Inferring Risk Perceptions and Preferences using Choice from Insurance Menus: Theory and Evidence

Short Title: Inferring Risk Perceptions and Preferences

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Abstract

Demand for insurance can be driven by high risk aversion or high risk. We show how to separately identify risk preferences and risk types using only choices from menus of insurance plans. Our revealed preference approach does not rely on rational expectations, nor does it require access to claims data. We show what can be learned non-parametrically about the type distributions from variation in insurance plans, offered separately to random cross-sections or offered as part of the same menu to one cross-section. We prove that our approach allows for full identification in the textbook model with binary risks and extend our results to continuous risks. We illustrate our approach using the Massachusetts Health Insurance Exchange, where choices provide informative bounds on the type distributions, especially for risks, but do not allow us to reject homogeneity in preferences.

JEL Codes: D81, D83, G22.

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1 Introduction

When people make choices over uncertain outcomes, it is difficult to distinguish between expectations about how an option will pay off and preferences for the option itself. A consumer could buy more insurance either because of a higher expected probability of making a claim, or because of more risk averse preferences. A student could choose a career either because they particularly enjoy that type of work, or because they expect their wage to be particularly high.[1] A worker's low retirement savings rate could be

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[1] See, for instance, Altonji *et al.* (2016).

driven by their time preference for consumption, or expectations about wage growth and asset returns.[2] One way of solving the problem is to identify expectations using observed outcomes, and assuming expectations are rational. Yet beliefs can be both heterogenous and biased; moreover they may be difficult to elicit. In this paper, we take another approach. In the context of insurance choice, we show how to separately identify expectations and preferences using data on choices alone, highlighting what can be learned from examining how choices vary when the choice menu varies, as well as what can be learned from choices from a single menu of plans.

Distinguishing between demand for insurance driven by variation in risk preferences (e.g., degree of risk aversion) and variation in risk types (e.g., probability of making a claim) is crucial for positive and normative analysis (e.g., Einav *et al.*, 2010; Chetty and Finkelstein, 2013). Adverse selection, in which consumers select into insurance plans based on expected expenditure, can lead to market unravelling and inefficiently low coverage. In contrast with heterogeneity in risks, preference heterogeneity alone cannot cause insurance markets to be adversely selected. In fact, recent empirical work finds advantageous selection in which low risk individuals purchase more generous insurance plans, which has been considered evidence for the importance of preference heterogeneity (e.g., Cutler *et al.*, 2008).

A growing empirical insurance literature estimates heterogeneity in both preference and risk types using data on plan choices and insurance claims (see reviews by Einav *et al.*, 2010, and Barseghyan *et al.*, 2018). This approach is data-demanding compared to standard demand estimation. Moreover, this literature relies on an unappealing assumption: that each individual has rational expectations over the distribution of their claims. However, evidence suggests that individuals have distorted perceptions of their risk exposure. For example, in the context of health insurance, individuals may not understand how different health states map into health expenditures due to the opacity of health care prices (Lieber, 2017). They may be overconfident about their own health states (Grubb, 2015) and underweight small probability events (Johnson *et al.*, 1993). If individuals do not have rational expectations over the distribution of their future claims, claims data cannot help to separate a low degree of risk aversion from overoptimistic beliefs about risk. A final challenge with the standard approach is that, even under rational expectations, inferring heterogeneity in (ex ante) risk types from (ex post) risk outcomes requires structural assumptions not only on the set of feasible risk types, but also on the potential distribution of risk types.

We present an alternative approach that is robust to incorrect beliefs. Our approach is based on revealed preference, and identifies heterogeneity in (perceived) risks and preferences from choice data alone. We start from a choice model with risk preferences indexed on one dimension and risk types indexed on another dimension. Our approach,

[2] For instance, Skinner (2007) shows the sensitivity of optimal retirement savings to both the rate of return on investment and the desired change in consumption at retirement.

though, does not require claims data, and relies neither on rational expectations nor on parametric assumptions regarding the type distribution. Instead, our approach exploits variation in the plans from which individuals can choose. The framework allows us to revisit the question how important preference heterogeneity is for the observed variation in insurance choices and provides an alternative approach to estimating perceived risks.

The key challenge in inferring risk perceptions and preferences from insurance choices is that both high risk and risk aversion increase the willingness to buy insurance. To overcome this challenge, we propose to use variation in insurance plan characteristics that differentially attract individuals along the risk and preference dimension. We prove identification using plan variation in a stylised model and then illustrate how these insights can be applied in our empirical setting. Our identification approach can be implemented using cross-sectional data on individuals choosing from a single menu of (at least three) plans. This is what we use in our empirical application. Moreover, the approach would be more powerful when applied to choice data from similar populations facing different menus of plans. Random variation in insurance options and prices for otherwise identical populations can be driven by differences in the regulatory environment, by differences in costs of insurance provision (across states or time), or by differences in market power of insurance providers.[3,4] Our results show other researchers how to use this variation to extract estimates of beliefs and preferences.

The first part of the paper conveys the key intuition for identification in a simple model with binary risks and binary choices (e.g., buy a plan or not). In this binary choice setting, data on insurance choices from a single menu is insufficient to reject homogeneity in risks or preference (even if heterogeneity was substantial). With cross-sectional variation in menus, the difference in plan shares under the menus allow us to put bounds on the distribution of both risk types and risk preferences. Our identification argument exploits the fact that the marginal willingness to buy insurance is more rapidly decreasing in coverage for individuals with high risk aversion than for individuals with low risk aversion (see also Barseghyan *et al.*, 2013; 2018). As a consequence, two plans that differ in their coverage level and premiums can differentially

[3]Our identification argument does not depend on the optimality of the contracts offered and therefore does not rely on the market structure either, but only on whether these contracts are actually offered. We do not attempt to characterise the menu of contracts offered in a market equilibrium with multi-dimensional heterogeneity (e.g., Azevedo and Gottlieb, 2017), since, as we discuss, variation can come from a variety of sources.

[4]Revealed preference arguments are often based on the same individuals choosing consumption bundles at different prices. In insurance markets we rarely have such data: insurance options for individuals often change when the characteristics of the individual changed and individuals' responses may not reflect their preference ranking due to inertia (Handel, 2013). Examples of between-individual variation in insurance options include discontinuities in prices at round numbered ages (Ericson and Starc, 2015), discontinuities in prices at state borders (Cabral and Mahoney, 2019), subsidy changes that affect some but not all employees (Gruber and McKnight, 2016), plausibly exogenous variation in market competition (Dafny *et al.*, 2015), retaliatory taxes (Starc, 2014), and state regulation (Kowalski *et al.*, 2008). We take such variation as given in our approach.

attract individuals along the risk and preference dimension. In particular, in the binary risk setting, a plan that provides more coverage at a higher premium, but at a lower price per unit of coverage will attract more types with low risk aversion (but high risk) and discourage types with high risk aversion (but low risks). In the absence of such variation, it is impossible to reject homogeneity in preferences, even if claims data is observed and expectations are rational (see also Aryal *et al.*, 2010).

Remaining with binary risks, we demonstrate the potential of plan variation for identification in the standard textbook insurance model. Here, individuals decide how much coverage to buy at a constant price per unit of coverage. This can be represented as choices among binary sets with high vs. low coverage, but with a large number of such choice sets this conveniently reduces to the textbook model where individuals may choose any amount of coverage at the specified unit price. As risk aversion determines the gradient of the marginal willingness to pay with respect to coverage, it also determines the *change* in preferred coverage when the unit price of coverage changes, while both an individual's risk and risk aversion determine the agent's preferred coverage *level.* We show how the joint distribution of binary risks and CARA preferences can be non-parametrically identified exploiting price variation in the textbook model. Full identification would require price variation over the full support, but more limited price variation suffices to identify key moments capturing the heterogeneity in both dimensions.

We then extend the model beyond binary risks and choice sets to settings that more closely resemble actual health insurance coverage. Health costs vary over a wide range, and health insurance plans provide non-linear coverage for these costs. Typical contract features include a deductible, co-insurance rate, and out-of-pocket maximum. How individuals value these contract features will depends on their preference type and risk type. For example, the decreasing returns to coverage imply that individuals with high risk aversion care more about reducing high out-of-pocket expenses (e.g., a decrease in the out-of-pocket maximum) than reducing of out-of-pocket expenses that are already low (e.g., a decrease in the deductible). We then show how the same type of plan variation drives identification when all plans are offered *within* one menu to a single cross-section of individuals. The key intuition is the same as in the case with cross-sectional variation in binary choice sets: plans need to differentially attract types along the different dimensions. *Within-menu* plan variation naturally arises in many practical settings, which is also what we exploit in our empirical analysis.

We apply our method to choice data from the Massachusetts Health Insurance Exchange (see Ericson and Starc, 2015). We find informative bounds on the distribution of preferences and risks exploiting variation in the features of the contracts offered. Interestingly, we cannot reject homogeneity: it is possible for observed plan choices to be rationalised with only heterogeneity in risks. However, we do reject homogeneity in risks. The required variance in risks increases as we restrict the analysis to reasonable preference parameters. We then compare our bounds to estimates from the existing literature. Our application shows what can be learned from choice data alone and highlights the strengths of the revealed preference approach.

Related Literature Our paper is motivated by the literature analysing heterogeneity in preferences and risks, reviewed in Einav *et al.* (2010) and Barseghyan *et al.* (2018). This literature started with empirical tests for asymmetric information in insurance markets, often finding a weak relationship between risk type and insurance choice (see Chiappori and Salanié, 2013, and Cohen and Siegelman, 2010). This inspired a new series of papers estimating the heterogeneity in risk preferences jointly with the heterogeneity in risk types and arguing that the former is important.[5] These studies use both choice and claims data to estimate a structural model of heterogeneity. Our work starts from a similar model of consumer choice in which individuals choose insurance plans that maximise their expected utility given their specific risk and preference parameters. Our approach, however, does not require the additional structure on heterogeneity and relaxes the assumption of rational expectations.

Indeed, a growing empirical literature documents evidence for deviations from rational expectations in insurance choices. For instance, Sydnor (2010) demonstrates that distorted beliefs could explain deductible choices in home insurance, while with rational expectations extreme risk aversion would be needed. The identification challenges in the absence of rational expectations have been previously addressed using survey data eliciting expectations (see Manski, 2004). Most similar in spirit to our paper is Barseghyan *et al.* (2013), who analyse choice data through the lens of a model in which individuals are allowed to perceive true risks in a distorted way. Different from us, they assume that all individuals distort true probabilities in the same way, and then use auto insurance choices and realised claims data for the estimation of the parametric preference and (true) risk type distributions. They separate the probability distortion from risk preferences using a single-crossing property based on the decreasing returns to coverage implied by risk aversion. This argument is further developed in the review paper by Barseghyan *et al.* (2018). We start from the same single-crossing property, but establish non-parametric identification of the type distribution, allowing for heterogeneity in both risk perceptions and preferences. In their review of the literature, Barseghyan *et al.* (2018, p. 521) state how "*to date, point identification of multidimensional heterogeneity in risk preferences has relied upon parametric assumptions about their joint distribution. It remains a question for future research, to find a field setting and the proper set of assumptions to obtain nonparametric identification.*" We characterise the plan variation, either across menus (offered to multiple cross-sections) or within a menu (offered to one cross-section), that is needed for non-parametric identifi-

[5] Examples are auto insurance (Cohen and Einav, 2007), annuities (Einav *et al.*, 2010) and health insurance (Bundorf *et al.*, 2012; Handel, 2013).

cation of a two-dimensional type distribution and apply our method to health insurance choices.

Our work uses only choices and relies on price or plan variation for identification, which is very close to the Revealed Preference (RP) paradigm.[6] Our methodology is, however, different from standard empirical RP techniques (see Crawford and De Rock, 2014), as we start from a choice model with risk preference and risk type, and aim to recover both preferences and risk perceptions underlying the observed choices. Our focus is to uncover heterogeneity in types and we do not require multiple observations for the same individual.[7,8] Our work is closely related to a number of recent papers analysing the non-parametric identification of type heterogeneity underlying choices under uncertainty. Assuming rational expectations, Aryal *et al.* (2016) study how identification depends on the observed number of claims, using choices from continuous and discrete choice sets. In contrast, our approach does not rely on claims data and rational expectations.

Our work also relates to the large literature on identification of demand systems (Berry and Haile, 2014; 2016). That literature generally abstracts from adverse selection, focusing instead on allowing rich taste heterogeneity or relaxing assumptions imposed on the form of the utility function (see, for example, Ichimura and Thompson, 1998, and Briesch *et al.*, 2010). We build on their insights and show how to separately identify risk and risk preferences in the specific, but important context of insurance choice. Identifying which types generate market shares is critical in our setting, since adverse selection is only generated by sorting based on risk type. Therefore, the details of the underlying heterogeneity beyond overall market shares have especially important implications for welfare. Unlike these approaches, we do not need to impose any linearity assumptions, which is especially useful within the insurance context. By placing restrictions on the marginal rate of substitution across states of the world, we can highlight the types of variation in insurance contracts and prices that allow us to place bounds on marginal distributions of risk preferences and risk types.

Related to this, Chiappori *et al.* (2019) and Gandhi and Serrano-Padial (2015) use shares of horse bets to estimate one-dimensional heterogeneity, in either the preference or perception dimension. Importantly, their identification approach requires the absence of heterogeneity in the other dimension, as we will demonstrate in our setting. We do provide an identification approach that allows for heterogeneity in both dimensions, but this requires plan variation.[9] Finally, Barseghyan *et al.* (2016) use in-

[6] See also work by Chetty (2006), who shows how bounds on the coefficient of relative risk aversion can be derived by examining how labour supply responds to wage changes. In contrast to our work, Chetty (2006) does not explicitly explore unobserved heterogeneity nor differences in beliefs.

[7] Examples in the RP literature are Crawford and Pendakur (2013), who study the minimum number of types necessary to explain observed choices in cross-sectional data, and Dean and Martin (2016), who study the largest subset of the data which is consistent with homogeneous preferences.

[8] Recent examples in the RP literature that allow for deviations from rational demand are Crawford (2010), Adams *et al.* (2014) and Caplin and Dean (2015).

[9] See also Chiappori *et al.* (2009) on the identification of preference heterogeneity from discrete

surance choices by the same individual across different domains and partially identify both preferences and beliefs. We provide conditions for full identification and use plan variation instead, both across and within menus.

Finally, an alternative literature documents mistakes and other deviations from the expected utility model. While we do not directly address mistakes in our analysis, our method could be augmented with any model of errors in choice. For instance, Abaluck and Gruber (2011) find that individuals buying Medicare Part D insurance are over-responsive to salient portions of the price – our method could be extended to account for this by modelling consumers as choosing a plan based on traditional expected utility plus an additional weight on salient characteristics. Other work documents misunderstanding of health insurance plans themselves (e.g. Loewenstein *et al.*, 2013). Indeed, Bhargava *et al.* (2015) show evidence for dominated choices of health plans, which cannot be explained by any standard risk preferences or beliefs; dominated choices are reduced when information is provided more clearly, suggesting consumers were making mistakes. A fruitful way forward may be to collect data on choice frictions or misunderstandings and estimate underlying preferences, as done by Handel and Kolstad (2015). Other work has found less consistency than expected in an individuals' risk preferences across domains, such as health and auto insurance (Dohmen *et al.*, 2011; Einav *et al.*, 2012). Our empirical application examines choices within a single domain, and identifies domain-specific beliefs. Our method could be extended to examine choices and beliefs in multiple domains to determine whether belief heterogeneity is an important cause of inconsistent risk-taking behaviour across domains.

The paper is organised as follows. Section 2 sets up our choice model and defines our object of interest for identification. Section 3 analyses the identification of type heterogeneity in a stylised model with binary risk and binary choices. We briefly extend these insights beyond our stylised model in Section 4 and apply them using insurance choices on the Massachusetts Health Exchange in Section 5. We discuss key steps of our proofs in the main text, and provide the formal proofs in the Appendix.

2 Setup

We consider a stochastic revealed preference problem (see, e.g., McFadden, 2005; Chiappori *et al.*, 2009) applied to an insurance market: a unit mass of consumers of insurance products appears to be homogeneous to the econometrician (possibly after controlling for observables), but may be heterogeneous in unobserved types distributed according to H. Consumers choose products from a budget set $\mathcal{M}$, which in our setting constitutes a menu of available insurance products. The econometrician observes the market share $D(X|\mathcal{M})$ for each available product $X \in \mathcal{M}$. Other consumers with

choices. Choi *et al.* (2007) avoid the bi-dimensionality by estimating preference heterogeneity for choices under risk with known probabilities and using experimental variation of prices.

unobserved types drawn from the same distribution H might be faced with a different budget set, yielding variation in market shares.[10] We aim to identify properties of the distribution H from this observed market share variation.

Specific to our setting is that we assume that market shares arise according to a known demand generating process: in particular, choices reflect expected utility maximisation over final monetary pay-offs. Individuals are assumed to have a two-dimensional type (π, σ), where π is a one-dimensional index that parametrises the consumer's risk (e.g., how likely it is that she will have an accident) and σ is a one-dimensional index for her preferences (e.g., how much she is willing to tolerate risk). The restriction to a one-dimensional index on each of the two dimensions usually entails some a priori restriction to particular classes, such as constant absolute risk aversion (CARA) for preferences and exponential distributions for risks. $H(\pi, \sigma)$ is the distribution of types in the population. We make no further assumption on H and treat it non-parametrically. Observed market shares have to coincide with the theoretical demands generated under distribution H. We exploit this to identify whether we can reject homogeneity in either risks or preferences in H and - more ambitiously - whether one can fully identify H or at least its key moments. Since we do not directly use information on realised risks, our approach does not rely on rational expectations. However, the observed demand can only identify perceived risks (which may differ from true risks). We further discuss the use of claims data in Section 4.2. The following provides more details on the most general model of demand we consider, while the subsequent sections discuss specific cases.

Risk and Preference. Consumers each face uncertain costs k. Each agent subjectively assigns cumulative distribution $F(k|\pi)$ to his costs. We assume that the risk type π ranks agents by first-order stochastic dominance: That is, for two types $\pi_1 > \pi_2$, $F(k|\pi_1) \leq F(k|\pi_2)$ for all k. Let $\Pi \subseteq \mathbb{R}_+$ denote the domain of possible risk types.

Consumer preferences are represented by expected utility with differentiable Bernoulli-utility function $u(L|\sigma)$ over final losses L. The agent's preference type is σ ranks individuals by their risk-aversion following Pratt (1964). This is naturally the case for CARA preferences with $u(L|\sigma) = -\exp(\sigma x)/\sigma$, where $\sigma_1 > \sigma_2$ implies that individual 1 is more risk-averse than individual 2. We re-scale the preference type σ such that for

[10] Our framework is set up to illustrate the theoretical underpinnings of our model and the non-parametric identification argument. Since we do not link individual decisions across multiple decisions, both π and σ can either be stable long-run preferences or can be the result of temporary shocks to risks or preference. We abstract, however, from additional idiosyncratic shocks to the utility of particular plans. Such shocks have been useful in the empirical literature to rationalise a wide variety of choices, especially when the number of types is assumed to be small. So in an empirical application, the econometrician may want to specify the distribution of idiosyncratic errors. In particular, one could estimate insurance choice using the discrete choice methods pioneered by McFadden (1973). When assuming a parametric distribution of error terms and provided with the variation in contracts characterised below, we can still rely on the same arguments to identify heterogeneity in risk perceptions and preferences using choices alone.

a risk-neutral agent $\sigma = 0$ and types with $\sigma \to \infty$ are infinitely risk averse, so that the domain of possible preference types Σ coincides with $\mathbb{R}_+$.[11]

An insurance product X is characterised by a premium P and a mapping from each cost k to an out-of-pocket expense $x(k) \leq k$. We refer to X as an insurance plan or contract. Purchasing no insurance means that the full costs are born by the individual. The expected utility of a plan X for an agent of risk-preference type (π, σ) is

$$U(X|\pi,\sigma) \equiv \int u(-P - x(k)|\sigma)\, dF(k|\pi). \tag{1}$$

While we assume that the (parametric) cost distribution $F(\cdot|\pi)$ and utility function $u(\cdot|\sigma)$ are known, the type distribution $H(\pi,\sigma)$ is not known.

Market Shares for a given Budget Set We want to infer the type distribution from observed market shares. The market share for plan X' is determined by types that find this product optimal given the budget set or menu $\mathcal{M}$ they face:

$$\mathcal{B}\left(X'|\mathcal{M}\right) := \left\{(\pi,\sigma)\,|X' \in \arg\max_{X\in\mathcal{M}} U(X|\pi,\sigma)\right\}.$$

The market share for any subset of products $\mathcal{M}' \subseteq \mathcal{M}$ thus arises from types in $\mathcal{U} = \cup_{X\in\mathcal{M}'} \mathcal{B}(C|\mathcal{M})$. If almost all of these types have a unique optimal choice, identification can simply exploit the fact that the measure of these types has to be equal to the observed demand:

$$\int_{X\in\mathcal{M}'} dD(X|\mathcal{M}) = \int_{(\pi,\sigma)\in\mathcal{U}} dH(\pi,\sigma). \tag{2}$$

In case a measure of types is indifferent, the equality in (2) has to be replaced by weak inequality "$\leq$ ", as types choose less options than they find optimal.

Data and Identification An observation $\mathcal{D}$ in our data set consists of market share distributions $D(\cdot|\mathcal{M}_j)$, possibly across multiple budget sets $\mathcal{M}_1, \mathcal{M}_2, \mathcal{M}_3, ...$ Type distribution H is consistent with this observation only if the identification condition (2) holds for each of its market share distributions $D(\cdot|\mathcal{M}_j)$. This limits the type distributions under consideration, given our specific demand-generating process. Obviously, throughout the paper we will only consider observations for which at least one consistent type distribution exists.

For a given variation in budget sets $\mathcal{M}_1, \mathcal{M}_2, \mathcal{M}_3, ...$ we say that full identification is possible if for each observation $\mathcal{D}$ there is a unique H that is consistent with it. We establish this in the textbook insurance problem, in which individuals choose how

[11] Convergence to infinite risk aversion means that for any two gambles where the lowest possible outcome in the first gamble is higher than the lowest possible outcome in the second, individuals with high enough risk preference strictly prefer the former.

much coverage to buy at a linear price. A more basic question relates to testing for the presence of heterogeneity. The early (theoretical) literature on insurance markets attributed variation in choices to heterogeneity in risks alone (given some homogeneous preference for risk), while the recent (empirical) literature has argued that preference heterogeneity is important. We therefore study whether one can in fact refute preference homogeneity: i.e., does there exist budget set variation and corresponding market share distributions such that any consistent type distribution H has at least two different preference types in its support?

More generally, we are interested in establishing bounds on the marginal distribution of preference and risk types. For example, for a given observation $\mathcal{D}$ we aim to establish a bound $\alpha' > 0$ on the mass of consumers that have preference types weakly below σ'. That is, any type distribution that is consistent with $\mathcal{D}$ has a marginal distribution H_σ over preference types such that $H_\sigma(\sigma') \geq \alpha'$. If one can then establish a second bound $\alpha'' > 0$ on consumers that have risk types above some $\sigma'' > \sigma'$, this shows mass both on preferences above σ'' and below σ' and, thus, the presence of preference heterogeneity. We say that we cannot reject preference homogeneity if, given the variation in budget sets, any observation can be rationalised with heterogeneity in risk alone, keeping the support over preference types to a singleton. Obviously, the same questions can be analysed for risk heterogeneity.

As it is useful for identification more generally, a bulk of our analysis aims to establish which type of budget set variation allows us to establish bounds on the marginal distributions.

3 Identification in a Stylised Model

We start by considering a stylised model in which individuals face binary risks and a binary choice. This stylised model helps us to demonstrate the potential for non-parametric identification of type heterogeneity using only choice data, but exploiting plan variation. In the next section, we then extend the model beyond binary risks and budget sets to settings that more closely resemble actual health insurance coverage choices to show the practical implementability of our choice-based approach.

Binary Risk and Choice Set Any individual (ex ante) faces a binary cost distribution $k \in \{0, L\}$, either losing L or nothing at all. For instance, the individual could become sick and require costly treatment, but faces no medical costs when healthy. The risk type π^i of agent i is simply his probability of incurring the cost L. Agent i chooses from a menu $\mathcal{M}^i$ that offers the choice between two insurance options. We focus on the simplest case where individuals can either choose no insurance ($\emptyset$) or some insurance (X), i.e., $\mathcal{M}^i = \{\emptyset, X^i\}$.

Since the risk is binary, a plan is fully determined by the premium P and the coverage q paid in case of loss, where we restrict attention to $P < q$ (as no plan with $P \geq q$ will ever be chosen). The expected utility of a plan $X = (P, q)$ simplifies to

$$U(X|\pi,\sigma) = (1-\pi)\, u(-P|\sigma) + \pi u(-P - [L-q]\,|\sigma),$$

while remaining uninsured gives utility

$$U(\emptyset|\pi,\sigma) = (1-\pi)\, u(0|\sigma) + \pi u(-L|\sigma).$$

An individual prefers plan X over remaining uninsured if and only if

$$\frac{\pi}{1-\pi}\frac{u(-P-[L-q]\,|\sigma) - u(-L|\sigma)}{u(0|\sigma) - u(-P|\sigma)} \geq 1. \tag{3}$$

The insurance plan entails a utility gain due to the coverage provided when the bad state realises (with probability π), but entails a utility loss due to the premium paid, even when the good state realises. The ratio of the utility gain relative to the utility loss is increasing in the individual's risk aversion (Pratt, 1964). As a consequence, an individual's willingness to buy the plan is not only increasing in the risk type π, but also in her preference type σ. We use short-hand notation $m_g(X)$ and $m_b(X)$ to refer to the net pay-offs of a plan X in the good and bad state respectively.

For this binary choice environment, the main tool for analysis is the type frontier $\mathcal{T}(\emptyset, X)$ which groups together all types that are indifferent between buying the plan X and remaining uninsured, i.e.,

$$\begin{aligned}\mathcal{T}(\emptyset, X) &= \{(\pi,\sigma)\,|U(X|\pi,\sigma) = U(\emptyset|\pi,\sigma)\} \\ &= \mathcal{B}(\emptyset|\mathcal{M}) \cap \mathcal{B}(X|\mathcal{M}).\end{aligned}$$

Represented in (π, σ)-space, the type frontier is monotonically decreasing as shown in Figure 1. A risk-neutral individual ($\sigma = 0$) is only willing to buy the plan if her loss probability exceeds the price per unit of coverage, i.e., $\pi \geq P/q$. If the loss probability converges to 0, an individual must become infinitely risk-averse to be willing to buy the insurance plan.

Single-Crossing Property We assume a single-crossing property among the types on a type frontier $\mathcal{T}(\emptyset, X)$, similar to the one established in Barseghyan *et al.* (2013; 2018).[12] While all individuals on the type frontier have the same willingness-to-pay for plan X, their marginal willingness-to-pay for additional coverage depends on their specific risk and preference combination. We consider families of utility functions with the following single-crossing property:

[12] See Proposition 3 in Barseghyan *et al.* (2013) and Result 1 in Barseghyan *et al.* (2018).

Assumption 1 *Along the type frontier $\mathcal{T}(\emptyset, X)$ the marginal rate of substitution $\frac{\pi}{1-\pi}\frac{u'(m_b(X)|\sigma)}{u'(m_g(X)|\sigma)}$ is increasing in π, and it converges to zero as π goes to zero.*

We explicitly check this property for CARA preferences, which are typically adopted in the empirical insurance literature (see Appendix A.1.2.1). The single-crossing property arises because the marginal return to coverage is more rapidly decreasing for types with higher risk aversion. To illustrate this, we can approximate the marginal rate of substitution (MRS) between consumption in the good and bad state as:

$$\frac{\pi}{1-\pi}\frac{u'(m_b(X)|\sigma)}{u'(m_g(X)|\sigma)} \cong \frac{\pi}{1-\pi}\left\{1-\frac{u''(m_g(X)|\sigma)}{u'(m_g(X)|\sigma)}[m_g(X)-m_b(X)]\right\}, \tag{4}$$

relying on the third and higher-order derivatives of the utility function being small. Like for the *total* willingness to pay, both a higher loss probability π and higher risk aversion σ increase the *marginal* willingness to pay for coverage. However, the relative weight of risk aversion in determining the marginal willingness to pay is smaller the more coverage the plan already provides (i.e., the smaller the consumption wedge, $m_g(X) - m_b(X)$).[13] In the extreme case that a plan provides full insurance, the willingness to pay for the last unit of coverage equals the loss probability. The role played by the individual's risk aversion has become of second order. This also allows us to rank the willingness to pay for additional coverage amongst those types who have the same willingness to pay for X. For two types on the type frontier $\mathcal{T}(\emptyset, X)$, the type with higher risk aversion ($\sigma' > \sigma$) needs to face lower risk ($\pi' < \pi$) for the total willingness to pay to be the same. However, the difference in willingness to insure at the margin is more affected by the difference in risks than by the difference in preferences, implying that the willingness to pay at the margin is lower for the type with lower risk. The above logic holds close to full insurance for any preferences satisfying Expected Utility theory. Assumption 1 restricts our focus to utility functions for which it holds for any coverage level (including CARA preferences).

The single-crossing property implies that we can replace contract X with a more generous, but more expensive contract X' such that there is a cut-off point on the type frontier $\mathcal{T}(\emptyset, X)$ with all higher risks strictly preferring to buy the new plan and the others strictly preferring not to. As we will show next, these crossings of type frontiers are required to identify bounds on the marginal type distributions. Under Assumption 1, we can characterise the exact plan variation that leads to crossings of type frontiers. For preferences not satisfying Assumption 1, we may have to resort to different plan variation to obtain crossings and thus identification.

[13] For CARA preferences, which we use below, the MRS equals

$$-\frac{dm_g}{dm_b}|_{U(X|\pi,\sigma)} = \frac{\pi}{1-\pi} \times \exp\left(\sigma\left(m_g(X)-m_b(X)\right)\right),$$

again demonstrating the lower weight of risk aversion in the marginal value of coverage when a plan provides higher coverage. (Taking a Taylor expansion of the exponential term centred at 0, we obtain the first-order approximation in (4).)

3.1 Identification using Plan Variation

We first consider a situation where each individual faces the same menu $\mathcal{M} = \{\emptyset, X\}$, as shown in Figure 1. With a single cross-section of choices and associated observations $z^i = \{C^i, \mathcal{M}\}$, we cannot put meaningful bounds on the preference heterogeneity, nor on the risk homogeneity. Neither can we reject preference homogeneity nor risk homogeneity. The intuition is straightforward. The share of individuals buying insurance, $\alpha = D(X|\mathcal{M})$, corresponds to the mass of types that lie above the type frontier in the left panel of Figure 1. We cannot exclude that the variation in the choice to buy the plan is driven by heterogeneity in risk types only or by heterogeneity in preference types only. Fix the fraction α of individuals who buy the plan.[14] If agents have preference type $\bar{\sigma}$ but differ in risks so that exactly $1-\alpha$ of them have a type below $\bar{\pi}$, exactly $1-\alpha$ would not buy insurance which would clearly rationalise the observed choices. This case is illustrated by the dashed density above the horizontal gray line, and the shaded area indicates the mass of individuals with risk type below $\bar{\pi}$ that would not buy insurance. Alternatively we could have assumed that all agents have the same risk type $\bar{\pi}$ but are heterogeneous in preferences such that exactly $1-\alpha$ of them have types below $\bar{\sigma}$. Again, such a type distribution would rationalise the observed choices, which is indicated by the dashed-dotted density above the vertical gray line, where again the gray area indicates those types that would not buy insurance. Therefore, we can rule out neither preference nor risk heterogeneity. Only very weak results can be obtained in this setting. Since individuals are risk-averse, only types with $\pi \geq P/q$ would be willing to buy insurance. The share of uninsured individuals $1-\alpha$ places a lower bound on the share of individuals with loss probability lower than P/q, i.e., $H_\pi(P/q) \geq 1-\alpha$.

We now introduce discrete variation in the plans offered. We consider two plans X_h and X_l, where plan X_h provides more coverage than plan X_l (i.e., $q_h > q_l$). We continue to analyse binary menus $\mathcal{M}_j = \{\emptyset, X_j\}$, but different plans are offered to different cross-sections of individuals. Section 4.3 shows that the same logic drives identification when the different plans are offered jointly to a single cross-section of individuals.

Consider two randomly selected cross-sections of individuals, where the first cross-section is offered the menu $\mathcal{M}_h = \{\emptyset, X_h\}$ and the second cross-section is offered the menu $\mathcal{M}_l = \{\emptyset, X_l\}$. The share of individuals buying insurance when each plan is offered separately equals $\alpha_h = D(X_h|\mathcal{M}_h)$ and $\alpha_l = D(X_l|\mathcal{M}_l)$ respectively.

If the high-coverage plan charges the same (or a lower) premium, it dominates the low-coverage plan. All types who would buy insurance when offered the low-coverage plan also buy insurance when offered the high-coverage plan (i.e., $\mathcal{B}(X_l|\mathcal{M}_l) \subset \mathcal{B}(X_h|\mathcal{M}_h)$). The high-coverage type frontier $\mathcal{T}(\emptyset, X_h)$ is illustrated by the dotted line in the left panel of Figure 2. The type frontier lies below the low-coverage type frontier

[14] In the right panel of Figure 1 type $(\bar{\sigma}, \bar{\pi})$ is chosen as an arbitrary point on the type frontier, implying that this type is indifferent between buying the contract or not.

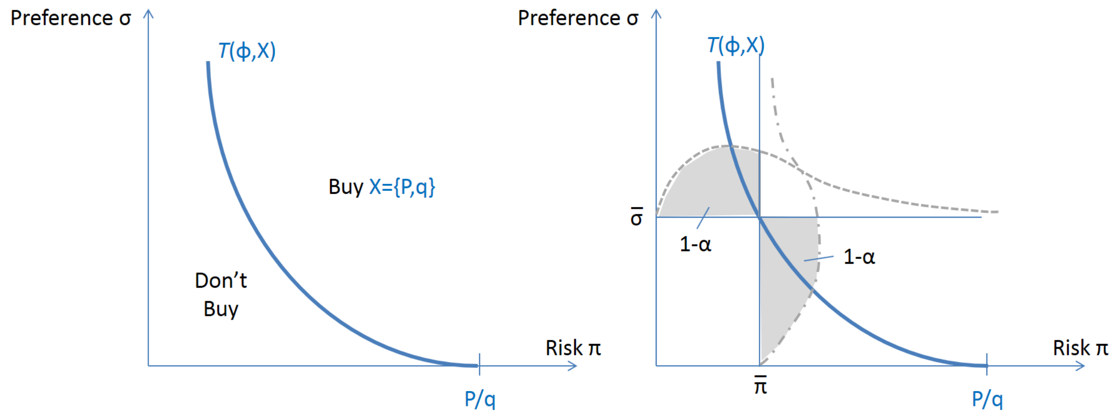

Figure 1: The left panel shows the type frontier for a binary menu $\mathcal{C} = \{\emptyset, X\}$ in (π, σ)-space. Types above the frontier buy the plan, while types below the frontier remain uninsured. The right panel illustrates an indifferent type $(\bar{\sigma}, \bar{\pi})$. If all other individuals have the same risk type $\bar{\pi}$ but a density of preferences as indicated by the dashed line, choices can be rationalised. Alternatively, all individuals could have same preference type $\bar{\sigma}$, but differ in risks as in the dashed-dotted density, and again choices can be rationalised.

$\mathcal{T}(\emptyset, X_l)$ which is illustrated by the solid line. We can assign the observed increase in shares $\alpha_h - \alpha_l$ to the types in between the two frontiers $\mathcal{T}(\emptyset, X_l)$ and $\mathcal{T}(\emptyset, X_h)$ (i.e., to $\mathcal{B}(X_h|\mathcal{M}_h) \setminus \mathcal{B}(X_l|\mathcal{M}_l)$). This would be useful for identifying bounds on heterogeneity in one dimension if we can exclude heterogeneity in the other dimension.[15] However, with heterogeneity in both dimensions, this type of plan variation sheds limited light on the plausible heterogeneity in either dimension. The observed variation in plan choices could either be explained by risk variation or by preference variation only. The former is illustrated by the horizontal line in the left panel of Figure 2, on which all types share the same preference $\bar{\sigma}$. The risk distribution is simply chosen to ensure that a fraction $1 - \alpha_h$ has low risk and buys neither contract, and fraction $\alpha_h - \alpha_l$ has intermediate risks and only buys the higher coverage contract, while α_l would buy either contract. Therefore, the observed plan shares do not allow us to put any bounds on the preference heterogeneity.

If the high-coverage plan X_h is offered at a higher premium, it becomes less attractive than the low-coverage plan to some individuals, but remains more attractive to others if the premium increase is relatively small (i.e., $\mathcal{B}\left(X_{j'}|\mathcal{M}_{j'}\right) \nsubseteq \mathcal{B}(X_j|\mathcal{M}_j)$ for $j' \neq j$). Assumption 1 implies that among those types that are indifferent at X, those with high risks prefer to buy more coverage. This implies that that the type frontiers cross only once, as shown in Lemma 1 below and depicted in the right panel of Figure 2. The high-coverage type frontier $\mathcal{T}(\emptyset, X_h)$, depicted by the dotted curve, is a clockwise

[15] Barseghyan *et al.* (2018) describe a similar identification strategy with only heterogeneity in preferences (see also Chiappori *et al.*, 2019, and Gandhi and Serrano-Padial, 2015), but this relies on the absence of heterogeneity in risks.

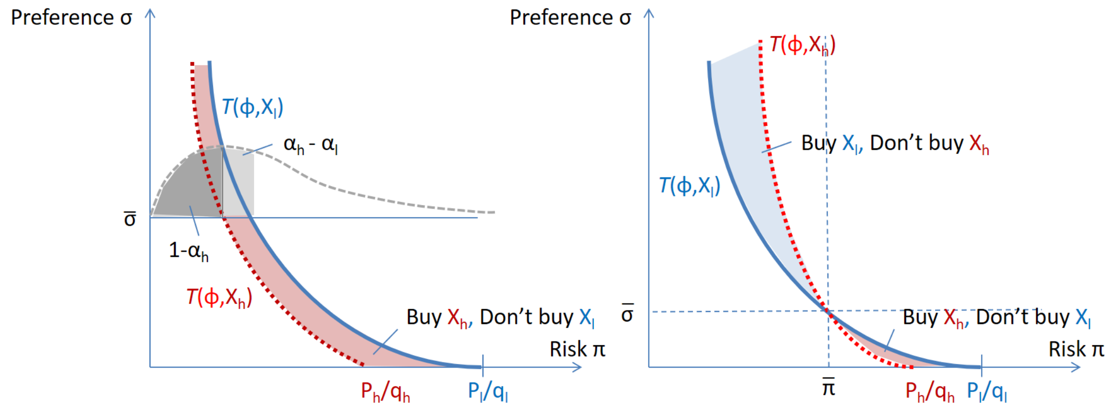

Figure 2: The solid and dotted line in both panels show the type frontiers in (π,σ)-space for the binary menu $\mathcal{C}=\{\emptyset,X_l\}$ and $\mathcal{C}=\{\emptyset,X_h\}$ respectively. In the left panel, the type frontiers do not intersect as the high-coverage plan charges the same (or a lower) premium and attracts all types that would also buy the low-coverage plan. In the right panel, the type frontiers intersect at $(\bar{\pi},\bar{\sigma})$. The cheaper low-coverage plan charges a higher price per unit of coverage and differentially attracts types with high risk aversion and low risk.

"rotation" around $(\bar{\pi},\bar{\sigma})$ relative to the low-coverage type frontier $\mathcal{T}(\emptyset,X_l)$, depicted by the solid curve. Low risk types between the two curves (with $\pi<\bar{\pi}$ and $\sigma>\bar{\sigma}$) buy the cheaper low-coverage plan but would remain uninsured when offered the more expensive plan, while high risk types between the two curves (with $\pi>\bar{\pi}$ and $\sigma<\bar{\sigma}$) remain uninsured when offered the cheaper low-coverage plan, but buy insurance when the plan provides the additional coverage so long as the premium increase is not too high. Note that the risk-neutral individual on the type frontier of plan X_j has risk type $\pi=P_j/q_j$. Only if its price per unit of coverage remains lower than for the low-coverage contract ($P_h/q_h<P_l/q_l$), the high-coverage contract can differentially attract some types to buy insurance.

Clearly, we could now set identify an individual's type if we were to observe the individual's choice under the two menus. For example, an individual who switches out of the insurance plan when offered X_h rather than X_l, must have a risk type higher than $\bar{\sigma}$ and a preference type lower than $\bar{\pi}$. In this case identification is rather straightforward. But since it is difficult in practice to observe multiple observations for the same individual, we rely only on observing choices across random cross-sections of individuals facing different menus. In that case, identification of types requires substantially more care since one cannot simply link a contract choice in the one cross-section to a contract choice in the other one. Still, observing the shares of individuals that choose the different contracts allows us to put bounds on the type distribution, as stated in the following Lemma:[16]

[16] This Lemma is related to Barseghyan *et al.* (2018); in their Result 1, they establish a single-crossing property under similar conditions, (illustrated in their Figure 4). Lemma 1 here uses the single-crossing

Lemma 1 *Under Assumption 1, the type frontiers for the pairwise menus* $\{\emptyset, X_h\}$ *and* $\{\emptyset, X_l\}$ *with* $q_h > q_l$*, have a unique intersection* $(\bar{\pi}, \bar{\sigma})$ *if and only if* $P_h > P_l$*, but* $P_l/q_l \geq P_h/q_h$*. Moreover,*

$$\int_{\pi \geq \bar{\pi}} \int_{\sigma \leq \bar{\sigma}} dH \geq \alpha_h - \alpha_l \geq -\int_{\pi \leq \bar{\pi}} \int_{\sigma \geq \bar{\sigma}} dH. \tag{5}$$

Proof. *See appendix.* ■

Very low risk types along the type frontier for contract X_l have near zero marginal willingness to pay for insurance, so they will not buy the additional insurance offered by X_h. This ensures that the dotted curve in the right panel of Figure 2 lies to the right of the solid curve at low risks. Moreover, by Assumption 1, the willingness to pay changes monotonically along the type frontier, so there can only be a unique type where the type frontiers cross: at that point all lower risks on the type frontier for contract X_l would buy the additional insurance while all higher risks would not. If $P_l/q_l > P_h/q_h$, for risk-neutral preference ($\sigma = 0$) the dotted curve has to be to the left of the solid one, and so there will be a crossing, as shown in the right panel of Figure 2. On the other hand, if the expensive insurance plan offers less coverage per dollar (i.e., $P_h/q_h > P_l/q_l$), the dotted curve would lie completely to the right of the solid curve.[17] In this case the type frontiers no longer intersect as the low-coverage contract dominates the high-coverage contract, and plan variation does not allow us to put bounds on preferences by a similar logic as that depicted in the left panel of Figure 2.[18]

The Lemma clearly describes the plan variation required for the type frontiers to intersect: the high-coverage plan needs to be more expensive, but provide coverage at a lower price per unit. If more people buy the high-coverage plan, the difference in plan shares $\alpha_h - \alpha_l$ places a lower bound on the share of individuals with $\pi > \bar{\pi}$ and $\sigma < \bar{\sigma}$. The additional coverage is relatively more attractive to individuals with higher risk than to individuals with higher risk aversion. If more people by the low-coverage plan, the difference $\alpha_l - \alpha_h$ imposes a lower bound on the share of individuals with $\pi < \bar{\pi}$ and $\sigma > \bar{\sigma}$. The exact shape of the type frontiers could help put tighter bounds on the joint distribution, but the more important observation is that the intersection of the frontiers enables placing bounds on the marginal distributions as well. For example, if the high-coverage plan is more popular, the share differential places a lower bound on the share of individuals with lower risk aversion, i.e., $H_\sigma(\bar{\sigma}) > \alpha_h - \alpha_l$. This is in contrast to the case discussed before where plan variation induced a shift in the type frontier (left panel of Figure 2) rather than a rotation (the right panel of Figure 2).

property of contracts to identify bounds on the type distribution in the population, and also provides additional information: it shows the conditions needed on the contract (i.e., $P_l/q_l \geq P_h/q_h$) for the single-crossing property to be informative for risk averse preferences.

[17] This is true since it lies to the right for both low and for high risks π (and can only cross once).

[18] Only that here the labels between X_h and X_l are reversed.

Intersections of the type frontiers are crucial for identification and more intersections help us to further tighten the bounds on the marginal distributions to obtain partial identification:

Proposition 1 *Consider a binary cost $k \in \{0, L\}$ and observations on the share of consumers who buy insurance for different $\mathcal{M}^i \in \{\mathcal{M}_1, .., \mathcal{M}_J\}$. There exist type distributions H for which we can (i) identify bounds on preference and risk heterogeneity with at least two appropriately chosen menus $\mathcal{M}_1$ and $\mathcal{M}_2$ and (ii) reject preference and/or risk homogeneity with at least three appropriately chosen menus $\mathcal{M}_1, \mathcal{M}_2$ and $\mathcal{M}_3$.*

Proof. *See appendix.* ■

This proposition follows relatively straightforwardly from Lemma 1.[19] Consider two menus $\{\emptyset, X_l\}$ and $\{\emptyset, X_h\}$ which generate type frontiers as depicted in the right panel of Figure 2, with crossing point $(\bar{\pi}, \bar{\sigma})$. Assume an underlying distribution of types such that more agents choose the low-coverage contract than the high-coverage contract. That means that there are more types in the shaded area above $\bar{\sigma}$ (and below $\bar{\pi}$) than in the shaded area below. This puts a lower bound on the number of agents with preference types above $\bar{\sigma}$ (and below $\bar{\pi}$), but does not yet rule out that all agents have the same preference or risk type. Consider now a third contract X_h' providing even higher coverage than X_h and the corresponding type frontier crossing the type frontier of the high-coverage contract X_h to the south-east of the intersection in the right panel of Figure 2 ($\bar{\pi}' > \bar{\pi}, \bar{\sigma}' < \bar{\sigma}$). If more agents buy insurance when offered this new generous contract than when offered the original high-coverage contract, we know that there exists a set of types in the underlying distribution that have preference types below $\bar{\sigma}'$ (and risk type above $\bar{\pi}'$). This places bounds on heterogeneity, since we can be sure that there are agents both with preferences above $\bar{\sigma}$ and below $\bar{\sigma}'$. The same holds for risks.

Proposition 1 suggests that more variation in insurance plans will further tighten bounds as the observation of each additional plan may provide an additional crossing relative to other plans.[20] More and more intersections therefore create more and more information about the underlying type distribution. Still, since we only rely on observed market shares, it may not seem straightforward whether sufficient plan vari-

[19] Barseghyan *et al.*'s (2013) Proposition 3 shows that choice with three contracts is necessary to establish an intersection of two type frontiers. In our Proposition, we add the link between the single-crossing property and the population shares, such that with two appropriately chosen menus (hence three contracts), we can identify bounds on preference and risk. We further make the claim that three appropriately chosen menus (from four contracts or more) is sufficient - and in fact necessary - to reject homogeneity in the population.

[20] For example, the previous construction can reveal a minimum share of types in the north-west quadrant above $(\bar{\pi}, \bar{\sigma})$ in the right panel of Figure 2, but it does not yet reveal how close these types are to $(\bar{\pi}, \bar{\sigma})$. Adding a fourth contract with crossing point within the north-west quadrant close to $(\bar{\pi}, \bar{\sigma})$ can put bounds on the number of types that are close. The same argument applies for contracts with crossing point within the south-east quadrant, but close to $(\bar{\pi}', \bar{\sigma}')$.

ation can allow for full identification and whether this depends on the underlying type distribution. The next section will investigate exactly this.

3.2 Full Identification in the Textbook Model

The previous subsection demonstrated how plan variation can place non-parametric bounds on the distribution of preferences and risks. This subsection turns to the question whether variation in menus across otherwise identical populations can in principle be enough for the full identification of any type distribution H.

In our binary setting, recall that a plan X_n is fully characterised by the premium P_n and the amount of insurance q_n. Defining the unit price of insurance as $p_n = P_n/q_n$, one can equivalently characterise the plan by (p_n, q_n). The question is whether enough variation in these two components identifies the underlying heterogeneity. This analysis can be split into two parts. First, one can consider plans with identical unit price $p_n = \hat{p}$ and determine the fraction of agents that choose plan $(\hat{p}, \hat{q})$ over any other plan $(\hat{p}, q)$ through pairwise comparisons. Alternatively, one can ask individuals to directly choose their preferred plan amongst all plans $(\hat{p}, q)$ with unit price $\hat{p}$. This alternative formulation entails less information, so identification here also implies identification under pairwise comparisons.[21] The alternative formulation is exactly the set-up in textbook insurance models where individuals choose the optimal quantity of insurance at given unit price to cover a binary risk (see for example Kreps, 1990; Varian, 1992; Mas-Colell *et al.*, 1995; Gravelle and Rees, 2004). In our notation, this corresponds to the selection of an insurance plan from a menu $\mathcal{M}_{\hat{p}} = \{(P, q) \,|P/q = \hat{p}, q \in \mathbb{R}_+\}$, and from choice data we can observe the fraction of agents $D(q|\mathcal{M}_{\hat{p}})$ buying an unrestricted coverage level $q \in \mathbb{R}_+$ offered at unit price $\hat{p}$, as well as the cumulative $\tilde{D}(q|\mathcal{M}_{\hat{p}})$ of agents that choose a coverage level no larger than q. For notational convenience and to highlight the connection to standard results, we continue with this textbook model, instead of pairwise plan comparisons.[22]

[21] Intuitively, for a given agent, pairwise comparisons provide strictly more information, since it provides pairwise information even for choices that are not optimal for this particular agent. This intuition does not simply generalise for our comparison: in the textbook model one observes the optimal choice among many contracts for any given individual, while in the binary comparisons one does not see the preferred choice for one particular individual but only the relative attractiveness overall across individuals. Nevertheless, note that in the textbook model, for a given agent the optimal choice q^* is unique as his utility is strictly concave in q. Consider now an agent who has to choose between two options q' and q'' that are either both larger or both smaller than his optimal q^*. Because of concavity he prefers the choice that is closest to his optimal choice. Now consider a binary choice set $\mathcal{M} = \{X_q, X_{q+\varepsilon}\}$ where both options have same unit price p but X_q has quantity q while $X_{q+\varepsilon}$ has quantity $q + \varepsilon$. By the preceding argument, all agents whose unconstrained choice q^* is below q prefer X^q, while those whose unconstrained choice is above $q + \varepsilon$ prefer $X_{q+\varepsilon}$. For ε sufficiently small, the mass of agents that prefer the middle vanishes, and we have uncovered the fraction of agents that have optimal choices below q as those that choose X_q. Formally, considering a sequence of populations we have $\lim_{\varepsilon \to 0} D\left(X_{q+\varepsilon} | \{X_q, X_{q+\varepsilon}\}\right) = \int^q D(x|\mathcal{M}_{\hat{p}})dx$. So pairwise comparisons entail at least the information from the textbook model.

[22] While, as mentioned before, pairwise plan comparisons provide in this setting at least the same information as what the textbook model provides, this is not generally true. We will discuss this further in Section 4.

This leads to the second step for identification: we also need variation in unit prices. Observing the fraction of individuals choosing between different coverage levels at constant unit price is not informative about risk or preference: following the logic of Lemma 1, the type sets $\mathcal{B}\left(q|\mathcal{M}_{\hat{p}}\right)$ for any available coverage choice q do not intersect as the price per unit of coverage remains constant, and we are in a choice environment akin to those depicted in the left panel of Figure 2. However, consider randomly assigning groups to different unit prices. That is, for a first random cross-section we observe their insurance choices from $\mathcal{M}_{p_h}$ and for a second cross-section we observe choices from $\mathcal{M}_{p_l}$. Consumers with the same coverage choice for the price p_h may choose different coverage levels at the reduced price $p_l < p_h$. The difference in willingness to buy additional coverage as prices change depends on the difference in their preferences and risks. In particular, due to the decreasing returns to coverage, the type with higher risk aversion (but lower risk) will increase her coverage less when the price decreases to p_l. This implies that the type sets $\mathcal{B}\left(q|\mathcal{M}_{p_h}\right)$ will be flatter than the type sets $\mathcal{B}\left(q|\mathcal{M}_{p_l}\right)$ at their respective intersections and allows us to use the difference in coverage shares to disentangle the heterogeneity in risk and preferences.

The textbook model allows for a direct illustration of this intuition. An individual chooses the level of coverage such that the marginal rate of substitution for her type equals the rate at which transfers can be made between the good and the bad state (as implied by the unit price),

$$\frac{\pi}{1-\pi}\frac{u'\left(m_b\left(q\right)|\sigma\right)}{u'\left(m_g\left(q\right)|\sigma\right)} = \frac{p}{1-p}. \tag{6}$$

An individual buys more coverage than another because she faces a higher risk or because she is more risk-averse. The variation in coverage choices across individuals at a constant price p could therefore be entirely driven by heterogeneity in preferences or heterogeneity in risks alone. Now taking logs on both sides of equation (6) and approximating $\log\left[u'\left(m_b|\sigma\right)/u'\left(m_g|\sigma\right)\right] \cong -\frac{u''(m_g|\sigma)}{u'(m_g|\sigma)}\left[m_g - m_b\right]$, we find an individual's demand for coverage as a function of the unit price,

$$q \cong A + B\log\left(p/\left[1-p\right]\right) \tag{7}$$

with

$$A = L - \frac{\log\left(\frac{\pi}{1-\pi}\right)}{u''\left(m_g|\sigma\right)/u'\left(m_g|\sigma\right)} \text{ and } B = \frac{1}{u''\left(m_g|\sigma\right)/u'\left(m_g|\sigma\right)}. \tag{8}$$

While both higher risk and higher risk aversion increases coverage choices, the response to a change in the price only depends on risk aversion. Those with higher risk aversion tend to increase their coverage less and are thus less responsive to a change in the price.

The above approximation is exact for CARA preferences. For such preferences there is a one-to-one mapping between (A,B) and (π,σ), since $A = L + \log\left(\pi/(1-\pi)\right)/\sigma$

and $B = -1/\sigma$. Therefore, the distribution H can be identified from the distribution of A and B in the population. We will show that sufficient price variation allows for such identification. The key step in this argument is to observe that prices determine the share of people with (A, B) for whom $\alpha A + \beta B \leq t$ along any ray defined by α and β and for any parameter t. In particular,

$$\Pr(\alpha A + \beta B \leq t) = \Pr\left(A + \frac{\beta}{\alpha} B \leq \frac{t}{\alpha}\right) = D\left(\frac{t}{\alpha} | M_{p(\alpha,\beta)}\right), \tag{9}$$

where $D\left(\frac{t}{\alpha}|M_{p(\alpha,\beta)}\right)$ is the observed share of people that buy no more insurance than $q = t/\alpha$ for for $p(\alpha, \beta) \equiv \exp(-\beta/\alpha) / [1 + \exp(-\beta/\alpha)]$. With sufficient price variation this can be observed for any level of α, β and t. This amounts to observing the marginal distribution (9) of the weighted sum of A and B, for all possible weights.

The remaining question is whether we can learn the joint distribution over A and B from observing all such marginal distributions over the sums of A and B. Cai *et al.* (2005) provide an affirmative answer based on a proof in the space of characteristic functions which we replicate in the appendix to make our arguments self-contained. This yields the following insight:

Proposition 2 *Consider a binary cost $k \in \{0, L\}$, a choice set $\mathcal{M}_p$ with constant unit price and any type distribution H with CARA risk preferences. When observing the distribution of coverage choices in $\mathcal{M}_p$ for each price $p \in [0, 1]$, the type distribution is fully identified.*

Proof. *See appendix.* ■

Full identification of the non-parametric type distribution requires observing coverage choices for the full support of prices. However, we can still uncover key moments of the respective distributions with limited (exogenous) price variation, in line with Proposition 1. Observing the distribution of coverage choices for two prices is sufficient to reject homogeneity in preferences, while three prices are sufficient to identify the variance in preferences. We show this formally in Appendix A.1.2.2.

4 From Theory to Practice

In this section, we do three things to show how to implement our identification approach in practice. First, we move beyond binary risks and simple insurance plans. In practice, costs can take many values and insurance plans are often complex (including deductibles, co-insurance rates, out-of-pocket maxima). The increase in the dimensionality of the contract space provides additional opportunities for identification. Second, we briefly consider the use of claims data for identification and the additional assumptions this entails. We view our approach using plan variation as complementary to the standard approach using claims data, allowing the researcher to test and relax the assumption of rational expectations. Finally, we show how *within-menu* plan variation can be used for identification even if there is no *between-menu* plan variation (obtained via random variation in menus faced by similar individuals). Even choices from a single menu can be informative enough to place bounds on the distribution of types. This approach is particularly useful, as within-menu plan variation naturally arises in many settings, including in our empirical setting, while between-menu variation typically requires experiments or quasi-experimental variation.

4.1 Plans and Expenses in Practice

We extend the previous insights for a known cost distribution $F(k|\pi)$, parametrised by the agent's unknown risk type π.[23] When costs are continuous, a plan X can in principle specify any out-of-pocket expense $x(k)$ for each possible cost $k \in \mathbb{R}_+$. We focus on three pre-dominant coverage features of insurance plans: a deductible D, below which all costs are paid out-of-pocket by the individual, an out-of-pocket maximum M above which the out-of-pocket expenses cannot increase, and a co-insurance rate β determining the individual's cost share in between. The out-of-pocket expense equals

$$x(k) = \begin{cases} k & \text{for} \quad k \leq D, \\ D + \beta(k - D) & \text{for} \quad k \in \left[D, \frac{1}{\beta}M - \frac{1-\beta}{\beta}D\right], \\ M & \text{for} \quad k > \frac{1}{\beta}M - \frac{1-\beta}{\beta}D. \end{cases}$$

Simple Plans Covering High Expenses The logic for identification remains essentially identical to the arguments from the previous sections if contracts cover high but not low expenses: consider insurance plans that set the deductible equal to the out-of-pocket maximum (i.e., $Z \equiv D = M$). This induces full cost sharing below Z but no cost sharing above Z. Now, the setting resembles our stylised setting with binary risks studied before. The valuation of the insurance plan depends crucially on the probability $1 - F(Z|\pi)$ that the coverage is received.

Both high risk aversion and high expected costs increase the willingness to pay for such a plan. We can compute the marginal willingness to reduce the threshold Z when the plan charges a premium P, which can be inverted to get an expression analogous to the marginal rate of substitution (4) that guided our understanding in the binary risk case:

$$\begin{aligned} \frac{\frac{dP}{dZ}|_{U(X|\pi,\sigma)}}{1 - \frac{dP}{dZ}|_{U(X|\pi,\sigma)}} &= -\frac{[1 - F(Z|\pi)]\, u'(-P - Z|\sigma)}{\int_0^Z u'(-P - k|\sigma)\, f(k|\pi) dk} \\ &= -\frac{1 - F(Z|\pi)}{F(Z|\pi)} \frac{u'(-P - Z|\sigma)}{E[u'(-P - k|\sigma)\, |k \leq Z; \pi]}. \end{aligned} \tag{10}$$

[23] In principle, an agent's risk type can be multi-dimensional (e.g., mean and variance of lognormally distributed costs), but more plan variation would be needed to identify the different risk dimensions.

The basic structure of this expression is very similar to (4) in the binary case. When risk types are ranked in a first-order stochastic dominant way (i.e., $F(k|\pi_i) \leq F(k|\pi_j)$ for all k), individuals with higher risk or higher risk aversion have a higher willingness-to-pay for additional coverage. However, the returns to coverage tend to decrease more rapidly for individuals with higher risk aversion. If among the marginal buyers of a plan, the marginal willingness to pay is indeed higher for those with higher risk but lower risk aversion, we can again invoke Lemma 1 and establish rotations of the type frontiers by changing the coverage and price paid.[24] Sufficient variation in prices and coverage allows us to uncover the underlying heterogeneity in the spirit of Proposition 2.

Plans Covering High vs. Low Expenses In practice, plans also differ in the type of expenses they cover: a plan could have lower deductible, but a higher out-of-pocket maximum, as well as different coinsurance rates. These different plan characteristics offer additional channels for identification.

The marginal expected utility from lowering the out-of-pocket expense $x(k)$ for a given cost k equals

$$dU(X|\pi,\sigma) = f(k|\pi)\, u'(x(k)|\sigma)\, dx.$$

The willingness to purchase additional coverage depends on the probability of the underlying cost (which is determined by the risk type π) and the utility from reducing the out-of-pocket expense (which is determined by the risk preference σ).

Arbitrary non-linear insurance plans could vary the out-of-pocket expenses for each cost realisation k. Such plan variation allows separating heterogeneity in risk and preferences. Yet even standard insurance contracts provide valuable identification. Out-of-pocket maxima, for example, affect the coverage for high expenses, while deductibles affect coverage for low expenses. For given risks, individuals with high risk aversion care more about reducing high out-of-pocket expenses than reducing low out-of-pocket expenses. In particular, a type with extreme risk aversion chooses based on the out-of-pocket maximum and premium only, trying to reduce spending in the worst case, in which both are paid. As a result, decreasing the wedge between out-of-pocket maximum and deductible attracts the more risk-averse and discourages the less risk-averse types from buying insurance. This tends to rotate the decreasing type frontier counter-clockwise.

How much individuals with different risk care about reducing the out-of-pocket maximum rather than the deductible depends on the likelihood ratio of the different expenses. Starting from a contract for which deductible and out-of-pocket maximum coincide at Z, the marginal willingness to reduce the deductible relative to the out-of-

[24] Note that a risk-neutral type is indifferent about buying when $(1 - F(Z|\pi))\, E(k - Z|k > Z, \pi) = P$. By analogy to the binary case, to obtain a crossing of the type frontiers, we would need the expected coverage to increase by more than the price for this indifferent risk-neutral type.

pocket maximum simplifies to the product of co-insurance and hazard rate:

$$\frac{dM}{dD}|_{U(X|\pi,\sigma)} = (1-\beta)\frac{f(Z|\pi)}{1-F(Z|\pi)}. \tag{11}$$

If the hazard rate were to decrease for higher risk types, they care more about reducing the out-of-pocket maximum.[25] Decreasing the wedge between the out-of-pocket maximum and deductible then tends to rotate type frontiers clockwise.

A formal characterisation of the plan variation needed for identification (like the variation in P/q for the binary risk case) is challenging and would require specifying the feasible risk types $F(\cdot|\pi)$ and preference types $u(\cdot|\sigma)$. Still, the insight that plan variation can help separating risk and preference types clearly extends beyond the binary risk case. We also illustrate this in our empirical application.

4.2 Using Claims Data

Our approach does not require the availability of claims data as we are not using information on realised costs. Claims data can help with the identification of preferences and risk heterogeneity, but this would always rely on two further assumptions.

The first is an assumption of rational expectations, or at least some model of how perceived risks relate to true risks. Most of the empirical literature studying insurance choices simply assumes rational expectations on risks. The importance of this assumption is well understood and some recent work has estimated models of risk distortions (e.g., Barseghyan *et al.*, 2013). Our approach can be viewed as an alternative method to relax assumptions on the relation between perceived and true risks. When claims data is available and linkable to choice data, it could also be simply used - without further identifying assumptions - to compare the realised risks to the perceived risks as revealed by the contract choices. This allows investigating whether individuals assess their risks correctly or over-/under-estimate it.

The second is an assumption on the functional form of the type distribution. The key challenge is to infer the distribution of (ex ante) risk types from a distribution of (ex post) risk realisations. For example, in the binary risk case, let $\pi_a \in (0,1)$ denote the average probability of a loss in the population. Without further information on people's insurance choices, the average loss probability is not helpful in identifying risk heterogeneity. In particular, individuals could all have the same risk type (i.e., $\pi^i = \pi_a$ for all i), all be certain to face the loss or not (i.e., $\pi^i = 1$ for share π_a of individuals and $\pi^i = 0$ for the remaining share $1-\pi_a$ of individuals), or anything between as long as the average loss probability equals π_a. This identification problem, even under rational expectations, is a general one that extends beyond binary risks for any family

[25] Note that when risk types are ranked by first-order stochastic dominance, the hazard rate and thus the marginal rate of substitution between D and M needs not to be monotone. A monotone likelihood ratio property for the risk types (i.e., $f(k+\varepsilon|\pi)/f(k|\pi)$ increasing in π for $\varepsilon > 0$), however, would imply both a first-order stochastic dominance ranking and a monotone hazard rate function.

of distribution functions that is convex in the sense that a convex combination of any two distributions is still in the family.[26]

The joint observation of plan choices and cost realisations helps circumventing this problem, but only partially. For example, in our binary choice setting, let $\pi_\emptyset = D(L|\emptyset)$ denote the average probability of a loss amongst individuals who do not buy insurance and let $\pi_X = D(L|X)$ denote the average probability among individuals who buy a contract. If these probabilities are not the same, the population who buys insurance faces a different risk on average than those who do not. While we can reject homogeneity in risks, we cannot bound the risk distribution much more, as we cannot identify the risk heterogeneity among those making the same choice, who again could all have the same risks (i.e., $\pi = \pi_\emptyset$ for those who don't buy insurance) or might be more heterogeneous with same average. In fact, as long as there is adverse selection ($\pi_X \geq \pi_\emptyset$), we will not be able to rule out preference homogeneity.[27] The same issue arises in the textbook model. Assuming CARA preferences, claims data can be sufficient to reject homogeneity in preferences, but will not allow identification of any additional moments capturing the variation in preferences. The issue is again that we cannot establish or reject homogeneity in preferences (nor in risk types) for the individuals choosing the same coverage level q at unit price p. The observed share of losses $D\left(L|q,p\right)$ pins down only the average risk type among these individuals and a preference type that rationalises the coverage choice given this average risk type. Hence, there is no way to identify heterogeneity in preferences or risks beyond these average types that rationalise the respective coverage choices.

A standard approach in the literature is therefore to rely on parametric assumptions about the type distributions instead and to use cross-sectional risk realisations to identify the distribution of risk types under specific functional forms (see Barseghyan *et al.*, 2018). Clearly, better data containing multiple observations of risk realisations for individuals or observables that help predicting an individual's risk type (e.g., Handel, 2013), or data from surveys eliciting beliefs about risks that help estimating perceived risks (e.g., Handel and Kolstad, 2015) could further relax this identification problem.

[26] For example, the convex combination of two normal distributions tends to have two peaks and is no longer normal. In this case the shape of the overall distribution of risks can identify the distribution of underlying types, but this relies very much on the choice of the underlying family of distributions. Putting structure on the risk distribution can be informative to varying degrees. Aryal *et al.* (2016) show that with the assumption of a Poisson distribution and information on the number of realised claims, non-parametric identification is possible. Then Aryal *et al.* (2010) show in the same set up that if risk is defined as having any realised claims, then the model is still not identified.

[27] To see this, let α be the share of individuals buying the plan, and let σ_X and $\sigma_\emptyset$ be the preference types such that a person with either type (π_X, σ_X) and type $(\pi_\emptyset, \sigma_\emptyset)$ is indifferent to buying insurance. Any individual with intermediate preference type $\hat{\sigma} \in (\sigma_X, \sigma_\emptyset)$ would buy insurance when having the high risk type $\pi^i = \pi_X$, but not with low risk type $\pi^i = \pi_\emptyset$. Hence, even if one presumed that all individuals share the same intermediate preference type, one could still rationalise the observed choices and costs by simply assigning the risk type π_X to share α of individuals and risk type $\pi_\emptyset$ to the remaining share.

4.3 Using Within-Menu Plan Variation

In practice, we often observe individuals picking a plan out of a menu providing the choice between several, different plans. We demonstrate how *within-menu* variation in plans can still be exploited for identification and link this to the *between-menu* variation in plans analysed before.

The first practical insight is that if identification is not possible for plans offered in different menus (i.e., from between-menu variation, as in our previous setting), identification is not possible either when these plans are offered together (i.e., from within-menu variation). This is the case when type frontiers do not intersect, as in the left panel of Figure 2. Consider again our original binary risk setting, but now with contracts X_h and X_l offered together in a three-plan menu $\mathcal{M} = \{\emptyset, X_l, X_h\}$. If contract X_h provides more coverage at higher unit price (such that $\mathcal{T}(\emptyset, X_h)$ lies above $\mathcal{T}(\emptyset, X_l)$), identification is not possible using choices from this menu, as any different choice can be explained either by higher risk aversion or higher risk. Starting from a type that buys no insurance, an agent switches first to the low-coverage plan X_l, when increasing either her risk or preference type, and eventually to the high-coverage plan X_h.

The counterpart of this result is that plan variation that leads to identification across menus can also provide identification when plans are offered together in one menu. Consider any two plans X_j and $X_{j'}$ for which the type frontiers $\mathcal{T}(\emptyset, X_j)$ and $\mathcal{T}\left(\emptyset, X_{j'}\right)$ intersect, as illustrated before in the right panel of Figure 2. The type $(\bar{\pi}, \bar{\sigma})$ at the intersection of the two frontiers is indifferent between all three options (including the outside option $\emptyset$). This type $(\bar{\pi}, \bar{\sigma})$ is a natural candidate to provide a bound on the support of one of the two plans.

We briefly illustrate this in our original binary risk setting. Consider again contracts X_h and X_l, but with X_h providing more coverage at lower price per unit. Figure 3 plots the different type sets corresponding to the choice of each of the plans when the plans are offered within the same menu $\mathcal{M} = \{\emptyset, X_l, X_h\}$. The low-coverage plan provides an intermediate option, but as it charges a higher price per unit of coverage, this is only attractive to individuals with relatively high risk aversion (and relatively low risk type). Such individuals strongly value the basic coverage provided by the low-coverage plan, but place less value on the additional coverage provided by the high-coverage plan. Hence, when increasing the risk type of an individual with risk aversion higher than $\bar{\sigma}$, she will first switch from no insurance to the low-coverage plan before eventually switching to the high-coverage plan. In contrast, individuals with risk aversion lower than $\bar{\sigma}$ will never buy the low-coverage plan. Their marginal valuation of coverage is more constant. As a consequence, these individuals remain uninsured when their risk type is low, but switch immediately to the high-coverage plan (charging a low price per unit) when their risk type is high.

In Figure 3 this gives rise to an area above $\bar{\sigma}$ where agents buy X_l, but not below. As a consequence, the share of individuals buying the low-coverage plan X_l places

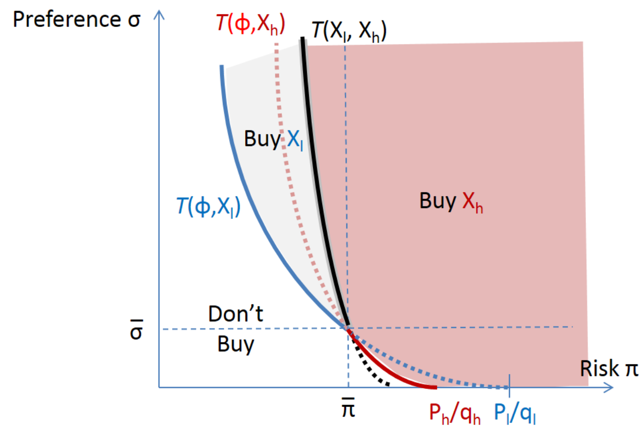

Figure 3: The figure shows the choices for types in (π, σ)-space from the menu $\mathcal{C} = \{\emptyset, X_l, X_h\}$. The lines show the type frontiers for any binary choice. All type frontiers intersect at $(\bar{\pi}, \bar{\sigma})$. Like in Figure 2, the low-coverage plan charges a higher price per unit of coverage and therefore differentially attracts types with high risk aversion (and low risk).

a lower bound on $1 - H_\sigma(\bar{\sigma})$. The following Lemma summarises identification using within-menu variation, in line with the potential of between-menu variation described in Lemma 1:

Lemma 2 *Under Assumption 1, the three type sets rationalising the respective plan choices from the menu $\mathcal{M} = \{\emptyset, X_l, X_h\}$ with $q_h > q_l$ meet at a unique pair $(\bar{\pi}, \bar{\sigma})$ if and only if $P_h > P_L$ and $P_l/q_l > P_h/q_h$. Moreover,*

$$\int_{\pi \leq \bar{\pi}} \int_{\sigma \geq \bar{\sigma}} dH \geq D(X_l|\mathcal{M}).$$

Proof. *See appendix.* ■

Comparing Lemmas 1 and 2, we note three important differences from observing plan shares when plans are offered jointly rather than pairwise. First, for a given set of plans, the market shares when all plans are offered jointly allow for tighter bounds, since for pairwise comparisons the bounds need to be constructed using share differentials. Second, with all plans offered jointly, the bounds only go in one direction (i.e., $\pi \leq \bar{\pi}$, $\sigma \geq \bar{\sigma}$). This, however, is due to the contract space we consider. For example, extra risk in the payments of the coverage would discourage the more risk-averse types and allow for bounds in the opposite direction.[28] In general, one-sided bounds are not an issue in more complex contractual environments for which the dimensionality exceeds the dimensionality of the type space as we demonstrate in our empirical application in the next section. Finally, we require the different plans to be offered jointly at the specified

[28] That is, a random contract X_r that covers the loss in case of accident with probability $r > 0$ would allow us to establish such bounds.

prices. A concern in the absence of random variation is whether the menus offered in a market equilibrium contain the plan variation that is required for identification.[29] By the same token, the fact that no random plan variation is needed is of course a major advantage for the applicability of the approach using within-menu variation. This is also what we exploit in our empirical application, in which the offered menu of health plans allows us to construct informative bounds. We turn to this now.

5 Application to Massachusetts' Health Insurance Exchange

In this section, we use health insurance plan choices by consumers on the Massachusetts Health Insurance Exchange (HIX) to illustrate our identification method. We use within-menu plan variation (as opposed to price variation) and derive informative bounds on the CDFs of risk preferences and expected costs of these consumers.

5.1 Exchange Context

Established by the 2006 Massachusetts Health Reform, the Massachusetts HIX was the forerunner of the HIXs established across the U.S. by the 2010 Affordable Care Act (ACA). Data from the Massachusetts HIX allow us to examine consumer choice from a menu with a variety of plans, offered at posted prices on a guaranteed issue, non-health rated basis. The menu was designed by the HIX regulator, while prices were set by individual insurers; premiums vary by plan tier and insurer. The exchange we study is unsubsidised and open to consumers with incomes over 300% of the federal poverty level who were not offered insurance through an employer. We restrict attention to consumers age 27-64; younger consumers are eligible for alternative plans while older consumers are eligible for Medicare. We further restrict attention to individual plans to avoid modelling household decision-making (see e.g. Adams *et al.*, 2014). Our data come from January and February of 2010. We examine the choices of first-time choosers on the exchange to avoid modelling consumer inertia (Ericson, 2014; Handel, 2013). Additional details on consumer choice, including screenshots of the exchange website, are available in Ericson and Starc (2016), and the background of the exchange is described in detail in Ericson and Starc (2012a,b).

To purchase an exchange plan, a consumer first enters their demographic information (age and location). Based on the information provided, consumers are shown the six standardised[30] benefit designs ("tiers"): bronze low, bronze medium, bronze high,

[29] With only heterogeneity in binary risks (Rothschild and Stiglitz, 1976), we would expect the equilibrium plans providing more coverage to charge a higher price per unit of coverage (i.e., $P_l/q_l < P_h/q_h$). However, even in binary risk settings, multi-dimensional heterogeneity, but also regulatory interventions or fixed costs (Cawley and Philipson, 1999) may give rise to the plan variation required for identification.

[30] Ericson and Starc (2016) describes the standardisation process in more detail. The Massachusetts HIX tiers in this time period are slightly different from the ACA tiers—for instance, gold on the Massachusetts HIX is similar to Platinum on the ACA exchanges.

silver low, silver high, and gold. Each metal tier has the same cost-sharing characteristics: for instance, all bronze low plans have a \$2000 deductible, 20% coinsurance for hospital charges, and a \$5000 out-of-pocket maximum. Similarly, all gold plans have the same financial features as each other. Each tier offers a higher actuarial value (the fraction of health care costs that would be insured for a representative sample of the population) than the tier below. Once picking a tier, consumers can then choose among different insurance carriers. Insurers are differentiated based on price and provider networks, but not based on plan design.

Due to modified community rating regulation, the premium for a given insurer-plan combination can only vary by geography and age. In particular, premiums are only allowed to differ for each 5-year age group. Thus, there is menu of several plans differing in coverage tier and price that is offered to each 5-year age group.[31] We use this within-menu plan variation for identification (as analysed in Subsection 4.3).

5.2 Choice Menu

In order to model consumer choice from the menu of plans, we translate each plan design into a simplified plan design characterised solely by a deductible D, a coinsurance rate β, and maximum out-of-pocket spending M. In a contract characterised solely by these parameters, an individual's out of pocket spending is simply a plan-specific function of their total spending. This simplification is motivated by the fact that contracts are in fact quite complex, with per-visit co-payments that vary based on service used and per admission charges to the hospital. Modelling choice from such a complex contract would require modelling a very detailed level of health care utilisation: for instance, how often consumers expect to use each type of specialist, each tier of prescription drug, and differentiating between expenditures for lab tests, durable medical equipment, allergy treatment, and inpatient spending. Our simplification procedure is also reasonable since it is unlikely that consumers observed, understood, and had well-formed expectations of the probability that they would use each of these varied services.

To translate the actual plan design into a simplified plan design X, we entered the original characteristics of each plan into the Center for Consumer Information & Insurance Oversight's (CCIIO) actuarial value calculator—including details such as per visit co-payments, which produced an estimated actuarial value (AV) for that plan. Then, we solve for the coinsurance rate (given that plan's actual deductible D and maximum OOP M) that would produce the same AV for the simplified version of each plan characterised by (D, β, M).[32] We explore results using a variety of other

[31] The discontinuities in price created by the 5-year age group pricing regulation provides arguably exogenous price variation for comparable populations around age cut-offs, but one would need a larger sample to achieve sufficient statistical power to use this *between-menu* plan variation (as analysed in Subsection 3.1).

[32] However, because the actual plans did indeed provide some coverage for spending below deductible (e.g. a \$100 doctor's visit resulted in a \$30 copay even if the deductible was not met), our method underestimated the degree of coinsurance. While the results were reasonably representative of the plans'

alternative plan translations in the Empirical Appendix (see Appendix Figure A.2). Table 1 presents the results of this exercise, while Table A.1 describes the detailed design of the plans as sold on the Massachusetts HIX.[33] Premiums are different for each 5-year age group; we present the premiums for the lowest and highest priced age group, and focus our analysis on these groups.[34]

Plans in the table are ordered by their actuarial value, from least to most generous. While the actuarial values of the Bronze plans are quite similar, the plans vary in where they apply coverage: Bronze High has a very low deductible but correspondingly higher coinsurance than Bronze Medium; all Bronze plans have the same maximum OOP. (Note that despite having a slightly higher actuarial value than Bronze Medium, Bronze High is priced slightly lower.) Silver Low is quite different as it has a lower maximum OOP, but a higher deductible relative to Bronze High. Silver High and Gold are quite similar again: both have zero deductible and a maximum OOP of \$2000. While Gold is more generous based on actuarial value and has a lower coinsurance rate, it has higher premiums.

While multiple insurers offer plans, we focus our analysis on the price menu of the most popular insurer (Neighborhood Health Plan), which has approximately 50% market share. (The price for each plan design varies across insurers; we have explored using the prices for other insurers, which give similar results.) In all cases, our results apply to the population of individuals who chose this insurer. We do not explicitly model individual's choice of insurers. Tighter bounds could be obtained by modelling individuals' pattern of substitution between insurers, but we have limited data to identify these patterns.[35]

The final columns of Table 1 present market shares for the plan designs, broken down by broad age groups. Though prices vary by 5 year age groups, we group those

characteristics, this method produced a 0% coinsurance rate for the Bronze Medium plan, even though this plan in fact did include cost-sharing after the deductible. We used a corrected coinsurance of 5% for Bronze Medium, based on dividing the \$500 hospital copay (as in the original plan characteristics) by the mean 2010 hospital stay cost of \$9700 (as reported in Pfuntner *et al.*, 2013).

[33] In some months, a Silver Medium plan is also offered; when it is, we drop it from our plan menu, along with the small number of people who choose it from our calculation of market shares. Because the remainder of the individuals revealed they preferred one of the other plans to Silver Medium, our bounds are still describing the preferences and beliefs of our sample population. (The bounds we present are slightly looser than if we had used information about Silver Medium.)

[34] Premiums are averaged over the two months (there is small variation between January and February) and across zipcodes for all people offered the Neighborhood Health Plan (most people live in the Boston region).

[35] Our model is consistent with a variety of different ways in which individuals trade off their preferred plan design versus price and preferred insurer. For instance, individuals could make a hierarchical decision, choosing their preferred insurer first (based on insurer network versus insurer's average price), then choosing their preferred plan design. Then, our results simply describe the population of people whose preferred insurer was Neighborhood Health Plan. Alternatively, an individual may have a more complex pattern of substitution—for instance, a Blue Cross Bronze High plan may be the closest substitute to a Neighborhood Health Plan Silver Low plan. In this case, our bounds on preferences and beliefs still describe the population of individuals whose preferred plan was offered by Neighborhood Health Plan, since the plan they chose was indeed revealed preferred to all other plans offered by this insurer.

above and below age 45 to get more accurate estimates of market shares (doing so reduced sampling error). See Appendix Table A.2 for detailed market shares within each 5 year age bin category.

5.3 Individual Model of Choice

We model individuals as having CARA utility over consumption: $u(-P - x(k)) = -\exp(\sigma(P + x(k)))/\sigma$, where OOP expenses $x(k)$ are a function of the individual's healthcare spending k and the insurance plan they choose. Individuals vary on two dimensions. First, they vary in their CARA coefficient σ. Second, they vary in their beliefs about the distribution of their own healthcare spending. While there are many dimensions on which individuals might vary in their distributional beliefs, we summarise variation in expected claims in a single risk-type index, π. For each risk-type π, the expected claims distribution is assumed to follow a log normal distribution with $mean = \pi$ and $variance = \frac{\pi}{4053}\left[\frac{1}{2} \times 10451\right]^2$.[36] Note that variance of expenditures scales with the mean expected risk. We take the \$4053 mean spending number from the 2010 Medical Expenditure Panel Survey, persons with private insurance. The standard deviation of expenses is \$10451. Someone with $\pi = 4053$ has the population average as his or her mean claim, but because individuals have information about their own risk type (age, gender, particular diseases, and expected patterns of care), we assume the individual's expected standard deviation is half the population standard deviation. Little is known about risk types and their structure. Under our assumptions, the variance of claims is lower for an individual with lower mean expected claims. We have explored alternative variance assumptions, including a model of constant variance of claims across all risk types.[37] Note as well that we have assumed no moral hazard: expected healthcare spending is the same, regardless of which contract individuals choose.

To determine what can be learned from consumers choosing from the menu of options in Table 1, we construct a grid of (π, σ) pairs, with σ ranging from 10^{-15} to 0.5×10^{-2} and π ranging from 1/100 the population expected claims (about \$40 in expected claims) to 5 times the population expected claims (about \$20,000 in expected claims). Each (π, σ) pair represents a combination of expected healthcare costs and risk aversion. We then calculate the plan that maximises expected utility for each pair.

The first column of Figure 4 displays the optimal plan choice for the youngest group (Panel A, upper panel) and oldest group (Panel B, lower panel). Recall that prices vary between age groups, and the older group faces a higher marginal cost of more generous coverage. For both groups, only individuals with relatively low expected costs choose the Bronze Low (dark black) plan: it is chosen for only the lowest value of π in Panel

[36] The mean π and variance are functions of the underlying parameters of the lognormal distribution that can be written as $\pi = \exp(\mu + \sigma^2/2)$ and $variance = \exp(2\mu + \sigma^2)\left(\exp(\sigma^2) - 1\right)$.

[37] Appendix Figure A.1 shows how choices would shift if alternative variance structures were assumed. Intuitively, higher variance at a given amount of expected costs tends to increase demand for insurance.

A, and the lowest two values of π in Panel B. It is attractive for all individuals with such low expected costs regardless of risk aversion. Bronze Medium is similar to Bronze Low but with a lower coinsurance rate and priced slightly higher. It is only chosen by the older consumers at this set of relative prices (it does not appear in Panel A), and attracts relatively risk averse, but low-risk individuals. Bronze High is the most popular plan with a market share of 40.2% and 29.0% for the young and old respectively. The plan is attractive to relatively risk-neutral individuals with a wide range of expected claims, and to low expected-cost individuals with a wide range of risk aversion. The plan has a low deductible ($250 vs. $2000 for the other Bronze plans) and is cheaper than Bronze Medium, but has a higher co-insurance rate above the deductible.

Turning to Silver plans, we find that individuals with the highest expected costs choose Silver Low rather than Silver High; individuals with intermediate expected costs choose Silver High. While the two silver plans have the same maximum OOP, the Silver High plan has a lower deductible but higher coinsurance; from the perspective of risk averse individuals, paying for first dollar coverage is less valuable than paying for lower coinsurance. Despite the fact that Silver Low is preferred for many (π, σ) pairs, the market share of Silver Low is relatively small: only about 3%. This indicates that there is not a large subset of the population with both very high risk aversion and very high expected claims.

Finally, note that no one in this menu chooses a Gold plan: its only advantage over Silver High is lower coinsurance, but it has substantially higher premiums. Thus, even though the Gold plan has the highest actuarial value, it exposes individuals to a worse worst-case scenario than the Silver plans. Someone who hits the maximum OOP of $2000 in both Silver High and Gold will spend more in the Gold plan due to the higher premiums (an additional $1392 at the premiums faced by older individuals). This explains why Gold is actually less attractive than Silver for someone who is very risk averse and expects to hit the OOP maximum.[38]

5.4 Bounds from Plan Choices

Since Figure 4 shows the optimal plan choice for each π and σ pair, we can combine its results with the plan shares in Table 1 to construct bounds on the CDFs of π and σ. Intuitively, about 20% of the younger age group chose bronze low; since bronze low is only rationalisable for the lowest value of expected claims, at least 20% of the population must fall in this risk type, providing a lower bound on the CDF.[39] Column

[38] The market share of Gold is relatively small (only 8% for the old), but non-zero. In exploratory analysis, we do find that the plan becomes rationalisable under certain menus and variance assumptions.

[39] We do not find values of π, σ that rationalise the choices of Bronze Medium and Gold for the younger group. When we present our CDFs, we rescale them to represent the CDF for the population who chose one of the rationalised plans. In an alternative parameterisation discussed in the appendix, we are able to rationalise Bronze Medium for a limited range of risk aversion parameters (high-variance specification, Panel B of Appendix Figure A.1).

2 of Figure 4 presents CDFs of π and σ independently.[40] The upper panel shows that choice provides virtually no restriction on the distribution of risk preferences in the population facing the young prices. Any single choice of the risk aversion parameter σ (except the most risk neutral one) could rationalise all the choices. The only restriction on the distribution is that individuals choosing Silver Low cannot have the most risk neutral value of σ. This bound, however, is coming from our restriction on the domain of risk types, having assumed that an individual's expected claims cannot exceed $\$20,000$.

The bottom panel of Figure 4 shows that there must be at least some relatively risk-averse individuals to rationalise choice for older individuals given the prices they face. The bound is coming from the difference in plan features between Bronze and Silver plans which differentially attract types along the risk and preference dimension. Bronze Medium offers relatively generous coverage for intermediate costs and only attracts types with risk aversion $\sigma \geq \bar{\sigma}_I = 9.32 \times 10^{-4}$. Types with lower risk aversion should either buy Bronze High, providing more generous coverage for low costs, or Silver Low, providing more generous coverage for high costs. Similarly, we find that Silver High only attracts types with risk aversion $\sigma \geq \bar{\sigma}_{II} = 0.0011$.[41]

In line with Lemma 2, the share of older individuals with risk aversion greater than $\bar{\sigma}_{II} = 0.0011$, $1 - H_\sigma(\bar{\sigma}_{II})$, is at least as high the market share of Silver High and thus provides an upper bound on the CDF. The share of individuals with risk aversion above $\bar{\sigma}_I = 9.32 \times 10^{-4}$ is at least the sum of the market shares of Silver High and Bronze Medium, providing a tighter upper bound on the CDF for this lower level of risk aversion. Despite our informative upper bound on the CDF, we cannot reject homogeneity in risk preferences since we cannot place a lower bound on the CDF for $\sigma < \bar{\sigma}_{II} = 0.0011$. As a consequence, we can fit a degenerate CDF that jumps from zero to one for risk-aversion levels above $\bar{\sigma}_{II} = 0.0011$. Note that the offered plans do not place any lower bound on the CDF for the preference range shown in Figure 4. So while we can reject that all individuals would have relatively low risk aversion, we cannot reject that all individuals have some relatively high yet homogeneous risk aversion.

Turning to the distribution of risk types (π), we note that for each bound on risk aversion coming from the plan variation corresponds to a bound on risk as well. For example, Bronze Medium attracts types who not only have relatively high risk aversion ($\sigma \geq \bar{\sigma}_I$), but also expect low costs ($\pi \leq \bar{\pi}_I = \$1170$). Types with higher expected costs prefer the higher actuarial value of Bronze High or Silver depending on their risk preferences. The same is true for Silver High, which only attracts types with expected expenses $\pi \leq \bar{\pi}_{II} = \$1067$. In addition, the choice of Bronze Low, which provides

[40] In the Appendix, we also perform a bootstrap analysis to assess how sampling error would affect our bounds. See Appendix Figure A.3.

[41] Types with lower risk aversion and relatively low risk should buy Bronze, providing lower coverage but at substantially lower premium. Types with lower risk aversion but high risk should again buy Silver Low.

the lowest coverage, can only be rationalised for types with very low expected costs ($\pi \leq \bar{\pi}_{III} = \$383$). The cumulative market shares of Bronze Low, Silver High and Bronze Medium provide a lower bound on the CDF of expected costs at respectively $\bar{\pi}_{III}, \bar{\pi}_{II}$ and $\bar{\pi}_{I}$. This is illustrated in the bottom figure of Column 2 of Figure 4

For the distribution of risk types, the market shares can also be used to provide upper bounds on the CDF. When risk preferences cannot exceed the extremely risk averse[42] $\sigma = 0.005$, as illustrated in Column 1 of Figure 4, we find strictly positive lower bounds on the support of expected expenses for each of the plan choices other than Bronze Low. The market shares for these plans allow us to construct upper bounds on the CDF of expected costs. Note that when we relax the constraint on the preference domain, we still find informative lower bounds on the support for some plans. For example, for the older individuals, Silver High (Bronze Medium) will only attract types with expected expenses above \$1069 (\$383), regardless of what their risk preferences could be.[43]

The derived upper and lower bounds on the CDF imply that we can reject homogeneity in expected expenses. (We cannot fit a degenerate CDF jumping from 0 to 1 for some π.) Hence, while we can rationalise the different plan choices with only heterogeneity in expected expenses, we cannot do it with only heterogeneity in risk preferences. Note that we have considered a wide candidate range for (σ, π). To the extent you are willing to put further restrictions on the range of reasonable parameters, tighter bounds can be obtained.

5.5 Discussion

A large empirical literature has argued that heterogeneity in risk preferences is a key feature of insurance markets and explains why adverse selection is a minor issue in several markets. The implementation of our non-parametric approach does not allow us to validate this claim in our empirical context. We cannot reject that all individuals have the same preferences, while they must differ in their (perceived) risks. However, the non-parametric bounds on risk preferences, using only plan variation, do not allow us to distinguish between quite extreme forms of preference heterogeneity either. A more structural approach could help to tighten bounds on preferences and prove complementary to our approach, but the tighter bounds would rely on the validity of the imposed structure.

For comparison, Figure 5 plots our bounds on CARA preferences for the old group with some well-known examples in the insurance literature of parametric estimates of CARA distributions using standard random utility models. These estimates are

[42] For $\sigma = 0.005$, an individual is indifferent between getting \$139 for certain and a 50-50 gamble for \$10,000 or \$0.

[43] Since in the high-variance specification in Panel B of Appendix Figure A.1, we can only rationalise Bronze Medium for a limited range of risk aversion parameters, the market share of Bronze Medium provides both a lower and upper bound on the CDF of risk types and preference types.

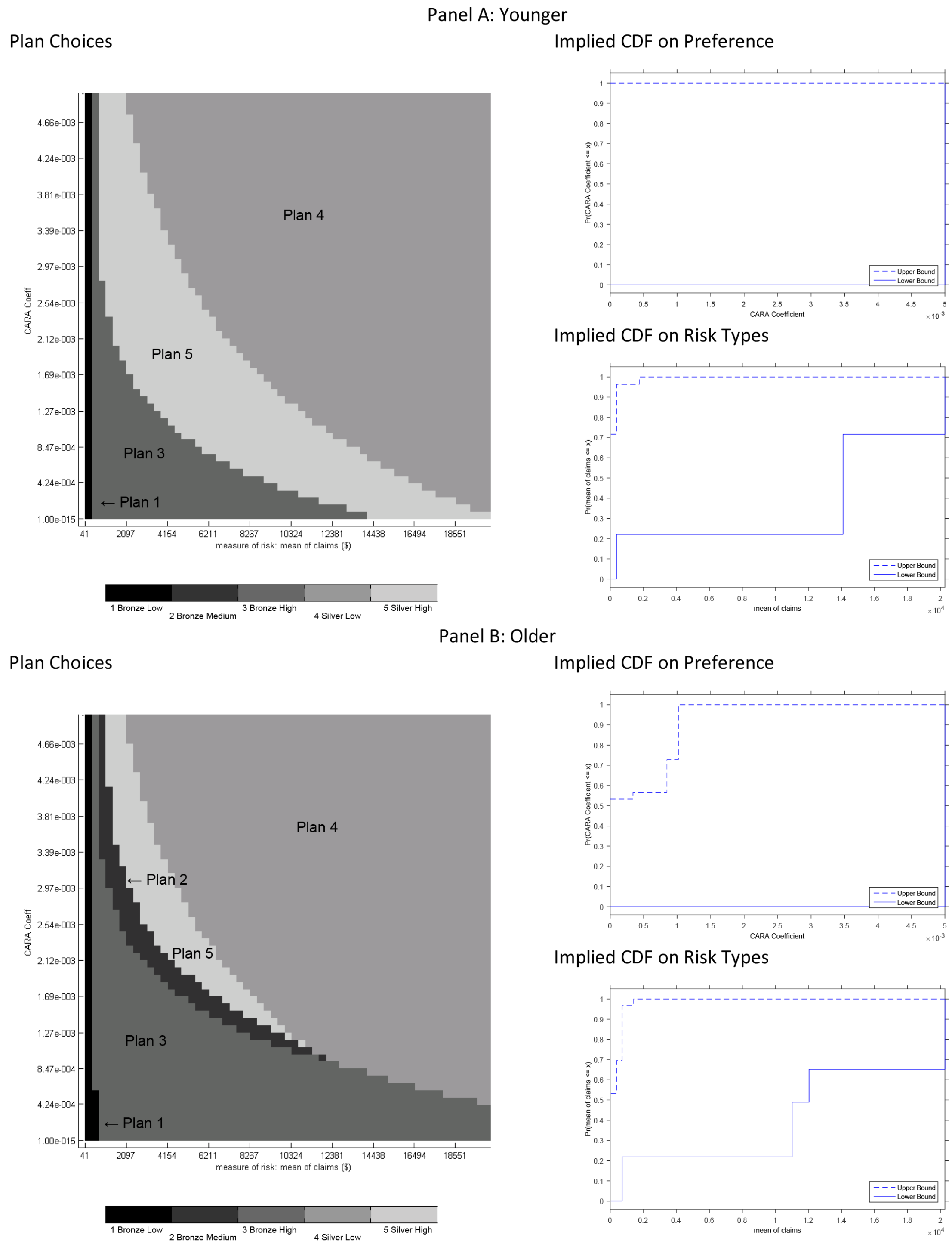

Figure 4: Choices and Implied Bounds on Risk Preferences and Risk Perceptions. Note: "Plan Choices" column presents the utility maximising plan for each π, σ type. "Implied CDFs" combine market shares of each plan with optimal plan choices to derive lower and upper bounds on the distributions of π and σ for the population of people who choose one of the plans shown in the "Plan Choices" column.

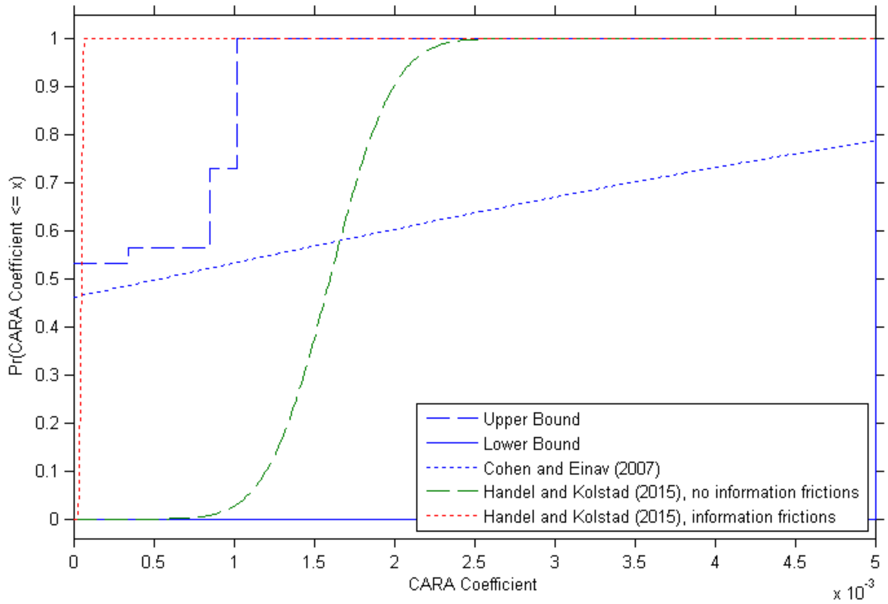

Figure 5: Comparing Bounds on Risk Preferences for Older Individuals on the Massachusetts HIX to Estimates from the Literature

obtained from different contexts and potentially very different populations. Our bounds do not reject the vast dispersion in risk aversion estimated by Cohen and Einav (2007), but are also consistent with the more homogeneous distribution estimated in Handel and Kolstad (2015). Interestingly, this is no longer true for the estimates in Handel and Kolstad (2015) obtained by augmenting the standard random utility model with survey data on information frictions. This could indicate that it is not sufficient to account for people's risk perceptions, and that our expected utility model should be augmented with other informational or behavioural frictions to provide consistent and tighter bounds on preference heterogeneity. Finally, more plan variation would allow us to further tighten bounds as well. The regulation of plan features or prices could provide promising variation for identification.[44]

6 Conclusion

This paper has shown how to identify both consumer risk preferences and their risk perceptions, using only insurance choice data. Our method uses variation in insurance plans that differentially attracts individuals along the preference and risk type dimensions, exploiting the fact that marginal willingness to buy insurance is more rapidly

[44] The discussed price variation across age groups would be useful for identification in combination with within-menu plan variation. Comparing the type sets at the young prices and the old prices reveals that changes in prices change the parameter values that bound the support of particular plans. When the price variation is exogenous, plan share differentials may be attributable to particular parameter ranges and thus provide further bounds.

decreasing in coverage for individuals with high risk aversion (but low risk) than for individuals with low risk aversion (but high risk).

Our approach allows us to relax strong assumptions about (rational) expectations and parametric type distributions, as well as to identify preferences and risk perceptions when claims data is unavailable. We applied our method to the Massachusetts HIX. For these individuals, we can reject homogeneity in risks, but not homogeneity in preferences. We estimate bounds on the distribution of preferences that are consistent with other papers, but provide limited power for identification. We also highlight the type of variation that is necessary to obtain tighter bounds on the distribution of preferences, which may be useful for experimentalists eliciting preferences. Future empirical work could pair our approach with claims data to directly test the assumption of rational expectations about individuals' distribution of insurance claims, since the accuracy of risk perceptions is relevant for welfare and policy analysis in insurance markets (Handel *et al.*, 2019; Spinnewijn, 2017). Moreover, future theoretical work could change the micro-foundations of the choice model (e.g., by adding loss aversion or ambiguity aversion) and then analyse which type of plan variation would allow to identify the primitives of that model.

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Table 1: HIX Plan Menu

	Deductible	Coinsurance	Max OOP	AV	Monthly Premium		Market Share	
					Youngest	Oldest	Under 45	Over 45
Bronze Low	2000	11.20%	5000	73.1	$193	$388	17.9%	19.9%
Bronze Medium	2000	5.00%	5000	79.8	$210	$420	7.0%	14.9%
Bronze High	250	15.40%	5000	85.2	$202	$405	40.2%	29.0%
Silver Low	1000	2.50%	2000	85.6	$273	$540	3.4%	2.9%
Silver High	0	12.20%	2000	92.2	$275	$543	19.6%	25.4%
Gold	0	10.30%	2000	93	$336	$659	12.0%	8.0%

Note: Deductible and maximum OOP are taken directly from the original plan design. Coinsurance rate calculated as defined in the text. Actuarial values are calculated from original plan design using the CCIIO calculator. Premiums and market shares are for Neighborhood Health Plan, Jan. and Feb. 2010. Premiums are averaged across the two sample months and across ZIP codes.

Online Appendix for "Inferring Risk Perceptions and Preferences using Choice from Insurance Menus: Theory and Evidence"

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A.1 Theory Appendix

A.1.1 Proofs

Proof of Proposition 1

This proof provides rigor to the outline in the main text. Using Lemma 1, we can find two menus $\{\emptyset, X_h\}$ and $\{\emptyset, X_l\}$ with $q_h > q_l$ that intersect at an interior intersection $(\bar{\pi}, \bar{\sigma})$. If $\alpha_h = D(X_h | \{\emptyset, X_h\})$ is higher than $\alpha_l = D(X_l | \{\emptyset, X_l\})$, we know that $H_\sigma(\bar{\sigma}) \geq \alpha_h - \alpha_l$ and thus $H_\sigma(\sigma) \geq \alpha_h - \alpha_l$ for any $\sigma \geq \bar{\sigma}$ since the CDF is (weakly) increasing. At the same time, $1 - H_\pi(\bar{\pi}) \geq \alpha_h - \alpha_l$ and thus $H_\pi(\pi) \leq H_\pi(\bar{\pi}) \leq 1 - [\alpha_h - \alpha_l]$ for any $\pi \leq \bar{\pi}$. Hence, the plan share difference $\alpha_h - \alpha_l$ provides a lower bound on the CDF of preferences (for $\sigma \geq \bar{\sigma}$) and its complement an upper bound on the CDF of risks (for $\pi \leq \bar{\pi}$). Similarly, if $\alpha_h < \alpha_l$, the plan share difference $\alpha_l - \alpha_h$ places an upper bound on the CDF of preferences (for $\sigma \leq \bar{\sigma}$) and its complement an upper bound on the CDF of risks (for $\pi \geq \bar{\pi}$). Hence, any permissible distribution with $\alpha_h \neq \alpha_l$ places a bound on the marginal CDFs.

Consider now a third menu $\{\emptyset, X'_h\}$, where the plan X'_h provides more coverage than the previous high-coverage plan X_h (i.e., $q'_h > q_h > q_l$). If the price of the new plan were set at P'_h such that the price per unit of coverage remains unchanged relative to the old high-coverage plan ($P'_h/q'_h = P_h/q_h$), the type $(\bar{\pi}', \bar{\sigma}')$ that is indifferent between these two plans is the risk-neutral type $(P_h/q_h, 0)$, while otherwise Assumption 1 implies that the type frontier $\mathcal{T}\{\emptyset, X'_h\}$ would be strictly steeper and therefore strictly above the type frontier of the previous plan $\mathcal{T}\{\emptyset, X_h\}$. Instead of this price, assume the price P'_h is set slightly lower so that $P'_h/q'_h < P_h/q_h$ but still $P'_h/q'_h \approx P_h/q_h$. The risk-neutral type $(P_h/q_h, 0)$ now strictly prefers the new plan over the old high-coverage plan, but by continuity the intersection $(\bar{\pi}', \bar{\sigma}')$ between $\mathcal{T}\{\emptyset, X'_h\}$ and $\mathcal{T}\{\emptyset, X_h\}$ remains close to $(P_h/q_h, 0)$. Since the intersection $(\bar{\pi}, \bar{\sigma})$ between the original plans $\mathcal{T}\{\emptyset, X_h\}$ and $\mathcal{T}\{\emptyset, X_l\}$ was placed in the interior of the type space, it had strictly higher risk-aversion and strictly lower risk than this risk-neutral type, and we have $\bar{\sigma} > \bar{\sigma}'$ and $\bar{\pi} < \bar{\pi}'$.

If now for a permissible distribution more agents choose the low contract X_l over no insurance than choose the high contract X_h over no insurance ($\alpha_l > \alpha_h$), but also more agents choose the new contract X'_h over no insurance than those that choose the old high contract over no insurance ($\alpha_h < \alpha'_h \equiv D\left(X'_h | \{\emptyset, X'_h\}\right)$), we will have that $H_\sigma\left(\bar{\sigma}\right) \leq 1 - [\alpha_l - \alpha_h] < 1$ while $H_\sigma\left(\bar{\sigma}'\right) \geq \alpha'_h - \alpha_h > 0$ by the logic of the first paragraph of this proof. Since a CDF is weakly increasing and $\bar{\sigma}' < \bar{\sigma}$, we cannot fit a degenerate CDF between this lower and upper bound. That is, the lower bound becomes binding at $\bar{\sigma}'$, before the upper bound stops binding at $\bar{\sigma}$. We can thus reject homogeneity in preferences. The same is true for risks.

The final step in the proof is to show that such a distribution exists. To do this, define for any risk π the preference $\sigma_l(\pi)$ that makes the person indifferent between no insurance and the low contract, i.e., $(\pi, \sigma_l(\pi)) \in \mathcal{T}\{\emptyset, X_l\}$, when it exists. Otherwise, $\sigma_l(\pi) = 0$. Define $\sigma_h(\pi)$ ($\sigma'_h(\pi)$) analogously via indifference between no insurance and the high insurance (new higher insurance) contract. The non-empty set of types $\Delta_{l,h} = \{(\pi, \sigma) | \sigma_h(\pi) > \sigma > \sigma_l(\pi)\}$ then prefer the low contract to no insurance which they prefer to the original high contract. Similarly, the non-empty set of types $\Delta_{h',h} = \{(\pi, \sigma) | \sigma_h(\pi) > \sigma > \sigma'_h(\pi)\}$ prefer the new contract to no insurance which they prefer to the old high coverage contract. Now we can construct a type distribution H by placing strictly positive mass on types both in $\Delta_{l,h}$ and in $\Delta_{h',h}$, but nowhere else. This implies that $\alpha_l > 0, \alpha'_h > 0$ but $\alpha_h = 0$, which fulfils the premise of the previous paragraph (as do an uncountable number of other distributions with less stark properties).□

Proof of Proposition 2

Equation (9) in the main text showed that $F_{(\alpha,\beta)}(t) = \Pr(\alpha A + \beta B \leq t)$ is observed for all α, β and t. So we observe the marginal distribution $F_{(\alpha,\beta)}$ of $\alpha A + \beta B$, for all α, β. Therefore we know its characteristic function $\hat{F}_{(\alpha,\beta)}(\tau)$ for all α and β. We are interested in the joint cumulative distribution function $F(A, B)$ over A and B, or equivalently in its characteristic function $\hat{F}(a, b)$.

The following just recalls the definition of the characteristic function for a random vector in $\mathbb{R}^k$ with cumulative distribution function $G(x)$ with $x \in \mathbb{R}^k$. Its characteristic function $\hat{G}(\omega)$ with $\omega \in \mathbb{R}^k$ is defined as

$$\hat{G}(\omega) = \int e^{i\omega^T x} dG(x)$$

where ω^T is the transpose of ω and i is the imaginary unit.

The remaining identification follows the proof in Cai *et al.* (2005). At any value of α and β we can apply the definition of the characteristic function twice (once for the two-dimensional random vector and once for the one-dimensional marginal random vector) to obtain

$$\begin{aligned}\hat{F}(\alpha\tau, \beta\tau) &= \int e^{i(\alpha\tau A+\beta\tau B)} dF \\ &= \int e^{i\tau(\alpha A+\beta B)} dF = \hat{F}_{(\alpha,\beta)}(\tau).\end{aligned}$$

Therefore, $\hat{F}_{(\alpha,\beta)}(1)$ varied over all α and β identifies $\hat{F}(\alpha, \beta)$ and therefore identifies $F(A, B)$. Finally, by the one-to-one mapping between (A, B) and (π, σ) in case of CARA preferences, this identifies the distribution of risk and preference types as well.$\square$

Proof of Lemma 1.

This proof follows the outline in the main text. We consider the type frontiers for two menus $\mathcal{M}_h = \{\emptyset, X_h\}$ and $\mathcal{M}_l = \{\emptyset, X_l\}$ with $q_h > q_l$. We first establish that if the two type frontiers intersect, they only intersect once and the high-coverage type frontier $\mathcal{T}(\emptyset, X_h)$ is a clockwise rotation of the low-coverage type frontier $\mathcal{T}(\emptyset, X_l)$. Denote the type at which the two frontiers intersect by $(\bar{\pi}, \bar{\sigma})$. Consider the case where $q_h = q_l + \varepsilon$ for some small ε. By Assumption 1, any type with higher risk π (lower preference σ) on $\mathcal{T}(\emptyset, X_l)$ than the type at the intersection, who is indifferent between the high-coverage and low-coverage plan, has higher marginal willingness to pay for the additional coverage. Therefore, they strictly prefer X_h to both X_l and $\emptyset$, which they are indifferent about. Hence, the type frontier $\mathcal{T}(\emptyset, X_h)$ lies to the left of $\mathcal{T}(\emptyset, X_l)$ for $\pi > \bar{\pi}$ and $\sigma < \bar{\sigma}$. Any type with lower risk π (higher preference σ) has lower willingness to pay for the additional coverage and thus strictly prefers X_l and $\emptyset$ to X_h. Hence, the type frontier $\mathcal{T}(\emptyset, X_h)$ lies to the right of $\mathcal{T}(\emptyset, X_l)$ for $\pi < \bar{\pi}$ and $\sigma > \bar{\sigma}$. This proves that $\mathcal{T}(\emptyset, X_h)$ intersects $\mathcal{T}(\emptyset, X_l)$ once and clockwise, if the two intersect. Now for a larger difference in coverage, we can find a sequence of contracts X_k with coverage q_k and price P_k, starting from X_l and converging to X_h, such that type $(\bar{\pi}, \bar{\sigma})$ is indifferent among any two contracts. The reasoning above now applies for any two consecutive contracts. Our sequence thus corresponds to a sequence of type frontiers that intersect only once and imply clockwise rotations around $(\bar{\pi}, \bar{\sigma})$. Hence, this is also true for $\mathcal{T}(\emptyset, X_h)$ relative to $\mathcal{T}(\emptyset, X_l)$.

We now establish when the two type frontiers intersect. Consider first the case $P_h/q_h > P_l/q_l$ (i.e., the average price per unit is higher for the high-coverage contract X_h). This implies that the risk-neutral type with $\pi = P_l/q_l$ strictly prefers X_l and $\emptyset$ (which he is indifferent about) to buying X_h. Hence, the type frontier $\mathcal{T}(\emptyset, X_h)$ lies to the right of the type frontier $\mathcal{T}(\emptyset, X_l)$ for $\sigma = 0$. This implies that the two frontiers cannot intersect, since $\mathcal{T}(\emptyset, X_h)$ would be a clockwise rotation of $\mathcal{T}(\emptyset, X_l)$ and thus to the left of it for $\sigma = 0$ in case the type frontiers were to intersect.

Consider now the case that $P_h/q_h \leq P_l/q_l$. In this case, the risk neutral type with $\pi = P_l/q_l$ prefers X_h above X_l and $\emptyset$. Moreover, since the marginal willingness to pay for the additional coverage converges to zero when moving up along the frontier

$\mathcal{T}(\emptyset, X_l)$, there is a type with sufficient low risk (and high preference) that prefers X_l (and thus $\emptyset$) above X_h as long as $P_h > P_l$. Hence, the two type frontiers intersect. However, if $P_h \leq P_l$, all types on $\mathcal{T}(\emptyset, X_l)$ strictly prefer X_h above X_l and thus $\emptyset$. The two type frontiers again do not intersect. This proves the first part of the Proposition.

Since $\mathcal{T}(\emptyset, X_h)$ is a clockwise rotation of $\mathcal{T}(\emptyset, X_l)$ around $(\bar{\pi}, \bar{\sigma})$, the high-coverage contract X_h differentially attracts types with high risk, but low preference. Types that prefer X_h above $\emptyset$, but $\emptyset$ above X_l (i.e., $\mathcal{B}(X_h|\{\emptyset, X_h\}) \backslash \mathcal{B}(X_l|\{\emptyset, X_l\})$), need to have preference $\sigma \leq \bar{\sigma}$ and risk $\pi \geq \bar{\pi}$. Only individuals with such types could rationalise that plan X_h attracts a larger share of the population than plan X_l. Similarly, types that prefer X_l above $\emptyset$, but $\emptyset$ above X_h (i.e., $\mathcal{B}(X_l|\{\emptyset, X_l\}) \backslash \mathcal{B}(X_h|\{\emptyset, X_h\})$), need to have preference $\sigma \geq \bar{\sigma}$ and risk $\pi \leq \bar{\pi}$. Only these types could rationalise that plan X_l attracts a larger share of the population than plan X_h. Hence, we have

$$\begin{aligned}
\int_{\pi \geq \bar{\pi}} \int_{\sigma \leq \bar{\sigma}} dH &\geq \int_{\mathcal{B}(X_h|\{\emptyset, X_h\}) \backslash \mathcal{B}(X_l|\{\emptyset, X_l\})} dH \\
&\geq \int_{\mathcal{B}(X_h|\{\emptyset, X_h\}) \backslash \mathcal{B}(X_l|\{\emptyset, X_l\})} dH - \int_{\mathcal{B}(X_l|\{\emptyset, X_l\}) \backslash \mathcal{B}(X_H|\{\emptyset, X_H\})} dH \\
&= \alpha_h - \alpha_l \\
&\geq -\int_{\mathcal{B}(X_l|\{\emptyset, X_l\}) \backslash \mathcal{B}(X_H|\{\emptyset, X_H\})} dH \\
&\geq -\int_{\pi \leq \bar{\pi}} \int_{\sigma \geq \bar{\sigma}} dH,
\end{aligned}$$

which proves the second part of the proposition. Note that if the type frontiers do not intersect, the support of the set of types that prefer the one plan, but not the other, covers the entire range of the preference domain. The differential plan share no longer places a bound on the distribution of preferences.□

Proof of Lemma 2.

By Lemma 1, we know that type frontiers $\mathcal{T}(\emptyset, X_h)$ and $\mathcal{T}(\emptyset, X_l)$ intersect if and only if $P_h/q_h \leq P_l/q_l$ and $P_h > P_l$. We denote this intersection by $(\bar{\pi}, \bar{\sigma})$. In this case, the type frontier $\mathcal{T}(X_h, X_l)$ intersects both frontiers again at $(\bar{\pi}, \bar{\sigma})$, since this intersection type is indifferent among both plans and the option not to buy insurance. Moreover, the type frontier $\mathcal{T}(X_h, X_l)$ is a clockwise rotation of $\mathcal{T}(\emptyset, X_h)$, which is a clockwise rotation of $\mathcal{T}(\emptyset, X_l)$. Note first that the willingness to choose the high-coverage plan over the low-coverage plan is increasing in both risk and preference. The type frontier is monotonically decreasing in (π, σ)-space, just like the original two frontiers. Now consider a type on the frontier $\mathcal{T}(\emptyset, X_h)$ above the intersection (with low risk, but high preference). This type strictly prefers X_l to $\emptyset$ and thus X_h, since $\mathcal{T}(\emptyset, X_h)$ is to the right of $\mathcal{T}(\emptyset, X_l)$. Hence, the type frontier $\mathcal{T}(X_h, X_l)$ is to the right of $\mathcal{T}(\emptyset, X_h)$. The set of types choosing X_l above both X_h and $\emptyset$, i.e., $\mathcal{B}(X_l|\{\emptyset, X_l, X_h\})$ corresponds to this region between the two frontiers $\mathcal{T}(\emptyset, X_l)$ and $\mathcal{T}(X_h, X_l)$ above

$(\bar{\pi}, \bar{\sigma})$. Indeed, consider a type on the frontier $\mathcal{T}(\emptyset, X_h)$ below the intersection (with high risk, but low preference). This type strictly prefers $\emptyset$ and thus X_h to X_l. Hence, the type frontier $\mathcal{T}(X_h, X_l)$ is to the left of $\mathcal{T}(\emptyset, X_h)$ (and thus to the left of $\mathcal{T}(\emptyset, X_l)$). This implies that no type with $\sigma < \bar{\sigma}$ or $\pi > \bar{\pi}$ will choose the low-coverage plan. It immediately follows that the share of individuals buying the low-coverage plan (out of this 3-options menu) puts the following lower bound,

$$\int_{\pi \leq \bar{\pi}} \int_{\sigma \geq \bar{\sigma}} dH \geq \int_{\mathcal{B}(X_l | \{\emptyset, X_l, X_h\})} dH \geq D(X_l | \mathcal{C}).$$

For completeness, the set of types choosing X_h above X_l and $\emptyset$, i.e., $\mathcal{B}(X_h | \{\emptyset, X_l, X_h\})$ corresponds to the region to the right of $\mathcal{T}(\emptyset, X_h)$ below $(\bar{\pi}, \bar{\sigma})$ and to the right of $\mathcal{T}(X_h, X_l)$ above $(\bar{\pi}, \bar{\sigma})$, as illustrated in Figure 3.

Note that if $P_h \leq P_l$, no type will ever buy the low-coverage plan. Hence, the only relevant type frontier is $\mathcal{T}(\emptyset, X_h)$. If $P_h > P_l$ and $P_h/q_h > P_l/q_l$, none of the type frontiers intersect. The type frontier $\mathcal{T}(X_h, X_l)$ now lies to the right of the type frontier $\mathcal{T}(\emptyset, X_h)$, which lies to the right of type frontier $\mathcal{T}(\emptyset, X_l)$. Types to the right of $\mathcal{T}(X_h, X_l)$ will buy the high-coverage plan. Types to the left of $\mathcal{T}(\emptyset, X_l)$ will buy no insurance. Types in between will buy the low-coverage plan. Since the support of any of the choices corresponds to the full preference domain, we can place no bounds on the distribution of preferences.□

A.1.2 Additional Results

A.1.2.1 CARA Preferences

We show that Assumption 1 holds for CARA preferences $u(k|\sigma) = -e^{-\sigma k}/\sigma$. The marginal rate of substitution (4) can be written as

$$MRS \equiv -\frac{dm_g}{dm_b}|_{U(X|\pi,\sigma)} = \frac{\pi}{1-\pi} \frac{e^{\sigma(P+L-q)}}{e^{\sigma P}} \tag{12}$$

The type frontier $\mathcal{T}(\emptyset, X)$ is the set of types (π, σ) for which (3) holds with equality, which for CARA preferences reads as:

$$\frac{\pi}{1-\pi} \frac{-e^{\sigma(P+L-q)} + e^{\sigma L}}{-1 + e^{\sigma P}} = 1 \tag{13}$$

Note that smaller π are associated with larger σ, and $\pi \to 0$ is associated with $\sigma \to \infty$. Since we evaluate (12) only along (13), we can substitute the latter into the former to obtain a marginal willingness to pay along the type frontier of

$$\begin{aligned} MRS|_{(\pi,\sigma)\in\mathcal{T}(\emptyset,X)} &= \frac{-1+e^{\sigma P}}{-e^{\sigma(P+L-q)}+e^{\sigma L}}\frac{e^{\sigma(P+L-q)}}{e^{\sigma P}} \\ &= \frac{1-e^{-\sigma P}}{-1+e^{\sigma(q-P)}}. \end{aligned}$$

Since $P<q$, it is immediate that $\lim_{\sigma\to\infty} MRS|_{(\pi,\sigma)\in\mathcal{T}(\emptyset,X)} = 1/\infty = 0$, which establishes that MRS goes to zero as π goes to zero. Moreover, MRS is monotonically decreasing in σ along the type frontier (and thus monotonically increasing in π) if

$$\frac{d\ MRS|_{(\pi,\sigma)\in T(\emptyset,X)}}{d\sigma} = \frac{Pe^{-\sigma P}\left(-1+e^{\sigma(q-P)}\right)-(q-P)e^{\sigma(q-P)}\left(1-e^{-\sigma P}\right)}{\left(-1+e^{\sigma(q-P)}\right)^2}$$

is strictly negative. This arises if the denominator is strictly negative, i.e., if

$$\begin{aligned} Pe^{-\sigma P}\left(-1+e^{\sigma(q-P)}\right)-(q-P)e^{\sigma(q-P)}\left(1-e^{-\sigma P}\right) &< 0 \\ \Leftrightarrow -q(1-e^{-\sigma P})+P(1-e^{-\sigma q}) &< 0 \\ \Leftrightarrow P\left(1-e^{-\sigma P}\right)^{-1}-q(1-e^{-\sigma q})^{-1} &< 0. \end{aligned}$$

which holds since $P<q$ and $x/(1-e^{-\sigma x})$ is increasing in x.□

A.1.2.2 Limited Price Variation in Textbook Model

Proposition 3 *Consider a binary risk $k\in\{0,L\}$, choice sets $\mathcal{M}_p$ with constant unit price and CARA preferences. Rejecting homogeneity in preferences (risks) is possible when observing the distribution of coverage choices in $\mathcal{M}_p$ for two prices in the unit interval. We can identify the variance in (inverse) preference types when observing the distribution of coverage choices in $\mathcal{M}_p$ for three prices.*

The demand specification in (7) for CARA preferences implies

$$Var\left(q|p\right)=Var\left(A\right)+Var\left(\sigma^{-1}\right)\times\tilde{p}^2-2Cov\left(A,\sigma^{-1}\right)\tilde{p} \tag{14}$$

for $\tilde{p}=\log\left(p/\left[1-p\right]\right)$. Hence, with two exogenous prices, we obtain

$$\left[Var\left(q|p_1\right)-Var\left(q|p_2\right)\right]/\left[\tilde{p}_1-\tilde{p}_2\right]=Var\left(\sigma^{-1}\right)\times\left[\tilde{p}_1+\tilde{p}_2\right]-2Cov\left(A,\sigma^{-1}\right). \tag{15}$$

We can use this to test for homogeneity in preferences and risks. This is easy to see for the preference types. Whenever the difference in variances in equation (15) is different from 0, we can reject that σ (or σ^{-1}) is constant and thus that the preference type is homogeneous. For a constant σ, both $Var\left(\sigma^{-1}\right)$ and $Cov\left(A,\sigma^{-1}\right)$ would be equal to 0.

It is left to show that we can test for homogeneity in risks with two prices. For this we can use equations (14) - (15) for the variance and we can exploit similar expressions for the average:

$$\begin{aligned} E(q|p) &= E(A) - E\left(\sigma^{-1}\right) \times \tilde{p}, \text{ and} \\ E(q|p_1) - E(q|p_2) &= E\left(\sigma^{-1}\right) \times [\tilde{p}_2 - \tilde{p}_1] \end{aligned} \tag{16}$$

Using the fact that $A = L + \log\left(\frac{\pi}{1-\pi}\right)\sigma^{-1}$ under CARA, we know that if the the risk type π were to be homogenous, we could infer the homogeneous risk type from

$$\begin{aligned} E(q|p) &= E(A) - E\left(\sigma^{-1}\right) \times \tilde{p} \\ &= L + \log\left(\frac{\pi}{1-\pi}\right) E\left(\sigma^{-1}\right) + E\left(\sigma^{-1}\right) \times \tilde{p}, \end{aligned}$$

where we know $E\left(\sigma^{-1}\right)$ from the difference in coverage choices in (16). For a homogeneous risk type, we also know that

$$\begin{aligned} Var(A) &= \log\left(\frac{\pi}{1-\pi}\right)^2 Var\left(\sigma^{-1}\right) \\ Cov\left(A, \sigma^{-1}\right) &= \log\left(\frac{\pi}{1-\pi}\right) Var\left(\sigma^{-1}\right). \end{aligned}$$

and thus

$$\begin{aligned} Var(q|p_k) &= Var(A) + Var\left(\sigma^{-1}\right) \times \tilde{p}_k^2 - 2Cov(A, B)\,\tilde{p}_k \\ &= \left[\log\left(\frac{\pi}{1-\pi}\right)^2 + \tilde{p}_k^2 - 2\log\left(\frac{\pi}{1-\pi}\right)\tilde{p}_k\right] Var\left(\sigma^{-1}\right). \end{aligned}$$

Hence, we can reject homogeneity in risk types if

$$\frac{Var(q|p_1)}{Var(q|p_2)} \neq \frac{\log\left(\frac{\pi}{1-\pi}\right)^2 + \tilde{p}_1^2 - 2\log\left(\frac{\pi}{1-\pi}\right)\tilde{p}_1}{\log\left(\frac{\pi}{1-\pi}\right)^2 + \tilde{p}_2^2 - 2\log\left(\frac{\pi}{1-\pi}\right)\tilde{p}_2}.$$

Finally, when observing three (exogenous) prices, we can also identify the variance of the inverse of the coefficient of absolute risk aversion

$$Var\left(\sigma^{-1}\right) = \left[\frac{Var(q|p_1) - Var(q|p_2)}{\tilde{p}_1 - \tilde{p}_2} - \frac{Var(q|p_2) - Var(q|p_3)}{\tilde{p}_2 - \tilde{p}_3}\right] / \left[\tilde{p}_1 - \tilde{p}_3\right].$$

□

A.2 Empirical Appendix

A.2.1 Alternative Modeling Assumptions

In this Appendix, we present the optimal plan choice results under different assumptions. In Figure A.1, we model alternative relationships between the mean and variance of claims. In our main analyses, for risk type π, the expected claims distribution is assumed to follow a log normal distribution with $mean = \pi$ and $variance = \frac{\pi}{4053}\left[\frac{1}{2} \times 10451\right]^2$

For comparison purposes, we show, once again, the optimal choice for each π, σ pair for older individuals in Panel C of Figure A.1. We then model choice with more or less variability in claims. In Panel A of Figure A.1, we show the choice assuming that the variance of claims is half of that in our main specifications: $variance = \frac{1}{2}\frac{\pi}{4053}\left[\frac{1}{2} \times 10451\right]^2$. This would correspond to a case in which individuals have additional information predicting about their expected costs, reducing variability. Then, in Panel B, we run a high variance specification where variance is twice that in our main specifications: $variance = 2 \times \frac{\pi}{4053}\left[\frac{1}{2} \times 10451\right]^2$. The results are intuitive: more variability increases the demand for more generous insurance.

We then turn to alternative menu designs in Figure A.2, again showing optimal choices for older individuals. Panel A examines a modified menu, in which the Bronze Medium plan has a deductible of \$1462 instead of \$2000; we make this modification so that the actuarial value of the Bronze Medium plan as modelled matches the actuarial value of the more complex Bronze Medium plan on the exchange. This menu leads to some modest changes in choice as compared to our main specification. In Panel B, we consider the case in which the Bronze Medium plan has zero coinsurance as produced by our original method described in the text. Unsurprisingly, this leads to Bronze Medium being a very favoured plan. However, this is unlikely to be a faithful representation of the Bronze Medium characteristics. Finally, Panel C of Figure A.2 examines a very different menu design. For Panel C, we construct coinsurance values (for plans that have co-payments instead of coinsurance) by taking the hospital co-payment value and dividing by the mean cost of a hospital admission of \$9700. This method, however, does not do a good job modelling the relative quality of Silver Low, as Silver Low requires paying the deductible and then has zero hospital co-payment. We then drop Silver Low from this menu. The menu of coinsurance values used in Panel C is given below:

	Coinsurance for Panel C of Figure A.2
Bronze Low	0.2
Bronze Medium	0.05
Bronze High	0.35
Silver High	0.05
Gold	0.02

A.2.2 Bounds

We perform a bootstrap analysis to assess how sampling error would affect our bounds. We drew 100 samples of consumers with replacement. Given consumer choices, we calculated market shares and used the method described in the paper to calculate the implied bounds. (Given the small range of parameters for which both the upper and lower bounds are informative, we do not consider the case in which the bounds cross, making the bootstrap invalid.) We superimpose the 5th and 95th percentile of the implied distribution point-by-point on original Figure 4. The figure shows that when the bounds are informative, they are fairly precisely measured.

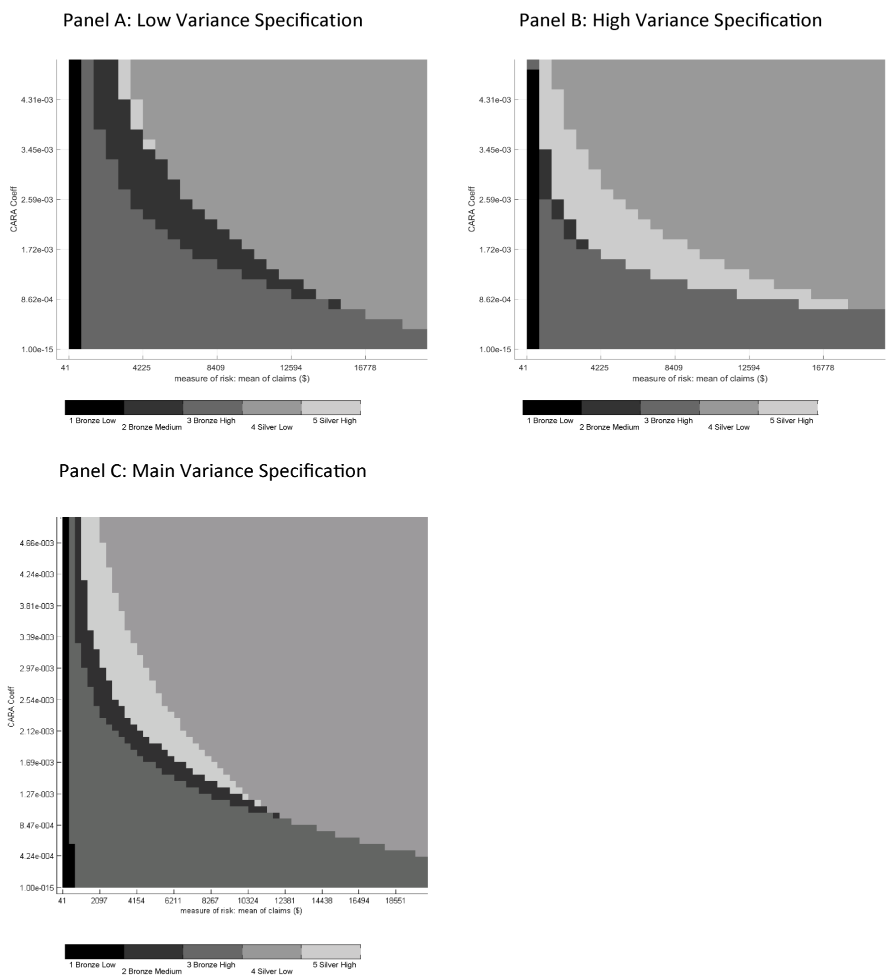

Figure A.1: Optimal Plan Choices for Older Individuals under Alternative Variance Assumptions.

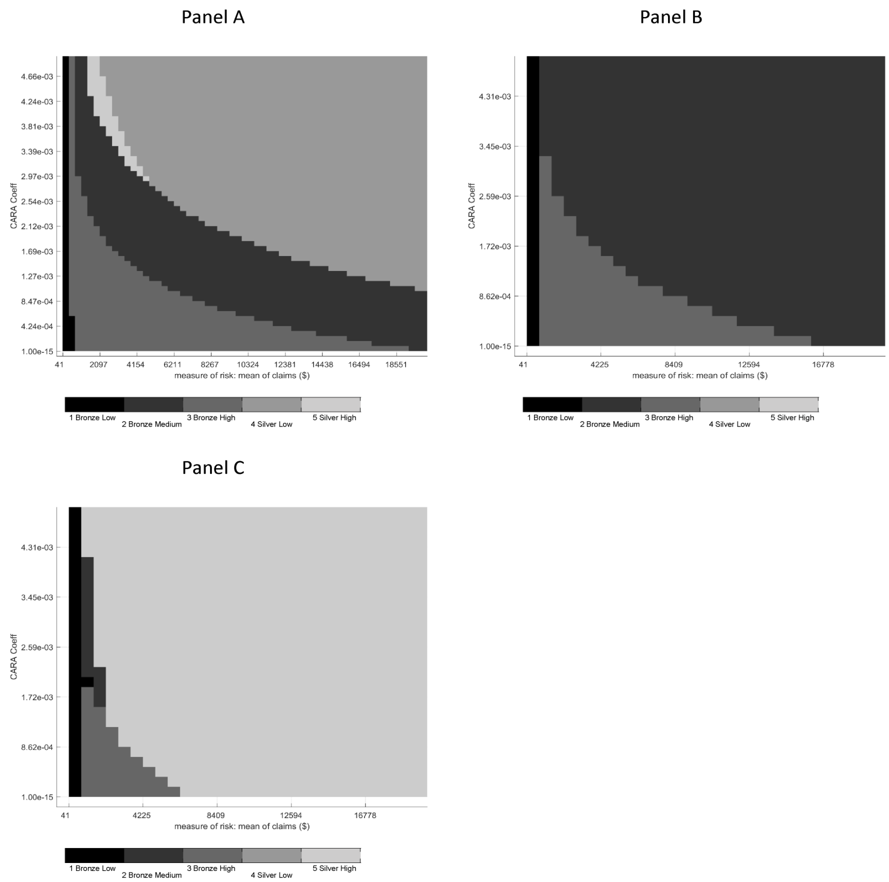

Figure A.2: Optimal Plan Choices for Older Individuals under Alternative Menu Designs.

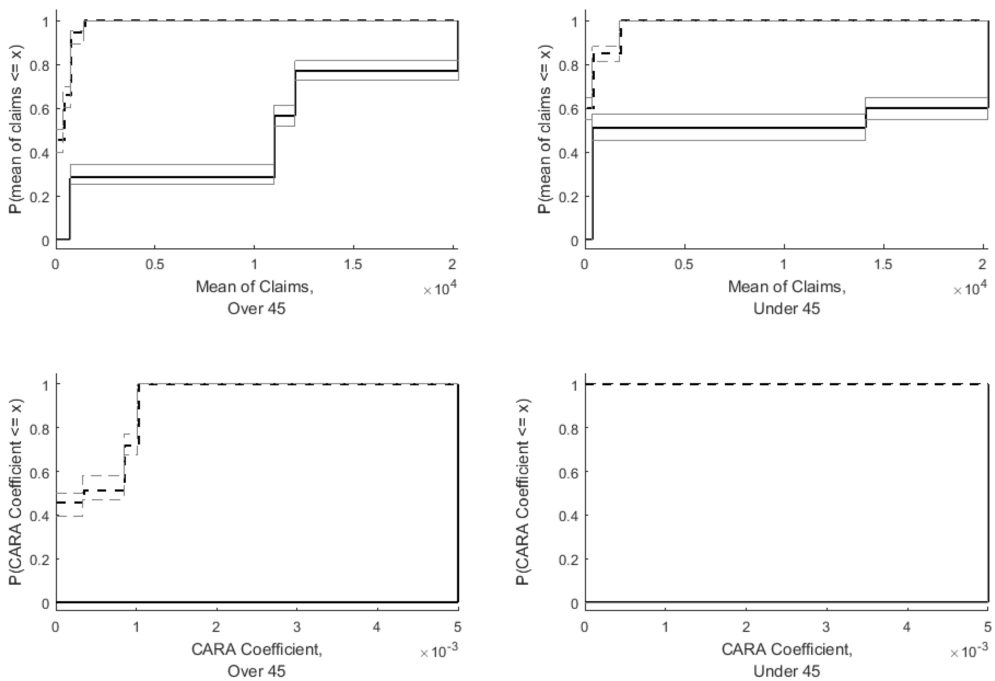

Figure A.3: Bounds with Bootstrapped Confidence Intervals. Note: Plots the 5th and 95th percentile of the implied distribution from a bootstrap procedure point-by-point on original Figure 4. Our bootstrap drew consumers (with replacement) to obtain 100 vectors of market shares. For each vector of market shares, we used the method described in the paper to calculate the implied bounds.

Table A.1: Summary of detailed plan parameters, taken from the HIX's website

Plan Design	Deductible	Max OOP	Doctor Visit	Generic Rx	Emergency Room	Hospital Stay
Bronze Low	\$2000	\$5000	deduct., then \$25 copay	deduct., then \$15 copay	deduct., then \$100 copay	deduct., then 20% co-insurance
Bronze Medium	\$2000	\$5000	\$30 copay	\$10 copay	deduct., then \$150 copay	deduct., then \$500 copay
Bronze High	\$250	\$5000	\$25 copay	\$15 copay	\$150 copay	deduct., then 35% co-insurance
Silver Low	\$1000	\$2000	\$20 copay	\$15 copay	deduct., then \$100 copay	deduct., then no copay
Silver High	\$0	\$2000	\$25 copay	\$15 copay	\$100 copay	\$500 copay
Gold	\$0	None	\$20 copay	\$15 copay	\$75 copay	\$150 copay

Table A.2: Detailed Plan Shares, among individuals who chose Neighborhood Health Plan.

	Age Group						
	27-29	30-34	35-39	40-44	45-49	50-54	55+
Bronze Low	13.3%	20.0%	20.0%	18.0%	20.5%	21.6%	18.2%
Bronze Medium	7.1%	7.3%	6.0%	8.0%	10.3%	18.2%	15.5%
Bronze High	49.0%	38.2%	35.0%	38.0%	37.2%	15.9%	33.6%
Silver Low	1.0%	4.5%	5.0%	2.0%	1.3%	3.4%	3.6%
Silver High	19.4%	19.1%	19.0%	22.0%	21.8%	28.4%	25.5%
Gold	10.2%	10.9%	15.0%	12.0%	9.0%	12.5%	3.6%