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Long-Term Care Insurance: Information Frictions and Selection†

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This paper conducts a stated-choice experiment where respondents are asked to rate various insurance products aimed to protect against financial risks associated with long-term care needs. Using exogenous variation in prices from the survey design and individual cost estimates, these stated-choice probabilities are used to predict market equilibrium for long-term care insurance. Our results are two-fold. First, information frictions are pervasive. Second, measuring the welfare losses associated with frictions in a framework that also allows for selection, it is found that information frictions reduce equilibrium take-up and lead to large welfare losses, while selection plays little role. (*JEL* D82, D83, G22, I13)

Because of a rapidly aging population, financing and providing long-term care (LTC hereafter) to older individuals is an important and growing problem in developed countries.[1] In OECD countries, the population of individuals 80 years old and older is expected to grow from 4 percent of the total population in 2010 to

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[1] Long-term care is defined as the care for people needing daily living support over a prolonged period of time. Support can be provided with activities of daily living (ADL) (such as bathing, dressing, eating, getting in and out of bed, toileting, and continence) or instrumental activities of daily living (which include preparing meals, cleaning, doing the laundry, taking medication, getting to places beyond walking distance, shopping, managing money affairs, and using the telephone and nowadays the Internet). The loss of autonomy is most often associated with old age and should be clearly distinguished from illness, disability, and handicap.

10 percent by 2050 (Colombo et al. 2011). Estimates of the probability that someone approaching retirement will use a nursing home at some point in his life range from 35 percent to 50 percent in the United States (Brown and Finkelstein 2009; Hurd, Michaud, and Rohwedder 2017). Despite increasing demand, OECD countries are still spending relatively little on long-term care services, at least as a percentage of GDP. Private LTC expenditures as a share of GDP were similar in Canada and the United States at roughly 0.3 percent of GDP.[2]

To get a sense of the magnitude of private expenditures in Canada, out-of-pocket costs for a public nursing home are at most $24,000 a year, representing roughly a third of total cost to the government[3] in the province of Québec (see Boyer et al. 2019b for more on the out-of-pocket costs in the different Canadian provinces), compared to over US$90,000 in the United States (Genworth 2019). Given that on average, individuals stay five years in these facilities, such long-term care expenses can represent a high burden for households with low savings. Moreover, public nursing homes only provide "minimum basic services" so that an individual who would like to receive "higher quality services" would have to resort to a private nursing home whose cost varies between $40,000 and $60,000 a year in Canada.[4] Finally, the waiting time for accessing the public service is close to ten months so that while waiting for a bed in a Canadian nursing home, individuals need to find alternative (private) solutions. Hence, LTC risk is associated with potentially important financial risks for households despite subsidies from the government. In order to cover for the risk that public care is not enough or is unavailable when additional services are required, Canadians can buy a private LTC insurance policy that pays off when they are declared to have two ADL impairments or more (payments cannot be retroactive). Contrary to some other countries, bundling LTC insurance with some other financial products is quite limited.

Despite the high potential financial risk for individuals and households, very few choose to insure privately against such risks (Pestieau and Ponthière 2012). In Canada, the share of total LTC spending covered by private insurance was around 0.5 percent in 2010, while for OECD countries, it was less than 2 percent (Colombo et al. 2011). According to a Canadian Life and Health Insurers Association representative, the take-up rate in Québec for long-term care insurance policies was around 1.7 percent in 2015.[5] This situation is often coined the *Long-Term Care Insurance Puzzle*.

[2] Recent OECD Health Statistics (2019) (see http://www.oecd.org/els/health-systems/health-data.htm) suggest that in 2016, the 30 OECD countries spent, on average, 1.33 percent of GDP on long-term care services (with 1.10 percent of GDP coming from public sources and 0.23 percent coming from private sources). For the same year, total expenditures on long-term care services in the United States represented 0.87 percent of GDP, with 0.24 percent of GDP coming from nongovernment sources. In Canada, total expenditures on long-term care services represented 1.48 percent of GDP, with private sources representing 0.31 percent of GDP.

[3] Unless otherwise specified, amounts are expressed in Canadian dollars throughout the paper.

[4] The two provinces in which we conducted our study, namely Québec and Ontario, provide dependents with means-tested reduction in fees. In addition, in the province of Québec, tax credits for formal care are available.

[5] In the United States, only about 10.8 percent of those 60 years and older held such a policy in 2009 (Brown and Finkelstein 2009). Put differently, in 2010, 10 million Americans were covered by some sort of long-term care insurance policy, compared to 385,000 Canadians (see clhia.uberflip.com/i/354914-clhia-report-on-long-term-care-policy/7?). Liu and Liu (2019) report that as of 2014, there were 7.2 million private LTCI policies in force in the United States.

The objective of this paper is to explain the low take-up rate of LTC insurance (LTCI hereafter) and to measure the welfare costs of (demand-side) choice frictions and (supply-side) asymmetric information. To do so, we partnered with Asking Canadians, a Canadian online panel survey organization, to field a survey on LTCI in the fall of 2016. We selected randomly 2,000 panel members aged 50 to 70 in the two most populous provinces of Canada, Ontario and Québec. We then matched each respondent with a health microsimulation model capable of estimating personalized lifetime exposure to disability, nursing home, and formal care (Boisclair et al. 2016). This allows us to estimate the actual risks faced by households and potentially covered by insurers and to compare those with risk perceptions we elicit in the survey. We also survey respondents about their knowledge of LTC and institutional details and preferences for care, which have been shown to be correlated with demand for LTCI (Brown, Goda, and McGarry 2012). We then build a stated-preferences experiment to study demand for LTCI.[6] The second part of our survey consists of an experiment where we presented each respondent with the prospect of purchasing an LTCI product. These scenarios differ in terms of the benefit paid in case of dependency, the premium paid, and the provision of an embedded term life insurance contract if the respondent dies prior to age 85. From survey responses and experimental variation in contract characteristics, we can infer the participants' demand for LTCI and investigate whether there is adverse or advantageous selection in this insurance market.

We build on the methodology developed by Einav, Finkelstein, and Cullen (2010) and Handel, Kolstad, and Spinnewijn (2019). The former uses revealed preferences to estimate the demand and supply curves of employer-provided health insurance using individual-level data from a multinational firm. The combination of estimated demand and supply curves enables to evaluate the welfare losses associated with mispricing due to asymmetric information (whether it is adverse or advantageous selection). We extend this approach to stated-preference data using experimental variation in prices. Handel, Kolstad, and Spinnewijn (2019) estimates the extent to which the presence of information frictions in the health insurance market would lead to inefficiencies and how policy interventions for correcting these frictions may effectively be welfare increasing or decreasing.[7] Following a similar approach, we estimate the welfare impact of those information frictions in the Canadian LTCI market according to our survey.

Our results confirm the existence of underinsurance for LTC. Focusing on the baseline contract offering a $2,000 LTC monthly benefit without any life insurance, our model predicts that the proportion of agents optimally buying LTC should be around 30 percent, while the equilibrium take-up rate is only 20 percent. Asymmetric information explains only a very tiny fraction of this gap (in the absence of asymmetric information, the equilibrium take-up rate would decrease by 0.4 percent) and consequently generates a very small welfare cost. The largest part of the take-up gap is rather explained by information frictions regarding the general knowledge of LTCI products (awareness) and the knowledge of LTC costs and institutional

[6] See Louviere, Hensher, and Swait (2000) on the merits and disadvantages of stated-choice experiments.
[7] See also Handel and Kolstad (2015) and Spinnewijn (2017).

context in general, with a much smaller role for misperceptions regarding survival and disability risks. We estimate the overall welfare cost of these information frictions at around 17 percent of the welfare obtained at the social optimum.

Few papers combine stated-preference and revealed preference data to study this market. Exceptions are Ameriks et al. (2020) and Ameriks et al. (2016). The latter study uses strategic survey questions along with balance sheet data from the Vanguard Research Initiative (VRI) to estimate preferences, within a well-defined life-cycle model, to explain the low demand for LTCI products. They find that 60 percent of the panel members would buy LTCI according to their model. This gap between actual and reported demand can be explained by a lack of interest on the demand side as well as poor insurance product features on the supply side. In our framework, we elicit directly preferences of respondents, allowing us to compute the demand curve using experimental variation in prices. We also consider the supply and demand side jointly, allowing us to investigate selection and equilibrium in that market. Another related paper is Dardanoni and Li Donni (2016), which uses a framework similar to ours but in a revealed preference context. Their approach rests on evaluating welfare losses from mixture-type models using external estimates of the price elasticity of demand for LTCI. They estimate large welfare loss from unpriced heterogeneity and use large estimates of the price elasticity of demand (-3.5 and -2). In our framework, we estimate this elasticity directly from the stated-preference experiment and find price elasticities (average around -0.7) consistent with Ameriks et al. (2016), who find demand price elasticity below 1 (in absolute value) for 80 percent of their sample.

Finally, our paper can be related to the developing literature on behavioral insurance.[8] This literature focuses on the importance of taking into account behavioral constraints (i.e., specific individual cognitive factors and limited rationality) when it comes to explaining individuals' insurance behavior. Insurance choices are quite different from other (risky) choices and, as such, are impacted differently by behavioral constraints. While some papers have already integrated these constraints into models of insurance for disasters (Friedl, de Miranda, and Schmidt 2014), for genetic testing (Hoy, Peter, and Richter 2014), for annuitization (Bommier and Le Grand 2014), for health damages (Handel and Kolstad 2015), etc., to the best of our knowledge, our paper is the first empirical paper to study the impact of behavioral constraints on LTCI take-up and to quantify their welfare impacts.

The paper is organized as follows. Section I describes the survey and the questionnaire we use. Section II shows descriptive evidence from the survey. We develop an equilibrium model for LTCI products, which we apply to stated-preference data from our survey, in Section III. Section IV contains the results we obtain, while Section V concludes.

[8] For an overview of the issues related to behavioral insurance, see Richter, Schiller, and Schlesinger (2014).

I. Data

We first describe the survey we have run, before moving to how we have computed the individuals' LTC risk from their survey answers.

A. *Survey*

Partnering with Asking Canadians, a Canadian online panel survey organization, we conducted a survey on LTCI in late autumn 2016. We randomly selected 2,000 panel members aged 50 to 70 residing in the two largest and most populous provinces of Canada, Ontario and Québec. Participants were rewarded for their participation with loyalty rewards from major retailers. Despite those efforts, some groups remain slightly underrepresented, in particular low-educated and low-income groups. We stratified by age, gender, province, and education groups (three levels) and used the Canadian Labor Force Survey of 2014 (the last year available) to reweigh the data. The effect of weighing was minimal on our analysis. For example, the median household income we estimate in the survey is \$65,000 for the province of Québec, while the equivalent number from the Social Policy Simulation Database (SPSD) for 2016 is \$69,000. The twenty-fifth percentile of household income in the SPSD is \$41,110 for Québec, while we estimate it to be \$38,000 in our survey. Hence, once reweighed, our survey appears representative of the population aged 50–70 in Québec and Ontario.

A copy of the questionnaire (in text format) is found in the online Appendix. It has four major parts.[9] The first three parts asked respondents about socioeconomic characteristics, reasons for having purchased (or not) LTCI, risk perceptions, and their preferences regarding the type of LTC they would prefer to receive. For some of these questions, we used a formulation taken from Brown, Goda, and McGarry (2012). For questions where we expected a significant fraction of missing information, such as savings and income, we used unfolding brackets. We then used multiple imputation to impute missing values with information from the bracketing, conditional on basic sociodemographic covariates (age, gender).

The fourth and last part of the survey consisted of a stated-preference experiment. Respondents were presented with the prospect of purchasing an LTCI product. These scenarios differ in the benefit paid under LTCI, the premium, and term life insurance if the respondent dies prior to age 85. The introductory text is reproduced below (the equivalent exists in French for Québec residents who are mostly French speakers):

> We are going to show you some simple insurance policies and ask you to rate those. You can assume that if you were to have two or more limitations in activities of daily living, the insurance company offering you this product would pay the benefits no matter what the circumstances. Once you receive benefits, you do not pay any premiums.
>
> Each product has three attributes: a) a monthly premium you have to pay; b) a monthly benefit if you have 2 or more limitations in activities

[9] Asking Canadians validates completed questionnaires based on a number of indicators, such as the time of completion, and drops respondents whose answers appear questionable.

> of daily living, starting 3 months after your limitations have been verified; and c) a payout to your survivors if you die before age 85. Assume that if you are healthy and you stop paying premiums for 3 consecutive months, the contract is cancelled and you lose coverage. The premium cannot increase once you have purchased the product. Finally, the benefits are adjusted for inflation (indexed).

We presented scenarios using the following representation (with p, b_{ltc}, and b_{life} replaced by values in Canadian dollars):

While healthy	Once you have at least 2 ADLs	When you die
You pay p	You receive b_{ltc}	Your survivors receive b_{life}

We use a simple LTCI contract on purpose. In order to avoid uncertainty about the future premiums, we explicitly mention that premiums could not increase once the contract is signed. This means of course that real premiums are decreasing. We also insisted on the possibility of lapse risk in the sense that respondents were made aware that if a payment was not made for some time, it would lead to the termination of the contract. We mentioned that there is no risk regarding payment of benefits. This meant that if the respondent had two or more ADL impairments, then the insurance company would for sure pay the benefits that were contracted upon. We also insisted that the product is offered by a trusted insurance company. We explicitly wanted respondents to dismiss the risks associated with nitpicky insurers (see Bourgeon and Picard 2014) and the insurer's credit risk; in other words, we wanted to avoid having them think of payment risk. Finally, LTCI benefits are indexed to inflation. Apart from wanting to offer a situation that replicates reality (i.e., LTCI protection is usually indexed to inflation), we also wanted respondents to know that the amount of LTC services they would receive is independent of when they become disabled.

We presented five of those scenarios to each respondent. Each time we asked respondents for the likelihood with which he or she would purchase this product if it were offered by a trusted insurance company. Possible answers ranged from 0 percent, meaning there was no chance whatsoever that the respondent would purchase the LTCI product, to 100 percent, meaning that the respondent would certainly purchase that product.[10] We consider jointly LTCI and term life insurance contracts because of the potential desirability of having some life insurance protection in case one dies early, prior to facing significant disability risk.[11] This bundling may be particularly interesting for respondents who have some bequest motive. The reason

[10] For analysis, we rescale those responses to be between zero and one.

[11] Note, however, that insurance products in which LTC and life insurance benefits are bundled are still not very common in Canada, even though bundled products that include LTC insurance have been discussed for a long time in the scientific community. In particular, these products offer a combination of annuities with LTC (Getzen 1988, Webb 2009, Brown and Warshawsky 2013, Glenzer and Achou 2019) as well as universal life insurance plans to which policyholders add the right to purchase at set dates (say, at the fifth and tenth year policy anniversary) home care insurance coverage. These are known as future purchase option benefits (see, for instance, www.rbcinsurance.com/files/00105/file-105623.pdf; file last retrieved October 23, 2019). In the United States, 260,000 so-called life-LTC hybrid policies were sold in 2017, compared to only 70,000 stand-alone LTCI policies

we asked for probabilities is that they convey considerably more information than a yes or no answer and allow to account for the fact that scenarios are incomplete (Manski 1999). One advantage of asking for the probability with which one would purchase a contract is that we can use these probabilities directly in our analysis without having to make any assumptions about the functional form that leads to a yes/no answer.[12]

Each scenario is constructed in the following way. For each respondent, a monthly LTCI benefit b_{ltc} is first picked randomly from the distribution $[2{,}000, 1/3; 3{,}000, 1/3; 4{,}000, 1/3]$. We also pick randomly a benefit for the life insurance component of the scenario, b_{life}, from the distribution $[0, 3/5; 10{,}000, 1/5, 25{,}000, 1/5]$. In Canada, most insurers only use information on age and gender to price this type of insurance. Some insurers will underwrite insurance on the basis of preexisting medical conditions, but premiums are not a function of health status. In our research design, we therefore concentrate on offering premiums consisting of an age-gender actuarial premium, computed from a microsimulation model, and a price adjustment factor which is randomized but centered on 1. Hence, the average premium offered to respondents of a certain age and gender group is equal to the actuarial premium we compute from our microsimulation approach. Hence, we first use the health microsimulation model COMPAS, which we describe below, to compute by age and gender the actuarial premium associated to these benefits, assuming a 3 percent discount rate. These premiums can be compared to those observed in the market. We obtained from CAA-Québec (which is the Québec equivalent of the AAA in the United States) premium data corresponding to similar levels of coverage to those presented to respondents. In Table 1, we report average estimates in the sample. These premiums are close to those observed in the market, although our model estimates are higher than market premiums for men in general and for women at younger ages. They are, however, lower for women at older ages. We conclude from this exercise that our modeling of disability risk is close to that used by insurance companies in the industry.

We denote by $\bar{c}_h$ the actuarial premium for each class of risk (by gender and age), h, representing the expected cost expressed monthly for the expected duration of the contract. Finally, we create exogenous variation in premiums by drawing a factor τ from the vector (0.6, 0.8, 1.0, 1.2, 1.4) with probability 1/5 for each element.

The premium is given by $p = \tau \bar{c}_h$. Hence, a scenario consists of a triple (p, b_{ltc}, b_{life}). Each respondent is offered five scenarios, drawn at random as explained above.

(https://www.forbes.com/sites/jamiehopkins/2018/10/10/hybrid-life-insurance-policies-increasingly-popular-as-long-term-care-funding-strategy/#32e4de7c1efa; file last retrieved October 23, 2019).

[12] Note that waiting to purchase LTCI has no significant option value. On the contrary, waiting runs the risk of sizable increases in the insurance premium as agents grow older. Also, there is little reclassification risk (the premium is fixed for the duration of the contract, and the lump-sum payment is made conditional on suffering from at least two ADL impairments, irrespective of the severity of dependency).

Table 1

Age		Female	Male
50–54	Model	139	119
	Data	130	97
55–59	Model	183	155
	Data	175	123
60–64	Model	220	194
	Data	238	174
65–69	Model	291	263
	Data	352	262

Note: Sample average for $2,000 and $3,000 per-month benefit.

Sources: Monthly premiums from data (CAA-Québec with a 2 percent inflation guarantee) and actuarial premiums from modeling (COMPAS microsimulation model)

B. *COMPAS*

There is no detailed projection of disability risk in Canada that would allow us to construct personalized risk estimates for respondents in our survey. We use the microsimulation model COMPAS that was developed to project the long-term evolution of health and health care use in Canada (Boisclair et al. 2016).[13] The structure of the model follows from other models such as the Future Elderly Model (Goldman et al. 2005). Each individual in the model has many characteristics:

- Sociodemographic characteristics: age, sex, immigration status, education level, income bracket
- Diseases: diabetes, high blood pressure, heart diseases, stroke, cancer, lung diseases, dementia
- Risk factors: smoking, obesity
- Disability: limitations in ADL and instrumental ADL (IADL)
- Long-term care: formal home care, nursing home

Based on these characteristics, the core of the model consists of a Markovian transition model of diseases, risk factors, disability, and long-term care characteristics. These transitions are based on a set of transition models which were estimated using the National Population Health Survey (NPHS) (1994–2010) (Statistics Canada 2010). The transition model has been satisfactorily tested by simulating on original 1994 data the trajectories of respondents in the NPHS until 2010 and comparing distribution of outcomes. The model delivers simulated life trajectories conditional on a set of initial conditions. Given the large number of variables, one cannot construct a transition matrix across all these states. Instead, each respondent can be simulated a large number of times, and an individualized set of disability and mortality risks can be computed by averaging over these simulations. When designing the questionnaire for our survey, we deliberately asked questions we

[13] A detailed description of the model can be found in the Inter-university Consortium for Political and Social Research (ICPSR) data and code archive.

could then feed directly into the health transition matrix of COMPAS. In particular, we asked respondents for their education level, their health conditions (same as in COMPAS), and smoking habits. Nevertheless, data limitations are likely to impact some of the calculations we make. COMPAS uses NPHS data which records the location of respondents at the time of the survey, but no location is available when the respondent has been found to have died. Since nursing home stays tend to occur more frequently at the end of life, this could impact our estimates. Hurd, Michaud, and Rohwedder (2017) find that shorter stays, in particular those near the end of life, are missed by core interviews in the Health and Retirement Study. Although short stays may be missed, they may matter more for policyholders than for insurers, as these stays are typically shorter than the deductible threshold of LTCI policies (3–5 months). In particular, it may be that we underestimate the individual risks, while respondents have correct expectations about such risks.

Hence, we are able to construct a distribution of individualized disability and mortality risks as a function of a large number of characteristics. Since insurers do not use these characteristics to price LTCI products, we will be able to use these unused pricing characteristics to test for asymmetric information and quantify its effect on take-up of LTCI.

II. Descriptive Evidence

We first focus on describing who has or has not bought LTCI in our survey and on their stated reason for (not) buying it.

A. *Take-Up, Knowledge, and Awareness of LTCI*

Table 2 reports the number of people with (the right-hand side) and without (the left-hand side) LTCI. We find that the take-up rate of LTCI is low, at 10.5 percent, at a similar level as that found in the United States (around 10.8 percent in 2009; see Brown and Finkelstein 2009). We also report the respondents' level of knowledge about LTCI products. Among those who did not purchase LTCI, 39.8 percent reported having no knowledge about the product, and 7.9 percent reported not knowing what the product was. Others judged that such policies were too expensive (19 percent) or unnecessary (14 percent).

Among the respondents who were covered by LTCI, close to two-thirds (65 percent) knew little about that type of product, whereas 5.5 percent said they knew nothing at all. The main reason for having purchased an LTCI policy is that they were offered one through one channel or another: only 9.2 percent of respondents having an LTCI policy declared having actively searched for such a protection, while 53.4 percent were offered the product, suggesting that the main channel for obtaining LTCI is likely to be through a financial advisor or direct marketing.[14]

The monthly premium paid was \$116 on average (at the time of the survey, C\$1 was worth the equivalent of US\$0.75) for monthly benefits of the

[14] Note that contrary to other countries (such as the United States), employer-provided LTCI is extremely rare in Canada.

Table 2—Holding of Long-Term Care and Life Insurance

No LTCI		LTCI	
Fraction (percent)	89.48	Fraction (percent)	10.52
Knowledge of LTCI (percent)		Knowledge of LTCI (percent)	
A lot	6.90	A lot	29.60
A little	53.27	A little	64.94
None at all	39.82	None at all	5.46
Why don't you have LTCI? (percent)		How did you come to purchase LTCI? (percent)	
Never offered one	44.1	Offered	53.43
Not yet made decision	7.77	Searched myself	9.19
Used to have one	0.5	Other	37.38
Too expensive	18.97		
Doesn't cover my needs	2.25	LTC policy	
Don't need such a policy	13.97	Premium	$115.8
Don't know what it is	7.93	Benefit	$2,467
Other	4.19		
Do you have life insurance? (percent)		Do you have life insurance? (percent)	
Yes	68.10	Yes	75.88
No	31.07	No	21.34
Don't know	0.83	Don't know	2.78

Note: Observations = 1,819 respondents with nonmissing response to whether or not they have long-term care insurance.

order of $2,467 in case of loss of autonomy. Finally, 76 percent of LTCI purchasers had some sort of life insurance policy (whether term life or other), whereas 21.3 percent did not have one. Hence, life insurance is much more widespread than LTCI.

B. *Risks and Perception*

From the microsimulation model, we compute mortality and disability risk for each respondent based on health and sociodemographic characteristics at the time of the survey. For each respondent, we need a set of probabilities of having limitations in activities of daily living at future ages (from the current age of respondent i to age 110) and similarly for survival probabilities. The microsimulation model yields simulated life trajectories for each of the respondents. We estimate a set of simulated probabilities by feeding each respondent 1,000 times into the simulator. We use as inputs gender, age, education, smoking status, and a set of health variables asked in the survey and used in COMPAS (whether the respondent has had heart disease, diabetes, hypertension, cancer, stroke, and mental health problems). In Figure 1, we report the mortality risk for various age groups at the time of the survey. We first compute the expected number of years of life remaining using individual-level survival risk. We then order respondents, for each age group, by percentile of the distribution of remaining life expectancy. We report the average mortality risk within each age group and quartile. We see substantial variation in mortality risk at all ages, which predictably becomes more pronounced at older ages. To give an idea of the magnitudes, an individual respondent in the bottom quartile of age bracket 50–54 has a mortality rate at age 85 that is 2.3 times higher than an individual in the top quartile of the same age bracket. This translates into a remaining life expectancy of 28.21 years in the bottom

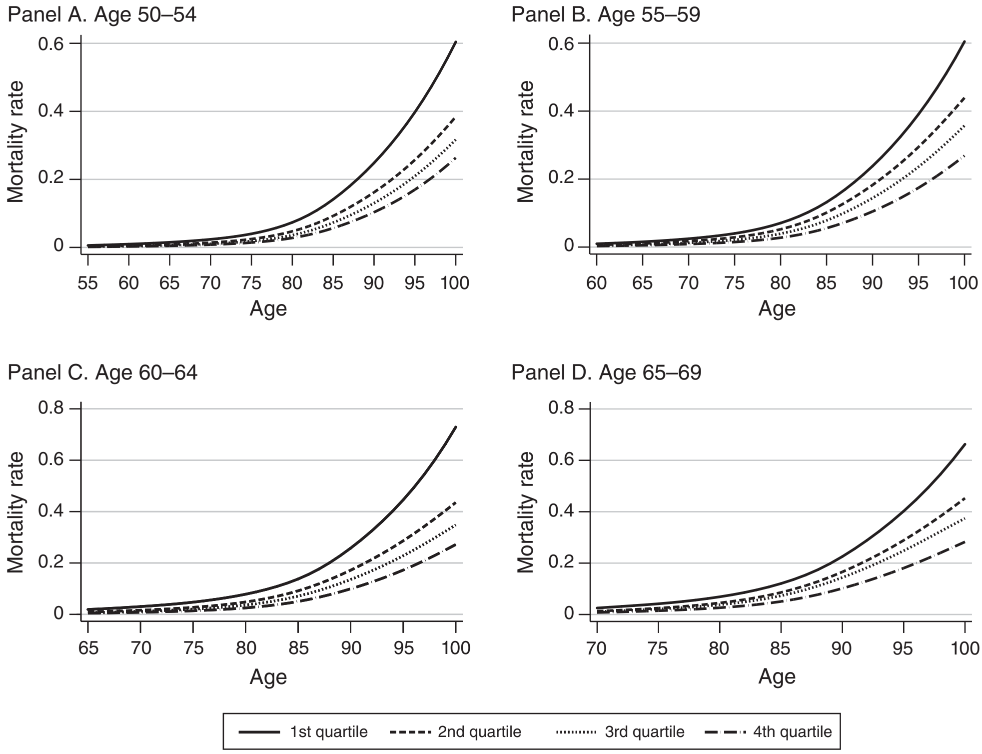

Figure 1. Mortality Risk Projections by Age Group

Note: For each age group, we sort respondents by projected remaining life expectancy and plot average mortality rates by quartiles.

quartile and 38.3 years in the top quartile. Hence, mortality risk modeling using survey respondent characteristics yields substantial heterogeneity in survival risk.

We conduct a similar exercise for disability risk. In Figure 2, we report estimates for disability risk conditional on having survived to a given age for each age group. We also see substantial heterogeneity in risk by age. A respondent aged 90 faces a probability of being disabled, and thus needing care, of the order of 20 percent to 30 percent. Given these risks, we can estimate the lifetime risk of ever being disabled and that of ever entering a nursing home for at least one year. We present these estimates from COMPAS in Figure 3. On average, respondents face a probability of being disabled of 56.1 percent, but this risk is quite heterogeneous in the population. Because nursing home stays are expensive, we also compute the lifetime risk of entering a nursing home. On average, respondents face a risk of 26.2 percent. Again, this risk is very heterogeneous in the population.

To get an idea of the financial exposure due to future LTC expenditures, we estimate the net present value of the expenditures associated with formal care and nursing homes for all respondents. To do this, we need estimates of the cost of a year in a nursing home. These costs vary. The annual cost for Québec public nursing homes is \$43,000 (Boisclair et al. 2016). We use this cost in both Québec and Ontario for

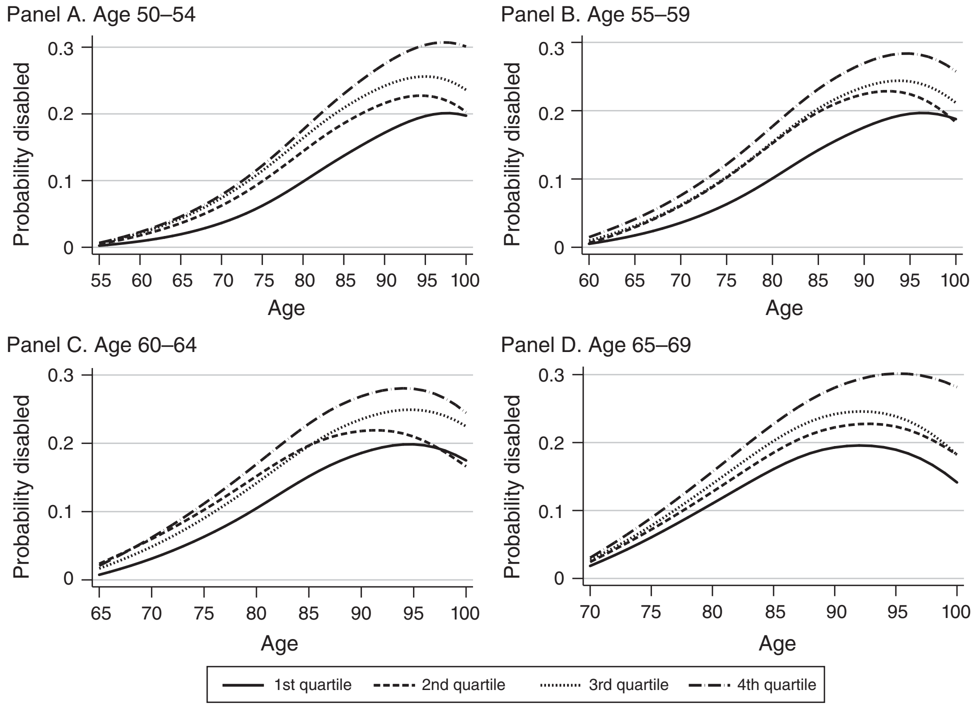

Figure 2. Disability Risk Projections by Age Group

Notes: For each age group, we sort respondents by projected expected number of years with disability and plot average disability rates by quartiles. These disability rates are conditional on survival at each age.

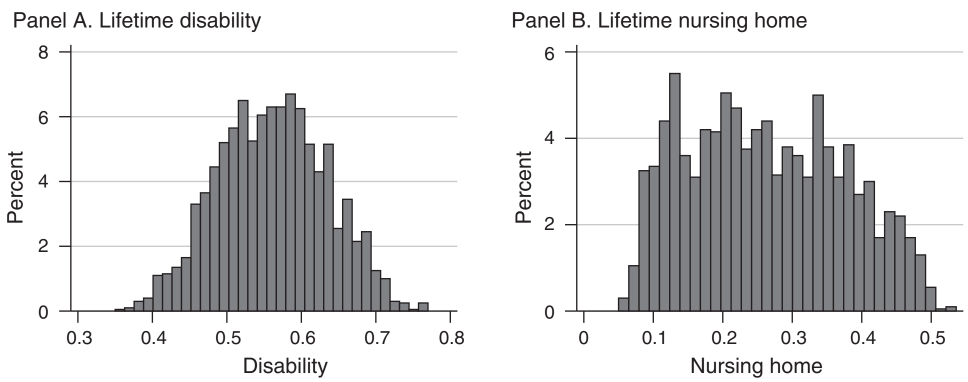

Figure 3. Probability of Ever Being Disabled or Entering a Nursing Home

Note: The distribution of these risks is computed from COMPAS.

illustrative purposes. Of course, respondents never pay the full cost. So we also compute the cost using the user contribution currently set by the Québec and Ontarian governments at roughly $2,000 per month, which amounts to $24,000 per year, out of pocket. For formal care, we use an estimate of $25 per hour of formal care and the number of hours of formal care predicted from the microsimulation model. Since the Québec government offers a tax credit of roughly 33 percent of expenditures, we

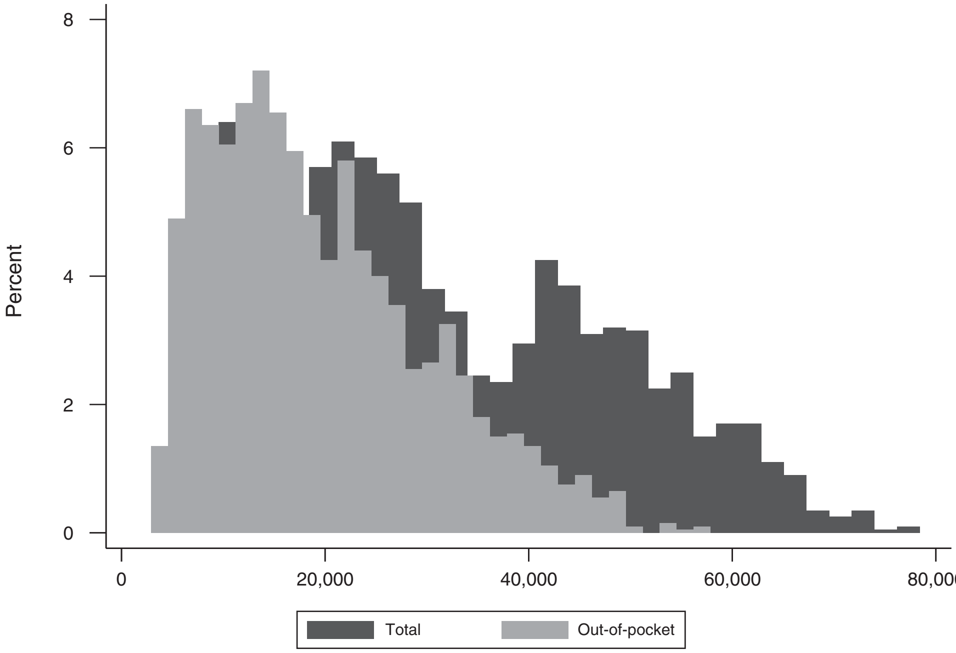

Figure 4. Expected Present Value of Cost to Respondents

Note: A discount rate of 3 percent is used.

also compute an out-of-pocket cost measure for formal care expenditures. There is no such credit in Ontario. We then combine these cost estimates with the probabilities presented earlier to estimate net present value measures of these costs (assuming a 3 percent real discount rate and no excess inflation in LTC costs). These estimates are shown in Figure 4. If there was no insurance from the government nor the private sector, on average, respondents would face an expected LTC cost of $30,788. There is considerable heterogeneity in that risk. More than 10 percent of respondents face a net present value of expenditures larger than $54,000. If we account for government participation and assume respondents use public care homes, we obtain an average estimate of $19,582 for out-of-pocket expenses. Again, more than 10 percent face a net present value of liability in excess of $34,000. As expected, public insurance reduces substantially the dispersion of the financial risk. Yet, for the median respondent, this exposure represents 25.9 percent of his/her total yearly household income or 16.2 percent of total savings at the time of the survey. Acknowledging that once in a nursing home, dependent people stay there, on average, for five years (data obtained from COMPAS), we conclude that the residual financial risk is substantial, at least for a large part of the population.[15]

But of course, decisions are based on perceptions of those risks rather than actual risks. In the survey, we asked respondents for their estimate of the probability they would live to age 85. Hence, we can compare that probability to the one

[15] The average length of time with one ADL limitation or more is, on average, four years.

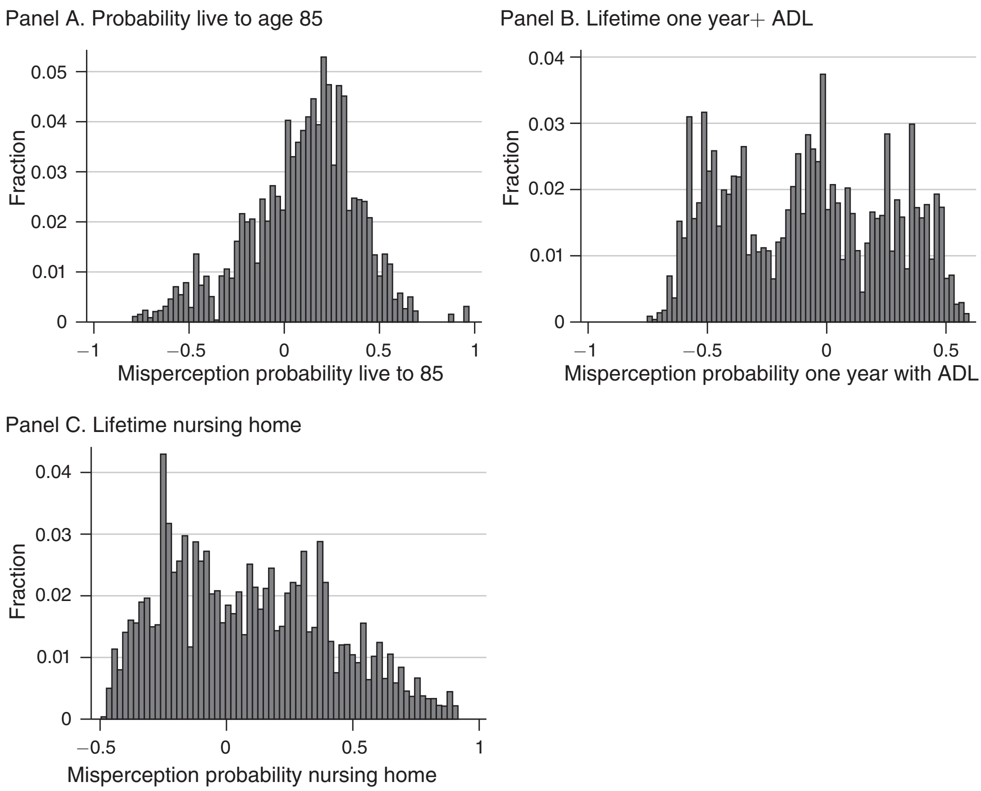

Figure 5. Difference between Subjective and Objective Risk (Misperception) for Survival, Disability, and Nursing Home Risks

Note: A positive (negative) number implies the respondent overestimates (underestimates) the risk.

we computed with COMPAS. We can compare the probability of spending at least one year with ADL limitations and the probability of ever needing to enter a nursing home as estimated by the respondents to the ones we computed with COMPAS. To compare to actual risks, we compute the deviation of subjective expectations with respect to the objective probability computed from COMPAS. A positive deviation indicates that the respondent overestimates the probability, while a negative deviation implies that he underestimates it. Results are shown in Figure 5. We find that respondents overestimate their survival probability to live up to age 85 on average (difference $=$ 0.045), while they underestimate their probability of living at least one year with ADL limitations (difference $=$ -0.080). Interestingly, however, they overestimate their risk of ever entering a nursing home by 10 percentage points, but one should take into account that risks computed for COMPAS exclude short stays, particularly at the end of life.[16] It is important to note that there is considerable

[16] Similarly, Finkelstein and McGarry (2006) compare the subjective probability of entering a nursing home within 5 years for respondents aged, on average, 78 to the actual decisions of the same respondents after 5 years. They find that most respondents do not estimate correctly their true probability of entering a nursing home.

Table 3

Number of 0% choice	Percent	Cumulative
0	36.55	36.55
1	13.64	50.19
2	9.38	59.57
3	8.79	68.37
4	8.01	76.38
5	23.62	100

Note: Distribution of agents by number of 0 percent probability choice to buy LTCI over the five scenarios presented.

heterogeneity in these risk perceptions. Furthermore, a large fraction of respondents have trouble forming probabilities on those events. For example, 35 percent of respondents could not provide a probability of the risk of living at least 1 year with an ADL limitation, and 32 percent could not report their probability of the risk of entering a nursing home. This number was only 17 percent for survival risk. Hence, for those who formed probabilities, we find widespread misperception and a significant fraction who have not formed probabilities over those events.

C. *Stated-Preference Choice Probabilities*

As shown in Table 3, overall, only 23.6 percent of respondents declare they have a 0 probability to buy all 5 LTCI contracts proposed to them. In other words, 76.7 percent of respondents declare a positive probability to buy at least 1 of these 5 contracts.

In Table 4, we report the average choice probability for each combination of benefits for LTC and for life insurance. Interestingly, choice probabilities decrease with the level of LTC benefit, while they increase with the level of life benefit (except for the contract with the highest LTC benefit). This may suggest that on average, respondents prefer lower LTC benefits, perhaps because of crowding-out from public insurance. This also suggests that there may be a joint preference for life and LTC benefits, at least for the contract with a low LTC benefit. The most popular contract appears to combine a monthly LTC benefit of $2,000 with a life insurance benefit of $25,000. Of course, the variation in equilibrium take-up could vary differently since costs vary across contracts.

III. Model

To understand the interplay between demand and supply constraints, we build a simple model following the framework of Einav, Finkelstein, and Cullen (2010). Results from the survey suggest that the fraction of respondents who own LTCI is low and that a significant fraction of respondents who do not have LTCI have limited awareness of the product. We integrate in this framework different types of demand-side frictions following Handel, Kolstad, and Spinnewijn (2019). The last component of our survey aims at eliciting preferences for LTCI products. We use elicited choice probabilities to construct estimates of demand as a function of the premium each

TABLE 4

LTC benefit	Life benefit			
	0	10,000	25,000	Total
2,000	0.2713	0.3128	0.3328	0.292
3,000	0.2491	0.2855	0.2858	0.2639
4,000	0.2044	0.2669	0.2559	0.2273
Total	0.2413	0.2891	0.29	0.2608

Note: Mean choice probability by combination of LTC and life benefit in scenarios.

respondent was given in the survey. Since premiums were randomized conditional on the actuarial premium (based on gender and age), this provides exogenous variations from which we can identify the demand function. Using this identified demand function and assuming competition in the LTCI market, we can then construct an estimate of the supply curve (using estimates from COMPAS) and compare market equilibrium under selection with the social optimum. This framework also allows us to construct counterfactuals to study the reasons behind low demand.

A. *Demand*

There are nine possible pairs (b_{ltc}, b_{life}) that can be offered to participants (see Section IA). Each pair corresponds to an LTCI contract j with $j = 1,\ldots,9$. For each respondent i, we draw at random five combinations of a contract j_t and a premium $p_{i,t} = \tau_{i,t}\bar{c}_{h,j_t}$. The multiplying factor $\tau_{i,t} \in \{0.6, 0.8, 1.0, 1.2, 1.4\}$ is chosen randomly and exogenous to the characteristics of the individual, while $\bar{c}_{h,j_t}$ is the actuarial premium under contract j_t for the risk class h defined by gender and age groups to which agent i belongs. For each individual, we then have five observations of a choice probability $q_{i,t}$ that she buys an LTCI contract j_t if it is offered at a price $p_{i,t}$.

We remain agnostic about the origin of these choice probabilities, but they may well originate from a well-defined expected utility model. Although approximating choice probabilities ultimately involves giving up on some of the nonlinearity a well-defined structural model would bring, we use a flexible demand model that can be estimated from the data. Let (censored) demand be represented by

$$q_{i,t} = \max\left(0, -\alpha\left(\mathbf{x}_i, \mathbf{z}_{i,t}, \eta_i\right) p_{i,t} + \mu\left(\mathbf{x}_i, \mathbf{z}_{i,t}, \nu_i\right) + \epsilon_{i,t}\right), \tag{1}$$

where $\alpha(\cdot)$ controls price sensitivity of demand. Note that $\alpha(\cdot)$ is a function of (i) a set of taste shifters, $\mathbf{x}_i$; (ii) a set of dummy variables for the contract offered to respondent i in choice situation t, $\mathbf{z}_{i,t}$; and (iii) an unobserved (to us) component $\eta_i \sim N\left(0, \sigma_\eta^2\right)$.[17] To insure well-behaved demand curves, we choose a specification that restricts price responses to be negative ($\alpha(\cdot) > 0$):

$$\alpha\left(\mathbf{x}_i, \mathbf{z}_{i,t}, \eta_i\right) = \exp\left(\mathbf{x}_i \psi + \mathbf{z}_{i,t}\delta + \eta_i\right). \tag{2}$$

[17] We chose to censor only from below (at zero) and not at one because there is no evidence of bunching at probability one.

The demand intercept $\mu(\cdot)$ is given by

$$(3) \qquad \mu(\mathbf{x}_i, \mathbf{z}_{i,t}, \nu_i) = \mathbf{x}_i\beta + \mathbf{z}_{i,t}\gamma + \nu_i,$$

with $\nu_i \sim N(0, \sigma_\nu^2)$. Finally, $\epsilon_{i,t} \sim N(0, \sigma_\epsilon^2)$ represents randomness associated with each choice situation which could, for example, account for uncertainty regarding the description of the scenarios (Manski 1999). The parameters of this model, $\theta = (\beta, \gamma, \delta, \psi, \sigma_\nu, \sigma_\eta, \sigma_\epsilon)$, can be estimated by maximum simulated likelihood (Hajivassiliou and Ruud 1994). Upon estimating parameters, we can construct a posterior mean for (ν_i, η_i), the unobserved heterogeneity terms, using Bayes' rules and the likelihood. We provide details on the likelihood in the online Appendix.

This demand model can be used at the respondent level to get an estimate of demand in counterfactual situations denoted $q_{i,j}(\tau\bar{c}_{h,j})$.[18] In particular, we will be interested in situations where some of the factors measuring knowledge frictions and risk perceptions included in $\mathbf{x}_i$ are neutralized. We include in $\mathbf{x}_i$ a large number of measures we obtain from the survey.

We include a set of *socioeconomic and health* controls: dummies for risk classes (age and sex), whether the respondent lives in Québec, educational attainment, number of kids, and whether the respondent is married. We then add measures of savings and income. We also include a dummy for home ownership. These serve as basic controls for the socioeconomic background of respondents. We also control for both expected number of years alive and disabled using microsimulation estimates for each respondent. This controls for the respondent's health status. We also control for the subjective probability that the family takes care of the respondent, and we include a dummy for whether respondents do not know this probability. This proxies for the family network of the respondent as well as for joint preferences for family.

In terms of *preferences*, we include three variables. First, we asked respondents whether they think that parents should set aside money to leave to their children once they die, even if it means somewhat sacrificing their own comfort in retirement. We create an indicator variable taking value one if they strongly agree or agree. We take this as an indication that the respondent's bequest motive may be driven by some underlying norm or value that leaving a bequest is desirable. We also asked them whether it is the responsibility of the family, when feasible, to take care of parents. We create a similar indicator variable. Finally, we asked respondents about their willingness to take risk. We create an indicator variable taking value one if the respondent is unwilling to take substantial or above-average financial risk expecting higher returns. These preference variables are coarse, and compared to a structural model, their effect to predict demand is limited. However, they provide some useful indication of whether standard preferences are predictive of demand for LTCI.

[18] We drop the subscript t on contracts when we consider counterfactual demands.

To account for *risk misperceptions*, we include the deviation between subjective (i.e., reported) and objective (i.e., computed with microsimulation) expected risks of survival, of becoming disabled, and of entering a nursing home. We also include indicator variables for whether respondents reported not to know the answers to these questions.

To measure *knowledge of the institutions*, we include an indicator variable for whether respondents understand that receiving private insurance benefits may influence the fee they pay for subsidized LTC (crowding-out). We include the amount they think a nursing home costs as well as an indicator variable if they do not know these costs and another indicator variable coding whether they think nursing homes are free. We also include their evaluation of the average waiting time for a place in a subsidized home (relative to the actual average waiting time) and an indicator variable if they do not know waiting times.

Since we observe that a large fraction of respondents know little or nothing about LTCI, we include controls for *awareness* of the product. We include two dummy variables taking the value one if they respond they know little and nothing, respectively.

B. *Supply*

We construct synthetic cost estimates using the microsimulation model we outlined in Section IB. Denote by $d_{i,a}$ the estimated disability risk of respondent i at age a and by $s_{i,a}$ the survival probability to age a. Voluntary lapsing occurs, i.e., respondents may stop payments and terminate their contract. We account for lapsing using an estimate of the fraction of contracts that voluntarily lapse each year from the Society of Actuaries (Purushotham 2011).[19] The fraction of LTCI customers who lapsed in 2011 was 1.8 percent. Since this fraction does not appear to differ by gender nor age, we use this uniform estimate. Denote by $z_{i,a} = (1 - 0.018)^{a-age_i}$ the survival rate of the contract owing to lapsing. We also set the real discount rate to $\rho = 0.03$ and the inflation rate to $\iota = 0.02$ (since premiums remain constant in nominal terms). We can then compute the expected discounted cost for the insurers of respondent i buying contract j as

$$C_{i,j} = \sum_{a \geq age_i} \frac{1}{(1 + \rho + \iota)^{a-age_i}} z_{i,a}\left(s_{i,a} d_{i,a} ben_{ltc,j} + m_{i,a} I_{(a<85)} ben_{life,j}\right),$$

where $m_{i,a} = 1 - s_{i,a}/s_{i,a-1}$ is the mortality rate at age a, and $I_{(a<85)} = 1$ when $a < 85$.

We plot on Figure 6 the distribution of costs, $C_{i,j}$, for the nine contracts offered to respondents. The median expected cost ranges from \$20,265 for the contract offering a monthly LTC benefit of \$2,000 and no life insurance benefit to \$46,515 for the contract offering a \$4,000 monthly LTC benefit and a \$25,000 life insurance benefit. We observe substantial variations in the individual costs for any given contract.

[19] See the online Appendix for details.

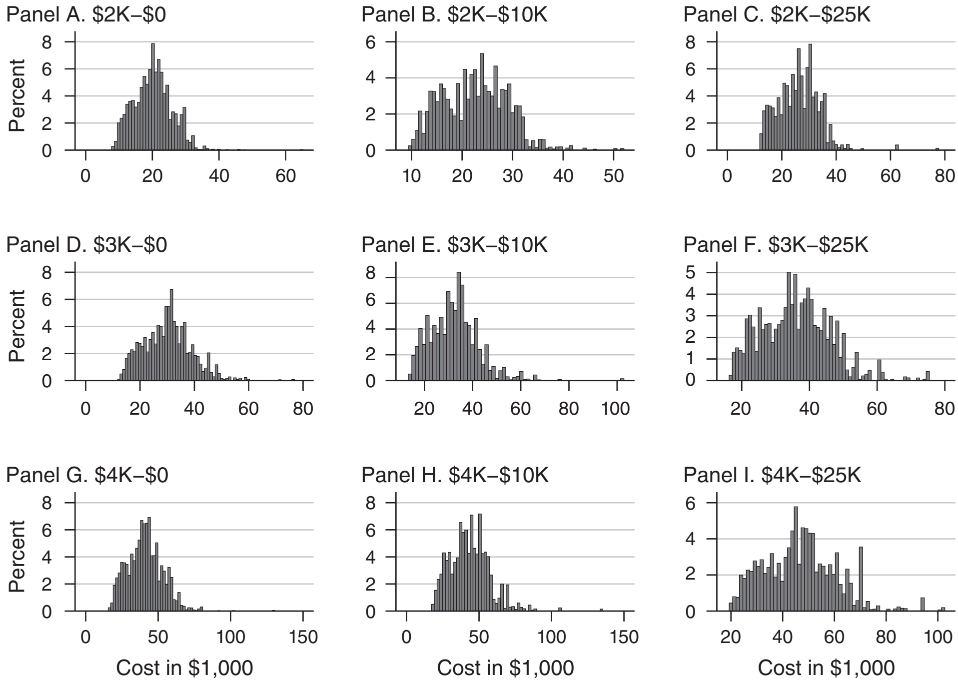

FIGURE 6. DISTRIBUTION OF EXPECTED COST BY CONTRACT

Note: In each panel, we report a histogram of the distribution of expected costs, as defined in the paper, for each contract defined by the LTC benefit and the life insurance benefit.

The largest variation occurs in the case of contracts that bundle life insurance with LTCI benefits. For instance, for a monthly LTCI benefit of $3,000 and a $10,000 life insurance benefit, expected cost to the insurer ranges from $19,685 to $44,481 at the ninety-fifth percentile.

We express the total expected discounted cost in terms of the equivalent monthly actuarial premium, denoted by $c_{i,j}$. The two quantities are related by $C_{i,j} = \Pi_i c_{i,j}$, where

$$\Pi_i = \sum_{a \geq age_i} \frac{1}{\left(1 + \rho + \iota\right)^{a - age_i}} z_{i,a} s_{i,a} \left(1 - d_{i,a}\right)$$

is the present value of one dollar of actuarial monthly premium. Therefore, the actuarial premium $c_{i,j} = C_{i,j}/\Pi_i$ is the constant monthly payment the insurance company would need to obtain from consumer i in order to satisfy the zero expected profit condition.

In the Canadian market, risk classification is based on gender and age. Denote by h a risk class (say, age 50–54 men) and H the set of risk classes. The average monthly cost of those who purchase the contract j in risk group h is obtained using information on the cost for each respondent and the choice probabilities,

$$AC_{h,j}\left(\tau_{h,j}\right) = \frac{1}{\bar{q}_j\left(\tau_{h,j} \bar{c}_{h,j}\right)} \sum_{i \in h} c_{i,j} q_{i,j}\left(\tau \bar{c}_{h,j}\right), \tag{4}$$

where $c_{i,j}$ is obtained from above, $\bar{c}_{h,j}$ is the average cost for risk group h in contract j to which individual i belongs, and $\bar{q}_j$ is the fraction of insured individuals with contract j. Adverse selection arises when there is a positive correlation between expected cost and demand at the respondent level. Indeed, this is the case if riskier agents (and hence more costly agents) buy more insurance. This leads to a positive relationship between $AC_{h,j}(\tau)$ and τ. To the opposite, when there is a negative correlation, i.e., less risky agents buy more insurance, propitious (or advantageous) selection arises. Hence, a direct test of selection can be conducted from these hypothetical data. Ideally, $c_{i,j}$ would be estimated from realized claims, which would allow for more heterogeneity in cost and hence a higher potential for selection. Despite our rich characterization of individual-level expected cost, it is possible that we miss some of the selection which may be present in reality. However, there is considerable variance in the cost and revenue estimates within sample, and it is sufficient to allow us to test for selection based on the characteristics we account for.

C. *Competitive Equilibrium*

The monthly premium is $p_{h,j} = \tau_{h,j}\bar{c}_{h,j}$, and $\tau_{h,j}$ is the multiplying factor yielding the market premium. Following Einav, Finkelstein, and Cullen (2010), perfect competition drives insurer profits to zero, thus implying that the equilibrium $\tau^*_{h,j}$ solves

$$\tau_{h,j} = \frac{1}{\bar{c}_{h,j}} AC_{h,j}(\tau_{h,j}), \tag{5}$$

where $AC_{h,j}(\tau_{h,j})$ is the average cost of agents i belonging to class h who therefore purchase the contract within class h. The equilibrium fraction of respondents insured in class h is then $\bar{q}_{h,j}(\tau^*_{h,j}\bar{c}_{h,j})$.

While we will provide a comparison between the case where $\tau_{h,j}$ is allowed to vary across risk classes, we will assume for graphical representation of the equilibrium that $\tau_{h,j} = \tau_{h',j}\ \forall h, h' \in H$. We refer to this situation as uniform pricing. Note that even if τ is the same across risk classes, premiums are not as they depend on $\bar{c}_{h,j}$. Assuming uniform pricing allows for a graphical representation of the overall equilibrium in terms of demand and supply in the space (τ, q). The competitive equilibrium τ^*_j solves

$$\tau_j = \frac{1}{\bar{c}_j} AC_j(\tau_j), \tag{6}$$

where $\bar{c}_j$ is the average cost over the whole population of potential customers and where

$$AC_j(\tau_j) = \frac{1}{\sum_h \bar{q}_j(\tau_j \bar{c}_{h,j})} \sum_h \sum_{i \in h} c_{i,j}\, q_{i,j}(\tau \bar{c}_{h,j}). \tag{7}$$

We will refer to $\overline{AC}_j := AC_j(\tau_j)/\bar{c}_j$ as the normalized average cost. There is adverse selection when the normalized average cost is above unity, i.e., $\tau^*_j > 1$, reflecting an overall positive covariance between demand and cost at the individual level. Conversely, there is advantageous selection when $\tau^*_j < 1$.

The competitive equilibrium without frictions is computed similarly as above, replacing $q_i(\cdot)$ with $\hat{q}_i(\cdot)$, which uses counterfactual $\hat{\alpha}_i = \alpha(\hat{\mathbf{x}}_i, \mathbf{z}_{i,t}, \eta_i)$ and $\hat{\mu}_i = \mu(\hat{\mathbf{x}}_i, \mathbf{z}_{i,t}, \eta_i)$ without frictions and where the $\hat{}$ refers to the true value of the parameters.

D. *Welfare in the Competitive Equilibrium*

To simplify notation, we henceforth drop the subscript j referring to the type of contract. Demand for individual i is

$$q_i(p_i) = \max(0, -\alpha_i p_i + \mu_i), \tag{8}$$

where α_i and μ_i are shorthand for the parameters in equation (1) that depend on the individual's characteristics (and contract type), and p_i is the price faced by the individual. We interpret $q_i(p_i)$ as the proportion of individuals with characteristic i purchasing the contract. This allows us to use standard welfare formulas except that the value to consumers is computed on the basis of the marginal value curve

$$\hat{q}_i(p_i) = \max(0, -\hat{\alpha}_i p_i + \hat{\mu}_i), \tag{9}$$

where $\hat{\alpha}_i$ and $\hat{\mu}_i$ are the counterfactuals without informational frictions.

At the price p_i, the total value to consumers with characteristic i is the area under the marginal value curve up to $q_i(p_i)$. This is computed as follows. Consumers behaving on the basis of the true marginal value curve (9) would purchase a positive quantity $q_i(p_i)$ if they faced a price $\hat{p}_i$ satisfying

$$-\hat{\alpha}_i \hat{p}_i + \hat{\mu}_i = -\alpha_i p_i + \mu_i.$$

We take it that $\hat{p}_i$ is positive, i.e., eliminating frictions would not reduce demand by too much (and may in fact increase it). The total value of $q_i(p_i)$ to consumers is then

$$V_i(q_i(p_i)) = \int_{\hat{p}_i}^{\infty} \hat{q}_i(p)\, dp + \hat{p}_i q_i(p_i). \tag{10}$$

Straightforward computations yield

$$V_i(q_i(p_i)) = \frac{1}{2} q_i(p_i) \left(\frac{\alpha_i p_i + 2\hat{\mu}_i - \mu_i}{\hat{\alpha}_i} \right). \tag{11}$$

Note that the latter expression is zero when consumers with characteristic i do not purchase the contract.

Welfare is the sum of values to consumer minus the total cost of providing the insurance policy:

$$W = \sum_i \left[V_i(q_i(p_i)) - c_i q_i(p_i) \right]. \tag{12}$$

In the competitive equilibrium, $p_i = \tau^* \bar{c}_h$ for i in the gender-age class h and where τ^* solves (6). Welfare at equilibrium can then be expressed as

$$W^{eq} = \sum_h \sum_{i \in h} \Big[V_i\big(q_i(\tau^* \bar{c}_h)\big) - c_i q_i(\tau^* \bar{c}_h) \Big].$$

E. *Optimum*

We consider a variant of the efficient uniform price discussed in the literature.[20] Individuals i in the age-gender class h face the price $p_i = \tau \bar{c}_h$, where τ is now chosen to maximize the welfare of potential purchasers over all age-gender classes. Welfare is computed with consumers behaving on the basis of their true marginal value. At price p_i and using (10), the total value to consumers i is

$$V_i\big(\hat{q}_i(p_i)\big) = \int_{p_i}^{\infty} \hat{q}_i(p)\, dp + p_i \hat{q}_i(p_i).$$

Using (11), this is easily seen to reduce to

$$V_i\big(\hat{q}_i(p_i)\big) = \frac{1}{2} \hat{q}_i(p_i) \left(p_i + \frac{\hat{\mu}_i}{\hat{\alpha}_i} \right).$$

Total welfare is now given by

$$W = \sum_i \Big[V_i\big(\hat{q}_i(p_i)\big) - c_i \hat{q}_i(p_i) \Big].$$

Substituting for $p_i = \tau \bar{c}_h$ and maximizing with respect to τ, optimal welfare is

$$W^{op} = \max_{\tau} \sum_h \sum_{i \in h} \Big[V_i\big(\hat{q}_i(\tau \bar{c}_h)\big) - c_i \hat{q}_i(\tau \bar{c}_h) \Big]. \tag{13}$$

The optimal markup (or markdown) is denoted τ^{**}.

In the next section, for any given contract, we show figures comparing the competitive equilibrium and the optimum with τ on the vertical axis and total quantity on the horizontal axis, where quantity is on the basis of the demand with or without frictions.[21] As τ is not a price strictly speaking, the figures warrant some explanation. A given τ yields a total quantity distributed between purchasers with different characteristics. To this quantity can be associated an average cost, normalized by the average cost over all potential purchasers as in equation (6). The normalized average cost may differ depending on whether the demand is with or without frictions because actual purchasers will sort differently. To draw marginal cost curves consistent with these figures, we also need to introduce an appropriate normalization. This allows, in particular, the optimal τ^{**} to be determined by the

[20] See Einav, Finkelstein, and Cullen (2010) and Dardanoni and Li Donni (2016). The uniform efficient price, also described as the constrained efficient benchmark, occurs when the marginal cost curve crosses the demand curve.

[21] In the figures, the quantity is the fraction of potential customers who purchase the policy.

intersection of the demand without frictions and the normalized marginal cost given the consumers' behavior.

The first-order condition of problem (13) is

$$\frac{d\sum_h \sum_{i\in h} V_i\big(\hat{q}_i(\tau\bar{c}_h)\big)}{d\tau} = \frac{d\sum_h \sum_{i\in h} c_i \hat{q}_i(\tau\bar{c}_h)}{d\tau}.$$

In words, the change in value owing to a small change in τ is equal to the change in costs. Note that $\partial V_i/\partial \hat{q}_i = \tau\bar{c}_h$ for individuals in risk class h and that $d\hat{q}_i(\tau\bar{c}_h)/d\tau = \bar{c}_h \hat{q}_i'(\tau\bar{c}_h)$, where $\hat{q}_i'(\cdot)$ is the derivative of each demand relative to the price.[22] The first-order condition then implies that the optimal τ^{**} solves

$$\tau = \frac{\sum_h \sum_{i\in h} c_i \bar{c}_h \hat{q}_i'(\tau\bar{c}_h)}{\sum_h \sum_{i\in h} \bar{c}_h^2 \hat{q}_i'(\tau\bar{c}_h)}. \tag{14}$$

We show that the right-hand side of (14) can be interpreted as the normalized marginal cost. Actual marginal cost is

$$MC(\tau) = \frac{d\sum_h \sum_{i\in h} c_i \hat{q}_i(\tau\bar{c}_h)/d\tau}{d\sum_h \sum_{i\in h} \hat{q}_i(\tau\bar{c}_h)/d\tau}, \tag{15}$$

that is, the change in total cost relative to the change in quantity. This rewrites as

$$MC(\tau) = \frac{\sum_h \sum_{i\in h} c_i \bar{c}_h \hat{q}_i'(\tau\bar{c}_h)}{\sum_h \sum_{i\in h} \bar{c}_h \hat{q}_i'(\tau\bar{c}_h)}. \tag{16}$$

Normalized marginal cost as defined by the right-hand side of (14) is

$$\overline{MC}(\tau) := \frac{MC(\tau)}{\gamma(\tau)}, \tag{17}$$

with the normalization factor

$$\gamma(\tau) := \frac{\sum_h \sum_{i\in h} \bar{c}_h^2 \hat{q}_i'(\tau\bar{c}_h)}{\sum_h \sum_{i\in h} \bar{c}_h \hat{q}_i'(\tau\bar{c}_h)}. \tag{18}$$

The normalization factor does not depend on individual costs. Only the average cost difference between age-gender classes matters. When all $\bar{c}_h$ are equal, i.e., $\bar{c}_h = \bar{c}$ for all h, then $\gamma(\tau) = \bar{c}$. The normalization is then the same as for the average cost.

A normalized marginal cost is derived similarly for the case where consumers behave according to their demand with frictions. In Section IVC, we discuss the

[22] When the demand is positive, $\hat{q}_i'(\cdot) = -\alpha_i$. When $\tau\bar{c}_h > \mu_i/\alpha_i$, the demand is nil, and $\hat{q}_i'(\cdot) = 0$.

case where τ is specific to each age-gender class. The normalization factor is then equal to $\bar{c}$ and is the same as for the average cost.

IV. Results

A. *Demand Estimation Results*

Estimates of the demand model are reported in Table 5. Given that characteristics affect both intercepts and slopes, their total effect depends on the derivative of demand with respect to these characteristics. Hence, we report average partial effects on demand evaluated at the average premium presented to respondents.[23]

Socioeconomic and Health.—There are small differences across age and sex for intercepts but significant differences for price sensitivity. Females (in particular those aged 60–64) have in general lower price sensitivity than their male counterparts. At average premiums, females have larger demand than men. College-educated individuals are also less price sensitive and therefore have slightly higher demand at average premiums than non-college-educated individuals. We find no statistically significant differences in terms of marital status. Demand (intercept and price sensitivity) is generally lower for individuals with higher income, both of which lead to a higher demand at the average premium.

In terms of expected number of years alive and disabled, only disability appears to impact demand with a lower intercept but also lower price sensitivity, which leads to higher demand at the average premium. Hence, individuals who are expected to have higher LTC costs also have higher demand. Although this is potentially evidence of adverse selection, it is the overall correlation between demand and costs within a risk class, i.e., the risk classification used by insurers, which determines whether or not there is adverse selection (Finkelstein and McGarry 2006). We come back to this point below.

Individuals who own a home have lower demand but are more price sensitive. As in Davidoff (2009), we obtain that the house may act as a substitute for LTCI, as it is mostly nonliquid until individuals either die or move into a nursing home, at which point it can be sold to finance extra LTC spending.

We find that individuals with a larger probability that the family provides care have slightly higher demand for LTCI. In Canada, the LTCI contract is generally conditioned on care needs rather than on reimbursements (i.e., actual consumption of external LTC services) so that one potential mechanism consists in providing financial relief for children who take care of their parents.[24] Interestingly, individuals who

[23] For a characteristic x_k, the average partial effect is $\left(-\sum_i \alpha_i \bar{p}_i \psi_k + \beta_k\right) P_i$, where α_i is the predicted slope of respondent i, $\bar{p}_i$ is the average premium presented to respondent i over scenarios, and P_i is the probability that demand is positive. We do the same for contract characteristics z.

[24] For instance, Pinquart and Sörensen (2002) show that dependent individuals in general prefer informal help or a combination of informal and formal support to purely formal support, at least for short-term needs.

Table 5—Demand Model Estimates

	Price: $\alpha(\cdot)$ ψ		Intercept: $\mu(\cdot)$ β		Marginal effect
Shifters	Estimate	SE	Estimate	SE	estimate
55–59 men	−0.3806	0.1322	−0.0508	0.043	0.0441
60–64 men	−0.0810	0.1065	0.0662	0.042	0.0506
65–69 men	−0.1766	0.1003	0.0512	0.040	0.0605
50–54 female	−0.4676	0.1281	0.0308	0.049	0.1041
55–59 female	−0.4102	0.1141	0.1042	0.046	0.1327
60–64 female	−0.8621	0.1562	0.0175	0.062	0.1708
65–69 female	−0.2932	0.1402	0.1005	0.055	0.1087
Québec	0.1937	0.0550	0.0130	0.022	−0.0293
College	−0.1774	0.0561	−0.0543	0.024	0.0042
Married	0.0074	0.0547	0.0142	0.024	0.0062
Number of kids	−0.0053	0.0170	−0.0129	0.008	−0.0059
Savings	0.2057	0.1042	0.0912	0.047	0.0103
Household income	−0.1324	0.0421	−0.0144	0.017	0.0171
$e_{s,x}$	−0.0083	0.0086	0.0042	0.003	0.0038
$e_{d,x}$	−0.1610	0.0563	−0.0345	0.024	0.0117
Own home	0.0964	0.0615	−0.0919	0.027	−0.0673
Bequest motive	−0.2825	0.0612	−0.0060	0.024	0.0497
Risk averse	−0.1928	0.0617	−0.0127	0.025	0.0293
Family	−0.2070	0.0497	−0.0433	0.021	0.0156
Pref formal care	−0.0837	0.0480	0.0393	0.021	0.0368
Pr family cares	0.1573	0.0718	0.1130	0.033	0.0311
Pr family cares dnk	−0.2721	0.0848	−0.0514	0.034	0.0234
Bias survival	−0.3475	0.0967	−0.0257	0.042	0.0513
Bias survival dnk	−0.0892	0.0785	−0.0796	0.031	−0.0259
Bias disability	−0.2814	0.0939	−0.0320	0.041	0.0355
Bias disability dnk	0.0582	0.0641	−0.0441	0.027	−0.0345
Bias NH	−0.1685	0.1013	0.1076	0.042	0.0892
Optimism NH dnk	0.0642	0.0703	0.0248	0.030	0.0012
Knows crowd-out	−0.2662	0.0579	−0.1451	0.027	−0.0279
Bias NH cost	−0.0274	0.0211	−0.0136	0.008	−0.0022
Dnk NH costs	−0.1311	0.0771	−0.1197	0.034	−0.0396
Thinks NH free	−0.1166	0.0969	−0.0497	0.039	−0.0048
Wait time NH	0.0023	0.0036	0.0023	0.002	0.0008
Dnk NH wait time	0.2726	0.0694	0.1527	0.030	0.0308
Knows little LTCI	0.3686	0.0794	−0.0342	0.034	−0.0873
Knows nothing LTCI	0.0296	0.0719	−0.0616	0.031	−0.0386
Intercept	−4.6458	0.3023	0.7745	0.125	1.2850
Contract, ref (2K, 0)	δ		γ		
(2K, 10K)	−0.1545	0.0721	0.0203	0.0264	0.0398
(2K, 25K)	0.0527	0.0627	0.1215	0.0267	0.0552
(3K, 0K)	0.0053	0.0499	0.0838	0.0210	0.0439
(3K, 10K)	−0.0230	0.0718	0.1334	0.0300	0.0758
(3K, 25K)	−0.1053	0.0629	0.1285	0.0289	0.0886
(4K, 0K)	−0.0857	0.0508	0.0961	0.0232	0.0675
(4K, 10K)	−0.1738	0.0645	0.1425	0.0306	0.1089
(4K, 25K)	−0.0950	0.0641	0.1918	0.0313	0.1206
Heterogeneity	σ_η		σ_ν		
	0.8518	0.0267	0.2785	0.0077	
log L	−3,054.1				

Notes: Estimates by maximum simulated likelihood with 50 draws. $e_{s,x}$ refers to remaining life expectancy at age x and $e_{d,x}$ refers to expected number of years with 2+ ADL limitations. Marginal effects are average partial effects of characteristics on the (censored) probability of purchase evaluated for the first contract (in the case of x) and for each contract (z). The average premium faced by respondents across scenarios is used to compute this marginal effect.

do not know this probability have higher demand at average premiums. The need to insure against uncertainty regarding family care may raise demand for LTCI.[25]

Preferences.—We find that individuals who are more risk averse and those with a bequest motive have lower price sensitivity. However, we do not find differences in intercepts for preferences, which leads to positive average partial effects at average premiums. Hence, more risk-averse respondents and those with a bequest motive have higher demand for LTCI. This is consistent with bequests raising the need to protect savings from future large LTC expenditures but not with studies finding that bequest motives reduce the opportunity cost of saving and hence generate lower demand for LTCI (Lockwood 2014).[26] Those who think the family should care for frail parents have slightly higher demand overall.

Risk Perceptions.—Biases in risk perceptions (positive implies pessimism for disability and nursing home and optimism for survival) for disability, survival, and nursing home visits generally lead to less price sensitivity and therefore to higher demand at average premiums.[27] The results suggest that higher demand is not due to higher intercepts but to lower price sensitivity, something that would be missed if one does not allow for heterogeneous price sensitivity. Generally, individuals who do not know these risks have lower demand.

Knowledge.—Individuals who do not know that LTCI crowds out government benefits have lower demand and lower price sensitivity, which leads to a negative effect on demand at average prices. Hence, crowd-out cannot explain why our respondents do not buy insurance. In Canada, public subsidies, such as lower co-payments for nursing homes and tax credit for formal care, are means tested, which should reduce the demand for long-term care insurance.[28]

There is little relationship between incorrect knowledge of nursing home cost and demand. But individuals who do not know nursing home costs have lower demand and price sensitivity. This is somewhat related to Tennyson and Yang (2014), who highlight the role of one's experience with LTC as a contributing factor to better knowing the risk of LTC costs. Interestingly, individuals who do not know waiting times have higher demand but also larger price sensitivity, which overall also leads to little change in demand. Hence, relatively small overall effects hide important price sensitivity responses, as in the case of crowding-out.

Awareness.—In Section IIA, we have shown that knowledge of LTCI itself is limited. We find that individuals who know nothing about LTCI prior to taking the survey have much lower demand (-3.9 percent). Individuals who know little about

[25] Bonsang (2009) obtains similar results, providing evidence of substitution between informal and formal help, the latter being monetary transfers that mostly result from public or private insurances.

[26] See also Ameriks et al. (2011) about the importance of bequest motives for late-in-life decisions to save.

[27] Studies by Zhou-Richter, Browne, and Gründl (2010) and Tennyson and Yang (2014) yield similar results.

[28] Brown and Finkelstein (2008) find that social insurance (in particular Medicaid) crowds out the demand for private insurance.

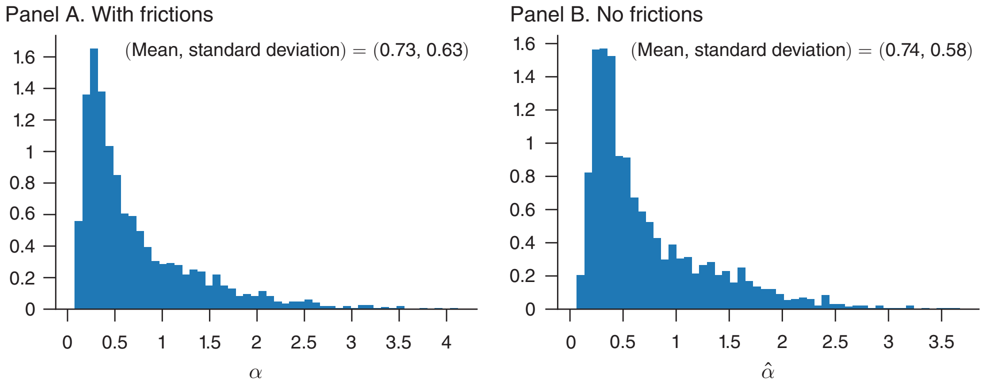

FIGURE 7. DISTRIBUTION OF ELASTICITY ESTIMATES FROM DEMAND MODEL

Notes: Estimates of α and $\hat{\alpha}$ in elasticity form using the demand model (equation (1)). These estimates are obtained for the baseline contract with a $2,000 LTCI benefit and no life insurance benefit.

LTCI have larger price sensitivity, which leads to even lower demand at average premiums (−8.7 percent).

Contract Features.—Demand for the different contracts varies. The highest demand is observed for contracts that offer life insurance benefits relative to those that do not. Demand is also larger for more generous LTCI benefits rather than less generous benefits. Price sensitivity is similar across contracts.

Unobserved Heterogeneity.—Overall, we find substantial unobserved heterogeneity in demand. The standard deviation of unobserved heterogeneity is large for both price sensitivity and intercepts. Hence, substantial variation in price sensitivity and intercepts is left even after controlling for a large set of demand shifters.

We construct individual estimates of $\alpha(\cdot)$ and $\mu(\cdot)$ with and without frictions. Estimates without friction are constructed by zeroing out risk perception biases, assuming perfect knowledge of institutions (of those measured) and good knowledge of LTCI generally. We denote estimates without frictions, $\hat{\alpha}(\cdot)$ and $\hat{\mu}(\cdot)$. In Figure 7, we report the distribution of the price sensitivities. We express these parameters as elasticities on censored demand (nonnegative demand) for the first contract (since elasticities vary little by contract).

The average elasticity in the sample with frictions is 0.73 with substantial variation across respondents. Without frictions, the price sensitivity is slightly larger at 0.74. Hence, our respondents have relatively inelastic demand. Only 24.3 percent of respondents have an elasticity above unit (24.9 percent without frictions). In a study using a life-cycle model approach, Ameriks et al. (2016) find comparable results (lower than unity elasticities). Yet, two other studies focus on the impact of tax incentives on individuals' purchase of LTCI and find higher elasticities. Courtemanche and He (2009) study the impact of the tax incentive prescribed in the Health Insurance Portability and Accountability Act (HIPAA) of 1996 and find a price elasticity of LTCI of −3.9, suggesting that the demand for LTCI is very price

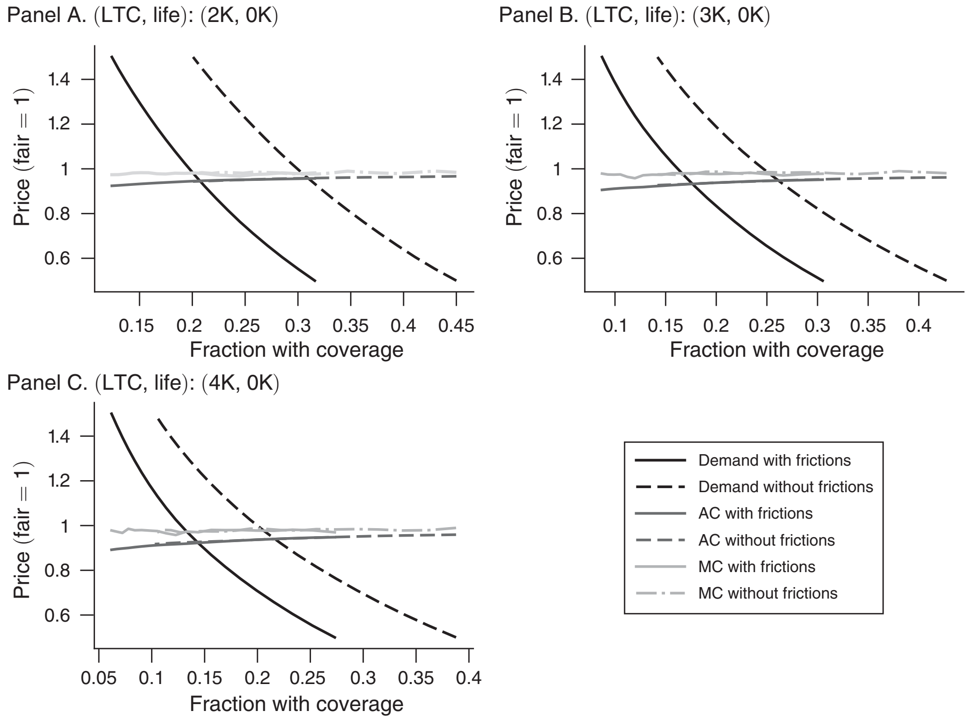

Figure 8. Market Equilibrium for Contracts without Life Insurance Benefits

Notes: For each contract, we compute the competitive equilibrium with and without frictions. We plot demand as well as average cost and marginal cost curves.

elastic. Also, Goda (2011) examines the effect of a variation in tax subsidies for private LTCI on insurance coverage rates and Medicaid expenditure for LTC. Using HRS data for the period 1996–2006, she finds that implementing tax subsidies on private LTCI yields an implied elasticity of -3.3.

Hence, our estimates are much smaller than estimates using natural experiments. There are many reasons why this may occur. First, it is possible that hypothetical stated-choice experiments yield lower price responses. Yet, we are not aware of consistent evidence that hypothetical studies underestimate price sensitivity. Second, it is possible that given the heterogeneity uncovered in price sensitivity, the set of individuals reacting to particular measures is different, which could explain why estimates vary substantially. A third possibility is that tax rebates make price changes explicit (salient), while variation in prices across scenarios does not. If consumers react more, or pay more attention, to explicit changes, this could explain the difference between our estimates and those from natural experiments.

B. *Equilibrium Results*

We now investigate the predicted equilibrium in the LTC market for the different contracts we offered. We first look at contracts that do not include a life insurance benefit. For each of these contracts, we construct demand as outlined in Section IIIA above and compute costs for each respondent as outlined in Section IIIB, which provides us with the average cost curve. We then solve for the equilibrium relative price and quantity as outlined in Section IIIC. We similarly derive the marginal cost function from the average cost function. This allows us to compute the social optimum as shown in Section IIIE, assuming τ does not vary across risk classes.

Plots of those markets are presented in Figure 8. The equilibrium fraction of respondents who purchase LTCI runs from 20.7 percent for the contract offering a \$2,000 LTCI benefit to 14.4 percent for the contract offering a \$4,000 benefit (with no life insurance benefit component). Hence, the fraction of individuals who would purchase LTCI is low (say, relative to life insurance). It remains higher than the actual fraction with LTCI in the sample. One reason is that close to 40 percent of those without LTCI were never offered LTCI and did not know about it. If we put their demand to zero, we obtain take-up rates which are consistent with the observed take-up rate. Hence, our experiment yields higher take-up rates simply because we offer contracts to respondents.

We do not find evidence of adverse selection. If anything, average cost is sloping upward, and the equilibrium relative price is below one. This would indicate evidence of advantageous selection. While health tends to lead to adverse selection (those with higher expected years with disability have higher demand), other characteristics, correlated with costs and demand but unused in pricing, counteract this effect. As the social optimum without asymmetric information in this case has a lower fraction insured, we can rule out asymmetric information as a reason for the low take-up of LTCI.

The role of information frictions is much larger. Demand without frictions (replacing $\alpha(\cdot)$ and $\mu(\cdot)$ by $\hat{\alpha}(\cdot)$ and $\hat{\mu}(\cdot)$) is much higher at any price. In Figure 8, we plot demand, average cost, and marginal cost without frictions. The equilibrium fraction with LTCI is 31 percent, 26.1 percent, and 21.6 percent for the contracts offering \$2,000, \$3,000, and \$4,000 LTCI benefits respectively. The displacement of demand is for the most part parallel, but this hides considerable displacement in terms of who is insured and who is not.

In Figure 9, we report similar market equilibrium plots for contracts with a varying level of the life insurance benefit, keeping constant the LTCI benefit at \$2,000 per month (similar figures emerge at other levels). We find very similar results with no evidence of adverse selection, some evidence of advantageous selection, and a large demand effect of frictions. Demand is slightly larger with a life insurance benefit, but that effect is not large. For example, offering a \$10,000 life insurance benefit increases equilibrium take-up from 20.7 percent to 22.6 percent. Hence, although we have shown in Table 4 that demand was at least 4 percentage points higher when a life insurance benefit was offered, a smaller effect is observed in equilibrium, due potentially to costs and selection.

In Table 6, we report the social optimum (i.e., without any supply-side or demand-side frictions) as well as welfare loss due to asymmetric information and information frictions. Overall, the social optimum is very close to the competitive equilibrium without frictions, confirming that asymmetric information plays a minor role. In fact, for the contract $(2\mathrm{K}, 0\mathrm{K})$, the welfare loss due to asymmetric

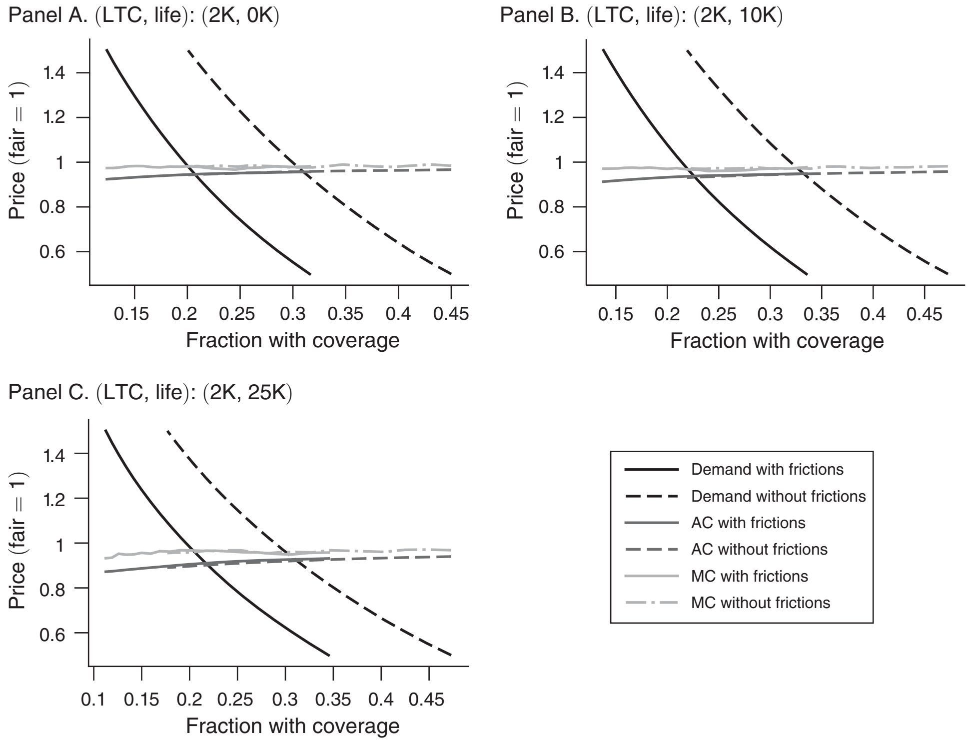

Figure 9. Market Equilibrium for Contracts with Varying Life Insurance Benefit

Notes: For each contract, we compute the competitive equilibrium with and without frictions. We plot demand as well as average cost and marginal cost curves.

Table 6—Equilibrium and Welfare Computations

	Equi (frictions)	Equi (no frictions)	Optimum	AS loss	Frictions loss	Total loss
(2K, 0K)	[0.946, 0.207]	[0.958, 0.31]	[0.977, 0.305]	−0.00013	−0.16253	−0.16265
(2K, 10K)	[0.938, 0.226]	[0.947, 0.333]	[0.975, 0.326]	−0.00023	−0.15474	−0.15497
(2K, 25K)	[0.91, 0.217]	[0.921, 0.312]	[0.963, 0.299]	−0.001	−0.15441	−0.1554
(3K, 0K)	[0.933, 0.176]	[0.948, 0.261]	[0.983, 0.251]	−0.00084	−0.17223	−0.17308
(3K, 10K)	[0.924, 0.192]	[0.937, 0.278]	[0.979, 0.265]	−0.00112	−0.16488	−0.16599
(3K, 25K)	[0.91, 0.185]	[0.923, 0.27]	[0.97, 0.256]	−0.00158	−0.16516	−0.16674
(4K, 0K)	[0.923, 0.144]	[0.94, 0.216]	[0.984, 0.204]	−0.00179	−0.18693	−0.18872
(4K, 10K)	[0.92, 0.171]	[0.935, 0.25]	[0.976, 0.238]	−0.00133	−0.17274	−0.17407
(4K, 25K)	[0.902, 0.161]	[0.918, 0.233]	[0.973, 0.216]	−0.0034	−0.17376	−0.17716

Notes: For each contract, we provide the equilibrium with and without frictions, the optimum (relative price, fraction insured), and the welfare loss due to asymmetric information and due to frictions (and total loss). These welfare losses are expressed in relative terms (relative to the optimum).

information (AS loss) represents less than 0.013 percent of the total social optimum welfare. The role of frictions is much larger. Across contracts, the welfare loss due to frictions is close to 17 percent of the total social optimum welfare. In Section IVD below, we decompose frictions and quantify their separate impact on total welfare loss in this market.

Table 7—Segmented Equilibrium and Welfare Computations

	Equi (frictions)	Equi (no frictions)	Optimum	AS loss	Frictions loss	Total loss
50–54 men	[0.931, 0.243]	[0.939, 0.348]	[0.974, 0.339]	−0.00037	−0.14898	−0.14935
55–59 men	[0.999, 0.233]	[1.01, 0.368]	[1.009, 0.368]	−0	−0.14513	−0.14513
60–64 men	[1.001, 0.215]	[1.014, 0.302]	[0.968, 0.314]	−0.00064	−0.16415	−0.16479
65–69 men	[0.974, 0.197]	[0.991, 0.302]	[0.981, 0.304]	−3e-05	−0.13084	−0.13087
50–54 female	[0.883, 0.181]	[0.898, 0.26]	[0.91, 0.257]	−7e-05	−0.17596	−0.17603
55–59 female	[1.012, 0.173]	[1.005, 0.291]	[1.019, 0.287]	−7e-05	−0.24435	−0.24441
60–64 female	[0.917, 0.217]	[0.92, 0.311]	[0.95, 0.304]	−0.00032	−0.14621	−0.14653
65–69 female	[1.022, 0.159]	[1.038, 0.246]	[0.999, 0.254]	−0.00067	−0.21792	−0.21859

Note: For the contract offering a \$2,000 LTCI benefit and no life insurance, we compute the equilibrium and optimum by risk segmentation groups (age and sex).

Table 8—Segmented Equilibrium and Welfare Computations

		Q equilibrium	Q no frictions	Q optimum	AS loss	Frictions loss	Total loss
(2K, 0K)	Segmented	0.2006	0.3006	0.3008	−0.0003	−0.1680	−0.1682
	Uniform	0.2070	0.3100	0.3050	−0.0001	−0.1625	−0.1626
(2K, 10K)	Segmented	0.2183	0.3225	0.3209	−0.0002	−0.1608	−0.1610
	Uniform	0.2260	0.3330	0.3260	−0.0002	−0.1547	−0.1550
(2K, 25K)	Segmented	0.2024	0.2932	0.2905	−0.0006	−0.1654	−0.1660
	Uniform	0.2170	0.3120	0.2990	−0.0010	−0.1544	−0.1554
(3K, 0K)	Segmented	0.1649	0.2468	0.2456	−0.0008	−0.1825	−0.1834
	Uniform	0.1760	0.2610	0.2510	−0.0008	−0.1722	−0.1731
(3K, 10K)	Segmented	0.1784	0.2608	0.2583	−0.0009	−0.1755	−0.1764
	Uniform	0.1920	0.2780	0.2650	−0.0011	−0.1649	−0.1660
(3K, 25K)	Segmented	0.1700	0.2500	0.2455	−0.0014	−0.1780	−0.1794
	Uniform	0.1850	0.2700	0.2560	−0.0016	−0.1652	−0.1667
(4K, 0K)	Segmented	0.1307	0.1999	0.1985	−0.0014	−0.2010	−0.2024
	Uniform	0.1440	0.2160	0.2040	−0.0018	−0.1869	−0.1887
(4K, 10K)	Segmented	0.1570	0.2319	0.2304	−0.0016	−0.1851	−0.1867
	Uniform	0.1710	0.2500	0.2380	−0.0013	−0.1727	−0.1741
(4K, 25K)	Segmented	0.1433	0.2101	0.2051	−0.0019	−0.1904	−0.1923
	Uniform	0.1610	0.2330	0.2160	−0.0034	−0.1738	−0.1772

Note: For each contract, we compare the results with segmentation by risk class (τ_h) and those without (uniform τ).

C. *Equilibrium Results with Segmentation*

In Table 7, we report equilibrium results for each risk class separately (age and gender). There is some evidence that despite having higher demand (see Table 5), the equilibrium take-up ends up being lower among females. But differences are not large. As for age, the equilibrium take-up tends to decrease with age for men, while the pattern is less clear for females. One reason why there is variation across risk classes could simply be sampling variation, and given that equilibrium calculations are based on a smaller set of respondents within each risk class, differences in simulations appear relatively small. The role of frictions remains important, even within risk class, while the loss due to adverse selection remains very small. In Table 8, we report a comparison of aggregate equilibrium take-up as well as optimum and welfare losses for the case where we allow pricing to be set within each risk class (segmented)

Table 9—Decomposition of Frictions

		(2K, 0K)	(2K, 10K)	(2K, 25K)
Q frictions	Total	0.2070	0.2260	0.2170
Q no frictions	Perceptions	0.2120	0.2320	0.2220
	Knowledge	0.2420	0.2630	0.2410
	Awareness	0.2630	0.2840	0.2760
	Total	0.3100	0.3330	0.3120
Welfare loss	Perceptions	0.0341	0.0345	0.0355
	Knowledge	−0.0809	−0.0791	−0.1302
	Awareness	−0.1157	−0.1102	−0.0597
	Total	−0.1626	−0.1550	−0.1554
		(3K, 0K)	(3K, 10K)	(3K, 25K)
Q frictions	Total	0.1760	0.1920	0.1850
Q no frictions	Perceptions	0.1800	0.1960	0.1900
	Knowledge	0.1960	0.2100	0.2030
	Awareness	0.2310	0.2490	0.2410
	Total	0.2610	0.2780	0.2700
Welfare loss	Perceptions	0.0339	0.0342	0.0362
	Knowledge	−0.1422	−0.1548	−0.1544
	Awareness	−0.0639	−0.0442	−0.0470
	Total	−0.1731	−0.1660	−0.1667
		(4K, 0K)	(4K, 10K)	(4K, 25K)
Q frictions	Total	0.1440	0.1710	0.1610
Q no frictions	Perceptions	0.1470	0.1750	0.1650
	Knowledge	0.1570	0.1860	0.1700
	Awareness	0.1940	0.2260	0.2150
	Total	0.2160	0.2500	0.2330
Welfare loss	Perceptions	0.0345	0.0348	0.0360
	Knowledge	−0.1746	−0.1741	−0.2043
	Awareness	−0.0468	−0.0334	−0.0054
	Total	−0.1887	−0.1741	−0.1772

Note: We compare the equilibrium quantity and welfare variation in scenarios that implement one friction at a time (risk perceptions, knowledge, awareness).

and when it is not (uniform). We always find a higher take-up rate under uniform pricing than under segmented pricing. In general, we see very small differences when comparing uniform and segmented prices, whether in terms of equilibrium take-up (with and without frictions) or welfare losses from asymmetric information and frictions.

D. *Decomposition of Frictions*

As outlined earlier, we consider three types of frictions: risk *perceptions*, *knowledge* of institutions, and *awareness* of LTCI. In Table 9, we report simulations which introduce one friction at a time and compute the effect on equilibrium take-up (Q) as well as the welfare loss associated with it. Risk perceptions have little effect on aggregate take-up despite correlating very well with demand (see Table 5). Indeed, despite risk perceptions being widespread in our population, at the aggregate level, positive biases cancel out negative biases so that the average bias in

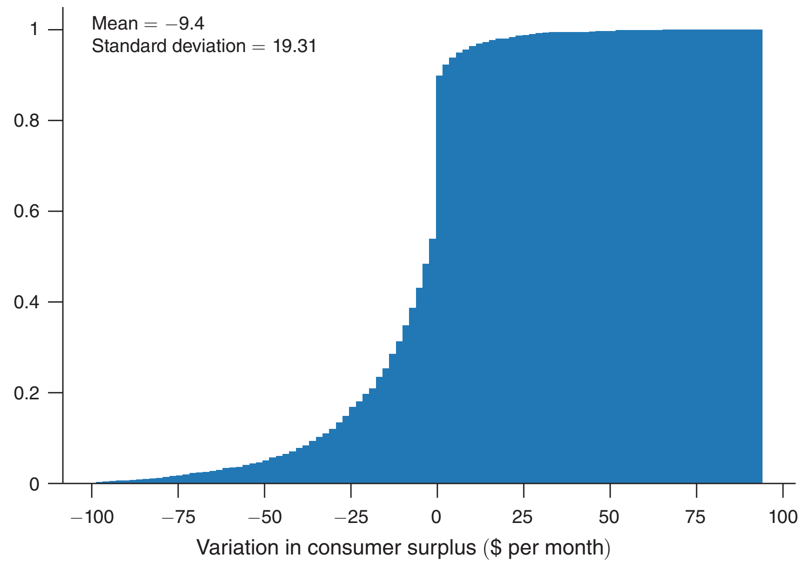

Figure 10. Variation of Consumer Surplus between Competitive Equilibrium with Frictions and Social Optimum

Notes: For the contract with an LTCI benefit of $2,000 and no life insurance benefit, we report, for each respondent, the welfare (consumer surplus) at the competitive equilibrium minus the welfare at the social optimum. The cumulative distribution function is plotted over discrete intervals.

risk perceptions is close to zero.[29] Overall, the welfare loss due to risk perceptions is small (less than 4 percent of welfare in the social optimum). Knowledge of institutions and awareness play a much larger role, but that role varies across contracts. The welfare loss due to knowledge seems to be more important when the contract provides larger LTCI and life insurance benefits. In contrast, the welfare loss due to the awareness that LTCI products exist appears more important for less generous contracts. Interestingly, the effect on equilibrium take-up of removing frictions is not always perfectly correlated with the welfare loss. For example, removing frictions due to knowledge of institutions has a larger effect on equilibrium quantity for less generous contracts but generates smaller welfare losses as a result of these frictions.

To understand the distribution of welfare changes, we compute each respondent's variation in consumer surplus between the equilibrium with frictions and the social optimum. This difference yields a monetary amount in dollar per month. This welfare change measures the potential individual benefit of acquiring information that collectively leads to optimal outcomes. This amount represents the respondents' willingness to pay in order to reach the social optimum, i.e., the maximum cost of acquiring information (to remove informational frictions) they are willing to bear. We report in Figure 10 the (cumulative) distribution of those welfare effects. We find that the average welfare cost of moving from optimum to equilibrium is

[29] For a detailed study of the impacts of risk misperceptions on the decision to buy LTCI, see Boyer et al. (2019a).

$9.40 per month with a large standard deviation. Close to 50 percent of respondents have a lower welfare at equilibrium (i.e., a negative number in Figure 10), close to 40 percent have similar surplus at equilibrium and at the social optimum, and a small fraction are indeed better off at the equilibrium. Given that the price is higher in the social optimum, some of those with higher demand obtain lower consumer surplus when we move to the social optimum. This illustrates that there are winners and losers and that the increase in welfare is not necessarily Pareto improving.

Overall, the low cost of ending up at the equilibrium with frictions, rather than at the social optimum, means that agents should have a low willingness to pay for removing informational frictions. This low willingness to pay is a viable explanation for the persistence of informational frictions.

V. Conclusion

In this paper, we provide new evidence on the determinants of low take-up rate of long-term care insurance in Canada using stated-choice probabilities. The typical LTCI product in Canada differs somewhat from what is observed in the United States. For example, most insurance companies offer a benefit paid on the basis of ADL limitations rather than reimbursing expenses for LTC. We exploit exogenous variation in prices across various scenarios differing on benefit structure to derive predictions for equilibrium under selection as in Einav, Finkelstein, and Cullen (2010). Since we ask directly about choice probabilities, we remain agnostic about the exact model that generates demand. With results from our baseline predictions, we then construct a number of counterfactuals correcting for a number of frictions (risk perceptions, knowledge, and awareness) in this market. We estimate the welfare losses associated to these frictions as in Handel, Kolstad, and Spinnewijn (2019).

Our key results are threefold. First, we find that part of the explanation for low take-up is simply that the near elderly, the prime target group, have limited awareness of the product, limited knowledge of the institutions, and biased perceptions about the costs and the risks surrounding LTC. Compared to a baseline projected fraction of the population of 20 percent that has access to a $2,000 monthly LTC insurance benefit, a counterfactual where we correct for frictions yields a take-up rate closer to 30 percent. Hence, information constraints (in particular, knowledge of institutions and costs and awareness of the LTCI products) play a large role. Second, we find evidence of weak advantageous selection, based on observed health status unused in pricing. Yet, this effect is very small in equilibrium. Third, exploiting exogenous variation in prices from the survey design, we estimate average price elasticities typically below 1 (-0.7), with less than 25 percent of respondents having elasticities below -1. This is in contrast to existing estimates in the literature (Courtemanche and He 2009, Goda 2011) but consistent with evidence presented in Ameriks et al. (2016).

Although we find that there would be important potential welfare gains from increased awareness of the products and knowledge of institutions in this market, our study suggests that there is limited scope for take-up to reach levels beyond 30 percent. We can think of three reasons why take-up may be low relative to what one would expect in other contexts. First, public provision of LTCI, e.g., through reduced user fees, shields consumers from a substantial part of the risk, in contrast to the United States where only low-income (and asset-poor) consumers can benefit from subsidized LTC services. Second, older Canadians have a generous safety net, which provides substantial income replacement rates for a significant portion of the population. Third, individuals could value consumption less when needing care than when healthy, even though empirical evidence on this channel is still rather unclear; Ameriks et al. (2020) find estimates that would suggest higher marginal value of money when in need of LTC, while Finkelstein, Luttmer, and Notowidigdo (2013) find the contrary when evaluating marginal utility in case of chronic diseases.

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