Equilibria in Health Exchanges: 
Adverse Selection vs. Reclassification Risk

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Abstract

This paper studies regulated health insurance markets known as exchanges, motivated in part by their inclusion in the Affordable Care Act (ACA). We develop a framework that combines data on health outcomes and insurance plan choices for a population of insured individuals with a model of a competitive insurance exchange to predict outcomes under different exchange designs. We apply this framework to examine the effects of regulations that govern insurers’ ability to use health status information in pricing as well as contract design. We investigate the welfare implications of these regulations with an emphasis on two potential sources of inefficiency: (i) adverse selection and (ii) premium reclassification risk. We also extend our analysis to investigate some related issues, including (i) age-based pricing regulation, (ii) exchange participation, and (iii) insurer risk-adjustment transfers.

1 Introduction

Health insurance markets almost everywhere are subject to a variety of regulations designed to encourage the efficient provision of insurance. One such approach is known as “Managed Competition” [see,
e.g., Enthoven (1993) or Enthoven et al. (2001)]. Under managed competition, a regulator sets up an insurance market called an exchange in which insurers compete to attract consumers, subject to a set of regulations on insurance contract characteristics and pricing. There are many important examples of managed competition in practice. A leading case is the state-by-state insurance exchanges set up under the Affordable Care Act (ACA) in the United States that were required to begin offering insurance to a population of otherwise uninsured consumers in 2014 [see, e.g., Kaiser Family Foundation (2010)]. Other examples include the national insurance exchanges set up in the Netherlands, starting in 2006, and Switzerland, starting in 1996 [see van de Ven (2008) and Leu et al. (2009)]. In addition, large employers in the United States have been increasingly outsourcing their insurance provision responsibilities to private health exchanges that resemble these publicly regulated exchanges [see, e.g., Pauly and Harrington (2013)].

This paper sets up and empirically investigates a model of insurer competition in a regulated marketplace, motivated by these exchanges. We develop a framework that combines data on health outcomes and insurance plan choices for a population of individuals with a model of a competitive insurance exchange to predict outcomes under different exchange designs. The challenges in conducting this analysis are both theoretical and empirical. From the theoretical perspective, the analysis of competitive markets under asymmetric information, specifically insurance markets, is delicate. Equilibria are difficult to characterize, can be sensitive to the contracting assumptions, and are often fraught with non-existence. On the empirical side, any prediction of exchange outcomes must naturally depend on the extent of information asymmetries, that is, on the distributions of risks and risk preferences, and the information in the hands of insurees. Thus, a key empirical challenge is identifying these distributions.

As the main application of our framework, we analyze one of the core issues faced by exchange regulators: the extent to which they should allow insurers to vary their prices based on individual-level characteristics, and especially health status (i.e., “pre-existing conditions”). For example, under the ACA, insurers in each state exchange are allowed to vary prices for the same policy based only on age, geographic location, and whether the individual is a smoker. Prohibitions on pricing an individual’s health status can directly impact two distinct determinants of consumer welfare: adverse selection and re-classification risk.¹ Adverse selection is present when there is individual-specific information that can’t be priced, and sicker individuals tend to select greater coverage.² Reclassification risk, on the other hand, arises when changes in health status lead to changes in premiums. Restrictions on the extent to which premiums can be based on health status are likely to increase the extent of adverse selection, but reduce the reclassification risk that insured individuals face. For example, when pricing based on health status is completely prohibited, reclassification risk is eliminated but adverse selection is likely to be present.³ At the other extreme, were unrestricted pricing based on health status allowed,

¹ Each of these phenomena is often cited as a key reason why market regulation is so prevalent in this sector in the first place.
² See Akerlof (1970) and Rothschild and Stiglitz (1976) for seminal theoretical work.
³ Insurer risk adjustment is one policy that regulators typically consider to reduce the extent of adverse selection in
adverse selection would be completely eliminated. We would then expect efficient insurance provision conditional on the set of allowed contracts, although at a very high price for sick consumers.\(^4\) Thus, in determining the degree to which pricing of health status should be allowed, a regulator needs to consider the potential trade-off between adverse selection and reclassification risk.\(^5\)

Our approach combines a model of a competitive insurance exchange with an empirical analysis aimed at uncovering the joint distribution of individuals' risks and risk preferences. To this end, we start by developing a stylized model of an insurance exchange that builds on work by Rothschild and Stiglitz (1976), Wilson (1977), Miyazaki (1977), Riley (1985) and Engers and Fernandez (1987) who all modeled competitive markets with asymmetric information. The model, which can be viewed as an extension of the model in Einav, Finkelstein, and Cullen (2010c) to the case of more than one privately-supplied policy. In the model, the population is characterized by a joint distribution of risk preferences and health risk and there is free entry of insurers. We assume that all individuals buy insurance in the marketplace as a result of either a fully-enforced individual mandate or participation subsidies. (We relax this assumption in an extension in Section 7.) Throughout the analysis, we fix two classes of insurance contracts that each insurer can offer. In our baseline analysis, the more comprehensive contract has 90% actuarial value and mimics the most generous coverage tier under the ACA, while the less comprehensive contract has 60% actuarial value and mimics the least generous coverage tier under the ACA.\(^6\) (We also examine other actuarial values in Section 7.)

To deal with the Nash equilibrium existence problems highlighted by Rothschild and Stiglitz (1976) we focus on another concept developed in the theoretical literature: Riley equilibria [Riley (1979)]. Under the Riley notion, firms consider the possibility that rivals may react to deviations by introducing new profitable policies so that deviations rendered unprofitable by such reactions are not undertaken. The main roles of our theoretical analysis are (i) to prove the existence and uniqueness of Riley equilibrium in our context and (ii) to develop algorithms to find both the Riley equilibrium and any Nash equilibria, should they exist.

As the second input into our analysis, we empirically estimate the joint distribution of risk preferences and ex ante health status for the employees of a large self-insured employer. We estimate these consumer micro-foundations using proprietary data on employee health plan choices and individual-level health claims (including dependents) over a three-year time period. To do so, we develop a structural choice model that generalizes Handel (2013).\(^7\) In particular, we estimate a distribution

\(^{4}\)This abstracts away from liquidity concerns that could be present in reality, especially for low income populations.

\(^{5}\)See, e.g., Bhattacharya et al. (2013) or Capretta and Miller (2010) for policy-oriented discussions that advocate relaxing the pricing restrictions present in the ACA (subject to some complementary market design changes).

\(^{6}\)Actuarial value reflects the proportion of total expenses that an insurance contract would cover if the entire population were enrolled. In addition to the contracts we study, the ACA permits insurers to offer two classes of intermediate contracts with 70% and 80% actuarial value respectively. In the legislation, 90% is referred to as “platinum”, 80% “gold”, 70% “silver”, and 60% “bronze.”

\(^{7}\)While we incorporate consumer inertia in estimation to correctly estimate risk preferences, as in Handel (2013), our
of heterogeneous risk preferences that is allowed to depend on an individual’s ex ante health status, since prior work on insurance markets reveals that correlation between health risk and risk preferences can have important implications for market outcomes [see e.g. Finkelstein and McGarry (2006) or Cohen and Einav (2007)]. To model health risk perceived by employees at the time of plan choice, we use the methodology developed in Handel (2013), which characterizes both total cost health risk and plan-specific out-of-pocket expenditure risk. The model incorporates past diagnostic and cost information into individual-level and plan-specific expense projections using both (i) sophisticated predictive software developed at Johns Hopkins Medical School and (ii) a detailed model of how different types of medical claims translate into out-of-pocket expenditures in each plan.

We then use these estimates, along with our theoretical model of an exchange, to simulate exchange equilibria under different pricing regulations. Because we study a sample of consumers from a large self-insured employer, our analysis is most relevant for a counterfactual private exchange offered by this employer, or other similar large employers. While less externally valid for exchanges with different populations (such as the uninsured qualifying for the ACA exchanges), the depth and scale of the data we use here present an excellent opportunity to illustrate our framework at a general level and, more specifically, to study the interplay between adverse selection and reclassification risk as a function of regulation in such markets. As we note below, as a step toward examining the possible outcomes under the ACA, in Section 7 we also analyze a sample that reweights our population to match the Medical Expenditure Panel Survey (MEPS) data.

The outputs of this equilibrium market analysis (premiums and consumers’ plan choices) then serve as inputs into a long-run welfare model that integrates year-to-year premium risk, conditional on the pricing regulation and underlying health transition process. The model thus incorporates the potential welfare loss from adverse selection (within each annual insurance market) and that from reclassification risk (over multiple years) to evaluate welfare from the perspective of an ex-ante unborn individual, following an individual through many consecutive one-year markets characterized by the static model. We evaluate lifetime welfare under two different scenarios. On the one hand, we consider fixed income over time, which is a reasonable assumption when borrowing is feasible. Alternatively, to capture potential borrowing frictions, we also evaluate welfare under the observed income profile. One benefit of pricing health conditions is that the population is healthier at younger ages, when their income is lower. Health-based pricing, which results in lower premiums early in life, can therefore be beneficial for steep enough income profiles if borrowing is not possible.

In our baseline scenario with 90% and 60% plans, our results show substantial within-market adverse selection with pure community rating. The Riley equilibrium results in full unravelling, with all consumers purchasing a 60% plan at a premium equal to plan average cost for the entire population. The welfare cost of this unraveling is large: a consumer with fixed income over time would be willing to pay $619 per year to be able to purchase instead the 90% plan at a premium equal to its average cost subsequent exchange equilibrium analysis studies a static marketplace where consumers make active non-inertial choices.
for the whole population. This amount is roughly 10% of the average medical expenses in the population. There is still full unravelling in each age cohort once we allow for age-based pricing, although the premiums for each age group reflect the plan average costs conditional on age.

To assess the effects of allowing health-based pricing, we then examine alternative regulations that allow insurers to price individuals to some extent based on their health status. These regulations range from requiring pure community rating to allowing perfect risk rating (full pricing of health risk). Between these two extremes, we consider, for example, the case in which insurers can price based on health status quartiles. As insurers can price on more and more health-relevant information the market share of consumers enrolled in the 90% policy increases due to reduced adverse selection.

Although greater ability to price health-status information reduces adverse selection, our long-run welfare results illustrate the extent to which such policies exacerbate reclassification risk. Under the case of fixed income from age 25 to 65, welfare is highest when health-status pricing is banned. For example, from an ex ante perspective an individual with median risk aversion would be willing to pay $3,082 each year from age 25 to 65 to be in a market with pure community rating rather than face pricing based on health-status quartiles, even though the latter yields greater within-year coverage. This is approximately five times the $619 welfare loss that occurs from adverse selection under pure community rating, and roughly half of the average annual medical expenses in the population. Thus, the welfare losses due to reclassification risk, even for fairly limited pricing of health status, can be quantitatively large. Moreover, as the ability to price on health-status becomes greater, the welfare loss becomes larger: an ex ante consumer with median risk aversion would be willing to pay over $10,000 each year to be in the market with pure community rating rather than face full risk rating. Finally, when we change the fixed lifetime income assumption and allow for increasing income profiles the losses from reclassification risk are attenuated because health-status based pricing decreases premiums earlier in life when income is lower (and thus smooths consumption over time). This beneficial effect of health-based pricing is eliminated, however, if age-based pricing is allowed.

We also consider several extensions that illustrate how our framework can be used to address other issues that arise in exchange design. In addition to investigating age-based pricing, discussed above, we use our framework and estimates to examine how altering the actuarial value of the lowest coverage plan affects market outcomes and welfare, as well as the tradeoff between adverse selection and reclassification risk. We find that lowering the coverage level of the low coverage plan increases the share of consumers that end up with high coverage; however, the net welfare effect of this increased coverage share can fail to offset the loss from the reduced low coverage for those who remain in it. The losses from reclassification risk arising with health-based pricing continue to far exceed any benefits it induces in reduced adverse selection.

We also study participation, allowing individuals to opt-out of the exchange. We find that, absent subsidies or penalties, approximately 26% of the population would opt out of the exchange under pure community rating in our baseline scenario with 90% and 60% actuarial value contracts. Those who opt
out are mostly younger and healthier individuals: about half of the 30 to 35 year old population would prefer to opt out. As the healthier types opt out premiums increase, leading to further desertions. With no subsidies or penalties, premiums in the market are approximately 30% higher than in the case of full participation.

We also illustrate how our model can incorporate risk adjustment transfers among insurers. These transfers are designed to subsidize insurers who take on higher risks and, consequently, ameliorate adverse selection [see e.g. Cutler and Reber (1998)]. As an example, we use our model to evaluate the impact of the risk adjustment formula proposed by the Federal government for exchanges under the ACA, applied to our exchange [see, e.g., Dept. of Health and Human Services (2012a) or Dept. of Health and Human Services (2012b)]. While in practice risk adjustment can lead to a number of problems, such as insurers up-coding enrollees to qualify for larger transfers, we abstract from such issues and assume that the government can perfectly observe the health status of each enrollee. In our baseline case with 90% and 60% plans, and pure community rating, the Riley equilibrium with this insurer risk-adjustment has 49% of the population in the higher-coverage 90% policy. Thus, implementing risk-adjustment as proposed under the ACA reduces adverse selection, but does not fully remove it. For a consumer with fixed income over time and median risk aversion, this risk adjustment reduces the loss due to adverse selection from $619 to $349 per year.

Finally, to move a step closer to evaluating the possible outcomes under the ACA, we consider an extension that reweights our population using weights derived from the Medical Expenditure Panel Survey, a nationally representative consumer survey of health insurance choice and health care costs. Using this reweighted sample, we find results under pure community rating that are very similar to those from our baseline analysis, with the market fully unraveling.

This paper builds on related work that studies the welfare consequences of adverse selection in insurance markets by examining it in the setting of a competitive exchange in which more than one type of policy is privately supplied and by adding in a long-term dimension whereby price regulation induces a potential trade-off with re-classification risk. Relevant work that focuses primarily on adverse selection includes Cutler and Reber (1998), Cardon and Hendel (2001), Carlin and Town (2009), Lustig (2010), Einav et al. (2010c), Bundorf et al. (2012), Handel (2013), and Einav et al. (2013). Ericson and Stare (2013) and Kolstad and Kowalski (2012) study plan selection and regulation in the Massachusetts Connector health insurance exchange. Perhaps the closest paper in spirit to ours is Finkelstein et al. (2009) which examines the welfare consequences of allowing gender-based pricing of annuities in the United Kingdom. These papers all focus on welfare in the context of a short-run or one-time

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8 We find all of the individuals in MEPS who (i) are between 25-65 (ii) are unemployed and (iii) are uninsured, and use them as a representative population for the ACA exchanges. Then, we reweight our sample and match the age, gender, and income profile of our reweighted sample to that from this ACA exchange representative MEPS sample.

9 See also Shi (2013) who studies the impact of risk adjustment and premium discrimination on the level of trade in health exchanges, finding that premium discrimination (across age groups) need not increase trade in the absence of risk adjustment transfers.
marketplace.10

There is more limited work studying reclassification risk and long-run welfare in insurance markets. Cochrane (1995) studies dynamic insurance from a purely theoretical perspective in an environment where fully contingent long-run contracts are possible. Herring and Pauly (2006) studies guaranteed renewable premiums and the extent to which they effectively protect consumers from reclassification risk. Hendel and Lizz`eri (2003) and Finkelstein at al. (2005) study dynamic insurance contracts with one-sided commitment, while Koch (2010) studies pricing regulations based on age from an efficiency perspective. Bundorf et al. (2012), while focusing on a static marketplace, also analyze reclassification risk in an employer setting using a two-year time horizon and subsidy and pricing regulations relevant to their large employer context.

The rest of the paper proceeds as follows: In Section 2 we present our model of insurance exchanges, characterize Riley and Nash equilibria in the context of our model, and discuss the trade-off between adverse selection and reclassification risk. Section 3 describes our data and estimation. In Section 4 we analyze exchange equilibria for a range of regulations on health-based pricing using our baseline case of 90% and 60% actuarial value policies. Section 5 analyzes the long-run welfare properties of these equilibria. In Section 6, we examine equilibria and welfare when we vary the actuarial value of the low coverage policy. Section 7 discusses the age-based pricing, participation, and reweighted sample extensions of our main analysis. Finally, Section 8 concludes.

2 Model of Health Exchanges

In this section, we describe our health exchange model and provide a set of characterization results. The model can be viewed as an extension of the model developed in Einav, Finkelstein, and Cullen (2010c) (henceforth, EFC) to the case in which competition occurs over more than one policy. (We discuss below the relation to their model.) Our results provide the algorithm for identifying equilibria using our data, which we do in Section 4.

Throughout the paper, we focus on a model of health exchanges in which two prescribed policies are traded, which we designate as \( H \) for “high coverage” and \( L \) for “low coverage.” We refer to these as the “\( H \) policy” and the “\( L \) policy.” In our baseline specification in Section 4, these policies will cover roughly 90% and 60% respectively of an insured individual’s costs. Within each exchange, the policies offered by different companies are regarded as perfectly homogeneous by consumers; only their premiums may differ. There is a set of consumers, who differ in their likelihood of needing medical procedures and in their preferences (e.g., their risk aversion). We denote by \( \theta \in [\theta, \bar{\theta}] \subseteq \mathbb{R}_+ \) a consumer’s “type,” which we take to be the price difference at which he is indifferent between the \( H \) policy and the \( L \) policy. That is, if \( P_H \) and \( P_L \) are the premiums (prices) of the two policies, then a consumer whose \( \theta \) is below

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10See also Crocker and Snow (1986) for a theoretical analysis of discriminatory pricing in insurance markets. They illustrate in a two-type model the potential for discrimination to generate Pareto improvements if combined with the right transfer scheme.
$P_H - P_L$ prefers the L policy, a consumer with $\theta$ above $P_H - P_L$ prefers the H policy, and one with $\theta = P_H - P_L$ is indifferent. We denote by $F$ the distribution function of $\theta$. Throughout our main specification, we assume that there is either an individual mandate or sufficient subsidies so that all individuals purchase one of the two policies. (But see Section 6.2 for an analysis of participation.)

Note that, as in EFC, consumers with a given $\theta$ may have different underlying medical risks and/or preferences, but will make identical choices between policies for any prices. Hence, there is no reason to distinguish among them in the model. Keep in mind, as we define below the costs of insuring type $\theta$ buyers, that those costs represent the expected costs of insuring all of the — possibly heterogeneous — individuals characterized by a specific $\theta$.

This setup involves two restrictions worth emphasizing. First, as in EFC, consumer choices depend only on price differences, not price levels; that is, there are no income effects. In our empirical work, we estimate constant absolute risk aversion preferences, which leads to this property. Second, we restrict attention to the case of an exchange with two policies. We do so because in this case we can derive a simple algorithm for identifying equilibria. With more than two policies, we would likely need to identify equilibria computationally.

We denote the costs of insuring an individual of type $\theta$ under policy $k$ by $C_k(\theta)$ for $k = H, L$. Recall that if the price difference is $\Delta P = P_H - P_L$, those consumers with $\theta < \Delta P$ prefer policy L, while those with $\theta > \Delta P$ prefer policy H. Given this fact, we can define the average costs of serving the populations who choose each policy for a given $\Delta P$ to be

$$AC_H(\Delta P) \equiv E[C_H(\theta) | \theta \geq \Delta P]$$

and

$$AC_L(\Delta P) \equiv E[C_L(\theta) | \theta \leq \Delta P].$$

We also define the difference in average costs between the two policies, conditional on a price difference $\Delta P \in [\underline{\theta}, \bar{\theta}]$, to be

$$\Delta AC(\Delta P) \equiv AC_H(\Delta P) - AC_L(\Delta P).$$

Our characterization results hinge on the following assumption (which we verify in Section 4 holds in our data):

**Adverse Selection Property** $AC_H(\cdot)$ and $AC_L(\cdot)$ are continuous functions that are strictly increasing at all $\Delta P \in (\underline{\theta}, \bar{\theta})$, with $AC_H(\theta) > AC_L(\theta)$ for all $\theta$.

This Adverse Selection Property will hold, for example, if $C_H(\theta)$ and $C_L(\theta)$ are continuous increasing functions, with $C_H(\theta) > C_L(\theta)$ for all $\theta$, and if the distribution function $F$ is continuous. In that case, a small increase in $\Delta P$ shifts consumers who were the best risks in policy H to becoming the worst risks in policy L, raising the average costs of both policies. We denote the lowest possible levels of average costs by $\overline{AC}_H \equiv AC_H(\underline{\theta})$ and $\overline{AC}_L \equiv AC_L(\underline{\theta})$, and the highest ones by $\underline{AC}_H \equiv AC_H(\bar{\theta})$ and $\underline{AC}_L \equiv AC_L(\bar{\theta})$. 


We refer to the lowest prices offered for the H and L policies as a price configuration. We next define the profits earned by the firms offering those prices. Specifically, for any price configuration \((P_H, P_L)\) define

\[
\Pi_H(P_H, P_L) \equiv \begin{cases} [P_H - AC_H(\Delta P)][1 - F(\Delta P)] & \text{if } \Delta P \leq \theta \\ 0 & \text{if } \Delta P > \theta \end{cases}
\]

and

\[
\Pi_L(P_H, P_L) \equiv \begin{cases} [P_L - AC_L(\Delta P)]F(\Delta P) & \text{if } \Delta P \geq \theta \\ 0 & \text{if } \Delta P < \theta \end{cases}.
\]

as the aggregate profit from consumers who choose each of the two policies. Let

\[
\Pi(P_H, P_L) = \Pi_H(P_H, P_L) + \Pi_L(P_H, P_L)
\]

be aggregate profit from the entire population.

The set of break-even price configurations, which lead each policy to earn zero profits, is \(P = \{(P_H, P_L): \Pi_H(P_H, P_L) = \Pi_L(P_H, P_L) = 0\}\). Note that the price configuration \((P_H, P_L) = (\overline{AC}_L + \theta, \overline{AC}_L)\), which results in all consumers purchasing the L policy, is a break-even price configuration (i.e., it is in set \(P\)), as is the “all-in-H” price configuration \((P_H, P_L) = (\overline{AC}_H, \overline{AC}_H - \theta)\). There may also be “interior” break-even price configurations, at which both policies have a positive market share. We let \(\Delta P^{BE}\) denote the lowest break-even \(\Delta P\) with positive sales of the L policy, defined formally as:

\[
\Delta P^{BE} \equiv \min\{\Delta P: \text{there is a } (P_H, P_L) \in P \text{ with } \Delta P = P_H - P_L > \theta\}
\]

The price difference \(\Delta P^{BE}\) will play a significant role in our equilibrium characterizations below.

### 2.1 Equilibrium Characterization

The literature on equilibria in insurance markets with adverse selection started with Rothschild and Stiglitz (1976). Motivated by the possibility of non-existence of equilibrium in their model, follow-on work by Riley (1979) [see also Engers and Fernandez (1987)] and Wilson (1977) proposed alternative notions of equilibrium in which existence was assured in the Rothschild-Stiglitz model. These alternative equilibrium notions each incorporated some kind of dynamic reaction to deviations [introduction of additional profitable policies in Riley (1979), and dropping of unprofitable policies in Wilson (1977)], in contrast to the Nash assumption made by Rothschild and Stiglitz. In addition, follow-on work also allowed for multi-policy firms [Miyazaki (1977), Riley (1979)], in contrast to Rothschild and Stiglitz’s assumption that each firm offers at most one policy.

Our model differs from the Rothschild-Stiglitz setting in four basic ways. First, the prescription of health exchanges limits the set of allowed policies. Figure 1, for example, shows the set of feasible policies in the Rothschild-Stiglitz model (in which each consumer faces just two health states: “healthy” and “sick”) with two contracts, one for a 90% policy and the other for a 60% policy. These lie on lines with slope equal to 1 since a decrease of $1 in a policy’s premium increases consumption by $1 in each
state. Second, in our model consumers face many possible health states. Third, while the Rothschild-Stiglitz model contemplated just two consumer types, we assume there is a continuum of consumer types. Finally, we allow for multi-policy firms.

In our main analysis we focus on the Riley equilibrium ("RE") notion, which we show always exists and is (generically) unique in our model. We also discuss how these compare to Nash equilibria ("NE"), which need not exist. (In addition, we consider Wilson equilibria in Appendix B.) In what follows, the phrase equilibrium outcome refers to the equilibrium price configuration and the shares of the two policies.

We present a formal definition of Riley equilibrium in the Appendix. In words, a price configuration is a RE if there is no profitable deviation that would remain profitable regardless of reactions by rivals that introduce new “safe” policy offers, where a safe policy offer is one that will not lose money regardless of any additional contracts that enter the market after it.

Our result for RE is:

**Proposition 1.** A Riley equilibrium always exists, and results in a unique outcome whenever $\Delta AC(\theta) \neq \theta$.

(i) If $\Delta AC(\theta) < \theta$, then it involves all consumers purchasing the H policy at price $P^*_H = \frac{AC_H}{\theta}$.

(ii) If $\Delta AC(\theta) > \theta$, it then involves the break-even price configuration $(P^*_H, P^*_L)$ with price difference...
Figure 2: The figure shows $\Delta P^{BE}$, the lowest price difference in any break-even price configuration that has positive sales of the 60 policy. It also shows a situation in which all-in-90 is not an equilibrium outcome, because $\Delta AC(\theta) > \bar{\theta}$.

$$\Delta P^* = \Delta P^{BE},$$ the lowest break-even $\Delta P$ with positive sales of the L policy.

We prove Proposition 1 in the Appendix. Here we discuss the result, contrast RE with Nash equilibria, and discuss the relation of our result to EFC and Hendren (2013).

Figure 2 illustrates the result. The figure illustrates a situation in which $\Delta AC(\theta) > \bar{\theta}$ and there are multiple price differences at which both policies break even (including price differences at which all consumers buy the H policy, and price differences at which all consumers buy policy L). In this case, our result tells us that the unique RE involves positive sales of policy L and price difference $\Delta P^{BE}$. In contrast, if instead we had $\Delta AC(\theta) < \bar{\theta}$, then all consumers purchasing policy H would have been the unique RE outcome. Finally, if instead $\Delta AC(\theta) > \bar{\theta}$ for all $\theta$, then $\Delta P^{BE} = \bar{\theta}$ and all consumers purchase policy L.

To understand the result, consider first when there is an all-in-H RE. In the Appendix, we first show that any RE must involve both policies breaking even. Given this fact, suppose, first, that $\Delta AC(\theta) > \bar{\theta}$, so that the consumer with the lowest willingness-to-pay for extra coverage is willing to pay less than the difference in the two policies’ average costs when (nearly) all consumers buy policy H, $\Delta AC(\theta) = AC_H - AC_L$. In that case, starting from a situation in which all consumers buy policy H and $P_H = AC_H$, a deviation offering price $\hat{P}_L = AC_H - \bar{\theta} - \varepsilon$ for small $\varepsilon > 0$ would cream-skim the lowest risk consumers into policy L at a price above $AC_L$, the average cost of serving them. Moreover, we show in the Appendix that no safe reaction to that deviation can cause the firm offering it to lose money: any reduction in $P_H$ can only lower the deviator’s average cost, while any undercutting in $P_L$
cannot result in losses for the deviator. On the other hand, when \( \Delta AC(\bar{\theta}) < \bar{\theta} \), a deviation from this all-in-H outcome that attempts to cream-skin must lose money, since then the deviation price satisfies \( \bar{P}_L \leq AC_H - \bar{\theta} < AC_L \), the lowest possible average cost for the L policy. Thus, in that case all-in-H is a RE.

Now consider break-even price configurations with \( \Delta P \leq \bar{\theta} \) above \( \Delta P^{BE} \) (and hence positive sales of the L policy). Starting from such a configuration, a deviation to \( \hat{P}_H = AC_H(\Delta P^{BE}) \) earns strictly positive profits [it results in a price difference lower than \( \Delta P^{BE} \), attracting a positive share of consumers to policy H at an average cost below \( AC_H(\Delta P^{BE}) \)]. Moreover, we show in the Appendix that the worst possible safe reaction to this deviation would involve a reduction in \( P_L \) to \( AC_L(\Delta P^{BE}) \) (a reaction that leads to zero profits for the reactor), which makes the deviator earn zero, rather than incur losses. Thus, no such price configuration can be a RE.

Finally, consider the price configuration \( P^* = (AC_H(\Delta P^{BE}), AC_L(\Delta P^{BE})) \) that results in price difference \( \Delta P^{BE} \). When \( \Delta AC(\bar{\theta}) < \bar{\theta} \), this is not a RE. To see this, observe that a deviation offering price \( \hat{P}_H = AC_L(\Delta P^{BE}) + \bar{\theta} \), attracts all consumers to policy H at a price above the cost of serving them, since

\[
\hat{P}_H = AC_L(\Delta P^{BE}) + \bar{\theta} \geq AC_L + \bar{\theta} > AC_H,
\]

where the last inequality holds because \( \Delta AC(\bar{\theta}) = AC_H - AC_L < \bar{\theta} \). Moreover, we show in the Appendix that the worst possible safe reaction to this deviation is an offer of the L policy at a price that breaks even given \( \hat{P}_H \); i.e., a \( P_L = AC_L(\hat{P}_H - P_L) \). Since we have \( \Delta AC(\Delta P) < \Delta P \) for all \( \Delta P \in [\bar{\theta}, \Delta P^{BE}] \) when \( \Delta AC(\bar{\theta}) < \bar{\theta} \), this implies that \( \hat{P}_H > AC_H(\hat{P}_H - P_L) \), so the reaction can’t make the deviator incur losses. On the other hand, when \( \Delta AC(\bar{\theta}) > \bar{\theta} \), the worst safe reaction makes the deviator lose money for any deviation that offers a lower \( P_H \) (and we show that only such deviations need be considered), so \( P^* \) is a RE.

While RE always exists in our model, NE need not.\(^{11}\) When \( \Delta AC(\bar{\theta}) < \bar{\theta} \), the all-in-H RE outcome is also the unique NE outcome since (as noted above) no cream-skimming deviation is then profitable. However, when \( \Delta AC(\bar{\theta}) > \bar{\theta} \), the RE — which has positive sales of the L policy — need not be a NE. In particular, we show that it will be a NE if and only if there is no profitable entry opportunity that slightly undercuts \( P^*_L \) and undercuts \( P^*_H \): i.e., if \( \max_{\hat{P}_H \leq P_H} \Pi(\hat{P}_H, P^*_H) = 0 \). In our empirical work, NE often fail to exist.\(^{12}\)

Our characterization differs in several respects from that in EFC. EFC considers a model in which only one policy is supplied by firms. This yields a Nash equilibrium at the lowest price \( P = AC \), where \( AC \) is the average cost of those consumers who purchase the policy.\(^{13}\) Their model

\(^{11}\) Note that any NE must be a RE since the set of deviations that are considered profitable under NE contains the set of Riley profitable deviations.

\(^{12}\) We also discuss in the Appendix Nash equilibria when firms can offer only a single policy, as in Rothschild and Stiglitz (1976). In our empirical work, these always coincide with the RE if they exist.

\(^{13}\) While EFC do not prove that the lowest break-even price with positive insurance sales is the unique Nash equilibrium, the argument is straightforward [see Mas-Colell et al (1995, pp. 443-4) for a similar argument].
can apply when there is only one possible type of insurance coverage, or when a higher coverage level is achieved through purchase of an add-on to a government-provided policy (such as Medigap coverage). In the latter case, \( P \) is the price of the add-on policy, while \( AC \) is the average cost of those consumers who purchase the extra coverage. EFC’s equilibrium always exists, and always involves a positive share of consumers purchasing insurance provided that all consumers are strictly risk averse and have a strictly positive probability of a loss (in the sense that their preferences are bounded away from risk neutrality, and their probability of a loss is bounded away from zero).\(^{14}\)

In contrast, in our model two policies are priced, and equilibrium when both policies are purchased involves the lowest \( \Delta P \) at which \( \Delta P = \Delta AC \), where \( \Delta AC \) is the difference in the average costs of the two plans, given the consumers who purchase each plan. In contrast to EFC, in this setting a NE may fail to exist, a fact that is driven by the possibility of cream skimming by low coverage plans, which is absent in their model.\(^{15}\) Moreover, while RE always exist, they may involve full unraveling, with all consumers purchasing the lowest coverage plan, even when all consumers are strictly risk averse and have a positive probability of a loss. Intuitively, unraveling is more likely here than in the EFC model because the price of the policy L reflects the lower costs of the consumers who choose it, leading even the consumers with the highest willingness-to-pay for higher coverage to pool with better risks in policy L.

Our results are also related to Hendren (2013). Hendren derives a sufficient condition for unsubsidized insurance provision to be impossible in a model with two states and asymmetric information about the probability of a loss by characterizing when the endowment is the only incentive-feasible allocation. As he notes, his condition cannot hold when all consumers are strictly risk averse and have a strictly positive probability of a loss. Consistent with this result, in our model, when the low coverage involves no insurance, some consumers must purchase high coverage in the RE. To see this, observe that in that case the average cost of the policy L is always zero, so \( \Delta AC(\Delta P) = AC_H(\Delta P) \). Thus, since \( \bar{\theta} > C_H(\bar{\theta}) = AC_H(\bar{\theta}) \) when type \( \bar{\theta} \) is strictly risk averse and has a positive probability of a loss, we then have \( \Delta AC(\bar{\theta}) < \bar{\theta} \), which implies that the RE has some consumers purchasing policy H. However, our results also show that when the lowest coverage policy in an exchange provides some coverage, the market can fully unravel even when all consumers are strictly risk averse and have a strictly positive probability of a loss.

\(^{14}\)The EFC model can also be used to derive equilibria when consumers must opt out of government-provided insurance if they purchase a higher coverage private plan. (In that case, \( AC \) would be the cost of the private plan for consumers who opt out.) However, in this scenario, EFC’s welfare analysis would not apply, as there would be externalities on the government’s budget.

\(^{15}\)Note that profitable cream-skimming deviations that reduce \( P_{ho} \) involve increases in \( \Delta P \), while in the EFC model only reductions in \( P \) can attract consumers.
2.2 Adverse Selection vs. Reclassification Risk

In the main application of our framework, we examine the trade-off between adverse selection and reclassification risk that arises with health-based pricing. In that empirical application, we study the welfare effects of health-based pricing over an individual’s lifetime. Here, to illustrate the main forces at work, we discuss this trade-off in a simpler static context.\(^\text{16}\)

Consider a single-period setting, in which a consumer’s medical expenses are \(\tilde{m} = \phi \tilde{e}_b + (1 - \phi) \tilde{e}_a\), where \(\tilde{e}_b\) and \(\tilde{e}_a\) are both independently drawn from some distribution \(H\), and \(\phi \in [0, 1]\). The realization of \(\tilde{e}_b\) occurs before contracting, while that of \(\tilde{e}_a\) occurs after. With pure community rating, health status — the realization of \(\tilde{e}_b\) — cannot be priced, while with health-based pricing it can. The parameter \(\phi\) captures how much information about health status is known at the time of contracting. (As we will see in the next section, in our data, this ranges between 0.18 and 0.29, depending on the age cohort. Perhaps surprisingly, it decreases with age.) With community rating, there is an adverse selection problem, as consumers know their \(\tilde{e}_b\) realization. In contrast, under perfect health-based pricing, each consumer’s insurance prices perfectly reflect the realization of \(\tilde{e}_b\). Consumers are therefore able to perfectly insure the risk in \(\tilde{e}_a\), but end up bearing all of the risk in \(\tilde{e}_b\). For example, if the market with community rating fully unravels so that all consumers end up with insurance covering share \(s_L\) of their medical expenses, then roughly speaking they pay for share \((1 - s_L)\) of their medical expenses with community rating and share \(\phi\) with perfect health-based pricing.\(^\text{17}\)

Figure 3 shows the results of a simulation in which the distribution of medical expenses \(H\) is log-normal, truncated at $200,000. Its parameters are set so that the mean of total medical expenditures is $6000 and the ratio of the variance of total medical expenses to this mean is \(R = 10,000\). The risk aversion coefficient is \(\gamma = 0.00005\). The policies in each panel are simple linear contracts, with the high coverage plan in each panel covering 90% and the low coverage plan covering share \(s_L\), which takes values of 0, 0.2, 0.4, and 0.6 in the four panels.\(^\text{18}\) Each panel plots three curves. The horizontal axis measures the share \(\phi\) of medical risk that is realized before contracting. For each \(\phi\), the curve marked with Xs shows the market share of the low coverage plan in the RE with pure community rating, the dashed curve shows a consumer’s (ex ante, before any medical realizations) certainty equivalent under pure community rating, and the gradually declining solid curve shows the certainty equivalent arising with perfect health-based pricing. Figure 4 is the same, except that \(R = 30,000\), reflecting greater medical expense risk.

Comparing the four panels in Figure 3, we see that the greater is \(s_L\), the coverage in the low-coverage

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\(^\text{16}\)The lifetime calculation we do later can be viewed as a sequence of static markets.

\(^\text{17}\)This is only a rough statement, because \(\tilde{e}_b\) and \(\tilde{e}_b\) are drawn independently, which reduces the risk under community rating relative to that in health-based pricing.

\(^\text{18}\)Our aim here is to illustrate the main forces at work in a simple setting. Note that these policies involve the possibility of consumers having much more extreme out-of-pocket expenses than the actual policies we explore later (which have caps on an individual’s total out-of-pocket spending), and the risk aversion coefficient is lower than what we estimate. Our analysis later also allows for a non-degenerate distribution of risk aversion levels, risk aversion that is correlated with health status, and partial pricing of health status.
Figure 3: Adverse selection vs. reclassification risk, $R = 10,000$.

Figure 4: Adverse selection vs. reclassification risk, $R = 30,000$. 
policy, the more unraveling there is – specifically, for larger $s_L$ the market unravels to all consumers in the low coverage plan at lower levels of $\phi$.\textsuperscript{19} This reflects the fact that cream-skimming is easier when the low coverage plan does not expose consumers to too much more risk. In each panel, the welfare of community rating and perfect health-based pricing is the same when $\phi = 0$ (there is then neither adverse selection nor reclassification risk). When $s_L = 0$, welfare in these two regimes is also the same when $\phi = 1$: in that case, the market fully unravels to zero coverage with community rating (consumers know exactly their medical expenses when contracting) and there is nothing left to insure once health status $\varepsilon_b$ is priced with perfect health-based pricing. Between these two extremes for $\phi$, when $s_L = 0$ health-based pricing is better at high $\phi$ at which the market nearly fully unravels with community rating, but worse at low $\phi$ where all consumers get high coverage. A similar pattern emerges at higher levels of $s_L$ except that full unraveling (which happens at $\phi = 1$) is now much more attractive than no coverage (which happens with health-based pricing when $\phi = 1$). Whether there is a range over which health-based pricing is better than community rating then depends on the level of $\phi$ at which the market unravels. In Figure 4 we see that this unraveling occurs at higher $\phi$ when $R$ is greater (larger variance of medical expenditures), reflecting the fact that with greater variance consumers are more reluctant to choose a low coverage plan. As a result, in that figure there is a smaller range of $\phi$ over which health-based pricing is better than community rating.

3 Data and Estimation

3.1 Data

Our analysis uses detailed administrative data on the health insurance choices and medical utilization of employees (and their dependents) at a large U.S.-based firm over the period 2004 to 2009. These proprietary panel data include the health insurance options available in each year, employee plan choices, and detailed, claim-level employee (and dependent) medical expenditure and utilization information. We describe the data at a high-level in this section: for a more in-depth description of different dimensions see Handel (2013).

The first column of Table 1 describes the demographic profile of the 11,253 employees who work at the firm for some period of time within 2004-2009 (the firm employs approximately 9,000 at one time). These employees cover 9,710 dependents, implying a total of 20,963 covered lives. 46.7% of the employees are male and the mean employee age is 40.1 (median of 37). The table also presents statistics on income, family composition, and employment characteristics.

Our analysis focuses on a three-year period in the data beginning with a year we denote $t_0$. For $t_0$, which is in the middle of the sample period, the firm substantially changed the menu of health plans that it offered to employees. At the time of this change, the firm forced all employees to leave their prior

\textsuperscript{19} Although it cannot be detected in the figures, when $s_L = 0$, there are some consumers in the high-coverage 90 policy at all $\phi < 1$. 

### Sample Demographics

<table>
<thead>
<tr>
<th></th>
<th>All Employees</th>
<th>PPO Ever</th>
<th>Final Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>N - Employee Only</td>
<td>11,253</td>
<td>5,667</td>
<td>2,023</td>
</tr>
<tr>
<td>N - All Family Members</td>
<td>20,963</td>
<td>10,713</td>
<td>4,544</td>
</tr>
<tr>
<td>Mean Employee Age (Median)</td>
<td>40.1</td>
<td>40.0</td>
<td>42.3</td>
</tr>
<tr>
<td>Gender (Male %)</td>
<td>46.7%</td>
<td>46.3%</td>
<td>46.7%</td>
</tr>
<tr>
<td>Income</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tier 1 (&lt; $41K)</td>
<td>33.9%</td>
<td>31.9%</td>
<td>19.0%</td>
</tr>
<tr>
<td>Tier 2 ($41K-$72K)</td>
<td>39.5%</td>
<td>39.7%</td>
<td>40.5%</td>
</tr>
<tr>
<td>Tier 3 ($72K-$124K)</td>
<td>17.9%</td>
<td>18.6%</td>
<td>25.0%</td>
</tr>
<tr>
<td>Tier 4 ($124K-$176K)</td>
<td>5.2%</td>
<td>5.4%</td>
<td>7.8%</td>
</tr>
<tr>
<td>Tier 5 (&gt; $176K)</td>
<td>3.5%</td>
<td>4.4%</td>
<td>7.7%</td>
</tr>
<tr>
<td>Family Size</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>58.0%</td>
<td>56.1%</td>
<td>41.3%</td>
</tr>
<tr>
<td>2</td>
<td>16.9%</td>
<td>18.8%</td>
<td>22.3%</td>
</tr>
<tr>
<td>3</td>
<td>11.0%</td>
<td>11.0%</td>
<td>14.1%</td>
</tr>
<tr>
<td>4+</td>
<td>14.1%</td>
<td>14.1%</td>
<td>22.3%</td>
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<tr>
<td>Staff Grouping</td>
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<td></td>
</tr>
<tr>
<td>Manager (%)</td>
<td>23.2%</td>
<td>25.1%</td>
<td>37.5%</td>
</tr>
<tr>
<td>White-Collar (%)</td>
<td>47.9%</td>
<td>47.5%</td>
<td>41.3%</td>
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<tr>
<td>Blue-Collar (%)</td>
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<td>21.1%</td>
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<tr>
<td>Additional Demographics</td>
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<td></td>
<td></td>
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<tr>
<td>Quantitative Manager</td>
<td>12.8%</td>
<td>13.3%</td>
<td>20.7%</td>
</tr>
<tr>
<td>Job Tenure Mean Years (Median)</td>
<td>7.2</td>
<td>7.1</td>
<td>10.1</td>
</tr>
</tbody>
</table>

Table 1: This table presents summary demographic statistics for the population we study. The first column describes demographics for the entire sample whether or not they ever enroll in insurance with the firm. The second column summarizes these variables for the sample of individuals who ever enroll in a PPO option, the choices we focus on in the empirical analysis. The third column describes our final estimation sample, which includes those employees who (i) are enrolled in PPO-1 at t-1 and (ii) remain enrolled in any plan at the firm through at least t1.
plan and actively re-enroll in one of five options from the new menu, with no default option. These five options were comprised of three PPOs and two HMOs. Our analysis focuses on choice among the three PPO options, which approximately 60% of health plan enrollees chose. We focus on this subset of the overall option set because (i) we have detailed claims data for PPO enrollees but not for HMO enrollees and (ii) the PPO options share the same doctors / cover the same treatments, eliminating a dimension of heterogeneity that would have to be identified separately from risk preferences. Analysis in Handel (2013) reveals, reassuringly, that while there is substitution across options within the set of PPO options, and across the set of HMO options, there is little substitution between these two subsets of plans, implying there is little loss of internal validity when considering choice between just the set of PPO options.

Within the nest of PPO options, consumers chose between three non-linear insurance contracts that differed on financial dimensions only. We denote the plans by their individual level deductibles: PPO_{250}, PPO_{500}, and PPO_{1200}. Post-deductible, the plans have coinsurance rates ranging from 10% to 20%, and out-of-pocket maximums at the family level. In terms of actuarial equivalence value (the proportion of expenditures covered for a representative population), PPO_{250} is approximately a 90% actuarial equivalence value plan while PPO_{1200} is approximately a 73% actuarial equivalence value plan (PPO_{500} is about halfway between PPO_{250} and PPO_{1200}). Over the three-year period that we study, t_0 to t_2, there is substantial variation in the premiums for these plans as well as for different income levels and family structure; this variation is helpful for identifying risk preferences separately from consumer inertia.

We restrict the final sample used in choice model estimation to those individuals / families that (i) enroll in one of the three PPO options and (ii) are present in all years from t_{-1}, the year before the menu change, through at least t_1, one year before the end of our study period. The reasons for the first restriction are discussed above. The second restriction, to more permanent employees, is made to leverage the panel nature of the data, especially the temporal variation in premiums and health risk, to more precisely identify risk preferences. Column 2 in Table 1 presents the summary statistics for the families that choose one of the PPO options, while Column 3 presents the summary statistics for the final estimation sample, incorporating the additional restriction of being present from t_{-1} to at least t_1. Comparing the second column to the first column reveals little selection on demographic dimensions into the PPO options, while comparing the third column to the others reveals some selection based on family size and age into the final sample, as expected given the restriction to longer tenure.

### 3.2 Health Status

We use detailed medical and demographic information together with the “ACG” software developed at Johns Hopkins Medical School to create individual-level measures of predicted expected medical
Figure 5: This figure presents the distribution of $\lambda$ predicted for $t_1$, for all individuals in the data (including dependents) present during both $t_0$ and $t_1$. Predicted expected expenses are normalized by the average in the population of $4,878$ (thus equal to 1 in this chart). The distribution presented is truncated at 5 times for this chart, but not in estimation / analysis.

expenses for the upcoming year at each point in time. We denote these ex ante predictions of the next year’s expected medical expenditures by $\lambda$ and compute these measures for each individual in the sample (including dependents as well as employees). We refer to $\lambda_{it}$ as individual $i$’s “health status” at time $t$.

Figure 5 presents the distribution of $\lambda$ for individuals in the data, as predicted for year $t_1$, for individuals (including dependents) present at both $t_0$ and $t_1$. The figure presents predicted health status (i.e., expected expenses) normalized by average predicted yearly expenditures of $4,878$ for these individuals for $t_1$. As is typical in the health care literature, the distribution is skewed with a large right tail (the chart truncates this right tail at 5 times the mean, though this is not done in our analysis).

3.3 Cost Model

The health status measure $\lambda$ measures expected total health expenses. However, to evaluate the expected utility for consumers from different coverage options we need to estimate an ex ante distribution of out-of-pocket expenses for each family $j$ choosing a given health plan $k$ (not just their mean out-of-pocket expense). We utilize the cost model developed in Handel (2013) to estimate these distributions, denoted $H_k(X_{jt}|\lambda_{jt}, Z_{jt})$. Here, $\lambda_{jt}$ is the vector of $\lambda_{i}$ for all $i$ in family $j$, $Z_{jt}$ are family demographics,

\footnote{The program, known as the Johns Hopkins ACG (Adjusted Clinical Groups) Case-Mix System, is one of the most widely used and respected risk adjustment and predictive modeling packages in the health care sector. It was specifically designed to use diagnostic claims data to predict future medical expenditures.}
and \(X_{jt}\) are out-of-pocket medical expenditure realizations for family \(j\) in plan \(k\) at time \(t\).

The cost model is described in Appendix C; here we provide a broad overview. The model has the following primary components:

1. For each individual and time period, we compute expected expenditure, \(\lambda_{jt}\), for four medical categories: (i) hospital/inpatient (ii) physician office visits (iii) mental health and (iv) pharmacy.

2. We next group individuals into cells based on \(\lambda_{jt}\). For each expenditure type and risk cell, we estimate an expenditure distribution for the upcoming year based on ex post cost realizations. Then we combine the marginal distributions across expenditure categories into joint distributions using empirical correlations and copula methods.

3. Finally, for each plan \(k\) we construct the detailed mappings from the vector of category-specific medical expenditures to plan out-of-pocket costs.

The output from this process, \(H_k(X_{jt}|\lambda_{jt}, Z_{jt})\), represents the distribution of out-of-pocket expenses associated with plan \(k\) used to compute expected utility in the choice model (and counterfactuals).

The cost model assumes both that there is no individual-level private information and no moral hazard (total expenditures do not vary with \(k\)). While both of these phenomena have the potential to be important in health care markets, and are studied extensively in other research, we believe that these assumptions do not materially impact our estimates. Because our cost model combines detailed individual-level prior medical utilization data with sophisticated medical diagnostic software there is less room for private information (and selection based on that information) than in prior work that uses coarser information to measure health risk.\(^{21}\)

### 3.4 Risk Preferences: Choice Model

We estimate risk preferences with a panel discrete choice model where choices are made by each household \(j\) at time \(t\), conditional on their household-plan specific ex ante out-of-pocket cost distributions \(H_k(X_{jt}|\lambda_{jt}, Z_{jt})\). Specifically, the utility of plan \(k\) for household \(j\) at time \(t\) is:

\[
U_{jkt} = \int_0^\infty u_j(M_{jkt}(X_{jt}), Z_{jt})dH_k(X_{jt}|\lambda_{jt}, Z_{jt})
\]

where \(u_j\) is the v-NM or “Bernoulli” expected utility index that measures utility conditional on a given ex post realized state \(X_{jt}\) from the expenditure distribution \(H_k\). \(Z_{jt}\) are individual-level observables (described shortly) and \(M_{jkt}\) is the effective household consumption, given by:

\[
M_{jkt} = W_j - P_{jkt} - X_{jt} + \eta(Z_{jt})1_{jk,t-1} + \delta_j(A_j)1_{1200} + \alpha HTC_{j,t-1}1_{250} + \varepsilon_{jkt}(A_j)
\]

\(^{21}\)Pregnancies, genetic pre-dispositions, and non-coded disease severity are possible examples of private information that could still exist. Cardon and Hendel (2001) find no evidence of selection based on private information with coarser data while Carlin and Town (2009) use claims data that are similarly detailed to ours and also argue that significant residual selection is unlikely.
where $W_j$ denotes household wealth, $P_{jk,t}$ is the premium contribution for plan $k$ at time $t$ and $1_{jk,t-1}$ is an indicator that equals one if plan $k$ is the household’s incumbent plan (default option) at choice year $t$. This variable captures consumer inertia, which is present for years with a default option ($t_1$ and $t_2$) (when the consumer may incur cost $\eta$ to switch). $\delta_j(A_j)$ is a random coefficient, with distribution estimated conditional on family status $A_j$ (single or covering dependents), that captures permanent horizontal preferences for PPO$_{1200}$ arising from the Health Savings Account linked to this plan option. Parameter $\alpha$ captures preferences for very high-expenditure consumers, who almost exclusively choose PPO$_{250}$ even when that option is not attractive financially ($HTC_{j,t-1}=1$ for the top 10% of the distribution of expected total costs). The utility of each option $k$ for family $j$ at $t$ is also affected by a mean zero idiosyncratic preference shock $\varepsilon_{jk,t}$ known to the decision-maker, with variance $\sigma^2$ to be estimated conditional on family status $A_j$.

We assume that households have constant absolute risk aversion (CARA) preferences:

$$u_j(M_{jk,t}) = -\frac{1}{\gamma_j} e^{-\gamma_j M_{jk,t}}$$  \hspace{1cm} (4)

Parameter $\gamma_j$ is a household-specific CARA risk preference parameter unobserved by the econometrician. We estimate a random-coefficient distribution of $\gamma_j$ that is assumed to have mean $\mu_\gamma(Z^A_j, \lambda_j)$ and be normally distributed with variance $\sigma^2_\gamma$. Note that observable heterogeneity impacts risk preference estimates through a shift in $\mu_{\gamma}$, while the level of unobserved heterogeneity measured by $\sigma^2_\gamma$ is assumed constant for the entire population. We use the following specification for $\mu_{\gamma}(Z^A_j, \lambda_j)$:

$$\mu_{\gamma}(Z^A_j, \lambda_j) = \beta_0 + \beta_1 \log(\Sigma_{i\epsilon j} \lambda_i) + \beta_2 age_j + \beta_3 \log(\Sigma_{i\epsilon j} \lambda_i) \ast age_j + \beta_4 1_{mj} + \beta_5 1_{mj} \tilde{v}_{mj} + \beta_6 1_{nmj} \tilde{v}_{nmj}$$  \hspace{1cm} (5)

In addition to expected household health expenditures ($\Sigma_{i\epsilon j} \lambda_i$), risk preferences depend on maximum household age, denoted $age_j$, and the interaction between health risk and age. $1_{mj}$ is an indicator variable that denotes whether the employee associated with the household is a “manager” (i.e., a high-level employee) at the firm. $1_{nmj}$ is the complement of $1_{mj}$. $\tilde{v}_{mj}$ is a measure of ability, and is computed as the residual to the following regression, run only on the sample of managers in the population:

$$Income_{jt} = \alpha_0 + \alpha_1 age_{jt} + \alpha_2 age^2_{jt} + v_{jt}$$  \hspace{1cm} (6)

The residual $\tilde{v}_{nmj}$ is computed from the corresponding regression for non-managers.

Regarding identification, risk preferences are identified separately from inertia by leveraging the firm’s insurance menu re-design for year $t_0$. Households in that year chose plans from a new menu of options with no default option, while in subsequent years they did have their previously chosen option as a default option. Conditional on this choice environment, changing prices and health status over time separately identify inertia from risk preference levels and risk preference heterogeneity. The different components of risk preference heterogeneity are identified by using exogenous price differences across both income tiers and coverage tiers (number of family members covered) and over time, as well as
changes to household expenditure distributions over time. Prices change substantially across income
tiers and family tiers, while across these tiers households can have similar expenditure risk distributions.
Changes over time in health status and premiums, assuming risk preferences are constant over time,
also provide identifying variation for risk preferences. Finally, consumer preference heterogeneity for
the high-deductible plan option with the linked health savings account (HSA) is distinguished from risk
preference heterogeneity by comparing choices between the two other plans to those between either of
those plans and the high-deductible plan.

We estimate the choice model using a random coefficients simulated maximum likelihood approach
similar to Train (2009). The likelihood function at the household level is computed for a sequence of
choices from \( t_0 \) to \( t_2 \), since inertia implies that the likelihood of a choice made in the current period
depends on the previous choice. Since the estimation algorithm is similar to a standard approach,
we describe the remainder of the details, including the specification for heterogeneity in inertia, in
Appendix D.

3.5 Preference Estimates

Table 2 presents our choice model estimates. The first column presents the estimates of our primary
specification while the second through fourth columns present robustness analyses to assess the impact
of linking different types of observable heterogeneity to risk preferences. The table presents detailed
risk preference estimates, including the links to observable and unobservable heterogeneity. Since we
only use these parameters in the upcoming exchange equilibrium analyses (plus \( \sigma_\varepsilon \)), for simplicity
we present and discuss the rest of the estimated parameters in Appendix C (e.g., inertia estimates,
\( PPO_{1200} \) random coefficients, \( \varepsilon_{jkt} \) standard deviations, and income regressions). Parameter standard
errors, which are generally quite small, are also presented in Appendix D.

For the primary specification, the population mean for \( \mu_\gamma \), the household mean risk-aversion level
given unobserved heterogeneity, is \( 4.39 \times 10^{-4} \). The standard deviation for \( \mu_\gamma \) (or the standard deviation
in risk preferences based on observable heterogeneity) equals \( 6.63 \times 10^{-5} \). The standard deviation of
unobservable heterogeneity in risk preferences, \( \sigma_\gamma \), equals \( 1.24 \times 10^{-4} \). In terms of observable hetero-
geneity, risk preferences are negatively correlated with health risk: a one point increase in \( \log(\sum \lambda_i) \)
reduces \( \mu_\gamma \) by \( 8.10 \times 10^{-5} \) for a 30-year old. While a negative correlation between risk type and risk
aversion may suggest less adverse selection than under independent types, Veiga and Weyl (2014) show
the opposite is the case in our application. Using our simulated sample they compute the product of
risk aversion times the variance of the risk faced. Such product is the right measure of insurance value.
In our case, the correlation between insurance value and risk is positive, thus exacerbating adverse
selection. Managers and those with higher ability are slightly more risk averse. With a log expected

\footnote{The coefficient on health risk is more negative than this, while the interaction between age and risk preferences has
a positive coefficient, indicating some reduction in the negative relationship between risk preferences and health risk as
one becomes older.}
### Empirical Model Results

<table>
<thead>
<tr>
<th>Parameter / Model</th>
<th>Primary Model</th>
<th>Robustness 1</th>
<th>Robustness 2</th>
<th>Robustness 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Risk Preference Estimates</strong></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>(\mu_\gamma) - Intercept, (\beta_0)</td>
<td>1.21 (\times 10^{-3})</td>
<td>1.63 (\times 10^{-4})</td>
<td>1.06 (\times 10^{-3})</td>
<td>2.54 (\times 10^{-4})</td>
</tr>
<tr>
<td>(\mu_\gamma) - (\log(\Sigma_{ij} \lambda_i)), (\beta_1)</td>
<td>-1.14 (\times 10^{-4})</td>
<td>-</td>
<td>-1.21 (\times 10^{-4})</td>
<td>-</td>
</tr>
<tr>
<td>(\mu_\gamma) - age, (\beta_2)</td>
<td>-5.21 (\times 10^{-6})</td>
<td>3.60 (\times 10^{-6})</td>
<td>-4.69 (\times 10^{-6})</td>
<td>3.99 (\times 10^{-6})</td>
</tr>
<tr>
<td>(\mu_\gamma) - (\log(\Sigma_{ij} \lambda_i))*age, (\beta_3)</td>
<td>1.10 (\times 10^{-6})</td>
<td>-</td>
<td>1.01 (\times 10^{-6})</td>
<td>-</td>
</tr>
<tr>
<td>(\mu_\gamma) - Manager, (\beta_4)</td>
<td>4.3 (\times 10^{-5})</td>
<td>7.45 (\times 10^{-5})</td>
<td>5.3 (\times 10^{-5})</td>
<td>5.4 (\times 10^{-5})</td>
</tr>
<tr>
<td>(\mu_\gamma) - Manager ability, (\beta_5)</td>
<td>1.4 (\times 10^{-5})</td>
<td>4.49 (\times 10^{-5})</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(\mu_\gamma) - Non-manager ability , (\beta_6)</td>
<td>7.5 (\times 10^{-6})</td>
<td>3.24 (\times 10^{-5})</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(\mu_\gamma) - Nominal Income, (\beta_7)</td>
<td>-</td>
<td>-</td>
<td>3.0 (\times 10^{-5})</td>
<td>-</td>
</tr>
<tr>
<td>(\mu_\gamma) - Population Mean</td>
<td>4.39 (\times 10^{-4})</td>
<td>3.71 (\times 10^{-4})</td>
<td>4.33 (\times 10^{-4})</td>
<td>4.73 (\times 10^{-4})</td>
</tr>
<tr>
<td>(\mu_\gamma) - Population (\sigma)</td>
<td>6.63 (\times 10^{-5})</td>
<td>7.45 (\times 10^{-5})</td>
<td>8.27 (\times 10^{-5})</td>
<td>6.30 (\times 10^{-5})</td>
</tr>
<tr>
<td>(\sigma_\gamma) - (\gamma) standard deviation</td>
<td>1.24 (\times 10^{-4})</td>
<td>1.14 (\times 10^{-4})</td>
<td>1.40 (\times 10^{-4})</td>
<td>1.20 (\times 10^{-4})</td>
</tr>
</tbody>
</table>

Gamble Interp.:

\(\mu_\gamma\) Mean 693 728 696 676
\(\mu_\gamma\) Mean + 25th Quantile \(\sigma_\gamma\) 736 772 748 717
\(\mu_\gamma\) Mean + 75th Quantile \(\sigma_\gamma\) 653 688 651 640
\(\mu_\gamma\) Mean + 95th Quantile \(\sigma_\gamma\) 604 638 596 593

Table 2: This table presents the our choice model estimates. The first column presents the results from our primary specification described in Section 3. The second through fourth columns present robustness analyses that assess the impact of linking preferences to health status and our measure of income earning ability. For each model, we present the detailed risk preference estimates, including the links to observable and unobservable heterogeneity. The rest of the parameters (inertia estimates, \(PPO_{1200}\) random coefficients, and \(\varepsilon_{jkt}\) standard errors) are provided in Appendix C. The bottom of the table interprets the population mean risk preference estimates: it provides the value \(X\) that would make someone indifferent about accepting a 50-50 gamble where you win $1000 and lose \(X\) versus a status quo where nothing happens. The population distributions of risk preferences are similar across the specifications, even though the additional links between health risk / income and risk preferences add richness.
total health spending value of 9 (around the median for a household) risk aversion is increasing in age by $4.69 \times 10^{-6}$ per year. The specifications in the second through fourth columns in the table, which investigate robustness with respect to the inclusion of and specification for health status / ability in risk preferences, estimate similar means and variances for risk preferences relative to our primary specification. While the estimates in the literature span a wide range, and should be interpreted differently depending on the different contexts being studied, our estimates generally fall in the middle of the range of prior work on insurance choice, while the extent of heterogeneity we estimate is somewhat lower in magnitude [see, e.g., Cohen and Einav (2007)]. The negative estimated correlation between expected health risk and risk preferences is consistent with that association in Finkelstein and McGarry (2006) but the opposite sign of the effect found in Cohen and Einav (2007).

### 3.6 Simulation Sample

We estimate the choice model at the family level because that is the unit that actually makes choices in the data. For our counterfactual insurance exchange simulations, we focus on individuals to simplify exposition.

The sample used in the simulations contains individuals between the ages of 25 and 65. Thus, our simulations include both individuals with single coverage in the data, and individuals who are members of families with family coverage in our data. To ensure that the data for a given individual are complete, we require a given simulated individual to be present for at least eight months in each of two consecutive years. The data from the first year are used to predict health status while the presence in the second year is used to ensure the individual was a relevant potential participant in the firm’s benefit program for that year. This ensures that the simulation sample reflects to some extent the presence / longevity of the choice model estimation sample. For risk preferences, some of the variables used in estimation are defined at the family level rather than the individual level (e.g., ability, manager status of the employee in the family). Every individual that comes from a given family is assigned the relevant family value for these variables when simulating risk preferences for that individual in the exchange counterfactuals.

---

23The bottom rows in Table 2 interpret the mean of the average estimated risk aversion $\mu_\gamma$, as well as several quantiles surrounding that average $\mu_\gamma$. We present the value $X$ that would make a household with our candidate risk aversion estimate indifferent between inaction and accepting a simple hypothetical gamble with a 50% chance of gaining $1000 and a 50% chance of losing $X$. Thus, a risk neutral individual will have $X = $1000 while an infinitely risk averse individual will have $X$ close to zero. For the population mean of $\mu_\gamma$ from the primary model we have $X = $693 while for the 25th, 75th, and 95th quantiles of unobserved heterogeneity around that mean $X$ is $736$, $653$ and $604$ respectively (these values are decreasing because they decrease as $\gamma$ increases).

24For individuals whose past year of cost data is less than one year (between eight months and one year) we assume that this past data represents one full year of health claims for the purposes of constructing their health status $\lambda$. We assume in all of the simulations that individuals buy a plan expecting to be in that plan for the full year (this is not an issue in choice model estimation, where the sample is restricted to those present for full years). The cost model estimation is done only for individuals with full years of cost data and these full-year distributions are the ones used in our analysis.
Simulation Sample

<table>
<thead>
<tr>
<th></th>
<th>Simulation Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>N - Families</td>
<td>-</td>
</tr>
<tr>
<td>N - Individuals 25-65</td>
<td>10,372</td>
</tr>
<tr>
<td>Mean Age</td>
<td>44.5</td>
</tr>
<tr>
<td>Median Age</td>
<td>45</td>
</tr>
<tr>
<td>Gender (Male %)</td>
<td>45</td>
</tr>
</tbody>
</table>

**Income**

<table>
<thead>
<tr>
<th>Tier</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tier 1 ( &lt; $41K)</td>
<td>20%</td>
</tr>
<tr>
<td>Tier 2 ($41K-$72K)</td>
<td>40%</td>
</tr>
<tr>
<td>Tier 3 ($72K-$124K)</td>
<td>24%</td>
</tr>
<tr>
<td>Tier 4 ($124K-$176K)</td>
<td>8%</td>
</tr>
<tr>
<td>Tier 5 ( &gt; $176K)</td>
<td>8%</td>
</tr>
</tbody>
</table>

**Predicted Mean Total Expenditures**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>$6,559</td>
</tr>
<tr>
<td>25th quantile</td>
<td>$1,673</td>
</tr>
<tr>
<td>Median</td>
<td>$3,675</td>
</tr>
<tr>
<td>75th quantile</td>
<td>$8,354</td>
</tr>
<tr>
<td>90th quantile</td>
<td>$13,937</td>
</tr>
<tr>
<td>95th quantile</td>
<td>$18,638</td>
</tr>
<tr>
<td>99th quantile</td>
<td>$33,835</td>
</tr>
</tbody>
</table>

**Risk Preferences**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean $\mu_\gamma$</td>
<td>$4.28 \times 10^{-4}$</td>
</tr>
<tr>
<td>Standard Deviation $\mu_\gamma$</td>
<td>$7.50 \times 10^{-5}$</td>
</tr>
</tbody>
</table>

Table 3: This table presents descriptive statistics for the pseudo-sample of individuals used in our insurance exchange simulations. The sample has risk preference means and standard deviations that are similar to those of the choice model estimation sample. Moreover, the distributions of income and health status are similar to those in the estimation sample and general population.
Final Sample Total Health Expenditure Statistics

<table>
<thead>
<tr>
<th>Ages</th>
<th>Mean</th>
<th>S. D.</th>
<th>S. D. of mean</th>
<th>S. D. around mean</th>
<th>R</th>
<th>φ</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>6,123</td>
<td>13,859</td>
<td>6,798</td>
<td>9,228</td>
<td>31,369</td>
<td>0.24</td>
</tr>
<tr>
<td>25-30</td>
<td>3,112</td>
<td>9,069</td>
<td>4,918</td>
<td>5,017</td>
<td>26,429</td>
<td>0.29</td>
</tr>
<tr>
<td>30-35</td>
<td>3,766</td>
<td>10,186</td>
<td>5,473</td>
<td>5,806</td>
<td>27,550</td>
<td>0.29</td>
</tr>
<tr>
<td>35-40</td>
<td>4,219</td>
<td>10,753</td>
<td>5,304</td>
<td>6,751</td>
<td>27,407</td>
<td>0.24</td>
</tr>
<tr>
<td>40-45</td>
<td>5,076</td>
<td>12,008</td>
<td>5,942</td>
<td>7,789</td>
<td>28,407</td>
<td>0.25</td>
</tr>
<tr>
<td>45-50</td>
<td>6,37</td>
<td>14,095</td>
<td>6,874</td>
<td>9,670</td>
<td>31,149</td>
<td>0.24</td>
</tr>
<tr>
<td>50-55</td>
<td>7,394</td>
<td>15,315</td>
<td>7,116</td>
<td>11,092</td>
<td>31,722</td>
<td>0.22</td>
</tr>
<tr>
<td>55-60</td>
<td>9,175</td>
<td>17,165</td>
<td>7,414</td>
<td>13,393</td>
<td>32,113</td>
<td>0.19</td>
</tr>
<tr>
<td>60-65</td>
<td>10,236</td>
<td>18,057</td>
<td>7,619</td>
<td>14,366</td>
<td>31,854</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Table 4: Sample statistics for total health expenditures for (i) the entire sample used in our equilibrium analysis and (ii) 5-year age buckets within that sample.

Table 3 describes some key descriptive numbers for this pseudo-sample of 10,372 individuals used for the insurance exchange simulations. Importantly, the distributions of income and health expenditures are similar to those of the main estimation sample and the population overall. The proportion female is also similar. Finally, as shown below, the simulation sample covers the range of ages from 25-65 fairly evenly, which is reflective of this characteristic in our data in general. This is relevant to our upcoming welfare analysis, which assumes that the population is in a steady state.

<table>
<thead>
<tr>
<th>Quantile</th>
<th>0.05</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
<th>0.95</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>26</td>
<td>28</td>
<td>33</td>
<td>37</td>
<td>41</td>
<td>45</td>
<td>49</td>
<td>52</td>
<td>56</td>
<td>60</td>
<td>62</td>
</tr>
</tbody>
</table>

Table 4 shows the distribution of expenses for the simulation sample. The first two columns show the mean and standard deviation of expenditure by age group. The next column represents the standard deviation within each group of the expected expenditure, followed by the standard deviation of expenses around the expectation. The last two columns show what we denoted as $R$ and $\phi$ in section 2.2. $R$ is defined as the variance of health expenses divided by the mean expenses, while $\phi$ represents the proportion of the variance of expenses that is revealed prior to contracting, namely, that is known at the time of purchasing coverage. Interestingly, $\phi$ decreases in age. Namely, unlike what one might expect, a lower proportion of the uncertainty is revealed prior to contracting for older groups. Moreover, the majority of the variance in expenses remains to be resolved after contracting.

The sample should be representative of the population likely to participate in private exchanges, namely, working age employed individuals.
4 Equilibrium Effects of Risk-Rating

We use the estimates from our choice and cost models to study the effects of pricing and contract regulations. As in Section 2, we study exchanges in which insurers can offer one of two policies. We assume the two policies cover either 90% or 60% of expenditures in the population, on average. While there are a variety of potential non-linear contract designs that would imply these coverage levels, following the discussion of such policies in Consumers Union (2009) we assume that the 90% policy has no deductible, a 20% coinsurance rate post-deductible, and a $1500 out-of-pocket maximum (all at the individual level we study here) while the 60% policy has a $3,000 deductible, a 20% coinsurance rate post-deductible, and a $5,950 out-of-pocket maximum. In section 6 we study other contract configurations.

The estimated model contains three sources of heterogeneity that we use in this analysis: risk type, risk aversion, and an idiosyncratic preference shock. For each individual in the population we compute, based on their demographics and prior diagnostics, the risk type \( \lambda \) discussed in the previous section. For a given \( \lambda \), we take 100 draws from the estimated distribution of \( \gamma \) (conditional on \( \lambda \) and the other demographics modeled in equation (5)), creating 100 “pseudo-individuals” for each actual individual in our sample. Doing so generates a joint distribution of risk preferences and risk type. For each of the two plan designs we compute the distribution of out-of-pocket expenses \( H_k(\cdot|\lambda_{it}, Z_{it}) \). With these objects, we compute the expected utility of each (pseudo) individual for each plan, and use them to find \( CE_{90} \) and \( CE_{60} \) (gross of premiums), as described in Section 2. Willingness to pay for the extra coverage of the 90% plan is \( \theta = CE_{90} - CE_{60} + \varepsilon \), where \( \varepsilon \) is distributed \( N(0, \sigma^2_\varepsilon) \). Thus, as in equation (3), there is a random shock to a consumer’s preference between the two plans. For the simulations that follow we use \( \sigma_\varepsilon = 525 \), which is the estimated standard deviation of \( \varepsilon \) for the single population for PPO\(_{1200}\) relative to PPO\(_{250}\). As we report below, our results are robust to medium-sized changes in \( \sigma_\varepsilon \).

The sample population and the estimated distributions determine \( F(\theta) \). Costs to each plan \( k \), \( C_k(\theta) \) for \( k = 90 \) and \( 60 \), are computed using expected plan costs \( \lambda_{it} - E[H_k(\cdot|\lambda_{it}, Z_{it})] \), aggregating over all individuals associated with each \( \theta \), while \( AC_{90}(\theta) \) and \( AC_{60}(\theta) \) are determined by aggregating these costs over the \( \theta \) that select a given plan.

The Adverse Selection Property introduced in Section 2, upon which our theoretical results hinge, can be verified in our sample: Figure 6 shows that \( AC_{90} \) and \( AC_{60} \) are increasing in \( \Delta P \) for each policy, and that \( AC_{90} \) exceeds \( AC_{60} \) at all \( \Delta P \).

4.1 Pure community Rating

We start by considering the case of pure community rating, where insurers must price everyone in the whole population identically. We follow the theoretical results of Section 2 as a roadmap to finding equilibria.
Figure 6: Plot of average costs vs. the price difference $\Delta P$. Average costs are increasing in this price difference, and are larger for the 90 policy at each $\Delta P$, consistent with the Adverse Selection Property maintained to derive our theoretical results.

The first step towards finding equilibria involves checking whether all consumers pooling in the 90 plan is an equilibrium. Figure 7, which plots $\Delta AC(\Delta P)$, shows that $\Delta AC(\theta) > \theta$ which guarantees that there is a profitable cream skimming deviation from all-in-90 that attracts the healthiest customers to the 60 policy. Thus, in our population all-in-90 is not an equilibrium. The equilibrium must involve purchases of the 60 policy.

The second step towards finding equilibrium involves finding the lowest break-even $\Delta P$, $\Delta P^{BE}$; i.e., the lowest interior $\Delta P$ at which $\Delta P = AC_{90}(\Delta P) - AC_{60}(\Delta P)$, if any exist, or $\Delta P = \theta$ otherwise. This is then the RE $\Delta P$.

Figure 7 shows that, for the case of pure community rating, there is no interior equilibrium. Namely, there is no pair of premiums at which both policies have positive market shares and both break even: for any premium gap between 60 and 90 coverage, the gap in average costs is larger than the gap in premiums. The market must fully unravel. Thus, by Proposition 1 all-in-60 must be the RE.

All-in-60 is not a Nash Equilibrium, a 90 deviation in conjunction with an $\varepsilon$ reduction of $P_{60}$ is profitable.\textsuperscript{25} The top section of Table 5 summarizes these findings for the case of a pure community rating pricing regulation.

\textsuperscript{25}The deviation is profitable in every all-in-60 RE reported throughout in the paper. The appendix discusses Nash equilibria when frims offer single policies (sp-NE). All the RE we found are sp-NE (they need not be, as the existence of of sp-NE unlike RE, is not guaranteed).
Figure 7: Plot of the average cost difference ΔAC(ΔP) and the price difference ΔP.

<table>
<thead>
<tr>
<th>Equilibrium Type</th>
<th>P_{60}</th>
<th>S_{60}</th>
<th>AC_{60}</th>
<th>P_{90}</th>
<th>S_{90}</th>
<th>AC_{90}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Riley</td>
<td>4,051</td>
<td>100.0</td>
<td>4,051</td>
<td>-</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Nash</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Does not exist</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Market</th>
<th>Equilibrium Type</th>
<th>P_{60}</th>
<th>S_{60}</th>
<th>AC_{60}</th>
<th>P_{90}</th>
<th>S_{90}</th>
<th>AC_{90}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quartile 1</td>
<td>RE/NE</td>
<td>289</td>
<td>64.8</td>
<td>289</td>
<td>1,550</td>
<td>35.2</td>
<td>1,550</td>
</tr>
<tr>
<td>Quartile 2</td>
<td>RE</td>
<td>1,467</td>
<td>100.0</td>
<td>1,467</td>
<td>-</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Quartile 3</td>
<td>RE</td>
<td>4,577</td>
<td>100.0</td>
<td>4,577</td>
<td>-</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Quartile 4</td>
<td>RE</td>
<td>9,802</td>
<td>100.0</td>
<td>9,802</td>
<td>-</td>
<td>0</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 5: The top section of this table presents the equilibrium results for the case of pure community rating (no pricing of pre-existing conditions). The bottom section presents the equilibrium results for the case where insurers can price based on health status information in the form of health status quartiles. The equilibrium results are presented for each health status quartile, which act as separate markets under this regulation.
4.2 Health Based Pricing

We now investigate the effects of allowing pricing of some health status information. Specifically, we first consider the case in which consumers are classified into quartiles based on their ex ante predicted total expenditures $\lambda$: e.g., the first quartile contains the healthiest consumers, while the last contains the sickest consumers. Insurers can target each quartile with different prices as they see fit. We later present results that vary the fineness of information insurers can price on, ranging from pure community rating all the way up to the case of unrestricted risk rating / price discrimination. These stylized regulations are meant to be illustrative of potentially more subtle regulations seen in real-world insurance markets that vary the ability of insurers to price discriminate (e.g., health based pricing). We follow the same steps as in the previous subsection to find equilibria, but now for each market segment separately.

The implications of this pricing regulation for adverse selection are seen directly when examining the pricing equilibrium for quartile 1, the healthiest quartile of consumers. For quartile 1, there is an interior equilibrium. The first step, as described above, is to check whether all-in-90 is an equilibrium. Figure 8 shows that, as in the pure community rating case, $\Delta AC(\theta) > \theta$, implying that all-in-90 is not an equilibrium.

The second step is to look for interior equilibrium candidates. Figure 8 shows two interior break-even $\Delta P$s. By Proposition 1 the lowest $\Delta P$, the one with the largest share of customers in the 90 policy, is the RE.

In contrast, equilibria in quartiles 2, 3 and 4 are qualitatively identical to the equilibrium under pure community rating. We omit the graphs, which look similar to Figure 7. The bottom section of
Table 5 summarizes the findings for the four quartiles under health status-based pricing. The table also highlights the potential for reclassification risk when moving from the static equilibrium analysis to the analysis of long-run consumer welfare: if insurers can price based on health status quartiles, buyers will find themselves paying premiums as low as $289 or as high as $9,802, corresponding to the different quartiles, as their health evolves over time. However, under these pricing regulations, many of the healthiest consumers in the population obtain a greater level of insurance coverage, and thus are less impacted by adverse selection.

To more completely analyze the trade-off between adverse selection and re-classification risk, we next consider a range of pricing regulations that allow insurers to price based on health status information with varying degrees of specificity. The second column in Table 6 describes the RE share in the 60 policy when insurers instead can price based on 2, 4, 6, 8, 10, 20, or 50 health status partitions, as well as the case of full risk-rating (labeled ∞). Adverse selection is reduced as the insurers are able to price on finer information: with 4, 10, and 50 partitions the 60 plan has 90%, 83%, and 63% market shares respectively, while with full risk-rating 73% of consumers choose to enroll in the 90 plan.26 (The welfare numbers in columns 3-5 of Table 6 will be discussed in Section 5.)

5 Welfare Effects

Our aim in this section is to evaluate the expected utility of an individual starting at age 25 from an ex-ante (“unborn”) perspective; that is, before he knows the evolution of his health. The unborn individual faces uncertainty about how his health status will transition from one year to the next, and thus what policies he will purchase and what premiums he will pay. Since individuals differ in their risk aversion, we will calculate this expected utility separately for different risk aversion levels.

To be more specific, for any pricing rule $x$ (e.g., pure community rating) the analysis in the previous section tells us what policy each individual will choose as a function of their health status ($\lambda$) and risk aversion ($\gamma$), and the premium they will pay. Given this information, we can compute the certainty equivalent $CE_x(\lambda, \gamma)$ of the uncertain consumption that this individual of type $(\lambda, \gamma)$ will face within a year because of uncertainty over his health realization.

To measure the welfare difference for an individual with age-25 risk aversion level $\gamma$ between any two regimes $x$ and $x'$, we define the fixed yearly payment $y_{x,x'}(\gamma)$ added to income in regime $x$ that makes the individual have the same expected utility starting at age 25 under regime $x$ and as under regime $x'$:

$$\sum_{t=25}^{65} \delta^t E[-e^{-\gamma(I_t - CE_x(\lambda_t, \gamma) + y_{x,x'}(\gamma))}] = \sum_{t=25}^{65} \delta^t E[-e^{-\gamma(I_t - CE_{x'}(\lambda_t, \gamma))}],$$

26 With no $\varepsilon$ preference shock, with full risk-rating all consumers would enroll in the 90% plan. Here, with the estimated $\varepsilon$ standard deviation incorporated, the first-best allocation has 73% of consumers in the 90% plan, since some prefer the 60% plan due to this preference shock.
### Equilibria Welfare Loss from Health Status-based Pricing: Varying Regulation

<table>
<thead>
<tr>
<th># of Health Buckets</th>
<th>$S_{60}$</th>
<th>Fixed Income</th>
<th>Non-Manager Income path</th>
<th>Manager Income Path</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>100.0</td>
<td>1,920</td>
<td>710</td>
<td>-102</td>
</tr>
<tr>
<td>4</td>
<td>90.0</td>
<td>3,082</td>
<td>1,821</td>
<td>-886</td>
</tr>
<tr>
<td>6</td>
<td>82.0</td>
<td>3,951</td>
<td>2,377</td>
<td>-232</td>
</tr>
<tr>
<td>8</td>
<td>85.1</td>
<td>4,649</td>
<td>2,084</td>
<td>-1,510</td>
</tr>
<tr>
<td>10</td>
<td>83.2</td>
<td>5,357</td>
<td>2,269</td>
<td>-1,364</td>
</tr>
<tr>
<td>20</td>
<td>81.4</td>
<td>8,590</td>
<td>4,621</td>
<td>-393</td>
</tr>
<tr>
<td>50</td>
<td>63.2</td>
<td>11,578</td>
<td>7,302</td>
<td>2,359</td>
</tr>
<tr>
<td>$\infty$</td>
<td>27.0</td>
<td>14,733</td>
<td>9,944</td>
<td>2,399</td>
</tr>
</tbody>
</table>

Table 6: Equilibria and long-run welfare comparison between the pricing regulations that allow some pricing based on health status and the case where no pricing on health status is allowed. The table shows the share of consumers choosing the 60 policy for each pricing regime. It also presents the values for $y_{HBx,PCR}$, the annual payment required under regulation that allows pricing of $x$ evenly sized health risk buckets that makes consumers indifferent between that regulation and the case of purecommunity rating ($PCR$). The regimes $x$ listed in column 1 correspond to how targeted pricing can be over the range of health status: e.g., 4 corresponds to the case of quartile pricing while $\infty$ is full risk rating. The results presented are for Riley Equilibria and $\gamma = 0.0004$. 


Table 7: Average costs as a function of age 25 risk preferences. Following the choice model estimates, costs are negatively related to risk aversion conditional on age.

<table>
<thead>
<tr>
<th>γ</th>
<th>30-35</th>
<th>45-50</th>
<th>55-60</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0002</td>
<td>5,586</td>
<td>7,196</td>
<td>10,857</td>
</tr>
<tr>
<td>0.0003</td>
<td>4,212</td>
<td>6,390</td>
<td>10,319</td>
</tr>
<tr>
<td>0.0004</td>
<td>3,100</td>
<td>5,687</td>
<td>9,767</td>
</tr>
<tr>
<td>0.0005</td>
<td>2,328</td>
<td>4,911</td>
<td>9,271</td>
</tr>
<tr>
<td>0.0006</td>
<td>1,775</td>
<td>4,373</td>
<td>8,813</td>
</tr>
</tbody>
</table>

To compute expected utility starting at age 25 from an ex ante perspective, we need to know how health status will transition over time for an individual with a given risk aversion $\gamma$ at age 25. If risk was independent of risk aversion the computation would be straightforward. The observed health realization of the whole population (at different ages) would be representative of the expected realization of any individual as he ages. Assuming that our sample represents a steady state population we would just draw from the realized cost distribution to capture the ex-ante distribution that any (unborn) individual faces.\(^27\)

However, our estimates imply that health and risk aversion are correlated, with more risk averse individuals being healthier on average. Table 7 shows for various risk aversion levels $\gamma$ the average costs of the individuals selected in this manner at ages 25-30, 45-50, and 60-65. The pattern of costs reflects the positive correlation between health status and risk aversion, as well as the attenuation of this positive relationship with increases in age. The correlation makes the population as a whole not representative of the health costs faced by individuals after they draw their own $\gamma$.

To identify the stochastic health outcomes a 25-year old with a given risk aversion $\gamma$ foresees at any given future age $t$, we isolate those individuals in our simulation sample of age $t$ whose risk-aversion $\gamma_t$ falls into a band around the level expected based on our estimates of equation (5), for individuals with risk aversion level $\gamma$ at age 25.\(^28\) For a given discount factor $\delta \leq 1$ and regime $x$, we calculate $\sum_{t} e^{-\gamma_t}E[-e^{-\gamma(I_t-C_{E_x}(\lambda_t,\gamma))}]$ as follows: first, we generate the value of $e^{-\gamma(I_t-C_{E_x}(\lambda_t,\gamma))}$ that each individual of age $t$ in the band associated with $\gamma$ would have if he chose between the 60 and 90 policies facing the equilibrium prices in regime $x$ and having risk aversion parameter $\gamma$.\(^29\) The income level $I_t$ is either held fixed (in which case, with CARA preferences, its level doesn’t matter) or comes from

\(^{27}\)Recall that the age distribution in our sample is close to uniform, as it should be in a steady state population.
\(^{28}\)We use a band radius of 0.00005.
\(^{29}\)Thus, we evaluate the welfare of an individual who at age 25 does not foresee his risk aversion changing.
Table 8: Long-run welfare comparison between the two pricing regulations of (i) pricing based on health status quartiles \( (x = "HB_4") \) and (ii) pure community rating \( (x' = "PCR") \). The table presents the values for \( y_{HB_4,PCR}(\gamma) \), the annual payment required under regime \( HB_4 \) to make consumers indifferent between \( HB_4 \) and \( PCR \). The results presented are based on the RE and sp-NE equilibria outcomes presented in Table 5. We present results for the differing cases of (i) “fixed income” (ii) “income path” for non-managers and (iii) “income path” for managers. The assumed discount rate is \( \delta = 0.975 \).

\[
E_{x_t}[-e^{-\gamma \{I_t-Cx_t(\lambda_t,\gamma)\}}] = \frac{\sum_{t=1}^{\infty} e^{-\delta t} E_{x_t}[-e^{-\gamma \{I_t-Cx_t(\lambda_t,\gamma)\}}]}{1-e^{-\delta}}.
\]

We proceed similarly for regime \( x' \).

We first compare two regimes: ACG-quartile pricing and pure community rating. The latter eliminates reclassification risk but exacerbates adverse selection. Health status-based pricing also involves some inter-temporal redistribution, as the young tend to face lower premiums. To the extent that this regime smooths consumption over time (given the fact that income generally rises with age), this creates some welfare gain as well if agents cannot otherwise borrow to smooth their consumption over time.

Table 8 shows the values of \( y_{x,x'}(\gamma) \) comparing pricing based on ACG-quartiles \( (x = "HB_4") \) and community rating \( (x' = "PCR") \). We take \( \delta = 0.975 \). Since we do not know the extent to which agents are able to borrow to smooth their consumption, we compute welfare both assuming that income is fixed over time (perfect smoothing) and assuming they cannot borrow at all.\(^{31}\) In the latter case we provide a calculation separately for managers and non-managers, whose expected incomes differ at each age.

With a fixed income, the welfare gains from eliminating reclassification through community rating

---

\(^{30}\)For managers, the mean income level \( I_t \) starts near income tier 1 at age 25 ($0-$40,000) and is near tier 4 at age 65 ($124,000-$176,000). Maximum income for managers occurs at age 66. For non-managers, mean income also starts near income tier 1 at age 25 and is halfway between tiers 2 ($40,000-$80,000) and 3 ($80,000-$124,000) at age 65. Income peaks at age 56 for non-managers, with an average near income tier 3. See the discussion of the estimates of equation (6) in Appendix C for more details.

\(^{31}\)Our calculations do not, however, consider any gains from self-insurance through precautionary saving.
greatly exceed any losses this rule introduces due to adverse selection. The loss from health-based pricing on quartiles ranges from $2,220 to $3,626 per year depending on risk aversion level. Losses are larger for those with greater risk aversion. The annual loss with health status quartile pricing at a risk aversion level of 0.0004, approximately the mean in our sample, is $3,082, which is about 47% of the size of the $6,559 annual average total expenses in the population (see Table 3 in Section 3). We can compare this to the welfare implications of just adverse selection: with fixed income and risk aversion 0.0004 a consumer would be willing to pay $619 per year to face a regime in which everyone receives the 90 policy at price $P_{90} = \overline{AC}_{90}$ rather than the community rating regime in which pre-existing conditions cannot be priced and everyone ends up buying the 60 policy at price $P_{60} = \overline{AC}_{60}$. Thus, the welfare loss from reclassification risk is at least 5 times as large as the welfare loss from adverse selection under pure community rating.\footnote{The range of CARA risk aversion levels we estimated can imply implausible levels of risk aversion when evaluating the scaled up monetary amounts entailed in the premium risk [see, e.g., Rabin (2000)]. To address this issue we compute long-run welfare under a range of CRRA coefficients. The macroeconomics literature has considered a range of CRRA coefficients from 1 up to 10. For a fixed $75,000 income an individual with a CRRA coefficient of 6.5 is indifferent between the community rating and health status quartile regimes.

When individuals cannot borrow, health-based pricing confers an additional benefit by moving consumption forward in life. For non-managers the losses from health-based pricing now range from $1,499 to $2,115 per year. For managers, however, whose income is higher and rises more steeply with age (see footnote 37), and therefore benefit more from moving consumption forward in time, health-based pricing is actually preferred to community rating. For this group, the benefits of smoothing income over time outweigh the costs of reclassification risk.

We revisit Table 6 to examine the welfare implications of varying the extent to which insurers can price health status information. Columns 3-5 illustrate the impact of finer pricing on long-run welfare. With fixed income (column 3), and for non-managers’ income paths (column 4), the welfare loss from increased reclassification risk swamps the welfare gain from reduced adverse selection: the welfare loss from pricing 20 health status categories is almost 3 times that from pricing quartiles. For managers’ income paths the effect is not monotone, because of the benefits of income smoothing, but fine enough pricing does lead to a welfare loss relative to community rating (e.g., with 50 health status groups). Overall, the results highlight the trade-off between adverse selection and reclassification risk, and suggest that reclassification risk is likely to be more important from a welfare perspective.\footnote{In addition to considering the fixed income case here, in the next section we consider the same comparison between community rating and pricing based on health status when there is also age-based pricing which eliminates the intertemporal consumption-shifting effect of health status-based pricing. When we do so, managers also prefer community rating.}
Equilibrium for Alternative Insurance Contract Designs

<table>
<thead>
<tr>
<th>Contracts</th>
<th>90% and 80%</th>
<th>90% and 40%</th>
<th>90% and 20%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P_{90}$</td>
<td>$S_{80}$</td>
<td>$P_{90}$</td>
</tr>
<tr>
<td>All</td>
<td>- 4800</td>
<td>100</td>
<td>- 2413</td>
</tr>
<tr>
<td>Q1</td>
<td>1434</td>
<td>652</td>
<td>71</td>
</tr>
<tr>
<td>Q2</td>
<td>- 2114</td>
<td>100</td>
<td>2855</td>
</tr>
<tr>
<td>Q3</td>
<td>- 5491</td>
<td>100</td>
<td>7519</td>
</tr>
<tr>
<td>Q4</td>
<td>- 10945</td>
<td>100</td>
<td>- 6224</td>
</tr>
</tbody>
</table>

Table 9: RE results for pricing regulations that allow insurers to price based on health status quartiles and age for a range of actuarial contract values allowed in the marketplace by the regulator.

6 Alternative Contracts and Contract Design

So far we have studied pricing regulation for a given set of contracts. Exchange designers regulate contract configuration. In this section we study how equilibria, specifically the extent of adverse selection and the trade off with reclassification risk, is affected by the contracts offered in the exchange. In addition, we study how price regulation interacts with contract design.

Table 9 shows equilibria for three different contract configurations. We hold the high coverage contract at an actuarial value of 90, and set the low coverage contract at 80, 40 and 20, respectively.

Consider first pure community rating. Under both the 90-80 and 90-40 configurations, community rating results in full unravelling just as it does for 90-60. However, under 90-20 less than a third of the market ends up with the lower coverage. The unattractiveness of the low option pushes more consumers to purchase 90, making it cheaper, spiraling into a high share of high coverage. The welfare consequence of having a less attractive low contract is not immediate. While over 70% of the population end up with high coverage, the rest has very little coverage.

The top row in each sub-section of Table 10 shows welfare numbers under community rating, relative to all-in-60 (the RE under pure community rating in the 90-60 configuration) for each pair of alternative contracts. Consider first pure community rating under fixed income. Namely, it compares ex-ante welfare relative to the equilibrium of community rating pricing in the configuration 90-60. Naturally, welfare for fixed income pooling in 80 is better than pooling in 60 ($278 better), which in turn is $4472 better than pooling in 40. More interestingly, the Riley equilibrium in the 90-20 configuration, while $3900 (=4472-572) better than pooling in 40, is $572 worse than pooling in 60. Trade increases quite a bit by lowering the minimal coverage from 60 to 20, but welfare goes down.

From the community rating row we also see, that mangers (who have a steeper income growth) may prefer to pool at 60 rather than at 80. Moreover, they also dislike less pooling at 40 (relative to pooling in 60). This is due to their preference for lower payments while young. In addition, only managers prefer the RE in 90-20, over pooling in 60.
Next we look at the impact of allowing health based pricing for different contract configurations. The first column of each configuration shows the market share of low coverage in each pricing regime. While it takes a lot of discrimination to get anyone in the 90 policy under the 90-80 configuration (with 50 categories only 15% of the population gets high coverage), in the 90-40 configuration even health quartile pricing gets more than 54% of consumers to chose the 90 policy. However, as trade increases with more partitions only managers benefit. Namely, if income growth is not steep, the gains from reducing adverse selection are smaller than the losses from reclassification risk. Even for managers, the gains are limited to few classes. That is, a lot of discrimination is disliked even by managers.

7 Extensions

7.1 Age-Based Pricing

Age-based pricing is one of the few exceptions to pure community rating typically allowed by health insurance regulation. In this section, we use our framework to study whether age-based pricing reduces adverse selection, and how the presence of age-based pricing affects the welfare impact of allowing health based pricing. For a further investigation of age-based pricing regulation see e.g. Ericson and Starc (2013).

We group consumers into five-year age bins as usually done in practice, for example in the Massachusetts connector. Table 4 (in Section 3) describes each age bucket. The first column shows mean total medical expenses by age in our sample: those age 30-35 have a mean of $3,766 while those age 60-65 have a mean of $10,236.

We study whether age-based pricing ameliorates the extent of adverse selection. As we saw in the previous section, by allowing some health status based pricing, additional trade was generated for the healthiest quartile of the population. Age — as shown in column 1 — is a proxy for health type, and may enable more trade in equilibrium.

Surprisingly perhaps, allowing for age-based pricing does not prevent full unraveling. For each age group, the Riley equilibrium involves all-in-60. Age-based pricing undoes some of the transfers from the younger, healthier age groups to the older groups that occur in pure community rating. However, the distributions of health risk still have substantial enough tails even for the younger age group that full unraveling occurs in equilibrium.34

Finally, we consider the simultaneous pricing of age and health status. The exercise is interesting for at least two reasons. First, pricing may have a different impact on equilibrium in a more homogenous population, grouped by age, than it has in the whole population. Second, when evaluating the welfare

34We note that these results are robust to medium-sized changes in $\sigma_\varepsilon$, even though this shock to preferences introduces a source of willingness to pay for coverage unrelated to risk type. As we increase the standard deviation of this shock, equilibria by age and for the whole population still involve unravelling to all-in-60. A $\sigma_\varepsilon$ over 2,000 is required for some sub-markets to not fully unravel.
<table>
<thead>
<tr>
<th># of Health Buckets</th>
<th>( S_{40} )</th>
<th>Fixed Income</th>
<th>Non-Manager Income path</th>
<th>Manager Income Path</th>
</tr>
</thead>
<tbody>
<tr>
<td>Community Rating</td>
<td>100.0</td>
<td>-278</td>
<td>-83</td>
<td>194</td>
</tr>
<tr>
<td>4</td>
<td>92.2</td>
<td>3,265</td>
<td>1,987</td>
<td>-896</td>
</tr>
<tr>
<td>10</td>
<td>90.8</td>
<td>5,585</td>
<td>2,974</td>
<td>-1,343</td>
</tr>
<tr>
<td>20</td>
<td>87.4</td>
<td>8,920</td>
<td>5,280</td>
<td>-491</td>
</tr>
<tr>
<td>50</td>
<td>85.1</td>
<td>11,895</td>
<td>7,409</td>
<td>2,323</td>
</tr>
<tr>
<td>500 (( \infty ))</td>
<td>0</td>
<td>15,295</td>
<td>12,066</td>
<td>4,698</td>
</tr>
</tbody>
</table>

**90% and 40%**

<table>
<thead>
<tr>
<th># of Health Buckets</th>
<th>( S_{40} )</th>
<th>Fixed Income</th>
<th>Non-Manager Income path</th>
<th>Manager Income Path</th>
</tr>
</thead>
<tbody>
<tr>
<td>Community Rating</td>
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<td>4,472</td>
<td>3,243</td>
<td>2,098</td>
</tr>
<tr>
<td>4</td>
<td>45.2</td>
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<td>4,790</td>
<td>953</td>
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<tr>
<td>10</td>
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<td>429</td>
</tr>
<tr>
<td>20</td>
<td>32.8</td>
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<td>7,396</td>
<td>1,538</td>
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<tr>
<td>50</td>
<td>36.6</td>
<td>14,010</td>
<td>9,491</td>
<td>4,247</td>
</tr>
<tr>
<td>500 (( \infty ))</td>
<td>0</td>
<td>15,295</td>
<td>12,066</td>
<td>4,698</td>
</tr>
</tbody>
</table>

**90% and 20%**

<table>
<thead>
<tr>
<th># of Health Buckets</th>
<th>( S_{20} )</th>
<th>Fixed Income</th>
<th>Non-Manager Income path</th>
<th>Manager Income Path</th>
</tr>
</thead>
<tbody>
<tr>
<td>Community Rating</td>
<td>28.0</td>
<td>572</td>
<td>573</td>
<td>-45</td>
</tr>
<tr>
<td>4</td>
<td>11.8</td>
<td>3,635</td>
<td>2,404</td>
<td>-487</td>
</tr>
<tr>
<td>10</td>
<td>18.3</td>
<td>14,885</td>
<td>11,355</td>
<td>3,487</td>
</tr>
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<td>6,075</td>
</tr>
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<td>50</td>
<td>12.4</td>
<td>19,399</td>
<td>14,715</td>
<td>9,957</td>
</tr>
<tr>
<td>500 (( \infty ))</td>
<td>0</td>
<td>15,295</td>
<td>12,066</td>
<td>4,698</td>
</tr>
</tbody>
</table>

Table 10: Equilibria and long-run welfare comparison between health-based pricing and pure community rating for three alternative pairs of contracts (differentiated by actuarial value) that the regulator allows insurers to offer. The welfare numbers presented are the yearly values that make a consumer indifferent between the contract / price regulatory regime and the baseline case of community rating where 90% and 60% contracts can be offered.
Joint Health Status Quartile and Age Pricing Regulation: Equilibrium Results

<table>
<thead>
<tr>
<th>Ages</th>
<th>S90</th>
<th>P60</th>
<th>P90</th>
<th>S90</th>
<th>P60</th>
<th>P90</th>
<th>S90</th>
<th>P60</th>
<th>S90</th>
<th>P60</th>
<th>S90</th>
</tr>
</thead>
<tbody>
<tr>
<td>25-30</td>
<td>63</td>
<td>126</td>
<td>616</td>
<td>25</td>
<td>375</td>
<td>1,935</td>
<td>0</td>
<td>930</td>
<td>0</td>
<td>5,520</td>
<td>22</td>
</tr>
<tr>
<td>30-35</td>
<td>63</td>
<td>156</td>
<td>676</td>
<td>42</td>
<td>337</td>
<td>1,597</td>
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<td>1,411</td>
<td>0</td>
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<td>26</td>
</tr>
<tr>
<td>35-40</td>
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<td>966</td>
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<td>1,867</td>
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<td>25</td>
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<td>40-45</td>
<td>38</td>
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<td>0</td>
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<td>0</td>
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<td>0</td>
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<td>10</td>
</tr>
<tr>
<td>45-50</td>
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<td>1,592</td>
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<td>1,574</td>
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<td>3,891</td>
<td>0</td>
<td>10,138</td>
<td>20</td>
</tr>
<tr>
<td>50-55</td>
<td>27</td>
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<td>2,936</td>
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<td>2,304</td>
<td>-</td>
<td>0</td>
<td>5,847</td>
<td>0</td>
<td>10,858</td>
<td>7</td>
</tr>
<tr>
<td>55-60</td>
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<td>1,477</td>
<td>3,617</td>
<td>0</td>
<td>5,159</td>
<td>-</td>
<td>0</td>
<td>6,733</td>
<td>0</td>
<td>11,702</td>
<td>8</td>
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<tr>
<td>60-65</td>
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<td>8,700</td>
<td>0</td>
<td>5,824</td>
<td>-</td>
<td>0</td>
<td>7,666</td>
<td>0</td>
<td>13,321</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 11: RE equilibrium results for pricing regulation that allows insurers to price based on health status quartiles and age.

Impact of health status-based pricing, age-based pricing may neutralize the benefits associated with consumption smoothing, by reducing the transfer from young to old that health status-based pricing otherwise induces.

Table 11 shows the equilibrium when insurers can separate each age group into health status quartiles. Unlike pure age-based pricing which involved full unraveling to all-in-60 for every age group, we now have a positive share in 90 for all of the healthiest quartiles except in the oldest cohort, as well as for the second quartile for the younger groups. The interaction of age and health based pricing thus reduces adverse selection, relative to each priced separately. Table 12 shows the compensation required to make an individual indifferent between a regime with health status quartile pricing for each age group, and another in which all individuals in each age band receive the 60 policy at its average cost for their age band. Once age is priced, health status-based pricing, which appealed to individuals with steeply increasing income, is no longer preferred by those consumers. The benefit of health status-based pricing is the reduction in adverse selection, and the postponement of premiums until later in life. With age-based pricing, the latter benefit is eliminated. The cost associated with reclassification risk then dominates the benefits of reducing adverse selection.

### 7.2 Participation

For all the equilibrium analysis so far we assumed full participation, for example, employers forcing all workers to remain in the pool. It is plausible that certain individuals, especially healthy ones, may prefer to opt out.

To understand the role of the mandate we allow individuals to opt out of the exchanges should their expected utility from being uninsured be higher than joining their favorite insurance plan in the
Table 12: Long-run welfare comparison between the two pricing regulations of (i) pricing based on health status quartiles by age ($x = "HB 4+ age") and (ii) pricing based on just age ($x' = "age")). The results presented are based on the RE outcomes for each of the two pricing regulations. As before, the assumed discount rate is $\delta = 0.975$.

market. Uninsured means that the consumer pays zero premium and pays for the total cost of their health expenses. We again focus on the case of a 90 policy and a 60 policy. We find equilibria allowing individuals to opt out without penalty.\footnote{More concretely, we find the equilibrium with the mandate, and eliminate from the sample those individuals that are better off uninsured. We then iterate finding equilibria and eliminating the worse off consumers, until all buyers want to remain in the market.}

Recall that equilibria without age-based pricing unravelled to all-in-60. The column “Better-off In” in the “Community Rating” section of Table 13 shows the percentage of each age group (and of the population as a whole) that is better off insured at the equilibrium premium of $4,068 than remaining uninsured. For example, 44.2\% ($= 100 - 55.8$) of 25 to 30 year old individuals prefer to opt out as their expected utility from non-insurance is higher than being pooled with the whole population.

Naturally, those that prefer to opt out are younger, healthier and less risk averse. The expected costs of insuring consumers who prefer to decline coverage is $3,107 versus $5,107 for those that prefer to participate. The average risk aversion coefficient of those that prefer to participate is $4.26 \times 10^{-4}$ versus $4.03 \times 10^{-4}$ for those that prefer to decline coverage.

Allowing healthier individuals to opt out increases the cost of covering the remaining pool, which in turn draws more people out of the pool. The process stops at a premium of $5,339 when no more individuals want to drop out. At that premium there are no profitable single-policy Nash deviations in 60 or 90 to draw buyers back in. Thus, a $P_{60} = 5,339$ is a RE of the remaining pool of individuals. The equilibrium without the mandate involves full unravelling to 60, with 74.3\% of the population voluntarily covered. The column “No Mandate: Participation” under “Community Rating” shows participation by age in the non-mandate equilibrium.

We can also compute the welfare impact of removing the mandate. Those individuals that remain covered, 74.3\% of the population, suffer a loss equal to the premium increase $1,271 (= 5,339 - 4,068)$.
Comparing the certainty equivalent of remaining uninsured versus participation in the exchange for the 25.7% of the population that opts out, we find that they are better off by $1,972, on average. Thus, removing the mandate entails a welfare loss of $434.3 \times 0.743(1,972) - 0.257(1,972) per person.

On the right side of Table 13 we show the corresponding numbers for age-based pricing. As we saw in Section 7.1, all the equilibria under the mandate (with no opting out) for the different age groups involve unravelling to 60. At the equilibrium premium, reported in the “Mandate: Premium” column, only a proportion of the population would voluntarily participate in the exchange. Column “Mandate: Better-off In,” shows that the share that prefers to participate is an increasing share in age. Older individuals are more likely to benefit from participation, but the differences across ages are less pronounced once age is priced.

For each age, as individuals opt out, the cost of coverage increases. The column “No Mandate: Premium” reports the equilibrium premia for each age group absent a mandate. It is substantially higher than under the mandate, especially so for younger cohorts for whom the mandate is binding for a larger proportion of individuals.

In a similar fashion we can use the model to study the participation level for different subsidy levels.

### 7.3 Risk Adjustment

A standard feature in health markets are risk adjustment transfers whose aim is to ameliorate adverse selection. To illustrate the impact of risk adjustments on equilibrium we use the risk adjustment formula proposed by the Federal government [see, e.g., Dept. of Health and Human Services (2012a) or Dept. of Health and Human Services (2012b)] for the ACA. In practice risk adjustment can lead to a number

<table>
<thead>
<tr>
<th>Ages</th>
<th>Community Rating</th>
<th>Age-Based Pricing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mandate: Better-Off In</td>
<td>Premium</td>
</tr>
<tr>
<td>All</td>
<td>78.3%</td>
<td>74.3%</td>
</tr>
<tr>
<td>25-30</td>
<td>55.8%</td>
<td>50.6%</td>
</tr>
<tr>
<td>30-35</td>
<td>59.6%</td>
<td>54.1%</td>
</tr>
<tr>
<td>35-40</td>
<td>68.7%</td>
<td>62.2%</td>
</tr>
<tr>
<td>40-45</td>
<td>75.1%</td>
<td>70.9%</td>
</tr>
<tr>
<td>45-50</td>
<td>82.5%</td>
<td>79.3%</td>
</tr>
<tr>
<td>50-55</td>
<td>90.6%</td>
<td>87.2%</td>
</tr>
<tr>
<td>55-60</td>
<td>94.7%</td>
<td>92.5%</td>
</tr>
<tr>
<td>60-65</td>
<td>95.8%</td>
<td>93.9%</td>
</tr>
</tbody>
</table>

Table 13: Implications of the individual mandate for equilibrium prices and market participation.
of problems, such as insurers up-coding enrollees to qualify for larger transfers. We will abstract from such issues and assume that the regulator can perfectly observe the health status of each enrollee.

It is tempting to think that risk adjustment can solve the adverse selection problem entirely, by simply providing a transfer to each firm that gives that firm an expected cost from each enrollee equal to the average cost if there was no selection, thereby “eliminating the impact of selection on cost.” Unfortunately, doing so can result in the government running a deficit.\textsuperscript{36} As a result, the formula proposed by the HHS is designed to always break even. It provides a transfer payment per member to each plan \( i \) equal to

\[
T_i = \left\{ \left( \frac{R_i}{\sum_i s_i R_i} \right) - \left( \frac{AV_i}{\sum_i s_i AV_i} \right) \right\} \mathcal{P},
\]

where \( R_i \) is plan \( i \)’s “risk score” (equal to plan \( i \)’s average cost divided by the average cost of all plans in the market), \( AV_i \) is plan \( i \)’s actuarial value (i.e., 60 or 90 in our model), \( s_i \) is plan \( i \)’s market share, and \( \mathcal{P} \) is the average premium in the market. Intuitively, if the average cost in the 90 policy was 50% more than in the 60 policy as it would be if each had a random sample of consumers, transfers would be zero. Note that \( \sum_i T_i = 0 \), so the transfers are balanced. These transfers alter insurers’ average costs, which are now \( AC_{90} - T_{90} \) and \( AC_{60} - T_{60} \) in the 90 and 60 policy, respectively.

Since in a RE all policies break even and the transfers are balanced, the market average premium must equal the market average cost:\textsuperscript{37}

\[
\mathcal{P} = \overline{AC} (\Delta P) \equiv s_{90}(\Delta P) AC_{90}(\Delta P) + s_{60}(\Delta P) AC_{60}(\Delta P).
\]

Plan \( i \)’s risk score is \( R_i = AC_{90}(\Delta P)/\overline{AC}(\Delta P) \).

Substituting into (8), we get

\[
T_{90}(\Delta P) = \left\{ \left( \frac{AC_{90}(\Delta P)}{\overline{AC}(\Delta P)} \right) - \left( \frac{0.9}{\overline{AV}(\Delta P)} \right) \right\} \overline{AC}(\Delta P)
\]

\[
= AC_{90}(\Delta P) - \overline{AC}(\Delta P) \left( \frac{0.9}{\overline{AV}(\Delta P)} \right)
\]

where

\[
\overline{AV}(\Delta P) \equiv s_{90}(\Delta P)(0.9) + s_{60}(\Delta P)(0.6).
\]

Observe that the transfers depend on the market prices (through \( \Delta P \)), while the market prices depend on the transfer rule. Thus, the equilibrium prices are determined as a fixed point. Specifically,\textsuperscript{38}

\[
\frac{\mathcal{P}}{\overline{AC}(\Delta P)} = s_{90}(\Delta P)(0.9) + s_{60}(\Delta P)(0.6).
\]

Moreover, even doing so will not stop some consumers from selecting low coverage.

\textsuperscript{37}Formally, in equilibrium each policy will break even given its post-transfer average cost. Thus, recalling that \( T_i \) is a per member transfer, we have

\[
P_{90} = AC_{90}(\Delta P) - T_{90}(\Delta P)
\]

and

\[
P_{60} = AC_{60}(\Delta P) + T_{90}(\Delta P) \left( \frac{s_{90}(\Delta P)}{s_{60}(\Delta P)} \right).
\]

The market average premium is therefore

\[
\mathcal{P} = s_{90}(\Delta P) P_{90} + s_{60}(\Delta P) P_{60} = \overline{AC}(\Delta P).
\]
the prices will be

\[ P_{90}(\Delta P) = AC_{90}(\Delta P) - T_{90}(\Delta P) \]

\[ = \overline{AC}(\Delta P) \left( \frac{0.9}{\overline{AV}(\Delta P)} \right) \]

and

\[ P_{60}(\Delta P) = \overline{AC}(\Delta P) \left( \frac{0.6}{\overline{AV}(\Delta P)} \right). \]

This leads to a fixed point condition for \( \Delta P \):

\[ \Delta P = \overline{AC}(\Delta P) \left( \frac{0.3}{\overline{AV}(\Delta P)} \right). \]  

(9)

Applying formula (9) to our data, we find that with pure community rating the equilibrium with risk adjustment has prices \( P_{90} = 6,189 \) and \( P_{60} = 4,139 \), and the 90 policy capturing a 49% market share for the whole population.

To study the welfare implications we compare the long-run implications of equilibrium outcomes with and without insurer risk adjustment, for the case of pure community rating. Table 14 shows the yearly amount \( y_{no-prc-risk-adj} \) an individual would be willing to pay to implement insurer risk adjustment relative to the case of pure community rating with no insurer transfers. The risk adjustment outcome is preferred, reflecting the reduction in adverse selection compared to the case with no insurer transfers.

### 7.4 Rebalancing of the Population

The analysis to this point has relied on health choice and utilization data from a large firm with approximately 10,000 employees and 20,000 covered lives. While these data have a lot of depth on dimensions
that are essential to model health risk and risk preferences, they represent a specific population working for a specific large employer. Our results thus represent the case of exchange design as if this population were the population of interest. This could correspond closely to the case where either (i) this large employer (or a similar one) sets up a private exchange or (ii) our population represents a population of general interest for a public exchange (such as the ACA state exchanges). While our analysis thus far is clearly relevant for (i), and conceptually relevant for (ii), it is also likely that our sample is not the same as the sample of interest for policymakers setting up state insurance exchanges under the ACA.

To provide a signal of how our results could change under a population similar to that likely to enroll in state insurance exchanges under the ACA, we extend the analysis by applying our framework to a more externally relevant sample from the Medical Expenditures Panel Survey (MEPS), which was specifically created to study medical care decisions for a nationally representative population. Column 1 in Table E.1 in Appendix E contains the summary statistics for the entire MEPS population during the years we focus on (2004-2008) with no sample cuts (N = 166,539). We analyze exchange equilibria and welfare outcomes using two-distinct sub-samples from MEPS that may be of interest to an exchange regulator. The first is the population of individuals between ages 25-65 in the MEPS data, which presents a nationally representative analog to our primary analysis in this paper (N = 81,733). The second is the sample of individuals between 25-65 who are uninsured, unemployed, or work for an employer that does not offer coverage, implying that if the individual has coverage, it is from the individual market (N = 21,856). This sample is more similar in spirit to the sample that will actually enroll in the state insurance exchanges proposed under the ACA (which at the outset will contain few people who already have access to employer sponsored insurance). Columns 2 and 3 in Table E.1 describe each of these samples in detail. Table E.2 in Appendix E provides additional detail on the insurance coverage for each of these samples.

Our analysis matches individuals in the employer data used throughout our analysis to the two MEPS populations of interest (Columns 2 and 3) and creates two new simulation samples with demographic weights similar to the MEPS samples, but with detailed health and risk preference data from our estimates. We match individuals in our data to those in the MEPS data based on three demographics: age, income, and gender. To do this, we probabilistically model cells of age, gender, and income in the MEPS samples, and then draw randomly from individuals in those bins in our data with weights proportional to the MEPS cell weights. We note that, before we construct the MEPS cell weights, we incorporate the sample weights in the MEPS data, which are intended to correct for sampling and response issues. Table E.3 in Appendix E describes the non-parametric age, income, and gender cell multivariate cell weights for these MEPS samples. For the remainder of this section we

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38 We bring in the cost data from our data set because it is more detailed on the health risk dimension and our setting provides more precise plan characterizations, with which it is possible to estimate risk preferences.

39 We note that in this analysis, we do not match our sample to MEPS using health expenditure data (conditional on the other demographics) since our sample has more detailed medical information on consumers. However, the analysis below and the tables in Appendix D show that average costs conditional on demographics bins are similar in our data and in the MEPS data. Table D.4 provides more detail on the health risk for both MEPS samples.
focus on our analysis of the uninsured / individual market sample described in Column 3. Appendix E presents similar results for the full 25-65 sample from Column 2. For the uninsured / individual market MEPS reweighted sample, we reproduce our earlier equilibrium and welfare analysis for the cases of (i) pure community rating and (ii) health status- based pricing for health status quartiles in the market setup where insurers can offer either 90% or 60% insurance contracts. Table 15 presents the main results for this sample, and can be directly compared to Table 5 from our primary analysis. The comparison yields several important insights. First, the equilibrium premia and market shares are similar in this MEPS re-weighted sample and our main analysis: the market fully unravels to all-in-60 for the case of pure community rating. Under health-based pricing, in both cases the healthiest quartile has substantial market share in both 60 and 90: in our main analysis 64.8% in this quartile choose 60% coverage, while 57.5% do in the exchange-relevant MEPS re-weighted sample. Interestingly, while no consumers from the second healthiest quartile enroll in 90% coverage in our primary analysis, in the MEPS re-weighted sample 30.4% do. Thus, under our framework, if the exchanges are comprised of only uninsured individuals and those that would have been on the individual market, there will be higher insurance rates for the within-exchange population under health status-based pricing. For both our primary and MEPS analysis, the market unravels for the two sickest quartiles. Finally, and importantly, we note that the population expense levels are very similar between our main sample and the re-weighted MEPS sample: if all enroll in 60, the average costs in the former are $3,852 while in the latter they are $3,901. Overall, the analysis of MEPS data in this section suggests that, at a first pass, our main results are not substantially changed when applied to a sample that more closely reflects the demographic profile of individuals who will sign up for the ACA state exchanges.

8 Conclusion

In this paper we have developed a framework to study equilibrium and welfare for a class of regulated health insurance markets known as exchanges. The framework combines a theoretical model of an exchange (and results characterizing equilibria) with estimates of the joint distribution of health risk and risk aversion in a population of interest, allowing us to analyze exchange outcomes under various possible regulations. In our main application of the framework, we study the effects of allowing health-based pricing on market outcomes and welfare in a population of employees at a large employer.

40 We note that Table D.1 presents the data “as is.” In our analysis, we use MEPS sample weights, which re-weight this “as is” population to correct for survey sampling bias. In addition, as in our main analysis, we assume that the market is purely an individual market: there could be multiple people from one family in each sample represented in Table D.1.
41 Though the means are similar, the exchange-relevant MEPS sample is more heavily skewed in both directions, with more very healthy and more very sick individuals.
42 The market unravelling we find under community rating (with or without age-based pricing) is somewhat consistent with experience in the Massachusetts exchange, where most buyers opted for the Bronze (60%) plan in the early years of this ACA-like exchange [see, e.g., Ericson and Starc (2013)].
Table 15: This table presents the analogous table to Table 5 on equilibrium outcomes, applied to the sample reweighted by characteristics of the uninsured / individual coverage MEPS, described in the text. The top presents the equilibrium results for the case of pure community rating (no pricing of pre-existing conditions) and the bottom for the case where insurers can price based on health status quartiles.
While allowing even partial health-based pricing increases coverage compared to the full unraveling that arises under health-based pricing, if consumers can borrow freely or if pricing based on age is also allowed (eliminating any consumption smoothing benefit of health-based pricing), the welfare loss from reclassification risk it induces far outweighs the welfare gain from reduced adverse selection. (For a more detailed summary of our results, refer back to the Introduction.) We have also illustrated how our framework can be applied to study other related questions, such as the effect of varying the coverage levels of available plans, allowing age-based pricing, and voluntary participation. We have also taken a step closer toward examining possible outcomes under the ACA by reweighting our sample to match the MEPS uninsured population.

There are a number of dimensions on which our stylized model could be extended to more closely model most exchange environments. In our setting, products are differentiated only on financial dimensions. While in some settings (e.g., the Netherlands and Germany) this is essentially true in reality, in the U.S. context exchanges include insurers that offer products that are differentiated in terms of medical care and the network of available physicians. Accounting for this fact could enrich our equilibrium predictions and understanding of long-run welfare. In addition, it would be interesting to model more subtle consumer micro-foundations such as inertia or decision-making in complex product environments.

Finally, the exchanges analyzed here (and those operating in reality) have short-term annual policies. An interesting question is the extent to which long-term contracts can serve to reduce reclassification risk. While these kinds of contracts have been discussed to some extent [Cochrane (1995), Hendel and Lizzeri (2003), Herring and Pauly (2006)], there has been little to no empirical analysis of the benefits of such contracts.

References


A Appendix: Proofs

We use (a slightly modified version of) the definition provided in Engers and Fernandez (1987):

**Definition 1.** A *Riley equilibrium* (RE) is a profitable market offering $S$, such that for any non-empty set $S'$ (the deviation), where $S \cup S'$ is closed and $S \cap S' = \emptyset$, if $S'$ is strictly profitable when $S \cup S'$ is offered then there exists a set $S''$ (the reaction), disjoint from $S \cup S'$ with $S \cup S' \cup S''$ closed, such that:

(i) $S'$ incurs losses when $S \cup S' \cup S''$ is tendered;

(ii) $S''$ does not incur losses when any market offering $\hat{S}$ containing $S \cup S' \cup S''$ is tendered (we then say $S''$ is “safe” or a “safe reaction”).

A deviation $S'$ that is strictly profitable when $S \cup S'$ is offered, and for which there is no safe reaction $S''$ that makes $S'$ incur losses (with market offering $S \cup S' \cup S''$), is a *profitable Riley deviation*.

In our setting, a market offering is simply a collection of prices offered for the two policies. Definition 1 says that a set of offered prices is a Riley equilibrium if no firm, including potential entrants, has a profitable deviation that also never leads it to incur losses should other firms introduce additional “safe” price offers (where a “safe” price offer is one that would never incur losses were any further price offers introduced).

**A.1 Safe price offers**

We begin by considering which price offers are “safe” in the sense that they do not incur losses regardless of any additional offers being introduced.

**Lemma 1.** Given price configuration $(P_H, P_L)$, single-policy offer $P''_L < P_L$ is safe if and only if $\Pi_L(P_H, P''_L) \geq 0$.

*Proof.* If $\Pi_L(P_H, P''_L) < 0$, then $P''_L$ makes losses absent any reaction, and hence is not safe. So suppose that $\Pi_L(P_H, P''_L) \geq 0$. Any price offers $\widehat{P} = (\widehat{P}_H, \widehat{P}_L)$ with $\widehat{P}_L < P''_L$ gives the firm offering $P''_L$ a profit of zero. Any price offers $\widehat{P}$ with $\widehat{P}_H \geq P_H$ and $\widehat{P}_L \geq P''_L$ cannot make the firm offering $P''_L$ incur losses. Finally, any price offers $\widehat{P}$ with $\widehat{P}_H < P_H$ and $\widehat{P}_L \geq P''_L$ weakly lowers the sales of the firm offering $P''_L$. If that firm makes no sales at $(\widehat{P}_H, P''_L)$, then its profit is zero. If it has positive sales at $(\widehat{P}_H, P''_L)$, then it must also at $(P_H, P''_L)$. This implies that $\Pi_L(\widehat{P}_H, P''_L) \geq 0$ since then $AC_L(\widehat{P}_H - P''_L) \leq AC_L(P_H - P''_L) \leq P''_L$.

**Definition 2.** The lowest safe policy $L$ price given $P_H$ is $P''_L(P_H) \equiv \min\{P''_L : \Pi_L(P_H, P''_L) \geq 0\}$.\footnote{In fact, it suffices to restrict attention to deviations by potential entrants.}