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Incorporating Discrete Choice Experiments into Policy Decisions:
Case of Designing Public Long-Term Care Insurance

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Abstract

Discrete choice experiments (DCEs) have been widely used to elicit preferences in the health economics field but recent reviews found that DCE results are rarely incorporated into health policy decisions. We conjecture that one reason is most health policy practitioners only focus on estimating marginal willingness to pay (MWTP), the measure that is not directly applicable for policy-related questions. We show that when designing a new program, translating preference information into the demand for packages and benefits of alternative schemes (the choices made available) can make the DCE results more policy relevant. This concept is illustrated using data collected to evaluate the benefits of introducing a public long-term care insurance program to a middle-income country, Thailand. We find that preferences are very heterogeneous, implying that no one-size-fits-all solution exists. The estimates from the preferred model are then used to calculate benefits and losses (based on the consumer surplus measure) for plausible implementation scenarios such as different universal schemes, multiple-tier schemes, and schemes in which premium are subsidized for low-income households.

Keywords: Discrete choice experiments; long-term care insurance; unobserved taste heterogeneity; consumer surplus; Thailand

JEL classification: I13, I18, J18, C35, D04

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1. Introduction

When designing a new program or product, understanding public preferences is crucial. Discrete choice experiments (DCEs) have been widely used to elicit public preferences when no similar product exists in the market (e.g., Louviere, Hensher, & Swait, 2000; Kesternich, Heiss, McFadden, & Winter, 2013; Ben-Akiva, McFadden, & Train, 2019). In the health economics and health policy field, reviews have identified over 300 DCE studies in the past two decades (Guttmann, Castle, & Fiebig, 2009; de Bekker-Grob, Ryan, & Gerard, 2012; Soekhai, de Bekker-Grob, Ellis, & Vass, 2019). These reviews, however, have also reported that DCE results are rarely incorporated into policy decisions.

One recommendation to make preferences elicited from DCE more policy relevant is to ensure its reliability by providing more descriptions of DCE development and conduct supplementary tests. Although we agree with the recommendation, we conjecture that another reason leading DCEs to remain only scholar exercises is that most health policy practitioners only focus on estimating marginal willingness to pay (MWTP). Knowing only attribute MWTPs is hardly sufficient to answer most policy relevant questions.

Consider the case of designing a new public long-term care insurance (LTCI) scheme that features different levels of premiums and types of coverage such as home visits and copayment for caregiver costs. Estimated mean MWTPs will tell us the relative importance of attributes on average, but it does not tell us what kind of package should be offered? Will the demand for a low-premium LTCI package that covers only the most popular attribute be higher than that for a more expensive one that covers multiple attributes? By further estimating dispersion of each attribute's MWTP, one learns about the degree of taste heterogeneity. But MWTP distributions do not tell us what to do when preferences are heterogeneous. Should the government provide a range of packages from which people can choose rather than a universal program? If some people do not like what being offered, should they be allowed to opt out?

In this study, we argue that these kinds of answers can be extracted from DCEs especially when designing a new public program. Specifically, DCEs can be used to (i) predict demand (i.e., the uptake rate) for several alternative programs; and (ii) evaluate benefits and losses generated by different schemes (or choices made available to consumers). We illustrate this concept with an application of designing a public LTCI program in Thailand. First, several flexible choice models are estimated. The estimates from the model that best captures observed choice behavior are then used to conduct counterfactual experiments and welfare analyses.

Measuring the welfare gain of an attribute improvement was once controversial in the health economics field, see Lancsar and Savage (2004) vs. Ryan (2004). The debate, however, was in the homogeneous preference context. While Lancsar and Savage (2004) argue that the general formula (Small & Rosen, 1981) that takes the probabilities of the choices being chosen into account should be used, Ryan (2004) contends that the simply sum of MWTPs across attributes is also a valid special case. We are not aware of much discussion on the welfare measure for models allowing for unobserved taste heterogeneity except different methods to estimate MWTP statistics. In the context of heterogeneous preference, the sum of mean MWTPs across attributes has no direct interpretation.

Our contribution is threefold. First, we illustrate why predicting demand for competing programs and benefits of competing schemes are more policy relevant than estimating MWTP alone. This is in line with a few health studies emphasizing the importance of predicting demand and uptake rates (e.g., Fiebig, Knox, Viney, Haas, & Street, 2011; Terris-Prestholt, Quaife, & Vickerman, 2016). However, these studies did not investigate the benefit trade-offs across consumers when preferences are heterogeneous.

Second, we estimate both the mixed logit model and the relatively new mixture-of-normal mixed multinomial logit (MM-MNL) models, the latter of which nests the mixed logit and latent class models. While the MM-MNL model has been shown to outperform other models (Keane & Wasi, 2013), it has received insufficient attention in the health economics literature. For instance, it does not appear in the recent review by Soekhai et al. (2019).

Finally, we contribute to the long-term care (LTC) literature. Although public LTCI schemes have been established in many high-income countries for at least two decades, policymakers in middle-income countries such as Thailand are still searching for an effective LTC solution. Increases in life expectancy and female labor force participation, together with declining family sizes, imply that relying on informal care (mostly provided by women) will become more challenging. This study thus takes the first step toward assessing the demand for LTCI and evaluating benefits of different LTCI implementation options.

The rest of the paper is organized as follows. The next section reviews recent developments in discrete choice models and the concepts of demand and welfare measures under the discrete goods context. Section 3 describes DCE data collected to elicit Thai people's preferences on LTCI packages and how to incorporate DCE results into designing a public LTCI scheme. The last section discusses and concludes.

2. Discrete Choice Models and their Demand and Welfare Measures

A broad class of discrete choice models are consistent with utility maximization behavior. In a situation where the consumer chooses one choice out of *J* available choices and the discrete goods are relatively inexpensive compared to the outside goods, the indirect utility that consumer *n* derives from choice *j* in scenario *t* can be written as

$$U_{njt} = V\left(p_{jt}, q_{jt} \middle| \theta, Z_n\right) + \varepsilon_{njt} \qquad \text{for } j = 1, \ldots, J;\ t=1,\ldots,T;\ n=1,\ldots,N$$

where *V(.)* and ε_{njt} are the observed and unobserved components of the utility, respectively; p_{jt} and $q_{jt} = \left(q_{jt}^1, \ldots, q_{jt}^K\right)$ denote the price and an attribute vector associated with each *j*; θ is a parameter vector; and Z_n is a vector of the observed characteristics.

The probability that *n* chooses *j* in scenario *t* is the probability that *j* yields the highest utility:

$$P(y_{njt} = 1|p_t, q_t, \theta, Z_n) = Prob\big(U_{njt} - U_{nit} > 0\big) \quad \forall i \neq j$$
$$= Prob\left(\varepsilon_{nit} - \varepsilon_{njt} < V\big(p_{jt}, q_{jt}\big|\theta, Z_n\big) - V(p_{it}, q_{it}|\theta, Z_n)\right) \; \forall i \neq j. \tag{1}$$

McFadden (1974) shows that under some weak assumptions, equation (1) is represents the person-specific demand function. This equation underpins most of the discrete choice models used today. To keep our notation more compact we define $X_{njt} = \big(p_{jt}, q_{jt}\big)$ and $\beta_n = \big(\beta_n^p, \beta_{n1}, \dots, \beta_{nk}, \dots, \beta_{nK}\big)$ as representing the utility weights that *n* places on price and other attributes. Assuming that *V(.)* is a linear additive function, (1) becomes:

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt} \qquad \text{for } n = 1,\dots,N;\ j = 1,\dots,J; \text{ and } t=1,\dots,T. \tag{2}$$

The ways the distributions of β_n and ε_{njt} are specified lead to different choice models. The multinomial choice model (MNL) assumes that consumer tastes on the observed attributes is homogeneous, $\beta_n = \beta$, and ε_{njt} is iid extreme value. Empirical research across different fields find that these assumptions are unrealistic. First, in situations with more than two choices, the unobserved factors of a certain pair or group of choices tend to be correlated; that is $cov(\varepsilon_{njt}, \varepsilon_{nit}) \neq 0$ for some j and i. Another reason is that consumer tastes are likely to be both heterogeneous and persistent. Some consumers may place a higher weight on price while others focus on a certain feature; that is $cov(\varepsilon_{njt}, \varepsilon_{nj\tau}) > 0$ for some t and τ from the same *n*.

Several models have been developed to overcome these limitations. Here we consider the mixed logit (McFadden & Train, 2000) and the MM-MNL model (Burda, Harding, & Hausman, 2008; Train, 2008). We choose these two because the former is very popular, and the latter has been shown to be remarkably flexible with the mixed logit and latent class models as its special cases. For other models, we refer interested readers to Train (2003), Fiebig, Keane, Louviere, & Wasi (2010); and Keane and Wasi (2013, 2016).

Both the mixed logit and MM-MNL models assume that $\varepsilon_{njt}\sim$ iid extreme value but specify β_n to be random coefficients, capturing some unobserved taste heterogeneity that was presented in the error term of the MNL model. For the mixed logit model, β_n is commonly assumed to be normal or lognormal distributed. Here we assume that β_n is multivariate normal distributed in the population, $\beta_n \sim MVN(\beta, \Sigma)$. The MM-MNL model assumes that β_n is distributed as a discrete mixture-of-multivariate normals: $\beta_n \sim MVN(\beta_s, \Sigma_s)$ with the probability w_s for $s = 1,\ldots,S$ where $\sum_{s=1}^{S} w_s = 1$. If $w_s \rightarrow 0$ for all but one class, MM-MNL becomes the mixed logit. If $\sum_s \rightarrow 0\ \forall s$, MM-MNL collapses to the latent class model. The choice probabilities *conditional* on β_n of these models still have the following logit form:

$$P(y_{njt} = 1 | X_{nt}, \beta_n) = \frac{\exp(\beta_n X_{njt})}{\sum_{i=1}^{J} \exp(\beta_n X_{nit})}. \qquad (3)$$

Note that β_n can be specified to depend on both observed and/or unobserved individual characteristics. For instance, for attribute *k*, we can let $\beta_{nk} = \bar{\beta}_k + \gamma_k Z_n + \eta_{nk}$ where $\bar{\beta}_k$ is the mean utility weight; and η_{nk} is person *n*-specific deviations from the mean. For MM-MNL, one can also allow w_s to be a function of Z_n. Whether the heterogeneity in taste can be captured by $\gamma_k Z_n$ or η_{nk} is an empirical question.

Regarding the estimation, note that β_n is not directly observed and the researcher must first estimate the parameters of the specified distribution. For MM-MNL, the *unconditional* choice probabilities are obtained by integrating over all the possible values of β_n:

$$P(\{y_{njt}\}_{t=1}^{T} | X_n, \beta, \Sigma) = \sum_{s=1}^{S} w_{n,s} \left\{ \int \left[\prod_t \prod_j \left(\frac{\exp(\beta_n X_{njt})}{\sum_{i=1}^{J} \exp(\beta_n X_{nit})} \right)^{y_{njt}} \right] f(\beta_{n|s}) d\beta_{n|s} \right\}$$

for $s = 1, \ldots, S$; and $f(\beta_{n|s}) \sim MVN(\beta_s, \Sigma_s)$. The product of the logit probabilities inside the integral is the probability that individual *n* chooses a sequence of choices over *T* scenarios.

Lancsar, Fiebig, and Hole (2017) review the software available to estimate the mixed logit model. For the estimation of the MM-MNL model, see Train (2008) for the expectation–maximization algorithm, and Keane and Wasi (2013) for the maximum simulated likelihood method. Most software report the mean and standard deviations of the random coefficients or MWTPs. The expected MWTP for an incremental change in attribute k is defined as $E[-\beta_{nk}/\beta_n^p]$ where the price coefficient is used as a proxy of the marginal utility of income.

To understand why it is useful to extract further information from the DCE data, we can consider a simple example. Suppose the government considers launching a new intervention program. Each program consists of two attributes: x_1 and x_2, both taking a value of zero or one, and price. Assume that there are four representative individuals, each of whom represents a different subgroup of the population. Table 1 (Panel A) shows their assumed underlying individual-specific coefficients and implied MWTPs. The mean and standard deviation of MWTPs at the bottom rows are often reported by practitioners.

While these estimates indicate that preferences are heterogeneous, they do not inform us about the uptake rates or demand for different types of programs. Issues remain unresolved concerning what kind of program the government should offer (e.g., program A featuring x_1 only, program B featuring both x_1 and x_2, or both programs); and whether an intervention should be compulsory. Let’s further assume that the government considers these two programs; and sets the prices based on their attributes’ average MWTP. That is program A is offered at 0.5, and program B is offered at 1.

To predict uptake rates (choice probabilities), we first need to specify the available choices. Panel B in Table 1 uses equation (3) to predict choice probabilities for four different scenarios. If either only A or only B were offered (Scenarios I and II), the average uptake rate would be similar at 54% and 56%, respectively. However, the participants are different individuals. This can be seen in Scenario III where consumers were asked to choose either A or B; the first two individuals prefer B whereas the last two prefer A. The last scenario shows that if opt-out is allowed, the average uptake rate would be 28+43 = 71%, higher than offering A or B alone. These kind of demand predictions at different price levels are useful when policymakers or businesses consider launching a new program or product.

The next question concerns which scheme would maximize consumer welfare. Plausible alternatives include (i) *universal-compulsory*; (ii) *universal-optional*; (iii) *multiple-tier-compulsory*; and (iv) *multiple-tier-optional*. The *universal vs. multiple-tier* scheme refers to whether one universal program (either A or B) or multiple programs are offered. The *compulsory vs. optional* scheme refers to whether everyone must take the intervention, or they are allowed to opt-out. To compare the benefits of these schemes, one can use the concept of consumer surplus (CS), which measures the difference between a person's willingness to pay and the price s/he actually paid.

If the scheme is *universal* and *mandatory*, for instance, everyone must take program A at a certain premium, CS_n is simply $\sum_k MWTP_{nk}^A - premium^A$. For individuals who are willing to pay more (less) than the premium, their CS_n will be positive (negative). However, when the government offers choices (either *multiple-tier* or allowing for *opt-out*), the choice each individual would pick is uncertain. The CS_n is then the weighted average of CS_n from all available choices where the weight on each choice depends on the probability that *n* would choose that choice.

Panel C in Table 1 provides examples of CS measures across five schemes. Among these schemes, the last column (two-tier optional) yields the highest aggregate and median CS. This is not surprising because all individuals can sort themselves to the program they like, or even opt-out. The last individual is predicted to incur negative CS for a compulsory scheme because s/he likes neither option. In any actual policy decision, these benefits – measured by CS – needs to be weighed against the cost of each implementation option.

In general, the change in consumer surplus when the attributes of choice *j* change from X_j^0 (attributes at the baseline) to X_j^1 (attributes at the new situation) can be written as

$$\Delta CS_n = \frac{1}{\lambda}\int_{X_j^0}^{X_j^1} P\big(y_{nj} = 1|p,q,Y\big)dX_j.$$

where λ is the marginal utility of income. When the probability function is in the logit form as in (3) and λ is approximated by the price coefficient, ΔCS_n is simplified to:

$$\Delta CS_n = -\frac{1}{\beta_n^p}\left[ln \textstyle\sum_{i=1}^{J} \exp\,(\beta_n X_i)\right]_{X_j^0}^{X_j^1}. \tag{4}$$

If the status quo is no intervention, X_j^0 is zero. A more accurate measure of benefits is the compensating variation (CV), which is based on the compensated demand function. Using CS to approximate CV implicitly assumes that the income effect is negligible. Small and Rosen (1981) provides more details on the derivation of CV and CS under the MNL model. The debate between Lancsar and Savage (2004) and Ryan (2004) on MNL welfare measure concerned the general form in (4) versus the special case of universal and compulsory scheme.

We estimate the distributions of MWTPs, demand, and CS by adopting the algorithm described by Train (2003). The model's estimated heterogeneity distribution is taken as the prior. The posterior means of the individual-specific coefficients or relevant functions are then calculated conditional on each respondent's observed choices (see Appendix A for details).

3. Evaluating the benefits of the introduction of public LTCI in Thailand

3.1 <u>Background</u>

As in many middle-income countries, the current provision of LTC in Thailand is mostly informal. Fewer than 5% of elderly people with LTC needs have paid caregivers (Chandoevwit, Phatchana, Kunakornwong, & Vajragupta, 2018) because of the country's filial piety culture and costly private caregivers and nursing homes. The number of public LTC facilities is limited. The proportion of the Thai population aged 65 years or older is projected to increase from 11% in 2015 to 19% in 2030 (United Nations, 2017). Wives and daughters, who used to be the main caregivers, have participated more in the labor market. The total fertility rate has declined from 2.0 in 1990 to 1.4 in 2013 (Chandeovwit, Paichayontvijit, & Vajragupta, 2016).

The growing LTC demand is likely to exceed the declining informal care supply, placing pressure on the government to search for effective LTC policies. Many volunteer-based programs have been initiated and more funding has been allocated to support community-based care. Yet, concerns remain about the sustainability of such programs and quality of the services, which can vary by community. This challenge has been faced by several OECD countries for at least two decades. One common solution was establishing a public LTCI scheme such as those implemented in the Netherlands, Belgium, Germany, Sweden, and Japan among others (see Costa-Font & Courbage, 2012; Yong & Saito, 2012).

Thai policymakers have started to consider introducing a public LTCI scheme. To make such decision, understanding the public's preferences and needs is crucial. If the offered package does not meet those needs, the investment could be wasted. Moreover, if the public is unwilling to contribute to the LTCI fund, the program would be unlikely to be sustainable. Given that LTCI does not exist in Thailand and little variation exists in the prices of private LTC services, the DCE technique is used herein to evaluate the benefits of LTCI.

3.2 Data

The sample was designed to be nationally representative, with respondents from Bangkok and ten other provinces representing all of the regions in Thailand. For each province, the population was stratified by district and the National Statistical Office's enumeration areas. Households in the selected areas were randomly drawn, and one member aged 25 to 60 years that had lived there for at least three months was interviewed. The interview took place between October and December 2017.

After discussing with elderly care experts, practitioners, and a sample of respondents aged 45–60 years, five attributes were identified as the key features for home-based LTC services: (i) whether LTCI provides home care products and assisted devices such as wheelchairs and disposable diapers (*Material*); (ii) whether a care manager regularly visits the elderly (*CM_visit*); (iii) the proportion of the government-subsidized caregiver cost (*Subsidy*); (iv) whether elderly daycare is available (*Daycare*); and (v) the annual premium (*Premium*). Table 2 presents the attributes and their levels. See Appendix B for DCE development details.

Using D-efficient criteria (Carlsson & Martinsson, 2003), we obtained 16 LTCI pairs from the 96 possible attribute-level combinations. These scenarios were divided into two blocks, and one block was randomly selected for each respondent. Respondents had the option of choosing no LTCI. Before answering the eight-scenario DCE, they were provided with information about the aging population, caring for the dependent elderly and approximate LTC costs, as well as how LTCI would potentially benefit them. They were also informed that the public LTCI scheme would collect an annual premium from those aged 40–65 years to support the eligible population aged 60 years or older. The information was presented in a 5.5-minute videoclip (see Appendix B).

Table 3 reports the sample characteristics. Over two-thirds (68%) were women, and approximately 10% were unemployed or retired. Forty four percent of the sample obtained primary education or lower, with only 18% finishing college or higher education. Approximately 54% lived in urban areas. Less than five percent of households had elderly members with LTC needs and only three households (0.15%) hired formal caregivers. Average annual household consumption per capita was THB 72,373 (approximately USD 2,200).

Low-income households were defined as those in the bottom quartile of the consumption per capita distribution, whereas those in the top-three quartiles were called *middle/high-income* households. Household consumption is used to proxy household's socioeconomic status in our study because income tends to be under-reported in household surveys, especially in a country with a large informal economy (see e.g., Deaton,1997). The consumption measure here is the sum of the 18 types of expenditure asked in the survey, including homemade and unpurchased food consumption which were monetized. When comparing with official statistics, the sample was representative across most dimensions, with the exception that men and workers in certain occupations being under represented.

3.3 Main empirical results

We estimated several versions of the mixed logit and MM-MNL models. For the mixed logit, the two best versions based on the Bayesian Information Criteria (BIC) assume that Σ is a full variance–covariance matrix. Mixed logit I does not include any observed characteristics while Mixed logit II includes the interaction between the observed characteristics and premium. Mixed logit II fits the data slightly better, but Mixed logit I is preferred by the BIC due to its fewer number of parameters.

For the MM-MNL model, we estimated the version with two, three, and four classes, and each case with both full and diagonal variance-covariance matrix specifications. We also estimated a version where we made class probabilities a function of observed characteristics. The three-class model with diagonal variance covariance matrix reported was preferred by the BIC. It was also preferred to the two mixed logit models. Note that this specification still allows taste on observed attributes to be correlated by being in the same class.

Table 4 reports the predicted changes in probabilities (marginal effects) from the two mixed logit models and the preferred MM-MNL model. Their estimated coefficients are reported in Appendix C. These estimates are computed by predicting individual-specific probabilities under two scenarios and take the difference. A baseline assumes the two LTCI policies (A and B) have identical attributes (and hence everyone has an equal chance to choose the two choices). Another scenario assumes that policy A changes one of its attributes. The attributes at the baseline only feature a caregiver subsidy at 25% and a premium of THB 500.

The top row reports the case in which A adds *Material* provision to the policy, the probabilities are estimated to increase for most individuals with the mean at 0.28 and the standard deviation at 0.17. The MM-MNL model gives a slightly higher mean at 0.29 and a lower standard deviation at 0.16. The fifth row reports the effects when A increases the premium from THB 500 to 1000. The average changes in probabilities are around -0.19.

Although the mean estimates across models are similar in magnitude, their implied shapes of distributions differ. The underlying distribution of the mixed logit is multivariate normal while that of the MM-MNL follows a discrete mixture of normal distribution. The last three columns present the estimates conditional on being in each class of MM-MNL. These three classes captured 48%, 24%, and 28% of respondents, respectively. Class 1 is responsive to changes in all attributes, but *Material* matters most. Class 2 appears least sensitive to price but prefers a choice with a high level of caregiver subsidy. Class 3 is sensitive to price but does not value *Material* and *Daycare* on average. Figure C1 (Appendix C) presents the entire distributions of estimated changes in probabilities by the Mixed logit I and MM-MNL models.

The estimated responses of a premium change by some selected demographic characteristics from Mixed logit II are also presented. We do not observe much differences across groups on average, except that the respondents aged 25-40 years with no children and those from the medium/high income households are less sensitive to premium. The fact that adding demographic variables did not improve the model fit for the mixed logit and MM-MNL models suggests that the random coefficients have absorbed most of the individual-specific taste heterogeneity. Intuitively, it means that by observing individuals making decisions over eight different scenarios, we have learned a great deal about their preferences without knowing their demographic characteristics.

To further examine preference heterogeneity, Figure 1 presents the estimated MWTP distributions, which are widely dispersed. Some are multi-modal and most have a long tail. The long-tail feature suggests that some consumers always prefer a package with a certain attribute regardless of the premium. The extremely high MWTPs from a small fraction of consumers should not be interpreted as the true value because the range of the premium in the choice experiment was between THB 300 and 2,000. Consumers who appear to be price insensitive in the experiment (and hence are estimated to have high MWTP) could be price sensitive if they were offered options with much higher prices. This implies that the high mean MWTP is driven by a small fraction of consumers. If we simply compare the median MWTPs, *Material* comes first, followed by the 50% *Subsidy* and *CM visit*.

3.4 <u>Predicting LTCI demand and evaluating benefits across LTCI schemes</u>

The estimates of the MWTP and change in probabilities by each attribute thus far reflect heterogeneous preferences. However, they do not tell us what kind of LTCI packages will be most demanded. Table 5 presents more realistic counterfactual experiments where a higher coverage package also charges a higher premium.

The first experiment started with the relatively low-premium options. The first two options charged a premium of THB 300 and provided a single attribute: either *Material* or 25% *Subsidy*. Option 3, charging THB 500, provided *Material* and 25% *Subsidy*. Option 4 also charged THB 500, and featured *Material* and a visit by a care manager. In this experiment, Option 4 is predicted to obtain the largest market share of 53%, whereas the other three packages each receive a 15–16% share.

Given that consumers seem willing to pay more for higher coverage, three more high-coverage, high-premium options (Options 5–7) were added into the second experiment. Here, Option 7 (THB 2,000) and Option 4 (THB 500) are demanded most, with market shares of 25% and 22%, respectively. The cheapest options (Options 1 and 2) have the lowest demand. When an opt-out or no LTCI option is allowed (the third experiment), approximately 10% of respondents would opt out.

Making seven options available for a national LTCI scheme might be too complicated to implement. The next two experiments, therefore, dropped the three least popular choices. In Experiment 4, Option 4 receives the largest share. This can be expected as option 4 is more similar to the options no longer available (and thus could substitute for them). The last experiment added an opt-out option. Comparing the fifth with the third experiment, a slightly higher proportion of respondents (14%) would opt out when a THB 300 option is not offered.

Table 6 further examines how demand differs by respondents' age and income proxy using the estimates from Experiment 5. Although the observed characteristics do not significantly improve the model fit and are not included in the model, the demand estimates are calculated at the individual level. Therefore, we can try to compute demand by various characteristics. We re-label Options 4–7 as low-tier, medium-1-tier, medium-2-tier, and high-tier, respectively. While the demand patterns are similar for all the groups, larger proportions of low-income and older consumers tend to opt out.

Although previous studies have found that the young may underestimate their risks and have lower demand, our opposite finding is explainable. First, the young cohort could be uncertain about relying on their offspring because many of them have not had (or do not plan to have) children. Moreover, the experiment stated that the government plans to collect a premium from those aged 40–65 years. This means that if a public LTCI scheme were launched, the respondents in this age range would have to pay. The young may thus imagine that they can assess the LTCI scheme first; if they do not like it, they can then opt out later.

The next natural question is that given these heterogeneous demand patterns, how the government should design an LTCI scheme to maximize social welfare. In a typical differentiated product setting, providing people with choices is likely to improve efficiency (see e.g., Small, Winston, & Yan, 2005). In the health insurance context, however, extra costs may be incurred. First, adverse selection (the sorting of high-risk consumers to high-coverage plans) could lead to an unsustainable insurance program. Second, consumers may be overwhelmed when offered many choices (Ericson & Sydnor, 2017; Louviere, Islam, Wasi, Street, & Burgess, 2008). Finally, the administrative cost could be considerably high, especially if the LTCI scheme is financed via a pay-as-you-go concept.

To measure the benefit, individual-specific CS was estimated under 12 policy scenarios, and the values at 25th, 50th and 75th percentiles are reported in Table 7. The top six scenarios include cases in which everyone pays the same premium regardless of their income (uniform premium). Scenarios 1-4 assume a universal compulsory LTCI program. The fifth scenario is a four-tier LTCI program under which people can choose one of the four plans. The sixth scenario adds an opt-out option. The six scenarios at the bottom are the same as Scenarios 1-6 except that premiums for the low-income group are subsidized (the middle/high-income group pay 20% more and the low-income group pay 50% less than the premiums listed in Table 6).

In the left and right panels, the estimated benefits are reported for the *middle/high-income* and *low-income* groups, respectively. Among the first four universal policies, the low-tier LTCI has the lowest proportion of respondents with negative CS (those who would prefer no LTCI to the available option). The multiple-tier LTCI programs (rows 5 and 6) lead to higher median CS as expected because people can sort themselves to their preferred policies. In the sixth scenario, none has negative CS, as those disliking LTCI can opt out.

Next if we compare the right and the left panels, under the uniform premium schemes, the low-income group benefits far less than the high-income. When their premium is subsidized, the benefit to the low-income group rises significantly. The middle/high-income group still gains positive, although slightly smaller, benefits. This pattern reflects the fact that the majority of the low-income group also want LTCI to be in place; however, their willingness to pay is lower.

Conducting a cost-benefit analysis across all implementation options is beyond the scope of this study. Nevertheless, if the costs of implementing all the LTCI schemes considered are similar, our results lead to three policy implications: (1) setting the low-tier package as a default LTCI would minimize the loss for those who do not like LTCI; (2) making supplemental LTCI plans available should raise the aggregate benefits because more than half of respondents are willing to pay more for higher coverage; and (3) ensuring equal access to LTC services requires making contributions to the LTCI fund proportional to income.

4. Discussion and conclusion

While a huge amount of effort and grant money have been put into designing and collecting DCE data, recent reviews have found that DCE results are rarely incorporated into policy making decisions. We conjecture that one reason is the past DCE studies for health policy often present only MWTP estimates (and sometimes their dispersion) which are not directly applicable to policy-relevant questions. We illustrated how more information can be extracted from DCEs studies by estimating demand for different kinds of packages; and evaluating benefits and losses generated from alternative implementation schemes.

We first estimated several discrete choice models on LTCI choice data collected by DCEs. The flexible MM-MNL model was found to outperform the popular mixed logit model. The model's estimated parameters were then used to compute the individual-specific MWTPs and individual's demand for different kinds of packages. We further calculated benefits of implementing different universal LTCI schemes, multiple-tier LTCI schemes, and schemes in which LTCI premium for low-income households are subsidized. Different programs imply different gains and losses across consumers because their preferences are heterogeneous.

We show that although all these measures are translated from the estimated coefficients, one should be careful about relying on mean MWTPs. If some respondents are insensitive to price in the experiment, their tiny price coefficients could drive their MWTPs to be extremely high, pushing up the mean. Relying on estimated demand is less problematic because respondents' choice probabilities only approach one or zero in this situation.

For our application of LTCI demand in Thailand, consumers' preferences appeared very heterogeneous. When offering packages with premium THB 500-2000, we predict an uptake rate of 86%. Twenty-nine percent of respondents preferred the THB 500 package covering only assisted devices/materials and a care manager visit, while 24% preferred the THB 2,000 package which further add a 50% caregiver cost subsidy and daycare facility. These demand patterns imply no one-size-fits-all solution exist, suggesting a higher aggregate benefit for a multiple-tier LTCI scheme compared to that from a universal LTCI scheme. Choosing an optimal LTCI scheme, however, requires evaluating all programs' benefit and costs as well as carefully studying other key issues such as financing options, transfer methods, and cost-sharing instruments.

This study takes the first step to encourage researchers who use DCE data to reflect what policy-relevant questions in the context of their studies are; and design the study to extract more straightforward answers from DCEs. Promising future research directions include analyzing cases in which respondents may make errors in their choices or underestimate their needs, and cases in which a public program generates externalities. For instance, a public LTCI scheme has been found to have a positive spillover on employment (Fu, Noguchi, Kawamura, Takahashi, & Tamiya, 2017), and reduce hospital admissions and length of stay (Costa-Font, Jimenez-Martin, & Vilaplana, 2018).

References

Ben-Akiva, M., McFadden, D., & Train, K. (2019). Foundations of Stated Preference Elicitation: Consumer Behavior and Choice-based Conjoint Analysis. *Foundations and Trends® in Econometrics, 10*(1-2), 1-144. doi:10.1561/0800000036

Burda, M., Harding, M., & Hausman, J. (2008). A Bayesian mixed logit–probit model for multinomial choice. *Journal of Econometrics, 147*(2), 232-246. doi:10.1016/j.jeconom.2008.09.029

Carlsson, F., & Martinsson, P. (2003). Design techniques for stated preference methods in health economics. *Health Econ, 12*(4), 281-294. doi:10.1002/hec.729

Chandeovwit, W., Paichayontvijit, T., & Vajragupta, Y. (2016). Thailand: how to consolidate social security systems: univeral healthcare/pension systems. In S. Kabe, R. Ushiyama, T. Kinkyo, & S. Hamori (Eds.), *Moving up the ladder: development challenges for low and middle-income Asia* (pp. 155-182). Singapore: World Scientific Publishing.

Chandoevwit, W., Phatchana, P., Kunakornwong, W., & Vajragupta, Y. (2018). Can we afford a universal long-term care insurance system in Thailand? *TDRI Quarterly Review, 33*(3), 2-23.

Costa-Font, J., & Courbage, C. (2012). Financing long-term care in Europe: new and unsolved questions. In J. Costa-Font & C. Courbage (Eds.), *Financing long-term care in Europe: institutions, markets and models*: Palgrave Macmillan UK, Kindle Edition.

Costa-Font, J., Jimenez-Martin, S., & Vilaplana, C. (2018). Does long-term care subsidization reduce hospital admissions and utilization? *Journal of Health Economics, 58*, 43-66. doi:10.1016/j.jhealeco.2018.01.002

de Bekker-Grob, E. W., Ryan, M., & Gerard, K. (2012). Discrete choice experiments in health economics: a review of the literature. *Health Economics, 21*(2), 145-172. doi:10.1002/hec.1697

Deaton, A. S. (1997). *The analysis of household surveys: A microeconometric approach to development policy*. Washington, D.C.: The World Bank.

Ericson, K. M., & Sydnor, J. (2017). The Questionable Value of Having a Choice of Levels of Health Insurance Coverage. *Journal of Economic Perspectives, 31*(4), 51-72.

Fiebig, D. G., Keane, M. P., Louviere, J., & Wasi, N. (2010). The Generalized Multinomial Logit Model: Accounting for Scale and Coefficient Heterogeneity. *Marketing Science, 29*(3), 393-421. doi:10.1287/mksc.1090.0508

Fiebig, D. G., Knox, S., Viney, R., Haas, M., & Street, D. J. (2011). Preferences for new and existing contraceptive products. *Health Economics, 20*(S1), 35-52. doi:10.1002/hec.1686

Fu, R., Noguchi, H., Kawamura, A., Takahashi, H., & Tamiya, N. (2017). Spillover effect of Japanese long-term care insurance as an employment promotion policy for family caregivers. *Journal of Health Economics, 56*, 103-112. doi:10.1016/j.jhealeco.2017.09.011

Guttmann, R., Castle, R., & Fiebig, D. G. (2009). Use of Discrete Choice Experiments in health economics: An update of the literature. *Working Papers 2009/2, CHERE, University of Technology, Sydney*.

Kamakura, W. A., & Russell, G. J. (1989). A Probabilistic Choice Model for Market Segmentation and Elasticity Structure. *Journal of Marketing Research, 26*(4), 379-390. doi:10.1177/002224378902600401

Keane, M., & Wasi, N. (2013). Comparing Alternative Models of Heterogeneity in Consumer Choice Behavior. *Journal of Applied Econometrics, 28*(6), 1018-1045. doi:10.1002/jae.2304

Keane, M. P., & Wasi, N. (2016). How to model consumer heterogeneity? Lessons from three case studies on SP and RP data. *Research in Economics, 70*(2), 197-231. doi:10.1016/j.rie.2016.02.002

Kesternich, I., Heiss, F., McFadden, D., & Winter, J. (2013). Suit the action to the word, the word to the action: Hypothetical choices and real decisions in Medicare Part D. *Journal of Health Economics, 32*(6), 1313-1324. doi:10.1016/j.jhealeco.2012.11.006

Lancsar, E., Fiebig, D., & Hole, A. (2017). Discrete Choice Experiments: A Guide to Model Specification, Estimation and Software. *PharmacoEconomics, 35*(7), 697-716. doi:10.1007/s40273-017-0506-4

Lancsar, E., & Savage, E. (2004). Deriving welfare measures from discrete choice experiments: inconsistency between current methods and random utility and welfare theory. *Health Economics, 13*(9), 901-907. doi:10.1002/hec.870

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated Choice Methods: Analysis and Applications*. Cambridge: Cambridge University Press.

Louviere, J. J., Islam, T., Wasi, N., Street, D., & Burgess, L. (2008). Designing discrete choice experiments: do optimal designs come at a price? *Journal of Consumer Research, 35*(2), 360-375.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behaviour. In P. Zarembka (Ed.), *Frontiers in econometrics*. New York: Academic Press.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics, 15*(5), 447-470. doi:10.1002/1099-1255(200009/10)15:5<447 ::AID-JAE570>3.0.CO;2-1

Ryan, M. (2004). Deriving welfare measures in discrete choice experiments: a comment to Lancsar and Savage (1). *Health Econonmics, 13*(9), 909-912. doi:10.1002/hec.869

Small, K., & Rosen, H. (1981). Applied welfare economics with discrete choice models. *Econometrica, 49*(1), 105-130. doi:10.2307/1911129

Small, K., Winston, C., & Yan, J. (2005). Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability. *Econometrica, 73*(4), 1367-1382. doi:10.1111/j.1468-0262.2005.00619.x

Soekhai, V., de Bekker-Grob, E. W., Ellis, A. R., & Vass, C. M. (2019). Discrete Choice Experiments in Health Economics: Past, Present and Future. *PharmacoEconomics, 37*(2), 201-226. doi:10.1007/s40273-018-0734-2

Terris-Prestholt, F., Quaife, M., & Vickerman, P. (2016). Parameterising User Uptake in Economic Evaluations: The role of discrete choice experiments. *Health Economics, 25,* 116-123. doi:10.1002/hec.3297

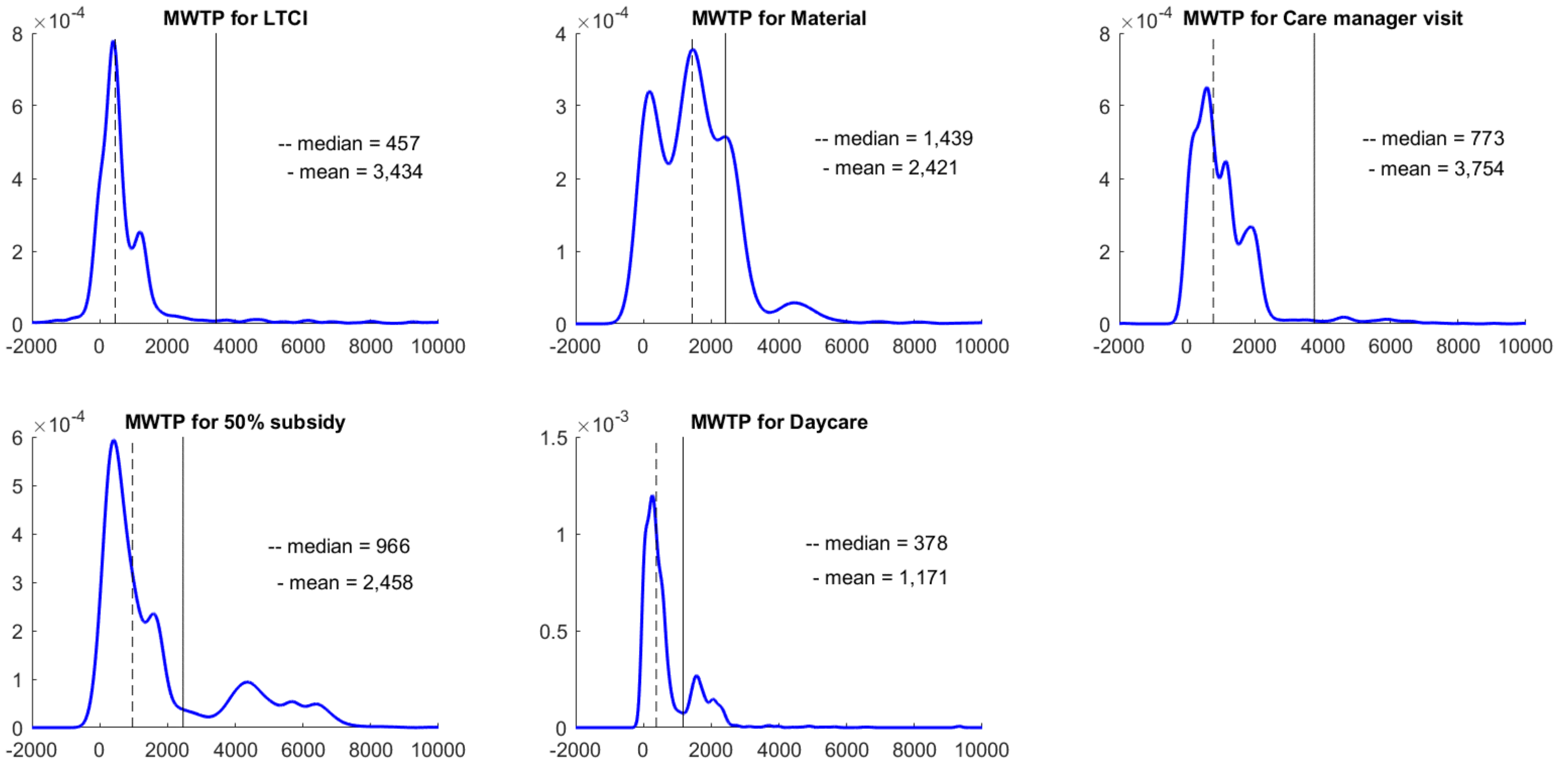
Train, K. (2003). *Discrete choice methods with simulation*. Cambridge: Cambridge University Press.

Train, K. E. (2008). EM Algorithms for nonparametric estimation of mixing distributions. *Journal of Choice Modelling, 1*(1), 40-69. doi:10.1016/S1755-5345(13)70022-8

United Nations, Department of Economic and Social Affairs, Population Division. (2017). World Population Prospects: The 2017 Revision. DVD edition. Retrieved 24 April 2018

Yong, V., & Saito, Y. (2012). National long-term care insurance policy in Japan a decade after implementation: some lessons for aging countries. *Ageing International, 37*(3), 271-284. doi:10.1007/s12126-011-9109-0

Figure 1: MWTP Distributions for LTCI attributes



Note: The caregiver subsidy is a continuous variable in the model, and its MWTP distribution plot is MWTP for a 50% subsidy. For other attributes, their MWTPs are whether such attributes are provided in the package.

Table 1: Examples of the MWTPs, Demand and Consumer Surplus Calculations

Panel A : Coefficients and MWTPs

Individual	β_n^1	β_n^2	β_n^p	$MWTP_n^1$	$MWTP_n^2$
1	1	3	-1	1	3
2	1	1	-1	1	1
3	1	-1	-0.5	2	-2
4	-1	0	-0.5	-2	0
Mean	0.5	0.75	-0.75	0.5	0.5
Stdev	1	1.71	0.29	1.73	2.08

Panel B: Choice probabilities (uptake rates)

	Scenario I	Scenario II	Scenario III		Scenario IV	
	A or none	B or none	A or B		A,B or none	
Individual	prob(A)	prob(B)	prob(A)	prob(B)	prob(A)	prob(B)
1	0.62	0.95	0.08	0.92	0.07	0.88
2	0.62	0.73	0.38	0.62	0.31	0.51
3	0.68	0.38	0.78	0.22	0.57	0.16
4	0.22	0.18	0.56	0.44	0.19	0.15
Mean	0.54	0.56	0.45	0.55	0.28	0.43

Panel C: Consumer surplus

	Universal Compulsory		Universal Optional		Two-tier Optional
Individual	A	B	A or none	B or none	A, B or none
1	0.5	3	0.97	3.05	3.12
2	0.5	1	0.97	1.31	1.68
3	1.5	-1	2.27	0.95	2.63
4	-2.5	-3	0.50	0.40	0.82
Aggregate	0	0	4.7	5.7	8
Median	0.5	0	0.97	1.13	2.15

Note: This example assumes that the unobserved component of the utility function is iid extreme value distributed, and hence the choice probabilities are in the logit form. The consumer surplus is calculated by $CS_n = -\frac{1}{\beta_n^p}\left[ln \sum_{i=1}^{J} \exp\left(\beta_n X_i\right)\right]$ where J = 1, 2, 3 for universal compulsory, universal optional and two-tier optional schemes, respectively.

Table 2: Attributes and their Levels of LTCI Policies in DCE

Attribute (variable name)	Level
a) Provide home care products and assisted devices (*Material*)	Yes / No
b) Provide care manager visit (*CM_visit*)	Yes / No
c) Government subsidizes a percentage of the caregiver cost (*Subsidy*)	0 / 25% / 50%
d) Provide daycare service for the elderly (*Daycare*)	Yes / No
e) Annual premium in THB (*Premium*)	300 / 500 / 1,000 / 2,000

Table 3: Sample Characteristics

	mean	stdev.
1 if female	0.68	0.46
Age (omitted 25-40)		
1 if Age 41-50	0.30	0.47
1 if Age 51-60	0.31	0.47
1 if no children	0.21	0.41
Education (omitted primary or lower)		
1 if lower secondary	0.16	0.37
1 if upper secondary	0.17	0.37
1 if diploma or vocational	0.05	0.23
1 if college or above	0.18	0.39
1 if unemployed or retired	0.10	0.30
1 if have caregiving experience	0.19	0.39
1 if HH has one or more dependent elderly	0.04	0.21
1 if expecting good health in the next 10 years	0.04	0.20
1 if live in an urban area	0.54	0.50
Annual consumption per capita (THB)	72,373	66,159
1 if low per capita household income	0.25	0.43
(per capita consumption < 25th percentile or THB 37,733)		
No. of observations	2,019	

Table 4: Estimated Average and Standard Deviations of Individual-Specific Changes in Probabilities

Change in an attribute		Mixed logit I		Mixed logit II		MM-MNL		MM-MNL by class		
		est	std err	est	std err	est	std err	class 1	class2	class 3
Providing material	mean	**0.277**	0.006	**0.275**	0.006	**0.291**	0.006	0.47	0.21	0.05
	stdev.	**0.173**	0.007	**0.177**	0.007	**0.162**	0.006			
Providing care manager visit	mean	**0.248**	0.006	**0.246**	0.006	**0.255**	0.006	0.41	0.08	0.14
	stdev.	**0.140**	0.008	**0.143**	0.008	**0.156**	0.007			
Increasing caregiver subsidy from 25% to 50%	mean	**0.183**	0.006	**0.183**	0.006	**0.199**	0.006	0.20	0.28	0.13
	stdev.	**0.084**	0.006	**0.085**	0.006	**0.061**	0.007			
Providing daycare	mean	**0.142**	0.007	**0.141**	0.007	**0.158**	0.008	0.21	0.21	0.02
	stdev.	**0.071**	0.008	**0.071**	0.008	**0.066**	0.008			
Increasing price from 500 to 1000	mean	**-0.194**	0.004	**-0.179**	0.009	**-0.191**	0.005	-0.25	-0.05	-0.22
	stdev.	**0.116**	0.004	**0.118**	0.004	**0.126**	0.004			
Increasing price from 500 to 1000										
with caregiving experience	mean			**-0.185**	0.013					
age 25-40, no children	mean			**-0.176**	0.010					
age 25-40, have children	mean			**-0.183**	0.010					
age 41-50, no children	mean			**-0.183**	0.010					
age 41-50, have children	mean			**-0.182**	0.010					
age 51-60, no children	mean			**-0.182**	0.010					
age 51-60, have children	mean			**-0.182**	0.010					
Medium/high per capita HH income	mean			**-0.177**	0.009					
Low per capita HH income	mean			**-0.184**	0.013					
class prob.								**0.48**	**0.24**	**0.28**
Likelihood		-10782		-10757		**-10512**				
No. of parameters		27		38		38				
BIC		21826		21882		**21392**				

Note: The individual-specific probabilities were calculated under the two scenarios: a baseline where two identical choices with caregiver subsidy at 25% and premium at THB 500 are offered, and a situation where an attribute on one choice change. The figures in the table are the average and standard deviations of these changes in probabilities.

Table 5: LTCI Demand Estimates from the MM-MNL Model

		option 1	option 2	option 3	option 4	option 5	option 6	option 7	no LTC
	Material	yes	no	yes	yes	yes	yes	yes	
	Care manager visit	no	no	no	yes	yes	yes	yes	
	Caregiver subsidy	0%	25%	25%	0%	25%	50%	50%	
	Daycare	no	no	no	no	no	no	yes	
	Premium (THB)	300	300	500	500	1,000	1,500	2,000	
Experiment 1	available options	x	x	x	x				
	predicted shares	15%	16%	15%	53%				
Experiment 2	available options	x	x	x	x	x	x	x	
	predicted shares	7%	7%	9%	22%	13%	17%	25%	
Experiment 3	available options	x	x	x	x	x	x	x	x
	predicted shares	7%	6%	8%	21%	12%	15%	21%	10%
Experiment 4	available options				x	x	x	x	
	predicted shares				33%	18%	20%	28%	
Experiment 5	available options				x	x	x	x	x
	predicted shares				29%	16%	18%	24%	14%

Table 6: Estimates of LTCI Demand by Age and Income Groups

	Low-tier	Medium-1-tier	Medium-2-tier	High-tier	no LTC
Material	yes	yes	yes	yes	
Care manager visit	yes	yes	yes	yes	
Caregiver subsidy	0%	25%	50%	50%	
Daycare	no	no	no	yes	
Premium (THB)	500	1,000	1,500	2,000	
Age 25-40					
Middle/high income	32%	17%	19%	25%	8%
Low income	24%	14%	18%	25%	19%
Age 41-50					
Middle/high income	31%	17%	19%	24%	9%
Low income	25%	14%	18%	26%	17%
Age 51-60					
Middle/high income	30%	16%	17%	22%	15%
Low income	24%	12%	13%	18%	32%

Note: The figures in each row sum to 100%. The individual-specific demand estimates are the same as those presented in experiment 5 in Table 5, but here, they are aggregated by age and income groups. Low income is proxied by being in the bottom quartile of the household consumption per capita.

Table 7: Distributions of CS from Different Policy Scenarios

	Middle/High income				Low income			
Uniform premium	**25th**	**50th**	**75th**	**%negative CS**	**25th**	**50th**	**75th**	**%negative CS**
Universal LTCI: low-tier	1,070	3,040	6,082	10%	26	1,612	5,935	25%
Universal LTCI: medium-1-tier	851	2,906	6,263	14%	-230	1,598	6,271	30%
Universal LTCI: medium-2-tier	644	2,769	6,573	16%	-576	2,043	6,675	35%
Universal LTCI: high-tier	329	2,629	6,684	20%	-1,017	1,770	6,714	39%
Four-tier LTCI	1,398	3,586	7,736	8%	249	3,029	8,043	22%
Four-tier LTCI + opt out	1,432	3,586	7,812	0%	380	3,030	8,060	0%
Lower premium for low income	**25th**	**50th**	**75th**	**%negative CS**	**25th**	**50th**	**75th**	**%negative CS**
Universal LTCI: low-tier	970	2,940	5,982	11%	276	1,862	6,185	18%
Universal LTCI: medium-1-tier	651	2,706	6,063	16%	270	2,098	6,771	20%
Universal LTCI: medium-2-tier	344	2,469	6,273	20%	174	2,793	7,425	23%
Universal LTCI: high-tier	-71	2,229	6,284	26%	-17	2,770	7,714	26%
Four-tier LTCI	1,251	3,402	7,509	9%	614	3,599	8,630	15%
Four-tier LTCI + opt out	1,294	3,403	7,537	0%	671	3,608	8,636	0%

Note: Attributes and premiums of low, medium-1, medium-2, and high-tier are as shown in Table 6. The top panel (uniform premium) refers to cases where everyone is charged the same premium regardless of their income. The bottom panel (lower premium for low income) refers to cases where the high-income group pays 20% more and the low-income group pays 50% less. Universal refers to a compulsory universal LTCI policy, and four-tier refers to a LTCI scheme where people can choose one from four LTCI options.

Web Appendices to Accompany

Incorporating Discrete Choice Experiments into Policy Decisions: Case of Designing Public Long-Term Care Insurance

January 2020

Appendix A: Estimation details

The mixed logit and mixture-of-normal mixed multinomial logit (MM-MNL) models capture unobserved differences in tastes by allowing random coefficients. The distribution of these coefficients in the population were estimated. In this appendix, we describe the "approximate Bayesian" approach to finding where in the distribution of taste a particular person lies. The algorithm is based on Train (2003, p.266) and Allenby and Rossi (1998). We use this algorithm to compute the posterior individual-specific coefficients and other individual-specific function, such as marginal willingness to pay (MWTP), demand, and consumer surplus (CS).

The procedure for MM-MNL is described here; however, it is straightforward to apply this to the mixed logit and latent class models because they are special cases of MM-MNL. For the MM-MNL model, we estimate the population distribution of β_n as:

$f(\beta_n) \sim MVN\left(\hat{\beta}_s, \hat{\Sigma}_s\right)$ with probability $\widehat{w}_s$ where $\sum_{s=1}^{S} \widehat{w}_s = 1, \;\; s = 1, \ldots, J.$

The aim is to discover β_n or other individual-specific functions, given we observe his or her choice situations and what he or she chooses in the experiment. Let $data_n$ denote $\{y_{nt}|X_{nt}\}$ *for t = 1, …, T*. Let the distribution of β_n conditional on the person's past choices be denoted by $f(\beta_n|data_n)$. Under the Bayes' rule, this distribution can be calculated by taking the model's estimated heterogeneity distribution as the prior as in:

$$f(\beta_n|data_n) \propto P(data_n|\beta_n)P(\beta_n|\, \hat{\beta}_s, \hat{\Sigma}_s, \widehat{w}_s).$$

The posterior mean of the individual-specific coefficients conditional on each respondent's observed data is given by:

$$\bar{\beta}_n = \int \beta_n \, f(\beta_n|data_n) d\beta_n \qquad \text{(A.1)}$$

To predict the individual-specific demand for a new situation X_n^*, the choice probability conditional on $data_n$ is:

$$P(y_{nj} = 1|X_n^*, data_n) = \int \frac{\exp\left(\beta_n X_{nj}^*\right)}{\sum_{i=1}^{J} \exp\left(\beta_n X_{ni}^*\right)} f(\beta_n|data_n) d\beta_n \qquad \text{(A.2)}$$

Similarly, an individual-specific CS for a situation change from X_j^0 to X_j^1, which depends on the individual-specific choice probability can be derived as:

$$\Delta CS_n|X_n^*, data_n = \int \frac{1}{\lambda_n}\left[ln \sum_{i=1}^{J} \exp\left(\beta_n X_{ni}^*\right)\right]_{X_j^0}^{X_j^1} f(\beta_n|data_n) d\beta_n \qquad \text{(A.3)}$$

The quantities in (A.1) - (A.3) can be calculated in the following steps:

<u>Step I</u>: Draw $\beta_{n,s}^r$ from $MVN(\beta_s, \Sigma_s)$ for *r = 1, …, R* and *s = 1,…, S*; where *R* is the number of draws and *S* is the number of classes.

<u>Step II</u>: Calculate the weight for each draw *r* for person *n* based on person *n*'s likelihood given by that particular $\beta_{n,s}^r$:

$$\pi_{n,s}^r = \frac{P(y_n|\beta_{n,s}^r, X_n) w_s}{\sum_s \sum_r P(y_n|\beta_{n,s}^r, X_n) w_s}$$

<u>Step III</u>: calculate the mean posterior estimates

$$\bar{\beta}_n = \sum\nolimits_s \sum\nolimits_r \pi_{n,s}^r \beta_{n,s}^r$$

The individual-specific MWTP can be then calculated from the individual-specific coefficients.

<u>Step IV</u>: Calculate the relevant functions for counterfactual situation X* such as the choice probabilities:

$$P(y_{nj} = 1|X_n^*, data_n) = \sum\nolimits_s \sum\nolimits_r \pi_{n,s}^r \frac{\exp\left(\beta_{n,s}^r X_{nj}^*\right)}{\sum_{i=1}^{J} \exp\left(\beta_{n,s}^r X_{ni}^*\right)}.$$

Note that assuming normal or mixture-of-normal distributions allows the coefficients to be driven by the data. In other words, for an individual who appears to be price insensitive in the experiment, or often chooses a higher price option in the data (either assuming that high price signaling unobserved quality or choosing irrationally), his or her price coefficient could be zero or positive. In theory, this implies that he or she has an infinite MWTP for all attributes. Constraining the distribution to be negative (e.g., lognormal) would help constrain the sign of price coefficient to be non-positive, but still have the same implication. In this study, under the MM-MNL model, we found that 4% of respondents are price insensitive and treat them as being in the top five percentile of MWTP or CS distributions without attempting to assign any value to it.

References

Allenby, G. M., & Rossi, P. E. (1998). Marketing models of consumer heterogeneity. *Journal of econometrics*, *89*(1-2), 57-78.

Train, K. (2003). *Discrete choice methods with simulation*. Cambridge: Cambridge university press.

Appendix B: Discrete Choice Experiment (DCE) Development

This appendix describes how we designed and developed the DCE to assess the benefits of introducing public long-term care insurance (LTCI). The aim is to identify what long-term care (LTC) services are essential for the elderly people with LTC needs, and in what range of insurance premiums, the scheme will be affordable for the Thai population. This is to ensure that the program meets the need and remains financial sustainable in the long run.

Our DCE development consists of five key steps:

Step 1*: Reviewing how other countries operate public LTCI schemes in terms of the LTC services provided, financing options, and their challenges as well as deciding on a plausible broad LTCI concept for Thailand.*

Common LTCI services provided include assistance with daily activities at home, home nursing care, and institutional care or nursing homes. Some countries also provide respite care, assistive devices, home adaptations and family caregiver training. Elderly daycare is a new service in several countries. This service, analogous to a childcare, is found valuable especially for caregivers. Some of the benefits provided are cash transfers, while others are in-kind, but most LTCI policies require a certain degree of cost sharing to help alleviate the moral hazard problem.

Three broad models of LTCI financing exist: (i) social health insurance providing universal coverage; (ii) LTCI financed by a general tax or a mixture of public funds, and (iii) a means-tested model financed by a general tax. Many European countries use option (i), with the exceptions of Germany, which allows those who have private LTCI to opt-out (Zuchandke et al 2012); and the UK which adopts option (iii) (Comas-Herrara et al., 2012). In Asia, only Japan, South Korea and Taiwan provide public universal LTCI. Their models are based on option (ii) under which regional or local governments manage the delivery of LTC services. Low income households typically pay a lower premium rate or are exempt from co-payments for services.

Differences in the value placed on social support, existing health insurance schemes, institutional factors and devolution have led to divergent LTCI schemes across countries. Thailand has three public health insurance schemes that cover about 98% of its population. These three schemes cover hospitalization and outpatient care services, but not home-based LTC expenses. The country has also attempted to gradually decentralize primary healthcare provision to the sub-district (Tambon) level. For example, in 2016 about one-seventh of sub-districts were received an additional THB 5,000 (USD 150) per year for each elderly individual with LTC needs (National Health Security Office, 2017). The funded programs, nonetheless, focus on health-related care services, rather than assisting with personal tasks (e.g., eating and bathing).

One common challenge faced by several countries is controlling the rising LTC expenditure. For example, Japan had to reform its LTCI scheme in 2006 to tighten eligibility criteria and reduce benefits as expenditure was much higher than initially expected. One OECD report (Colombo, Llena-Nozal, Mercier, & Tjadens, 2011) recommends that LTCI be constructed in a sustainable and transparent manner, rather than piecemeal responding to immediate political or financial problems. It has also been emphasized that family caregivers are the backbone of any LTCI system and home-based LTC services are more efficient than institutional care.

Based on the lessons learned from international experiences, a home-based LTC scheme seems more appropriate for Thailand where over 80 percent of the elderly own their residency. Family ties are typically strong and cohabitation between parents and adult children remains common. In addition, a LTCI system covering institutional care would be too expensive and unaffordable for the majority of the population in middle-income countries such as Thailand. The following steps then focus on a home-based care LTCI scheme only.

Step 2: *Obtaining expert opinions on what is needed to care for the dependent elderly.*

A focus group discussion was conducted with seven informants with a broad understanding of elderly care (gerontologists, senior physicians and nurses). The discussion centered on home-based caring for the dependent elderly, specifically on the minimum requirements for the dependent elderly to maintain good personal hygiene and an acceptable quality of life. Table B1 presents the list of what these experts considered essential for LTC.

Table B1: LTC Benefits Considered Necessary by the Experts

Benefit types	Explanation
1. Providing equipment and assistive devices to help the dependent elderly be mobile and live comfortably	Equipment and assisted devices include mobility-enhancing walking aids (canes, walkers), wheelchairs, pressure relief mattresses, transfer belts, bathroom aids, home blood pressure monitors, oxygen devices and tanks (if needed)
2. Maintaining good personal hygiene and a clean home environment	This includes personal hygiene accessories (cotton buds, wipes), incontinence care products, proper waste disposal
3. Caregiver	Main tasks include assisting elderly people with their daily activities and providing suitable health-related care.
4. Caregiver training and supervision	Family caregivers are trained by public health personnel free of charge or by a formal training organized by other government departments. Caregivers are supervised by nurses or public health personnel from nearby hospitals.

Step 3: *Obtaining further opinions on necessary LTC services and costs from professional and experienced caregivers.*

This step involved a semi-structured interview with professional and experienced caregivers including physicians, nurses, public health personnel and volunteers. To select key informants, we consulted with the National Health Security Office to seek recommendation on which hospitals operate long-term care programs with their local government and volunteers. Seven hospitals from four provinces were selected. Request letters for an interview were sent out to each hospital's director to invite their staff and volunteers in the community network involving in the LTC program. Altogether, we interviewed 35 key informants whose participation was secured on a voluntarily basis.

We tried to capture two pieces of information in these interviews: does this group of practitioners agree with the attributes identified by the experts in the previous step? and is any other equipment or services necessary? and what are the monetary and time costs incurred in LTC provisions? Caregivers were asked how long it takes to assist a dependent elderly person with each daily living activity. For equipment and assistive devices, they were asked about purchase prices and product lifetime. Caregivers were also asked about their travel time and the costs of visiting dependent elderly people in their local area.

Step 4: *Estimating the costs of necessary LTC services in order to decide the premium range*

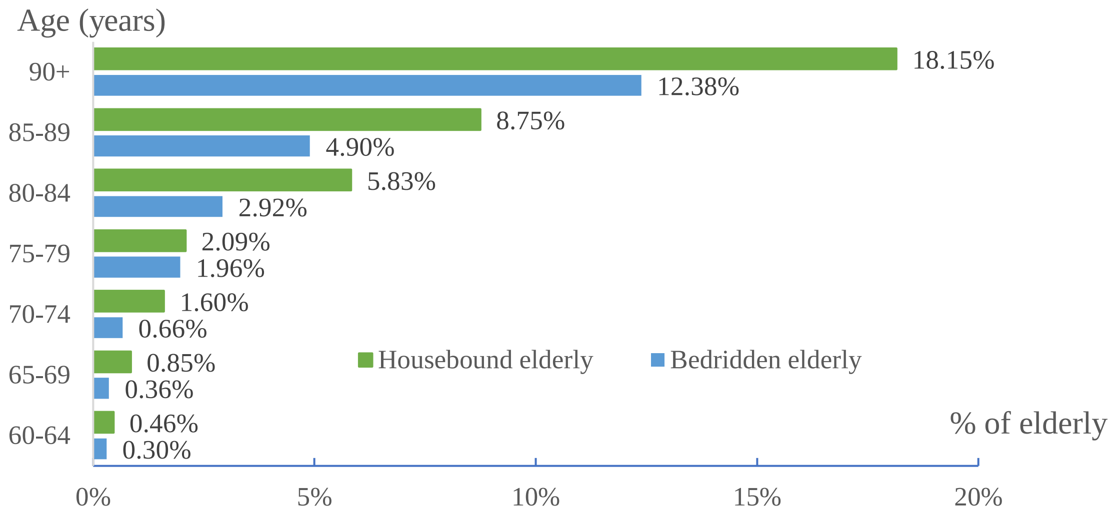
The estimated costs obtained from practitioners in the previous step, together with the market prices of products and paid caregivers are used to estimate the cost of home-based LTC programs. The attributes include those listed in Table B1, except for caregiver training, which has been already supported by several government departments. The estimated private cost of LTC in

2018 was around THB 120,000–230,000 per year, with the caregiver salary accounting for more than 60% (see more details in Chandoevwit, Phatchano, Kunakornwong, & Vajragupta, 2018).

To calculate the aggregate cost of providing home-based LTC in the long run, the risks of LTC needs by age were calculated from the Thai Survey of Older Persons 2014. Figure B1 shows the estimates of the proportions of the Thai elderly with two levels of LTC needs. "Housebound" refers to individuals who can carry out some self-care tasks at home, but are unable to go outside without assistance. "Bedridden" refers to individuals being confined to their beds and requiring a higher level of care. This classification is defined by the Thai Ministry of Public Health (2015) using the activities of daily living scores.

Using the risk information, together with the projected population and inflation, Chandoevwit, Phatchano, Kunakornwong, & Vajragupta (2018) assessed whether a public LTC program would be financially sustainable. They find that if every employable person aged 40-65 contribute 500-1500 THB per year with additional contributions from local and central governments, and that the caregiver salary is subsidized by up to 50%, the program would be sustainable. A fully subsidized caregiver salary LTCI would not be sustainable.

Figure B1: Estimated Risks of LTC Needs by Age



Source: Authors' calculations from the Thai Survey of Older Persons 2014, National Statistical Office

<u>Step 5</u>: *Obtaining further opinions on LTC care from potential LTC fund contributors and assessing whether the designed premium range is affordable.*

This step also involved a semi-structured interview with 12 key informants aged 40 to 65. Following the Japan case, this age group was selected as the LTC fund contributors because their salary is relatively high, and they should start seeing benefits of LTCI. We sent a letter to three non-profit organizations to invite their members aged 40 to 65 for an interview. This group was first asked about their current public health insurance coverage and whether it covered any non-medical LTC costs. Then, they were asked "if you were to care for a dependent elderly person at home, what kinds of equipment would you need to maintain good personal hygiene and a safe environment?" Additional attributes mentioned included home improvement equipment for the frail elderly people, such as handrails, and elderly-friendly public transport facilities. We did not add these attributes to the LTC experiment as they have already been supported by local public administrations on a means-test basis.

The informants were then asked to think more about LTCI. Would you pay for a caregiver? What should the co-payment rate for LTC services be? Who should train you to care for the dependent elderly? What kind of supervision should a care manager provide to caregivers and the dependent elderly? Do you know about respite daycare for the elderly? Given an annual premium of 300-2000 THB per year, would you purchase a LTCI policy? We found that the premium range is acceptable, but most people were unfamiliar with daycare for elderly initiatives.

The information derived from the five steps above helped us identify the important LTCI attributes and their plausible levels. These are (i) home care products and assistive devices (yes or no); (ii) care manager visit (yes or no); (iii) the proportion of caregiver salary being subsidized by the government (none, 25% or 50%) ; (iv) elderly daycare (yes or no); and (v) annual premium (THB 300, 500, 1000 or 2000).

A D-efficient design from the 96 possible attribute-level combinations (2x2x3x2x4) was generated by the *dcreate* module in Stata (Hole, 2015). We chose a DCE with two choices in each choice set to avoid respondents needing to process too much information, given that LTCI is an unfamiliar social insurance concept. Respondents could choose no LTCI. The generated 16 LTCI pairs were split into two blocks. Each respondent answered a set of eight scenarios. Table B2 shows an example of a choice scenario.

To ensure that all respondents understood the context, believed the scenario to be plausible, and received the same information before making their LTCI choices, all participants were shown the same videoclip containing necessary information concerning the risk of LTC needs, approximate costs of LTC care, and descriptions of each attribute. Box B1 presents the transcript of the videoclip. The DCE was then piloted with a small sample in two provinces before collecting the data from the full sample.

Table B2: An Example of DCE Choice Scenarios

Attribute	Choice 1	Choice 2	Choice 3
a) Provide home care products and assistive devices 	Yes	No	Neither choice 1 nor choice 2
b) Provide care manager visit	No	Yes	
c) Government subsidizes a percentage of the caregiver costs	25% of the caregiver cost or THB 20,250 per year for the housebound elderly THB 45,000 per year for the bedridden elderly	50% of the caregiver cost or THB 40,500 per year for the housebound elderly THB 90,000 per year for the bedridden elderly	
d) Provide daycare services for the elderly 	Yes	No	
e) Annual premium	THB 300	THB 1,000	
I choose	☐	☐	☐

Box B1: Transcript of the Information Presented to the Respondents

Many elderly people in Thailand are now at risk of being dependent. Being dependent means they are unable to brush their teeth, use the toilet, take a shower, or eat by themselves. They need a caregiver to assist with their daily living activities. Further, many of the dependent elderly people also need assistive devices and equipment, such as medical air mattresses, wheelchairs, walking sticks and adult diapers. These devices and equipment are all costly, but necessary to improve hygiene and the quality of life.

In essence, the expense of such items and caregivers is prohibitive. For a housebound elderly person, necessary materials and assistive devices can cost around 34,000 baht per year. These include a walking cane, a walker, a wheelchair, a bed and mattress, a toilet seat, adult diapers, disposable underpads, toilet paper and cotton wool. A caregiver salary is approximately 81,000 baht per year. In addition, the transportation cost for a nurse and a public health officer to visit the elderly person at least once a month is around 1,800 baht per year. This would bring the total annual expenses to around 120,000 baht.

For a bedridden elderly person, the necessary material and assistive devices can cost around 46,000 baht per year. Such items include a wheelchair, a medical air or water pressure mattress/medical mattress, a hospital rubber sheet, an overbed table, adult diapers, toilet paper, cotton wool and disposable underpads. The caregiver salary can be around 180,000 baht per year. Moreover, the transportation cost for a nurse and a public health officer to visit the elderly person at least twice a month is around 3,600 baht per year. This would sum to around 230,000 baht per year.

Caregivers comprise a crucial component of care provision. Most of them are children, grandchildren, a spouse or a paid caregiver. Taking care of the dependent elderly is often hard and depressive work. Having a respite care center would give caregivers some free time to rest or run errands. Similar to childcare, elderly people at the center can socialize and change their daily activities. We may call this new service a social care service center.

Since Thailand does not have a long-term care insurance system, elderly people needing assistance, or their families must pay for the expenses mentioned earlier. If they are unable to afford them, the elderly may live in poverty and face serious survival problems.

If Thailand were to establish a long-term care insurance scheme, the scheme would provide benefits to people who are older than 60 years and certified by a doctor that they need of help to perform daily activities. Their family would not have to pay the full amount to care for them. However, we must pay a premium in advance. This premium would still be lower than the full cost of long-term care.

To make this happen, we can do the followings. Every employable individual aged 40-65 years should pay an annual premium to a long-term care insurance fund. The revenue from premium will be spent on long-term care benefit packages. The annual premium would be small. However, if most people do not want to pay for such a premium, the system could not exist.

You may ask yourself whether you would benefit from long-term care insurance. We would like to remind you that the current life expectancy among Thais is 78. You could be among those Thais who live a long life and benefit from this scheme. In addition, our family sizes are getting smaller, making it less possible to rely on offspring – who also have to work and take care of their own children. A long-term care insurance system could relieve the burden on the elderly’s family members. Such scheme has been implemented in many countries, such as Japan, China and other developed countries.

Next, we will ask you about your preference for a long-term care insurance package. Before you choose, we will ask you to think seriously about which insurance package you would like the most. Imagine that you were a dependent elderly person. Would these benefits benefit you and your children? The benefits you would receive may include the necessary materials and assistive devices, visits from nurses and public health officers, caregiver costs shared by the government and social services at an elderly daycare center.

Please note that if you pay the annual premium, you would have less money to spend on other goods and services. However, your payment today could reduce your future expenses on long term care. Please think carefully about paying for the premium today versus paying for long-term care in the future.

References

Hole, Arne Risa (2015). “DCREATE: Stata module to create efficient designs for discrete choice experiments” Statistical Software Components S458059, Boston College Department of Economics, revised 25 Aug 2017.

Chandoevwit, W., Phatchana, P., Kunakornwong, W., & Vajragupta, Y. (2018). Can we afford a universal long-term care insurance system in Thailand? *TDRI Quarterly Review*, *33*(3), 2-23.

Colombo, F., Llena-Nozal, A., Mercier, J., & Tjadens, F. (2011). *Help wanted? Providing and paying for long-term care*. OECD Health Policy Studies. OECD Publishing.

Comas-Herrera, A., Wittenberg, R & Pickard, L. (2012) “From Commission to Commission: Financing Long-Term Care in England,” In J. Costa-Font & C. Courbage (Eds.), *Financing long-term care in Europe: institutions, markets and models*, Palgrave Macmillan UK, Kindle Edition.

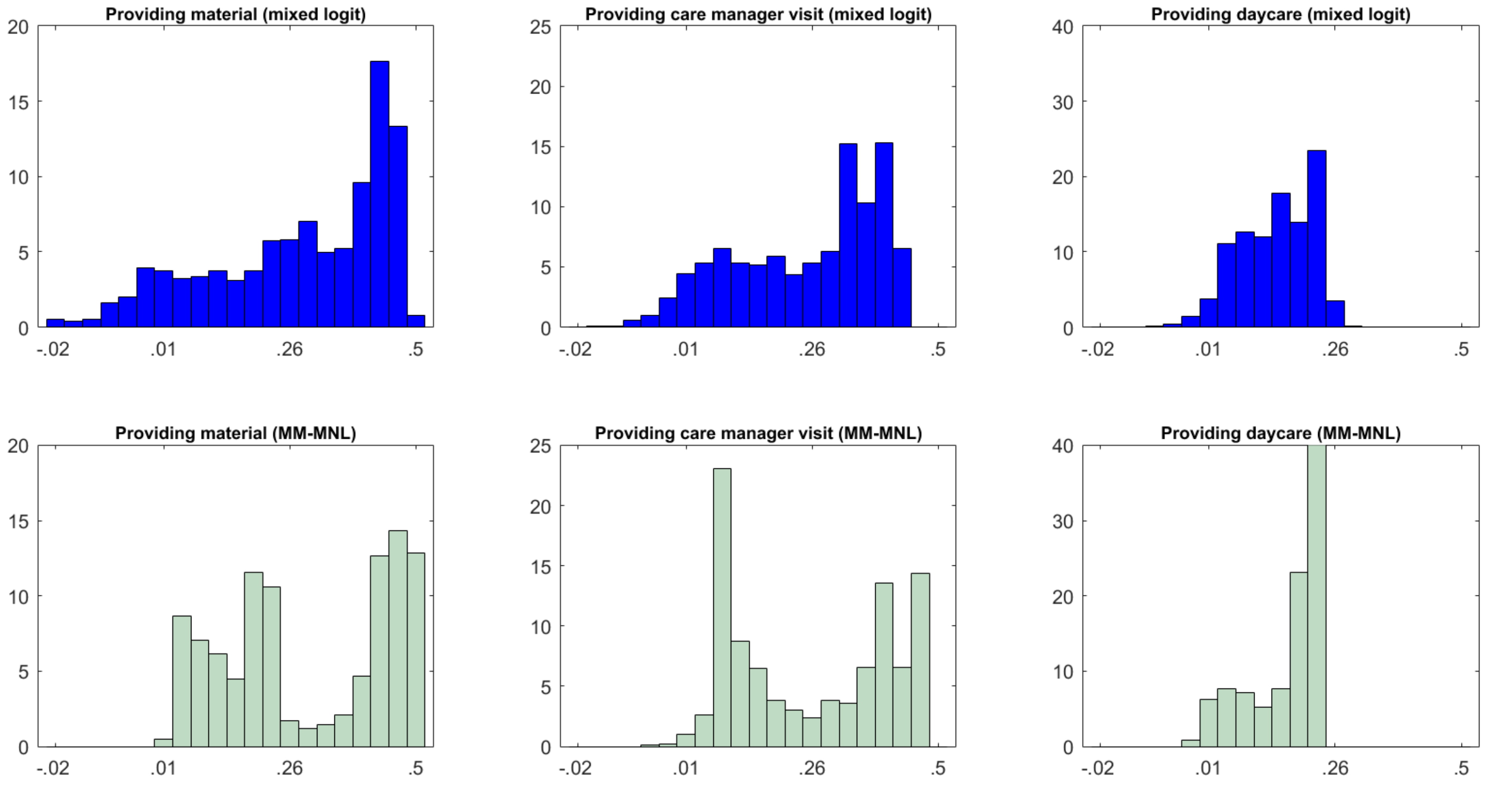
Ministry of Public Health. (2015). *A Manual for Screening/Evaluating the Elderly*. *(in Thai)*. Bangkok: Office of Printing Mill, The War Veterans Organization of Thailand.

National Health Security Office. (2017). *Manual for National Health Security Fund Management Book 1 (in Thai)*. Bangkok: National Health Security Office.

Zuchandke, A, Reddemann, S. & Krummaker, S. (2012) “Financing Long-Term Care in Germany In J. Costa-Font & C. Courbage (Eds.), *Financing long-term care in Europe: institutions, markets and models*, Palgrave Macmillan UK, Kindle Edition.

Appendix C: Distributions of Changes in Probabilities and Coefficient Estimates from Selected Models

Figure C1: Distributions of Changes in Probabilities Predicted by Mixed logit I and MM-MNL



Note: For each individual, we predict his or her choice probabilities under two scenarios and take the difference. A baseline assumes the two LTCI policies have identical attributes (providing only a caregiver subsidy at 25% and charging a premium of THB 500). Another scenario assumes that one of the policy changes one of its attribute, i.e., adding *material*, *care manager visit* or *daycare* provision.

Table C1: Coefficient Estimates from Selected Models

	MNL		**Mixed logit I**		**Mixed logit II**		**MM-MNL class 1**		**MM-MNL class 2**		**MM-MNL class 3**	
	coef	std.err	coef	std.err	coef	std.err	coef	std err	coef	std err	coef	std err
Mean												
dLTCI	0.01	0.044	**2.16**	0.159	**2.10**	0.160	**0.60**	0.28	**1.50**	1.34	**1.99**	0.16
Material	**1.11**	0.024	**1.90**	0.068	**1.90**	0.069	**4.47**	0.30	**0.89**	0.13	**0.20**	0.10
CM_Visit	**0.75**	0.022	**1.37**	0.053	**1.38**	0.053	**3.29**	0.25	**0.32**	0.10	**0.61**	0.09
Subsidy for caregiver/100	**1.91**	0.064	**3.32**	0.148	**3.35**	0.148	**3.68**	0.29	**5.03**	0.39	**2.26**	0.23
Daycare	**0.36**	0.021	**0.62**	0.038	**0.62**	0.039	**0.89**	0.08	**0.92**	0.09	**0.10**	0.07
Premium/100	**-0.05**	0.006	**-0.19**	0.007	**-0.16**	0.018	**-0.25**	0.01	**-0.04**	0.01	**-0.23**	0.02
*Premium/100** caregiving experience	**-0.05**	0.004			**-0.04**	0.013						
omitted (age 25-40, no children)												
*Premium/100** age 25-40, have children	**-0.01**	0.006			-0.03	0.018						
*Premium/100** age 41-50, no children	0.01	0.011			0.004	0.034						
*Premium/100** age 41-50, have children	-0.01	0.006			-0.02	0.019						
*Premium/100** age 51-60, no children	**-0.04**	0.011			-0.05	0.036						
*Premium/100** age 51-60, have children	**-0.04**	0.006			**-0.05**	0.019						
*Premium/100** No job	**-0.02**	0.006			**0.03**	0.017						
*Premium/100** College degree	0.01	0.005			**0.05**	0.017						
*Premium/100** Expect good health in the future	-0.01	0.008			**0.06**	0.024						
*Premium/100** Live in an urban area	0.00	0.003			0.00	0.011						
*Premium/100** Low-income household*	**-0.04**	0.004			-0.02	0.012						
Standard deviation												
dLTCI			**3.13**	0.174	**3.14**	0.175	**1.39**	0.31	**15.12**	2.92	**1.32**	0.18
Material			**1.71**	0.094	**1.73**	0.095	**1.37**	0.17	0.02	2.47	0.22	0.26
CM_Visit			**0.85**	0.061	**0.85**	0.061	**1.63**	0.15	0.02	1.94	**0.62**	0.13
Subsidy for caregiver			**1.28**	0.388	**1.23**	0.389	**2.60**	0.40	0.42	1.42	**1.32**	0.36
Daycare			0.10	0.109	0.05	0.108	0.03	1.19	0.05	1.06	**0.34**	0.13
Premium			**0.12**	0.036	**0.11**	0.038	**0.17**	0.01	0.004	0.16	**0.22**	0.02
off-diagonal elements			Yes		yes		no		no		no	
class prob.							**0.48**	0.02	**0.24**	0.02	**0.28**	0.02
Likelihood	-14267		-10782		-10757		**-10512**					
No. of parameters	17		27		38		38					
BIC	28699		21826		21882		**21392**					

Note: Bold estimates are statistically significant at 5%. The mixed logit and MM-MNL are estimated by simulated maximum likelihood with 500 draws. Standard errors are calculated using 5,000 draws.

Table C2: Estimates of the Variance–Covariance Matrix of the Mixed Logit I Model

	dLTCI	*material*	*CM_visit*	*subsidy*	*daycare*	*premium*
dLTCI	10.10					
	(1.09)					
Material	1.57	3.43				
	(0.31)	(0.32)				
CM_visit	1.68	1.40	1.48			
	(0.26)	(0.19)	(0.17)			
Subsidy	0.79	0.53	-1.51	6.43		
	(0.72)	(0.35)	(0.21)	(0.88)		
Daycare	0.05	0.65	0.03	1.09	0.35	
	(0.21)	(0.11)	(0.07)	(0.17)	(0.07)	
Premium	0.19	-0.02	-0.04	0.06	0.00	0.03
	(0.03)	(0.02)	(0.01)	(0.03)	(0.01)	(0.00)

Note: The number in the parentheses are the standard errors, calculated using 5,000 draws.

Table C3: Estimates of the Variance–Covariance Matrix of the Mixed Logit II Model

	dLTCI	*material*	*CM_visit*	*subsidy*	*daycare*	*premium*
dLTCI	10.04					
	(0.08)					
Material	1.60	3.34				
	(0.05)	(0.06)				
CM_visit	1.69	1.34	1.42			
	(0.54)	(0.09)	(0.19)			
Subsidy	0.88	0.48	-1.52	6.21		
	(0.26)	(0.16)	(0.11)	(0.12)		
Daycare	0.06	0.61	0.02	1.03	0.33	
	(0.25)	(0.05)	(0.07)	(0.11)	(0.03)	
Premium	0.20	-0.03	-0.04	0.06	-0.001	0.03
	(0.20)	(0.32)	(0.14)	(0.44)	(0.13)	(0.03)

Note: The number in the parentheses are the standard errors, calculated using 5,000 draws.