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Estimating demand for long-term care insurance in Thailand: evidence from a discrete choice experiment

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Abstract

At present, the Thai public health insurance schemes cover medical care. However, the financial risk associated with long-term care needs is unprotected. The increasing likelihood of Thai elderly living longer and living alone has raised great concern about their quality of life. In the wake of the declining informal support capacity, a public long-term care insurance (LTCI) system has been considered as a potential alternative. Because the public will have to contribute to the LTCI fund, this paper explores whether the Thai people are willing to pay for such a provision. The LTCI demand is estimated based on the stated preference survey data. Our results show that most respondents are willing to pay to insure against their risk associated with long-term care expenditure, but their preferences are very heterogeneous. Gains and losses for different policy scenarios, measured by consumer surplus, are discussed.

Keywords: long-term care insurance, discrete choice experiment, discrete choice model, unobserved heterogeneity, demand for LTCI, willingness to pay
JEL classification: I13, I18, I31, J58, C35, C90

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I. Introduction

When the Netherlands established a long-term care insurance (LTCI) system in 1968 (Schut and Van den Berg, 2012), approximately 10% of the country's population were aged 65 years old and older (United Nations, 2017). Many Organization for Economic Co-operation and Development (OECD) countries established their LTCI systems approximately 25 years after the Netherlands. The proportions of the older population in the OECD countries when they established their LTCI systems were between 10% and 17%.

Thailand is among the countries with the largest aging population in Asia. The proportions of the Thai population aged 65 years old or older are projected to increase from 11% in 2015 to 19% in 2030 (United Nations, 2017). The older population in Thailand is universally covered by public health insurance schemes. Hospitalization and outpatient care services are free. Home-based care expenses, however, are not covered. The current provision of LTC is mostly informal, with less than 5% of elderly with LTC needs having paid caregivers (Chandoevwit et al., 2018). The country's filial piety culture, together with the limited number of public LTC facilities and costly private nursing homes, contribute to this pattern.

The difficulty of providing adequate LTC looms on the horizon. Life expectancy has increased. Women, the main caregivers, have obtained higher education and participated more in the labor market. The total fertility rate and family size have been declining (Chandeovwit et al., 2016). All of these demographic and social transitions imply that the declining informal care supply is unlikely to keep up with the growing LTC demand.

Recently, the Thai government has made more efforts to support community-based care services. Public funds have been allocated to local authorities. Yet, concerns remain regarding whether these supports are adequate because communities' management skills and local resources vary to a large extent. In addition, funded programs tend to focus on health-related care services and health education rather than personal care for daily living. Reports continue to circulate that many elderly with functional problems reside alone, and some stay in a public hospital for a longer-than-necessary period.

A public LTCI has been brought to the Thai policymakers' attention because this policy could improve the quality of life of the older population and their family members. Although there has been an ongoing debate on the benefit of providing LTCI, no studies have investigated public demand and preference for such a provision. This is important because the public must contribute to the LTCI fund. In this paper, we study whether and how much the Thai people are willing to pay to insure against their financial risk associated with the LTC and what kind of LTCI packages they want. The result will also inform policymakers regarding whether the current LTC provision is sufficient.

Today, the LTCI barely exists in the market; thus, we designed a national representative survey and collected stated preference data using a discrete choice experiment. This technique is widely used to study the demand for new products in several fields. Based on flexible choice models, our results show that most of the respondents are willing to pay for public LTCI, but their preferences are very heterogeneous. Although some respondents prefer a basic package with a low premium, many respondents are willing to pay more for higher coverage. We also provide discussions about the pros and cons of implementing universal and multi-tier LTCI policies and estimate the distributions of consumer surplus for several policy options.

The paper proceeds as follows. Section II provides a background of the Thai healthcare system and related literature. Section III discusses the discrete choice experiment. Sections IV and V present the details about the sample and empirical models. Section VI presents the results, and Section VII provides conclusions and discussion.

II. Background and related literature

Approximately 98% of Thai citizens are covered by one of three public health insurance schemes. The Universal Coverage Scheme (UCS) covers most of the population. Civil servants and their dependents are covered by the Civil Servant Medical Benefit Scheme (CSMBS). Employees in the formal sector are covered by the Social Security Scheme. Although these schemes cover medical care services, home-based care expenses such as a wheelchair, an adjustable bed, disposable diapers, or a caregiver's salary is mainly paid out-of-pocket; the exception is that some CSMBS patients receive wheelchair based on need. Forgone wages or interrupted careers of informal caregivers are also significant LTC costs (see e.g., Langa et al., 2001), but are usually not considered.

Although several age-related illnesses require medical treatment, most elderly only develop functional problems that require ongoing personal care assistance. Figure 1 shows the estimates of the proportions of Thai elderly with two levels of limitations derived from their activities of daily living (ADL) scores, a Thai version of Barthel 0–20 index score (Ministry of

Public Health, 2015). In this version, "Housebound" refers to individuals who can carry out some self-care tasks at home but could not go outside without assistance (an index score between 5 and 11). "Bedridden" refers to individuals being confined to their beds and requiring a higher level of care (an index score between 1 and 4).

The Thai government has been concerned about the well-being of the older population for more than two decades, and has developed the National Plan on the Elderly. The key strategy is to gradually decentralize the primary healthcare provision to the sub-district (Tambon) level. Since 2011, a small part of the UCS's budget has been allocated to the "Tambon Health Fund" to promote communities' well-being. The fund supports each sub-district's primary care center, training volunteers who perform home visits and programs encouraging preventive cares. These programs, nonetheless, focus on health-related care services (e.g., monitoring blood pressure and sugar levels) rather than assisting with personal care services (e.g., eating and bathing). Private foundations, charitable nongovernmental organizations, temples, and village volunteers also play roles in providing LTC.[1]

Although the UCS planned to include LTC services at some point (Chunharas and Boonthamchareon, 2003), a concrete LTC provision has not been implemented. Another small reallocation of the fund occurred in 2016, where 1,000 pilot sub-districts could receive an additional THB 5,000 (USD 150) per year per elderly individual that needed care (National Health Security Office, 2017). The added fund, however, was small compared with the estimated private cost of LTC at THB 120,000–230,000 per year (Chandoevwit et al., 2018).

Although Thai insurance companies are legally allowed to offer LTCI policies, no pure private LTCI is bought and sold in the market.[2] Even in the countries where LTCI products clearly exist, the market for private LTCIs is very thin. Pauly (1990) conjectured that the elderly may prefer to be cared for by their children; hence, these parents strategically choose not to buy LTCI. Brown and Finkelstein (2011) asserted that public provision of LTCI crowded out the private demand. Other explanations for the absence of LTCI demand have included insufficient knowledge about LTCI coverage (Bacon et al., 1989; Pauly, 1990), underestimation of the risk of LTC needs (Cremer and Roeder, 2013), and the absence of experience with LTC (Coe et al., 2015).

[1] The Tambon Health Fund started in 2006 and expanded nationwide in 2011. Thailand also provides tax incentives for children who purchase health insurance for their parents. Thai citizens aged 60 or over without a government pension are eligible for monthly subsistence allowance of THB 600–1,000.

[2] One existing product offers LTC coverage for chronic patients after being discharged, but this is rare.

Recent research has also studied the benefits of LTCI beyond protecting the elderly's financial risks. Fu et al. (2017) found that the public LTCI in Japan has a positive spillover effect on employment. Having more support from the government allows family member caregivers to increase their labor supply in the formal labor market. For Spain, Costa-Font et al. (2018) found that a more generous LTCI helps reduce the number of hospital admissions and patients' length of stay. Similarly, Holland et al. (2014) and Kim and Lim (2015) found that LTCI could reduce medical care expenditure among the dependent elderly.

III. Discrete choice experiment

When the products of interest rarely exist in the market, estimating demand using actual purchase (revealed preference) data is not plausible. A discrete choice experiment (DCE), a stated preference technique, has proven to be a successful alternative to study the demand for new products in several fields. This includes transportation, marketing, environmental and health economics (Fiebig et al., 2010; Lancsar et al., 2017; Louviere et al., 2000; Propper, 1995). For LTCI, Brau and Lippi Bruni (2008) and Nieboer et al. (2010) have used DCE to elicit public preference for insurance packages in Italy and the Netherlands, respectively.

In a DCE survey, respondents are presented with a sequence of hypothetical choice scenarios and asked to state their most preferred choice. For stated preference data to be reliable, the scenario presented to the respondents should be plausible and product attributes should be relevant. For our study, we conducted three focus groups to determine what type of LTCI services should be provided to fulfill the needs and acceptable quality of care. The first group was a discussion with doctors and nurses who care for elderly patients. The other two groups were discussions with volunteer caregivers and a sample of the population aged between 20 and 75 years.

The final five attributes (Table 1) used in the experiment are (i) whether LTCI provides home care products and assisted devices such as wheelchairs and disposable diapers (Material); (ii) whether there will be a regular visit from a care manager (CM_Visit); (iii) the level of caregiver cost-sharing from the government (Subsidy); (iv) whether an elderly daycare is available (Daycare), that is, an analogue to respite care or childcare where an elderly person can socialize with other elderly people at the daycare facility and the caregiver can take a day off; and (v) the annual premium (Premium).

To avoid asking the respondents to process too much information, we constructed three alternative-choice sets with two hypothetical LTCI options and a status quo. Based on the Defficient design (Carlsson and Martinsson, 2003), we obtained 16 LTCI pairs from the 96 possible attribute-level combinations (2x2x3x2x4). The 16 scenarios were divided into two blocks, and each block comprised eight choice sets. One block was randomly selected for each respondent.

Before the respondents chose their preferred LTCI option, they were provided information about the aging population, the likely cost of home care for housebound and bedridden elderly,[3] the concept of LTCI, and the attributes of LTCI. The information was presented in a 5.5-minute video clip. The respondents were also informed that the public LTCI intends to collect annual premium from the population aged 40–65 years, and the program will support the eligible population aged 60 years or older. Table 2 shows an example of a choice set in the survey.

III. Data

The sample included respondents from all five regions of Thailand. For the Bangkok and vicinity region, three provinces were selected: Bangkok, Nonthaburi, and Samut Prakarn. For the other four regions, two provinces were selected for each region: Chiang Mai and Nakhonsawan from the North; Khon Kaen and Mukdaharn from the Northeast; Kanchanaburi and Chainat from the Central; and Surat Thani and Pattalung from the South.

For each province, its population was stratified by districts and official enumeration areas. Households in the selected areas were randomly drawn, and one member aged 25 to 60 years that had lived in that house for at least 3 months was interviewed. The data was collected from October–December 2017. The duration of the interview was 20 minutes.

Due to some missing information, the final number of observations was 16,038 (2019 respondents x 8 choice scenarios from the DCE). The summary statistics of the sample is reported in the first column of Table 3: 68% were female, 48% were older than 45 years old, 43% had a primary education, and 48% worked in the service sector. Average annual household consumption per capita was THB 72,373 (approximately USD 2,200).[4] Only 4.2% of the households had elderly who needed assistance with ADL, and only three respondents (0.15%)

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[3] These terms, as defined earlier, are commonly used among the Thai official health personnel (Ministry of Public Health, 2015).

[4] Household consumption is used to proxy household's economic status because income tends to be under-reported in a household survey, especially in a country with a large informal economy (Deaton, 1997). In our survey, we asked about 18 types of consumption and then aggregated them. Homemade and unpurchased food consumption were monetized and included.

paid for formal caregivers. The second column of Table 3 shows the distribution of population aged 25–60 years, as derived from the National Statistical Office's Socio-Economic Survey in 2015. Males and manufacturing workers were under represented in our sample.

IV. Empirical specification

Discrete choice models

Our empirical model is based on the random utility model (RUM) of McFadden (1974). In this framework, the utility function of individual *n* deriving from choosing alternative *j* in choice set *t*, U_{njt}, can be specified as

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

where X_{njt} is the vector of choice attributes; β_n is the vector of utility weight individual *n*; and ε_{njt} is the idiosyncratic (random) component. In our context, X_{njt} includes a dummy variable (*dLTCI*) indicating whether the option is an LTCI or the status quo (no LTCI) and the attributes described in Table 1. The coefficient of *dLTCI* is negative if individual *n* dislikes having LTCI, regardless of the coverage and the premium.

The probability that an individual *n* chooses alternative *j* in choice scenario *t* is the probability that *j* would provide the highest utility in that scenario:

$$\begin{aligned} P(y_{njt} = 1|X_{nt}) &= Prob\big(U_{njt} - U_{nit} > 0\big)\ \forall i \neq j \\ &= Prob\big((\beta_n X_{njt} + \varepsilon_{njt}) - (\beta_n X_{nit} + \varepsilon_{nit}) > 0\big)\ \forall i \neq j \\ &= Prob\big(\varepsilon_{nit} - \varepsilon_{njt} < \beta_n X_{njt} - \beta_n X_{nit}\big)\ \forall i \neq j\,. \end{aligned} \tag{2}$$

How researchers specify distributions of the coefficients β_n and the stochastic component ε_{njt} leads to different choice models. In the simplest case, the (conditional) multinomial logit model (MNL), McFadden (1974) assumes that consumers have homogeneous tastes for observed attributes, $\beta_n = \beta$, and ε_{njt}~ iid extreme value.

Although MNL is easy to estimate, it has two well-known limitations. First, MNL rules out persistent unobserved heterogeneity in taste. Second, the *iid* assumption leads to unrealistic substitution patterns. The coefficients of MNL can be allowed to vary systematically with observed characteristics (Z_n). For example, we can specify the coefficient of attribute *k* as $\beta_n^k = \beta_0^k + \alpha^k Z_n$. MNL, however, still assumes homogeneous tastes for individuals with the same Z_n.

Several alternative models that overcome the limitations of MNL have been proposed. The popular mixed logit model (McFadden and Train, 2000) extends MNL to allow for random coefficients on observed attributes but continues to assume that ε_{njt} is *iid* extreme value. The mixed logit model is often written as

$$U_{njt} = (\beta + \eta_n)X_{njt} + \varepsilon_{njt} \qquad \text{for } n = 1,\ldots,N;\ j = 1,\ldots,J; \text{ and } t=1,\ldots,T, \tag{3}$$

where β is the vector of mean attribute utility weights in the population, and η_n is the person n specific deviation from the mean. Although the distribution of η_n in principle can be anything, assuming normal or lognormal distributions is most common. If η_n is distributed as multivariate normal in the population, then we can write

$$\beta_n \sim MVN(\beta, \Sigma). \tag{4}$$

The choice probabilities *conditional* on β_n of the mixed logit model still have the logit form:

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

For the panel data, the probability that an individual n chooses a sequence of choices is the product of logit probabilities. Because β_n is unobserved, the *unconditional* choice probabilities are obtained by integrating over all possible values of β_n:

$$P(\{y_{njt}\}_{t=1}^{T} | X_n, \beta_n) = \int \left[\prod_t \prod_j \left(\frac{\exp(\beta_n X_{njt})}{\sum_{i=1}^{J} \exp(\beta_n X_{nit})} \right)^{y_{njt}} \right] f(\beta_n) d\beta_n. \tag{5}$$

One drawback of (4) is that it does not accommodate a multi-model taste distribution or does not capture respondents with a lexicographical preference. Another alternative is the latent class model (Kamakura and Russell, 1989), assuming that the underlying unobserved taste distribution is discrete. More recently, the generalized-MNL (Fiebig et al., 2010) and the mixture-of-normal mixed MNL models (MM-MNL; Burda et al., 2008; Train, 2008) are found to outperform the mixed logit and latent class models (Keane and Wasi, 2013). In this paper, we estimate MNL, mixed logit, and MM-MNL, the most flexible one.[5]

We can think of MM-MNL as an extension of mixed logit by replacing (4) with a discrete mixture-of-multivariate normals:

$$\beta_n \sim MVN(\beta_s, \Sigma_s) \text{ with probability } w_{n,s} \text{ for } s = 1,\ldots,S.$$

Note that if $w_{n,s} \to 0$ for all but one class, MM-MNL becomes mixed logit. If $\sum_s \to 0\ \forall s$, MM-MNL collapses to the latent class model. The MM-MNL choice probabilities are given by

[5] See Keane and Wasi (2016) and Geweke and Keane (1999).

$$P(\{y_{njt}\}_{t=1}^{T}|X_n, \beta_n) = \sum_{s=1}^{S} w_{n,s} \left\{ \int \left[\prod_t \prod_j \left(\frac{\exp(\beta_n x_{njt})}{\sum_{i=1}^{J} \exp(\beta_n x_{nit})} \right)^{y_{njt}} \right] f(\beta_{n|s}) d\beta_{n|s} \right\}, \qquad (6)$$

where $f(\beta_{n|s})$ refers to $MVN(\beta_s, \Sigma_s)$ Equations (5) and (6) are estimated by maximum simulated likelihood. For MM-MNL, the number of classes is unknown *a priori*, and the best model is chosen by the Bayes Information Criteria (BIC).

Demand and welfare implications

For continuous choices with no qualitative attribute, the minimum expenditure required to compensate consumers for a price change (compensating variation) is the area to the left of the compensated demand curve. Empirically, the compensated demand is often approximated by the Marshallian (uncompensated) demand, assuming that the considered goods are sufficiently unimportant, so that the income effect is small. Hence, the change in consumer surplus (CS) is often used to approximate the benefit.

For discrete choices, Small and Rosen (1981) demonstrated that the choice probability function under RUM can be considered the expected Marshallian demand curve of a certain alternative, and the change in CS from a change in qualitative attributes of a choice can be converted to monetary units as follows.[6]

For consumer *n* facing a choice situation with *J* alternatives, the change in CS when attributes of choice *i* change from X_i^0 to X_i^1 is given by

$$\Delta CS_n = -\frac{1}{\lambda_n} \int_{X_i^0}^{X_i^1} P(y_{ni} = 1 | X_1, X_2, \dots, X_J) dX_i \qquad (7)$$

where λ_n denotes marginal utility of income. In practice, λ_n is often approximated by the price coefficient. When the probability function is in the logit form, (7) can be expressed as

$$\Delta CS_n = -\frac{1}{\lambda_n} \left[ln \sum_j \exp(\beta_n X_j) \right]_{X_i^0}^{X_i^1}. \qquad (8)$$

The aforementioned formulas consider that the researcher is uncertain regarding which alternative the consumer would choose before and after the change. If the researcher knew with certainty that consumer *n* never chooses choice *i*, there would not be any change in the CS. By contrast, if the researcher knows that consumer *n* choosing choice *i* with the probability of one both before and after the change, then (8) becomes $\Delta CS_n = -\frac{1}{\lambda_n}\left(\beta_n X_i^1 - \beta_n X_i^0\right)$.

[6] Small and Rosen (1981) derived CS for the case of MNL model. The same concept can be applied to the mixed logit, latent class, and their extensions (see Small et al. (2005) and Hynes et al. (2008)).

If the change is from a single attribute k (changing by one unit) and λ_n is replaced by the price coefficient, we have the familiar formula of marginal willingness to pay (MWTP) for an incremental change in attribute k:

$$MWTP_{n,k} = -\frac{\beta_n^k}{\beta_n^p}\,. \tag{9}$$

β_n^k and β_n^p denote the utility weight person n places on attribute k and price, respectively. Lancsar and Savage (2004) discussed the use of (8) and (9) in health economics literature.

We adopt an "approximate Bayesian" approach when calculating posterior distributions of individual-specific coefficients, MWTP, demand, and CS. 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 choices (see Train (2003) Chapter 11 for details).

V. Empirical results

Coefficient and marginal willingness to pay estimates

We estimated several versions of consumer choice models. Selected results are reported in Table 4. The first model is the MNL model where we allow the coefficient of premium to vary across individual characteristics. The coefficients of all attributes have expected signs. Holding other things constant, on average, the respondents assign positive values to all types of coverage. Respondents aged 51–60 years, individuals with caregiving experience, individuals who reported they were unemployed, and low-income households appear more sensitive to a premium. The "low income" is proxied by being in the lowest quartile of household's per capita consumption.

Next, we estimated two versions of the mixed logit model. Both versions assume that β_n are distributed multivariate normal in the population with full variance–covariance matrix. Model 2 does not include any observed characteristics, but Model 3 includes the interaction between the observed characteristics and premium (mean-shifting). We find that both models fit much better than the MNL model. The model log-likelihood significantly improves from -14,267 to -10,772 (model 2), suggesting that unobserved heterogeneity is very important. Once we allow for unobserved heterogeneity, adding observed characteristics do not improve the model fit significantly. In fact, Model 2 is marginally preferred to Model 3 by BIC.[7] The

[7] Average in-sample correct choice predictions are .41, for MNL and .513, .514 for the two mixed logit models, respectively. Given the three choice situations, the random chance to predict correctly would be .33.

estimated standard deviations are statistically significant and quite large, except for that of daycare. The estimates of the variance–covariance matrices are presented in Appendix A.

Next, the MM-MNL with two, three, and four classes are estimated. The 3-class (Model 4) is preferred by BIC, and is also preferred to Model 2. Model 4 suggests three major classes of preferences, capturing 48%, 24%, and 28% of respondents, respectively. On average, the first class places similar weights on all attributes but prefers material the most. The second class is observed to be the least sensitive to price and extremely prefers a package with a high level of caregiver subsidy. Class 3 is similar to class 2 in the sense that it places a relatively high value on caregiver subsidy, but this class is more sensitive to price. Within each class, there also exists unobserved taste heterogeneity as the estimated standard deviations are quite large.

To further examine the preference heterogeneity, the posterior distributions of individual-specific coefficients are plotted in Figure 2. For most attributes, the distributions depart substantially from normality. Most respondents possess positive but heterogeneous utility weights for product attributes and a negative weight for premium. Because it is difficult to interpret the magnitude of the coefficients in a non-linear model, we will first present the MWTP estimates, a restricted but somewhat common welfare measure. Then, we will discuss the demand and CS estimates.

Figure 3 presents the estimated MWTP distributions for each attribute. These MWTP distributions are widely dispersed. Some exhibit multi-modal, and some have a very long tail. The last feature suggests that some consumers have an extreme preference for some attributes regardless of the premium. If we simply compare the median MWTPs, material and assisted devices rank first, followed by caregiver subsidy (50%) and care manager visit.

One explanation for this result is that material and assisted devices such as a wheelchair, an adjustable bed, and disposeable diapers are commonly needed to support housebound or bedridden elderly. The caregiver subsidy might be viewed as unnecessary for some households, especially households whose elderly members prefer to be assisted by their family members. The unpopularity of elderly daycare might be because the main benefit of the daycare availability is to reduce the burden of a caregiver, but most of our respondents do not have caregiving experience.

Notably, the extremely high figures of MWTP should not be interpreted as the true value because the premiums in the choice experiment range from only THB 300–2,000. Consumers who appear 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. In addition, the MWTPs demonstrate that preferences are heterogeneous, but they do not tell us what kind of LTCI packages will be demanded at a given price. Will a low premium LTCI policy that covers only material be in more demand than an expensive policy that provides multiple types of coverage? The next subsection answers this type of question.

Predicting demand and consumer surplus

Table 5 presents predicted market share (demand) estimates from five counterfactual experiments.[8] The first experiment starts with relatively low premium options. The first two options charge the annual premium THB 300 and provide a single attribute: either material or 25% subsidy. Option 3, charging THB 500, provides material and 25% subsidy. Option 4 also charges THB 500 and features material and care manager visit. In this experiment, option 4 is predicted to obtain the largest market share of 53% and the other three packages would receive a 15%–16% share each.

Given that consumers seem willing to pay more for higher coverage, in the second experiment, we add three more high-coverage high-premium options (options 5–7). In this situation, Option 7 (THB 2,000) and Option 4 (THB 500) are the two most preferred options, and their market shares are 25% and 22%, respectively. For options 1 and 2, the cheapest options with a single attribute coverage, have the least demand. The third experiment simply adds an opt-out option. Here, we estimate that approximately 10% of respondents would switch to the opt-out option if allowed to do so.

Because having seven options for a national LTCI system might be too many options to operate, the next two experiments drop the three unpopular options. In experiment 4, option 4 receives the largest share. This result is not surprising because option 4 is more similar to the options no longer available; thus, option 4 can be a substitute. The last experiment adds an opt-out option to experiment 4. Comparing the fifth to the third experiment, a slightly higher fraction of respondents (14%) would choose to opt out when a THB 300 option is not offered.

Table 6 further examines how the demand differs by the respondents' age and income by using demand estimates from experiment 5.[9] Now, we re-label options 4–7 as low-tier, medium-1-tier, medium-2-tier, and high-tier. While the general demand patterns are similar for

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[8] The demand for each LTCI option is calculated by first predicting individual's choice probabilities of choosing the available options and then aggregating across respondents.

[9] Although the observed characteristics do not significantly improve the model fit and are not included in the model, the demand estimates are at the individual level. Therefore, we can provide summary statistics by some observed characteristics.

all groups, it is noticeable that low-income consumers are more likely to choose to opt out. This result could reflect the respondents' inability to pay. Similar to Brau and Lippi Bruni (2008) and Costa-Font and Rovira-Forns (2008), we find that the young respondents are less likely to choose to opt out.

Although some studies had predicted that the young may underestimate their risk and have lower demand, possible explanations are as follows. First, some elderly might know that their children are able to take care of them; hence, they do not feel the need for LTCI. The young cohort could be uncertain about relying on their offspring because many of them have not started their family. Second, because our income cutoff is approximated, the old individuals may have lower actual income than the young individuals in the same category. Finally, the experiment stated that the government plans to collect the premium from the population aged 40–65 years. This result implies that if a public LTCI were launched, the respondents in this age range would have to pay now. The young may imagine that they would like to assess the operation of the LTCI first; if they do not like it, they can opt out in the future.

The next natural question is how should the government design LTCI packages to maximize welfare gain in the context of heterogeneous preferences? In a usual differentiated product setting, providing people with choices is likely to maximize welfare gains (see e.g., Small et al., 2005). In the health insurance context, however, extra costs can be associated with offering people choices. First, the adverse selection problem may lead to a non-sustainable insurance program (all the people in the low-risk category would choose to opt out). Second, consumers may be overwhelmed when offered too many choices (Ericson and Sydnor, 2017; Louviere et al., 2008). Finally, if low-income households opt out because they cannot pay, such an LTCI system could widen the inequalities in access to LTC services.

Although conducting a complete cost-benefit analysis across different implementation options is beyond the scope of this paper, we can examine the benefit side. Table 7 reports the estimated CS for several LTCI options. In the top panel, "uniform premium" refers to cases where everyone pays the same premium regardless of their income. Rows 1–4 evaluate CS if a compulsory universal LTCI program (either low, medium-1, medium-2, or high-tier, according to Table 6) is introduced. Among these four options, the low-tier yields the highest median CS[10] and has the lowest number of respondents with negative CS, which is the number of respondents who would prefer no LTCI rather than the available option(s).

[10] Although the high-tier has more consumers with negative CS, some consumers value this tier highly because its CS at the 75th percentile is higher than other universal options.

Row 5 is the case of a multiple-tier LTCI program where the individuals can choose from one of the four LTCI plans. As expected, its estimated CS is higher than any universal LTCI option because people can sort themselves to their preferred policies. Row 6 evaluates the case where an opt-out option is available. None has a negative CS here as those who do not like LTCI can choose to opt out.

Among all the schemes, the low-income group is estimated to gain smaller benefits and has a higher fraction of respondents with negative CS. However, this pattern might reflect their ability to pay rather than their preference. In the bottom of the panel, we then consider cases where the middle/high-income group would pay 20% more and the low-income group would pay 50% less from the premiums listed in Table 6. The results indicate that the middle/high-income group would gain slightly less but the low-income group would be much better off.

VI. Conclusions and discussion

Similar to many countries, the growing needs for long-term care services and the lower capacity of the informal support system have put more pressure on the Thai government to search for effective LTC policies. Many volunteer-based and local government programs have been initiated. As concerns about the sustainability of such programs have been increasing, a public LTCI system has been considered as a potential alternative. The implementation of such a provision, however, would require additional public funds that may come from premiums, co-payments, social contributions, or taxes.

This paper attempts to shed light on the public LTCI demand from the consumer perspective. Our results suggest that most people are willing to pay to insure against their LTC needs, implying that the current LTC supports are perceived as inadequate. Specifically, we find that 86% of respondents want a public LTCI system if the annual premium is between THB 500–2000. Their preferences, however, are very heterogeneous. Some respondents prefer a basic low-premium package and others are willing to pay more for a larger coverage. Successfully implementing a public LTCI is definitely not easy. Although more comprehensive research is required, we draw three policy implications from our results.

First, if a compulsory universal policy is to be implemented, the basic package (providing only materials, assisted devices, and care manager visits and charging THB 500) would minimize the number of consumers with negative CS. Implementing this option, however, implies that families and/or local communities must play key roles in ensuring that caregivers, formal or informal, are available and affordable when needed.

Second, because approximately two thirds of people are willing to pay more for higher coverage, making supplemental LTCI plans available can achieve higher aggregate benefits. This supplemental insurance can be offered at the national level, for example, like the Medicare Part B in the United States, or at the local government level, for example, like in Spain. The central government may provide grants to local governments for the universal basic package and let the local governments design the supplementary packages to fit the needs of their residents.

Third, low-income households would tend to opt out if they can because they cannot afford the premium. To mitigate this problem, Thailand may choose to combine different approaches used in other countries; contributions to the LTCI fund could be proportional to income (Japan, Belgium, and Germany); free access to LTC services could be means-tested (England and Canada); and only those with private LTCI would be allowed to opt out (Germany). Many countries also provide safety nets for low-income households to have access to LTC services.

Our paper is a first step to study LTCI demand in Thailand. Promising directions for further research include a more complete welfare analysis across policy options, especially regarding the cost side; a pilot LTCI experiment to confirm our finding with revealed preference data; and a large-scale study to explore whether the variation in community's LTC is an impetus for the difference in demand. Another crucial issue to consider in designing a public LTCI system is financial sustainability (Costa-Font et al., 2017). Deciding among different financing schemes, transfer methods, cost-sharing instruments, and eligibility criteria often involves a trade-off between efficiency and equity.

For instance, some researchers consider a pay-as-you-go scheme unfair because when a public LTCI system is introduced, some elderly with LTC needs would receive benefits without contributing to the LTC fund (Zuchandke et al., 2012). By contrast, a save-as-you-earn scheme implies that the current elderly would not receive the support. Similarly, measures that help alleviate the moral hazard problem (e.g., co-payment) or suppress the adverse selection (e.g., setting a minimum contribution period) imply that individuals who are poor and sick would have less access to care. The challenge for any government is how to strike the correct balance between efficiency, access, fairness, and quality of care.

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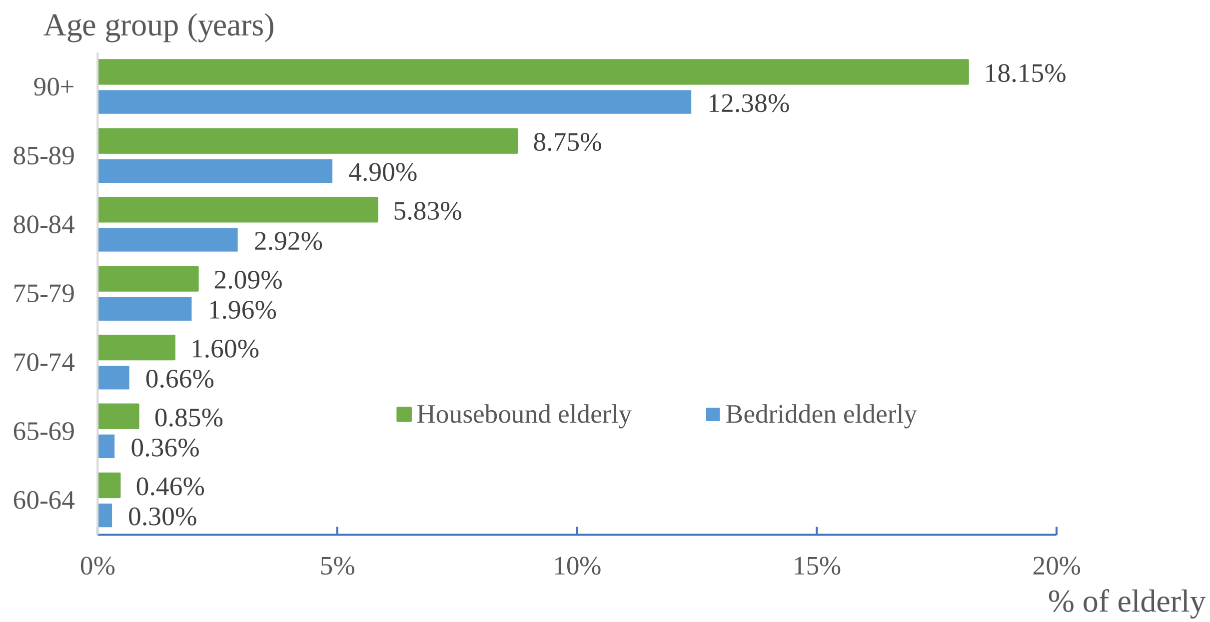
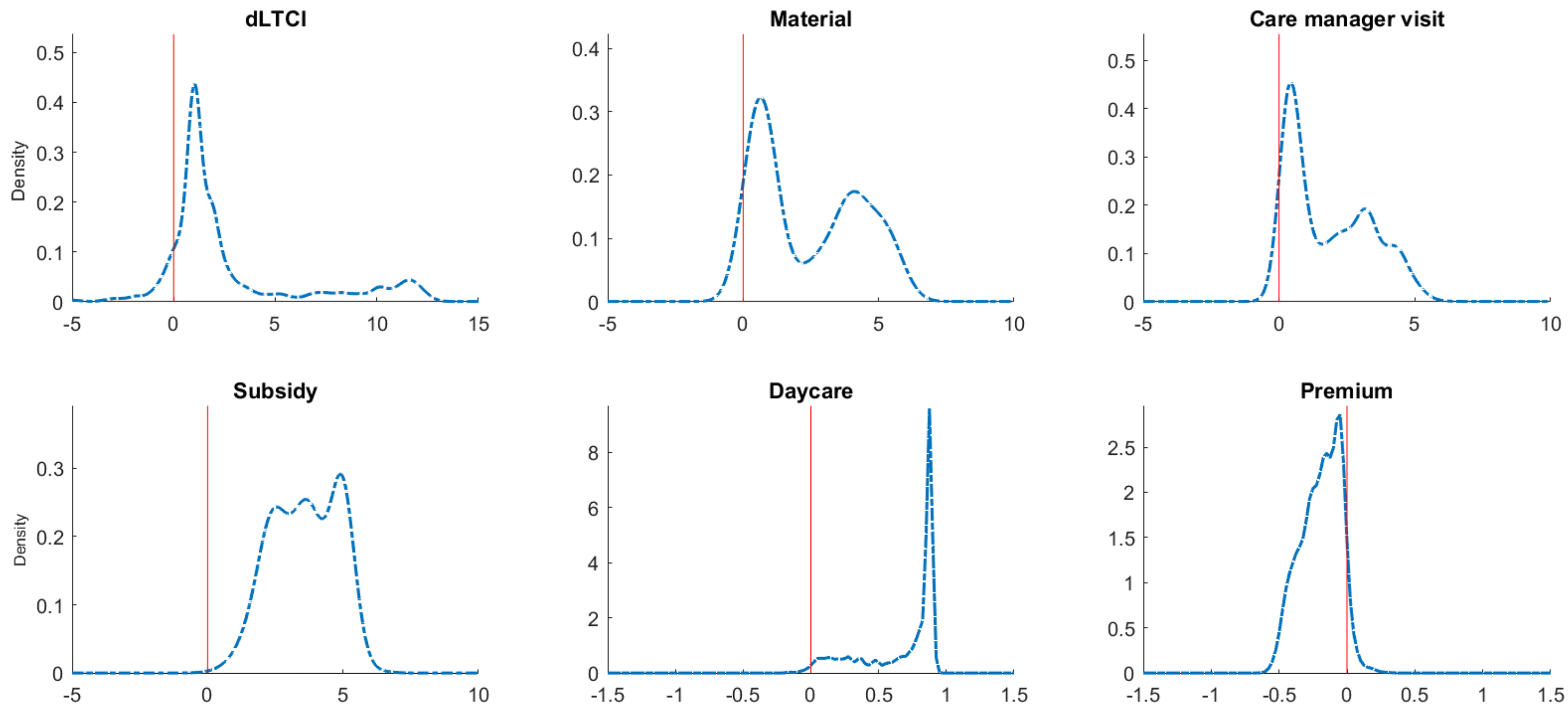
Figure 1: Estimated proportions of elderly with limitations of ADL by age



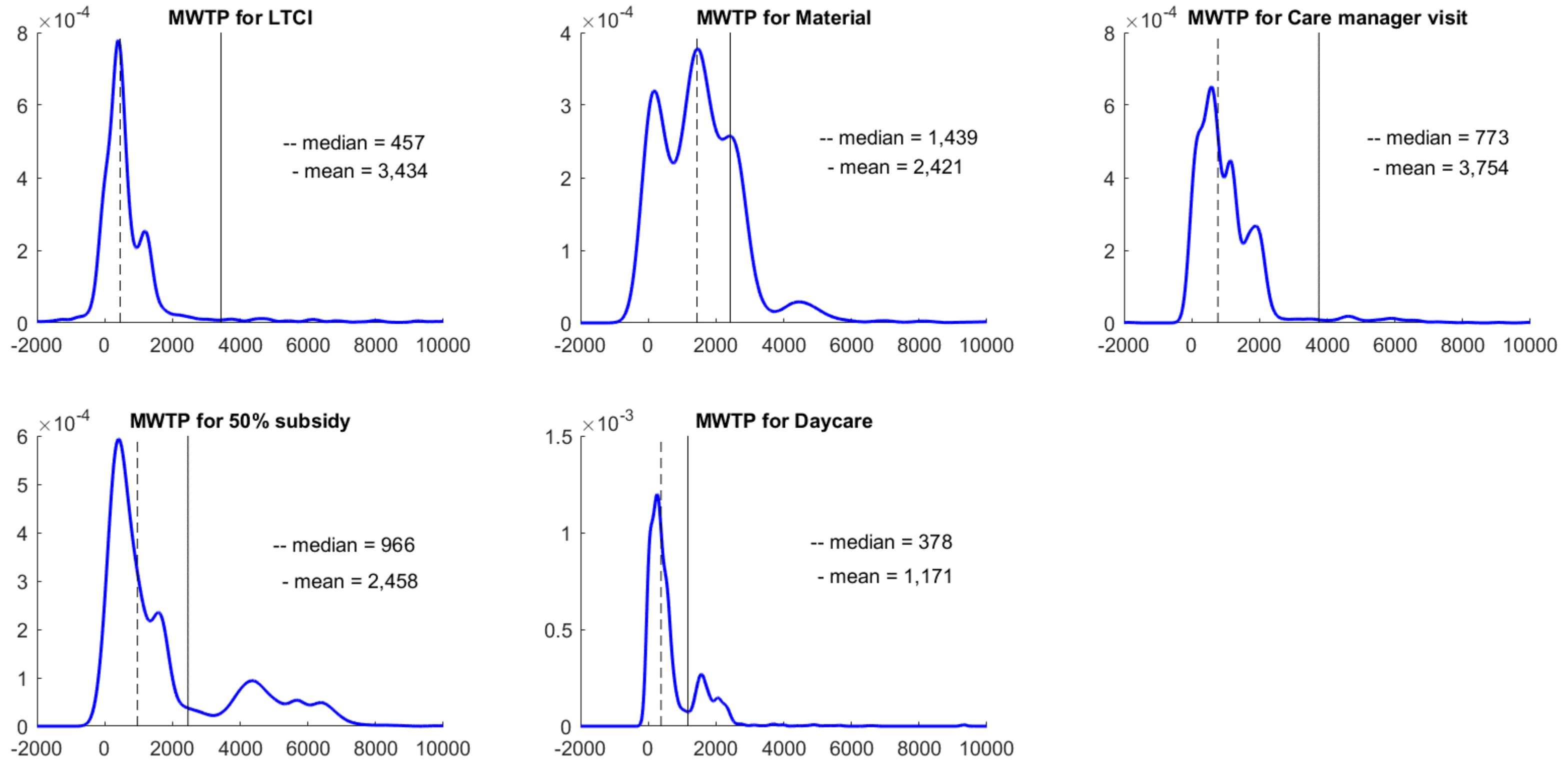
Source: Authors' calculations from the Thai Survey of Older Persons 2014 conducted by the National Statistical Office.

Figure 2: Posterior distributions of individual-specific coefficients from the MM-MNL model



Note: Each kernel density estimate uses a normal kernel. LTCI, material, care manager visit, and daycare are binary variables. The percent of caregiver subsidy is a continuous variable, ranging between 0 and 1. The premium is scaled down by a factor of 100.

Figure 3: MWTP distribution for each product attribute



Note: Each kernel density estimate uses a normal kernel. The caregiver subsidy is a continuous variable in the model. The MWTP distribution plot is MWTP for a 50% subsidy.

Table 1: The attributes and levels of the LTC policy

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 shares some percentage of the caregiver cost (Subsidy)	0 / 25% / 50%
d) Provide daycare service for the elderly (Daycare)	Yes / No
e) Annual premium (Premium)	THB300 / 500 / 1,000 / 2,000

Table 2: Example of a choice scenario used in the survey

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

Table 3: Sample characteristics compared with a national survey

Socio-economic characteristics	Sample (%)	National survey (%)
Gender		
Female	67.61	47.48
Male	32.39	52.52
Age		
25-35 years old	24.57	25.34
36-45 years old	27.39	29.78
46-60 years old	48.04	44.87
No children	20.95	n.a.
Education		
Primary or lower	43.09	50.07
Lower secondary	16.30	14.4
Upper secondary	16.99	11.72
Diploma / vocational	5.40	3.66
University degree	18.23	20.15
Sector of employment		
No job	10.20	11.37
Agriculture	36.80	28.33
Manufacturing	5.40	21.02
Services	47.60	39.27
Live in urban area	53.74	47.8
With caregiving experience	19.27	n.a.
Expecting good health in the future	4.36	n.a.
Household with dependent elderly	4.16	n.a.
Annual consumption per capita	THB 72,373 (USD 2,113)	THB 88,488 (USD 2,583)
Annual consumption per capita (0-25 percentile)	THB 27,546	THB 33,019
Annual consumption per capita (26-100 percentile)	THB 87,323	THB 105,184
Household size	3.87	3.09
No. of sample	2,019	36,005

Table 4: Coefficient estimates from selected models

		Model 1 MNL		Model 2 mixed logit I		Model 3 mixed logit II		Model 4 (MM-MNL) class 1		class 2		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		28,699		21,826		21,882		**21,392**					

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 5: LTCI demand estimates from 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 25-35					
Middle/high income	32%	17%	19%	25%	7%
Low income	26%	14%	18%	23%	19%
Age 36-45					
Middle/high income	32%	17%	18%	23%	9%
Low income	24%	15%	19%	26%	15%
Age 46-60					
Middle/high income	30%	16%	18%	24%	13%
Low income	24%	12%	15%	20%	29%

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) assess 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 LTCI where people can choose among four policy options.

Appendix A.

Estimates of variance–covariance matrix elements of mixed logit models

Table A1: Estimates of variance–covariance matrix of mixed logit model (Model 2)

	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)

Table A2: Estimates of variance–covariance matrix of mixed logit model (Model 3)

	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.