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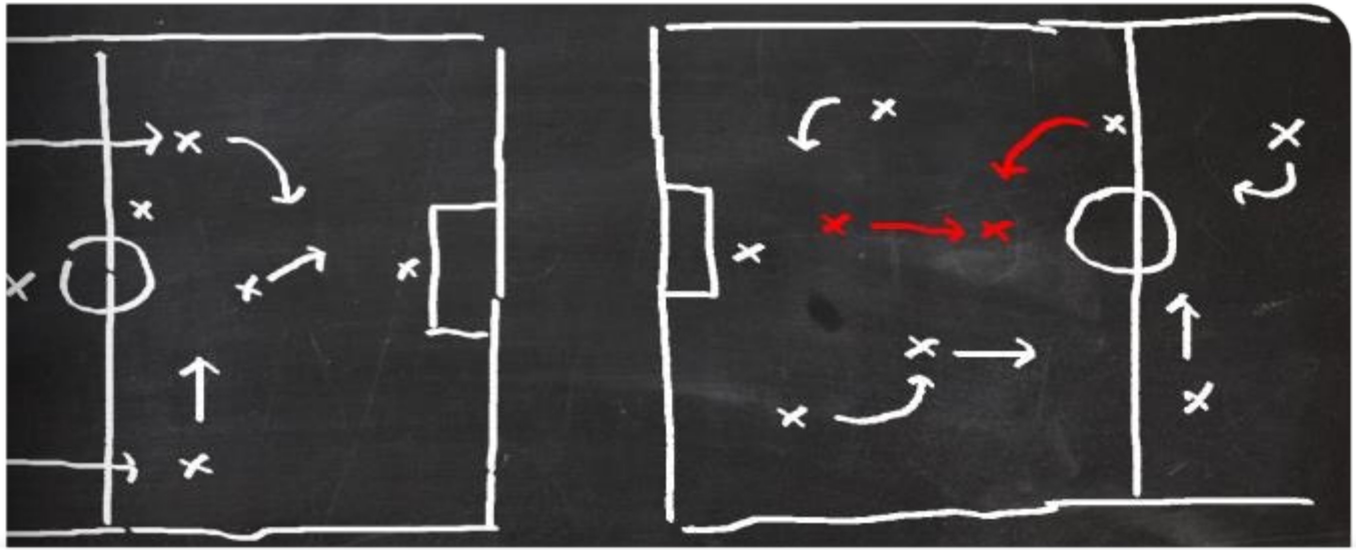

On potential information asymmetries in long-term care insurance: a simulation study using data from Switzerland

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| le savoir vivant |

Structure

1. **Motivation**
2. Methodology
3. Submodels
4. Results
5. Discussion

Motivation

→We have established that only around 40% of individuals aged 40 to 65 years would be interested in purchasing an LTCI policy in Switzerland. Moreover, these individuals share the following characteristics:

- They tend to better understand the way LTCI works
- They tend to better understand the costs linked to dependence
- They show a higher level of concern about their own future dependence, which is linked to a higher self-perceived probability to lose autonomy

→These findings indeed hint that there could be important information asymmetries in the future Swiss LTCI market, as all these factors are not easily observable by insurers.

- **Question to answer: are potential insurers in the market likely to end up with a pool of contracts that is riskier than the average person would be?**

Motivation

- Information asymmetries can be a real problem as “small amounts of imperfect information could have a significant effect on competitive markets” (Rothschild and Stiglitz, 1976).
- No historical information to compute premiums in Switzerland since very few policies have been offered.
- It is not possible to 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).

Structure

Methodology

→We will use previously knowledge about dependence in Switzerland, as well as new findings, to simulate the future of a sample in the country

→We use a sample of N=1066 individuals, males and females, aged between 40 and 65 years, living in the German- and French-speaking regions of Switzerland.

→Our model will assess the expected frequency (probability to lose autonomy in a lifetime) and severity (duration) of dependence within our sample, and aims to establish if we can expect the risk types of those seeking insurance and the rest to be different

Methodology

- The outline of the methodology is presented in Figure 1.
  - We will require:
    - A model to assess likelihood to buy LTCI
    - A model to assess how much coverage the individual may want
    - A mortality model
    - Probabilities to lose autonomy
    - Model for duration

- To assess differences between subpopulations, we apply t-tests and Wilcoxon tests to the hypothesis

$$H_0 : \mu_A = \mu_B,$$
$$H_1 : \mu_A \neq \mu_B,$$

With A and B two groups, and the mean refers to the mean of an indicator of interest.

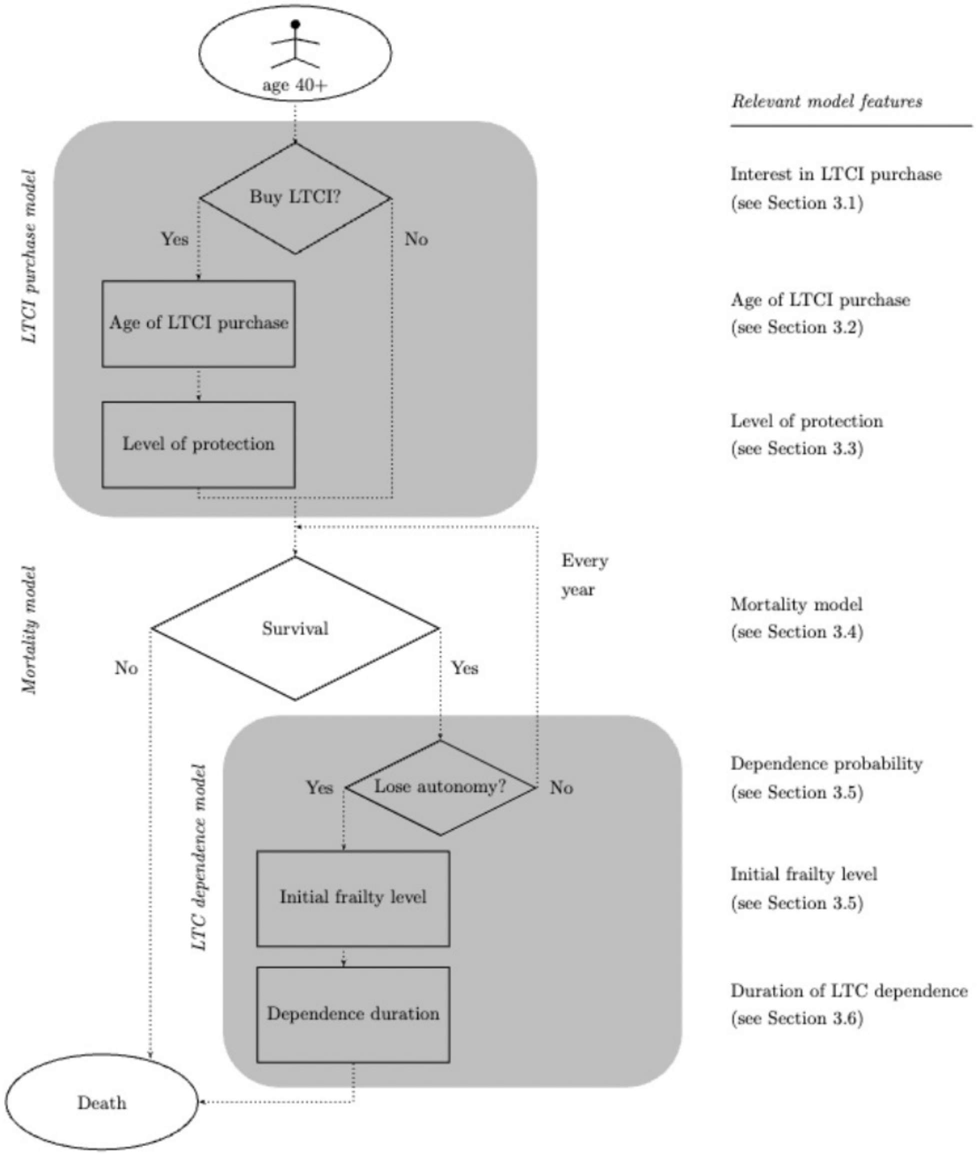


Figure 1: Outline of the model setup for the Monte Carlo simulations.

Structure

Submodels

- **Interest in Purchase of LTCI**

Fuino et al (2021) identify a set of characteristics that drive the interest in buying LTCI in the Swiss population. The level of interest is surveyed through the following question:

$$g(INTEREST) = \boldsymbol{\beta}_0 + \sum_{i \in \mathcal{V}} \boldsymbol{\beta}_i \mathbf{1}_i,$$

Variable	Label	Variable	Label
GE	Gender	UC	Understanding of care costs
SH	Size of household	PI	Private insurance participation
ED	Education	DP	Dependent's participation
MI	Monthly income	EX	Dependent parents and help
CH	Self-perceived health	PO	Political orientation
CD	Concern for future dependence	SR	State's role
CO	Contact with parents	IR	Insurers' role
CP	Care preference	PM	LTC policy model region
UI	Understanding of care insurance	NB	Nationality

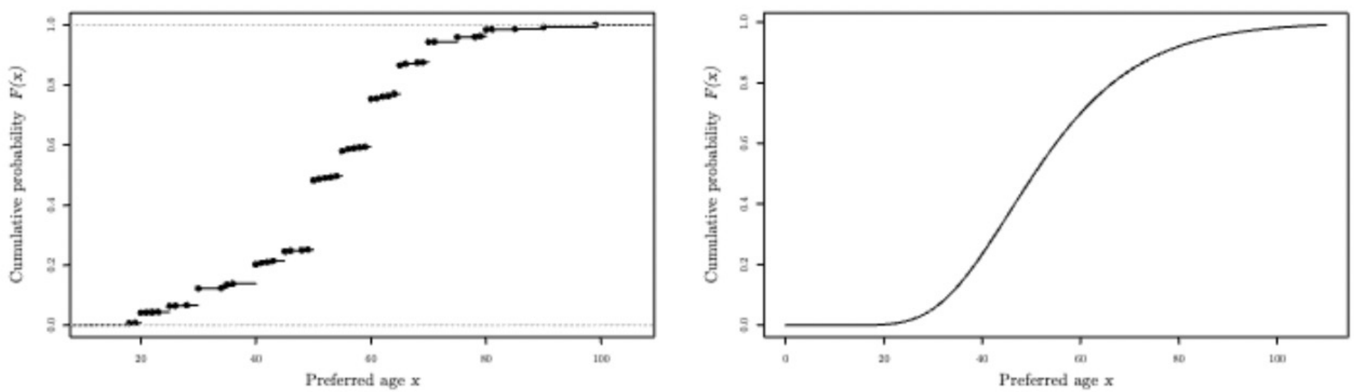
Submodels

- **Age of LTCI insurance purchase**

Regarding the age of purchase, the survey by Fuino et al. (2021) included the 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 the figure below. Their answers are smoothed using a lognormal distribution with mean 3.92 and standard deviation of 0.325 on the log scale.



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

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Submodels

- **Level of protection**

We are further interested in understanding what makes a person choose a certain level of LTCI coverage. In the survey, different ``insurance plans'' are presented with fictitious choices of coverage in exchange of different premium levels.

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.

Submodels

- **Level of protection**

For each question we classify individuals as either wanting ``low'' cover (insuring less than half of losses) or high (insuring half of losses or more). 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 for further analysis (598 in the "high" class and 293 in the "low" category).

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.

Table 2: Models and model performance indicators for "high" LTCI cover preference.

Submodels

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 2).

Submodels

- **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.

$$\log(m_{x,t}) = a_x + b_x k_t + \epsilon_{x,t},$$

Where $m_{x,t}$ represents the central death rate for age *x* and year *t*,
a_x represents the general shape of the age-specific death rates,
b_x reflects the relative change in the log-mortality at each age,
k_t is a measure of the general level of mortality
$\epsilon_{x,t}$ is the residual

Submodels

- **Mortality model**

Specifics of our mortality model

- ✓ Fitting period starting in 1950
- ✓ Adjustments of mortality in time using the evolution of life expectancy instead of evolution of total deaths
- ✓ Jump-off rates taken from the actual rates instead of fitted ones
- ✓ Information coming from the Human Mortality Database to project the next 60 years
- ✓ We obtain upper and lower bounds to the mortality projections

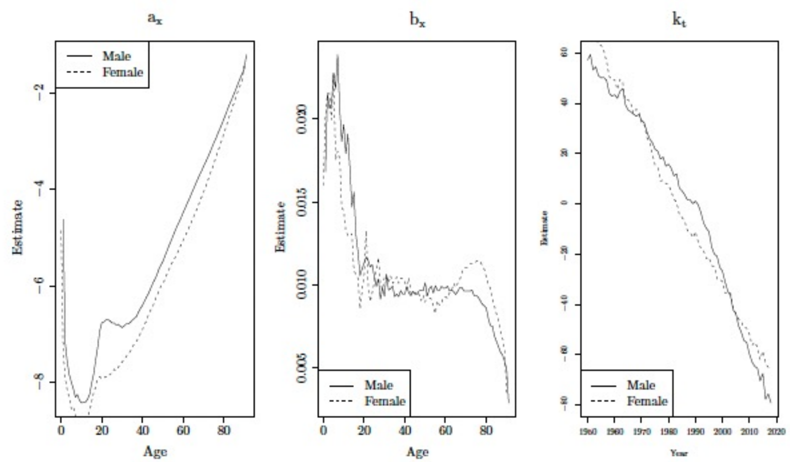

Figure 3: Graphical representation of the Lee-Miller estimates for a_x, b_x, k_t.

Submodels

• Dependence and Frailty Level

This aspect 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 presented in Figure 4. We observe that the probability substantially increases with age, the slope for both genders becoming more pronounced at ages over 80 years.

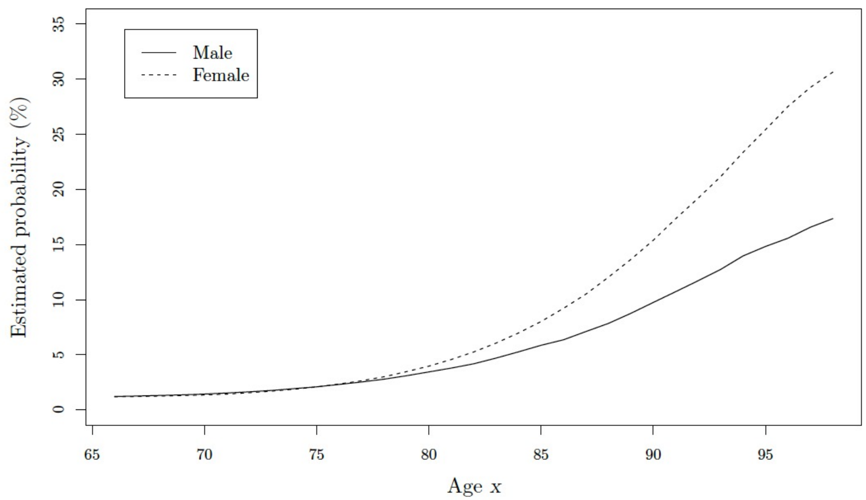

Figure 4: Probability of losing autonomy by age and gender.

Submodels

- **Duration of LTC dependence**

Given a person loses autonomy, we are interested in knowing for how long they will live in this condition. Fuino and Wagner (2020) study the duration of dependence in Switzerland and conclude that it is affected by factors such as the age of autonomy loss (*AG*), their gender (*GE*), their language region in Switzerland (*LR*), the acuity level of entry (*AL*), and the type of care required at entry (*TC*). They present an equation of the form:

$$\log(D_i) = \alpha + \boldsymbol{\beta}_{AG} AG + \boldsymbol{\beta}_{GE} GE + \boldsymbol{\beta}_{LR} LR + \boldsymbol{\beta}_{AL} AL + \boldsymbol{\beta}_{TC} TC + \gamma + \epsilon_i,$$

- Where D_i denotes the duration, and $\alpha = \log(\frac{\sigma}{\theta})$ with σ a shape parameter and θ a scale parameter. In additioin, is a year fixed effect.

Model parameters	Value
Shape σ	1.58
Scale θ	0.001
Age AG_i	–0.039
Gender GE_i (baseline: female)	
Male	–0.293
Language region LR_i (baseline: German-speaking)	
French-speaking	0.085
Italian-speaking	0.290
Acuity level AL_i (baseline: moderate)	
Mild	0.5
Severe	-0.203

Structure

1. Motivation
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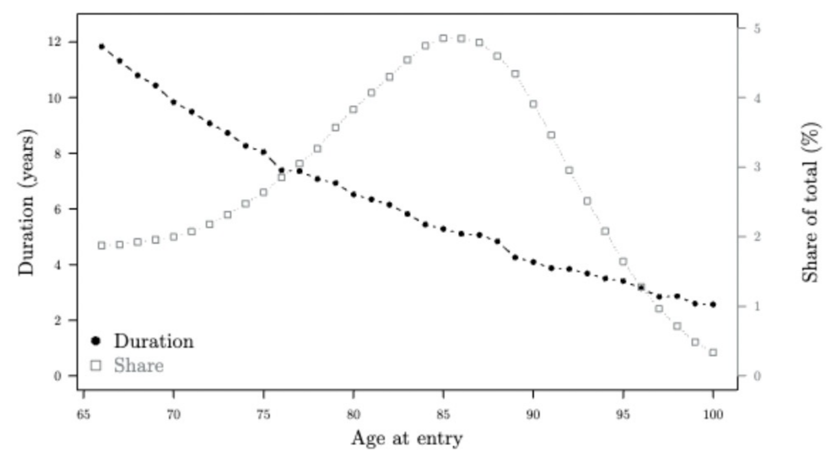
Results

- **Total population**:
  - 61.15% is the average probability to lose autonomy in a lifetime
  - We observe important differences in the probabilities to lose autonomy between males and females: 69.88% for women and 52.13% for men.
  - Simulated age of death: 85.25 years or 83.60 in the case of males and 86.84 in the case of females.

Indicator	Probability of dependence (%)	Age of dependence (years)	Duration of dependence (years)
Average	61.15	82.54	3.77
Ranges	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

Table 5: Simulated probability, age at entry and duration of dependence in the total population.



Results

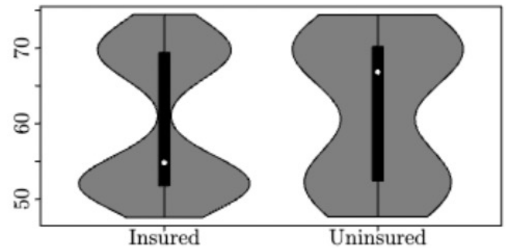
- **Mortality sensitivity**:
  - We see that dependence is a state mostly linked to higher ages, with the strongest impact in the category 80+. It is thus reasonable to assume that a person's probability to lose autonomy in a lifetime is closely linked to the probability of reachingthese ages.
  - To assess the impact of this, we extract lower and upper mortality bounds through the use of the *demography* package in R.

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

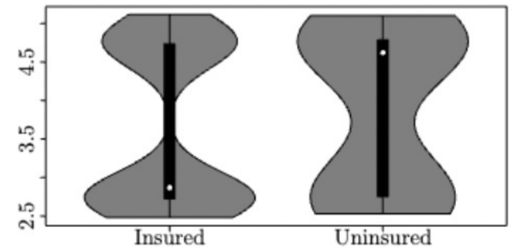
Results

- **Insured vs. Uninsured**:
  - In order to assess the differences in their risk types, we obtain the indicators of interest for the insured and the 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



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



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

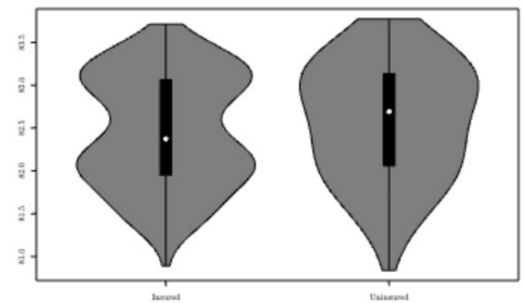

(c) Expected age of dependence (in years).

Figure 7: Representation of indicators for the insured and uninsured subsamples.

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Results

- **Low vs. High**:
  - We also assess the potential differences to be found between those expected to seek «low» or «high» cover.

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

Results

- Hypothesis tests:
  - We then perform statistical tests to see if there is reason to judge the different populations as «different» in terms of their risk. In the subscripts, I stands for «insured», U for «uninsured», L for «low» (cover), and H for «high» cover.

Hypothesis	t-test		Wilcoxon test	
	p-value	Conclusion	p-value	Conclusion
Insured vs. uninsured				
$H_0 : p_I = p_U$ vs. $H_1 : p_I \neq p_U$	0.0027	Reject null	0.0045	Reject null
$H_0 : d_I = d_U$ vs. $H_1 : d_I \neq d_U$	0.0027	Reject null	0.0051	Reject null
Low vs. high LTCI cover				
$H_0 : p_L = p_H$ vs. $H_1 : p_L \neq p_H$	0.1008	Not reject null	0.0671	Not reject null
$H_0 : d_L = d_H$ vs. $H_1 : d_L \neq d_H$	0.1219	Not reject null	0.0834	Not reject null
Insured vs. uninsured (inequalities)				
$H_0 : p_I \leq p_U$ vs $H_1 : p_I > p_U$	0.9986	Not reject null	0.9977	Not reject null
$H_0 : d_I \leq d_U$ vs $H_1 : d_I > d_U$	0.9987	Not reject null	0.9974	Not reject null

Structure

Discussion

- Some key points from our results:
  - We find that individuals interested in LTCI are not a higher risk than the others: indeed their indicators are lower than the rest as shown on the statistical tests!
    - **Indeed what happens is that individuals tend to understimate their own risk type when it comes to LTCI!!!**

		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

- 24% of individuals match their own risk assessment with the models'.
- 68% of individuals underestimate their own risk assessment.
- 8% overestimate their own risk assessment.

Discussion

- Some key points from our results:
  - 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.
  - 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.
  - Individuals may **lack the tools to understand or assess their own risk type** when it comes to LTCI. Many individuals lack experience making similar choices. In addition, the risk is constantly evolving as mortality changes (as shown by our mortality sensitivity analysis).

Image taken from https://www.familytreedentist.com/oral-cancer-prevention/

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