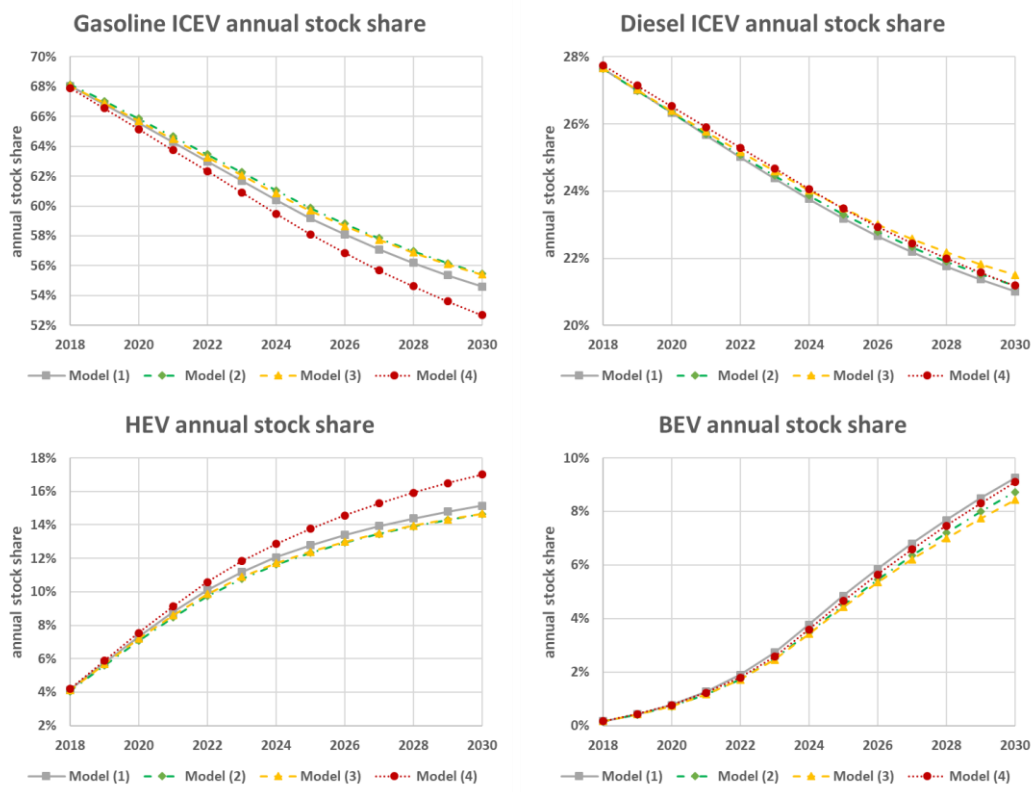



**Figure 11.** Stock share forecasts for Case 1-A by operating method (Scenario (1))

Next, since the analysis in Case 1-A only considers a single scenario, it is hard

to analyze changes in consumer behavior by policy situations. Therefore, Case 1-B focus on this point by comparing the results of two scenarios. To be specific, I compare the case of Scenario (4) (financial incentive until the end of timeline) with Scenario (2) (financial incentive until 2021). However, as mentioned in Section 3, the incentives decrease annually by 10% for both scenarios. The point to note here is that since the same model introduction plan is assumed for all of the analysis in Analysis 1, the two cases differ only by the provision of financial incentives for BEVs after 2022.

Case 1-B is designed to answer the following two questions. First, does the start or end of a policy *delay or advance* consumers' BEV purchase? Second, can policy intervention expand or shrink the market size? To answer to the first question, I conduct a market simulation for each case and draw a figure that shows the difference in the annual sales share for BEVs in % unit (forecast for Scenario (2) divided by those of Scenario (4)). Figure 12 shows such results.

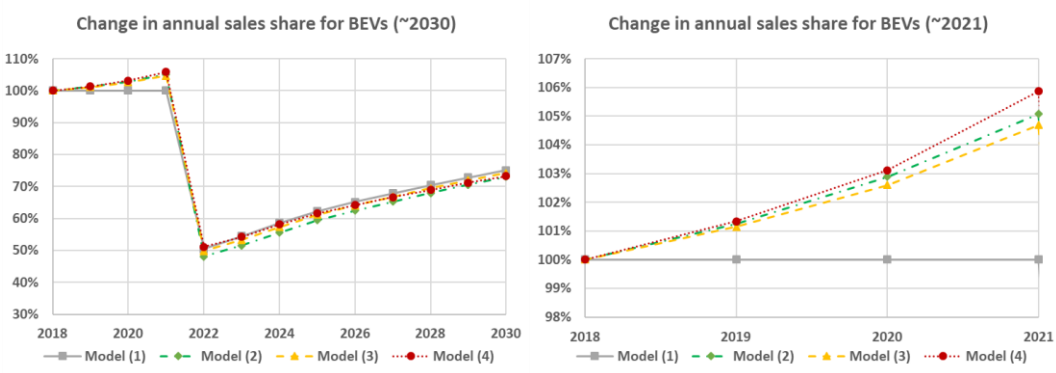



**Figure 12.** Change in annual sales share forecasts for BEVs for Case 1-B (end of financial incentives for BEVs in 2021)

The figure of the left-hand side of Figure 12 shows the results for the whole timeline, and the right-hand side highlights the results for the years 2018 to 2021. It can be observed that the models that include the future alternatives in the consumer's current choice set show an increase in BEV market shares from 2019 to 2021 (since I assume three years of forward-looking, the consumer recognizes the end of subsidies from 2019). For example, the suggested vehicle replacement model in this study (Model (4)) shows roughly a 6% increase in the BEV market share in 2021. The extent of the increase grows as the end of the incentives get closer. This is because as the end of the incentives approaches, the number of future BEVs that will benefit from policy incentives decreases. For example, in 2019, future alternatives in 2020 and 2021 also receive financial incentives. However, in 2021, no future alternatives receive financial incentives.

On the other hand, such a pattern was not observed in the myopic model when not including future alternatives in Model (1). From such observations, I can conclude that incorporating future alternatives in the current vehicle adoption (forward-looking) enables the model to analyze consumers' strategic decisions of advancing or delaying their purchase, according to the start or end of the policy. Considering such strategic behavior, I advise policy makers to provide positive news for BEVs as late as possible (to prevent delaying), and negative news for BEVs as soon as possible (to promote advancing) when providing policy information to consumers, to maximize the current purchase for BEVs. Moreover, policy makers may secure an additional budget by the end

of the policy to cope with more BEV buyers that may advance their purchase. Finally, such tendencies may also indicate the importance of the rapid expansion of related charging infrastructure, and the introduction of more EV models. If the charging infrastructure is sufficiently expanded and consumers do not expect a significant advantage in delaying their EV purchase for better charging infrastructure, they will be less likely to postpone their purchase.

Next, the policy makers and other stakeholders may be interested in whether policy intervention may shrink or expand the market size. There are many ways to measure market size. Here, I analyzed the number of vehicles sold each year (annual sales by units of vehicles sold). Since annual sales are proportional to the replacement rate (stock turnover) in my study, I used a percent change in the average replacement rate between the base policy scenario and the fast abolishment scenario. Note that for Group 1 (Models (1) and (2)), such an analysis was impossible because the replacement rate should be exogenously given (in other words, the amount of sales should be fixed). Therefore, only the results for Group 2 (Models (3) and (4)) are presented in Figure 13. The capability of analyzing fluctuating sales by policy intervention is one of the core strengths of the suggested model in this study. Two points can be observed here. First, an increase in annual sales from advanced purchase due to the policy ending in 2021 was observed for 2019–2021. The sales increase was observed not only for BEVs, but for the other vehicles as well. Second, a decrease in annual sales due to the abolishment of BEV incentives was observed after 2021. The second point may be observable in studies that

can derive sales using information about the relationship between cost and demand (Fox et al., 2017; Sykes & Axsen, 2017), but the first point is unique for the suggested model.

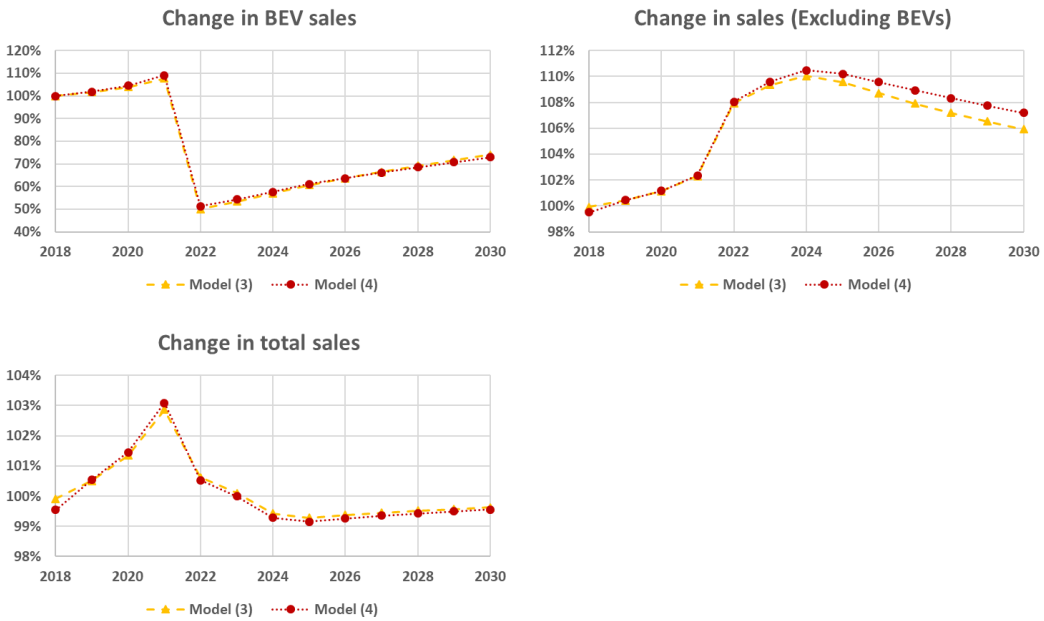



**Figure 13.** Change in BEV sales, sales excluding BEV, and total sales for Case 1-B (end of financial incentives for BEVs in 2021)

To summarize, the suggested consumer choice model (vehicle replacement model) in this dissertation can analyze the consumer's strategic behavior of delaying or advancing their purchase when considering positive or negative future market situations by including future alternatives within the consumer's current choice set. Moreover, since the model can identify new car buyers in each time period by including SQ in the consumer's current choice set and take the replacement viewpoint, it can analyze sales

fluctuations by time periods and stock compositions of the market. Therefore, considering the massive impact of the automotive industry on the national/regional economy, policy makers should consider such market shrinkage/expansion when they are considering the start, end, or modification of policy interventions.

#### 4.2.2.2 Validation of the Proposed Model

Until now, I have showed that Models (1) to (4) generate different forecasts. However, is the proposed model (Model (4)) a “better” model when compared to others? A validation process to show the excellence of the proposed model should be carried out.

First, I conducted a performance analysis of the econometric models used for models compared in Case 1-A. When comparing models with different specifications, the use of log-likelihood can be inappropriate, since log-likelihood values cannot be worse off when there are more parameters explaining the model. Therefore, performance indexes such as AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), or CAIC (Consistent AIC) are widely used to evaluate models with different number of parameters (Greene & Hensher, 2003; Hansen, 2005; M. Lee et al., 2017). Calculations of these performance indices can be done as shown in Table 18. As one can observe, these indices penalize the model with the number of estimated parameters (m), and number of observations used for model estimation (N).

**Table 18**. Calculation of AIC, BIC, and CAIC

| Performance index | Calculation |
|---|---|
| AIC (Akaike Information Criterion) | $-2\ln L + 2m$ |
| BIC (Bayesian Information Criterion) | $-2\ln L + m(\ln(N))$ |
| CAIC (Consistent AIC) | $-2\ln L + m(1+\ln(N))$ |

Note: $\ln L$ represents log-likelihood of the model, m represents number of estimated parameters, and N represents number of observations used for estimation

The performance of Models (1) to (4) using performance indices presented in Table 18 are compared in Table 19. It should be noted that Models (1) and (2) use the same empirical model, since the waiting penalty for future alternatives is not estimated but calculated, and is only used for simulation analysis. In Table 19 the proposed model, Model (4), displayed the best value for each AIC, BIC, and CAIC. Therefore, the proposed model shows the best performance when modelling consumer choice.

**Table 19**. Performance indices of compared models

| | Model (1) & (2) | Model (3) | Model (4) |
|---|---|---|---|
| Utility function | $V_{njt} = \boldsymbol{\beta}'\mathbf{X}_{njt} + \beta_{sq,n} d_{sq,njt} + \varepsilon_{njt}$ | $V_{njt} = \boldsymbol{\beta}'\mathbf{X}_{njt} + \beta_{obs,n} X_{obs,jt} + \varepsilon_{njt}$ | $V_{njt} = \boldsymbol{\beta}'\mathbf{X}_{njt} + \beta_{obs,n} X_{obs,jt} + \beta_{sd\_op,n} X_{sd\_op,jt} + \beta_{sd\_cls,n} X_{sd\_cls,jt} + \varepsilon_{njt}$ |
| # of parameters | 10 | 10 | 12 |
| # of observations | 5,328 | 5,328 | 5,328 |
| Log-likelihood | -2699.99 | -2700.44 | -2601.88 |
| AIC | 5419.987 | 5420.871 | 5227.764 |
| BIC | 5485.794 | 5486.679 | 5306.733 |
| CAIC | 5495.794 | 5496.679 | 5318.733 |

Next, I analyze the model's validity by estimating the model with a hold-out sample, and use the other parts to estimate the model and predict the consumer choice of the hold-out sample (Arlot & Celisse, 2010; Shao, 1993). To be specific, I use 75% of the data to estimate the model and predict the consumer choice for the remaining 25% of the data. Four possible cases are analyzed, and the average choice probability for the actual choice of the hold-out sample was compared. A plot of the analysis is provided in Figure 14 and the results are presented in Table 20. As one can observe, Model (4) also displayed the best performance in validation when using a hold-out sample.

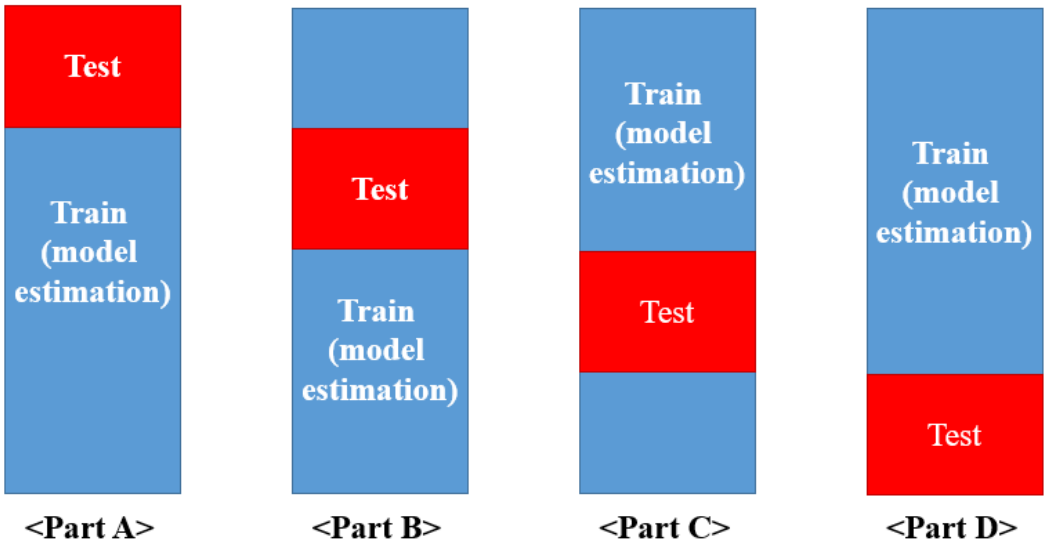



**Figure 14**. Plot of validation using hold-out sample

**Table 20**. Results of validation using hold-out sample

| | Part A | Part B | Part C | Part D | Average |
|---|---|---|---|---|---|
| Model (1)&(2) | 69.7% | 68.7% | 66.5% | 64.4% | **67.3%** |
| Model (3) | 68.8% | 67.9% | 66.0% | 64.0% | **66.7%** |
| Model (4) | 69.6% | 69.5% | 67.1% | 65.0% | **67.8%** |

Finally, the proposed model is different from other models in two ways: the incorporation of obsolescence of SQ, and the state dependence by the type of SQ. The

background of these aspects are provided in Section 3.2.1. To summarize, it is emphasized in various literatures that obsolescence occurs by passage of time (Granberg, 1997; I. Lee & Lee, 1998; Levinthal & Purohit, 1989; Prince, 2009; Stacchetti & Stolyarov, 2015), and the existence of state dependence in consumer choice is observed in various studies (de Jong, Lehmann, & Netzer, 2012; Dubé et al., 2010; Hortaçsu et al., 2017; Keane, 1997). Moreover, Smith (2005) states that many studies neglect the existence of state dependence due to a lack of appropriate data. This study has generated such data by designing a structured survey and conducting choice experiments that include SQ.

## 4.3 Analysis 2: Impact of Product Line Extension on Consumers' Intertemporal Choice for New Products

In this section, I focus on analyzing the change in product-line extension pattern to policy intervention for consumers, and the corresponding impact on consumers' intertemporal choice for new products and the new technology product diffusion. The key points to be analyzed are:

1) How does the product-line extension plan change in response to given policy situations?
2) Do such changes leverage or offset the impact of policy intervention?

Section 4.3.1 provides the background to the proposed product-line extension model used in Analysis 2 and introduces a simple comparable method; the greedy product-line extension method. In Section 4.3.2, I conduct simulation analyses using the proposed product-line extension model. The simulation analyses mainly consists of three parts. First, I compare the product-line extension plan derived from the proposed model with those derived from the greedy method. Second, I focus on analyzing the impact of the varying product supply on consumers' intertemporal choice for new products. Thirdly, I conduct an additional policy analysis using the proposed model to aid decisions of the government and policy makers on the promotion of BEVs and the reducing of GHG emissions in the road transport sector of South Korea.

## 4.3.1 Background

### 4.3.1.1 Settings

In Analysis 2, I consider the timeframe from 2018 to 2030 (13 years) and assume three years of forward-looking for consumers. For the product-line extension, two models are introduced annually from 2019 to 2025 (14 models). Only the new technology products, HEVs and BEVs, can be introduced. New models are selected from the candidate pool of 42 vehicles as introduced in Section 4.1.1, with six vehicle types and seven levels of quality for each vehicle type. Finally, there are already 50 existing models in the product line[25] with no discontinuance of existing or newly introduced models. The discount for

[25] 28 gasoline ICEVs, 13 diesel ICEVs, 6 HEVs, and 3 BEVs. For more detail, see Table 5 in Section 4.1.1.

future revenue is 5% per year. For the optimization of the product-line extension model, I used the best results from five trials with n=100.

#### 4.3.1.2 Comparable Method: Greedy Product Line Extension

The proposed product-line extension model uses the NP method to derive product-line extension plans, considering the cannibalization between models and the timing of revenue realization. Why, then, is such consideration needed? To answer to this question, I define a comparable product line extension method; the greedy product-line extension method that sequentially introduces models that maximize revenue for each corresponding year.

For example, for the new model introduction decision of 2019, models that can maximize revenue for 2019 are introduced. While calculating the expected revenue for each model (or set of models), future follow-up models of the corresponding model are considered, but future introduction of new product models are cannot be considered. After calculating the expected revenue for *all* of the candidate models, the vehicle model (or set of models) with the highest revenue is introduced, and the same procedure is repeated for the next year. Considering all possible cases can be an option for the greedy method, since there are relatively few cases to be considered when compared to the proposed method (4,466 versus $3.6\times10^{19}$ for the assumed settings in Analysis 2). The differences between the two methods are graphically illustrated in Figure 15.

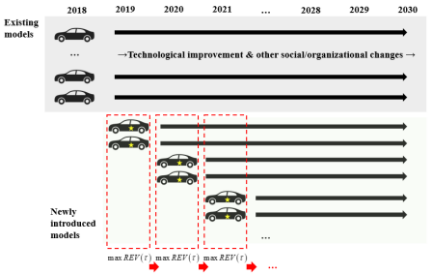
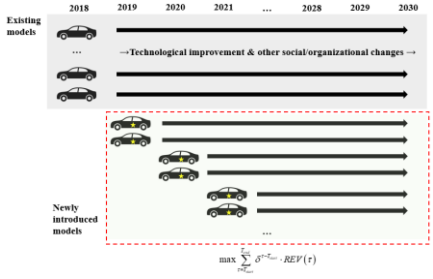
| | Plan for each timing is determined sequentially (greedy) | Plan for the whole analysis period is determined at once (proposed) |
|---|---|---|
| Graphical summary |  |  |
| Total number of cases | ${}_{42}C_2 + {}_{40}C_2 + \ldots + {}_{30}C_2$ $= 4,466$ | ${}_{42}C_2 \times {}_{40}C_2 \times \ldots \times {}_{30}C_2$ $= 3.6 \times 10^{19}$ |

**Figure 15**. Graphical illustration of greedy and proposed product line extension planning

The main difference between this greedy method and the proposed method is that while the determinant of the new model introduction is revenue of the corresponding time period for the greedy method, the proposed method uses the total revenue of the whole analysis period, and determines the plan for the whole period at once. Thus, the greedy method can consider the cannibalization between existing products and new products for the corresponding period, but cannot consider cannibalization between potential new future models (new model now, versus new model one year later). Moreover, it cannot consider the revenue that the newly introduced model may generate in the future. However, the number of cases to be considered are extremely large for the proposed method since it derives an optimal solution over a long timeframe at once, which is why the optimization algorithm (NP algorithm in this case) is required for the

proposed product-line extension planning. The comparison between the greedy method and the proposed method is summarized in Table 4.

### 4.3.2 Simulation Analysis

The simulation analysis for Analysis 2 consists of three main parts. The first part compares the results of the proposed product-line extension planning with those of the greedy method, to highlight the potential benefit that may be acquired using the proposed method. Then, the second part analyzes the impact of product-line extension changes on consumers' intertemporal choice behavior under various policy situations. Finally, Analysis 2 concludes with useful policy analysis and implications for the government and policy makers using the results of the proposed model.

#### 4.3.2.1 Comparison with Greedy Product Line Extension

This section compares the proposed product-line extension model's plan with those of the greedy method. When comparing the model introduction plan between these two methods, I use "increment in total revenue" achieved by the product-line extension (new model introduction). To calculate the increment, the baseline total revenue for each scenario should first be calculated. Here, the baseline total revenue means the total revenue for the whole timeline when no new models are introduced. The results are shown in Table 21. It can be observed that the total revenue increases as the financial incentives for BEVs grow.

**Table 21.** Total revenue of each scenario without product line extension (no new models are introduced)

| | Scenario (1) | Scenario (2) | Scenario (3) | Scenario (4) | Scenario (5) | Scenario (6) |
|---|---|---|---|---|---|---|
| Total Revenue | 2.420 | 2.469 | 2.494 | 2.508 | 2.499 | 2.476 |

Next, the product-line extension plan that uses the greedy method is presented in Table 22, and the product-line extension plan that uses the proposed model is presented in Table 23.

**Table 22.** Product line extension plan derived from greedy method

| | Scenario (1) | Scenario (2) | Scenario (3) | Scenario (4) | Scenario (5) | Scenario (6) |
|---|---|---|---|---|---|---|
| 2019 | HM1, HS1 | EM7, ES7 | HS1, ES7 | HS1, ES7 | EM7, ES7 | HS1, ES7 |
| 2020 | HM2, HF1 | HM1, EF1 | HM1, EF1 | HM1, EF1 | HM1, EF1 | HM1, EF1 |
| 2021 | EF1, EF2 | HM2, HF1 | HM2, HF1 | HM2, HF1 | HM2, HF1 | EM1, EM2 |
| 2022 | HF2, HF3 | HF2, HF3 | HF2, HS7 | HF2, HS7 | HF2, HF3 | HM2, HF1 |
| 2023 | HF4, HS7 | HF4, HF5 | HF3, HF4 | HF3, HF4 | HF4, HF5 | HM3, HM4 |
| 2024 | EM1, EM7 | HF6, HF7 | HF5, HF6 | HF5, HF6 | HF6, HF7 | HF2, EM7 |
| 2025 | HF5, HF6 | HM3, HM4 | HF7, HS2 | HF7, HS2 | HM3, HM4 | HF3, HF4 |
| Total revenue | 2.534 | 2.589 | 2.613 | 2.627 | 2.629 | 2.605 |
| Introduced BEVs | 4 | 3 | 2 | 2 | 3 | 4 |
| BEV sales (stock) share in 2030 | 8.4% (4.9%) | 9.2% (6.1%) | 7.7% (6.1%) | 10.7% (7.5%) | 13.0% (9.0%) | 10.9% (7.2%) |

**Table 23.** Product line extension plan derived from the proposed method

| | Scenario (1) | Scenario (2) | Scenario (3) | Scenario (4) | Scenario (5) | Scenario (6) |
|---|---|---|---|---|---|---|
| 2019 | HS1, HS2 | ES2, ES4 | ES3, ES6 | ES4, ES2 | ES4, ES2 | HS1, HS2 |
| 2020 | HM1, HM2 | ES1, ES3 | ES4, ES2 | ES5, ES6 | ES5, ES6 | HM1, HM2 |
| 2021 | ES1, ES3 | HS1, HM2 | ES5, ES1 | ES1, EM4 | ES1, EM4 | ES3, ES1 |
| 2022 | HF3, HF1 | HM1, EF4 | EF1, EF2 | ES3, EM1 | ES3, EM1 | HF3, HF1 |
| 2023 | ES2, EF4 | HF4, HF3 | EF3, EF4 | EM3, EF1 | EM3, EF1 | ES2, EF4 |
| 2024 | EF2, EF1 | EF1, EF2 | HF2, HF3 | EM2, HF2 | EM2, HF2 | EF3, EF1 |
| 2025 | EF3, HF2 | EF3, HF1 | HM1, HF1 | EF2, HF1 | EF2, HF1 | EF2, HF2 |
| Total revenue | 2.552 | 2.607 | 2.650 | 2.676 | 2.667 | 2.617 |
| BEVs | 7 | 8 | 10 | 12 | 12 | 7 |
| BEV sales (stock) share in 2030 | 9.5% (5.5%) | 10.5% (6.8%) | 12.8% (9.4%) | 18.8% (12.3%) | 18.8% (12.4%) | 10.3% (6.7%) |

First, in the results of the greedy method (Table 22), a difference in the model supply by policy scenarios were observed; yet, the results for some policy scenarios were the same. To be specific, Scenario (1) and (6) showed a unique introduction plan, but Scenario (2), (5) and Scenario (3), (4) showed same plan, respectively. For all of the scenarios, more than 10 HEV models were introduced among a total of 14 new introductions. One point to be noted is that, although financial incentives were sustained for longer, the number of introduced BEVs decreased (Scenario (1)→(2)→(3)→(4)). Moreover, Scenario (3) showed the lowest sales and stock shares of BEVs in 2030, even though it was not the scenario with the least incentives for BEVs.

On the other hand, the product-line extension plan derived from the proposed model (Table 23) showed heterogeneous patterns by policy scenarios. Overall, as financial incentives were sustained for longer (Scenario (1)→(2)→(3)→(4)), more BEV models tended to be introduced, and the timing of their introduction increased. In general, the product-line extension tended to introduce expensive high-end EV models rather than cheaper low-end EV models. This is because the proposed method considered the cannibalization between new models and existing models, especially the cannibalization between cheap new models and expensive existing models.

Another point to be noted here is that Scenarios (4) and (5) derived the same product-line extension, which implies that the existence of HEV incentives did not have a significant impact on the new product model supply when incentives for BEVs were continued throughout the timeline. Moreover, Scenario (6), which had a faster incentive

reduction rate when compared to Scenario (4), displayed a similar model supply with those of Scenario (1). This may imply that the faster decrease in subsidy may critically affect the product-line extension pattern, which is almost the same as not providing any incentives.

Compared to the greedy method, the results of the proposed product-line extension method introduced more BEVs. This may be because the future revenue of newly introduced models was considered in the proposed method, and the market situation for BEVs improved in terms of charging infrastructure, regardless of the policy scenarios considered. On the other hand, while the greedy method introduced few low-end BEV models, the proposed method introduced more high-end BEV models. Moreover, the total revenue of the derived model introduction plan was higher for the proposed method than those of the greedy method for every scenario. However, since the number of newly introduced models was only 14 while the number of existing models was 50, the existing models still constituted a significant share in the total revenue. Thus, as mentioned previously, I compared the increment in total revenue achieved by the introduction of new models. Therefore, to calculate the increment, the baseline total revenue in Table 21 was deducted from the total revenue of Table 22 and Table 23. The results are presented in Table 24.

**Table 24.** Incremental revenue generated from product line extension (greedy versus proposed method)

| | Scenario (1) | Scenario (2) | Scenario (3) | Scenario (4) | Scenario (5) | Scenario (6) |
|---|---|---|---|---|---|---|
| Greedy | 0.115 | 0.121 | 0.119 | 0.119 | 0.130 | 0.130 |
| Proposed | 0.132 | 0.138 | 0.156 | 0.168 | 0.169 | 0.142 |
| Advantage of proposed method | 15.0% | 14.4% | 31.1% | 41.1% | 30.0% | 9.1% |

The results show that when the "incremental" total revenue was compared, the advantage of the proposed method was approximately 10~40%. Therefore, it can be confirmed that the proposed method introduction plan can bring a significant amount of additional revenue.

#### 4.3.2.2 Impact of Product Line Extension for Different Policy Scenarios

In this section, I analyze the change of the product-line extension plan by policy intervention using the proposed product-line extension model. I define cases that observe the impact of supply response on the diffusion of BEVs. The four cases defined for this section are presented in Table 25.

**Table 25.** Cases to be considered in Analysis 2

| | Compared scenarios | Analysis objective |
|---|---|---|
| Case 2-A | Scenario (1) | Impact of change in supply response and future vehicle market from steady incentives for BEVs |
| | Scenario (4) | |
| Case 2-B | Scenario (4) | Impact of change in supply response and future vehicle market from faster decrease in BEV incentives |
| | Scenario (6) | |
| Case 2-C | Scenario (1) | Impact of change in supply response and future vehicle market vehicle market from the duration of BEV incentives and its abolition timing |
| | Scenario (2) | |
| | Scenario (3) | |
| | Scenario (4) | |
| Case 2-D | Scenario (4) | Impact of change in supply response and future vehicle market from the abolition of HEV incentives |
| | Scenario (5) | |

First, the objective of Case 2-A is to divide the impact of policy intervention and the response of model supply (change in product-line extension) for such policy intervention when the policy situations change from no incentives (Scenario (1)) to steady incentives throughout the timeline (Scenario (4)). The analysis will compare three situations as presented in Table 26. To be specific, I compare situations where the supply responds appropriately to Scenario (1) and (4) respectively (Situation A and C), and situations where the policy situation is changed from Scenario (1) to (4), but the supply still remains with the optimal plan for Scenario (1) (Situation B). Then, by comparing each situation, I can separately analyze the market change derived from the change in the

policy situation itself (Situation A versus B), and the market change derived from the change in the product-line extension plan (Situation B versus C).

**Table 26.** Situations to be compared for Case 2-A

| | Policy situation | Product line extension plan | Descriptions |
|---|---|---|---|
| Situation A | Scenario (1) (no incentives) | Optimal plan for Scenario (1) | Product line extended in response to Scenario (1) |
| Situation B | Scenario (4) (incentives ~33) | Optimal plan for Scenario (1) | Policy situation is changed from Scenario (1) to Scenario (4), but the product line extension plan do not respond |
| Situation C | Scenario (4) (incentives ~33) | Optimal plan for Scenario (4) | Product line extended in response to Scenario (4) |

The analysis results for Case 2-A are presented in Figure 16. The first row in Figure 16 shows the cumulative revenue for each situation (where revenue after 2019 is discounted with the discount factor). The second and third row shows the annual sales and stock shares of BEVs, respectively. For each row, the first column shows the absolute value while the second column shows the relative value when compared to the first situation (Situation A in this case).

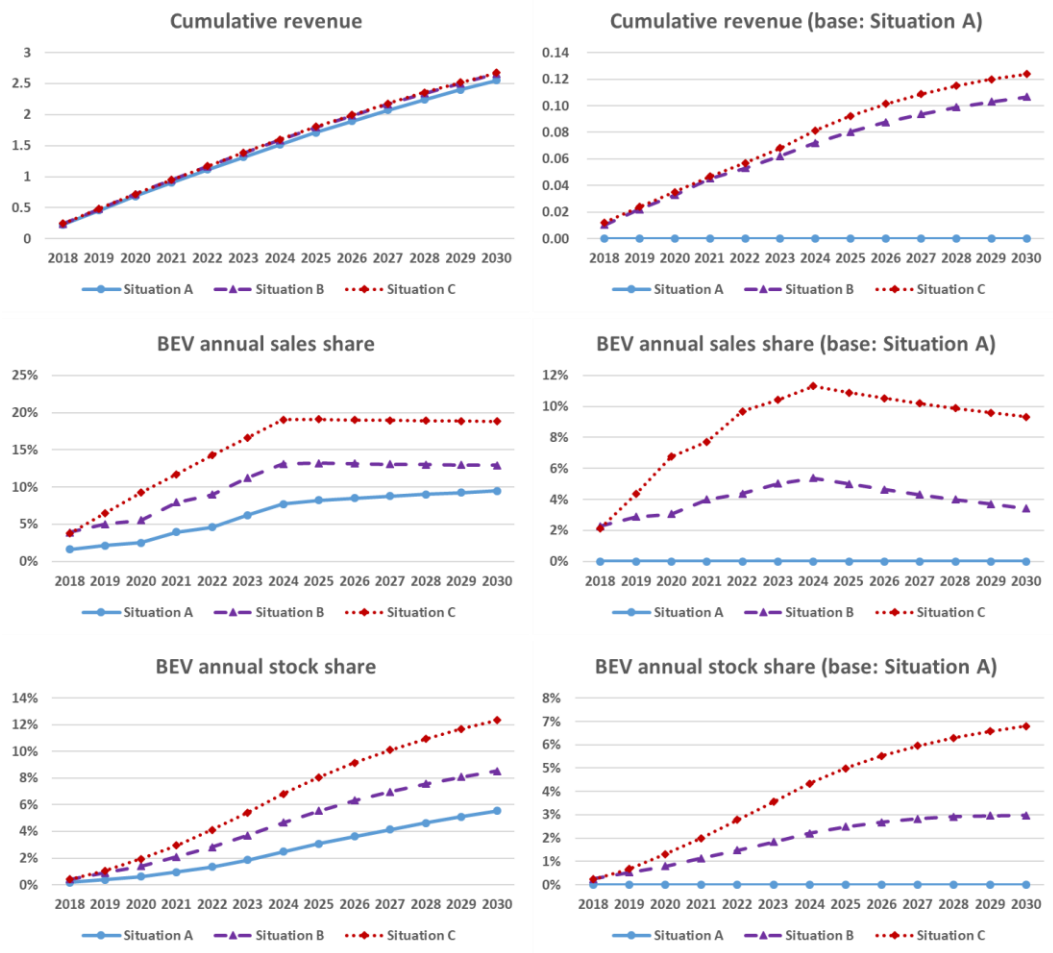



**Figure 16.** Analysis results for Case 2-A

The results in the first row of Figure 16 shows that the change in the product-line extension may enhance revenue by appropriately responding to change in the policy situation. Specifically, if steady financial incentives are provided for BEVs, revenue increases from the solid line to the dashed line without any effort. However, if the supply responds to the policy intervention and the product-line extension plan is changed,

additional revenue can be achieved and it reaches the revenue of the dotted line. If we compare the optimal plan for Scenario (1) and (4) in Table 23, the product-line extension plan introduces more BEVs to take advantage of more financial incentives for BEVs (4 → 10).

Next, the second and third rows in Figure 16 show the rate of new technology (BEVs) diffusion for each situation. It can be observed that the impact of considering the response of supply is as significant as the effect of policy intervention itself. Specifically, if policy incentives are provided but the supply does not respond, the annual sales and stock shares of BEVs increase up to 5%p and 3%p respectively. On the other hand, if the supply appropriately responds to such policy intervention, then the annual sales and stock shares of BEVs increase up to 11%p and 7%p[26]. These results show that the consideration of the supply response is as important as the consideration of policy intervention itself when analyzing new technology adoption. Although the financial incentives for BEVs are policy interventions that target consumers, consumers' choice directly influences supply (product-line extension). Since more incentives make a promoted product more attractive, the response of supply leverages the impact of the government's policy intervention.

Next, I consider Case 2-B, which analyzes the change to pessimistic policy situations for new technology. Specifically, I compare the results of Scenarios (4) and (6), where incentives for both scenarios are provided throughout the whole timeline, but incentives for Scenario (6) decrease at a faster rate. As in Case 2-A, I compare three

[26] The reason behind a decrease in difference after 2025 is because no new models are introduced after 2026, and financial incentives for BEVs decrease 10% annually for all scenarios in my analysis.

situations as presented in Table 27 below.

**Table 27.** Situations to be compared for Case 2-B

| | Policy situation | Product line extension plan | Descriptions |
|---|---|---|---|
| Situation D | Scenario (4) (10% annual decrease) | Optimal plan for Scenario (4) | Product line extended in response to Scenario (4) |
| Situation E | Scenario (6) (20% annual decrease) | Optimal plan for Scenario (4) | Policy situation is changed from Scenario (4) to Scenario (6), but the product line extension do not respond |
| Situation F | Scenario (6) (20% annual decrease) | Optimal plan for Scenario (6) | Product line extended in response to Scenario (6) |

The results for Case 2-B are presented in Figure 17. It is observed that a faster decrease in financial incentives harms revenue, but a supplier can decrease such a loss by appropriately changing their model introduction plan. Specifically, if we compare the product-line extension plan for Scenario (4) and (6) in Table 23, more HEV models are supplied to cope with the rapid decrease in financial incentives for BEVs (4 → 7).

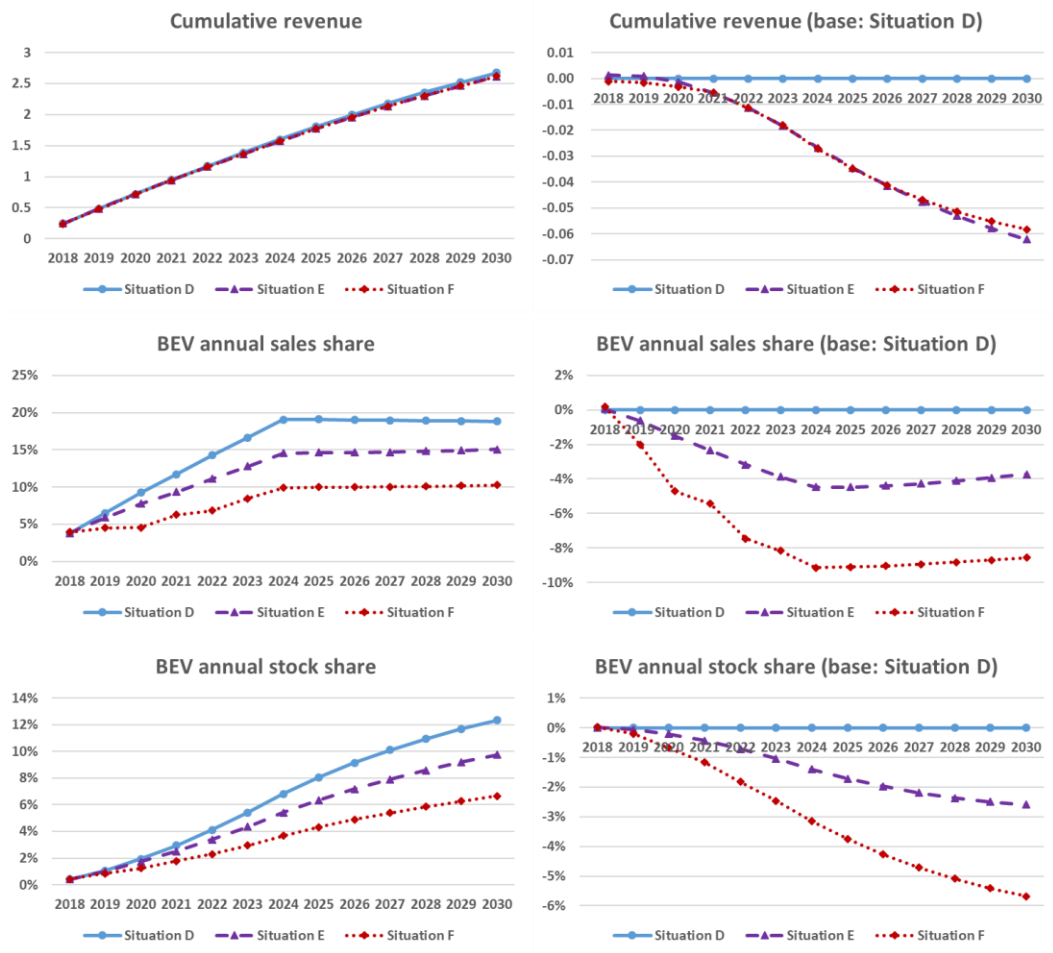



**Figure 17.** Analysis results for Case 2-B

However, such revenue maximizing behavior had a negative impact on BEV diffusion. Specifically, the rapid decrease in financial incentives and the corresponding response of the supply made the BEV annual sales and stock shares decrease up to 4%p and 3%p respectively. However, if the supply responds to policy change and introduces more HEVs instead of BEVs, such decreases grow by up to 9%p and 6%p respectively.

These results also imply that a change in the model supply may leverage the effect of the government's policy intervention, also in a negative direction.

Next, I analyze Case 2-C to discuss the impact of the timing of policy discontinuance. Specifically, I analyze the shock of the sudden discontinuance of policy incentives. Unlike Case 2-A and Case 2-B, I compare the results of each scenario where the product-line extension plan appropriately responds to each policy scenario. The situations to be compared for Case 2-C are presented in Table 28.

**Table 28.** Situations to be compared for Case 2-C

| Label | Policy situation | Product line extension plan | Descriptions |
|---|---|---|---|
| Scenario (1) | Scenario (1) (no incentives) | Optimal plan for Scenario (1) | Product line extended in response to Scenario (1) |
| Scenario (2) | Scenario (2) (incentives ~21) | Optimal plan for Scenario (2) | Product line extended in response to Scenario (2) |
| Scenario (3) | Scenario (3) (incentives ~25) | Optimal plan for Scenario (3) | Product line extended in response to Scenario (3) |
| Scenario (4) | Scenario (4) (incentives ~33) | Optimal plan for Scenario (4) | Product line extended in response to Scenario (4) |

The analysis results for Case 2-C are presented in Figure 18. First, when comparing the revenue, it was noticed that before the end of the policy, a soar in revenue was observed, which is closely related to the strategic behavior of consumers (advancing one's purchase to take advantage of policy incentives) as analyzed in Analysis 1.

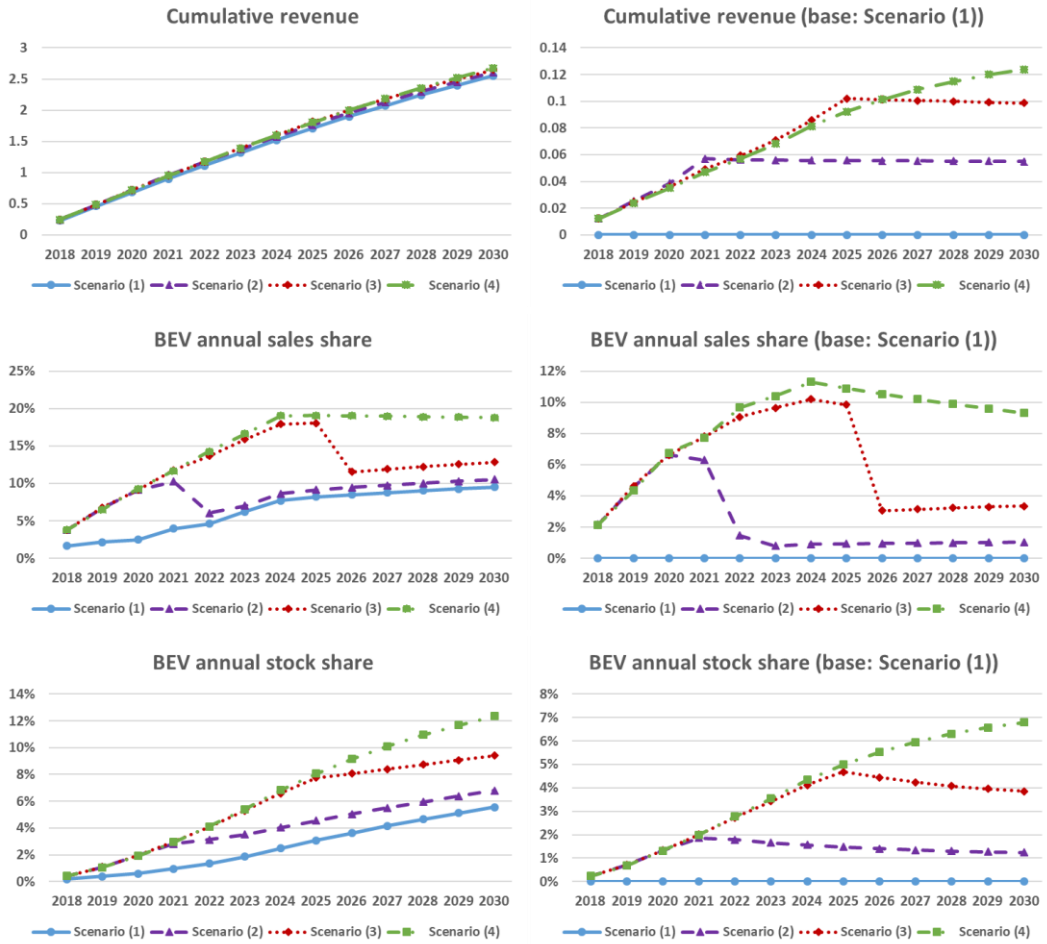



**Figure 18.** Analysis results for Case 2-C

In terms of new technology diffusion, a significant decrease in annual sales shares was observed after the timing of policy discontinuance. However, if I had used the myopic consumer model that only considers new vehicles that are now in the market and have a fixed product-line extension, then the annual sales share in Scenario (2) and (3),

after the discontinuance, would have been the same as those in Scenario (1). However, the results in Figure 18 show that the BEV annual sales shares in Scenario (2) and (3) fall after policy discontinuance, but not as low as those in Scenario (1). There are two reasons behind this difference. The first is because the product model that is introduced by the product-line extension plan for each policy scenario is different. The second reason is because the stock composition until policy discontinuance is different, and thus, the effect of different SQs and state dependences exist. Such differences increase as incentives are provided for longer, and bigger differences in product-line extension are observed. Specifically, Scenario (2) displayed around a 1%p higher annual sales share for BEVs after the policy discontinuance, while Scenario (3) displayed around a 4%p higher annual sales share for BEVs, even after the policy discontinuance. This is because Scenario (3) made the product-line extension plan introduce more low-end popular models earlier than in Scenario (2). On the other hand, the stock shares of BEVs increased even after the discontinuance of policy for all scenarios. However, when the policy incentives end, the upturn of BEV stocks slowed down.

Finally, I analyze Case 2-D, which compares Scenarios (4) and (5). These two scenarios differ only by whether incentives for HEVs are provided for 2019~2021. The objective of Case 2-D is to analyze whether policy incentives for HEVs affect the diffusion of BEVs. As the performance of HEVs improves and the cost of the technology reduces, some argue that HEVs can compete with conventional ICEVs without financial incentives. Moreover, some argue that the promotion of HEVs may hinder the diffusion

of BEVs. In South Korea, all of the financial incentives for HEVs were expected to be abolished after 2019; yet, due to environmental issues and economic concerns, incentives are now to be provided until 2021.

The situations to be compared in Case 2-D are presented in Table 29. As one can observe from the product-line extension plan for each scenario (Table 23), the product-line extension plan for Scenario (4) and (5) are the same. In other words, the provision of financial incentives for HEVs from 2019 to 2021 did not affect the decision of the product-line extension.

**Table 29.** Situations to be compared for Case 2-D

| Label | Policy situation | Product line extension plan | Descriptions |
|---|---|---|---|
| Scenario (4) | Scenario (4) (incentives ~33) | Optimal plan for Scenario (4) | Product line extended in response to Scenario (4) |
| Scenario (5) | Scenario (5) (incentives ~33, no incentives for hybrids) | Optimal plan for Scenario (5) | Product line extended in response to Scenario (5) |

The analysis results for Case 2-D are provided in Figure 19. The results show that despite some differences between the scenarios, the level of differences was quite small. Specifically, the BEV annual sales share differences were up to 0.25%p, and stock

share differences were up to 0.05%p.

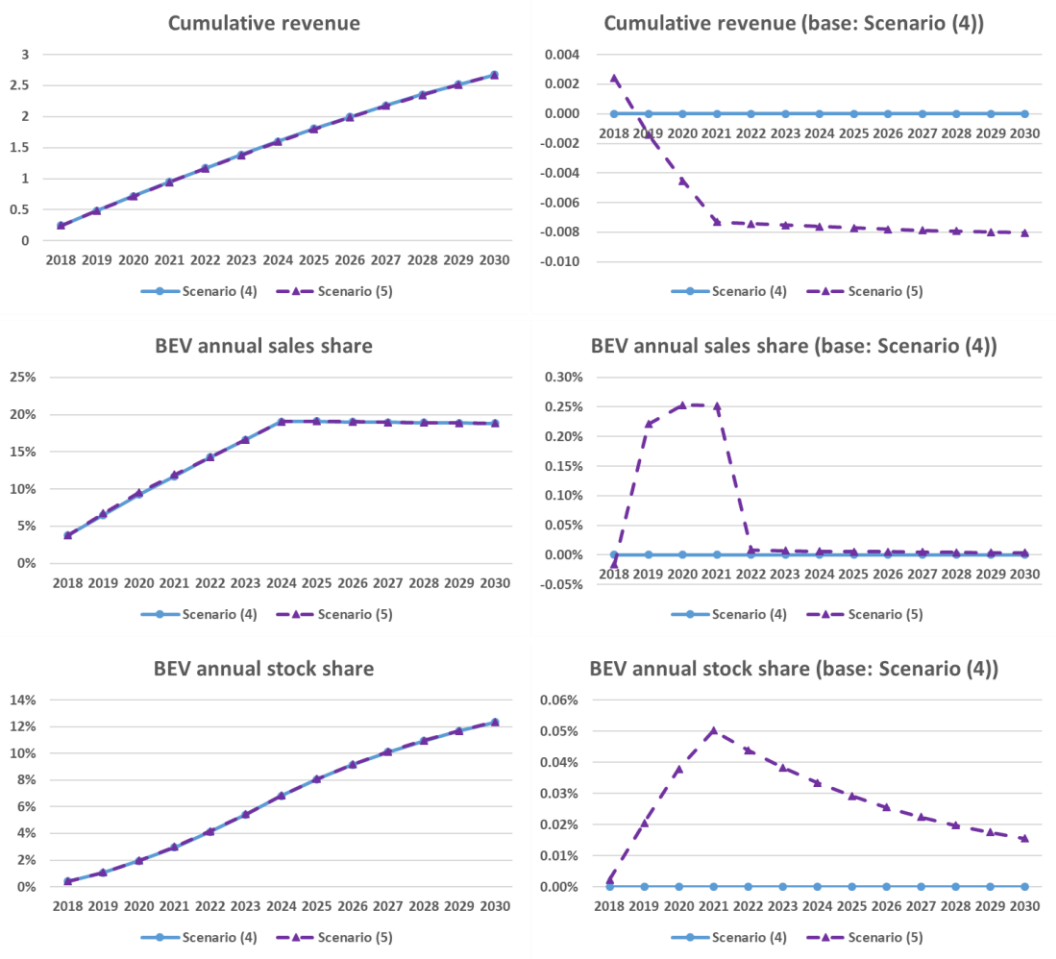



**Figure 19.** Analysis results for Case 2-D

However, if we look at the change in the annual sales and stock shares for the other operating methods (Figure 20), the results show that HEVs lose a significant amount of the market share (up to 3%p). This means that most market shares lost by

HEVs have gone to conventional ICEVs; mainly gasoline ICEVs. This is because in 2019~2021, BEVs are not viewed as attractive due to lack of related infrastructure and model availability. Therefore, by making HEVs less attractive does not hold much benefit for BEVs. In other words, abolishing the HEV incentives due to concerns about hindering BEV diffusion could be seen as a weak argument. However, if the incentives for BEVs were also to diminish rapidly, the results may differ.

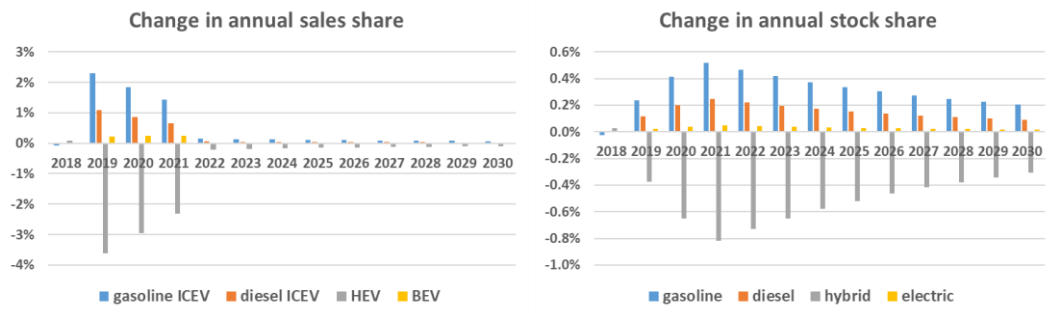



**Figure 20.** Change in annual sales share and stock share for different operating methods for Case 2-D

To summarize, when the government intervenes the market with consumer targeted policies, it not only induces a change in consumer behavior due to the policies themselves, but also induces changes in product-line extension patterns. Moreover, such changes provide forecasts that may leverage the impact of policy intervention, and such results emphasize the role of the government's policy intervention, which can work as a stimulus in new technology diffusion.

#### 4.3.2.3 Policy Analysis for Policy Makers

The main objective of the proposed model is to assist the decision making of the government and policy makers. Therefore, this section aims to conduct some policy analysis that may actually help the South Korean government and policy makers regarding the diffusion of EVs.

In South Korea, the legal basis of promoting environment-friendly vehicles (including EVs) stem from laws such as the Clean Air Conservation Act and the Act on Promotion of Development and Distribution of Environment-friendly Motor Vehicles. Considering the purpose of these laws, the easily observable policy objectives are the annual and cumulative sales of environment-friendly vehicles, but the actual objectives are of climate change correspondence (mitigating greenhouse gas emissions) and air pollutant emissions reduction (especially particulate matters) that result from the promotion of these environment-friendly vehicles. Therefore, this section considers the three following types of policy objectives:

1. Annual and cumulative BEV sales
2. Annual greenhouse gas (GHG) emissions
3. Annual particulate matter 10 (PM10) emissions

First, annual and cumulative BEV sales were calculated by assuming that the

stock of main vehicles for South Korean consumers was 10 million. Next, the annual GHG emissions were calculated for each vehicle type using the well-to-wheel approach as presented in Woo, Choi, & Ahn (2017). To be specific, I compared the average GHG emissions per unit for distance driven (g/km) of the stock in different policy scenarios. Next, for the PM10 emissions, I used the air pollutant emission factors as provided in the National Institute of Environment Research (2015). A point to be noted here is that only diesel ICEVs emit PM10, which means zero PM10 emissions are assumed for gasoline ICEVs, HEVs, and BEVs. Moreover, since the data provide different emission factors for different vehicle types within the same operating method, different emissions factors are applied for each vehicle class. The data shows that diesel SUVs emit around 50% more PM10 when compared to other vehicle classes. As of GHG emissions, I compared the average GHG emissions per unit for distance driven (g/km) of the stock in different policy scenarios.

Considering these policy objectives, three policy analyses are conducted. To be specific, I would like to answer to following questions:

1. (Policy Analysis 1) Can the same policy objectives be achieved with lesser government expenditure if a change in product supply is considered?
2. (Policy Analysis 2) Which form of policy intervention is more effective considering a change in product supply?
3. (Policy Analysis 3) What is the impact of the policy intervention that

focuses on regulating diesel ICEVs?

First, I introduce the Policy Analysis 1, which aims to seek potential budget savings of policy intervention. As already shown in Section 4.3.2.2, a change in product supply can induce significant differences in future market forecasts. To be specific, the consideration of a change in product supply leverages the impact of policy intervention in future forecasts. Therefore, if a change in product supply is not considered, the impact of policy intervention may be underestimated, and thus, new technology products may be over-subsidized. Therefore, policy makers may be interested in the extent of possible budget savings by considering a product supply change. The situations to be compared for Policy Analysis 1 are presented in Table 30.

**Table 30**. Situations to be compared for Policy Analysis 1

| | Policy situation | Product line extension plan |
|---|---|---|
| Situation A | Scenario (1) (no incentives) | Optimal response to Scenario (1) |
| Situation B | Scenario (3) (incentives ~2025) | Optimal response to Scenario (1) |
| Situation C | Scenario (3) (incentives ~2025) | Optimal response to Scenario (3) |
| Situation D | 10% less incentives compared to Scenario (3) | Optimal response to 10% less incentives from Scenario (3) |
| Situation E | 20% less incentives compared to Scenario (3) | Optimal response to 20% less incentives from Scenario (3) |
| Situation F | 30% less incentives compared to Scenario (3) | Optimal response to 30% less incentives from Scenario (3) |

Before observing the BEV sales and the environmental impact of situations presented in Table 30, I first present the optimal product-line extension plan for these situations (Table 31). First, the product-line extension plan of Situations A and B are the same by definition. The product-line extension plan for Situations D and E show 10% and 20% lower subsidies for BEVs when compared to Situation C, which showed a similar but different product-line extension plan when compared to Situation C. To be specific, low-end models tend to be introduced more quickly. However, Situation F, which shows 30% lower subsidies for BEVs, displayed a significantly different product-line extension plan when compared to Situation C. To be specific, more hybrid models are introduced,

and they are introduced much earlier.

**Table 31**. Product line extension plan for situations in Policy Analysis 1

| | Situation A | Situation B | Situation C | Situation D | Situation E | Situation F |
|---|---|---|---|---|---|---|
| 2019 | HS1, HS2 | HS1, HS2 | ES3, ES6 | ES4, ES6 | ES4, ES6 | HS1, HM2 |
| 2020 | HM1, HM2 | HM1, HM2 | ES4, ES2 | ES3, ES2 | ES3, ES2 | ES2, EF1 |
| 2021 | ES1, ES3 | ES1, ES3 | ES5, ES1 | ES5, ES1 | ES5, ES1 | ES1, EM2 |
| 2022 | HF3, HF1 | HF3, HF1 | EF2, EF1 | EF5, HM2 | EF5, HM2 | EF5, HF1 |
| 2023 | EF4, ES2 | EF4, ES2 | EF4, EF3 | EF3, EF1 | EF3, EF1 | EF4, HM1 |
| 2024 | EF1, EF2 | EF1, EF2 | HF3, HF2 | EF2, HM1 | EF2, HM1 | EF3, EF2 |
| 2025 | EF3, HF2 | EF3, HF2 | HM1, HF1 | HF2, HF1 | HF2, HF1 | HF3, HF2 |
| Total revenue | 2.552 | 2.640 | 2.650 | 2.635 | 2.622 | 2.611 |
| BEVs | 7 | 7 | 10 | 10 | 10 | 8 |
| BEV sales (stock) share in 2030 | 9.5% (5.6%) | 9.7% (7.0%) | 12.8% (9.4%) | 12.7% (9.0%) | 12.7% (8.8%) | 9.9% (6.7%) |

Next, the future forecast results for Policy Analysis 1 are presented in Figure 21 and Figure 22. Figure 21 shows the annual and cumulative BEV sales for each situation. On the other hand, Figure 22 shows the annual GHG and PM10 emissions for each situation. First, in Figure 21, forecasts that did not consider a product supply change from the policy intervention (Situation B) displayed lower cumulative BEV sales when compared to forecasts considering a product supply change from the policy intervention, even with a 10% and 20% less incentive (Situation D and E). Moreover, the cumulative BEV sales with 30% less incentives (Situation F) was lower but did not have much

difference from those not considering a product supply change (Situation B). In other words, the government may save 20-30% of its subsidies by considering a change in the product-line extension in response to policy intervention, to achieve the same (or similar) sales of the BEVs. Moreover, there is a significant gap between the resulting 20% and 30% decrease in incentives (Situations E and F). This difference is due to the significant change in product supply shown in Table 31.

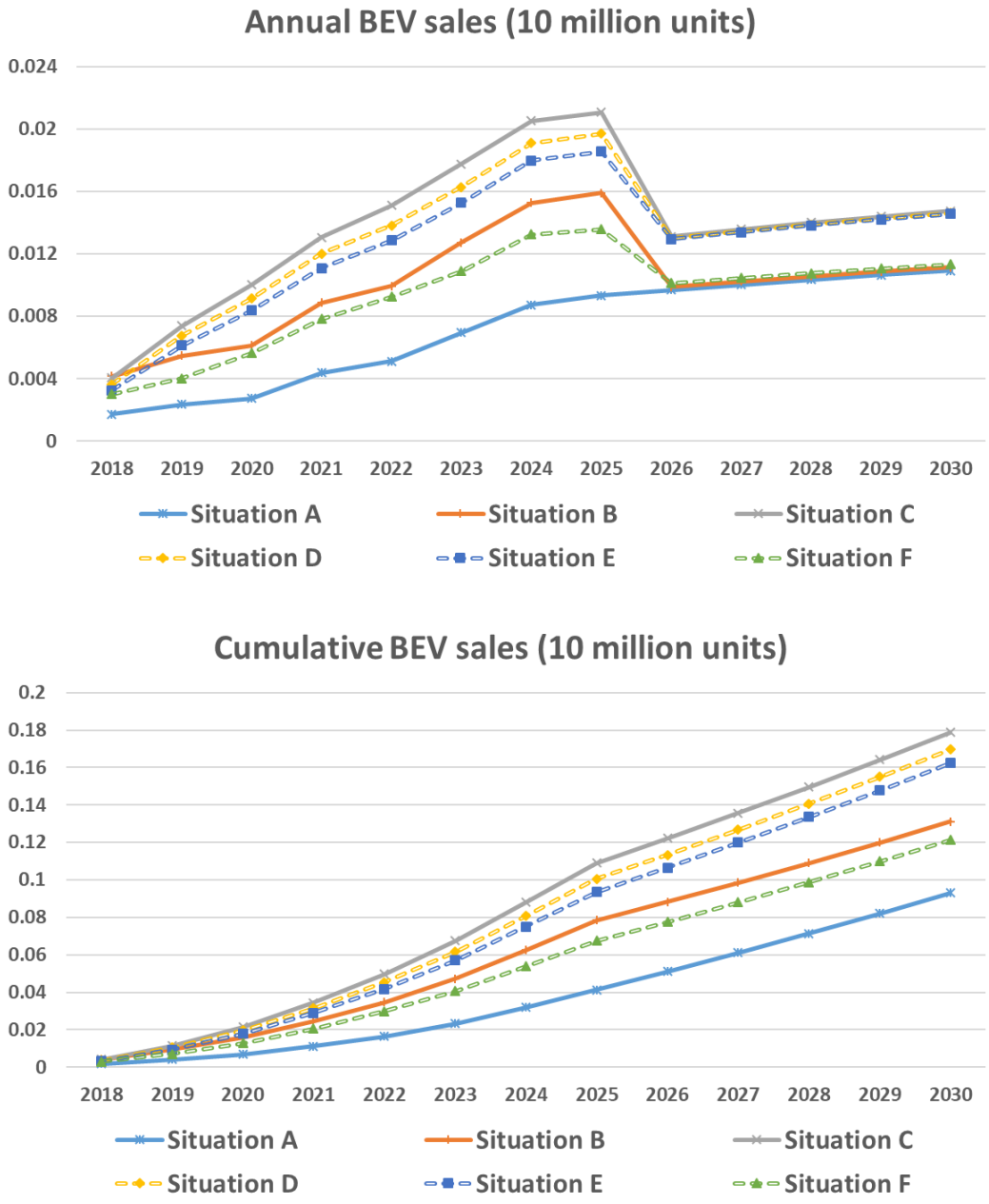



**Figure 21**. Analysis results of Policy Analysis 1 – annual and cumulative BEV sales

Next, I analyze the results of the GHG and PM10 emissions in Figure 22. For

the results of annual GHG emissions, a similar pattern of cumulative BEV sales was observed (20-30% lower subsidies may achieve the same policy objective when a change in the product supply is considered). On the other hand, the results of the annual PM10 emissions indicate that PM10 emissions of Situations C-F get worse after the incentives for BEVs end in 2025. By 2029, PM10 emissions of Situations C-F were even higher than Situation A(no incentives). On the other hand, Situation b, which assumes the product-line extension plan for no incentives for BEVs, showed the lowest PM10 emissions throughout the timeline. This is because if the incentives for BEVs are provided until 2025 and the product supply appropriately responds (Situation C-F), then the product-line extension is focused on electric SUVs, and hybrid SUVs are not introduced (See Table 31). Hybrid SUVs are powerful competitors of diesel SUVs regardless of financial incentives. However, electric SUVs are not as competitive when compared to diesel SUVs against hybrid SUVs, after the end of policy incentives. In other words, the focus on the supply of electric SUVs, and having no supply of hybrid SUVs due to incentives for BEVs, has contradictorily increased the PM10 emissions.

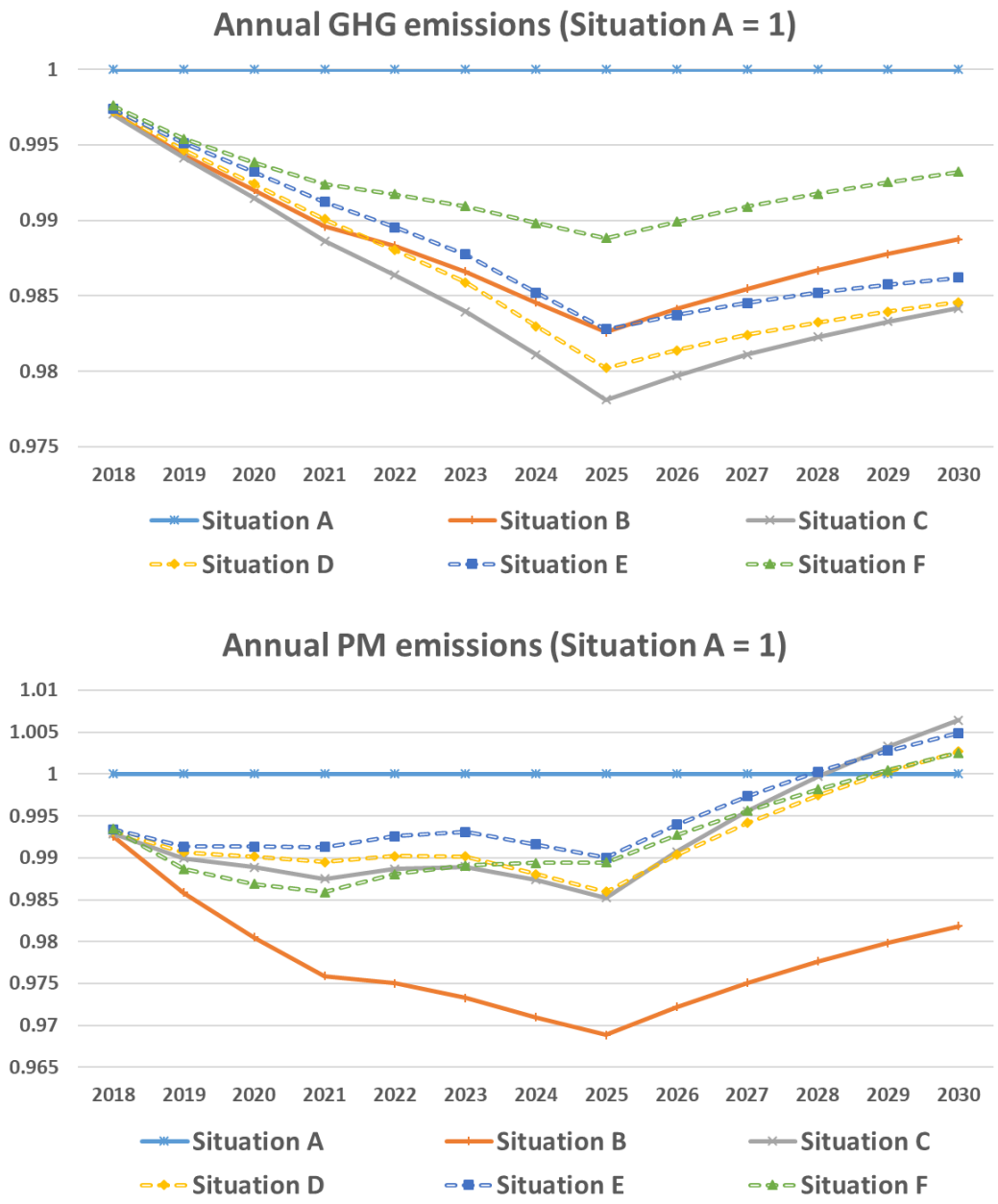



**Figure 22**. Analysis results of Policy Analysis 1 - GHG and PM10 emissions

Second, I introduce the results of Policy Analysis 2, which aims to seek a more

favorable form of policy intervention. As the proposed model forecasts the impact of policy intervention, along with the diffusion of new technology and changes in stock, the model can compare the effectiveness of policy intervention by its type. To be specific, I compare two policy options as presented in Table 32. The first option is to strongly incentivize BEVs for a short period (~2025), with the other being to weakly incentivize BEVs for a long period (~2033). The two options presented in Table 32 can be compared since they display almost the same total policy expenditure throughout the timeline.

**Table 32**. Policy options to be compared in Policy Analysis 2

| Policy option | Financial incentives until | Initial incentives | Annual incentives reduction |
|---|---|---|---|
| *SS* (strong and short) | 2025 | 10% less than Scenario (3) | 10% |
| *WL* (weak and long) | 2033 | Same as Scenario (3) | 15% |

First, Table 33 shows the product-line extension plan when each policy option is used. The two plans are similar, but the use of the *SS* option tends to introduce more low-end models earlier.

**Table 33**. Product line extension plan for policy options in Policy Analysis 2

| | Strong and Short (*SS*) | Weak and Long (*WL*) |
|---|---|---|
| 2019 | ES4, ES6 | ES2, ES3 |
| 2020 | ES3, ES2 | ES1, ES4 |
| 2021 | ES5, ES1 | ES5, EM1 |
| 2022 | EF5, HM2 | EF3, EF2 |
| 2023 | EF3, EF1 | EF4, HM1 |
| 2024 | EF2, HM1 | EF1, HF1 |
| 2025 | HF2, HF1 | HF3, HF2 |
| Total revenue | 2.635 | 2.635 |
| BEVs | 10 | 10 |
| BEV sales (stock) share in 2030 | 12.7%<br>(9.0%) | 13.9%<br>(9.3%) |

Next, I present the results of each of the policy options. All of the results are introduced along with the results of the baseline situation (Situation a in Policy Analysis 1, no policy incentives for EVs at all). First, the annual and cumulative sales of BEVs for Policy Analysis 2 are presented in Figure 23. The results show that the annual sales of the *SS* option is higher than that of the *WL* option before 2025, but is lower afterwards. For the cumulative sales, the SS option showed higher cumulative sales throughout the timeline, but the cumulative sales of the two options eventually became similar by 2030.

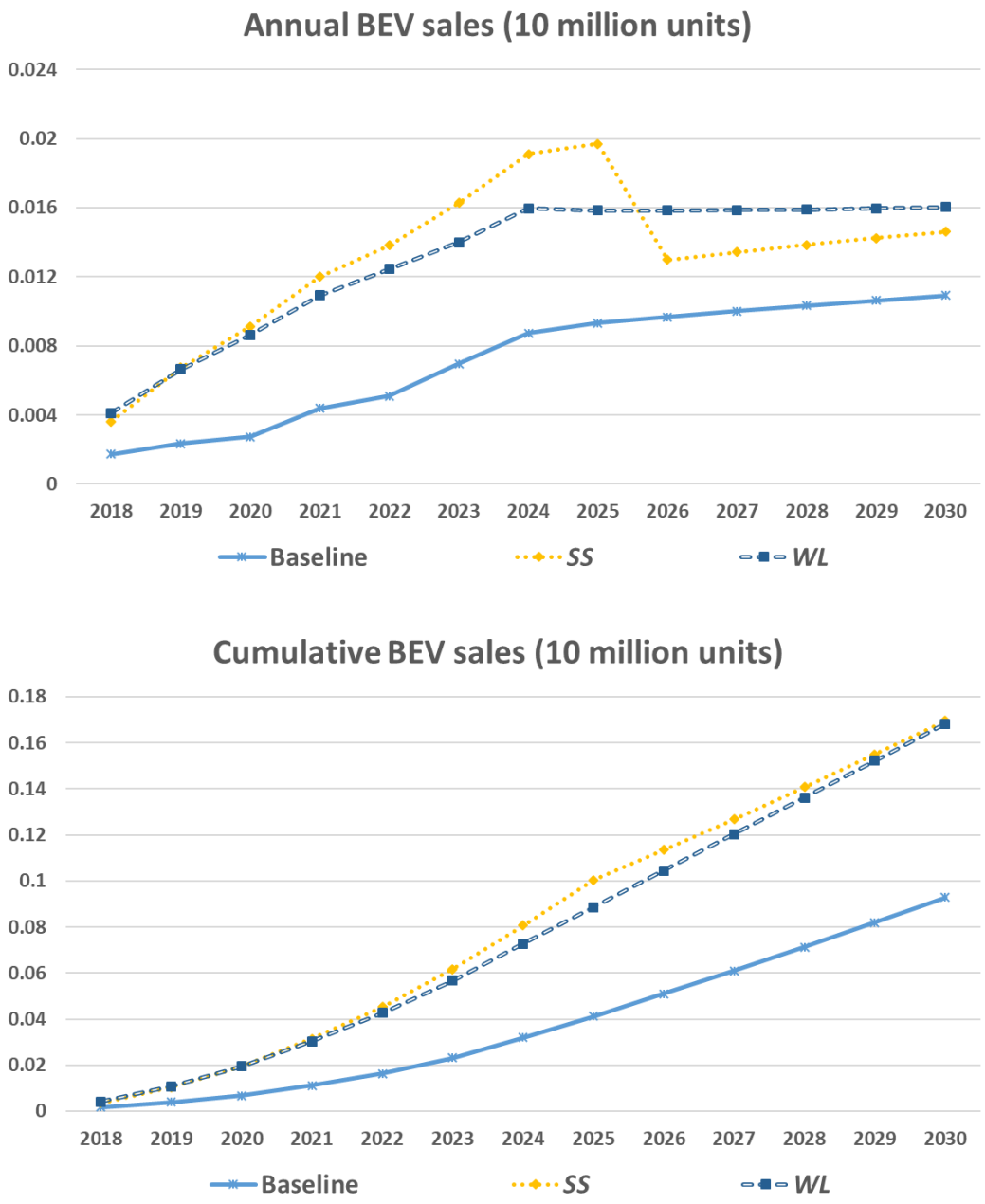



**Figure 23**. Analysis results of Policy Analysis 2 – annual and cumulative BEV sales

Next, the GHG and PM10 emissions of Policy Analysis 2 are provided in Figure

24. Although annual emissions in 2030 were similar for both GHG and PM10, the *SS* option derived more environment-friendly results from 2022 to 2029. This is because the strong and short policy intervention (*SS*) induces the early introduction of the more popular low-end BEV and HEV models, as shown in Table 33. In this aspect, short and strong policy intervention could be seen as being superior to weak and long policy intervention.

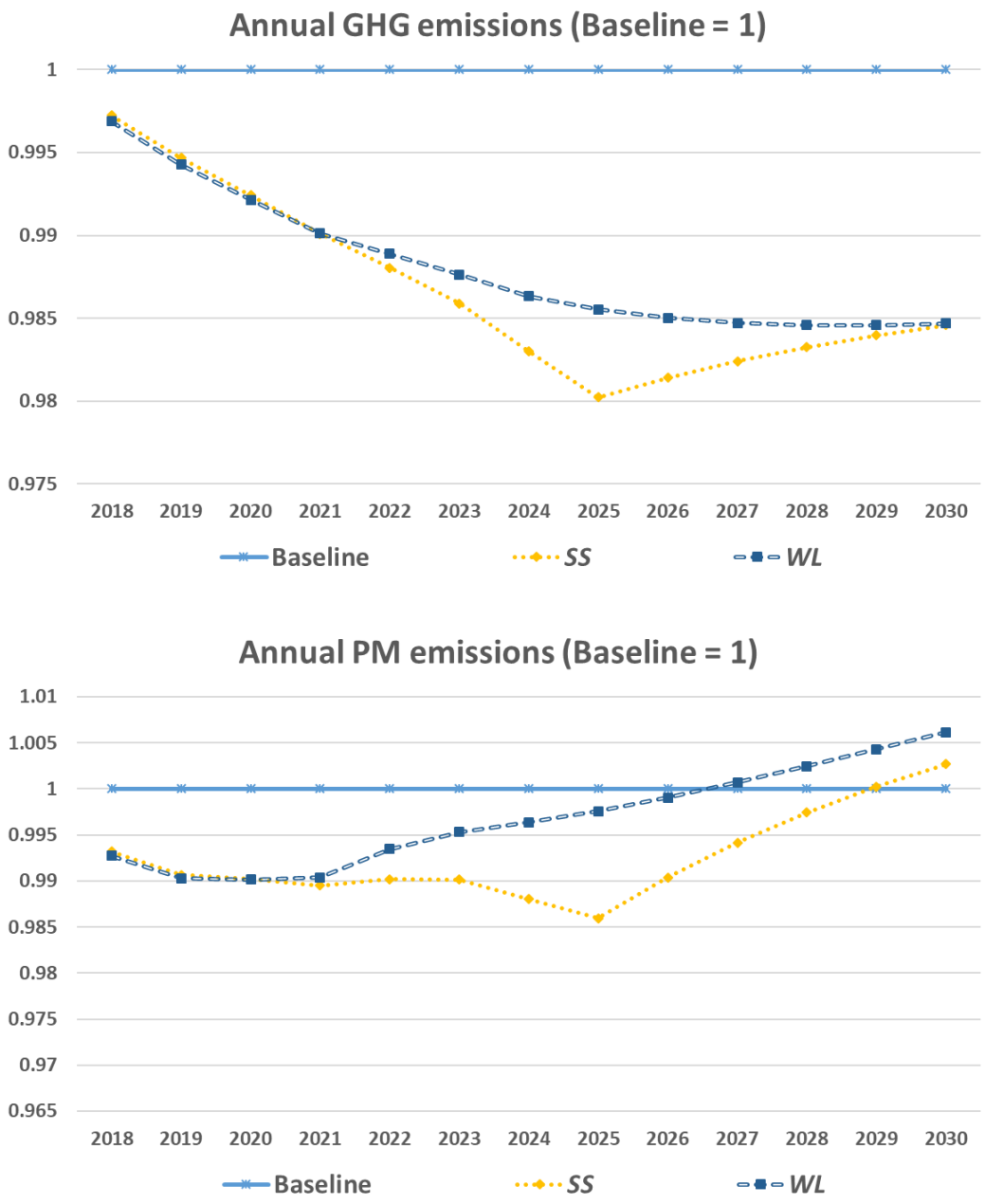



**Figure 24**. Analysis results of Policy Analysis 2 - GHG and PM10 emissions

Finally, I introduce Policy Analysis 3 which aims to analyze the impact of

directly regulating diesel ICEVs. PM10 emissions are directly dependent on the stock of diesel ICEVs, especially diesel SUVs. Although reducing PM10 emissions is one of the key policy objectives in South Korea, the results of Policy Analyses 1 and 2 show that the impact of lowering PM10 emissions is not very large in BEV promotion policies. These results imply that the promotion of BEVs do not necessarily result in the reduction of diesel ICEV stocks.

Therefore, in Policy Analysis 3, I analyze the impact of policies that directly regulate diesel ICEVs. To be specific, I compare the situations presented in Table 34. The baseline for all policy situations in Table 34 is Situation C in Policy Analysis 1 (incentives for BEVs until 2025). In other words, financial incentives for BEVs are provided until 2025 for all situations. I consider two types of policy intervention for diesel ICEVs. The first is to penalize the fuel price, and the second is to penalize the price of the vehicle. To be specific, Situation G assumes a 14% increase in diesel price, which makes the price of diesel the same as gasoline. On the other hand, Situation H assumes a KRW 2 million penalty on the vehicle price of diesel ICEVs. Situation I assumes an additional KRW 2 million penalty for diesel SUVs from Situation H.

**Table 34**. Situations to be compared for Policy Analysis 3

| | Disincentives for diesel ICEV purchase price | Disincentives for diesel fuel price |
|---|---|---|
| Situation C | None | None |
| Situation G | None | 14% increase in diesel fuel price (diesel price = gasoline price) |
| Situation H | 2 million KRW | None |
| Situation I | 2 million KRW (additional 2 million KRW for SUVs) | None |

First, I analyze the product-line extension plan for each situation. The results are presented in Table 35. It can be observed that the product-line extension plan for Situations G-I are all the same. Compared to the product-line extension plan of Situation C, mid-sized BEVs are introduced instead of full-size BEVs, and HEVs are introduced earlier.

**Table 35.** Product line extension plan for Situations in Policy Analysis 3

| | Situation C | Situation G | Situation H | Situation I |
|---|---|---|---|---|
| 2019 | ES3, ES6 | ES4, ES6 | ES4, ES6 | ES4, ES6 |
| 2020 | ES4, ES2 | ES5, ES2 | ES5, ES2 | ES5, ES2 |
| 2021 | ES5, ES1 | ES3, ES1 | ES3, ES1 | ES3, ES1 |
| 2022 | EF2, EF1 | EM1, EM2 | EM1, EM2 | EM1, EM2 |
| 2023 | EF4, EF3 | HM1, HF1 | HM1, HF1 | HM1, HF1 |
| 2024 | HF3, HF2 | EF1, EF2 | EF1, EF2 | EF1, EF2 |
| 2025 | HM1, HF1 | HF3, HF1 | HF3, HF1 | HF3, HF1 |
| Total revenue | 2.650 | 2.651 | 2.645 | 2.641 |
| BEVs | 10 | 10 | 10 | 8 |
| BEV sales (stock) share in 2030 | 12.8% (9.4%) | 13.1% (9.6%) | 13.3% (9.7%) | 13.5% (9.8%) |

Finally, the analysis results of Policy Analysis 3 are presented in Figure 25 and Figure 26. First, in Figure 25 the annual and cumulative BEV sales did not vary much within direct regulations on diesel ICEVs. Such small differences imply a weak substitutional relationship between BEVs and diesel ICEVs. Considering that the main causes of PM10 emissions are diesel ICEVs, the promotion of only the BEVs may not be effective in trying to reduce PM10 emissions.

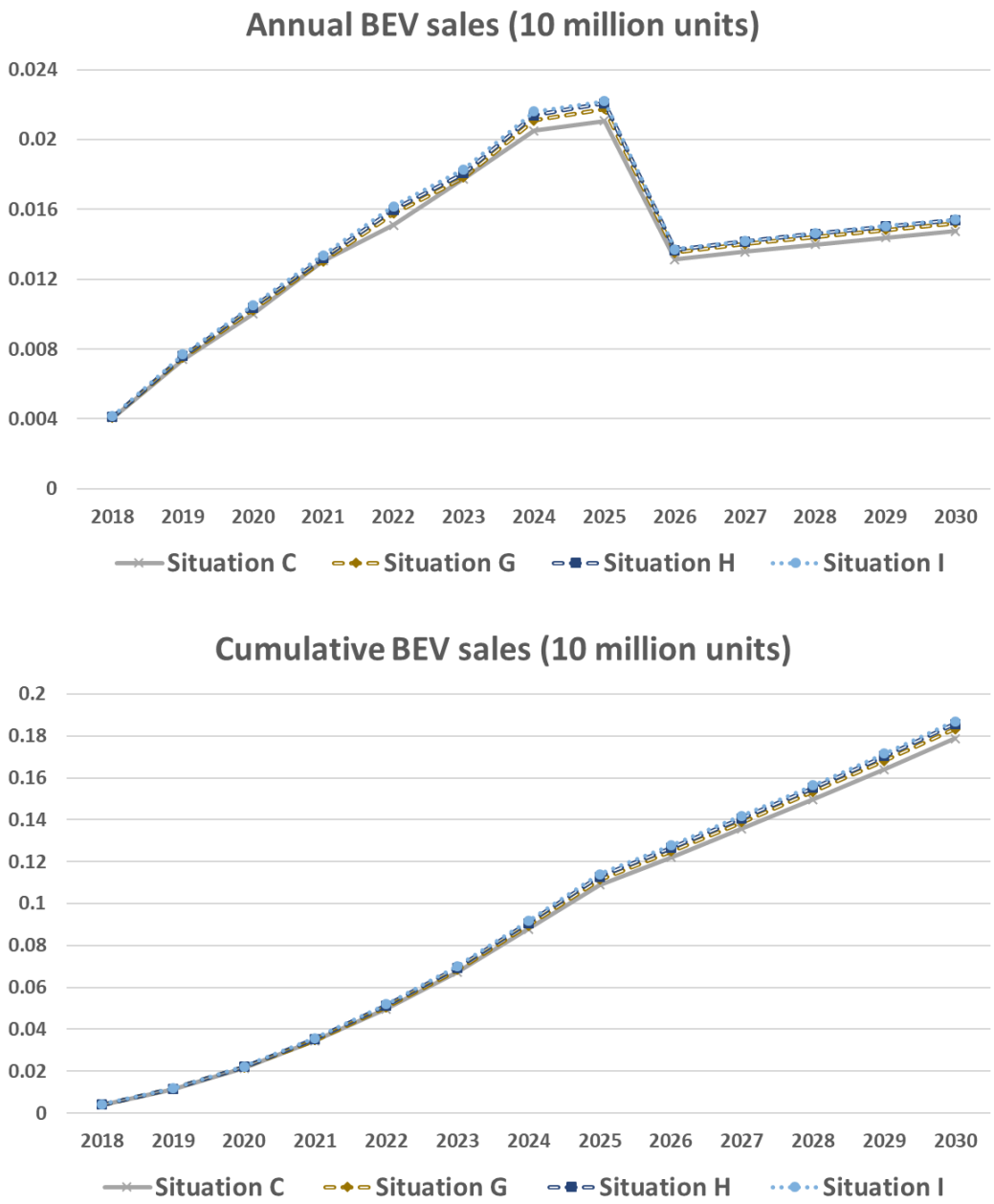



**Figure 25**. Analysis results of Policy Analysis 3 – annual and cumulative BEV sales

Next, Figure 26 shows the environmental impact of the regulations on diesel

ICEVs. The results are presented in relative values, setting the value of Situation C as 1. For Policy Analysis 3, I first observe the results of PM10 emissions. The results of PM10 emissions show that the regulations on vehicle price displayed a higher impact on PM10 emissions reductions when compared to those of regulations on fuel price. Moreover, additional regulations on diesel SUVs, which are the main contributor of PM10 emissions, showed significantly large emissions reduction. These results imply that direct regulations on diesel ICEVs are needed for the reduction of PM10 emissions, mainly due to the weak substitutional relationship between BEVs and diesel ICEVs.

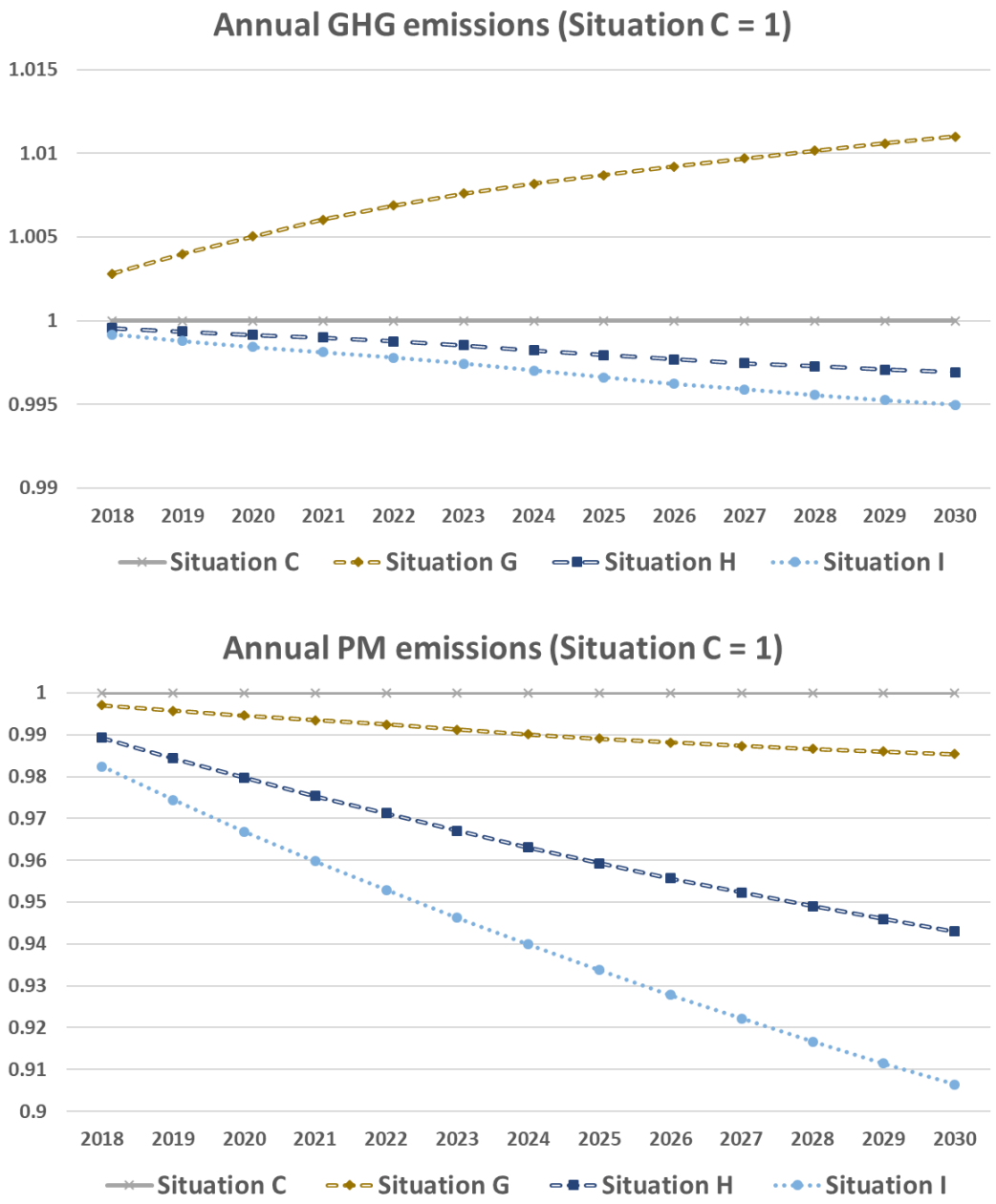



**Figure 26**. Analysis results of Policy Analysis 3 - GHG and PM10 emissions

In terms of GHG emissions, the taxing of vehicle price (Situation H, I) has

reduced GHG emissions, but the taxing of fuel price (Situation G) has increased GHG emissions when compared to the baseline case. The reason behind such a change can be explained using Figure 27 and Figure 28.

First, Figure 27 shows the annual sales and stock shares of diesel ICEVs. The results show that regulations on fuel price had a minor impact when compared to regulations on vehicle price. To be specific, regulations on fuel price had around a 0.5%p difference to the baseline in the 2030 stocks. On the other hand, regulations on vehicle price showed more than a 2%p difference, with additional regulations on diesel SUVs showing a 3.5%p difference.

However, why then are the GHG emissions of Situation G higher than the baseline, despite it having a lower (even though its extent is small) stock of diesel ICEVs? It is because regulations on diesel ICEVs make the stock of diesel ICEVs more environmentally unfriendly. Figure 28 shows the average GHG emissions of an average diesel fuel vehicle in the stock. As one can observe, Situation G makes the average environmental performance of diesel ICEVs worse. This is mainly because regulations on diesel ICEVs make the replacement rate of diesel ICEVs slower. Many consumers will move on to other operating methods, as in Figure 27, but those who want to remain with the diesel ICEVs will simply purchase new vehicles less often. Moreover, such environmental inefficiencies of diesel ICEV stocks is worse for fuel regulation. This is because the regulation on fuel is for both the SQ and the new diesel ICEVs, but the regulation on vehicle price is only for new vehicles. In other words, the incentive to

purchase a new diesel ICEV is larger for a vehicle price regulation case.

To summarize, the direct regulations on diesel ICEVs could significantly contribute to the reduction in PM10 emissions by reducing stocks of diesel ICEVs. The promotion to BEVs could not achieve a significant amount of PM10 reductions in South Korea, since the substitutional relationship between BEVs and diesel ICEVs was weak. In terms of the method to use for regulations, fuel taxation had a minor impact when compared to taxation of the purchase price of the vehicle.

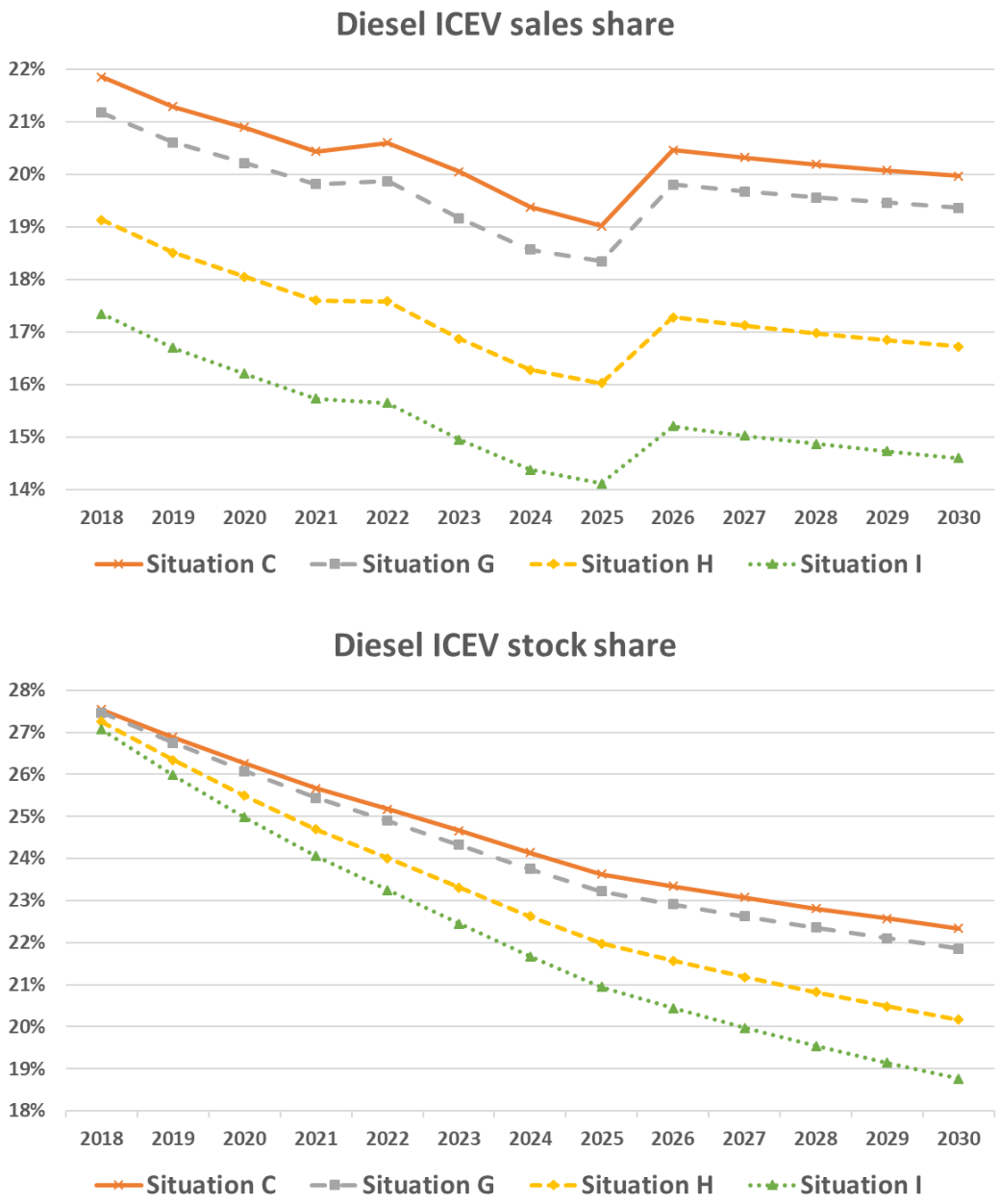



**Figure 27**. Diesel ICEV sales and stock share for Policy Analysis 3

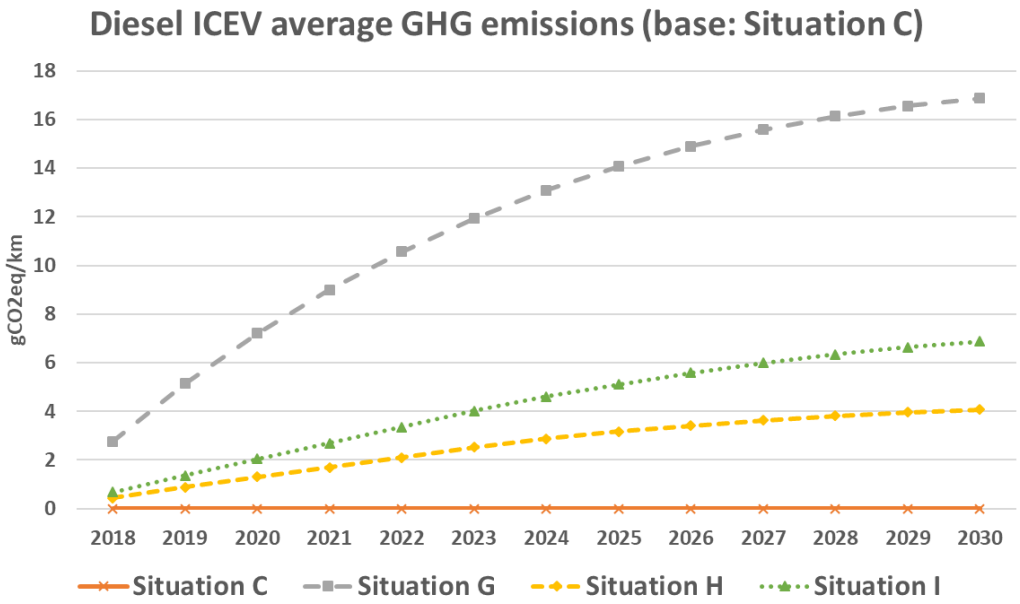



**Figure 28**. Diesel ICEV average GHG emissions for Policy Analysis 3

## 4.4 Analysis 3: Impact of New Entrant on Consumers' Intertemporal Choice for New Products

The objective of Analysis 3 is to analyze the impact of the market entrance of a new entrant that can only introduce new technology products (BEVs) on new technology diffusion. Specifically, I would like to answer to the following research questions:

1. How will the incumbent respond to the new entrant?
2. How much will the new entrant contribute to the diffusion of EVs?

In short, the entrance of a new entrant (and the corresponding product introduction) will affect the product line that consumers will face, thus directly affecting consumer choice. Moreover, such an entrance will induce responses of the incumbent. The impact of such responses are the key points to be analyzed in this section, and various simulation analysis will be conducted to analyze the extent of the impact.

### 4.4.1 Background

#### 4.4.1.1 Settings

In Analysis 3, I consider the timeframe from the years 2018 to 2030 (13 years total) and assume three years of forward-looking for consumers. Each supplier (the new entrant and the incumbent) introduces new models from 2019 to 2025 (7 years), while the incumbent introduces two models annually and the new entrant introduces one model annually (total 21). Each supplier cannot introduce the same model again, but can introduce the same model that the other supplier introduces (or has already introduced). Moreover, the new entrant can only introduce BEVs, while the incumbent can introduce both HEVs and BEVs. Finally, once a specific model is introduced, the model is then continuously introduced for the remaining timeframe with technological improvements, and there is no discontinuance of models. For the optimization of the product-line extension model, I used the best results from five trials with n=100.

### 4.4.2 Simulation Analysis

#### 4.4.2.1 Change in Product Line Extension

The product-line extension plan for the two suppliers is derived by the process introduced in Section 3.3.3. The equilibrium process for Scenarios (1) to (6) is presented in Table 36. Considering the stop condition, the incumbent's second plan (the first response to a new entrant) is the final plan for the incumbent, and the new entrant's first plan (which is the same with the second plan) is the final plan for the new entrant. This is because the market entry strategy for the new entrant is rather simple when compared to the incumbent. Since the new entrant does not have to consider cannibalization for existing products, the main objective of the new entrant is to steal as much of the market share of the incumbent as possible with the BEVs. Therefore, the new entrant only sequentially introduces popular low-end SUVs and mid-sized vehicle models. The equilibrium plan of the new entrant, in response to the results in Table 23 (the monopolist supplier's optimal plan), is presented in Table 37.

**Table 36.** Process of deriving optimal product line extension plan for duopoly market

| | Optimization process |
|---|---|
| Scenario (1) | Incumbent's first plan → new entrant's first plan → incumbent's second plan → new entrant's second plan |
| Scenario (2) | Incumbent's first plan → new entrant's first plan → incumbent's second plan → new entrant's second plan |
| Scenario (3) | Incumbent's first plan → new entrant's first plan → incumbent's second plan → new entrant's second plan |
| Scenario (4) | Incumbent's first plan → new entrant's first plan → incumbent's second plan → new entrant's second plan |
| Scenario (5) | Incumbent's first plan → new entrant's first plan → incumbent's second plan → new entrant's second plan |
| Scenario (6) | Incumbent's first plan → new entrant's first plan → incumbent's second plan → new entrant's second plan |

**Table 37.** Product line extension plan of the new entrant considering the incumbent

| | Scenario (1) | Scenario (2) | Scenario (3) | Scenario (4) | Scenario (5) | Scenario (6) |
|---|---|---|---|---|---|---|
| 2019 | EM7 | EM7 | EM7 | EM7 | EM7 | EM7 |
| 2020 | ES7 | ES7 | ES7 | ES7 | ES7 | ES7 |
| 2021 | EM6 | ES6 | ES6 | ES6 | ES6 | ES6 |
| 2022 | ES6 | EM6 | EM6 | EM6 | EM6 | EM6 |
| 2023 | ES5 | ES5 | ES5 | ES5 | ES5 | ES5 |
| 2024 | ES4 | ES4 | ES4 | ES4 | ES4 | ES4 |
| 2025 | EM5 | EM5 | EM5 | EM5 | EM5 | EM5 |
| Total revenue | 0.189 | 0.207 | 0.247 | 0.271 | 0.271 | 0.243 |

Table 37 shows the product-line extension plan for the new entrant. It can be observed that the plan for each scenario is quite similar. Specifically, although the optimal

plan for Scenario (1) is unique, the optimal plans for Scenarios (2)-(6) are all the same. The optimal plan for Scenario (1) and the other Scenarios only differ for the models introduced in 2021 and 2022. While Scenario (1) introduces EM6 first and then ES6, the other Scenarios introduce ES6 first and then EM6. This may because in Scenario (1), no incentives existed for BEVs, and thus, the new entrant wanted to introduce the cheaper model.

Next, the incumbent's product-line extension plan when the new entrant enters the market is presented in Table 38. When compared to the monopolist case in Analysis 2, the incumbent, when in competition, tended to introduce more low-end models. Specifically, the introduction of full-size vehicles decreased significantly. Moreover, in Scenarios (4) and (5), where the policy incentives for BEVs were continued for the whole timeframe, the incumbent only introduced BEVs.

**Table 38.** Product line extension plan of the incumbent considering the new entrant

| | Scenario (1) | Scenario (2) | Scenario (3) | Scenario (4) | Scenario (5) | Scenario (6) |
|---|---|---|---|---|---|---|
| 2019 | HS2, HS3 | ES6, HS2 | ES7, EM7 | ES6, EM7 | ES6, EM7 | ES7, ES6 |
| 2020 | HM2, HM1 | ES5, ES7 | ES6, ES5 | ES7, ES5 | ES7, ES5 | ES5, ES3 |
| 2021 | ES6, HS1 | EM2, HS1 | ES4, ES3 | ES4, EM6 | ES4, EM6 | EM7, EF7 |
| 2022 | ES2, HM3 | HM2, HF7 | ES2, EM5 | ES3, EM5 | ES3, EM5 | ES4, EM3 |
| 2023 | ES7, ES5 | ES3, HM1 | EM6, ES1 | ES2, ES1 | ES2, ES1 | EM6, ES2 |
| 2024 | ES4, ES3 | ES2, ES4 | EM4, EM3 | EM4, EM3 | EM4, EM3 | ES1, HS1 |
| 2025 | ES1, EM1 | ES1, EM1 | HS1, HF1 | EM2, EM1 | EM2, EM1 | EM4, HF1 |
| Total revenue | 2.409 | 2.450 | 2.466 | 2.468 | 2.460 | 2.445 |
| Introduced BEVs | 8 | 9 | 12 | 14 | 14 | 12 |
| BEV sales (stock) share in 2030 | 16.2% (9.1%) | 17.0% (10.3%) | 20.0% (14.0%) | 27.1% (17.3%) | 27.1% (17.3%) | 20.8% (13.2%) |

The results in Table 37 and Table 38 show the final equilibrium plan between the two suppliers. Next, I present the amount that the incumbent suffers in revenue loss by the entrance of the new entrant, and show how the incumbent may reduce such a loss by changing its product-line extension plan (from Table 23 to Table 38). The results are summarized in Table 39. Without an appropriate response, the loss of the incumbent is around 5.9~8.4% of its total revenue (the initial loss). The level of loss increases as the level of policy incentives for BEVs gets stronger (which means a favorable environment for BEVs). However, when the incumbent appropriately responds to the entrance of the new entrant, the loss is decreased to 5.6~7.8% (the loss after response). In other words, the incumbent can reduce its loss by 5.8 to 9.8% by appropriately responding to the new

entrant (the loss reduction by response). The results in Table 39 show that the incumbent's appropriate response to the new entrant can have a significant impact on defending one's revenue.

**Table 39.** Incumbent's loss by entrance of new entrant and loss reduction from appropriate response

| | Scenario (1) | Scenario (2) | Scenario (3) | Scenario (4) | Scenario (5) | Scenario (6) |
|---|---|---|---|---|---|---|
| Initial loss | -5.9% | -6.4% | -7.7% | -8.4% | -8.4% | -7.2% |
| Loss after response | -5.6% | -6.0% | -6.9% | -7.7% | -7.8% | -6.5% |
| Loss reduction by response | 5.8% | 6.2% | 9.7% | 8.0% | 8.1% | 9.8% |

#### 4.4.2.2 Impact of the New Entrant's Market Entrance

In this section, I analyze the impact of the new entrant on new technology diffusion. Specifically, I disaggregate the impact of the new entrant itself and the impact of response of the incumbent. As in Analysis 1 and 2, I define cases to analyze such aspects. The cases considered in Analysis 3 are provided in Table 40. To summarize, each case analyzes the impact of the new entrant on the incumbent's product line extension and the new technology diffusion for various policy scenarios.

**Table 40.** Cases to be considered in Analysis 3

| | Compared scenario | Entrance of new entrant | Analysis objective |
|---|---|---|---|
| Case 3-A | Scenario (1) | No | Impact of entrance of new entrant on the product line extension (model supply) and future vehicle market when no financial incentives exist for electric vehicles |
| | | Yes | |
| Case 3-B | Scenario (2) | No | Impact of entrance of new entrant on the product line extension (model supply) and future vehicle market when financial incentives for BEVs last until 2021 |
| | | Yes | |
| Case 3-C | Scenario (3) | No | Impact of entrance of new entrant on the product line extension (model supply) and future vehicle market when financial incentives for BEVs last until 2025 |
| | | Yes | |
| Case 3-D | Scenario (4) | No | Impact of entrance of new entrant on the product line extension (model supply) and future vehicle market when financial incentives for BEVs last until 2033 |
| | | Yes | |

First, for Case 3-A, I analyze the impact of the new entrant on new technology diffusions for Scenario 1, where incentives for both HEVs and BEVs are not provided at all. The situations to be compared for Case 3-A are provided in Table 41. The cases in Analysis 3 compare the impact of the new entrant itself (Situation A versus B) and the incumbent appropriately responding to the market entrance of the new entrant (Situation B versus C) when the policy situation is fixed. The analysis results for Case 3-A are provided in Figure 29.

**Table 41.** Situations to be compared for Case 3-A

| | Policy situation | New entrant | Incumbent's plan | Descriptions |
|---|---|---|---|---|
| Situation A | Scenario (1) (no incentives) | No | Optimal plan for the monopolist case | Incumbent appropriately respond to monopolistic market situation |
| Situation B | | Yes | Optimal plan for the monopolist case | New entrant enters the market, but the incumbent do not respond |
| Situation C | | Yes | Optimal plan in response to new entrant | Incumbent appropriately respond to the entrance of new entrant |

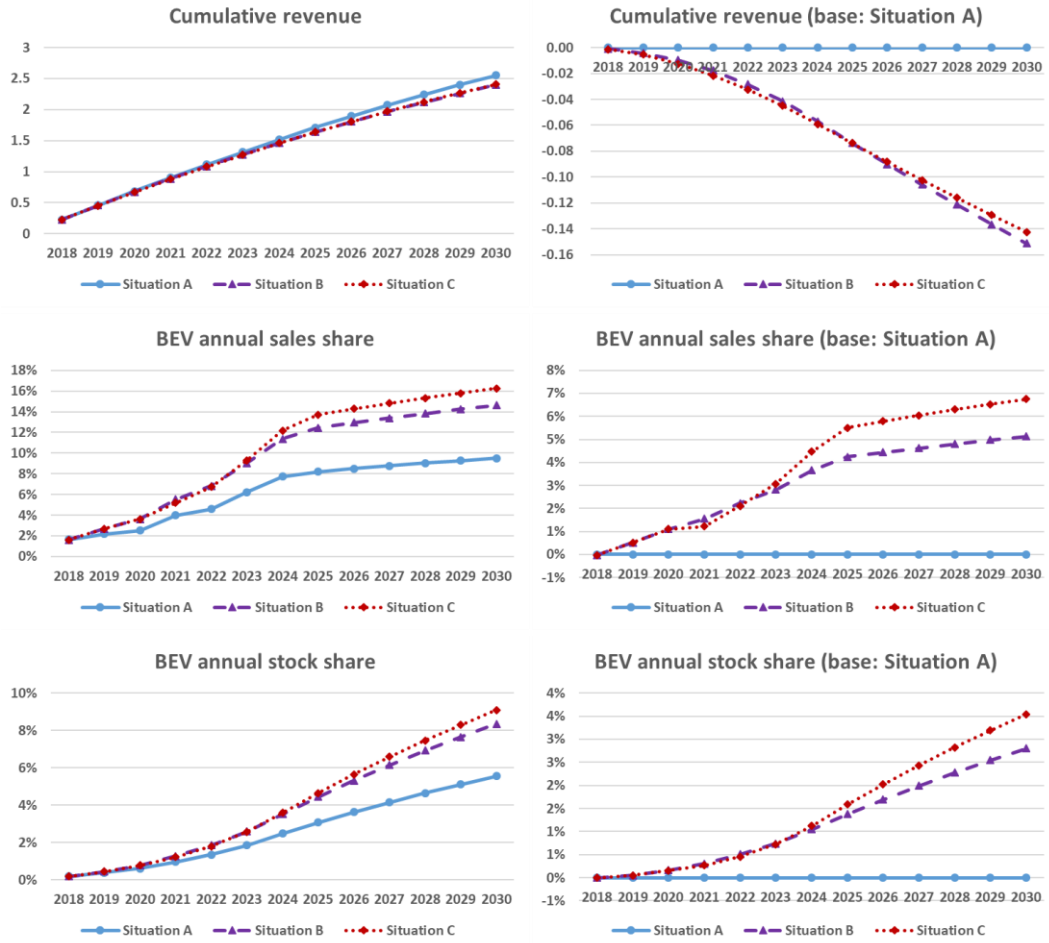



**Figure 29.** Analysis results for Case 3-A

The results show that the entrance of a new entrant has a significant impact on BEV diffusion. Specifically, as the new entrant enters the market, the annual sales and stock shares of BEVs increased up to 5%p and 3.5%p respectively. Moreover, if the incumbent responded appropriately to the new entrant, the annual sales and stock shares of BEVs can be additionally increased up to 2%p and 1%p respectively. Such additional

increase is seen after 2024, since the incumbent focused on introducing low-end BEVs after 2023.

Next, Case 3-B to 3-D analyze cases similar to those in Table 41, and only the policy scenarios are changed. Therefore, I bypass introductions of situations for each case and move on to results. The results of Case 3-B, 3-C, and 3-D are presented in Figure 30, Figure 31, and Figure 32 respectively. Since the key patterns observed are similar to those of Case 3-A, I do not provide separate explanations for each case.

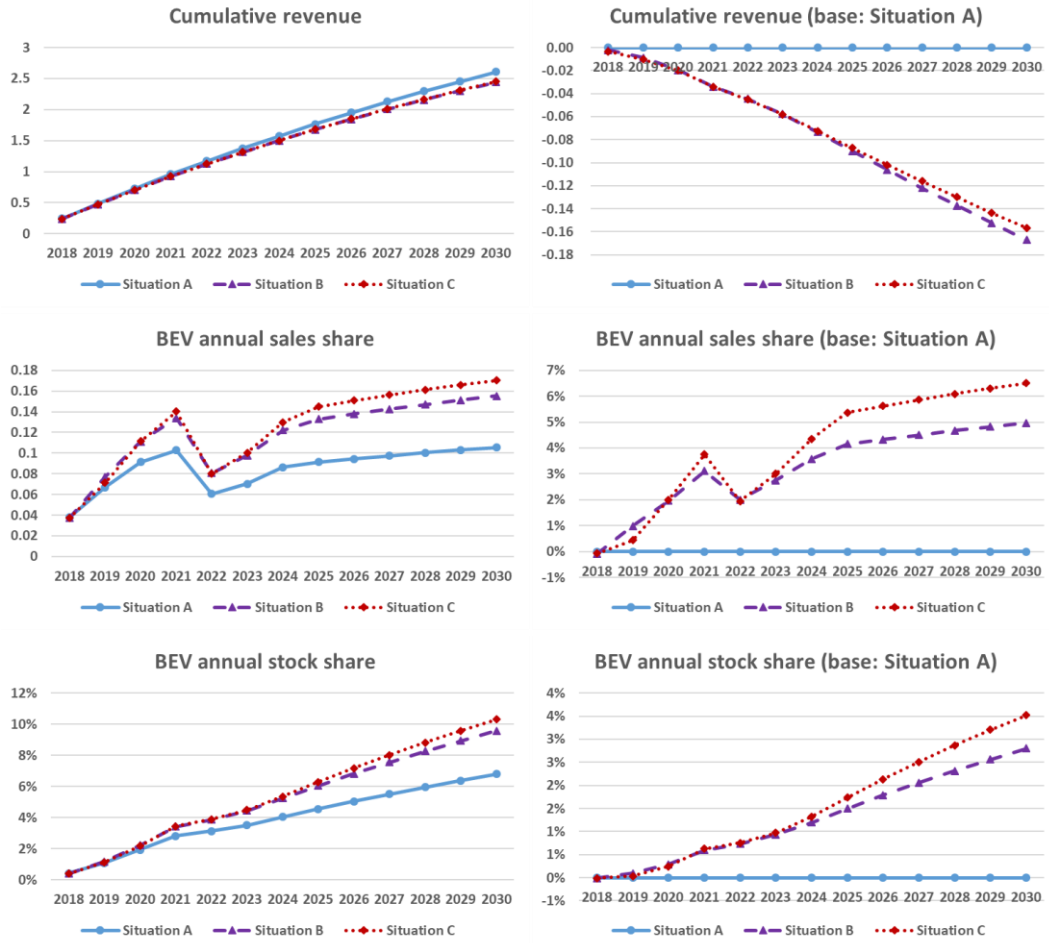



**Figure 30.** Analysis results for Case 3-B

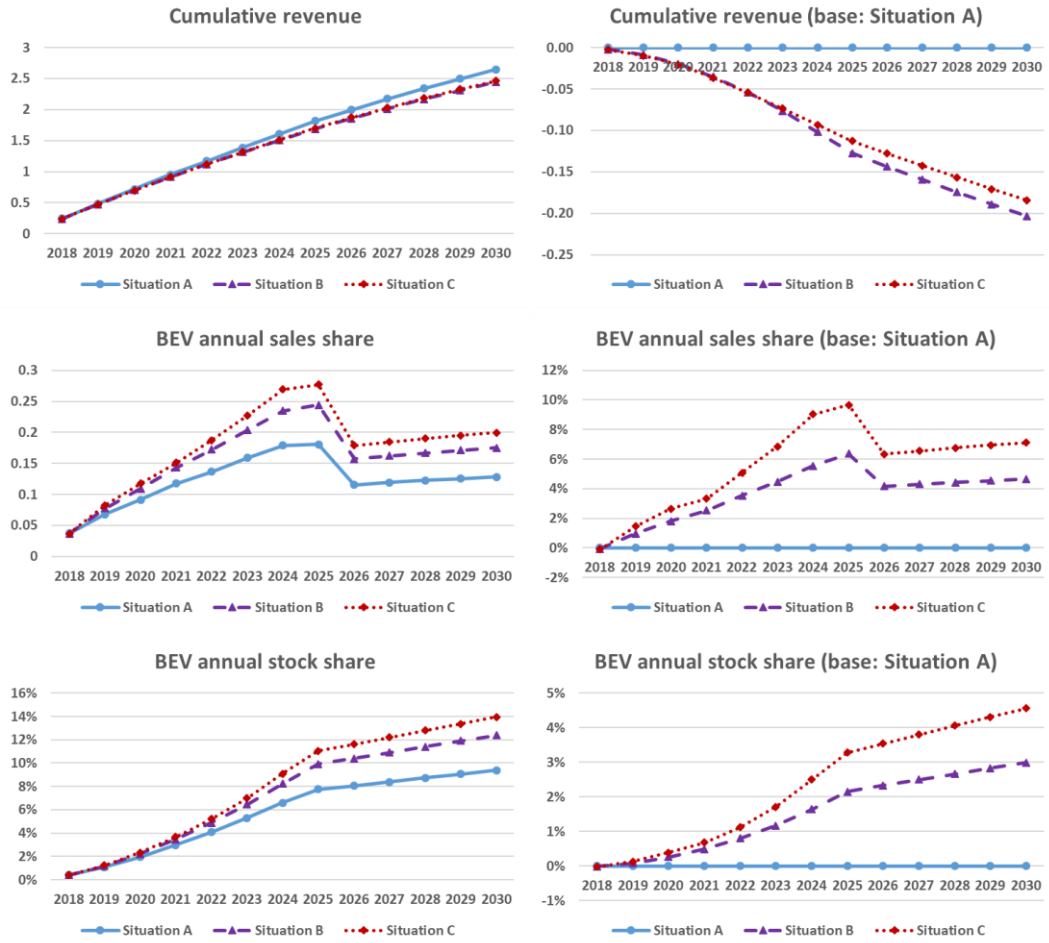



**Figure 31.** Analysis results for Case 3-C

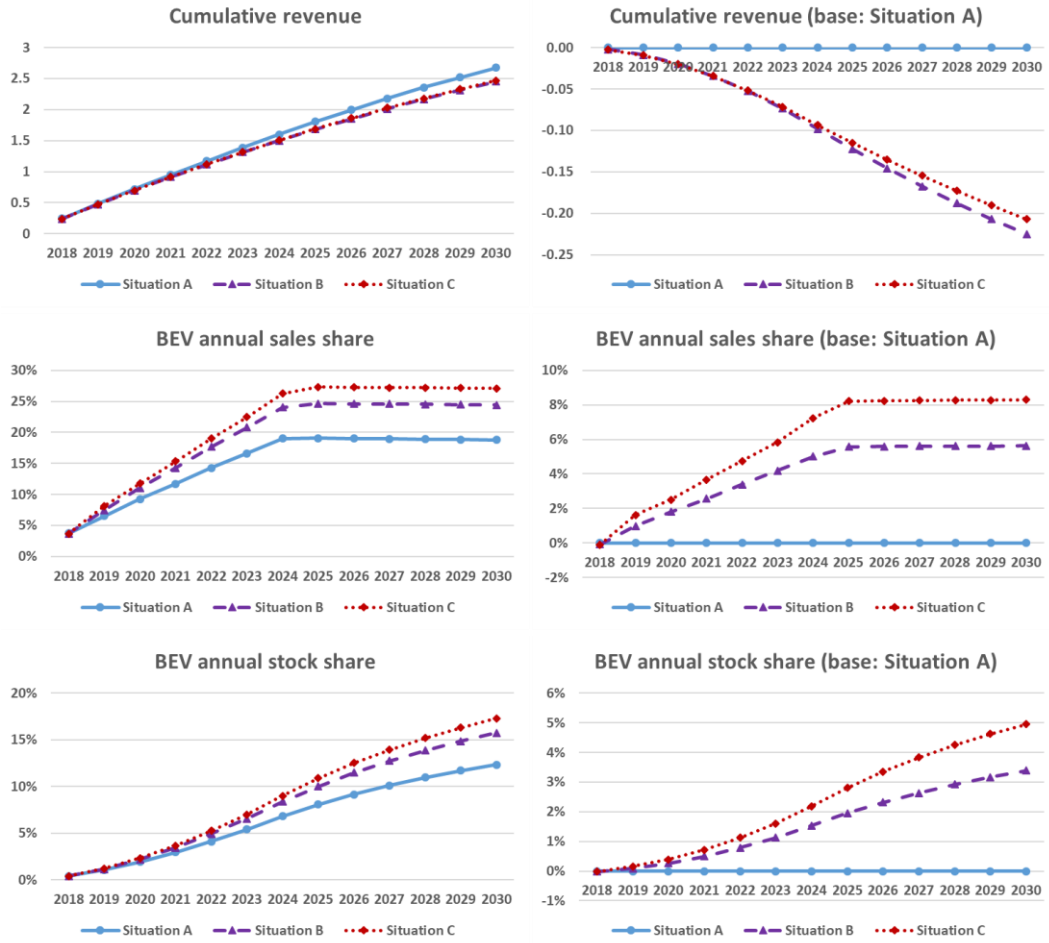



**Figure 32.** Analysis results for Case 3-D

To summarize, when the new entrant with new technology products enters the market, the entrance itself has a significant impact on diffusion of new technology. Moreover, the entrance of the new entrant induces a response by the incumbent (product-line extension plan), which also has a significant impact on new technology diffusion. Such results imply the positive impact of competition on new technology diffusion.

# Chapter 5. Conclusion

## 5.1 Key Findings and Contributions of the Research

When and under which circumstances consumers may purchase a new product is of interest to various stakeholders. This study aims to provide a tool that can aid the decision making of policymakers, by proposing a model that can analyze consumers' intertemporal choice considering a product-line extension. The proposed model is applied to the case of electric vehicle diffusion in South Korea. The empirical analysis in this study consists of three main parts. In the first part, I focused on the consumer model to analyze consumers' strategic intertemporal choice of delaying or advancing one's purchase, and the corresponding shrink or expansion of the market. In the second part, I analyzed the impact of a varying product-line extension plan (new model introduction) by policy intervention on consumer choice and new technology product diffusion. Finally, I investigated the case of a new entrant to the market, and analyzed the resulting change in the product-line extension plan and its impact on new technology product diffusion.

The key findings of the current study can be summarized as follows: First, the intertemporal consumer-choice model considering an extended choice set (including the SQ product and future products) showed results that are quite different compared to those from consumer models only considering products currently in the market. This is because when SQ and future products are included in the choice set (the proposed model), the model can identify the consumers' purchase time, which means the model can identify the

new-product buyers for each time period. However, if only new products in the market are considered (myopic model), the entire sample is implicitly considered to comprise new-product buyers. Identifying consumers' purchase time can have significant implications for the government and for policymakers, since this means the model can also analyze the shrink or expansion of the market, which was not possible in conventional myopic-choice models. Moreover, the results of the empirical analysis show that, not only the enactment of policy itself but also the timing of the policy's start or end also has a significant impact. Specifically, the purchase of the product tends to be concentrated near the start or end of the policy. Therefore, policymakers should consider the shrink or expansion of the market at the timing of the policy intervention in the regional and national economy when designing relevant policies.

Moreover, the proposed model can incorporate consumers' strategic behavior of delaying or advancing their purchase to take advantage or avoid a disadvantage. Such strategic behavior affects new technology diffusion in a certain pattern. Since new technologies develop rapidly compared to conventional technologies and, thus, the performance of new technology products improves faster, there exists larger incentives for consumers to delay their purchase for new technology products compared to conventional technology products. Therefore, new technology products suffer more from consumers' purchase delaying than conventional technology products. In other words, if future products are not considered, demand for the new technology products may be overestimated. Finally, considering strategic behavior or delaying/advancing one's

purchase based on future market/policy situations, the government can maximize new technology product sales for each time period by providing negative future policy information as fast as possible to induce consumers advance their purchases, and providing positive future policy information as late as possible to prevent consumers delay their purchase.

Furthermore, the results of the intertemporal consumer choice model linked with the product line extension model show that the government's policy intervention induces a significant change in the product model supply, which has a significant impact on new technology diffusion. Specifically, the supply response leverages the impact of the government's policy intervention. In this respect, fixing a specific model supply situation in policy analysis may result in significantly biased forecasts and suboptimal policy design.

Moreover, compared to a myopic product-line extension, the proposed product-line extension using the NP algorithm could generate a significantly higher total revenue and more realistic results. This is because the proposed method considers various forms of cannibalization among products to reduce cannibalization and maximize total revenue. Considering such cannibalization, a monopolistic supplier tends to introduce high-end products rather than low-end products. This may be because, if the monopolistic supplier introduces low-end EVs, its existing ICEV models would suffer significantly because of cannibalization. Introducing low-end models would accelerate new technology diffusion, but diffusion of new technology may not help in increasing revenue.

Finally, when a new entrant only capable of introducing a new technology product appears in the market, not only the model introduction of the new entrant itself but also the change in the product-line extension of the incumbent has a significant impact on new technology diffusion. In other words, it was observed that competition can accelerate the diffusion of new technology by inducing a change in model supply. Specifically, in the empirical analysis, the new entrant introduced low-end BEV models since it did not have to care for cannibalization of existing products. In this situation, the incumbent changed its product-line extension plan to focus on more low-end BEV models, since loss due to the new entrant is larger than loss by cannibalization between its existing and newly introduced products. Therefore, promoting a new entrant's market appearance can be an option that policymakers use to induce the desired product model supply. However, in practice, a thorough empirical analysis should be conducted beforehand to analyze a new entrant's impact on the incumbent and regional/national economy.

The results of this dissertation may be used in new technology diffusion analysis of various products. Specifically, high-cost and high-technology consumer durables, which have incentives for product diversification and need for a policy intervention by the government, are most appropriate for the proposed model. Vehicles, which are analyzed in this study, are one example of such a product. Future studies may analyze the diffusion of new technology in products like PCs, mobile devices, smart home appliances, and various health care devices using the proposed model.

## 5.2 Limitations and Future Research Topics

Although this study proposed an intertemporal consumer-choice model considering product-line extension, some limitations, which can be addressed in future studies, exist. In this section, I describe the limitations of the current study and suggest possible research topics that could be addressed in future studies.

First, the suggested consumer model uses cross-sectional data collected by a consumer survey at a specific time period. As in most studies using choice model, this study also assumes that consumer preference is fixed throughout the timeline. However, future studies may remove this limitation by considering a dynamic preference for consumers. For example, improvement in consumer awareness or a network effect may have significant impact on new technology diffusion (Axsen, Mountain, & Jaccard, 2009; Mau, Eyzaguirre, Jaccard, Collins-Dodd, & Tiedemann, 2008; Shafiei et al., 2012; Wolinetz & Axsen, 2017). Consideration of such factors can be significant since they may work against the state dependence by the type of the SQ assumed in this study. Moreover, although the proposed consumer model acquired various analytical strengths by taking the replacement viewpoint, the model has a limitation in that it cannot consider “first buyers.” Since first buyers do not have the SQ product, they may show quite different patterns of vehicle adoption compared to vehicle owners. Future studies may analyze the vehicle adoption of first buyers to address the difference between first buyers and others, along with discussions about the impact of first buyers in new technology diffusion.

Furthermore, this study has only considered new vehicles for purchase; future studies may consider the impact of the used car market in consumers' vehicle purchase behavior (Iwata and Matsumoto, 2016).

Moreover, although this dissertation has *estimated* the impact of obsolescence of the past alternative (SQ) along with the impact of other vehicle attributes in the consumers' utility function, the waiting penalties for future alternatives are *calculated*, not estimated, at the individual level from a separate choice experiment. Moreover, the calculated waiting penalty is then exogenously inserted in the consumers' utility function. Such an approach is unusual in the related literature and may potentially cause some problems. For example, since calculation of the individual-level waiting penalty in this study is based on the specific vehicle type that a consumer responded that one expects to purchase in the future, the extent of the waiting penalty may actually vary when the vehicle type changes. In this study, it was necessary to use cross-sectional data collected from a consumer survey since long-term market data for new technology products are typically not available or are limited. If I had included past, present, and future alternatives in a single choice set in the choice experiment, it may have significantly confused respondents. However, there can always be a better design or approach. Therefore, future studies may consider such aspects from the design of the survey, and estimate the penalty for both past and future alternatives in a single utility function.

Finally, for the product-line extension model, more insights may be derived if the model can endogenously determine the number of new models to introduce in each

time period. This point can be especially important for the case of a new entrant appearing in the market, since the entrance itself is the key problem for the new entrant (with zero new models or otherwise). This study could not conduct such an analysis since it was hard to reasonably assume upfront and maintenance cost for a new model introduction. However, if such values can be attained or reasonably assumed, an analysis for the optimal number of new products can also be conducted. However, since such flexibility is expected to significantly increase the complexity of the problem, the optimization procedure may be reexamined to derive the optimal solution with a reasonable amount of resources.

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# Appendix 1: Estimates of Comparable Models

**Appendix 1-1.**

**Parameter Estimates for Model (1) and (2)**

**Model specification:**

| Item | Description |
|---|---|
| Utility function | $U_{nj} = \boldsymbol{\beta}_{n,gasoline}\mathbf{X}_{j,gasoline} + \boldsymbol{\beta}_{n,diesel}\mathbf{X}_{j,diesel} + \boldsymbol{\beta}_{n,electric}\mathbf{X}_{j,electric} + \boldsymbol{\beta}_{n,mid}\mathbf{X}_{j,mid} + \boldsymbol{\beta}_{n,big}\mathbf{X}_{j,big} + \boldsymbol{\beta}_{n,SUV}\mathbf{X}_{j,SUV} + \boldsymbol{\beta}_{n,infra}\mathbf{X}_{j,infra} + \boldsymbol{\beta}_{n,fuel\_cost}\mathbf{X}_{j,fuel\_cost} + \boldsymbol{\beta}_{n,buy\_cost}\mathbf{X}_{j,buy\_cost} + \boldsymbol{\beta}_{n,sq}\mathbf{d}_{sq} + \varepsilon_{nj}$ |

**Parameter Estimates:**

| | | **Mean estimate** | **95% conf. int.** | |
|---|---|---|---|---|
| Operating method (base: hybrid) | Gasoline | -0.665*** | -0.880 | -0.475 |
| | Diesel | -1.024*** | -1.2 | -0.838 |
| | Electric | -0.746*** | -1.089 | -0.446 |
| Vehicle class (base: economy) | Compact/mid-size | 2.300*** | 2.041 | 2.660 |
| | Full-size | 2.353*** | 2.070 | 2.660 |
| | SUV | 2.346*** | 2.115 | 2.562 |
| Infrastructure (ln(%)) | | 0.928*** | 0.630 | 1.238 |
| Fuel cost (100 KRW/km) | | -0.220*** | -0.398 | -0.075 |
| Purchase price (10 million KRW) | | -1.046*** | -1.160 | -0.935 |
| SQ parameter | | -3.246*** | -3.674 | -2.888 |

**Appendix 1-2. Parameter Estimates for Model (3)**

**Model Specification:**

| Item | Description |
|---|---|
| Utility function | $U_{nj} = \boldsymbol{\beta}_{n,gasoline}\mathbf{X}_{j,gasoline} + \boldsymbol{\beta}_{n,diesel}\mathbf{X}_{j,diesel} + \boldsymbol{\beta}_{n,electric}\mathbf{X}_{j,electric} + \boldsymbol{\beta}_{n,mid}\mathbf{X}_{j,mid} + \boldsymbol{\beta}_{n,big}\mathbf{X}_{j,big} + \boldsymbol{\beta}_{n,SUV}\mathbf{X}_{j,SUV} + \boldsymbol{\beta}_{n,infra}\mathbf{X}_{j,infra} + \boldsymbol{\beta}_{n,fuel\_cost}\mathbf{X}_{j,fuel\_cost} + \boldsymbol{\beta}_{n,buy\_cost}\mathbf{X}_{j,buy\_cost} + \boldsymbol{\beta}_{n,obsol}\ln(\mathbf{X}_{j,obsol}+1) + \varepsilon_{nj}$ |

**Parameter Estimates:**

| | | **Mean estimate** | **95% conf. int.** | |
|---|---|---|---|---|
| Operating method (base: hybrid) | Gasoline | -0.669*** | -1.481 | -0.941 |
| | Diesel | -1.030*** | -1.536 | -1.114 |
| | Electric | -0.870*** | -1.222 | -0.597 |
| Vehicle class (base: economy) | Compact/mid-size | 2.243*** | 1.951 | 2.454 |
| | Full-size | 2.292*** | 2.009 | 2.502 |
| | SUV | 2.304*** | 1.995 | 2.498 |
| Infrastructure (ln(%)) | | 0.893*** | 1.248 | 0.660 |
| Fuel cost (100 KRW/km) | | -0.233*** | -0.226 | -0.498 |
| Purchase price (10 million KRW) | | -0.995*** | -0.920 | -1.114 |
| Obsolescence (ln(years of ownership+1)) | | -2.020*** | -1.910 | -2.413 |

***: significant in 99% confidence level

# Abstract (Korean)

신기술 제품은 기존 제품과의 경쟁을 거쳐 시간의 흐름에 따라 점진적으로 확산된다. 정부는 이 확산의 속도를 조절하기 위해 다양한 정책 수단을 소비자 대상으로 활용할 수 있으며, 장기 정책의 경우 시점 별로 달라지는 정책 수준이 소비자의 제품 구입 시점 선택에 영향을 미칠 수 있다. 그런데, 시점 별로 달라지는 제품 공급 상황 역시 소비자의 선택 및 신기술 제품 확산에 영향을 미칠 수 있다. 예를 들어, 확산 초기에 신기술 제품의 제품 라인은 상당히 제한적이겠지만, 시간의 흐름에 따라 제품 라인 확장을 통해 새로운 제품이 출시될 것이다. 따라서, 본 연구는 제품 라인 확장을 고려한 소비자의 시점 간 선택을 분석할 수 있는 모형을 제시하였다. 또한, 해당 모형을 국내 자동차 시장의 전기차 확산 케이스에 적용하여 제품 라인 확장 패턴에 따른 소비자의 시점 간 선택을 실증 분석하였다. 본 논문에서 제안한 모형은 크게 소비자의 시점 간 선택 모형과 소비자 선택 및 정책 상황을 고려하여 미래 신기술 제품 출시 계획을 결정하는 제품 라인 확장 모형으로 구성된다. 제안된 모형에서 소비자는 시간 측면에서 확장된 선택 집합을 고려하여 전략적으로 자신의 제품 구매 시점을 결정한다. 제품 라인 확장 모형의 경우, 신제품 출시에 따른 다양한 형태의 자기 잠식을 고려하여 수익을 극대화하는 최적 제품 라인 확장 계획을 분석기간 전체에 대해 한번에 결정한다. 본 연구의 실증 분석은 크게 세 파트로 이루어져 있다. 첫 파트에서는 제품 라인 확장을 특정 케이스로 고정한 상태에서 소비자의 전략적 시점 간 선택 행위에 대해 분석한다. 구체적

으로는 정책 개입에 따른 구매 당김/미룸 행위와, 이로 인한 시장의 매출 변화를 분석하였다. 두 번째 파트에서는 정부의 정책 개입으로 인한 제품 라인 확장 (제품 공급) 변화가 소비자의 선택 및 신기술 확산에 미치는 영향에 대해 분석하였다. 구체적으로, 정책 개입 그 자체로 인한 효과와, 이에 따라 제품 공급이 변화하여 나타나는 효과를 구분하여 분석하였다. 마지막으로 세번째 파트에서는 신규 진입자가 시장에 진입하는 경우에 대해, 신규 진입자의 시장 진입 및 제품 출시 그 자체로 인한 효과와 신규 진입자의 진입으로 인한 기존 공급자의 제품 공급 변화의 효과를 구분하여 분석하였다. 실증 분석 결과, 제안된 모형의 소비자는 근시안적인 소비자와는 상당히 다른 선택을 하였으며, 정책 상황에 따른 제품 라인 확장 변화를 고려하는 것이 미래 신기술 확산 예측에 상당한 영향을 미치는 것이 관찰되었다.

**주요어** : 기술 확산; 소비자 선호; 수요 예측; 이산선택모형; 제품 라인 설계; 제품 공급

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