Choice Data Generation using Usage Scenarios and Discounted Cash Flow Analysis

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Abstract

Discrete choice analysis with hierarchical Bayesian (HB) modeling is a popular methodology to estimate heterogeneous customer preferences. Despite the increased model accuracy gained from more choice data, this option is untenable due to the increased cost and time required to acquire substantial choice data of target customers. We thus propose a method for choice data generation for commercial products whose expected money value is a key factor in consumer choice (e.g., commercial vehicles and financial product). Using an individual usage scenario, we generate a discounted cash flow (DCF) model instead of a utility model to estimate the discount rates—than partworths—of individual consumers. The DCF model helps spawn numerous synthetic choice data with almost full factorial design. Using these data, we employ an HB-based discrete choice analysis. We conclude the study with a case study regarding preference estimation of hybrid courier truck conversion. The results reveal that the usage scenario-based HB estimation outperforms the traditional HB estimation.

Keywords: Discounted cash flow, discount rate, discrete choice analysis, hierarchical Bayesian

1. Introduction

When assessing a product with the intent to purchase it, consumers tend to consider the product's aesthetic, functionality, and economic value, for example. This decision-making process has attracted tremendous interest in consumer research (Bettman et al., 1998), operations management (Karniouchina et al., 2009), design for market systems (Frischknecht et al., 2010; Kang, 2014), environment (Alriksson and Öberg, 2008), food studies (Halbrendt et al., 1991; Darby et al., 2008; Annunziata and Vecchio, 2013; Caputo et al., 2018), and healthcare (Bridges et al., 2008, 2011; Marshall et al., 2010). One such technique to explore this decision-making is the discrete choice analysis—a statistical technique that uses choice data obtained through surveys to measure consumers' tradeoffs among products or services with assorted attributes (Green and Srinivasan, 1990).

In discrete choice analysis, one of the decision rules is for the analysis to use a utility model and assume that the consumer chooses a product with a larger utility, which is the sum of the *partworths* that the consumer assigns to the product attributes (Michalek et al., 2005; Lewis et al., 2006; Raghavarao et al., 2011; Kang et al., 2019; Wong et al., 2019).

The choice data needed for estimating partworths can be, in general, collected through a survey completed by potential customers (MacKerron, 2011; Kang et al., 2016). In a discrete choice experiment, a series of choice questions on a set of products with different combinations of attributes are presented. The respondent is asked to choose the most preferred product option among the other alternatives (Louviere and Woodworth, 1983; DeSarbo et al., 1995; Halme and Kallio, 2011). The individual partworths are then estimated via a hierarchical Bayesian (HB) approach, which determines the probability of a respondent choosing one product over the others as a function of its attributes (Train, 2001; Rossi et al., 2005; Orme, 2009; Hein et al., 2019). Then, the intermediate attribute values are interpolated using a natural cubic spline to obtain a continuous individual-level utility model (Kang et al., 2017a). The HB approach has found especially wide use for estimating customer preferences for vehicles under various market conditions (Kang et al., 2015, 2018). Along this line, we also consider a commercial vehicle case study.

The precision of the discrete choice model's parameter estimates strongly depends on the sample size. Particularly, when the target customers are specified to a certain group, obtaining choice data can be costly and time-consuming. Sometimes, it may not even be possible to obtain enough data to perform discrete choice analysis. We thus pose a question to readers: How do we improve the precision of the discrete choice model's parameter estimates even when the sample size is not adequately large?

We confine the scope of the problem to commercial products—that is, products used for business or investment with a profit motive. For commercial products, such as a financial product or commercial vehicle, consumers make a reasonable decision considering their current investment and usage scenario. The latter term deals with the gains or costs that the product will bring to the customers during the total period of use. Personal experience and learning about the risks also affect the value of expected future cash flow and, therefore, have a significant impact on the customer's decision (Botsch and Malmendier, 2015; Kuchler and Zafar, 2015; Malmendier and Nagel, 2016). Customers will normally consider the functional and non-functional attributes of general products. In case of commercial products, we assume that the customer prioritizes the expected money value obtained by using the product during selection. We thus apply the discounted cash flow (DCF) model based on the usage scenario and DCF analysis to discrete choice analysis.

DCF analysis is a valuation technique that can estimate the attractiveness of an investment project and value of an enterprise. This valuation especially involves the *time value of money* (TVM), that is, money available at the present time is worth more than the identical sum in the future (Myers, 1984; Wee and Law, 2001; Kruschwitz and Löffler, 2005). A DCF analysis uses the discounted future cash flow—where the discount rate is the basis for the discounting—to derive present value, which is the future sum of the stream of cash flows converted to the current value (Ross, 1995; Weiss and Majkuthová, 2005). The discount rate includes the cost of risky investments or uncertainty of future values (Brealey et al., 2006). Then, net present value (NPV), a measure of the difference between the present value of cash inflows and outflows over a period of time, can be calculated based on the usage scenario and discount rate. Ultimately, the profitability of the investment can be determined (Srivastava et al., 1998). In this case, DCF model can predict consumer choice of a product by calculating the NPV of a given product.

We first apply the DCF model to discrete choice analysis instead of the utility model. Table 1 compares both models. We find that the utility model assumes that the utility of choice options determines the choice probability, whereas the DCF model assumes that the NPV of the choice options determines the choice probability. Notably, the objective of the utility model is to estimate partworths for an individual. On the other hand, the DCF model estimates the discount rate for the individual based on *how* the usage scenario and product attributes affect cash flows over the total period of use as well as *how* future cash flows are valued through the discount rate. Unlike the utility model, the DCF model reveals the evaluation of attributes *over time* through the discount rate. For a given product option, the utility model calculates the utility through the estimated partworths of the attributes. This method is characteristic of the model. However, the DCF model calculates the NPV without the parameters directly related to the product attributes. We assume that the discount rate varies with individual experience and propensity to risk. Thus, we use it as a criterion for each individual when converting the future cash flow into its present value. This rate is also a factor for determining the investment of a given product.

Table 1 Comparison of the DCF model and the utility model

	DCF model	Utility model
Parameter (estimated)	Discount rate	Partworths
Data (required)	Usage scenario	Choice data
Input	Only functional attributes which affect financial returns	Both perceptual and functional attributes
Output	NPV	Utility
Use of population data	None	Apply HB shrinkage

Note: DCF: discounted cash flow; HB: hierarchical Bayesian; NPV: net present value

However, the DCF model has a disadvantage—It does not reflect the preference of other individuals, which the utility model with HB estimation. Because the DCF model estimates the discount rate based on the usage scenario and choice data of each individual *only*, each individual DCF model is developed without factoring in the influence of other individuals. Therefore, it is necessary to develop a method that can overcome this drawback of working with separate, individual DCF models without using the data of other individuals. Though numerous such methods exist, we propose generating the choice data via DCF model, and then performing the HB estimation on these data. The HB shrinkage also means that the choice data generated from the DCF model of multiple respondents enables the use of other individuals' choice data (Orme and Howell, 2009). Further, the synthetic choice data generated herein contains the usage scenario that the original choice data do not have. It is assumed that HB, which learns these synthetic choice data, can indirectly learn the usage scenario as well. To simplify, the HB discrete choice model is developed using the synthetic choice data, which, in turn, are generated using the DCF model. We validate this overall framework through a case study.

Finally, we propose a method of choice data generation for commercial products. The proposed method consists of three steps: 1) A DCF model is developed by constructing a cash flow function based on the usage scenario and by estimating the discount rate using the DCF analysis. Individual demographic data (e.g., duration of use, frequency of use, and utility of the product) are used as parameters in the usage scenario. The discount rate is obtained by calculating the individual NPV of the choice options using the choice data as training data. 2) The design of numerous questionnaires is almost a full factorial simulation. 3) We generate synthetic choice data for HB and partworths estimation. The proposed method is applied to a case study of hybrid courier truck conversion, a project of the Korean government (Ministry of Land, Infrastructure and Transport, 2016; Koh et al., 2019). The three attributes employed in questionnaires are (1) conversion cost, (2) fuel efficiency improvement percentage, and (3) maintenance cost.

The remainder of this paper is organized as follows. Section 2 introduces the proposed choice data generation method using usage scenarios and DCF analysis. In section 3, a case study on hybrid courier truck conversion is presented. Section 4 shows the simulation results of the model parameters' recovery. Finally, Section 5 concludes the study and suggests future research directions.

2. Method

In the DCF model, the usage scenario contains the main information about the product selection of each individual; the choice data is then used to determine the individual discount rate, which, by itself, is not revealed in these choice data. Because the cash flow function in the discount rate estimation is only related to commercial attributes affecting the financial return of the consumer, non-commercial attributes cannot be considered in DCF modeling. The first proposed method is to develop a DCF model that can calculate the NPV and predict consumer choice. The second proposed method is to generate the choice data using the DCF model and perform an HB estimation. The information flow of the proposed methods is presented in Fig. 1.

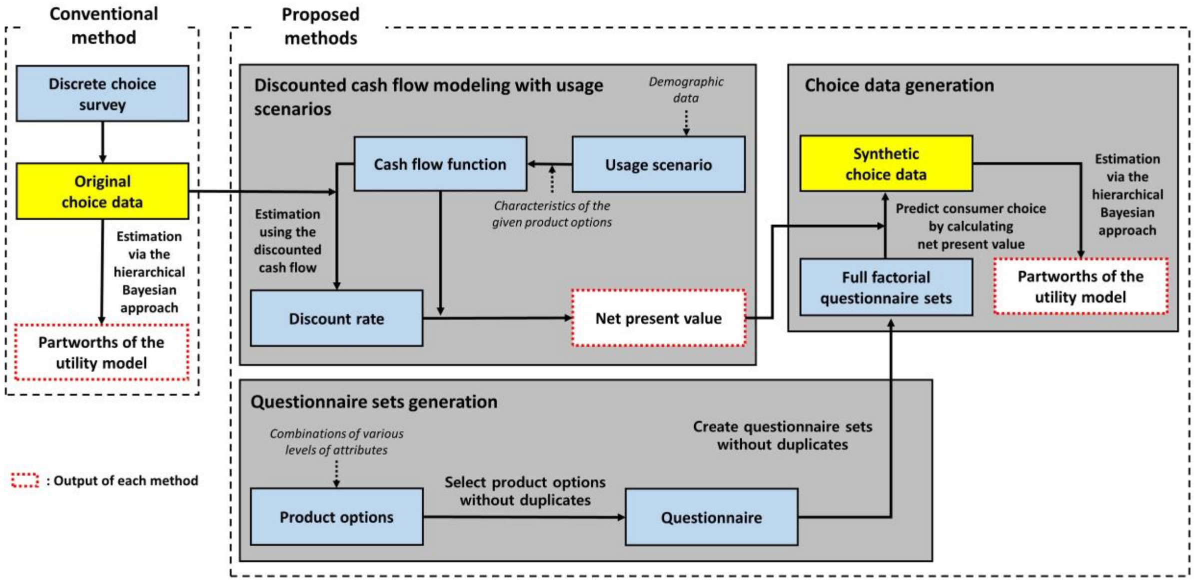


Fig. 1. Information flow of the proposed methods: Discounted cash flow modeling and choice data generation using the discounted cash flow model

The cash flow function that includes the cash flow expected from the product and the duration of the product used can be established by the usage scenario consisting of individual demographic data related to product use. After each individual's discount rate is ascertained through optimization techniques using original choice data as training data, the DCF model can be built. This model can predict each individual's choice for the given product options once the NPV is calculated. To generate synthetic choice data, first, we create questionnaire sets (a questionnaire similar to the discrete choice survey), which includes a variety of product options and a "none" option. To do this, we create a variety of product options with combinations of various levels of attributes; the questionnaire is developed by selecting product options without duplication. Next, questionnaire sets are created by selecting questionnaires also without duplication. Then, the NPV of each questionnaire's product options can be calculated by using the DCF model, which allows us to label the respondent's choice results on the generated questionnaire.

Finally, the performance of discrete choice model can be improved using the HB approach and with large amount of synthetic choice data. Some of the original choice data are used to estimate the discount rate, whereas other data are used to calculate the hit rate (i.e., the rate at which the estimated consumer choice matches the actual survey results).

2.1. DCF modeling with usage scenarios

This section presents the DCF model built to predict the customer's choice of the given product options. As shown in the DCF modeling with usage scenarios in Fig. 1, the individual demographic data, which are considered when each customer chooses a product, are included in the usage scenario in the form of parameters; a cash flow function can be established based on the usage scenario and the characteristics of a given product option. The DCF analysis converts a future sum of the cash flow stream into the present value by considering the TVM; it thus estimates the benefit that a consumer would receive from an investment. The discount rate, also known as the opportunity cost of capital, is employed to study economic behaviors such as a lump-sum or annuity choice (Stiglitz, 1982; Warner and Pleeter, 2001); it reflects the risk of the investment and the uncertainty of future cash flow, thus being responsible for discounting the future cash flow in our DCF analysis. Further, in the NPV, the net profit subtracts the required investment from the present value of the sum of future cash flows; it can be calculated through the DCF analysis to measure the attractiveness of the investment (Smith-Daniels and Smith-Daniels, 1987; Remer and Nieto, 1995; Sanchez Fernandez et al., 2012). Thus,

$$\pi_{ij} = \sum_{t=1}^{N} \frac{CF_t(\mathbf{z}_j, \mathbf{s}_i)}{(1+r_i)^t} - p_j, \qquad (1)$$

where π_{ij} is the NPV of product j to individual i; t is the time of cash flow, N is the total period of use; CF_t is the cash flow function; $\mathbf{z}_j$ is characteristics of product j; $\mathbf{s}_i$ is usage scenario of individual i; r_i is discount rate of individual i; and p_j is price (or initial investment cost) of product j. Even if customers use the same product, the cash flow function can be changed depending on the usage scenario of the individual. For example, in the case of hybrid courier truck conversion, the expected benefit of fuel efficiency depends on individual's actual fuel mileage, average daily driving distance, and remaining period of use.

As aforementioned, the discount rate contains the risk of investment and the uncertainty of the future cash flow; it serves as a measure to convert the future cash flow to the present value for each individual. For example, if an individual's discount rate is high, the expected future cash flow converted to the present value will be small because the risk and uncertainty of investment is highly recognized. Thus, the individual is unlikely to be attracted to the investment. After establishing the cash flow function and estimating the individual discount rate, DCF modeling is completed. Then, we can estimate the consumer's choice of the given product options by calculating the NPV.

2.2. Discount rate estimation

The future cash flow expected from the product is determined by how useful the product is to each individual and, thereby, the present value can be calculated using the individual's cash flow function and discount rate. By using each individual's demographic data on product use, we can establish the cash flow function that includes the cash flow expected from the product and the duration of the product used. DCF model assumes that NPV of given product options determines choice probability:

$$P_{ij} = \frac{e^{\pi_{ij}}}{\sum_{j' \in J} e^{\pi_{ij'}}}, \tag{2}$$

where P_{ij} is the probability that individual i chooses product j from a set of alternative products J. Then, each individual's discount rate can be confirmed through the optimization technique using the individual's original choice data as the training problem. That is,

$$r_i = \underset{r_i}{\operatorname{argmax}} \sum_{j=1}^{n_j} \Phi_{ij} \log P_{ij}, \tag{3}$$

where r_i is the discount rate of individual i; Φ_{ij} is equal to 1 if individual i chooses product j or 0 otherwise; and n_j is the number of product alternatives.

After creating the DCF model by estimating the discount rate with a part of the original choice data, the hit rate is calculated using the remaining validation data to present the accuracy of the DCF model, as in the case of HB discrete choice analysis.

2.3. Choice data generation

Because each DCF model is created based on only individual usage scenario and original choice data, the preferences of other individuals are not reflected. As noted earlier, HB shrinkage allows us to overcome this limitation when we use the synthetic choice data generated by the DCF model. We thus propose such a method in this section.

After completing the DCF model by establishing the cash flow function and finding the optimum discount rate of each individual, the consumer choice of the given product options can be predicted by calculating the NPV through the DCF model. Then, the individual's choice of the synthetic survey questionnaire sets can be estimated through simulation. Here, we assume that the respondent's judgment of the product options is contained in the DCF model and that the survey the respondent *does not partake* in can be done by the DCF model instead of the respondent. Therefore, a large volume of choice data that is not actually generated from the respondent, but extracted from the DCF model of the respondent, can be produced. In the synthetic survey questionnaire sets, each questionnaire consists of non-overlapping combinations of various product attribute levels and almost full factorial questionnaire sets can be created by selecting the questionnaire without duplication. In the simulation, the DCF model calculates the NPV of the given product options, including the "none" option, and the synthetic choice data are generated by selecting the option with the largest expected NPV.

2.4. HB estimation

This section introduces the conventional HB approach and discusses how to estimate the partworths of the utility model with the synthetic choice data generated using the DCF model in the proposed method. The discrete choice analysis is a survey-based statistical technique in marketing that is used to estimate the importance of each product attribute and to predict consumer decision-making. Estimating the consumer choice of a product requires consumer choice data, which can be gathered from questionnaires answered by potential consumers using the discrete choice analysis (Chrzan and Orme, 2000; Netzer et al., 2008; Train, 2009; Lee et al., 2019).

There are several multiple-choice questions in the questionnaire, and a set of designs with different combinations of various attributes is shown to respondents. The respondents select the most preferred design and the "none" option can be selected when all alternative designs are not satisfactory.

Then, the HB approach, which consists of two levels, quantifies the respondents' preference (Allenby et al., 1995; Lenk et al., 1996). An upper-level model is pooled across the respondents and a lower individual-level model is treated within the respondents (Kruschke, 2013). The heterogeneity in the individual-level partworths throughout the respondent population is explained in the upper-level model. Individual-level utility v_{ij}, which is the sum of partworths of the designed product, can be defined as follows:

$$v_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \boldsymbol{\beta}_{ikl} z_{jkl}, \tag{4}$$

where $\boldsymbol{\beta}_{ikl}$ represents the partworth of the l^{th} level of the k^{th} attribute for the i^{th} individual and z_{jkl} corresponds to a binary dummy number, which is equal to 1 if level l of the k^{th} attribute is selected for alternative j and 0 otherwise. An individual's partworths $\boldsymbol{\beta}_i$ are assumed to be derived from a multivariate normal distribution, $\boldsymbol{\beta}_i \sim N(\boldsymbol{\theta}, \boldsymbol{\Lambda})$, where $\boldsymbol{\theta}$ is a mean vector of individual distributions and $\boldsymbol{\Lambda}$ is the distribution's covariance matrix. At the lower level, choice probability, which is determined using a mixed logit model, is calculated by

$$P_{ij} = \frac{e^{v_{ij}}}{\sum_{j' \in J} e^{v_{ij'}}}, \tag{5}$$

which is similar to the probability of the i^{th} individual selecting option j from a set of alternatives J. Then, the optimal weight of the upper- and lower-level models in estimating each individual's partworth can be determined using the HB approach. We use the Markov chain Monte Carlo to draw individual's partworths. Though the levels of the attributes are discrete, an interpolation of the intermediate levels enables individual-level utility models to work with continuous attributes through a natural cubic spline. To evaluate how accurately the utility model is established, the hit rate is calculated: Some of the choice data are left as validation data and the utility model derived from the remaining data calculates the rate at which the utility model matches the consumer's choice contained in the validation data. For example, if the estimated utility model accurately predicts three out of the five questions of the respondent's choice, then the hit rate is 0.6.

In the case of the existing discrete choice model, the HB approach is performed with the original choice data obtained from the actual respondents, whereas the proposed method estimates the partworths of the utility model by performing the HB approach with the synthetic choice data. Using the large amount of synthetic choice data generated from the DCF model, individual-level partworths of the utility model can be estimated through the conventional HB approach and the performance of the discrete choice model can be enhanced. This way, the accuracy of the consumer choice estimation can be improved. Because the synthetic choice data are generated from the DCF model, it becomes easier to reflect an individual's judgment of the value of the product attributes and the perception of the potential risks in the future. Thus, this step has an effect similar to as if the respondent actually responded to a large number of survey questionnaires.

3. Results

3.1. Choice experiment results

3.1.1 Case study on hybrid courier truck conversion

Ecofriendly vehicles are globally popular for their reduced transport-generated CO_2 emissions; thus, they cause less fewer deleterious effects on the environment compared with vehicles powered by conventional internal combustion engines (Tilagone et al., 2006; Situ, 2009; Hamada et al., 2015). The recent rise in oil prices and urban air quality concerns have accelerated the advent of fuel-efficient, low-pollutant emission power train technologies as well as hybrid electric vehicles (HEVs) (Fontaras et al., 2008; Gallagher and Muehlegger, 2011). In response to these demands, the conversion of conventional internal combustion engine vehicles into HEVs has become appealing, with active research on the topic (EERE, 2018).

We focus on applying the proposed method derived in *section 2* to the conversion of small diesel courier trucks to HEVs. Our subject for this case study includes truck operators in South Korea. To meet the needs of truck operators and to secure market demand during conversion, it is imperative to explore the consumer's choice depending on the conversion cost, fuel efficiency improvement, and maintenance cost reflected in the actual product design. The truck operators consider three factors when deciding whether to convert the truck: conversion cost, which is the initial investment; maintenance cost that occurs every four years; and the fuel cost savings from the conversion. Therefore, a survey of the hybrid courier truck conversion that is targeted to truck operators should precede gathering choice data and estimating consumer choices. However, this process is both expensive and laborious because it would require the surveyor has to find and survey truck drivers individually.

In this study, 70 courier truck operators in South Korea are surveyed and the respondents are asked to answer 15 choice questions. The number of choice questions is determined to the extent that respondents perform the choice task without fatigue. The choice experiment design uses the Sawtooth Software and is based on a D-optimal design with constraints, wherein one product option does not dominate another (Sawtooth, 2014). The attributes in questionnaires are as follows: (1) conversion cost; (2) fuel efficiency improvement percentage; and (3) maintenance cost. Several multiple-choice questions are presented in the questionnaire and a set of product options with combinations of various levels of attributes (shown in Table 2) is presented to the respondents. The respondents then select the most preferred product option. When no satisfactory product options exist, the respondents may pick none of the options. In addition, truck operators' demographic data, such as annual income, actual fuel mileage, daily driving distance, current mileage, and target mileage, are also included in the survey. An actual example of the survey is shown in Fig. 2. The mean and standard deviation of annual income, actual fuel mileage, daily driving distance, current mileage, and target mileage are \$33,036 and \$11,220, 16.0 mpg and 2.6 mpg, 28.6 mi and 15.1 mi, 54,006 mi and 43,084 mi, and 124,948 mi and 41,337 mi, respectively. After gathering choice data from the survey, the HB approach is used to find the individual-level partworths to establish the importance of each attribute

Table 2 Attribute levels and their partworths (Method 1)

Attributes		Partworth				Importance
Conversion cost ($)	Level	1,000	2,500	4,500	6,000	61.3%
	Mean	4.865	2.391	−0.107	−7.172	
	(Std.)	(1.623)	(0.638)	(1.086)	(2.941)	
Fuel efficiency improvement percentage (%)	Level	15	20	25	30	22.5%
	Mean	−2.558	0.195	0.509	1.853	
	(Std.)	(2.447)	(0.373)	(0.487)	(2.105)	
Maintenance cost ($/4 years)	Level	350	450	550	650	16.2%
	Mean	1.287	0.554	0.061	−1.902	
	(Std.)	(1.091)	(0.453)	(0.394)	(1.421)	

Question A (Basic Question)

Question A1. What is your average monthly fuel cost?

Fuel costs		$

Question A2. Please write down the current mileage (mi) and the target mileage (mi) of your courier truck.

Current mileage		mi
Target mileage		mi

Question A3. What is your daily driving distance?

Daily driving distance		mi

Question A4. What is your actual fuel mileage?

Actual fuel mileage		mpg

Question A5. What is your annual income?

Annual income		$

Question B (Main Question)

Question B1. If these were your only options, which would you choose?

	1) Option A	2) Option B	3) Option C	4) None: Maintain current vehicle status
Conversion cost	$2,500	$6,000	$4,500	
Fuel efficiency improvement percentage	20%	25%	15%	
Maintenance cost (every 4 years)	$450	$350	$350	
	☐	☐	☐	☐

Fig. 2. Actual example of the survey

By using Eq. (1), which calculates the NPV using the initial investment cost, discount rate, and the cash flow function over the total period of use, the equation of DCF model for hybrid courier truck conversion can be given as follows:

$$\pi_{ij} = \sum_{t=1}^{N} \frac{A_{i,t} - F_{ij,t}}{(1+r_i)^t} - \sum_{t=1}^{N/4} \frac{M_{j,t}}{(1+r_i)^t} - p_j,$$
$$\text{where } F_{ij,t} = \frac{D_{i,t}}{FM_{i,t}} \times Fuel\ price \times \left(1 - \frac{I_j}{100}\right) \times 365. \tag{6}$$

In the above equation, N is the total period of use; $A_{i,t}$ and $M_{j,t}$ indicate the annual income of individual i and maintenance cost of conversion option j at time t, respectively; $F_{ij,t}$ is fuel cost of individual i with conversion option j at time t; $D_{i,t}$ and $FM_{i,t}$ are the daily driving distance and the actual fuel mileage of individual i at time t, respectively; I_j is the fuel efficiency improvement percentage of the conversion option j; and p_j is the conversion cost of the conversion option j. For example, when the discount rate, annual income, actual fuel mileage, daily driving distance, current mileage, target mileage, conversion cost, fuel efficiency improvement percentage, maintenance cost, and oil price are 30%, $33,000, 15.5 mpg, 29.3 mi, 53,000 mi, 120,000 mi, $4,500, 20%, $450, and $3 per gallon, respectively, the NPV is $83,676.

3.1.2 Comparison and discussion of model performance

To present and investigate the novelty of the proposed methods, three different methods that estimate consumer choice are compared: (1) Method 1 is the conventional method shown in Fig. 1 that estimates partworths using the utility model for HB discrete choice analysis. (2) Method 2 is the first proposed method using the DCF model that estimates the discount rate using the usage scenario and choice data; it predicts consumer choice by calculating the NPV of the given product options (DCF modeling with usage scenarios in Fig. 1). (3) Method 3 is the second proposed method that improves the accuracy of the consumer choice estimation by supporting HB discrete choice analysis with the synthetic choice data generated using the DCF model (choice data generation in Fig. 1). To assess the accuracy of the consumer choice estimation of the three methods that use different models, five choice datum chosen from the respondent's 15 choice datum are used to calculate the hit rate (see *section 2.4*). Because the hit rate may vary with the set of the test data, the mean value of the hit rates obtained from 300 sets of survey questions and test data is used herein.

Fig. 3 presents the hit rate results of the consumer choice estimation depending on the number of respondents and survey questions using only the original choice data, as in the conventional consumer choice estimation based on the utility model for discrete choice analysis (Method 1). Additionally, the mean value of the hit rates obtained from 200 sets of respondents is used if the number of respondents is less than 70. As the number of survey questions reduces, the hit rate tends to decrease because the individual's choice data used to estimate the individual's partworths is not sufficient. In addition, due to the nature of the HB approach, the individual-level partworths are estimated not only using individual data but also leveraging the population data. Therefore, as the number of respondents reduces, the population data becomes smaller and, thus, the hit rate decreases.

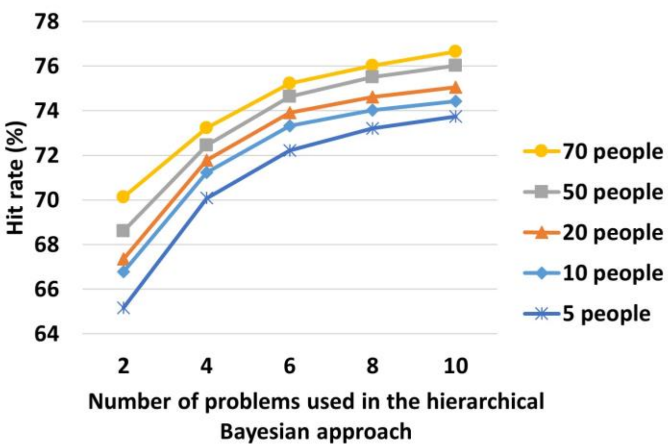
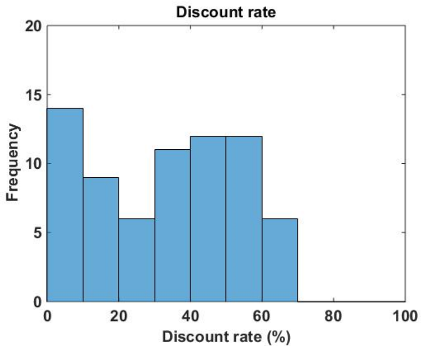


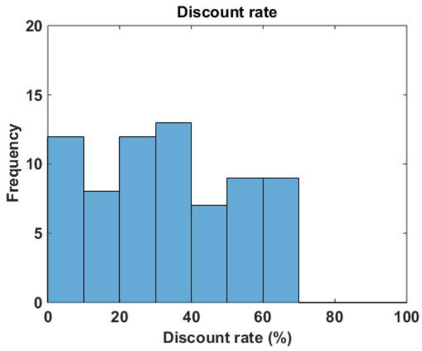
Fig. 3. Hit rate of consumer choice estimation based on actual choice data (Method 1)

In Method 2, the DCF model that predicts consumer choice can be completed after determining the optimum discount rate through the optimization technique using the individual's choice data as the training problem (see *section 2.2*). We solve the optimization problem in Eq. (3) and establish each respondent's optimum discount rate using a genetic algorithm for global search and sequential quadratic programming for local search. The genetic algorithm population size is 300 and computation requires 1 hour on average using a standard desktop (Intel i7 6900 CPU @ 3.20 GHz and 64.0 GB RAM).

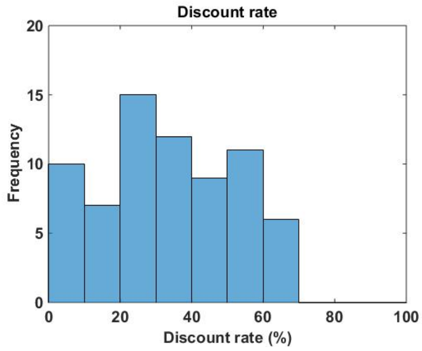
Fig. 4 and Table 3 show the 70 respondents' optimum discount rate results and distributions depending on the number of training problems. As shown in Table 3, the mean value of the optimum discount rates tends to increase as the number of training problems increases. A large variance in the optimum discount rate shows that the respondents' assessments of future gains or outcomes expected from the product are highly heterogeneous.



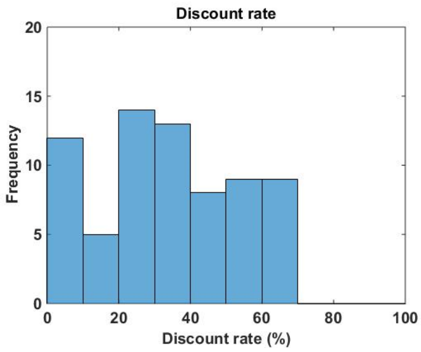
(a) Two training problems



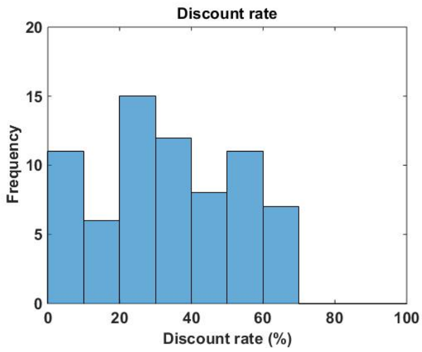
(b) Four training problems



(c) Six training problems



(d) Eight training problems



(e) Ten training problems

Fig. 4. Optimum discount rate distributions depending on the number of training problems (70 respondents)

Table 3 Mean and standard deviation of optimum discount rates

	Number of training problems				
	2	4	6	8	10
Mean	32.7%	32.8%	32.9%	33.6%	33.7%
(Std.)	(20.3%)	(20.1%)	(18.7%)	(19.6%)	(19.4%)

After establishing the optimum discount rate, the DCF model can predict each respondent's choice of the given product options based on the NPV calculation. The hit rate of the DCF model, which indicates how accurately the DCF model predicts the choice of the respondent, is shown in Fig. 5 (Method 2).

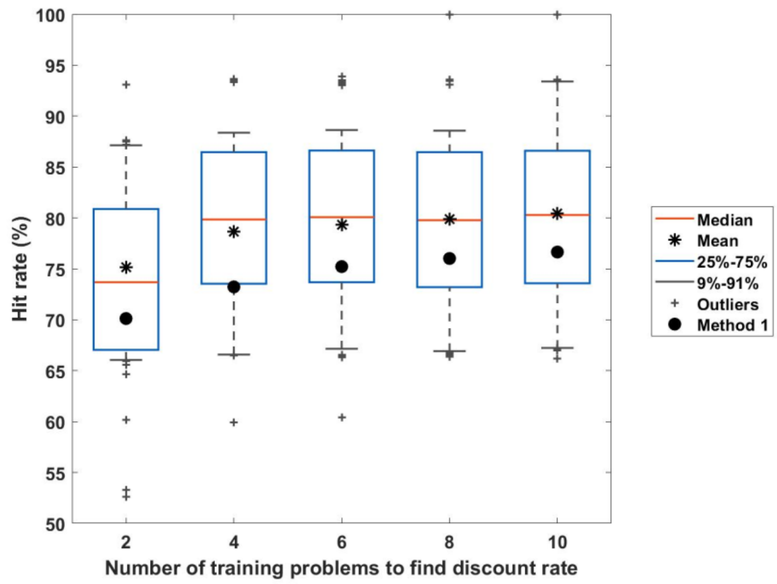


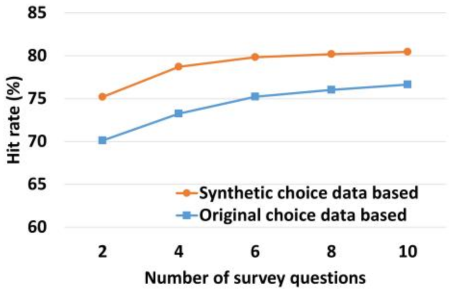
Fig. 5. Hit rate of discounted cash flow model depending on the number of training problems to find discount rate (70 respondents)

The results show that the DCF model predicts the choice of the respondents more accurately, as the number of training problems used to find the optimal discount rate increases. This indicates that the more training data there are, the more accurately the discount rate of each respondent can be estimated. Thereby, the DCF model can more accurately represent the respondent's value judgment of the future profits resulting from personal experience and the risk perception of the investment. This is because, even if optimization is performed using original choice data as training data, there may exist several discount rate candidates when the training data are small. However, as the training data increase, the range of discount rates narrows and ultimately approaches the discount rate that best represents each individual's judgment. Compared with the hit rate results of Method 1 using the choice data of 70 respondents, the hit rate of Method 2 tends to be higher for all numbers of training problems (4.4% point higher on average). In case of Method 1, the performance of the utility model is affected by the number of respondents, whereas the proposed Method 2 is not affected by the number of respondents primarily because the DCF model is created for each respondent and does not affect the model of other respondents.

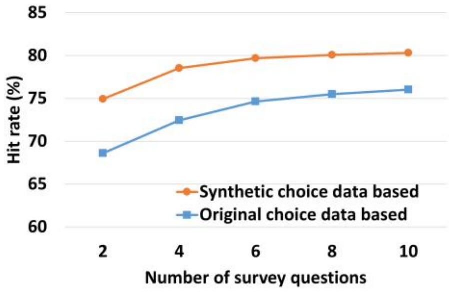
As explained in *section 2.3*, an HB estimation is performed with synthetic choice data produced by the DCF model to solve the problem of Method 2, namely, that it does not reflect the preferences of other customers. In Method 3, a large amount of synthetic choice data generated from the DCF model are used to estimate the partworths through the HB approach; the estimated partworths are presented in Table 4. Comparisons of the hit rate results of the consumer choice estimation obtained using only the original choice data (Method 1) and the synthetic choice data (Method 3) are shown in Fig. 6.

Table 4 Estimated partworths (Method 3)

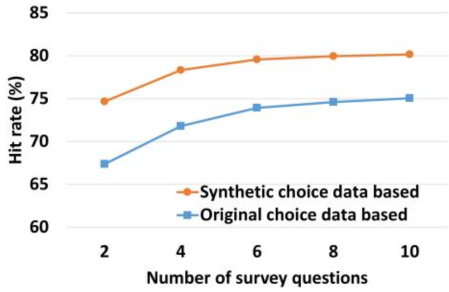
Attributes		Partworth				Importance
Conversion cost ($)	Level	1,000	2,500	4,500	6,000	75.1%
	Mean	6.248	2.109	−2.981	−5.579	
	(Std.)	(3.019)	(0.992)	(1.271)	(2.114)	
Fuel efficiency improvement percentage (%)	Level	15	20	25	30	16.8%
	Mean	−1.454	−0.456	0.404	1.269	
	(Std.)	1.647	1.379	1.171	1.087	
Maintenance cost ($/4 years)	Level	350	450	550	650	8.1%
	Mean	0.754	0.215	−0.064	−0.688	
	(Std.)	1.899	1.733	1.592	1.394	



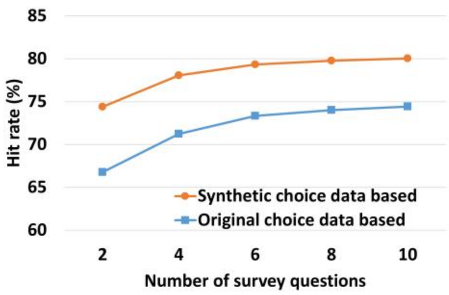
(a) 70 respondents



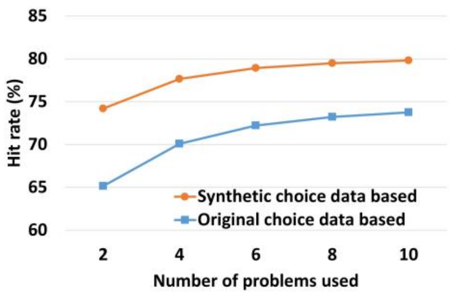
(b) 50 respondents



(c) 20 respondents



(d) 10 respondents



(e) 5 respondents

Fig. 6. Comparisons of the hit rate of the estimated consumer choice obtained using only original choice data (Method 1) and using the synthetic choice data (Method 3)

In Method 3, which uses the synthetic choice data, the number of survey questionnaires used is equal to the number of training problems in establishing the optimum discount rate. Almost full factorial design sets of the survey questionnaires are used to generate the synthetic choice data and the hit rate is converged for a given number of survey questions and respondents in Method 3.

The result of Method 3 is highly robust to the number of respondents compared with Method 1 because the amount of synthetic choice data for each respondent is already large. Hence, a large amount of total choice data of the respondents compensates for when the number of respondents is relatively small. For instance, when there are two respondents and ten survey questions, the hit rates of Method 1 and Method 3 are 66.86% and 75.29%, respectively. Compared with the results obtained when the number of respondents is 70, the decrease in the hit rate of Method 3 (5.26%) is smaller than that of Method 1 (9.79%).

Thus, the hit rate is significantly affected by the number of training problems to establish the discount rate and is slightly influenced by the number of respondents. As the training data used to establish the optimum discount rate increase, the DCF model becomes more precise. This way, we can produce more accurate synthetic choice data, which, in turn, enables a more accurate consumer choice estimation.

The results show that the overall hit rate improves when the consumer choice is estimated using the synthetic choice data generated by the DCF model, as a large amount of synthetic choice data play a supporting role for each respondent's data and the population data. The hit rate increases drastically when the number of respondents and survey questionnaires used is small (insufficient choice data), but it also improves in the opposite case when the choice data are relatively sufficient.

Table 5 shows how the accuracy of the consumer choice estimation improves when we estimate consumer choice based on the synthetic choice data (i.e., Method 3) compared with an estimation using only original choice data (i.e., Method 1). Evident from the table, the improvement percentage is based on the hit rate results of each method.

Table 5 Improved accuracy of Method 3 compared with Method 1

Number of people	Number of survey questions				
	2	4	6	8	10
70	7.24%	7.06%	6.13%	5.49%	4.96%
50	9.23%	8.41%	6.78%	6.07%	5.64%
20	10.84%	9.10%	7.64%	7.14%	6.82%
10	11.43%	9.60%	8.17%	7.75%	7.57%
5	13.89%	10.82%	9.28%	8.56%	8.23%

The results in Fig. 5 show that the hit rate obtained using the synthetic choice data improves as the number of respondents increases. This is because the amount of population data increases as the number of respondents increases; the HB approach leverages the population data to estimate individual-level partworths. Because the synthetic choice data generated from Method 2 is used as the choice data for the HB approach in Method 3, the hit rate results of Method 2 tend affect those of Method 3. Further, the hit rate of Method 3 tends to be higher than that of Method 2 when the number of people is large: 0.67, 0.37, and 0.16 percentage points lower when the number of people is 5, 10, and 20, respectively; and 0.02 and 0.19 percentage points higher when the number of people is 50 and 70, respectively. Both these results indicate that, as the number of questionnaires used and respondents increase, the hit rate increases because more accurate synthetic choice data can be generated. Thereby, the amount of total choice data increase at the same time.

To further explore the characteristics of the DCF model, we compare the importance of product attributes when the HB estimation is performed with original choice data and synthetic choice data (shown in Tables 2 and 4, respectively). When carrying out the HB estimation with synthetic choice data generated by the DCF model, the importance of the conversion cost increases (from 61.3% to 75.1%) and that of the fuel efficiency improvement percentage decreases (22.5% to 16.8%). Thus, the DCF model is relatively resistant to initial investment costs and is negative for future gains. The survey respondents, however, are prone to errors owing to an emotional and irrational affect; because the survey question is focused on fuel efficiency improvement, customers prioritize its importance more. However, in the case of the DCF model, usage scenarios, which are accurately quantified by each individual, are used for a more bias-free objective judgment.

3.2. Simulation results

The usefulness of the proposed methods can be demonstrated by a simulation comparing the estimated parameters of the simulated respondents with the true parameters (Evgeniou et al., 2005; Kang, 2014). In addition, the willingness to pay (WTP) estimation, which estimates the exchange rate between utility and price, is also used to verify the predictive ability of the proposed methods (Kang et al., 2017b). The basic contents of the simulation are based on the case study of hybrid courier truck conversion (see *section 3.1.1*) and the process of the simulation is shown in Fig. 7. In the respondent generation process, the true discount rate and true usage scenario of 100 respondents are assumed to be generated from the normal distribution determined based on the survey results of the case study: The mean and standard deviation of the discount rate, annual income, actual fuel mileage, daily driving distance, current mileage, and target mileage are assumed to be 33% and 10%, $38,498 and $8,555, 14.1 mpg and 2.4 mpg, 31.1 mi and 6.2 mi, 49,710 mi and 18,641 mi, and 124,274 mi and 26,364 mi, respectively.

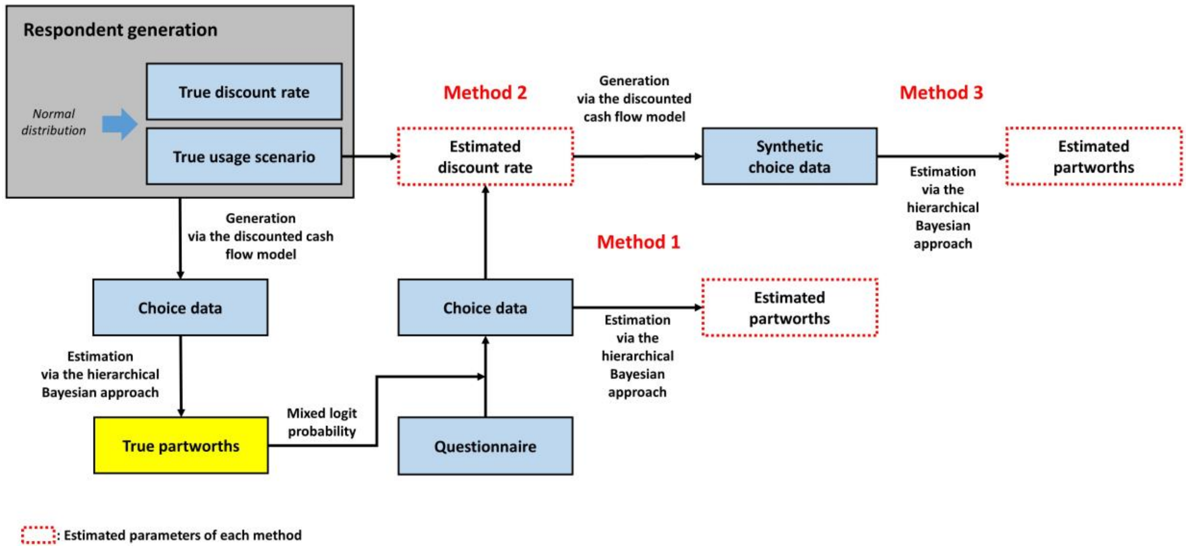


Fig. 7. Process of simulation for recovery of model parameters

To test the methods proposed in this study, we must generate true partworths reflecting the usage scenario and discount rate of the respondents. A large amount of choice data (generated from the DCF model with both true usage scenario and true discount rate) can estimate the partworths through the HB approach. Then, we assume that the estimated partworths can reflect the true usage scenario and true discount rate, and these partworths can be assumed to be true partworths.

To generate the choice data of each respondent, mixed logit probability calculated using the true partworths is used for the 15 questionnaires generated in the manner presented in *section 3.1.1*. The estimated partworths obtained using HB with the choice data are the results of Method 1; developing the DCF model by estimating the discount rate with the true usage scenario and choice data of each respondent corresponds to Method 2. The estimated partworths obtained using the HB approach with the synthetic choice data generated by the DCF model are the results of Method 3.

The methods are compared using the hit rate and root mean square error (RMSE) of the estimated partworths and estimated WTP. Both the true and estimated partworths are normalized before comparison such that the sum of the partworths of each attribute is 0 and the sum of their absolute values is 1. The results of the hit rate and RMSE of the estimated parameters of the three methods are shown in Table 6.

Table 6 Hit rate and RMSE of the estimated parameters of three methods

	Number of survey questions				
	2	4	6	8	10
Method 1	63.16%	64.71%	65.62%	66.26%	66.51%
	(0.593)†	(0.546)	(0.509)	(0.481)	(0.456)
Method 2	74.35%	75.61%*	76.54%	77.27%*	77.82%*
	(0.145)	(0.137)	(0.125)	(0.113)	(0.087)
Method 3	74.65%*	76.01%*	76.91%*	77.75%*	78.06%*
	(0.445)	(0.429)	(0.411)	(0.371)	(0.316)

†RMSEs of the estimated partworths are enclosed in parentheses

*Best, or not significantly different from the best, at $p<0.05$, across all models

The RMSE of the estimated parameter in Method 2 indicates the RMSE of the estimated discount rate. The simulation results are similar to those of the case study presented in *Section 3.1.2*. The hit rates of Methods 2 and 3 are higher than that of Method 1 and the RMSE of the estimated partworths is lower in Method 3 than in Method 1. As the number of survey questions increases, the DCF model in Method 2 becomes more accurate and, thus, the RMSE of the estimated discount rate decreases. Therefore, accurate synthetic choice data are generated, increasing the hit rate of Method 3 and reducing the RMSE of the estimated partworths. The result shows that the performance of Method 3 is the best in all cases and that the difference between Method 3 and Method 2 tends to decrease as the number of questions increases.

Table 7 shows the hit rate according to the number of respondents, when the number of questions is 10. When the number of respondents decreases from 100 to 2, the decrease in the hit rate of Method 3 (1.65%) is less than that of Method 1 (3.88%). Thus, Method 3 is robust to the number of respondents, as in the case study.

Table 7 Comparisons of the hit rate according to the number of respondents

	Number of respondents					
	2	5	10	20	50	100
Method 1	62.63%	64.84%	65.26%	65.63%	66.14%	66.51%
Method 3	76.41%	77.53%	77.72%	77.91%	78.01%	78.06%

The RMSE of the estimated WTP can be obtained by comparing the WTP obtained using the true partworths with the WTP obtained using the estimated partworths. We calculate the WTP based on the slope connecting level 2 and level 3 of each attribute because of the presence of discrete levels. As the WTP estimation is based on the estimated partworths, the result of the RMSE of the estimated WTP shows a tendency similar to that of the estimated partworths (shown in Fig. 8). The RMSE of the estimated WTP of Method 3 is smaller than that of Method 1. As the number of survey questions increases, the RMSE of the estimated WTP decreases because the estimated partworths become accurate.

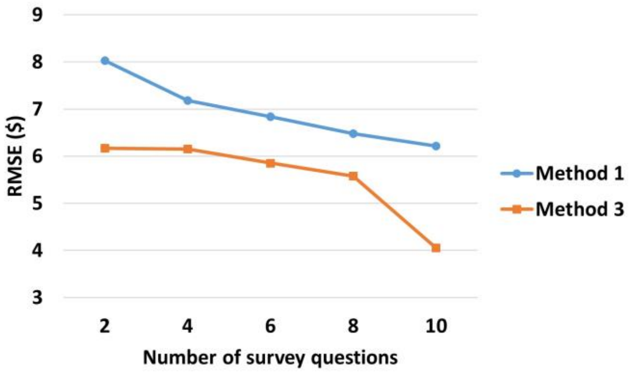


Fig. 8. Comparison of RMSE of the estimated WTP

4. Discussion and Conclusion

To predict a consumer's choice of products, the work presented in this paper suggests a method using the individual usage scenario and discount rate estimated by DCF analysis to calculate the NPV for the given product options. The DCF model that can predict consumer choice can be developed after establishing the optimum discount rate—that is, the respondent's evaluation of the future cash flows—through the optimization technique based on the cash flow function and using the respondents' choice data as the training problems. The cash flow function depends on the characteristics of the product and usage scenario of each individual. In addition, a method that generates synthetic choice data for an HB estimation using the DCF model and improves the accuracy of consumer choice prediction is proposed as well. The case study results show that the predictive power of the DCF model is higher than that of the conventional discrete choice analysis that uses the utility model. Further, the overall hit rate of the estimated consumer choice improves when using synthetic choice data obtained from the DCF model for the HB approach. The number of questionnaires and respondents affects the accuracy of the consumer choice estimation in terms of the number of training problems used to obtain the optimum discount rate and the amount of population data, respectively.

One of the main contributions of this paper is that a model is suggested to predict the consumer's choice of a commercial product by considering the individual usage scenario and estimating the discount rate *not revealed* in the choice data. Also, higher accuracy of the consumer choice estimation can be achieved even in the case of lack of choice data from using a small number of questionnaires and respondents. As the number of questionnaires increases, the repeated choice questions induce fatigue in the respondents, forcing them to provide distorted responses. Conducting surveys of potential customers is also time-consuming and costly in some cases. This study has the advantage of enabling accurate consumer choice estimation with each respondent's demographic data and a small amount of questionnaires even when the number of respondents is inadequate. The existing consumer choice estimation considers only the current response of the respondent, but the suggested method considers an individual's evaluation on future cash flows by extracting the discount rate. That is, by adding the discount rate to the consumer choice estimation, the time axis can be considered, and a more accurate estimation can be made. Our approach predicts the customer's choice of product options by estimating the discount rate. To this effect, a choice question design that consists of a set of future gain after certain years of time can be used. This is simpler than the conventional choice question design consisting of product attributes.

The results of the case study and simulation show that, if a model that resembles the true model is built by estimating the important parameters that are properly selected from the true model, the data generated from the model function in ways similar to the data generated from the true model. The higher hit rate of Method 2, than Method 1, in both the case study and the simulation verifies that a well-selected parameter—namely, discount rate—is an important factor for respondents making decisions about product options for commercial products. As the choice data used to estimate the discount rate increase, the DCF model approaches the true respondent because the estimated discount rate approaches the true discount rate. Therefore, the estimated partworths approach the true partworths owing to an increase in the accuracy of the synthetic choice data.

This study assumes that, for commercial products, consumers will make a reasonable decision by considering their current investment and usage scenario over the total period of use. However, the bias of the original choice data can cause errors in the discount rate estimated by the DCF analysis, thus reducing the reliability of the DCF model. This further amplifies the errors in the synthetic choice data. Therefore, methods that reduce errors in the respondents' choice data or filter biased data should be considered to establish a more accurate DCF model. In addition, this approach only considers commercial attributes and, thus, requires improvements to include non-commercial attributes. Future work can calibrate the results of the estimated consumer choice obtained from the original and synthetic choice data. An accurate estimate of the population that provides information for the HB approach when the number of respondents is small along with more case studies in finance could also expand the current work.

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Declaration of interest

The authors declare that there is no conflict of interest.

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