Master Dissertation in Engineering

Consumer Strategic Electric Vehicle Adoption under Uncertain Attribute Changes in the future

February 2023

Graduate School of Seoul National University
Technology Management, Economics, and Policy Program
Woo-je Seong

Consumer Strategic Electric Vehicle Adoption under Uncertain Attribute Changes in the future

지도교수 구윤모

이 논문을 공학석사학위 논문으로 제출함

2022 년 12 월

서울대학교 대학원

협동과정 기술경영경제정책 전공

성우제

성우제의 공학석사학위 논문을 인준함

2022 년 12 월

위 원 장 ____이정동____(인)

부위원장 ____구윤모____(인)

위 원 ____최현홍____(인)

Abstract

Consumer Strategic Electric Vehicle Adoption under Uncertain Attribute Changes in the future

Woo-je Seong
Technology Management, Economics and Policy
The Graduate School
of Seoul National University

The existing static models used to analyze electric-vehicle purchase preferences is limited in its ability to explain strategic purchasing behavior of durable goods, i.e., purchase decisions following a period of postponement. This study proposes a higher-fidelity diffusion model in which the electric-vehicle consumer's strategic purchasing decision—in context of an uncertain future—is extrapolated using the Markov decision process. The presented model provides a framework for analyzing the consumer's intertemporal choices based on their stated preferences and can confirm changes in purchase timing in response to perceived technological and market changes that are both ongoing and indeterminate. A choice experiment was conducted on Korean car owners, and the results were used to inform electric-vehicle market predictions. Following the Markov process, this study sets the accessibility of gas stations and charging infrastructure as stochastically changing properties, and based on the estimation results, the market simulation was performed by changing the distribution of the future charging infrastructure diffusion rate. The simulation demonstrates that the more positive the consumers is regarding the future accessibility of charging infrastructure, the faster the time to replace their internal combustion vehicles, suggesting that supporting the expectation that charging infrastructure will become increasingly accessible has a significant positive impact on the rate of electric vehicle adoption.

Keywords: Electric vehicle diffusion, market simulation, dynamic discrete choice model, forward-looking behavior, Markov decision process

Student Number: 2021-28651

Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Research Background

When it comes to new products or new services, identifying consumers' preferences has long been a concern for academia and businesses. As quantitative innovation diffusion model arrives in the marketing domain (Bass, 1969), the spread of new technologies, and the replacement of existing technologies have been continuously studied (Mahajan & Muller, 1996; Norton & Bass 1987).

The new technology diffusion model based on the Bass model has been developed in various ways. For example, a model containing individual-level data has been developed to compensate for the limitations caused by the aggregate data approach of the Bass model(Schwartz & Oren, 1988 ; Bemmaor, 1992 ; Bridges , Coughlan & Kalish, 1991), and many studies also added flexibility to the model to improve the diffusion pathway along the symmetric curve, one of the strong assumptions of the existing models(Mahajan, Muller & Bass, 1993 ; Parker, 1994).

Meanwhile, as conjoint analysis has attracted attention in the marketing field since the 1970s, consumers' part-worth utility among the multiple attributes of the products or services can be analyzed (Green & Srinivasan, 1990; Louviere, 1988; Green and Rao, 1971; Johnson, 1974). Since then, conjoint analysis has been developed in many ways for the purpose of analyzing consumers' preferences and collecting virtual data.

In the marketing area, conjoint analysis has been used to overcome the limitations of the Bass model. Since the existing Bass model-based approach does not reflect the heterogeneity of individual consumers, it entails limitations in providing information on market demand before the product released. However, it is possible to predict market demand by combining a conjoint analysis specialized for consumer preference analysis with Bass model mainly used for a macro product diffusion analysis(Leem Cho, Lee & Lee, 2006).

Many documents have conducted market demand prediction studies using Conjoint analysis (Lavasani, Jin, & Du, 2016; Wolinetz & Axsen, 2017; Byun, Shin & Lee, 2018; Qian & Soopranied, 2015), especially in the case of goods with durable properties, which made it rather difficult to analyze because of the time lag between purchase decision making and actual purchase.

In this respect, I have focused on the analysis of consumer preference in durable goods market, especially the vehicle adoption, which is relatively long between the decision to buy and the timing of actual purchase. My research proposes a model that analyzes consumers' strategic product purchases, i.e., intertemporal choice behavior, in the conjoint analysis, representative stated preference approach.

Therefore, my research problem starts with the following question. When respondents facing a questionnaire, would they recognize the attributes of products or services as if they purchase now? In the case of durable goods which is common to have time lags between purchase and the survey situation, is it not the attribute level specified in the survey, but rather the respondent's potential point of purchase? The following study proposes a model that explicitly reveals the behavior of these consumers' recognition when they make decision in questionnaire situations.

1.2 Research objectives

The purpose of this paper is to propose a model that analyzes consumers' intertemporal choices. The biggest difference from existing studies is that consumers' preferred options at the time of the survey are not viewed as "preferred at the moment", but as "preferred at the time of future purchase". In addition, the model differs in that it reflects viewpoint of consumers' preference in the utility specification stage, not in the simulation stage, unlike the previously discussed method.

In addition, the model also differs in that respondents' decisions are viewed as being made under uncertainty. This is closely related to durable goods purchasing behavior. One of the main characteristics of durable goods purchasing behavior is the so-called forward-looking behavior of making decisions based on expectations of uncertain changes in attributes in the future. Evidence of decision-making under these consumer uncertainties has been investigated in various past studies (Zhang & Chang, 2021; Saengchote & Nakavachara, 2018; Prince, 2009; Copejans et al, 2007; Henderson & Ioannnides, 1989). In short, my research proposes a model that can consider consumers' forward-looking behavior for joint analysis.

My research is divided into two processes, the first model construction process, and the second model validation. First of all, to outline the research process, I first defined how respondents expect changes in certain attributes in the future, and through this, I constructed two expected utility functions. First, ‘the expected utility function of a specific alternative at a specific time’ and secondly, 'the utility function to withhold purchases until an unspecified time' were defined. Afterwards, I generated virtual data using the constructed model and re-estimated it to check whether the constructed model recovers true parameters, and finally applied it to empirical analysis.

1.3 Research Outline

This paper consists of five chapters. In Chapter 2, I review the discrete choice model, widely used to analyze consumer choice behavior, and the dynamic programming used in the econometric field, which Rust (1987) pave the road to analyze intertemporal choice behavior, and finally the empirical literature regarding the intertemporal choice. In this process, I will specifically describe where I got the idea of building the model.

Chapter 3 provides a detailed description of the proposed model and describes how the proposed model differs from the existing model.

Chapter 4 will discuss the estimation strategy and data generation for the proposed model, the process of recovering it, and the implications of its estimation results to perform market simulation.

I conducted a choice experiment between November 7 and November 16, 2022 in order to apply the proposed model to empirical data. In the last chapter 5, I will show the results of applying the proposed model to the data obtained through the choice experiment and the market simulation results using them, and explain how it differs from the existing models.

Chapter 2. Literature Review

In this chapter, I will first review the discrete choice model and dynamic programming, which are the theoretical background of the proposed model. After that, I will review literatures dealing with intertemporal choice behavior, which is referred to as the existing consumer's strategic choice behavior. Lastly, I will consider the contributions and limitations of the models built in the existing discussion.

2.1 Discrete choice model ; main tool for conjoint analysis

Since the 1970s, conjoint analysis has opened the door to consumer analysis (Srinivasan, 1978). Conjoint analysis has been widely used, especially when the data are absent, and it has been used in several ways to supplement product demand predictions. According to Hair, Anderson, Tatham and Black (1995), conjoint analysis is defined as a multivariate technique used to understand how respondents represent their preferences for goods or services. More specifically, it is a technique for predicting the preference of a certain product to be chosen by the customer by mathematically defining the consumer's preference for multi-attribute stimuli constructed by the experimental design and by estimating the part-worth utility that the respondent would take from each attribute of the product.

Thanks to this usefulness, conjoint analysis has been actively used as a tool to assess the potential market for new products based on respondents' stated preferences in marketing and policy analysis (Louviere, 1988; Green & Srinivasan, 1990, Gatin and Wittink, 1982). Conjoint analysis provides questions to respondents allowing them to make choices, and is mainly used with the Discrete choice model due to these design structure. Through this, the purpose is to estimate the parameters that represent part-worth utility given by respondents and consumers to predict which product/service the consumer will prefer and how many people will buy when these are released.

Train (2009) summarizes and well organizes discrete choice model framework. The discrete choice model basically follows McFadden (1974)'s Random Utility Model. According to him, each agent i takes the following utility by purchasing a j alternative.

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

The first term of the right-hand side represents the deterministic term that the researcher can observe among the components describing utility U, and ϵ represents the probabilistic error term that the researcher cannot observe. This randomness can be transformed into the following probabilistic formula.

$$\begin{aligned} &Prob(agent\ i\ choose\ j) \\ &\quad = Prob\left(U_{ij} > U_{ik}\right) \\ &\quad = Prob\left(V_{ij} + \epsilon_{ij} > V_{ik} + \epsilon_{ik}\right) \cdots\cdots \text{Eq. (2)} \\ &\quad = Prob(\epsilon_{ij} < \epsilon_{ik} + V_{ik} - V_{ij}\ for\ all\ j \neq i) \end{aligned}$$

We can assume a distribution for ϵ, the error term. Typically, a normal distribution or Type 1 extreme value distribution may be assumed[1]. According to the probability distribution of this error term, each of the above formula is called the Probit model and the Logit model, respectively. Note that this study will only discuss the Logit model, that is, the case where the error term is following Type 1 extreme value distribution. If the error term follows the type 1 extreme value distribution, the above probability is re-formulated as follows.

$$Prob(agent\ i\ choose\ j) \equiv P_{ij} = \frac{exp(V_{ij})}{\sum_{k=1}^{J} exp(V_{ik})} \cdots\cdots \text{Eq. (3)}$$

The above probability equation is called Conditional choice probability, meaning that the probability when given parameters(β) and is accurately expressed as follows with a bar symbol indicating 'conditional'.

$$P_{ij\,|\,\beta} \equiv Prob(agent\ i\ choose\ j\ given\ \beta) = \frac{\exp(\beta' X_{ij})}{\sum_{k=1}^{J} \exp(\beta' X_{ik})} \cdots\cdots \text{Eq. (4)}$$

In the estimation process, Eq. (4) is re-written as the following formula, called Likelihood.

---

[1] PDF function of Type 1 extreme value distribution： $f(\epsilon) = \exp(-\epsilon) * \exp(-\exp(-\epsilon))$

$$Likelihood = \prod_i \prod_j P_{ij}^{y_{ij}} \cdots\cdots \text{Eq. (5)}$$

$$where\ y_{ij} = \begin{cases} 1\ if\ i\ choose\ j \\ 0\quad otherwise \end{cases}$$

The probability P_{ij} used as Likelihood is no longer a conditional probability, but a probability function with respect to β as a domain. In addition, it is assumed that y_{ij} is a binary variable as a dependent variable, which represents a stated and the most preferred choice given by each agent. By finding the parameters that maximize this likelihood, it is possible to find the parameters that best fit the given data.

$$\beta^* = argmax_\beta Likelihood = \prod_i \prod_j P_{ij}^{y_{ij}} (\beta\ given\ X) \cdots\cdots \text{Eq. (6)}$$

2.2 Markov Decision Process

Rust (1987) laid the foundation for modeling agents' decision making in uncertain environments. His model presents a framework for whether an agent will calculate all future utility in consideration of its future behavior at present value when environmental changes follow the Markov Process, i.e., when environmental changes are defined solely on the last-period. The model he presented basically starts with the multi-period utility function.

$$\max_{d_t} \sum_{t=0}^{T} \delta^t u_t(d_t, s_t) \cdots\cdots \text{Eq. (7)}$$

d_t is called the decision variables or action variables for the agent to make in *t* period, δ represents the discount factor for future utility, s_t is the environment variable for *t* period, which is a variable changed stochastically relying on the previous agent's decision (d_t) or external stochastic properties of the environment, and lastly u_t represents the utility given action variables(d_t) and state variables(s_t). This is a utility that occurs only in the *t*-period called a per-period utility or a single-period utility.

The primitives of the model presented by Rust (1987) are the per-period utility u_t, transition matrix $p(s_{t+1} \mid s_t, d_t)$ that determines the stochastic change in this environment, and the discount rate $\delta \in (0,1)$. Note that, as mentioned earlier, state changes follow the Markov process, which is relying on the previous period, so that only two period s_{t+1} and (s_t, d_t), exist as input values representing the transition matrix.

Based on this, the utility consumers receive during a given time horizon is described as follows. What should be noted in the expression is that there is a max operator with respect to *d*, which indicates that the agent will take optimal action to maximize utility for all future situations. *d* is called the decision rule, or more often a policy. By following the optimal decision rule, agents can receive maximized summation of utility given time horizon. In this respect, max operator can be seen as reflecting the optimal decision rule or optimal policy here, and Eq (6) is more specifically defined as follows.

$$V(s) = \max_{d}[\textstyle\sum_{t=0}^{T} \delta^t u(d_t, s_t) | s_{intial} = s] \quad \cdots\cdots \text{Eq. (8)}$$

In other words, the above equation indicates that the summation of the utility from the present to the T period is the optimal utility that can be received in the current state(s). In such a given state (s), while following the optimal decision rule, the utility that can be received throughout the time horizon is called the value function, a function with respect to s. As can be seen in this process, one of the important assumptions in this model is the cardinal utility function.

Rust(1987) made several major assumptions to expand the above Markov Decision Process, which deals with agents' decision-making in the environment that follows the Markov Process, into the domain of Econometrics. First of all, the first assumption is the so-called Additive Separable(AS) assumption. This assumes that in determining the value of the agent's per-period utility(u_t), part of the state variable that the researcher cannot observe independently affects the utility function and can be treated as if it were an error term. Expressing this as formula is as follows.

$$u(s,d) = u(x,\epsilon,d) = u(x,d) + \epsilon \cdots\cdots \text{Eq. (9)}$$

$$where\ x_t{:}\ observable\ state\ variables,$$

$$\epsilon_t{:}\ unobservable\ state\ variables$$

Meanwhile, the other Rust(1987)'s main assumption was the Conditional Independence (CI) assumption. In addition to the assumption that the state change follows a Markov process that changes relying only on the previous period, the CI assumption is stricter than this. During the state change, the unobservable state(ϵ) occurs independently from the past. This is expressed by a formula as follows.

$$p(s_{t+1}|s_t, d_t) = p(x_{t+1}, \epsilon_{t+1}|x_t, d_t, \epsilon_t) = p(x_{t+1}|x_t, d_t) \times p(\epsilon_{t+1}) \cdots\cdots \text{ Eq. (10)}$$

These two assumptions are particularly the main discussion in this research in that it enables to simplify the formula. The so-called AS-CI assumption allows the unobservable state error term to be integrated out of the mentioned equation, so that the expression can be simply represented. In the following contents, for convenience of explanation, the following subscripts for t will be added on Eq. (8).

$$V(s_t) = \max_d [\textstyle\sum_{\tau=0}^{T} \delta^\tau u(d_\tau, s_\tau)|s_{intial} = s_t] \cdots\cdots \text{ Eq. (11)}$$

If the optimal decision rule (d^*) or optimal policy that governed what to act in period t is defined, the above equation is expressed as Bellman equation as follows.

$$\begin{aligned} V(s_t) &= max\{u_t(s_t, d_t) + \delta E[V(s_{t+1})]\} \cdots\cdots \text{ Eq. (12)} \\ &= max\left\{u_t(s_t, d_t) + \delta \int V(s_{t+1}) \times p(s_{t+1}|s_t, d_t)\right\} \end{aligned}$$

When the AS-CI assumption is applied to the above Bellman equation(Eq. (12)), it is modified to make it simpler through the below process.

$$V(s_t) = V(x_t, \epsilon_t) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (13)}$$

$$= max\left[u(x_t, d_t) + \epsilon_t + \delta \int V(x_{t+1}, \epsilon_{t+1}) * p(\epsilon_{t+1}) * p(x_{t+1}|x_t, d_t)\right]$$

As the value function(V) is recursively defined both left and right-hand side as above, it can be re-written in simpler form by defining $v(x_t, d_t)$

$$v(x_t\ , d_t)$$

$$= u(x_t, d_t) + \delta \iint \max[v(x_{t+1}, d_{t+1}) + \epsilon_{t+1}]p(\epsilon_{t+1})p(x_{t+1}|x_t, d_t) \cdots\cdots \text{Eq. (14)}$$

$$where\ v(x_t, d_t) \equiv u(x_t, d_t) + \delta \int V(x_{t+1}, \epsilon_{t+1})p(\epsilon_{t+1})p(x_{t+1}|x_t, d_t)$$

According to the property of type 1 extreme value distribution, the second term of the right-hand side of the Eq. (14) is transformed into closed form.

$$v(x_t\ , d_t) = u(x_t, d_t) + \delta \int ln\left[\sum \exp\left(v(x_{t+1}, d_{t+1})\right)\right] p(x_{t+1}|x_t, d_t) \cdots\cdots \text{Eq. (15)}$$

In other words, what the above equation means is that the value of *t* as of $v(x_t, d_t)$ can be expressed as the sum of $u(x_t, d_t)$, which is a per-period utility that occurs in t, and the utility that occurs thereafter (second term of right-hand side).

Accordingly, the utility of an agent following the optimal decision rule at *t* eventually becomes $v(x_t, d_t) + \epsilon_t$, and assuming that this ϵ_t follows type 1 extreme valud distribution, the probability of the decision maker making d in a given (observable) state x can be formed as the general equation below.

$$Prob(agent\ take\ action\ d\ under\ state\ x\ at\ t)$$
$$= \frac{\exp(v(x_t, d_t))}{\sum \exp(v(x_t, d_t'))} \cdots\cdots \text{Eq. (16)}$$

As mentioned above in section 2.1, the equation can find the optimal parameter that satisfies the condition using the Maximum Likelihood estimation method, and in the case of such a Dynamic discrete choice model, the process of solving the Bellman equation is included in the middle of the estimation process, this process is called Nested Fixed Point Algorithm.

2.3 Intertemporal Choice behavior

Using the above logit model and Rust's dynamic MDP-based discrete choice model framework, there are many studies that have applied and improved these combined framework. The following contents review the studies.

Melnikov (2000) applied Rust's approach to consumer analysis to expand the applicability of the model in durable goods market. This literature mathematically models consumers' expectations of market evolution and consumers' forward-looking behavior based on the Markov Decision Process. By applying this to the printer market, consumers' decisions reflecting the durable properties of the product, the product differentiation, unlike the Bass model, and above all, the durable goods market where consumers' intertemporal demand substitution occurs are explicitly explained.

Song and Chintagunta (2003) developed the Melnikov (2000) model. Their literature further simplified the model by internalizing the agent's decision rule, policy function, into bellman equation. In addition, the model they presented reflected consumer heterogeneity in parameters, product differentiation, and forward-looking behavior of consumers in the spread of new products, and model patterns in the spread of products were captured.

Lee (2013) applied a dynamic model approach to the contraction between suppliers and consumers on the platform, known as the two-sided market. In particular, his model internalized the Markov equailibrium between consumer and suppliers within the model by reflecting consideration of changes in the consumer's supply aspect in the consumer's choice model.

Schiraldi (2011) and Ishihara & Ching (2019) presented a dynamic choice model that considers repeated choice that reflects consumers' resale behavior and purchasing behavior in the used market. Each document was applied to the automobile market and video game market, and accordingly, the model constructed a consumer model that makes decisions by reflecting the transaction cost of the resale and repurchase behaviors.

Osborne (2011), Prince (2008), and Erdem & Keane (1996) based on the Dynamic choice model, estimated the learning effects from consumers' repeated purchases and the switching cost of replacing them with choices to other categories arising from repeated use and repeated purchases.

Gowrisankaran (2012) showed a forward-looking purchase behavior according to consumers' predictions of product evolution for new products in purchasing durable goods. In particular, this literature contributes to the reduction of the dimension of market and product evolution determined by very high-dimensional factors in building the markov transition matrix.

Gordon (2009) presented a consumer model for product replacement according to the maturity of the high-tech market under uncertainty in the evolution of product attributes.

All of the above studies were analyzed based on the market level, aggregate data, the main topic of the following studies is intertemporal choice models based on individual level data. Such a dynamic choice model is rarely applied to stated preference analysis. For example, Conjoint analysis is commonly used while not including information about purchase timing in the questionnaire design, or even if it is reflected, its application is very limited due to the complexity of the questionnaire design. Accordingly, efforts have been made to reflect consumer intertemporal choices by supplementing static model structure in various ways. For example, Choi & Koo (2019) and Choi & Koo (2023) performed a static conjoint analysis(i.e. static utility function) through a static discrete choice model but supplemented the limitations of the static model through additional questions. For example, the discount rate of consumers was estimated by asking repeated questions for a specific preferred product, and some information on consumers' intertemporal choice behavior was taken based on questions whether to buy selected option within a year or not. They finally perform market simulation by combining static utility functions and externally estimated results from several questions.

As mentioned, the application of the dynamic choice model is limited for conjoint analysis. This is because the characteristics of dynamic model-based utility function and data structure commonly obtained by static Conjoint survey design are not matched. Nevertheless, a few studies have tried to overcome this problem. Studies by Dube, Hitsch & Jindal (2014), Liu & Cirillo (2017), and Cirillo Xu & Bastin (2016) are representative, first of all, Dube et al (2014) applied to the blue-ray player market, and Liu & Cirillo (2017) performed a model reflecting the repetitive purchase behavior of automobiles. Each model will be one of the few pioneering papers that apply an MDP-based dynamic choice model to stated preference analysis.

2.4 Limitations of past studies

There have been various approaches to applying dynamic discrete choice model, but the analysis conducted so far has several limitations. First of all, the analysis performed on aggregate data used the probability distribution of people's predictions (i.e. the Markov transition matrix), which is the most important primitive in describing consumers' forward-looking behavior, externally computed from historical market evaluation data. In other words, there is a very strong assumption here, and it has to be assumed that consumers' predictions for the future have followed the same distribution as the spread of the market, called rational expectation.

These limitations can be supplemented in stated preference analysis. In the survey, information on how consumers think and expect about the real market can be taken through preliminary questions. Nevertheless, the intertemporal choice model using the dynamic discrete choice model applied to the aforementioned stated preference analysis is insufficient. In particular, Dube et al (2014) provided consumers with assumed perfect foresight information on the future during the survey process. In addition, Liu & Cirillo (2017), Cirillo, Xu & Bastin (2016) complemented the Dube et al (2014)'s study in that it did not fully provide information about the future in the choice situation, but it still distorts respondents' expectations for market changes by giving them a pre-defined market simulation for each choice set. In addition, in this literature, consumers' expectations for market evolution are also built on historical data, which means there is still a limit to using the same model before the product launch, which is one of the main purposes of conjoint analysis. In particular, since the dynamic model reflecting consumer expectations is a complement to Lucas' criticism that consumers' current choices are the result of reflecting people's expectations under the current policy, providing a predetermined scenario suggests that Lucas critique (Olesen, 2016) cannot be completely avoided.

Therefore, the model provided in this study will be a model based entirely on consumer expectations. I reviewed the previous literature and felt the need for a model that relied entirely on consumer expectations, without information about the future. These models are particularly well suited to the stated preference analysis that performs the questionnaire, because we can find out the specific intentions of the respondents, such as their personal thoughts. Therefore, the model I propose will present a framework that can analyze consumers who make decisions under uncertainty in the context of no information about the future.

Chapter 3. Methodology

3.1 Model specification

First of all, to reduce confusion in terminologies, terms have been organized in advance.

t	the time after current point $t : 1, \ldots, T$
i	Consumers $i : 1, \ldots, N$
j	Alternatives $j: 1, \ldots, J$ It's limited to electric cars and gasoline cars
δ	Discount factor
S_t	State vectors after t period $S_t = (s_{1t}, s_{2t}, \ldots, s_{Jt})$ s_{jt}: State variables corresponding to the *j*-th alternative
V_{jT}^{Exp}	The value of reserving purchase *j* until *T-1* period and then purchasing *j* in *T* period
$v^{own}(s_{jt})$	Per-period utility caused by maintaining current status without purchasing a new car at time *t*
V_{ik}^{No}	Utility of agent *i* with alternative *k* not buying vehicle ; Expected Value of purchasing a vehicle at an unspecified time in the future

u_j, v_j	The utility of purchasing the j-th alternative $u_j = v_j + \epsilon$ v_j is a deterministic term of the utility of the alternative j, which can be observed by researchers. ϵ is an error term of the utility of the alternative j, which cannot be observed by researchers. It follows type 1 extreme value distribution/

Table 1. Overall Terminology organization

Considering the brevity of our model and the purpose of the study, the alternative (j) considered only two categories, gasoline-powered and electric-powered cars. In addition, accessibility of gas stations and charging stations were considered as state variables that the consumers recognized it as a probabilistic variable as time goes, and the remaining suggested attributes were considered fixed over time. Therefore, the state vector S_t is expressed as follows.

$$S_t = (t, s_t^{electric}, s_t^{gasoline}) \cdots\cdots \text{Eq. (17)}$$

We assume the following consumers. When consumers choose a vehicle from a questionnaire, they make decisions about their preferred vehicle, and their preferences reflect expectations for changes in attributes at the time of purchase. In other words, respondents make decisions considering that attributes will gradually change in the future, rather than accepting the attribute levels of each alternative as they face in the survey situation. Therefore, their responded alternatives reveal preferences that reflect their expectations, not the attributes of the specified vehicles written in the questionnaire.

To model this decision-making process, I need to define a utility function for 'what will give better utility in the future' and a utility function for 'how long they will withhold purchases'. The following description shows the process of constructing a model of the functions.

For the brevity of the model, I made assumptions as follows.

- Respondents have their own purchase cycle and make purchase decisions within that time-horizon.
- Respondents do not look ahaed for more than that time-horizon.
- Respondents do not consider repurchasing or resale. In other words, they do not consider other actions after the future purchase choice.
- To make the compatible choice set, I assume that respondents would consider the infinite utility occurring after the purchase.

The per-period utility function is defined as follows.

$$u_{ijT}(s_{jT}) = v_{ijT}(s_{jT}) + \epsilon_{ijT} \cdots\cdots \text{Eq. (18)}$$

$$where \;\; v_{ijT}(s_{jT})$$
$$= \sum_{\tau=T}^{\infty}\{\alpha_{ij} + \beta_i^{annual\ cost} * annual\ cost_j + \beta_{ij}^{s} * E[s_{j\tau}|\Omega]\} + \beta_i^{price} * price$$

$u_{ijT}\ (s_{jT})$	When a purchase is decided in the state corresponding to alternative j (s_{jT}) at T, the utility that occurs indefinitely after the purchase.

$v_{ijT}(s_{jT})$:	Among the utility constituting the above $u_{ijT}(s_{jT})$, it represents the utility term that the researcher can observe
ϵ_{ijT}	Among the utility constituting the above $u_{ijT}\ (s_{jT})$, it represents an unobservable utility term.[2]
α_{ij}	Intrinsic preference that respondent *i* has for alternative *j*
$\text{annual cost}_{\text{j}}$ $\beta_i^{annual\ cost}$	Each represents the annual cost of the alternative *j*, and corresponding parameter.
s_{jt}, Ω	The state variable corresponding to the alternative *j* is presented, and Ω represents the Markov transition probability in which the state variable will change.
$price_j$ β_i^{price}	Alternative j's purchase price and the respondent's response to the purchase price. Note that this is outside the Summation operator, so that it will be a utility term that occurs only once at the time of purchase at *T*.

Table 2. Terminology regarding per-period purchase utility

Intrinsic Preference, annual cost, and infrastructure(station) accessibility to alternatives occur indefinitely even after purchase. Considering the simplicity of the model and the scope of the study, we only defined the accessibility to refueling/charging infrastructure only as stochastically changing state variables. Thus, the above equation is expressed as follows. Note that Intrinsic preference(α) and annual cost(cost) are considered constants, and thus become simple infinite geometric series.

[2] What to note is that the CI assumption is added in the specification. In other words, among the utility of respondents, state variables that cannot be observed by the researcher influence independently in changes caused by state variables.

$$v_{ijT}(s_{jT}) = \frac{\alpha_{ij}+\beta_i^{cost}*cost_j}{1-\delta} + \sum_{\tau=T}^{\infty} \beta_{ij}^{s} * E[s_{j\tau}|\Omega] + \beta_i^{price} * price_j \cdots\cdots\cdots \text{Eq. (18)}$$

If the above equation represents the utility that arises from purchasing at a particular time, now it is necessary to define the value that will not be purchased at a given point. This is defined as follows.

$$v_{ikt}^{own}(s_{kt}) \cdots\cdots\cdots \text{Eq. (19)}$$

$$= \begin{cases} \alpha_i^{status\ quo} & if\ not\ owning\ car \\ \alpha_i^{status\ quo} + \beta_i^{cost} * cost_k + \beta_i^{station} * E[s_{kt}|\Omega] + \beta_i^{year} * (year_i + t) & o.w \end{cases}$$

$v_{ikt}^{own}(s_{kt})$	Per-period utility that occurs when respondent *i* who owns an alternative *k* withholds purchase at *t*. Note that the annual cost and infrastructure accessibility contained herein are values corresponding to the vehicle *k* owned.
$year_i$ β_i^{year}	Coefficient and its level of utility arising from the ownership period
$\alpha_i^{status\ quo}$	The value that respondent *i* receives by maintaining their status quo in each period, excluding utility of the annual cost, accessibility to the corresponding infrastructure, and the period of ownership.

Table 3. Terminology regarding per-period reserving utility

Now, using the per-period utility, it is possible to build 'the utility of the reservation' and 'the utility of the purchase in the future' that respondents consider at the time of the survey. First of all, 'utility to withhold purchase' is defined as follows.

$$U_{ik}^{No}(S_t) = V_{ik}^{No}(S_t) + \epsilon_{\mathrm{ikt}} \cdots\cdots \text{Eq. (20)}$$
$$= v_{ikt}^{own}(s_{kt}) + \delta * E\left[\max\left(\max_j\left(u_j(s_{jt+1})\right), U_{ik}^{No}(S_{t+1})\right); \Omega\right] + \epsilon_{\mathrm{ikt}}$$

As mentioned earlier, we assumed that AS assumption in utility, so that the above equation (20) is expressed as a bellman equation as follows.

$$V_{ik}^{No}(S_t) \cdots\cdots \text{Eq. (21)}$$
$$= v_{ik}^{own}(s_{kt}) + \delta * E\left[\max\left(\max_j\left(v_{ijt+1} + \epsilon_{ijt+1}\right), V_{ik}^{No}(S_{t+1}) + \epsilon_{ikt+1}\right); \Omega\right]$$

At the same time, by assuming CI assumption and error term as type 1 extreme value distribution, the second term of the right-hand side is expressed as closed form.

$$E\left[\max\left(\max_j\left(v_{ijt+1} + \epsilon_{ijt+1}\right), V_{ikt+1}^{No}(S_{t+1}) + \epsilon_{ikt+1}\right); \Omega\right] \cdots\cdots \text{Eq. (22)}$$
$$= ln\left(\sum_{j=1}^{J} exp\left(v_{ijt+1}(s_{jt+1})\right) + exp\left(V_{ikt+1}^{No}(S_{t+1})\right)\right)$$

I defined the state variable as time-dependent. Accordingly, the time horizon of the above Bellman equation is defined within a finite time range arbitrarily determined by the researcher. Therefore, the bellman equation above is defined as the Finite-time horizon optimal stopping problem. This naturally entails the assumption that the value function after the last time state becomes zero value. For example, if the researcher sets the time range to 100 years, the probability of moving from 100 to 101 years is zero, which is the same case where the value function is a constant function with all values of zero. This is one of the parts that should be assumed in the research process. However, most car buyers make purchase decisions within a certain time horizon. It is very counterintuitive for a decision maker to consider changes in the state(infrastructure accessibility in our case) after 100 years. Accordingly, given that the situation after the time range considered by the decision maker does not affect the value of the current decision maker's purchase reservation positively or negatively, it would not be a very strong assumption to give a zero value that does not affect any form of value function after a particular time range.

Finally, the expected value that the alternatives will be given after T is described as follows.

$$U_{ijT}^{Exp}(S_T) = V_{ijT}^{Exp}(S_T) + \epsilon_{ijT}$$

$$V_{ijT}^{Exp}(S_T) = \sum_{\tau=0}^{T-1} \delta^{\tau} * v_{ikj}^{own}(s_{kt}) + \delta^{T} * v_{ijT}(s_{jT}) \quad \cdots\cdots \text{Eq. (23)}$$

$U_{ijT}^{Exp}(S_T)$: The expected utility that respondent *i* receives when choosing alternative *j* at *T* time after withholding the purchase until *T-1*. Note that is indicated by S_T in the bracket. This is because this value depends both on the status change of the alternative currently owned by the respondent and the status change of the alternative to be purchased in the future.

The decision-making of the respondents we assumed is represented by the following schematic diagram.

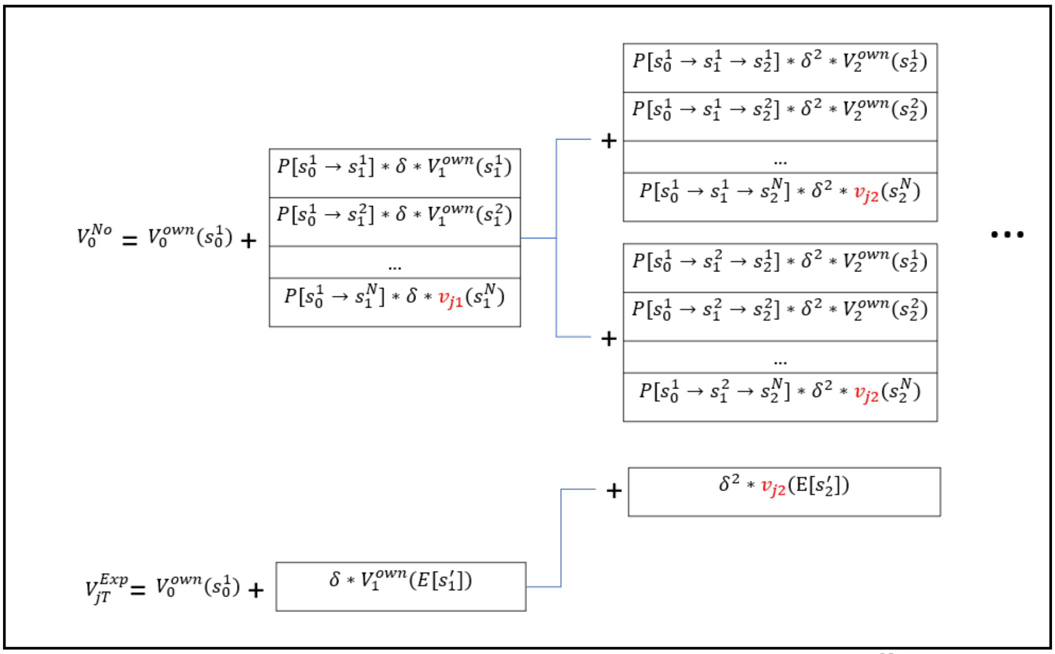

Figure 1. schematic diagram of 'No purchase expected utility(V^{No})'

and 'Expected utility of buying j at T(V^{Exp})'

$V_{ik}^{No}(s_0)$[3], obtained through solving the Bellman equation, represents the expected value to be purchased at an unspecified time as drawn in the figure above, meaning the sum of all cells in the figure. Each cell consists of (probability of the state arrived) * (discount

[3] $V_{ik}^{No}(s_0)$: This means the no purchase value of respondents at the current time (t=0)

rate) * (decision making of the agent in that state). On the other hand, V^{Exp} represents the expected utility that decision-makers obtain when purchasing a specific alternative *j* at a specific time *t*.

Note that No purchase expected utility(V^{No}) is regarded as a reference, because it does not tell when to buy a particular alternative, but it tells respondents' the optimal, maximized utility they can get by withholding purchases. No purchase expected utility is compared with $\mathrm{V}^{\mathrm{Exp}}$. By doing so, we can identify to which point the No purchase utility is greater than $\mathrm{V}^{\mathrm{Exp}}$ and from which point the utility of the purchase is greater. In other words, it is expressed as an inequality.

utility to buy j at T > no purchase (withholding for someday) > utility to buy j at T-1

⇨ Respondents have a greater expected utility of purchase than withholding at T

This is expressed in a formula as follows.

$$\mathrm{U}_{iJT}^{\mathrm{Exp}}(S_T) > \mathrm{U}_{ik}^{\mathrm{No}} > \mathrm{U}_{iJT-1}^{\mathrm{Exp}}(S_{T-1}) \cdots\cdots \text{Eq. (24)}$$

In short, V^{No} acts as a reference to how long the purchase will be delayed, and $\mathrm{V}^{\mathrm{Exp}}$ determines whether a specific alternative at a specific point in time is larger or smaller than the reference. As a result, it makes the proposed model different from the existing one. Because all existing studies have seen which alternatives are chosen according to the "pre-defined future scenario", assuming that these "future situations" are realized. In this regard, I doubt that this approach might distort respondents' decisions. However, the model I present here eventually regards respondents' decisions about the future, based on their expectations of changing attributes(state variables).

3.2 Estimation

Based on the idea that When "the expected utility($\mathrm{V}_{jT}^{\mathrm{Exp}}$) for the alternative j after T" is greater than the "expected utility to reserve purchase(V_0^{No})" Respondents decide to purchase the alternative j after T, I established the following estimation strategy.

$Prob$[agent i choose J at T] ·· Eq. (25)

$$= prob\left[U_{ijT}^{Exp} > U_{\mathrm{ik}}^{No}(\mathrm{s}_0), U_{ijT}^{Exp} \;\middle|\; U_{ijT}^{Exp}, U_{iJt}^{Exp} < U_{\mathrm{ik}}^{No}(\mathrm{s}_0)\ \forall\, j \neq J,\ t < T-1\right]$$

If the respondent responded that vehicle j would be purchased after T period, the hazard rate and conditional probability can be defined as follows.

$$h_{\mathrm{ikt}}^{No} = \frac{\exp(V_{\mathrm{ik}}^{No}(\mathrm{S_t}))}{\exp\left(V_{\mathrm{i\,gasoline}\,T}^{Exp}\right) + \exp\left(V_{\mathrm{i\,electric}\,T}^{Exp}\right) + \exp\left(V_{ik}^{No}(S_t)\right)}$$

$$h_{\mathrm{ijT}} = \frac{\exp(V_{ijT}^{Exp}(\mathrm{E}(\mathrm{S_T})))}{\exp\left(V_{\mathrm{i\,gassoline}\,T}^{Exp}\right) + \exp\left(V_{\mathrm{i\,electric}\,T}^{Exp}\right) + \exp\left(V_{ik}^{No}(S_T)\right)}$$

$$\mathrm{Prob}[purchase\ j\ at\ T\ while\ reserving\ until\ T-1]$$

$$= \left(\prod_{\tau=0}^{T-1} h_{ikt}^{No}\right) * h_{ijT} \quad \text{········· Eq. (26)}$$

As previously discussed in Chapter 2, the above probability can be regarded as the likelihood function. Accordingly, a maximum likelihood estimation or Bayesian approach can be taken. In the simulation below, I constructed a homogeneous model, and in this case, I used the maximum likelihood approach[4], and the empirical data were estimated by Nested Fixed Point algorithm, which is MLE based estimation approach.

$$Likelihood = \prod_i \{ (\prod_{\tau=0}^{T-1} h_{ikt}^{No}) * h_{ijT} \} \cdots\cdots\cdots\cdots \text{Eq. (27)}$$

3.3 Monte Carlo simulation

I conducted Monte Carlo simulation to check the proposed model is able to recover true parameters. I specified pre-determined parameters and re-estimate it based on the parameters. Consumer heterogeneity was not reflected, and the estimation used the Maximum Likelihood technique[5].

		True value	Dynamic discrete choice	MNL with No_purchase	MNL
Fuel type	Gasoline	1(baseline)	1	1	1
	Electric	0.9	0.9144^{***} (0.0174)	1.3462^{***} (0.0503)	1.6502^{***} (0.0807)
Price		−1,5	-1.4795^{***} (0.0440)	-0.6381^{***} (0.0209)	-0.8096^{***} (0.0282)
Annual cost		−0.1	-0.1061^{***} (0.0147)	-0.1391^{***} (0.0267)	-0.2710^{**} (0.0463)
Station accessibility		1	0.9942^{***} (0.0210)	0.9436^{***} (0.0874)	1.5480^{***} (0.1594)
Status quo		1	1.0175^{***}	0.9366^{***}	-

4 Because of the computational burden in using Bayesian approach.

5 As mentioned earlier, the maximum likelihood of Rust's MDP-based Dynamic Choice model is called the Nested Fixed Point algorithm.

		(0.0608)	(0.0954)	
$log(own\ year + 1)$	-0.8	-0.7981^{***} (0.0359)	-1.6054^{***} (0.1136)	-
Discount Factor $\frac{\exp(\beta)}{1+\exp(\beta)}$	0.7311 ($\beta = 1$)	0.7291 $\beta = 0.9901^{***}$ (0.0051)	-	-

*: 90% confidence, **: 95% confidence, ***: significant in 99% confidence

Table 4. Estimation results of Monte Carlo simulation

The random draw was performed 5,000 times, and charging accessibility was selected as a variable that consumers would recognize as uncertainly changeable in the future[6]. Therefore, state variables for charging accessibility should be defined, and these are defined by dividing from 10% to 100% of station accessibility into 10 parts division so that a total of 10^3 state variables are defined[7]. By separating the accessibility of electric vehicle charging stations and the accessibility of refueling stations, an agent was established to consider deforming/improving station accessibility in the survey situation.

The transition probability below shows how much the agent sees the accessibility of the refueling station as decreasing each year and how much the accessibility of the charging station is improved.

$$Prob_{gasoline}[s_{t+1}|s_t] = \begin{cases} s_t - 20\%p & with\ prob\ 0.25 \\ s_t - 10\%p & with\ prob\ 0.5 \\ s_t & with\ prob\ 0.25 \end{cases} \cdots\cdots\cdots\cdots \text{Eq. (28)}$$

[6] Other independent variables such as purchase price and annual cost are also technically possible uncertain variables, but the scope of the study was narrowed down to the infrastructure.

[7] 10 charging station accessibility * 10 refueling station accessibility * 10 times

$$Prob_{electric}[s_{t+1}|s_t] = \begin{cases} s_t + 20\%p & with\,prob\ 0.25 \\ s_t + 10\%p & with\,prob\ 0.5 \\ s_t & with\,prob\ 0.25 \end{cases} \quad \text{Eq. (29)}$$

As the transition probability is defined as above, the agent predicts that the accessibility to charging increases by 10%p on average every year and the accessibility to the refueling station decreases by 10%p.

$$E_{electric}[s_{t+1}|s_t] = s_t + 10\%p\ , E_{gasoline}[s_{t+1}|s_t] = s_t - 10\%p \quad \text{Eq. (30)}$$

In addition, 10% and 100% of the last states of the state variable definition were defined as absorbing states, making it impossible for unrealistic state variables (e.g. negative refueling station accessibility) to be reflected in the model[8].

When the parameters are set as described above, the preferred alternative of the (virtual) respondent and the distribution of the preferred time point are shown in the following table 5. Note that the static model used only the "Present" column for estimation.

	Present (within a yr)	2 yrs later (within 3 yrs)	4 yrs later (within 5 yrs)	6 yrs later (within 7 yrs)
Gasoline	1038	188	114	76
Electric	629	249	175	154

[8] This will be a part that strictly hurts the consistency of the model. However, considering that the actual survey respondents did not look ahead the future too far away, that is, that the forward-looking behavior of consumers (although they saw it as infinitely occurring in the model) actually occurred within a limited range, it was considered trivial assumption.

No Purchase	3333	2896	2607	2377

Table 5. Choice distribution of simulated data

Looking at the estimation results in table 4, it can be seen that the proposed model has recovered the true parameters well. In addition, to compare with the commonly used static model, the results estimated with Multi-Nomial Logit(MNL) model were reported using the same data. I estimated using the two different MNL models. One is when there is a 'No purchase' alternative, and the other is without 'No purchase' alternative. In the former case, unlike the dynamic model, it was considered that the decision was made by whether or not the purchase was made within a year, that is, this static model did not use the information on purchasing timing. The utility function for each case is defined as follows.

Case 1) MNL – with No purchase alternative

$$U_{ij} = V_{ij} + \epsilon_{ij}$$

$$V_{ij} = \alpha_j + \beta^{price} * price_j + \beta^{annual\ cost} * annual\ cost_j + \beta^{station} * station_j$$

$$for\ \ j = \ gasoline, electric \quad \text{Eq. (31)}$$

$$V_{ij} = \alpha^{status\ quo} + \beta^{annual\ cost} * annual\ cost_k + \beta^{station} * station_k$$

$$for\ \ \ j = No\ purchase \quad \text{Eq. (32)}$$

Note that the annual cost and charging accessibility in "No purchase" alternative depend on the vehicle type (k) that the respondent already owned. If the (virtual) respondents said they would not purchase it within that year, it was considered No purchase.

Case 2) MNL – without No purchase alternative

$$U_{ij} = V_{ij} + \epsilon_{ij}$$

$$V_{ij} = \alpha_j + \beta^{price} * price_j + \beta^{annual\ cost} * annual\ cost_j + \beta^{station} * station_j$$

$$for\ j = \ gasoline, electric \quad \text{Eq. (33)}$$

The results of both static model cases show significance in 1% confidence level for all attributes. It should be noted that the static model evaluated the intrinsic preference of the electric vehicle with the same data higher than the dynamic model. This can be seen as a result of the static model that does not capture the positive expectations for the accessibility of electric vehicle charging stations and the negative expectations of access to refueling stations. In other words, in the static model, (virtual) respondents are considered to prefer electric vehicles despite lower accessibility to electric vehicle charging stations, which can be seen that the preference for electric vehicles is evaluated upwardly.

Another difference is in the estimated value of the price. The estimation result for the price of the static model is somewhat lower than that of the dynamic model. This is because in the dynamic model, as the respondent decides on the future choice, it is viewed that a discount is multiplied to the price to make the decision. Accordingly, since the estimation is made using a smaller price value than the static model, a higher price coefficient is derived.

Chapter 4. Empirical analysis

4.1 Choice Experiment

We conducted a choice experiment to verify that this model is well applicable to actual conjoint analysis and describes consumers' preferences. Our experiments were conducted for a total of 10 days from November 7, 2022, to November 16, 2022, for 1,220 respondents.

Table 5 below represents the attributes and attribute levels of the questionnaire presented to the respondents.

<table>
<tr><td>Attributes</td><td colspan="3">Description and attribute levels</td></tr>
<tr><td rowspan="2">Operating method (fuel type)</td><td>Description</td><td colspan="2">(1) Gasoline engine
(2) Electric motor</td></tr>
<tr><td>Level (2)</td><td colspan="2">(1) Gasoline
(2) Electric</td></tr>
<tr><td rowspan="3">Annual Cost (million KRW)</td><td>Description</td><td colspan="2">Annual cost containing fuel, tax, o&m cost.
Fuel costs are based on average driving distance
(39.6 km/mon, 14,454 km/year)</td></tr>
<tr><td rowspan="2">Level (3)</td><td>Gasoline</td><td>Electric</td></tr>
<tr><td>(1) 2 million KRW/year
(2) 3 million KRW/year
(3) 4 million KRW/year</td><td>(1) 1 million KRW/year
(2) 2 million KRW/year
(3) 3 million KRW /year</td></tr>
<tr><td rowspan="3">Purchase price</td><td>Description</td><td colspan="2">Purchase cost</td></tr>
<tr><td rowspan="2">Level (3)</td><td>Gasoline</td><td>Electric</td></tr>
<tr><td>(1) 20 million KRW
(2) 40 million KRW
(3) 60 million KRW</td><td>(1) 30 million KRW
(2) 50 million KRW
(3) 70 million KRW</td></tr>
<tr><td>Charging station availability</td><td>Description</td><td colspan="2">As of 2022, charging accessibility around the radius of activity.
(with a gasoline station as the standard 100%)</td></tr>
</table>

		Gasoline	Electric
	Level (3)	100%(Fixed)	(1) 30% (2) 50% (3) 80%

Table 6. Attributes and attributes level presented in the questionnaire

Since the research scope is consumers' decision on 'when to adopt electric vehicles', the properties largely consist of two categories: electric and gasoline cars. At this time, considering that the average price of the vehicle as of 2021 was 44 million KRW[9], the purchase price was constructed, and each purchase price was composed of three attribute levels. As of 2021, the average mileage of drivers is 14,454 km per year[10], and the annual cost was constructed considering that the fuel cost of gasoline vehicles in the last three months was about 1650 KRW/L and the charging cost of electric vehicles was about 100 to 300 KRW/kWh. Lastly, the accessibility of charging stations was limited to 30%, 50%, and 80%, respectively, considering gas station accessibility as a 100% baseline.

I attempted to reflect the expectations of consumers in the model. Accordingly, through the following questions, consumers were asked to answer the following questions in advance before starting the questionnaire to see how much they expected to increase access to charging stations and how much they expected to decrease access to refueling stations. The question is as follows.

---

[9] According to the report of Korea Automobile Manufacturers Association (KAMA) in 2022

[10] According to the report of Korea Statistical Information Service (KOSIS) in 2022

Question about electric vehicle charging station improvement rate

Q1. What percentage of electric vehicle charging station access do you currently see? (Assume gas station access is 100%)

1) 10% 2) 20% 3) 30% 4) 40% 5) 50% 6) other ____%

Q2. How many years does it take for EV charging station access to be comparable to gas station access(100%)?

1) 1) 5 year 2) 10 year 3) 15 year 4) 20 year 5) 25 year 6) 30 year 7) other __ year

Question about the average annual reduction in accessibility to internal combustion gas stations

Q3. What percentage of gas station accessibility do you expect in the next five years? (Assuming that the current year of 2022 is 100%)

1) 95% (-1%p/year) 2) 90% (-2%p/year) 3) 85% (-3%p /year)
4) 80% (-4%p /year) 5) 75% (-5%p/year) 6) other___%

Figure 2. Preliminary questionnaire presented to the respondents

After the preliminary question was completed, I presented the following screen to the respondents to obtain information on 'preferred alternatives' and 'timing of purchase'. The notable point is that respondents were presented with a question in two stages along with a screen as shown in firugre 3.

Q 1-1. Please respond to your preferred vehicle

Attributes	Vehicle A	Vehicle B
1. Operation type	Gasoline 	Electric 
2. Annual Cost (million KRW/year) Costs include fuel, tax, o&m cost. Fuel costs are based on following driving distance (39.6 km/mon, 14,454 km/year)	4 Million KRW/year	2 Million KRW/year
3. Price (million KRW)	40 Million KRW	70 Million KRW
4. Station Accessibility (When purchasing as of 2022)	100% ■■■■■■■■■■	80% ■■■■■■■■□□
Preferred Vehicle		

Q 1-2. According to your previous response, the following changes in accessibility to the gas station/charging station are expected.

- Gas station accessibility: reduced by ##%p per year
- Accessibility to electric vehicle charging stations: Increase ##%p every year

Please choose your preferred time to purchase each of the vehicle.

year	**2023**	**2025**	**2027**	…	**2041**	**After 2042**	**other**	**Never purchase**
A							____	
B							____	

Figure 3. Questionnaire for choice experiment

As shown in figure 3 above, the timing of the purchase is considered to range from a few years to a few decades, and the next 20 years are divided into 10 equal parts to reduce the burden on respondents' choices. In addition, if respondents prefer a specific point in time, they were able to respond by entering a specific purchase year, and an option to never purchase was added as an option. In addition, the expectations of station accessibility that respondents responded to in advance were guided so that respondents could better reflect on their perception of the changes in the refueling/charging infrastructure.

The above conjoint questionnaire was conducted 9 times for each respondent. According to the orthogonality test, it was optimal to provide a total of 12 questions per individual. However, considering the complexity of the questionnaire was quite high, 9 times questionnaires were randomly presented to each respondent, and the respondent group was divided into three groups to supplement it.

I collected a total of 1220 people's data through the above process. However, with two alternative options, I captured a significant number of unstable responses. The examples are as follows, and I screened all of these responses.

- the case in which the response for all 9 questions are the same.
- Respondents who chose a point of purchase outside of the purchase cycle that was answered in the preliminary question
- If the annual cost of a vehicle owned is significantly out of a common sense

In addition, this model was constructed to see when non-vehicle owners and internal combustion vehicle owners adopt electric vehicles. Technically, it can also reflect electric vehicle owners in the model, but due to the survey structure, it is not suitable to reflect electric vehicle owners' responses in the model.[11] Therefore, the owner of the electric vehicle was also excluded from the data set. Accordingly, a total of 825 screened respondents were selected, and their demographic distribution is shown in table 7.

		number of respondents
Gender	Males	411 (49.8%)
	Females	414 (50.2%)
	Total	825
Age	20-29	186 (22.5%)
	30-39	188 (22.8%)
	40-49	231 (28.0%)
	50-59	220 (26.7%)
	Total	825
Region	Metropolitan province	425 (51.5%)
	Gyeonsang province	181 (21.9%)
	Jeolla province	77 (9.3%)
	Chungcheong province	102 (12.4%)
	Gangwon-do	24 (2.9%)
	Jeju	16 (1.9%)
	Total	825

Table 7. Demographic distribution after screening

As shown in the above results, gender, age, and regional distribution were well

[11] The model itself can also reflect electric vehicle owners. However, since the questionnaire presented the question of 'charge station accessibility assuming a vehicle is purchased', it is inappropriate to reflect the responses of those who already own an electric vehicle.
This is because the values of "accessibility of electric vehicle charging stations currently considered by respondents" included in the v^{own} part and "accessibility of electric vehicle charging stations as of 2022" presented in the questionnaire are inconsistent.

reflected, so I judged that we could proceed with the analysis. The following contents will summarize the results of the annual average increase or decrease rate in accessibility to stations for a total of 1220 people and the results of the choice experiment conducted for 825 people.

4.2 Result (1) People's prospects for infrastructure

First of all, the average annual increase or decrease rate of access to stations responded by 1220 respondents is as follows.

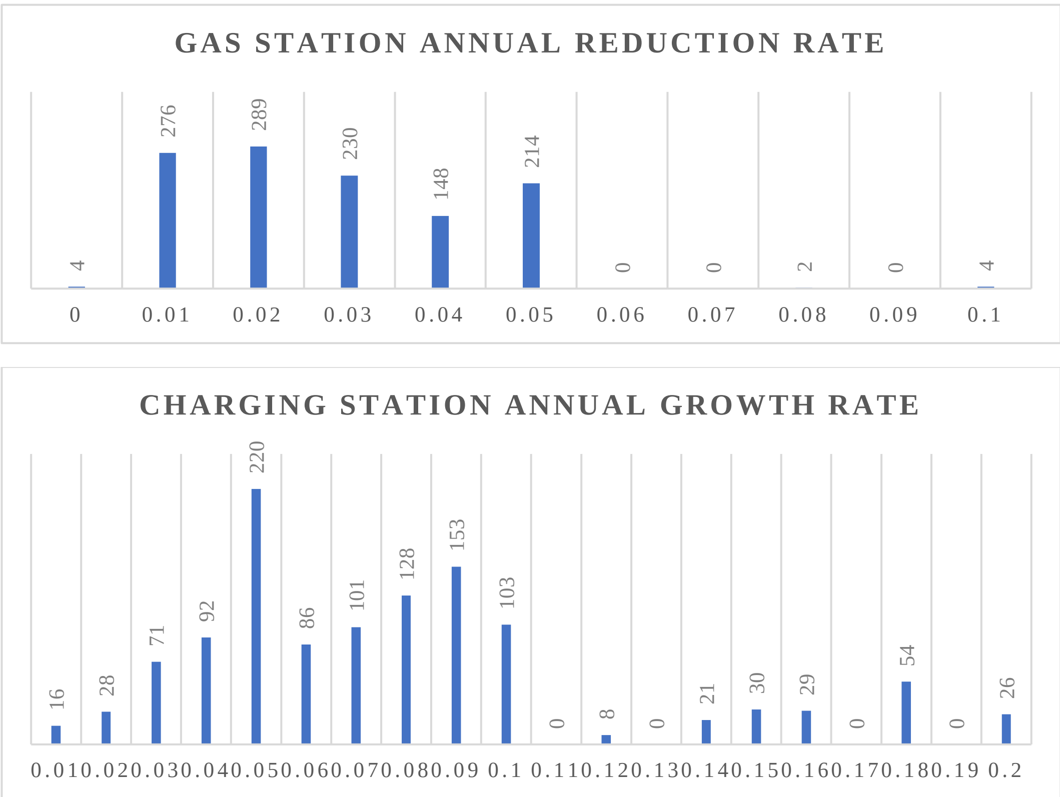

Figure 4. average annual increase/decrease rate of access to infrastructure

According to the above results, the average annual reduction rate of access to refueling stations predicted by respondents was 2.8%p with a standard deviation was 1.5%p. Accordingly, I considered that the rate of decrease in accessibility to the gas station follows truncated normal distribution with drift at -2.8%p for each year and a standard deviation of 1.5%p.

$$Prob_{gasoline}(s_{t+1}|s_t) \sim Truncated\ Normal(s_t - 2.8,\ 1.5^2) \cdots\cdots\cdots\cdots\cdots \text{Eq. (34)}$$

Similarly, the average annual growth rate of access to electric vehicle charging stations predicted by respondents was 8%p on average, and the standard deviation was 4%p. I considered that the rate of increase in accessibility to the charging station considered by the respondents was by 8%p annual drift and followed a truncated normal distribution with a standard deviation of 4%p.

$$Prob_{electric}(s_{t+1}|s_t) \sim Truncated\ Normal(s_t + 8,\ 4^2) \cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (35)}$$

Similar to Monte Carlo simulation, the state variable was constructed for the average increase over the next 10 years, and the changes in accessibility after 10 years was considered an absorbing state[12].

I assume here that everyone has homogeneous expectations for refueling/charging

[12] In other words, the state of gas station accessibility being 100% - 2.8%*10 (year) and charging station access being (charging station accessibility presented in the response sheet) + 8%*10 (year) was considered an absorbed state.

infrastructure. Of course, assuming a certain distribution in the response value of each individual, it can be shown that each individual has different expectations. However, in this case, in terms of the increasing rate of charging stations for electric vehicles, the deviation of individuals was too large to be somewhat suspicious of stability.

4.3 Result (2) Result of Choice experiment

After configuring the transition matrix using the above results, I performed an analysis of the proposed model based on the choice experiment data. In the same way as the Monte-Carlo simulation performed earlier in chapter 3, estimation was performed here through Nested Fixed Point Algorithm.

Based on these responses, I estimated the model for the data obtained from the choice experiment. Using 7 of the 9 responses of each 825 respondents, 5775 data were randomly extracted and used as training data.

	Present (within a yr)	2 yrs later (within 3 yrs)	4 yrs later (within 5 yrs)	6 yrs later (within 7 yrs)	8 yrs later (within 9 yrs)	after 10 yrs
Gasoline	970	778	669	209	188	104
Electric	310	696	911	343	240	140
No Purchase	4495	3021	1441	889	461	217

Table 8. Choice distribution of training data

The questionnaire includes a time-horizon up to 20 years, but I considered all responses after 10 years to have chosen the "No purchase after 10 years" alternative.[13]

		Dynamic model	Multi-nomial logit
Parameters	Intrinsic preference for Electric	0.9463^{***} (0.0192)	0.9415^{***} (0.1366)
	Price	-0.0496^{***} (0.0021)	-0.0234^{***} (0.0020)
	Annual Cost	-0.0645^{***} (0.0109)	0.0319^{*} (0.0209)
	Station Accessibility	1.0179^{***} (0.0624)	1.8822^{***} (0.2831)
	Status quo	0.6446^{***} (0.0413)	1.8215^{***} (0.0822)
	Ownership period	-0.0079^{***} (0.0025)	-0.0159^{**} (0.0074)
	Discount rate $\beta \rightarrow \frac{\exp(\beta)}{1+\exp(\beta)}$	1.0012^{***} (0.0256) $\rightarrow 0.73$	-
Likelihood	LL(0)	-17160.092	-7989.5932
	LL($\hat{\beta}$)	-13403.540	-3664.4286
	Likelihood ratio	0.781	0.459

$*$: 90% confidence, $**$: 95% confidence, $***$: significant in 99% confidence

Table 9. Estimation results of Choice experiments

[13] As a preliminary question, I asked, "How many years later will you buy a new car?" and only 12 out of 1220 respondents said they would buy it after 10 years. Therefore, the above decision is not a very unreasonable decision.

First of all, as same in the simulation result performed in Chapter 3, we can see that the absolute value of the price coefficient is estimated to be larger. This is technically due to the multiplication of the discount rate on the price, and on the other hand, it can be interpreted as a dynamic model capturing that the long-term response to the prices is more elastic.[14]

It is also worth noting that unlike the 0.8-0.99 discount rate assumed in existing studies, a relatively low value of 0.73 is derived. This suggests that existing literature has been rather over-applied to consumers' discount rates.

4.4 Model validation

Meanwhile, I regarded the rest of the data except for the data used in the training step as test data. Validation of the model was performed on a total of 1650 data for 2 responses of each 825 respondents.

The observed distribution of preferred choices and timing is as shown in Table 10, and the results of comparing them with the static model and the dynamic model are shown in figure 5.

	Present (within a yr)	2 yrs later (within 3 yrs)	4 yrs later (within 5 yrs)	6 yrs later (within 7 yrs)	8 yrs later (within 9 yrs)	after 10 yrs
Gasoline	247	215	199	60	35	26
Electric	91	191	289	116	69	37
No Purchase	1312	906	418	242	138	75

[14] In this result, the coefficient for annual cost was positive, contrary to common sense. However, since this relies heavily on the design of the questionnaire, it is difficult to say that the dynamic model performed better in estimation.

Table 10. Choice distribution of test data

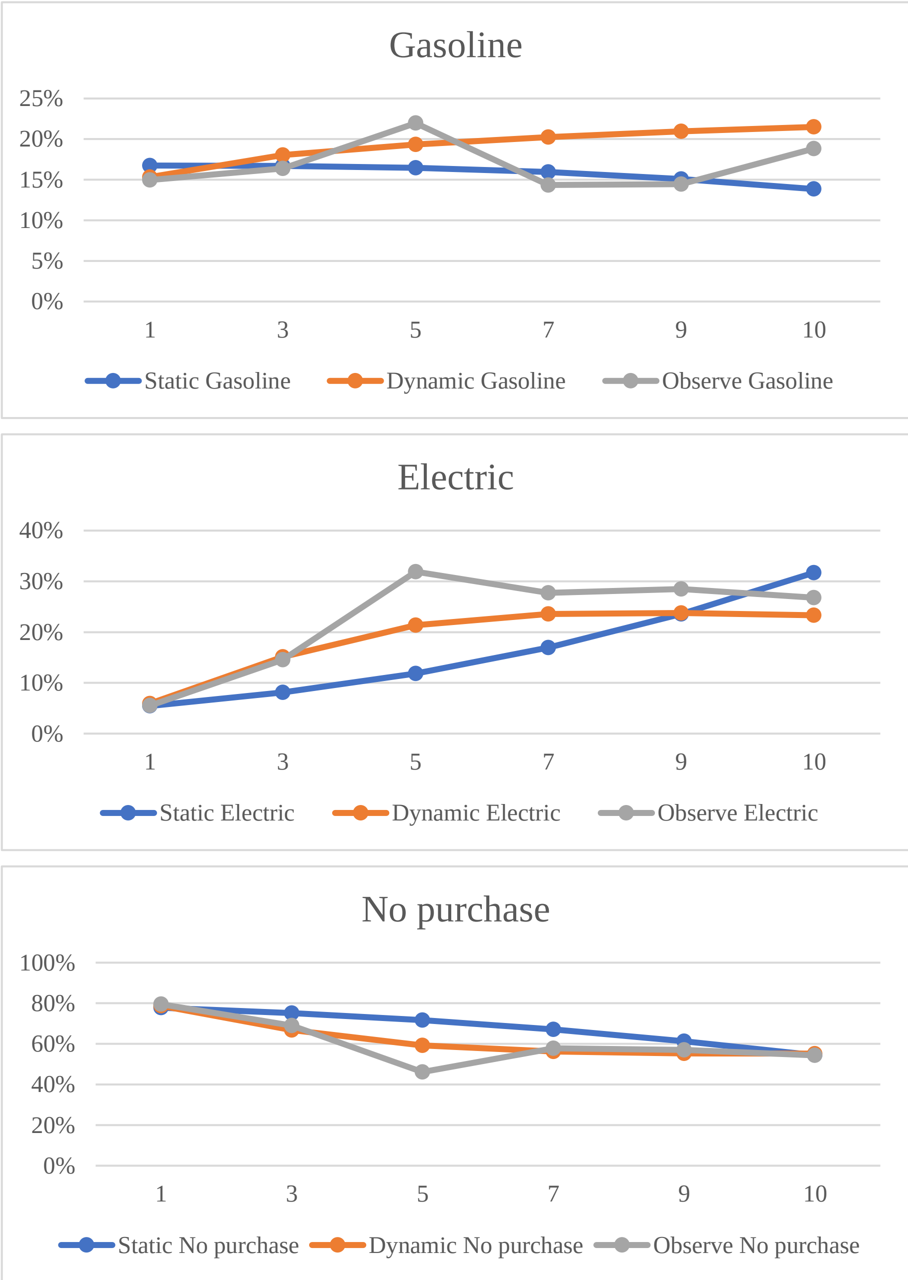

Figure 5. Choice Probability for the test data set

Each graph in Figure 5 shows the probability of choosing a gasoline vehicle, an electric vehicle, and a no purchase by time using the trained parameter values. In order to make the static model comparable to the dynamic model, I made two properties change over time even in the static model. One is infrastructure accessibility and the other is ownership period. Thus, the changes in choice probability in the static model according to time depends only on the change of these two variables. The tendency in the choice probability follows observed distribution. As shown in Figure 5, some of the static models and others of the dynamic models recovered the observed distribution better. Therefore, an indicator is needed to compare these two, and I obtained RMSE to compare the performance of each model.

Root Mean Square Error(RMSE) between results and observed data was calculated to compare how well these two different models restore the observations similarly, and the results are shown in the following figure.

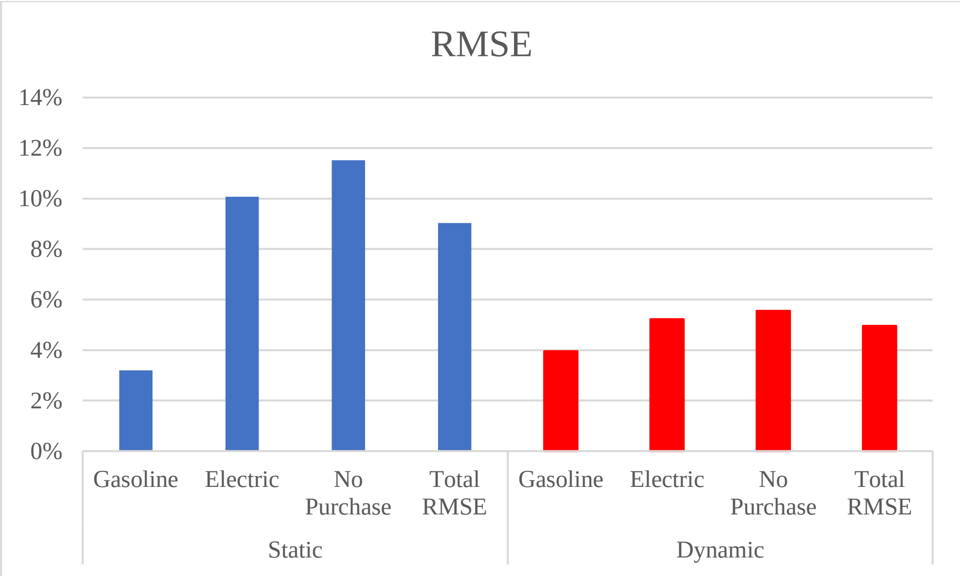

Figure 6. RMSE comparison

The value of each bar represents the RMSE of the choice probability for each Gasoline, Electric, and No purchase alternatives and the RMSE of the entire choice probability. According to the above results, although the dynamic model lacks explanatory power for Gasoline vehicles, it shows better greater explanatory power for electric vehicle, No purchase and overall explanatory power. This result indicate the performance of the dynamic model is higher than that of the static model.

Chapter 5. Simulation

I performed simulation by changing the attributes, based on the estimated parameters, and describe how the proposed model exhibits differently from existing static model-based analyses and what usefulness does this model have.

5.1 Changes in choice probability according to attribute level

I simulated the 'probability of purchasing within a year' of respondents to see how the static and dynamic models behave differently by changing the Gasoline car price and present charging infrastructure accessibility which were the main attributes in the survey. The random draw was performed 10,000 times, and each drawn agent was a different in their period of ownership and annual cost. The following shows the above results.

I performed sensitivity analysis only on changes in each of the attributes level related to the spread of electric vehicles. The base is summarized in the table below.

	Gasoline	Electric
Purchase price	30 KRW million	50 KRW million
Annual Cost	3 KRW million	1 KRW million
Station accessibility	100%	30%

Table 11. Base scenario

$$Prob_{gasoline}[s_{t+1}|s_t] = \begin{cases} s_t - 0\%p & with\ prob\ 0.25 \\ s_t - 2\%p & with\ prob\ 0.5 \\ s_t - 4\%p & with\ prob\ 0.25 \end{cases} \cdots\cdots \text{Eq. (36)}$$

$$Prob_{electric}[s_{t+1}|s_t] = \begin{cases} s_t + 0\%p & with\ prob\ 0.25 \\ s_t + 5\%p & with\ prob\ 0.5 \\ s_t + 10\%p & with\ prob\ 0.25 \end{cases} \cdots\cdots \text{Eq. (37)}$$

I set the average rate of increase in charging stations (5%) and the rate of decrease in gas stations (2%). Eq. (36) and (37) show the base scenario transition probability that I used to compare with the other scenario.

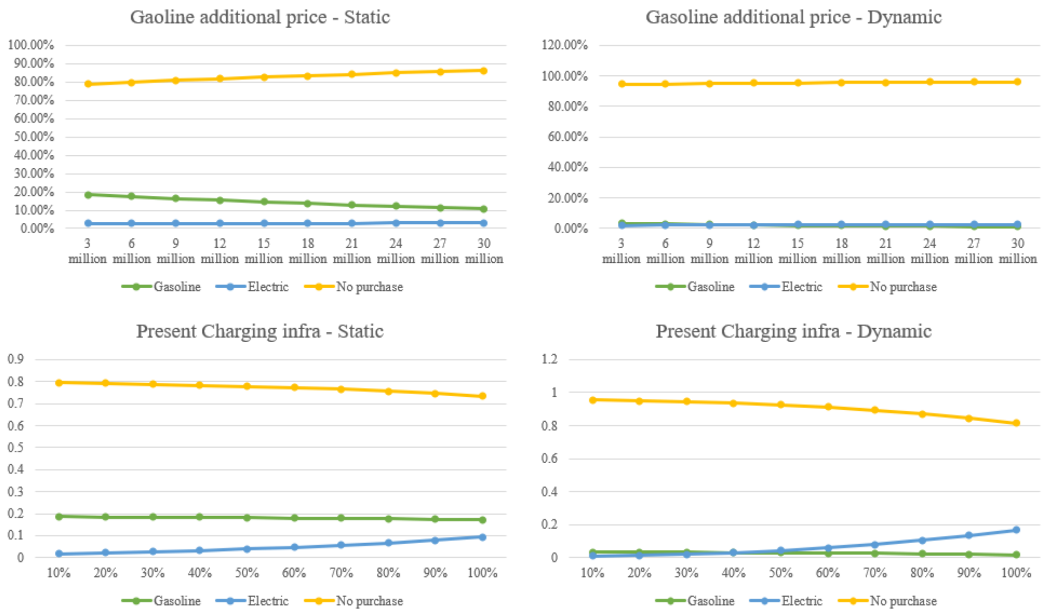

Figure 7. Choice probability according to the changes in attribute levels

Figure 7 shows the change in the purchase probability within one year according to the change in attributes. Note that the x-axis does not represent time but the level of changes in attributes.

As shown in figure 7, the static model moves relatively much more sensitively than the dynamic model in response to the price change. In contrast, the dynamic model is more sensitive to infrastructure changes. Note that each of the two models derives very different choice probabilities. The static model derived choice probability for the gasoline vehicles at about 10-20%, but the dynamic model shows that, in most cases, the probability of purchasing gasoline vehicles is around 3%. As a result, the two models yield very different results even in the same base scenario, and thus, we need to be careful in performing market simulations on both models. In particular, in the case of the dynamic model, the ratio to the No purchase is rather higher than that of the static model.

In the first case where the price of gasoline cars increased by 5 million KRW. The proportion of gasoline vehicles purchased in the dynamic model decreases, but there is no significant change in the purchase rate of electric vehicles, and it leads to an increase in the proportion of no-purchase. A similar pattern can be seen in the static model. However, the rate of decrease in the purchase of gasoline cars is steeper, and thus the proportion of no-purchases increases steeply as well.

The last case is that accessibility to electric vehicle charging stations is increased by 10% for each scenario. Since increased charing infrastructures have a positive impact on purchasing electric vehicles, the result shows that the purchase rate of electric vehicles increases and the purchase rate of gasoline vehicles decreases. Moreover, in the case of the dynamic model, due to the cumulative utility of the charging infrastructure that occurs even after purchase, the choice probability of electric vehicles increases faster than in the case of the static model.

The above results show just how different the two models produce in performing simulations. The two sections below show the results that imply the usefulness of the dynamic model.

5.2 Changes in expectation on station accessibility

To see changes in purchasing behavior that occur within a year according to people's expectations for charging infrastructure, a graph comparing 'probability of purchasing gasoline/electric vehicles within a year' is shown as follows.

Figure 8. Choice probability according to the changes in people’s expectation

The green line represents a change in the probability of purchasing an “electric vehicle” according to the rate of increase in the charging infrastructure of the electric vehicle (1 ~ 20%/year). The blue line represents the change in the probability of purchasing a “gasoline car” according to the rate of increase in the charging infrastructure of the electric vehicle (1 ~ 20%/yr).

As shown in Figure 8, since the Static model cannot show a change in consumers’ choice according to their expectations, no matter how much the rate of increase in the charging infrastructure changes, it does not have any effect on the current decision. On the other hand, the dynamic model can explicitly describe how the purchase probability changes according to the change in expectations. Naturally, as expectations for an increase in electric vehicle charging infrastructure are faster, the probability of purchasing electric vehicles within a year increases, while the probability of purchasing gasoline cars decreases.

5.3 Changes in expectation on price

Although I only considered charging accessibility as a state variable in the estimation step, due to the nature of the dynamic model, all other variables can be considered dynamically changing variables in simulation. Thus, I applied price level as a dynamic variables. The dynamic model can show how, unlike typical static model-based market simulation, the changes in prices that will be occurred in the future affect the probability of a current purchase. In other words, when the price is a variable that changes in the future, not the present, the dynamic model can describe people’s decision done in advance .What is different from Section 5.1 is that this section differs in that consumers know when the prices will be changed in the future. The price is a variable that is not stochastic but does change deterministically in the future. I refer to this scenario as a subsidy scenario. As same in my scenario, most subsidy policies are usually announced before implementation, thereby facilitating strategic behavior for potential consumers. I show in the graph below how the probability of purchase appears, assuming that the existing base scenario will be subsidized for KRW 30 million after three years and all the consumers know it.

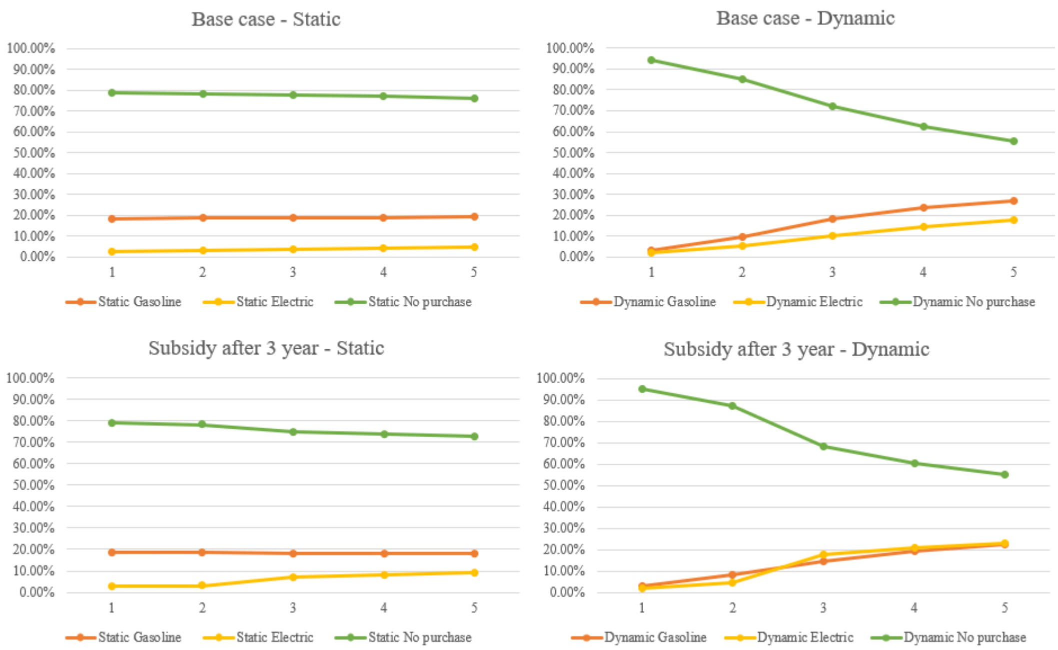

Figure 9. Choice probability in future discount scenario

	Base Case (No subsidy)			Subsidy after 3 years			Difference		
year	Gasoline	Electric	No purchase	Gasoline	Electric	No purchase	Gasoline	Electric	No purchase
1	18.5%	2.7%	78.8%	18.5%	2.7%	78.8%	0.0%	0.0%	0.0%

2	18.6%	3.1%	78.2%	18.6%	3.1%	78.2%	0.0%	0.0%	0.0%
3	18.8%	3.6%	77.6%	18.1%	7.1%	74.9%	-0.7%	3.4%	-2.8%
4	18.9%	4.2%	76.9%	18.1%	8.1%	73.8%	-0.8%	3.9%	-3.1%
5	19.0%	4.8%	76.2%	18.1%	9.2%	72.7%	-0.9%	4.4%	-3.5%

Table 12. Difference between the Subsidy scenario and Base case in the static model

	Base Case (No subsidy)			Subsidy after 3 years			Difference		
	Gasoline	Electric	No purchase	Gasoline	Electric	No purchase	Gasoline	Electric	No purchase
1	3.3%	2.2%	94.5%	2.8%	1.9%	95.3%	-0.5%	-0.3%	0.8%
2	9.7%	5.5%	84.9%	8.4%	4.7%	86.9%	-1.3%	-0.7%	2.0%
3	18.0%	9.8%	72.2%	14.4%	17.4%	68.2%	-3.6%	**7.6%**	-4.0%
4	23.6%	14.1%	62.3%	19.3%	20.6%	60.1%	-4.3%	6.5%	-2.2%
5	26.7%	17.7%	55.6%	22.3%	22.7%	55.0%	-4.4%	5.0%	-0.6%

Table 13. Difference between the Subsidy scenario and Base case in the dynamic model

As shown in Figure 9 and Table 12, since the Static model cannot model the current behavior change according to expectations of price in the future, there is no difference between two scenarios in which the subsidy is paid three years later and the base scenario. On the other hand, the dynamic model not only reflected this proactive actions in response to future changes, but also modeled the explosive increase in the purchase probability (+7.6%) after the subsidy was paid after waiting for the purchase until there was a subsidy.

The characteristics of the dynamic model shown in the sections 5.2 and 5.3 are advantageous in that they can represent two things that cannot be described in the static model. One is the behavioral change according to the expectation of attribute change, and the other is, even if such behavioral change occurs in the future, consumers’ proactive behavior change in advance.

Chapter 6. Conclusion

6.1 Summary & Conclusion

This study proposed a model that could reflect consumers' forward-looking behavior in conjoint analysis, and applied it to actual survey data. Unlike previous studies that applied dynamic models to stated preference analysis, this study did not provide any information on the future, and allowed respondents to choose their preferred alternatives and preferred purchase timing based on their own expectations and preferences. This approach significantly reduces the possibility that the researcher distorts the respondents' preferences and strategic decision on time of purchase.

Also, the biggest difference from the existing approaches is that the model I propose sees respondents' future choices as future choices themselves. Since past studies using dynamic approaches have provided pre-defined future scenarios to the respondents, what will happen in the future is considered as if respondents know the future. I doubt this approach could distort respondents’ forward-looking view. Not only that, the past approaches do not fully depict the forward-looking behavior, considering that forward-looking behavior means the “decision-making made now under uncertainty about the future”. To compensate for these limitations, as mentioned above, I designed a survey without giving any information about the future, and to this end, I regarded their choice as it reveals the greatest ‘expected utility’ not the current utility.

Lastly, I did not assume rational expectations, mainly used in existing studies. This is because rational expectation relies on historical data, which limits the applicability of the proposed model in that the main usage of conjoint analysis is to examine the potential consumers’ preference of new products/services before released.

It was confirmed that not only did the simulated model recover the true parameter well, but also it was well applied to the empirical data. The proposed model outperforms the common static approach in describing consumers’ preferred timing. In particular, the proposed model is significant in that it can explicitly reveal that respondents' expectations are affecting the proactive adoption of electric vehicle, suggesting that "how fast the public trusts a political plan" or “When will the subsidy policy change” can also be an important factor in the adoption speed by affecting people’s strategy.

6.2 Limitation and further research

I faced some difficulties while building a model. Due to the nature of the model in which the researcher should arbitrarily determine the range of the state space and establish a distribution within the range, the distribution is distorted within the defined state space. This distortion became more severe as it approached the boundary state, for example, as the state reaches the upper/lower bound of the state I defined. Of course, this can also be overcome with an approach to broadening the range of state space, but in that case, the computing burden increases exponentially.

Also, as mentioned, there is a large variation in the expectations of respondents for the charging infrastructure. I tried to reflect different expectations for each individual in the initial model, but It made too complicated model due to the people's highly deviated expectations[15]. People's expectation was directly related to the problem of setting the range of state space, and thus I rejected the initial heterogenous expectation model.

For this reason, I suppose that the development of an approach to more systematically models individual respondents' expectations would compensate for the mentioned problems.

Bibliography

Bayus, B. L., & Gupta, S. (1992). An empirical analysis of consumer durable replacement intentions. International Journal of Research in Marketing, 9(3), 257–267

Bass, F. M. (1969). A new product growth for model consumer durables. Management science, 15(5), 215-227.

Bemmaor, A. C. (1992). Modeling the diffusion of new durable goods: Word-of-mouth effect versus consumer heterogeneity. In Research traditions in marketing (pp. 201-229). Springer, Dordrecht.

Byun, H., Shin, J., & Lee, C. Y. (2018). Using a discrete choice experiment to predict the penetration possibility of environmentally friendly vehicles. Energy, 144, 312-321.

Bridges, E., Coughlan, A. T., & Kalish, S. (1991). New technology adoption in an

[15] Charing station increasing rate from 1% to 20% per year.

innovative marketplace: Micro-and macro-level decision making models. International Journal of Forecasting, 7(3), 257-270.

Choi, H., & Koo, Y. (2019). Do I have to buy it now? A vehicle replacement model considering strategic consumer behavior. Transportation Research Part D: Transport and Environment, 73, 318-337.

Choi, H., & Koo, Y. (2023). New technology product introduction strategy with considerations for consumer-targeted policy intervention and new market entrant. Technological Forecasting and Social Change, 186, 122126.

Cirillo, C., Xu, R., & Bastin, F. (2016). A dynamic formulation for car ownership modeling. Transportation Science, 50(1), 322-335.

Coppejans, M., Gilleskie, D., Sieg, H., & Strumpf, K. (2007). Consumer demand under price uncertainty: Empirical evidence from the market for cigarettes. The Review of Economics and Statistics, 89(3), 510-521.

Dubé, J. P., Hitsch, G. J., & Jindal, P. (2014). The joint identification of utility and discount functions from stated choice data: An application to durable goods adoption. Quantitative Marketing and Economics, 12(4), 331-377.

Easingwood, C. J., Mahajan, V., & Muller, E. (1983). A nonuniform influence innovation diffusion model of new product acceptance. Marketing Science, 2(3), 273-295.

Erdem, T., & Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. Marketing science, 15(1), 1-20.

Gordon, B. R. (2009). A dynamic model of consumer replacement cycles in the PC processor industry. Marketing Science, 28(5), 846-867

Gowrisankaran, G., & Rysman, M. (2012). Dynamics of consumer demand for new durable goods. Journal of political Economy, 120(6), 1173-1219.

Green, P. E., & Rao, V. R. (1971). Conjoint measurement-for quantifying judgmental data. Journal of Marketing research, 8(3), 355-363. a

Green, P. E., & Srinivasan, V. (1990). Conjoint analysis in marketing: new developments with implications for research and practice. Journal of marketing, 54(4), 3-19.

Grubel, H. G. & Lloyd, P. J. (1975). Intra-industry Trade. London: Macmillan Press.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1984). Multivariate data analysis with readings, 1995. Tulsa, OK: Petroleum Publishing.

Henderson, J. V., & Ioannides, Y. M. (1989). Dynamic aspects of consumer decisions in housing markets. Journal of Urban Economics, 26(2), 212-230.

Henderson, J. M. & Quandt, R. E. (1987). Financing structure. American Economic Review, 39(1), 123-145.

Ishihara, M., & Ching, A. T. (2019). Dynamic demand for new and used durable goods without physical depreciation: The case of Japanese video games. Marketing Science, 38(3), 392-416.

Johnson, R. M. (1974). Trade-off analysis of consumer values. Journal of marketing research, 11(2), 121-127.

Lavasani, M., Jin, X., & Du, Y. (2016). Market penetration model for autonomous vehicles on the basis of earlier technology adoption experience. Transportation Research Record, 2597(1), 67-74.

Levinthal, D. A., & Purohit, D. (1989). Durable goods and product obsolescence. Marketing Science, 8(1), 35–56.

Lee, J., Cho, Y., Lee, J. D., & Lee, C. Y. (2006). Forecasting future demand for large-screen television sets using conjoint analysis with diffusion model. Technological Forecasting and Social Change, 73(4), 362-376.

Lee, R. S. (2013). Vertical integration and exclusivity in platform and two-sided markets. American Economic Review, 103(7), 2960-3000.

Liu, Y., & Cirillo, C. (2017). A generalized dynamic discrete choice model for green vehicle adoption. Transportation research procedia, 23, 868-886.

Louviere, J. J. (1988). Conjoint analysis modelling of stated preferences: a review of theory, methods, recent developments and external validity. Journal of transport economics and policy, 93-119.

Mahajan, V., & Muller, E. (1996). Timing, diffusion, and substitution of successive generations of technological innovations: The IBM mainframe case. Technological Forecasting and Social Change, 51(2), 109-132.

Mahajan, V., Muller, E., & Bass, F. M. (1993). New-product diffusion models. Handbooks in operations research and management science, 5, 349-408.

Melnikov, O. (2000). Demand for differentiated durable products: the case of the US computer printer market. working paper, Yale University.

Norton, J. A., & Bass, F. M. (1987). A diffusion theory model of adoption and substitution for successive generations of high-technology products. Management 202 Science, 33(9), 1069–1086.

Olesen, F. (2016). The Lucas Critique–is it really relevant?. Department of Business and Management, Department of Business and Management Working Paper Series, 7.

Osborne, M. (2011). Consumer learning, switching costs, and heterogeneity: A structural examination. Quantitative Marketing and Economics, 9(1), 25-70.

Parker, P. M. (1994). Aggregate diffusion forecasting models in marketing: A critical review. International journal of forecasting, 10(2), 353-380.

Prince, J. T. (2008). Repeat purchase amid rapid quality improvement: Structural estimation of demand for personal computers. Journal of Economics & Management Strategy, 17(1), 1-33.

Prince, J. T. (2009). How do households choose quality and time to replacement for a rapidly improving durable good? International Journal of Industrial Organization, 27(2), 302–311.

Qian, L., & Soopramanien, D. (2015). Incorporating heterogeneity to forecast the demand of new products in emerging markets: Green cars in China. Technological Forecasting and Social Change, 91, 33-46.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. Econometrica: Journal of the Econometric Society, 999-1033.

Saengchote, K., & Nakavachara, V. (2018). Are consumers forward looking? Evidence from used iPhones. Applied Economics Letters, 25(13), 905-909.

Schiraldi, P. (2011). Automobile replacement: a dynamic structural approach. The RAND journal of economics, 42(2), 266-291.

Schwartz, R. G., & Oren, S. S. (1988). Using analytic hierarchies for consumer research and market modeling. Mathematical and Computer Modelling, 11, 266-271.

Song, I., & Chintagunta, P. K. (2003). A micromodel of new product adoption with heterogeneous and forward-looking consumers: application to the digital camera category. Quantitative Marketing and Economics, 1(4), 371-407.

Stacchetti, E., & Stolyarov, D. (2015). Obsolescence of durable goods and optimal purchase timing. Review of Economic Dynamics, 18(4), 752–773.

Train, K. E. (2009). Discrete choice methods with simulation. Cambridge university press.

Wolinetz, M., & Axsen, J. (2017). How policy can build the plug-in electric vehicle market: Insights from the REspondent-based Preference And Constraints (REPAC) model. Technological Forecasting and Social Change, 117, 238-250.

Zhang, J. Z., & Chang, C. W. (2021). Consumer dynamics: Theories, methods, and emerging directions. Journal of the Academy of Marketing Science, 49(1), 166-196.

Abstract (Korean)

기존의 정적 모형을 바탕으로 수행된 전기차 선호에 대한 분석은 차량과 같은 내구재를 구매하는 소비자들의 전략적 구매 행태, 즉 구매를 일정 기간 유보한 뒤 적절한 시점에 구매하는 행위를 설명하기에 한계를 지닌다. 본 연구는 이러한 문제의식을 토대로, 소비자들이 전략적으로 전기차를 구매하는 행태를 반영한 전기차 확산 모형을 제시한다. 제시된 모형에서 소비자는 불확실한 미래에 대한 선견적 예측에 따라 차량 구매 시점을 전략적으로 결정하는 주체로 묘사되며, 이러한 불확실한 미래에 대응하는 소비자의 의사결정은 마르코프 선택 과정을 이용하여 모형화된다. 제시된 모형은 진술 선호 기반 차량 선호 분석에 있어, 소비자들의 전략적 시점간 선택을 분석하는 틀을 제공하며, 미래의 기술 변화에 대한 불확실한 기대에 따른 소비자의 전기차 대체 시점의 변화를 확인할 수 있다. 2022년 한국의 자동차 소유자를 대상으로 선택 실험이 진행되었으며, 이로부터 얻은 결과는 미래 자동차 시장 예측을 위한 분석에 활용되었다. 본 연구는 주유소 및 충전 인프라 접근성을 마르코프 과정을 따르며 미래에 확률적으로 변화하는 속성으로 설정하였으며, 추정 결과를 토대로 미래 충전 인프라 확산 속도에 대한 분포에 변화를 주어 반사실적 시뮬레이션을 수행하였다. 시뮬레이션 결과 소비자가 전기차 충전 인프라 증

가 속도에 긍정적인 기대를 할수록 전기차 대체 시점은 빨라짐을 볼 수 있으며, 이는 전기차 확산 정책에 있어, 충전 인프라 확산 속도에 긍정적인 기대를 주는 것이 전기차 확산 속도에 상당한 영향을 미침을 시사한다.

주요어 : 전기차 확산, 시장 시뮬레이션, 동적 이산 선택 모형, 선견적 행동, 마르코프 선택 과정
학 번 : 2021-28651