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On potential information asymmetries in long-term care insurance: A simulation study using data from Switzerland

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ABSTRACT

The long-term care insurance (LTCI) market in Switzerland is still in a very early development stage. In this work, we make use of a representative sample of the Swiss population to simulate the likely effects of previously discovered information asymmetries in the LTCI market. By resorting to LTCI preferences of potential customers, and using Monte Carlo simulations, we provide estimations of the expected probability and duration of dependence indicators. Thereby, we compare the frequency and severity of the sub-population that has shown interest in LTCI with the rest in different mortality scenarios. While in the Swiss demographic context, individuals have a high probability to experience loss of autonomy in their lifetime, we do not find evidence to believe that those interested in LTCI coverage are so based on privileged information about them being at greater risk. In fact, we discover that most people are not aware of their own risk to lose autonomy, which makes potential adverse selection in the LTCI market rather difficult.

1. Introduction

While the proportion of older adults in most populations grows rapidly, demographic change is "poised to become one of the most significant social transformations of the twenty-first century" (United Nations, 2021). Between 2017 and 2050, the number of people aged 80+ years is expected to more than triple, from 137 to 425 million (United Nations, 2017). This is critical as this age group is vulnerable to experience long-term dependence, i.e., they are more likely to lose their capacity to independently perform activities of daily living such as getting dressed, getting up, sitting or lying down, eating, using the toilet, or walking, among others. Given the uncertainty on the evolution of healthy life expectancy, the consequences on the frequency and severity of long-term dependence are more difficult to quantify. However, the demand for long-term care (LTC) services required by older adults who lose their autonomy is likely to increase, and costs for health and LTC spending are projected to rise (Actuarial Association of Europe, 2019). While some researchers claim that extended lifetimes come along with shorter times in dependence (Fries, 1989, 2005), others claim that this duration remains the same (Fuino and Wagner, 2020), or that it will increase (Kramer, 1980; Olshansky et al., 1990; Gruenberg, 2005). This lack of understanding often prevents LTC from receiving proper attention, although its evolution represents a financial threat to governments and citizens alike (Colombo et al., 2011; Kaye et al., 2010). Further, most individuals consider losing their autonomy as an unlikely event, even though losing autonomy becomes more likely as people get older and gradually lose physical abilities (Mayhew, 2000; Fuino and Wagner, 2018; Federal Statistical Office, 2020).

In this paper, we investigate the role that adverse selection and information asymmetries can have in the development of the Swiss long-term care insurance (LTCI) market. Fuino et al. (2022) estimate that only around 40% of individuals aged 40 to 65 years would be interested in purchasing an LTCI policy in Switzerland. Moreover, they point out that individuals with interest in such a purchase have in common three main characteristics, they tend to better understand the way how LTCI works, they tend to better understand the costs linked to dependence, and they show a higher level of concern about their own future dependence, which is linked to a higher self-perceived probability to lose autonomy in the future. These findings hint important information asymmetries in potential LTCI contracts as the three identified drivers are not easily observed by the insurer. Further, adverse selection could play a role in the market since it is well known that "small amounts of

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imperfect information could have a significant effect on competitive markets" (Rothschild and Stiglitz, 1976). While most insurance lines count on an established insurance market with comprehensive historical information to compute premiums (Adams et al., 2015), such information is not available for private LTCI in Switzerland, since very few policies have been offered. Merely relying on general knowledge about adverse selection is problematic as coverage-risk correlation has been found "in some markets, but not for others, and for some pools of insurance in a given market, but not for others" (Cohen and Siegelman, 2010). Even when one finds evidence for groups of people buying insurance based on privileged private information, such information asymmetries do not necessarily signal a problem of overall adverse selection. For example, Finkelstein and McGarry (2006) find that, in the US LTCI market, two types of policyholders can be identified,"those with private information that they are high risk", and those who buy insurance based on "psychologically cautious tempers". Other studies suggest that another type of policyholders exists, namely, those that buy LTCI based on knowledge and experience of family members (Coe et al., 2015). This information, unobservable by the insurer, plays an important role in the market as bringing different subgroups of policyholders together may end up balancing individual effects in a pool of contracts (Cohen and Siegelman, 2010).

For our analysis, based on a Swiss population sample, we simulate the characteristics of an insurance portfolio to assess the effects of potential information asymmetries. This can help insurers better understand if potential LTCI clients are expected to be a greater risk than those not interested in LTCI, which allows to comprehend whether or not insured pools of risk are likely to be balanced in terms of risk. To operationalize our research, we build on recent data regarding LTCI interest (Fuino et al., 2022), probabilities to lose autonomy (Fuino and Wagner, 2018), and expected duration in dependence in Switzerland (Fuino and Wagner, 2020). We complement that information with new results on the individuals' preferred age of LTCI purchase, and cover selection. We develop a Monte Carlo simulation model to evaluate expected key indicators on the frequency and severity of dependence. Comparing the results of the simulated LTCI portfolio (insured population) and the others, we study potential differences in terms of risks. Our main results indicate that the expected probability to lose autonomy in a lifetime is estimated at about 60% in both population groups. We also document, for the first time, that there is a very low chance of adverse selection in the market, at least at an initial stage, as individuals themselves tend to underestimate their own risk level of losing autonomy.

The remainder of the paper is structured as follows: In Section 2 we describe the methodology of the paper, lay out the idea and the main aspects of the model, incorporating insurance take up and dependence probabilities. Section 3 highlights the partial models that explain the phenomena involved in the simulation, and in Section 4, we present and discuss the main results from the Monte Carlo simulation. We start by displaying our results for the overall population to show later how results are expected to change as mortality prospects vary. We then quantify the potential differences when considering two populations, the (potential) insureds and the rest. We conclude in Section 5.

2. Outline of the methodology

To assess differences between the potential LTCI customers and the remaining population, we numerically simulate individuals' course of life.[1] We start with a population sample from Switzerland for which we have access to personal information including demographic, socioeconomic, health and behavior, LTC literacy and political factors to fill the parameter values in our modeling. Indeed, we rely on the survey population described by Fuino et al. (2022) and the characteristics summarized in the Appendix (see Table 7). The sample comprises 1 066 individuals, males and females, aged between 40 and 65 years, living in the German- and French-speaking regions of Switzerland.[2]

We first use a model to determine for each individual if he or she buys LTCI. Therefore, we use individuals' characteristics and preferences identified as key drivers for LTCI interest by Fuino et al. (2022) (see also Section 3.1). Their findings provide a framework to split the initial population sample in (potential) insurance buyers and the rest. If a person buys LTCI, we evaluate the age at purchase (see Section 3.2) and the level of insurance protection that is bought (see Section 3.3). Individual preferences regarding the level of benefits to be paid out in case of dependence let us differentiate the insurance takers into two groups which we assume to buy either "low" or "high" coverage.

With the individuals growing older, we determine every year if they survive using a mortality model. We fit a dynamic mortality model for Switzerland in the form of a Lee-Miller model (see Section 3.4). At each age, given the individual survives, we stochastically assess the potential LTC dependence (see Section 3.5) based on the probabilities of losing autonomy in the Swiss population reported by Fuino and Wagner (2018). Note that, by doing this, we only conclude that the person has been affected by dependence. Whether or not an event leads to an insurance payment (if insured) would depend on policy design, which we don't speculate about as we are interested in assessing overall risk profiles only. The probabilities of losing autonomy consider three different frailty levels. For each initial level of dependence and by age, the time individuals' stay in dependence before death is modeled by Fuino and Wagner (2020). We report their setup in Section 3.6.

In Fig. 1, we display an outline of the simulation models. Since LTCI and dependence are in our focus, we consider a time horizon long enough to see the evolution of dependence of the population at risk. Thus, we set the time horizon for the simulation to 60 years.

3. Models and implementation

Following the outline of Fig. 1, we introduce the different models that appear in our simulation. Since the model outcomes are probabilistic, we run 3 000 Monte Carlo simulations to sketch the life course of each person in the population sample. The relevant outcomes are:

- buying or not buying an LTCI contract (Fuino et al., 2022),
- age of LTCI purchase,
- level of LTCI protection,
- mortality or survival in each year,
- loss of autonomy given survival and initial frailty level (Fuino and Wagner, 2018),
- duration of LTC dependence until death, given loss of autonomy (Fuino and Wagner, 2020).

[1] These simulations do not take a specific perspective of the insurer or the customer. In addition, we do not perform calculations of assets or liabilities as our interest is to compare risk types only.

[2] Handled by a professional polling agency, the panel is balanced among males and females, has a homogeneous distribution of 40%, 40%, and 20% of the individuals in the age classes 40–49, 50–59, and 60–65 years, and is representative for the German- and French-speaking regions (67% and 33%, respectively). The limitation to individuals older than 40 years does not impede our research since typically LTCI policies target older persons that are aware of dependence issues, typically through their own parents having lost autonomy. The Italian- and the Romansh-speaking regions are left out since they correspond to only around 8 percent and less than 1 percent of the population, respectively. Given the size of the sample, these subpopulations would yield only a small number of answers with limited statistical power to draw inferences.

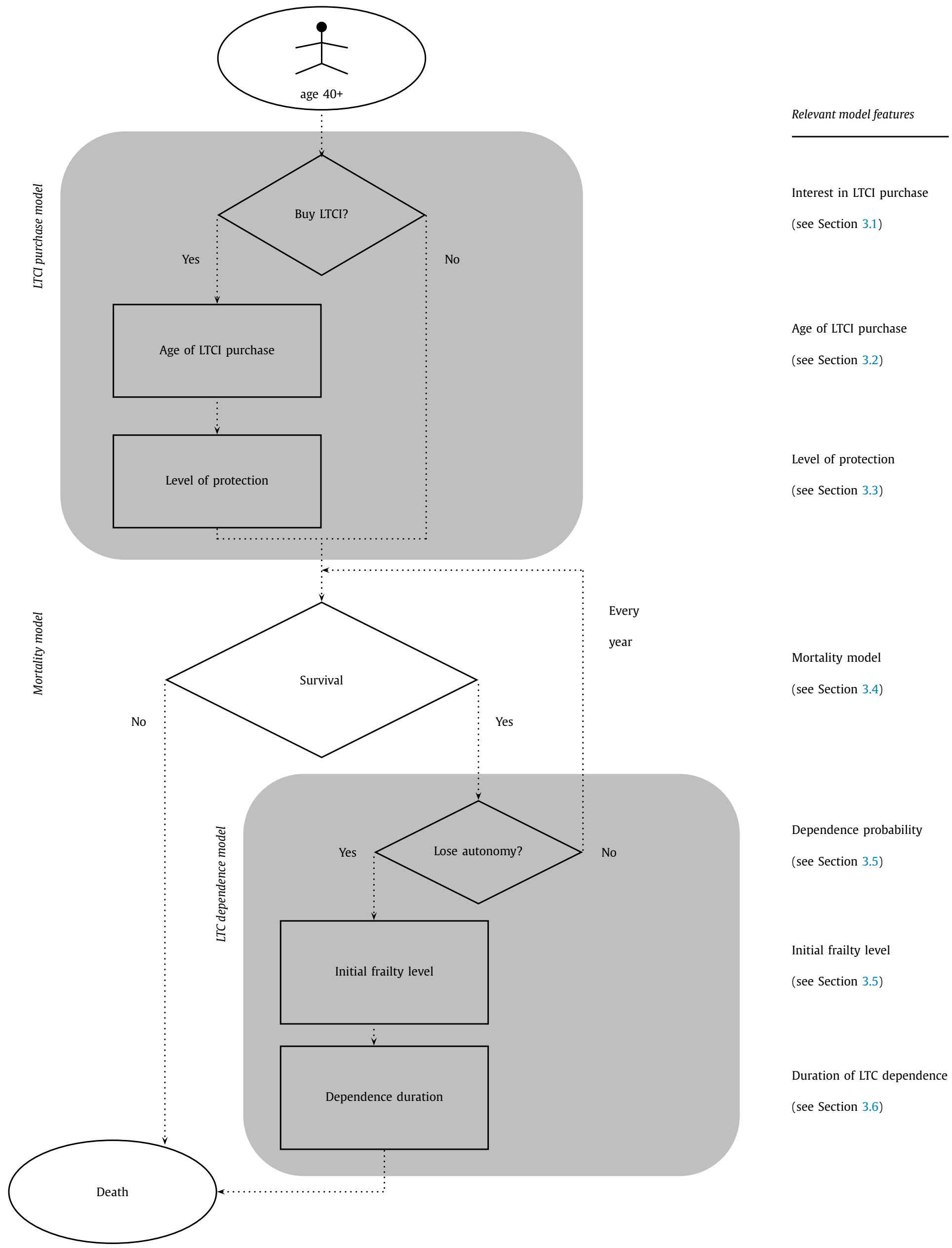


Fig. 1. Outline of the model setup for the Monte Carlo simulations.

Note that the first and the two last outcomes are based on existing models from the literature (see Sections 3.1, 3.5, and 3.6), while we develop the others in the present work (see Sections 3.2, 3.3, and 3.4, as well as the related sections in the Appendix). With these outcomes, we compute the indicators related to the frequency of events (e.g., insurance purchase, loss of autonomy). Regarding the severity, i.e. the duration of dependence, we use information coming from the simulation such as the age of dependence, and the initial level (mild, moderate or severe) as well as information directly taken from the dataset in accordance to the model described in Section 3.6. These results allow us to assess potential differences between subsamples using t-tests and the Wilcoxon test to conclude on hypotheses of the form

$$H_0 : \mu_{\mathrm{A}} = \mu_{\mathrm{B}},$$

$$H_1 : \mu_{\mathrm{A}} \neq \mu_{\mathrm{B}},$$

where μ_{A} and μ_{B} are the mean values of an indicator relating to two subsamples identified by the subscripts A and B. For the study of possible adverse selection in the market, we use the subscripts I and U to differentiate the insured from the uninsured subsample of individuals. Similarly, the subscripts L and H are used to differentiate the insured individuals with a preference for “low” and “high” levels of insurance cover, respectively. Further, $\mu = p$ denotes the mean frequency, i.e. the probability to lose autonomy, and $\mu = d$ the mean severity, i.e. the duration of dependence. If we find evidence to reject H_0, we perform additional analysis to decide whether the mean of one group is smaller than that of the other.

3.1. Interest in LTCI purchase

Fuino et al. (2022) identify a set of characteristics that drive the interest in buying LTCI in the Swiss population. The level of interest is surveyed through their Question F4 where participants are given information about how LTCI works, the cover it offers, the costs linked to dependence, and finally asked if they would be interested in buying insurance.

The most relevant characteristics explaining the responses are the individual's concern about future dependence, the understanding of the costs linked to LTC, and the understanding of how LTCI works. Other factors include the individual's self-perceived health state and their monthly income. Information on the model, the relevant factors, and the numerical results are available in Fuino et al. (2022, Equation 2 for the regression model, Table 4 for the included covariates, Tables 6 and 7 for the results). The available information from the survey data for both LTCI interested and not interested subgroups provides us with all the necessary details based on the responses of the participants residing in Switzerland. Thanks to the regression model, we are able to compute each person's probability to be interested, and make it available for our simulation model.

3.2. Age of LTCI purchase

Regarding the age of purchase, the same survey by Fuino et al. (2022) included the following question: *Imagine that, with a high probability, you will require professional help either at home or at a facility after having turned 80 years old. At what age would you start saving or buying a "care insurance"?* Participants answered this open question by typing a number, and we use their responses to construct the cumulative distribution for their age preference as shown in Fig. 5(a) in Appendix B. Because participants tended to answer in multiples of five, we smoothen the results by fitting a continuous distribution. The best fit corresponds to a log-normal distribution with parameters mean 3.924 and standard deviation 0.325 on the log scale (see Fig. 5b).

Since it is unrealistic to assume that individuals could buy LTCI at any age, it is necessary to make an assumption about the maximum age of purchase. In fact, insurers are likely to reject issuing a policy after a potential policyholder has reached a certain age, given the additional risk this may pose and the shorter period for distributing the total premium. We account for this in the simulations by assuming that a person can buy insurance up to a maximum age $x_{\max} = 65$ years. In our implementation, we simulate the age of insurance purchase by generating a random number, $r_{\log}$, coming from the log-normal distribution. Thereby, we ensure that individuals cannot purchase insurance at an age lower than their current age x nor at an age greater than the maximum age $x_{\max}$. In consequence, we define the age of beginning of the insurance contract as $x_I = \min(x_{\max}, \max(r_{\log}, x))$.

3.3. Level of protection

We are further interested in understanding what makes a person choose a certain level of LTCI coverage. In the survey by Fuino et al. (2022) different "insurance plans" are presented with fictitious choices of coverage in exchange of different premium levels. Two questions with the following parameters (the second question's parameters are in brackets) have been asked: *Imagine that you are 55 (44) years old. Among the insurance premiums and benefit payments below, which combination would you choose?*

- *Monthly premium of CHF 18 (11) giving the right to a monthly benefit of CHF 750;*
- *Monthly premium of CHF 36 (23) giving the right to a monthly benefit of CHF 1 500;*
- *Monthly premium of CHF 72 (45) giving the right to a monthly benefit of CHF 3 000;*
- *Monthly premium of CHF 108 (68) giving the right to a monthly benefit of CHF 4 500.*

With this setup, the idea that higher levels of protection, as well as purchasing a contract at an older age, come with higher premiums is reinforced. For each question we classify individuals as either wanting "low" cover (insuring less than half of the out-of-pocket payment of CHF 4 500 for institutional care as stated in Question F4, see Section 3.1) or "high" cover (insuring more than half of the expected losses). We fit multiple econometric models and retain a random forest model as final choice (see the Appendix C and Table 9 for details on the model selection).

Based on the retained model, we find that individuals' preferences for high or low LTCI cover can be well explained by their monthly income, age group, and beliefs about how costs would be split between them, private insurance participation, governmental subsidies, and the level of contact they have with their parents. In Table 10 in Appendix C, we display selected descriptive statistics and model results. On that basis, we estimate each individual's probability to choose a "high" cover level in a potential LTCI contract. We use this probability in the simulation to determine the expected level of protection bought (see Fig. 1).

3.4. Mortality model

We make use of a dynamic mortality model in the form of a Lee-Miller model, a variant of the Lee-Carter Method, viewed as standard and found to produce more accurate forecasts (Booth et al., 2005; Booth, 2006). We fit the model with information for Switzerland up to year 2018 from the Human Mortality Database (2021), and project the expected mortality patterns for the next 60 years, including upper and lower bounds for the expected mortality rates. Based on this analysis, we compute the survival probability for individuals at a given age in a given year. The probability is then used to assess future survival in our simulation. In Appendix D we provide more details on the method and on the results.

3.5. Dependence probability and initial frailty level

The probability to lose autonomy in the Swiss population has been studied by Fuino and Wagner (2018). Their results provide dependence probabilities by age and gender for individuals aged 65+ years. A graphical representation of the overall probability to lose autonomy, by age and gender, is provided in Fuino and Wagner (2018, Figure 3). The findings indicate that probabilities to lose autonomy are very similar and rather low for both males and females under an age of 80 years. However, the chances to lose autonomy steadily increase after 80 years, with females' probability to lose autonomy becoming much higher than men's at the more advanced ages. The original results also include information that allows to estimate the initial acuity level (when entering dependence) on the scale: mild, moderate, severe. In this work, we translate these probabilities by age and gender into the overall probability to lose independence in a lifetime. To achieve this, we simulate individual paths and, in case of loss of autonomy, we record the simulated initial frailty level.

3.6. Duration of LTC dependence

Once a person becomes dependent, we model how long the individual is expected to live in this condition. Fuino and Wagner (2020) study the duration of dependence in Switzerland through the regression model laid out in their Equation 2, and conclude that it is affected by factors such as the age at which the person loses autonomy, the gender, the language region, the acuity level at entry, and the type of care they require. We estimate the expected duration of LTC dependence by using their model and the coefficients reported in Fuino and Wagner (2020, Table 7).

4. Simulation results

We divide the results section into three parts: first, we display the results for the entire population, then we develop a sensitivity analysis on mortality to see how the results change under adjustments of mortality forecasts, and finally we report the indicators distinguishing the insurance portfolio from the rest.

4.1. Total population

The average simulated age of death in our sample (as of now referred to as the "simulated lifetime") is 85.25 years, which corresponds to 83.60 years in the case of males and 86.84 years for females. These figures are in line with projections by the Swiss government. For example, authorities estimate the life expectancy at the age of 50 to be 33.3 years for men (yielding an average age of death of 83.3 years) and 36.5 years for females (yielding a total of 86.5 years, Federal Statistical Office, 2020).

Under our assumptions, the average probability to lose autonomy in a lifetime is 61.15%. For the sake of comparison, in countries like the US, around 50% of the population over 65 years is estimated to require a "high level of assistance" with LTC services in their lifetime by Favreault et al. (2015), while others claim that dependence could potentially affect 7 out of 10 of these individuals (ACL, 2020; Long Term Care Poll, 2017). Such high chances to lose autonomy originate in the large probability of survival to advanced ages. At first, chances to lose autonomy seem rather low as discussed in Section 3.5. However, when growing old, individuals face an increasing chance to lose their autonomy that does not subside until death. This effect combined with high probabilities of surviving to ages 80+ results in a big share of individuals experiencing loss of autonomy, to some degree, before death. We observe important differences between the probability to lose autonomy in a lifetime of males and females: we estimate women's probability at 69.88% while men's reaches 52.13%. This important difference essentially stems from women living longer, thus implying higher chances to reach higher ages where the probability to lose autonomy is (much) higher. This high probability to lose autonomy for both sexes, and potential differences in the population, signal an urgent necessity to counteract the social consequences. This becomes particularly important as the pace of population aging accelerates (World Health Organization, 2018). Even if mortality does not improve substantially in the future, the probability to lose autonomy may remain high. For example, as depicted in Fig. 2, mortality improvements from model projections at the age of 80 years are much more modest when compared to the historical observations.

The median of the predicted probability to lose autonomy is estimated at 65.78%. We observe on Table 1 how the frequency (probability of dependence) and severity indicators (duration of dependence) are much higher for women. For instance, individuals are expected to live 3.77 years in dependence, which corresponds to 2.74 years in the case of males and 4.77 years for females. This is consistent with the Swiss Federal Statistical Office (2018) stating that a higher longevity of women "consists, for a significant portion, of years lived in poor health". ACL (2020) highlights similar results for the US.

We estimate the average age of loss of autonomy to be 82.54 years, with a difference of more than a year between males (81.96) and females (83.09). The results in Table 1 suggest that 75% of the cases of loss of autonomy are expected to occur before age 83.11. Naturally, we observe a decreasing trend in the time spent in dependence along the age at which autonomy is lost (see Fig. 3). For instance, when a person becomes dependent at the age of 66 years, help is required for an expected duration of 11.83 years. Conversely, when losing autonomy at the age of 80 years, the expected duration reduces to 6.52 years. To assess the amount of cases underlying these estimations, we also compute the share of the total dependence cases associated with each age of entry. This is depicted along the second vertical axis with numbers reported in gray color in Fig. 3. We find that individuals losing autonomy at ages below 70 years consistently represent less than 2% of the total cases. By the age of 80, this percentage grows to around 4% and continues to increase until the age of 85. Afterwards, numbers decrease rapidly, linked to the higher mortality. The population aged between 80 and 85 years is key when studying dependence since it combines both important absolute numbers and duration, leading to a large share of the overall LTC demand.

4.2. Mortality sensitivity

As discussed in Section 3.5 and shown in Fig. 3, dependence is a state linked to high ages, with strongest impact in the category 80+. It is thus reasonable to assume that a person's probability to lose autonomy in a lifetime is closely linked to their probability to reach these ages. In this sense, we now quantify the impact of changes in the mortality hypothesis. We extract lower and upper mortality bounds. This is done with the help of the `demography` package in R, where the plausible mortality scenarios are obtained by simulating the forecast log-mortality rates to then add "disturbances" to the basis scenario through the coefficients (see Booth et al., 2020 for details). Based on the projections, we compare the results obtained when adjusting mortality prospects. This allows us to quantify the impact of mortality changes on the dependence estimators.

On the one hand, we see that under the low mortality forecast, the simulated lifetime increases to 85.87 years (see Table 2), which represents an increment of 0.62 years with respect to the base scenario reported above. On the other hand, when considering the high mortality forecast, the simulated lifetime reaches only 84.56 years, i.e., a decrease of 0.69 years. The change in mortality entails a variation of the probability of losing autonomy of more than $\pm 3.5\%$. Hence, under the lower mortality scenario, this indicator goes up to 64.68% whereas its value goes down to 57.45% under the higher mortality assumption. We observe that the gender gap persists under both scenarios. Further, we find that, the lower the mortality prospect, the higher the age where individuals are expected to lose autonomy. Regarding the duration of dependence, older adults are expected to stay about four months longer in the low mortality scenario when compared to the high mortality scenario.

4.3. Insured vs uninsured population

As reported in Table 3, we estimate the probability of loss of autonomy for the insured and uninsured subsamples at 60.09% and 61.81%, respectively. However, population differences become more evident when looking at the median value. We find that the potential LTCI clients have a median probability to lose autonomy of 55.83% whereas those not seeking LTCI protection reach 66.83%. The differences in distributions are presented in Fig. 4(a). Moreover, the expected age of dependence for the insureds is predicted to be 82.46 years, whereas the estimation for the others is 82.58 (years). Finally, the expected duration of dependence is 3.65 years for the population interested in insurance and 3.85 years for the other. Here, the median duration is estimated to be 2.87 years for the ones seeking insurance coverage and 4.62 years for the others (see Fig. 4b).

Regarding the LTCI coverage preferences, we find that those choosing high levels of protection have a lower probability to lose autonomy in their lifetime (59.59% compared to 61.17%). The age

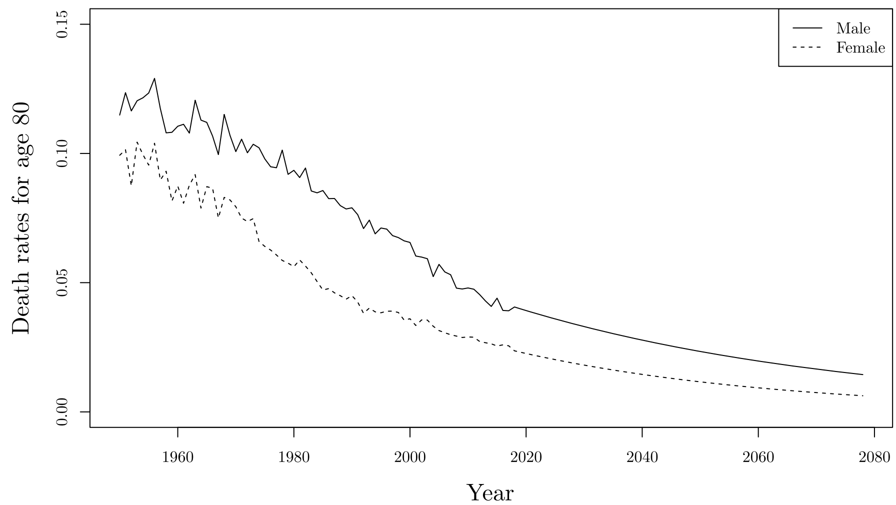


Fig. 2. Historical mortality and projections after 2018 at the age of 80 years.

Table 1
Simulated probability, age at entry and duration of dependence in the total population.

Indicator	Probability of dependence (%)	Age of dependence (years)	Duration of dependence (years)
Average	61.15	82.54	3.77
Range	47.53 – 74.47	80.84 – 83.77	2.48 – 5.12
First quantile	53.13	82.01	2.74
Median	65.78	82.57	4.54
Third quantile	69.96	83.11	4.77
Average men	52.13	81.96	2.74
Average women	69.88	83.09	4.77

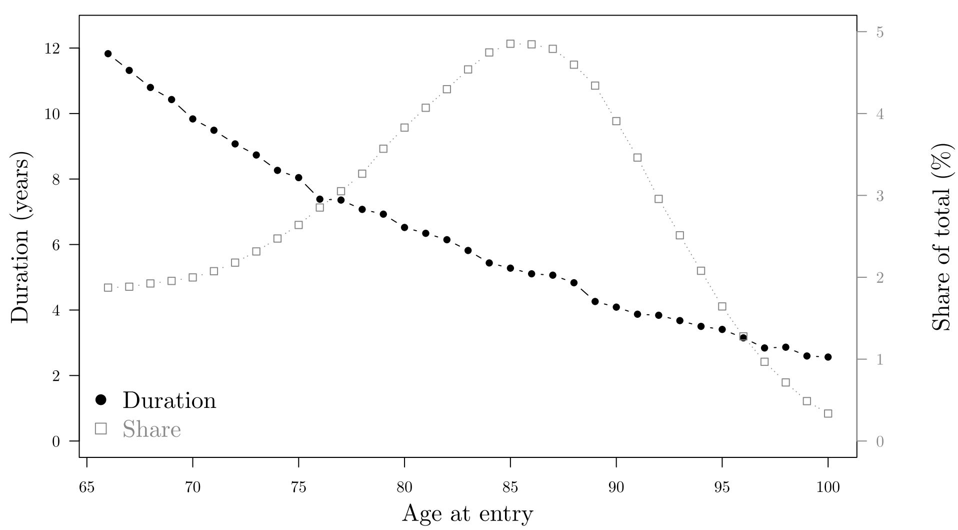
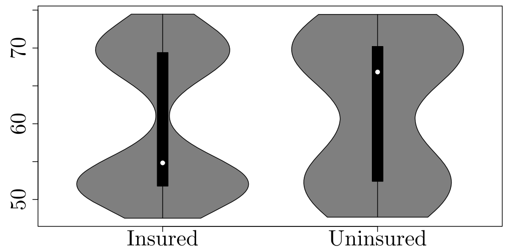


Fig. 3. Comparison of the duration of dependence and the share of dependent persons by age of entry in dependence.

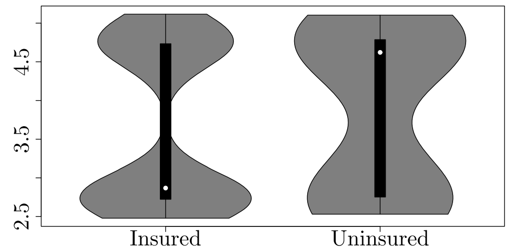
of loss of autonomy and the duration of dependence are both slightly lower for those choosing high coverage as shown in Table 4. We find that those policyholders who lose autonomy and are more likely to have chosen a higher coverage would fall in dependence at age 82.42 on average which compares to 82.54 for those with low LTCI coverage.

We further test whether or not the registered differences are statistically significant. For this we resort to both t-tests, which assume a normal distribution of the data, and Wilcoxon tests, which do not. We present our findings in Table 5. We start by testing the hypothesis that the means of the indicators are equal. We observe very low p-values under both tests when we compare the insured and uninsured population samples. The results lead, in fact, to reject the null hypothesis. However, we cannot reject the hypothesis that the means are different when comparing the LTCI coverage preferences in the population (low vs. high LTCI cover).

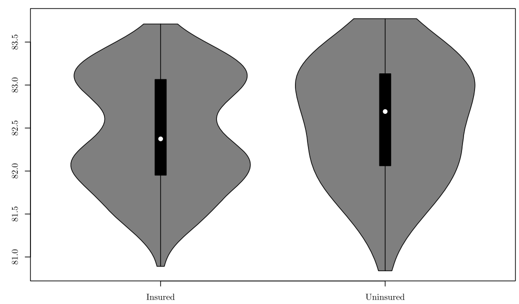
We now proceed to confirm that the insured come, in fact, from a population with a lower expected probability to lose autonomy and duration in dependence. To achieve this, we perform additional tests, this time including in the null hypothesis the respective inequality. The change made to the null hypothesis leads to p-values above 0.99, confirming that we find statistical evidence to conclude that the population interested in LTCI purchase can be



(a) Expected probability of dependence (in %).



(b) Expected duration of dependence (in years).



(c) Expected age of dependence (in years).

Fig. 4. Representation of indicators for the insured and uninsured subsamples.

Table 2
Comparison of average indicators under low and high mortality forecasts.

Indicator	Units	Low mortality	High mortality
Probability of dependence			
Overall	(%)	64.68	57.44
Range	(%)	50.37 – 78.57	44.83 – 70.17
Men	(%)	55.66	48.52
Women	(%)	73.39	66.07
Age of dependence			
Overall	(years)	82.92	82.12
Range	(years)	81.28 – 84.03	80.56 – 83.45
Men	(years)	84.44	81.46
Women	(years)	83.38	82.76
Duration of dependence			
Overall	(years)	3.93	3.61
Range	(years)	2.59 – 5.27	2.38 – 4.90
Men	(years)	2.87	2.60
Women	(years)	4.95	4.58
Simulated lifetime			
Overall	(years)	85.87	84.56
Range	(years)	83.63 – 88.20	82.23 – 86.81
Men	(years)	84.30	82.85
Women	(years)	87.38	86.21

Table 3
Comparison of indicators of interest between the population insured vs. population uninsured.

Indicator	Unit	Insured	Uninsured
Probability of dependence			
Mean	(%)	60.09	61.81
Range	(%)	47.53 – 74.47	47.67 – 74.43
Age of dependence			
Mean	(years)	82.46	82.58
Range	(years)	80.89 – 83.71	80.84 – 83.77
Duration of dependence			
Mean	(years)	3.65	3.85
Range	(years)	2.48 – 5.12	2.53 – 5.10

Table 4
Comparison of indicators for the insured population along the level of coverage.

Indicator	Unit	Low cover	High cover
Probability of dependence			
Mean	(%)	61.17	59.59
Range	(%)	48.47 – 73.67	47.53 – 74.47
Age of dependence			
Mean	(years)	82.54	82.42
Range	(years)	81.34 – 83.71	80.89 – 83.70
Duration of dependence			
Mean	(years)	3.77	3.60
Range	(years)	2.56 – 5.02	2.48 – 5.12

expected to have lower risk indicators than the rest of the population.

4.4. Discussion

Our results show that those interested in LTCI policies are likely to have lower indicators for the probability and duration of dependence. This could be a hint for a phenomenon usually referred to as "advantageous selection". Such selection is believed to occur when insurance appears to be more attractive for individuals who present a lower risk type but that have a higher tendency to limiting risk exposures (De Meza and Webb, 2001). In this sense, our evidence suggests that, at least at an early stage, most potential policyholders seek protection because they are more aware of the risk that dependence poses, as well as psychologically "cautious behavior" as described by Finkelstein and McGarry (2006). Moreover, based on our results, they have good reasons to take future dependence with caution as we estimate the probability to lose autonomy in a lifetime to be between 57.44% and 64.68%, depending on mortality prospects. This seems reasonable in the Swiss demographic context. Indeed, life expectancy at age 60 has increased 5.6 years for males and 4.3 years for females from 1981 to 2020 (Federal Statistical Office, 2022b,a). Moreover, estimations indicate that in 2016 about half a million people belonged to the age group of 80 years and more. This number is expected to reach over one

Table 5
Hypothesis testing results.

Hypothesis	t-test		Wilcoxon test	
	p-value	Conclusion	p-value	Conclusion
Insured vs. uninsured				
$H_0: p_\mathrm{I} = p_\mathrm{U}$ vs. $H_1: p_\mathrm{I} \neq p_\mathrm{U}$	0.0027	Reject null	0.0045	Reject null
$H_0: d_\mathrm{I} = d_\mathrm{U}$ vs. $H_1: d_\mathrm{I} \neq d_\mathrm{U}$	0.0027	Reject null	0.0051	Reject null
Low vs. high LTCI cover				
$H_0: p_\mathrm{L} = p_\mathrm{H}$ vs. $H_1: p_L \neq p_H$	0.1008	Not reject null	0.0671	Not reject null
$H_0: d_\mathrm{L} = d_\mathrm{H}$ vs. $H_1: d_\mathrm{L} \neq d_\mathrm{H}$	0.1219	Not reject null	0.0834	Not reject null
Insured vs. uninsured (inequalities)				
$H_0: p_\mathrm{I} \leq p_\mathrm{U}$ vs $H_1: p_\mathrm{I} > p_\mathrm{U}$	0.9986	Not reject null	0.9977	Not reject null
$H_0: d_\mathrm{I} \leq d_\mathrm{U}$ vs $H_1: d_\mathrm{I} > d_\mathrm{U}$	0.9987	Not reject null	0.9974	Not reject null

Table 6
Comparison of the self-assessed risk group and groups obtained from modeling.

		Self-assessed			
		Group 1	Group 2	Group 3	Group 4
Simulated	Group 1	0	0	0	0
	Group 2	16	25	30	6
	Group 3	264	434	235	56
	Group 4	0	0	0	0

million individuals in the next 30 years (Federal Statistical Office, 2018). Consequently, the Swiss Federal Council (2016) has already signaled potential dependence as one of the greatest challenges for the country.

Although potential policyholders seem to be more of an exception, most respondents are not well aware of the risk that dependence poses. Indeed, we find results that suggest that people are likely not to be aware of their own risk type. As previously reported by Fuino et al. (2022), when asked the question "how likely are you to lose your independence to carry out activities of daily living in the future?", 26% of the population reply that they have a chance lower than 25% to lose their autonomy (group 1), 43% think this probability is between 25% and 50% (group 2). Only 25% of respondents consider to have a chance to lose autonomy between 50% and 75% (group 3) whereas the rest (group 4, with 6%) consider the probability to be above 75%. Our results place the average individual with those that classified themselves in the third group. This shows that, in reality, a vast majority of the population is likely to underestimate their risk to lose autonomy.

As an additional illustration, we present in Table 6 a comparison of the self-assessed risk class of respondents with the one assigned by the model. We find that only 24% (25+235=260 out of 1066) of individuals indicated a future probability to lose autonomy that belongs to the same class suggested by the actuarial calculations. This is a key challenge as individuals' perception of the risk is relevant to develop an insurance market. The understanding of this perception becomes even more important when knowledge about dependence and the levels of concern about future loss of autonomy are found to be key triggers of interest in LTCI as it is the case in Switzerland (Fuino et al., 2022). As Kunreuther et al. (1978) point out, to increase voluntary purchases of an insurance product, and to understand whether or not compulsory programs may be necessary, it is key to understand how psychological, economic, and environmental factors could affect the market.

Since individuals lack the tools to assess their own risk type, we argue that it is unlikely to experience significant levels of adverse selection in an eventual LTCI market in Switzerland. In fact, people's tendency to underestimate the risk may lead to a level of insurance uptake that is lower than optimal, making it insufficient to deal with the social consequences of dependence. This underestimation of the risk is understandable as many people lack the necessary experience making similar choices, which could lead to incomplete information that discourages LTCI uptake (Coe et al., 2015). As seen through our mortality sensitivity analysis, we add that people's chances to suffer from loss of autonomy could be in constant evolution as mortality patterns are adjusted by medical improvements. In this sense, we show that relatively small mortality changes can result in important differences in the probability to lose autonomy in a lifetime, registering an overall change in the indicator that amounts to more than 7% between two extreme plausible scenarios. These results suggest that, with the important mortality improvements registered in the last decades, a person's probability to lose autonomy in their lifetime must have silently increased as individuals have become more likely to survive to critical ages. Abstract factors like these mortality changes are extremely difficult to assess for an average person, which could leave them in a position of great vulnerability. In fact, insurers are likely to have better tools to assess the risk of potential policyholders than individuals themselves. Technical knowledge about mortality development, loss of autonomy, and stochastic modeling makes a potential insurer more capable to better understand the future of dependence. This entails that information asymmetries may be stronger and better justified from insurer to policyholder than the other way around.

5. Conclusion

As exemplified by the Swiss case, the on-going demographic changes pose a challenge to the financial stability and welfare of countries and their populations, and the demand of LTC services is likely to become a reflection of that in the years to come. Many individuals, however, seem not to be aware of the magnitude of the risk of losing independence at advanced ages. We are able to show this by resorting to stochastic models to simulate the future of dependence of a representative sample of the country, and later we compare our findings with the subjective beliefs and self-assessed risk of the study participants. During the modeling process, we use results from previous analysis on LTCI preferences of potential customers (Fuino et al., 2022), probabilities to lose autonomy by age and gender (Fuino and Wagner, 2018), and duration of care (Fuino and Wagner, 2020).

In this context, we find that the average individual in our sample is expected to have a 61.15% chance of experiencing dependence in their lifetime. Through our analysis, we also show how this probability is highly sensitive to mortality changes. In addition, we compute expected duration indicators based on the possible acuity levels of entry in dependence for both the overall population and potential LTCI portfolios. We conclude that we have no evidence to believe that potential LTCI clients seek protection because they are likely to be at greater risk to lose autonomy. In fact, we show that most individuals tend to underestimate their own risk level.

We consider that the knowledge of these results is highly beneficial to society. For instance, by better understanding the future of the potential LTCI market, companies that consider the development of a related business line can make informed decisions, which can be particularly valuable for LTCI since the social value of these policies tends to exceed the private benefits (Akaichi et al., 2020). In addition, governmental authorities can make use of the results when designing public policies.

Declaration of competing interest

None declared. I can confirm that we declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in our paper.

Data availability

The data that has been used is confidential.

Appendix A. Variables involved in the analysis

Table 7
List of variables used in the study.

Variable	Label	Description
Demographic factors		
AG	Age	Age class in years (from numeric age)
GE	Gender	Gender of the respondent
SH	Size of household	Number of people in the household (from numeric answer)
LR	Linguistic region	Region in Switzerland of respondent
Socioeconomic factors		
ED	Education	Highest level of education (from 5 classes)
MI	Monthly income	Monthly net income in CHF (from 7 classes)
Health and behavior		
CH	Self-perceived health	General health rating
CD	Concern about dependence	Degree of concern for future dependence
CO	Contact with parents	Frequency of Contact with parents
CP	Care preference	Type of care for help with ADL
PD	Probability of dependence	Self-perceived probability to lose independence
AL	Acuity level	Severity of dependence at entry
TC	Type of care	Type of Care received when in dependence
LTC literacy		
UI	Understanding of care insurance	Understanding of insurance protection
UC	Understanding of care costs	Understanding of the costs in case of dependence (from 4 classes)
PI	Private insurance participation	Complementary health and life insurance participation in costs
DP	Dependent's participation	Personal or family participation in costs
SI	Social insurance participation	Health insurance and helplessness allowance participation in costs
GS	Governmental subsidies	Pension supplements, cantonal and municipal subsidies to costs
EX	Dependent parents and help	Exposure to dependent parents(-in-law) and personal help
Political factors		
PO	Political orientation	Political orientation rank (from 11 classes)
SR	State's role	Role of the State in financing of care (from 5 classes)
IR	Insurers' role	Role of private insurers in financing of care (from 5 classes)
Other background variables		
PM	LTC policy model region	Region of main residence (from postal code)
NB	Nationality	Nationality at birth

Appendix B. Details on the age of LTCI purchase model (Section 3.2)

The cumulative distribution for the age preference is shown in Fig. 5(a). We observe that only a small number of participants claim that they would start saving for future dependence or buying insurance by the age of 30 (12.20% of respondents). It is at around an age of 50 years where we record the biggest jump (see Fig. 5a). Results show that, whereas only around 20% of participants claim they would start preparing by the age of 40, 48.2% would prefer to do so at the age of 50, and, cumulatively, 75.3% and 86.5% by the ages of 60 and 65 years, respectively. Table 8 shows the results for an extended group of selected ages.

From the underlying data, we do not find, however, clear patterns to develop a model to justify the choice based on covariates. In fact, the main trend that we observe is the relationship between the preferred age to prepare and the age of the participants when taking the survey. The older the individual, the higher the preferred age, which could signal that many respondents only consider feasible options to buy in relation to their current age. This trend alone is, in fact, not useful to build an entire model predicting the preferred age based on characteristics. Further, the responses are biased since individuals tend to answer in ages in multiples of five to the open question. For this reason, we smoothen the results by fitting a continuous distribution approximating the results (see Fig. 5b).

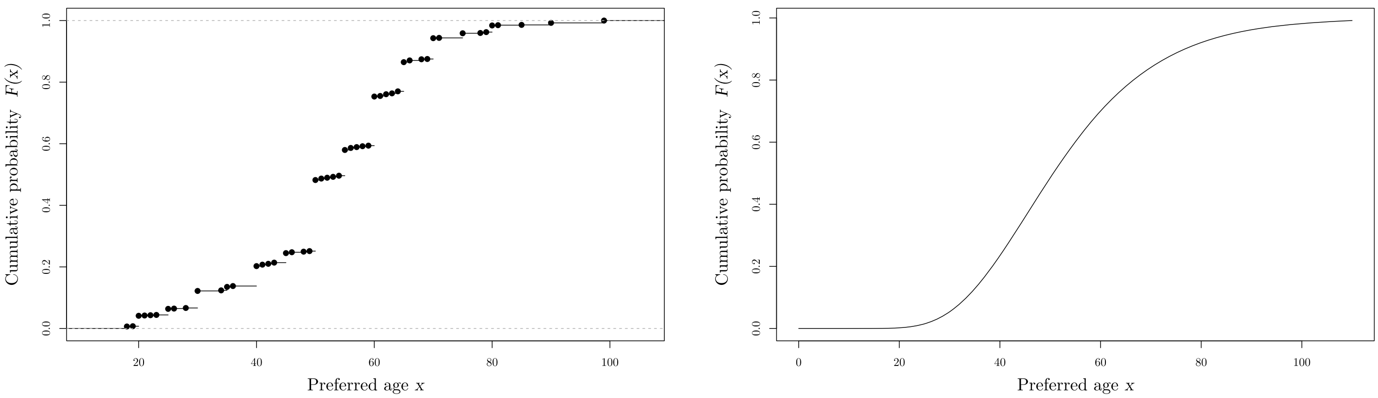
Appendix C. Details on the level of protection model (Section 3.3)

When analyzing the respondents' preferences for “low” or “high” cover, we observe that 891 individuals out of 1 066 respondents (83.6%) consistently classify in the same class for both plans at the ages of 55 and 44 years, respectively. We retain these individuals and analyze their characteristics fitting classification models for the cover response in the form of logistic regressions and random forest (RF) models using the available covariates (see Table 7).

The number of records is unbalanced between both classes, with 598 individuals classified in the “high” cover category and 293 in the “low” one. Unbalanced samples can lead to problems in machine learning algorithms as classification rules tend to learn from the majority class and neglect information from the minority (Lunardon et al., 2014). To account for this, beyond fitting models with the imbalanced data, we also use a data set with balance correction using random over-sampling examples (ROSE). For the model selection, we give particular attention to the F-score since it is a better indicator of how the model performs when considering both classes. As part of our analysis, we perform recursive feature selection with cross-validation, and also obtain the variable importance ranking from the models. We conclude that including the seven most important variables suffices to achieve accuracy levels of over 80% under a RF methodology (see Table 9). Based on these results, we retain the RF model as our final choice since it is more parsimonious than the AIC-minimizing logit model, and it performs much better in terms of F-Score (77.48%) and overall accuracy (83.95%).

In Table 10, we display selected descriptive statistics and model results. The column “Share of sample” reports the percentage of individuals in each variable's category, “Share of “high” cover” shows the percentage of respondents having chosen “high” cover, and “PD coefficient” displays the partial dependence coefficient (expressed in logodds) estimated in the retained RF model for each of the covariates' categories.

The descriptive statistics outline that most relationships between the interest in “high” cover and the explanatory variables are not monotone. These irregular tendencies are mirrored by



(a) Raw cumulative distribution (b) Smoothed cumulative distribution

Fig. 5. Observed distribution of preferred age to start saving for future dependence or buying "care insurance".

Table 8
Cumulative distribution of answers for selected ages.

Age (years)	20	25	30	35	40	45	50	55	60	65	70	75
Cumulative %	4.10	6.40	12.20	13.50	20.30	24.50	48.20	58.00	75.30	86.50	94.30	95.90

Table 9
Models and model performance indicators for "high" LTCI cover preference.

Models and included variables	Recall	Precision	F-score	Accuracy
Logistic regression model (imbalanced data) $GE+NB+MS+RT+CD+FC+PM+UI+UC+PO+SR+IR+GS$	23.89%	56.91%	33.65%	69.02%
Random forest model (imbalanced data) $NB+IR+SR$	1.71%	50.00%	3.31.%	67.12%
Logistic regression model (data with balance correction) $GE+NB+MI+OW+RT+PM+UI+UC+PO+SR+IR+CO+EX+PI+DP$	64.51%	46.32%	53.92%	63.75%
Random forest model (data with balance correction) $MI+AG+DP+PI+GS+CO+SI$	83.95%	71.93%	77.48%	83.95%

Note: The model highlighted in gray performs best.

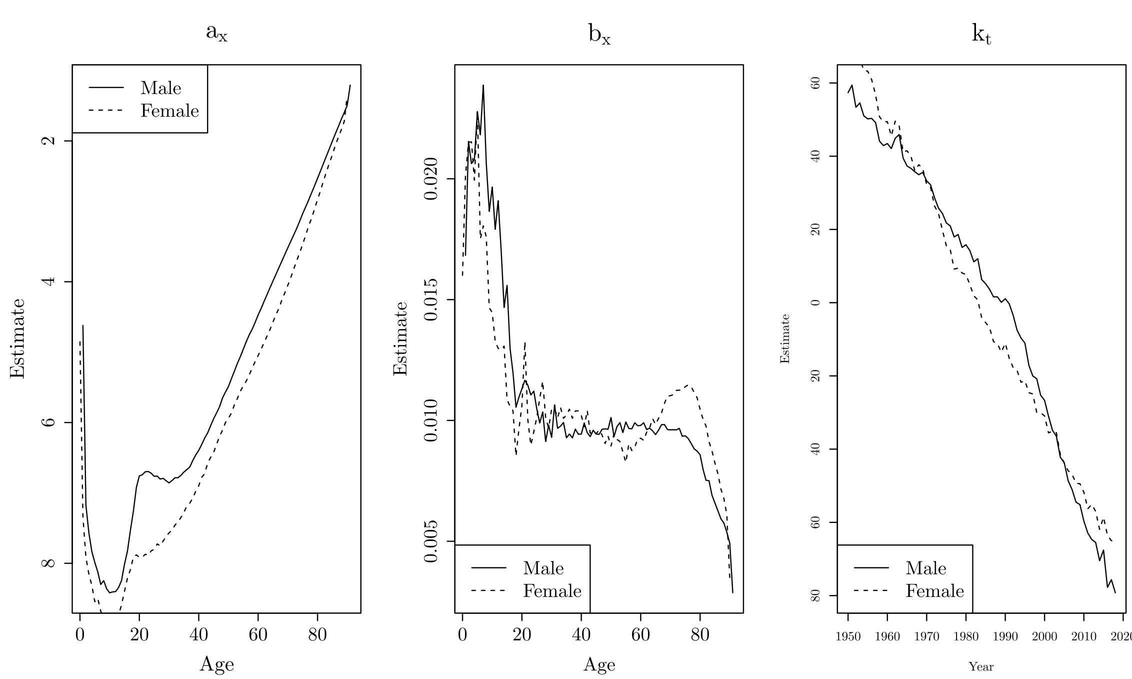


Fig. 6. Graphical representation of the Lee-Miller estimates for a_x, b_x, k_t.

Table 10
Descriptive statistics ($N = 891$) and random forest model effects for "high" LTCI cover preference.

Variable	Share of sample	Share of "high" cover	PD coefficient
Monthly income MI			
$\leq 3\,000$	12.91%	60.87%	0.0447
3 000–5 000	23.91%	65.26%	0.0771
5 001–7 000	19.75%	69.89%	0.2132
7 001–9 000	12.57%	66.96%	0.0583
$\geq 9\,001$	13.13%	77.77%	0.3674
No info.	17.73%	63.29%	−0.0012
Age group AG			
40 – 45	26.26%	65.38%	0.0666
46 – 50	20.20%	68.33%	0.1266
51 – 55	22.00%	67.86%	0.1732
56 – 60	16.16%	63.89%	0.0267
61 – 65	15.38%	70.80%	0.1579
Dependent's participation DP			
Nothing	21.44%	67.02%	0.1501
Small share	24.69%	65.00%	0.1032
Significant share	25.93%	63.64%	0.0700
Almost all	15.26%	74.26%	0.2791
Don't know	12.68%	69.91%	0.2264
Private insurance participation PI			
Nothing	24.35%	65.90%	0.2108
Small share	31.09%	65.34%	0.1018
Significant share	20.76%	71.89%	0.1619
Almost all	7.08%	58.73%	−0.0483
Don't know	16.72%	69.80%	0.1473
Governmental subsidies GS			
Nothing	9.54%	71.76%	0.1970
Small share	32.77%	67.81%	0.1600
Significant share	28.28%	65.48%	0.0861
Almost all	14.81%	59.85%	0.0817
Don't know	14.59%	73.08%	0.1840
Contact with parents CO			
Very often	34.01%	64.69%	0.0669
Often	25.36%	68.58%	0.1002
Not very often	13.92%	68.55%	0.2042
Never	2.24%	45.00%	-0.1690
No parents	24.47%	70.18%	0.1365
Social insurance SI			
Nothing	4.04%	58.33%	0.2457
Small share	30.98%	70.29%	0.1082
Significant share	32.77%	64.73%	0.0900
Almost all	15.38%	64.96%	0.2033
Don't know	16.84%	70.00%	0.1818

Note: "PD coefficient" stands for partial dependence coefficient. Coefficients stem from the random forest model based on the data with balance correction (see Table 9).

the partial dependence effects found from the RFM. We find that belonging to the highest monthly income group ($\geq$ CHF 9 000) substantially increases the preference for "high" insurance cover ($PD = 0.3674$). Regarding the effect of age, the model suggests that the age groups 51–55 and 61–65 rather relate to "high" cover, whereas the groups 40–45 and 56–60 are expected to tend to "low" cover. We find that individuals who believe dependents have to cover themselves almost all of the care expenses rather buy insurance at a high cover ($PD = 0.2791$). Further, those who believe that their private insurance policy would cover almost all costs are most likely to choose low LTCI cover ($PD = -0.0483$). Conversely, those believing that governmental subsidies will not help in the financing of their LTC costs choose higher cover ($PD = 0.197$). Moreover, when individuals believe that they will receive more important help from the government, or that social insurance would pay an important share of LTC, their probability to choose "low" cover increases. Conversely, those thinking that social insurance pays nothing at all are most interested in getting high protection levels ($PD = 0.2457$). Finally, we observe that the absence of contact with parents makes a person more likely to choose a "low" cover ($PD = -0.1690$).

Appendix D. Details on the mortality model (Section 3.4)

For the mortality modeling, we use the Lee and Miller (2001) model. Thereby, the fitting period starts in 1950, the adjustments of mortality in time are done using the evolution of life expectancy instead of the evolution of total deaths, and the jump-off rates are taken from the actual rates instead of fitted ones (Booth et al., 2020; Shang et al., 2011; Charpentier, 2016). The model structure is given by $\log(m_{x,t}) = a_x + b_x k_t + \epsilon_{x,t}$, where $m_{x,t}$ is the central death rate for age x and year t, a_x describes the general shape of the age-specific death rates, b_x is the first principal component reflecting relative change in the log-mortality rate at each age, k_t is a measure of the general level of the log mortality rates, and $\epsilon_{x,t}$ is the residual. The adjustments including the evolution of life expectancy are captured by k_t.

In Fig. 6, we present a graphical representation of the values obtained for a_x, b_x, k_t. The graph for a_x shows an increasing pattern for the mortality after the age of 40 years. The known "accident hump" is also present around ages of 20 years and is more pronounced for men than for women. Regarding b_x, the relative response at age x to changes in k_t, we find a much higher response for ages below 20 years, an important increment at ages 70–80 for women, and a decreasing trend after the age of 80 years for both genders. Finally, the component k_t captures the decrease in overall mortality registered since 1950.

References

ACL, 2020. How Much Care Will You Need? Association for Community Living of the US Department of Health&Human Services.
Actuarial Association of Europe, 2019. Meeting the Challenge of Ageing in the EU. Technical Report. March.
Adams, C., Donnelly, C., Macdonald, A., 2015. Adverse selection in a start-up long-term care insurance market, vol. 20.
Akaichi, F., Costa-Font, J., Frank, R., 2020. Uninsured by choice? A choice experiment on long term care insurance. Journal of Economic Behavior & Organization 173, 422–434.
Booth, H., 2006. Demographic forecasting: 1980 to 2005 in review. International Journal of Forecasting 22 (3), 547–581.
Booth, H., Hyndman, R.J., Tickle, L., 2020. Prospective life tables. In: Computational Actuarial Science with R, pp. 351–376.
Booth, H., Tickle, L., Smith, L., 2005. Evaluation of the variants of the Lee-Carter method of forecasting mortality: a multi-country comparison. New Zealand Population Review, Special Issue 31 (1), 13–34.
Charpentier, A. (Ed.), 2016. Computational Actuarial Science with R. Chapman and Hall/CRC.
Coe, N.B., Skira, M.M., Van Houtven, C.H., 2015. Long-term care insurance: does experience matter? Journal of Health Economics 40, 122–131.
Cohen, A., Siegelman, P., 2010. Testing for adverse selection in insurance markets. The Journal of Risk and Insurance 77 (1), 39–84.
Colombo, F., Llena-Nozal, A., Mercier, J., Tjadens, F., 2011. Help Wanted? Providing and Paying for Long-Term Care, OECD Health Policy Studies.
De Meza, D., Webb, D.C., 2001. Advantageous selection in insurance markets. The Rand Journal of Economics 32 (2), 249–262.
Favreault, M.M., Gleckman, H., Johnson, R.W., 2015. Financing long-term services and supports: options reflect trade-offs for older Americans and federal spending. Health Affairs 34 (12), 2181–2191.
Federal Statistical Office, 2018. Active Ageing. Technical Report.
Federal Statistical Office, 2020. Espérance de Vie.
Federal Statistical Office, 2022a. Espérance de vie selon l'âge (femmes), de 1981 à 2020.
Federal Statistical Office, 2022b. Espérance de vie selon l'âge (hommes), de 1981 à 2020.
Finkelstein, A., McGarry, K., 2006. Multiple dimensions of private information: evidence from the long-term care insurance market. American Economic Review 96 (4), 938–958.
Fries, J.F., 1989. The compression of morbidity: near or far? Milbank Quarterly 67 (3), 208–232.
Fries, J.F., 2005. The compression of morbidity. Milbank Quarterly 83 (4), 801–823.
Fuino, M., Ugarte Montero, A., Wagner, J., 2022. On the drivers of potential customers' interest in long-term care insurance: evidence from Switzerland. Risk Management and Insurance Review 25 (3), 271–302.

Fuino, M., Wagner, J., 2018. Long-term care models and dependence probability tables by acuity level: new empirical evidence from Switzerland. Insurance. Mathematics & Economics 81, 51–70.
Fuino, M., Wagner, J., 2020. Duration of long-term care: socio-economic factors, type of care interactions and evolution. Insurance. Mathematics & Economics 90, 151–168.
Gruenberg, E.M., 2005. The failures of success. Milbank Quarterly 83 (4), 779–800.
Human Mortality Database, 2021. HMD. University of California Berkeley and Max Planck Institute for Demographic Research.
Kaye, H.S., Harrington, C., LaPlante, M.P., 2010. Long-term care: who gets it, who provides it, who pays it, and how much? Health Affairs 21 (1), 11–21.
Kramer, M., 1980. The rising pandemic of mental disorders and associated chronic diseases and disabilities. Acta Psychiatrica Scandinavica 62 (285), 382–397.
Kunreuther, H., Slovic, P., Kunreuther, B.H., Slovici, P., 1978. Economics, psychology, and protective behavior. American Economic Review 68 (2), 64–69.
Lee, R.D., Miller, T., 2001. Evaluating the performance of the Lee-Carter method for forecasting mortality. Demography 38 (4), 537–549.
Long Term Care Poll, 2017. Long-Term Care in America: Increasing Access to Care.
Lunardon, N., Menardi, G., Torelli, N., 2014. ROSE: a package for binary imbalanced learning. R Journal 6 (1), 79–89.
Mayhew, L., 2000. Health and Elderly Care Expenditure in an Aging World. September.
Olshansky, S., Carnes, B.A., Cassel, C., 1990. In search of methuselah: estimating the upper limits to human longevity. Science 250 (4981), 634–640.
Rothschild, M., Stiglitz, J., 1976. Equilibrium in competitive insurance markets: an essay on the economics of imperfect information. The Quarterly Journal of Economics 90 (4), 629–649.
Shang, H.L., Booth, H., Hyndman, R.J., 2011. Point and interval forecasts of mortality rates and life expectancy: a comparison of ten principal component methods. Demographic Research 25, 173–214.
Swiss Federal Council, 2016. Etat des Lieux et Perspectives dans le Secteur des Soins de Longue Durée. Technical Report.
United Nations, 2017. World Population Ageing. Technical Report, New York.
United Nations, 2021. Ageing.
World Health Organization, 2018. Ageing and health.