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Equilibria in Health Exchanges: Adverse Selection vs. Reclassification Risk

Ben Handel*, Igal Hendel[†] and Michael D. Whinston^{‡§}

January 7, 2015

Abstract

This paper studies regulated health insurance markets known as exchanges, motivated by the increasingly important role they play in both public and private insurance provision. 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. 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 find substantial adverse selection leading to full unraveling of our simulated exchange, even when age can be priced. While the welfare cost of adverse selection is substantial when health status cannot be priced, that of reclassification risk is five times larger when insurers can price based on some health status information. We investigate several extensions including (i) contract design regulation, (ii) self-insurance through saving and borrowing, 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

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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 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 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 that insurers can act on relative to that in the hands of insureds. 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 reclassification 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, adverse selection would be completely eliminated when consumers and firms possess the same information. We would then expect efficient insurance provision conditional on the set of allowed contracts, although at

¹Each of these phenomena is often cited as a key reason why market regulation is so prevalent in this sector in the first place.

²See Akerlof (1970) and Rothschild and Stiglitz (1976) for seminal theoretical work.

³Insurer risk adjustment is one policy that regulators typically consider to reduce the extent of adverse selection in an exchange, conditional on a given set of price regulations. We consider insurer risk adjustment, and its implications for equilibrium outcomes and welfare, in Section 6.

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. Our approach 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, each of which must break even in an equilibrium.⁶ 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 Online Appendix E.) 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.⁷ (We also examine other actuarial values in Section 6.)

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), leveraging the unusually detailed information in our data

⁴This abstracts away from liquidity concerns that could be present in reality, especially for low income populations.

⁵See, 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).

⁶In contrast, in the Einav, Finkelstein and Cullen (2010c) model, there is only one privately-supplied policy that must break even. As we discuss in Section 2, this difference can lead to substantially different outcomes.

⁷Actuarial 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.”

about individuals' health status. 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 use these estimates, along with our theoretical model of an exchange, to simulate exchange equilibria under different pricing regulations. 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. 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.

We use the outputs of this equilibrium market analysis (premiums and consumers' plan choices) to evaluate long-run welfare under the different pricing regulations. Our analysis measures the gain or loss from allowing health-based pricing from the perspective of a 25-year old consumer, who anticipates participating in many consecutive one-year markets characterized by the static model, taking into account the underlying health transition process. 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 for the whole population. This amount is roughly 10% of the average medical expenses in the population. Health-based pricing reduces this unraveling: 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, we show that as the ability to price on health-status becomes greater, the welfare loss grows. 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 examine several extensions that address the robustness of our findings, or illustrate how our framework can be used to address other issues that arise in exchange design. We consider (i) the effects of altering the actuarial value of the low coverage policy, (ii) the implications of allowing age-based pricing, with and without health-based pricing, (iii) the possibilities for self-insurance through saving and borrowing to ameliorate the losses due to reclassification risk, and (iv) the effect of introducing insurer risk adjustment transfers to mitigate adverse selection (as seen in many insurance exchanges in practice).

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 reclassification risk. Relevant empirical 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).⁸ Ericson and Starc (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.⁹ These papers all focus on welfare in the context of a short-run or one-time marketplace.

There is more limited work studying reclassification risk and long-run welfare in insurance markets.

⁸See also Crocker and Snow (1986) and Hoy (1982) for theoretical analyses of discriminatory pricing in insurance markets. Both papers show the possibility for such pricing to generate Pareto improvements in the two-type Rothschild-Stiglitz model, with the former paper considering an equilibrium environment (focusing on “Wilson” equilibria) and the latter demonstrating an expansion of the second-best Pareto frontier.

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

Cochrane (1995) studies dynamic insurance from a purely theoretical perspective, showing that in the absence of asymmetric information first-best insurance can be achieved using single-period contracts that are priced based on a consumer’s health status and that insure both current medical expenses and changes in health status, provided that both consumers and firms can commit to making the required payments (perhaps through bonding). Herring and Pauly (2006) studies guaranteed renewable premiums and the extent to which they effectively protect consumers from reclassification risk. Hendel and Lizzeri (2003) and Finkelstein et 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.¹⁰ Crocker and Moran (2003) study the role that job immobility plays in committing employees to employer sponsored insurance contracts and shows that the quantity of employer provided insurance is larger in professions with greater employee commitment / longevity.

The rest of the paper proceeds as follows: In Section 2 we present our model of insurance exchanges, characterize Riley and Nash equilibria, 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. Section 6 discusses a number of extensions including (i) alternative contract configurations (ii) age-based pricing (iii) self-insurance through saving and borrowing and (iv) insurer risk adjustment. Finally, Section 7 concludes.

2 Model of Health Exchanges

Our 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, designated as H for “high coverage” and L for “low coverage.” 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

¹⁰We find substantially larger welfare consequences of reclassification risk than Bundorf et al. (2012). This reflects the different contexts studied and modeling assumptions employed. First, their environment includes a cheap HMO option, which consumers can always switch to, that substantially lessens total expenditures for high risk consumers. Second, their model of risk-rated premiums truncates premiums at 2 times the spending of the population average health risk in each plan (for the HMO, this premium is quite low). Third, they study two sequential utilization years for a young and healthy population.

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 $\theta \in [\underline{\theta}, \bar{\theta}] \subseteq \mathbb{R}_+$ 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 θ is below $P_H - P_L$ prefers the L policy, a consumer with θ 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 θ . 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. (See Online Appendix F for an analysis of participation.)

Note that consumers with a given θ 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 θ consumers, that those costs represent the expected costs of insuring all of the — possibly heterogeneous — individuals characterized by a specific θ .

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 θ under policy k by $C_k(\theta)$ for $k = H, L$ and define $\Delta P = P_H - P_L$. Given this, we define the average costs of serving the populations who choose each policy for a given ΔP 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 θ .

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 θ , and if the distribution function F is continuous. In that case, a small increase in ΔP shifts the consumers who were the best risks in policy H to being the worst risks in policy L, raising the average costs of both policies. We denote the lowest possible levels of average costs by $\underline{AC}_H \equiv AC_H(\underline{\theta})$ and $\underline{AC}_L \equiv AC_L(\underline{\theta})$, and the highest ones by $\overline{AC}_H \equiv AC_H(\overline{\theta})$ and $\overline{AC}_L \equiv AC_L(\overline{\theta})$.

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

$$\Pi_H(P_H, P_L) \equiv [P_H - AC_H(\Delta P)][1 - F(\Delta P)]$$

and

$$\Pi_L(P_H, P_L) \equiv [P_L - AC_L(\Delta P)]F(\Delta P)$$

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

$$\Pi(P_H, P_L) \equiv \Pi_H(P_H, P_L) + \Pi_L(P_H, P_L)$$

be aggregate profit from the entire population.

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

$$\underline{\Delta P}^{BE} \equiv \min\{\Delta P : \text{there is a } (P_H, P_L) \in \mathcal{P} \text{ with } \Delta P = P_H - P_L > \underline{\theta}\}^{11} \quad (1)$$

The price difference $\underline{\Delta P}^{BE}$ 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.

¹¹The price difference $\underline{\Delta P}^{BE}$ is well-defined provided that $\Delta AC(\underline{\theta}) \neq \underline{\theta}$.

Our health exchange model differs from the Rothschild-Stiglitz setting in four basic ways. First, the prescription of two standardized policies limits the set of allowed policies. 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 Online 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 Appendix A. 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 $\Delta AC(\underline{\theta}) \neq \underline{\theta}$.*

- (i) *If $\Delta AC(\underline{\theta}) < \underline{\theta}$, then it involves all consumers purchasing policy H at price $P_H^* = \underline{AC}_H$.*
- (ii) *If $\Delta AC(\underline{\theta}) > \underline{\theta}$, it then involves the break-even price configuration (P_H^*, P_L^*) with price difference $\Delta P^* = \underline{\Delta P}^{BE}$, the lowest break-even ΔP with positive sales of policy L.*

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

Figure 1 illustrates the result. The figure shows a situation in which $\Delta AC(\underline{\theta}) > \underline{\theta}$ and there are multiple price differences at which both policies break even (including price differences at which all consumers buy policy H, 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 $\underline{\Delta P}^{BE}$. In contrast, if instead we had $\Delta AC(\underline{\theta}) < \underline{\theta}$, then all consumers purchasing policy H would have been the unique RE outcome. Finally, if instead $\Delta AC(\underline{\theta}) > \underline{\theta}$ for all $\underline{\theta}$, then $\underline{\Delta P}^{BE} = \bar{\theta}$ and all consumers purchase policy L.

To understand the result, consider first when there is an all-in-H RE. (Readers not interested in the details of why the RE take the form described in Proposition 1 can skip this and the next two paragraphs.) In Appendix A, we first show that any RE must involve both policies breaking even. Given this fact, suppose, first, that $\Delta AC(\underline{\theta}) > \underline{\theta}$, 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, $\Delta AC(\underline{\theta}) = \underline{AC}_H - \underline{AC}_L$. In that case, starting from a situation

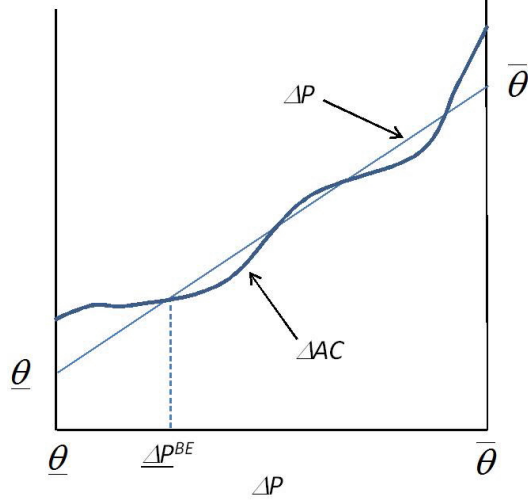


Figure 1: The figure shows $\underline{\Delta P}^{BE}$, the lowest price difference in any break-even price configuration that has positive sales of the 60 policy. It also shows a situation in which all-in-90 is not an equilibrium outcome, because $\Delta AC(\underline{\theta}) > \underline{\theta}$.

in which all consumers buy policy H and $P_H^* = \underline{AC}_H$, a deviation offering price $\hat{P}_L = \underline{AC}_H - \underline{\theta} - \varepsilon$ for small $\varepsilon > 0$ would cream-skim the lowest risk consumers into policy L at a price above \underline{AC}_L , the average cost of serving them. Moreover, 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 $\Delta AC(\underline{\theta}) < \underline{\theta}$, a deviation from this all-in-H outcome that attempts to cream-skim must lose money, since then the deviation price satisfies $\hat{P}_L \leq \underline{AC}_H - \underline{\theta} < \underline{AC}_L$, the lowest possible average cost for policy L. Thus, in that case all-in-H is a RE.

Now consider break-even price configurations with $\Delta P \in (\underline{\Delta P}^{BE}, \bar{\theta}]$ (and hence positive sales of policy L). Starting from such a configuration, a deviation to $\hat{P}_H = AC_H(\underline{\Delta P}^{BE})$ earns strictly positive profits [it results in a price difference lower than $\underline{\Delta P}^{BE}$, attracting a positive share of consumers to policy H at an average cost below $AC_H(\underline{\Delta P}^{BE})$]. Moreover, we show in Appendix A that the worst possible safe reaction to this deviation would involve a reduction in P_L to $AC_L(\underline{\Delta P}^{BE})$ (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 $P^* = (AC_H(\underline{\Delta P}^{BE}), AC_L(\underline{\Delta P}^{BE}))$ that results in price difference $\underline{\Delta P}^{BE}$. When $\Delta AC(\underline{\theta}) < \underline{\theta}$, this is not a RE. To see this, observe that a deviation offering price $\hat{P}_H = AC_L(\underline{\Delta P}^{BE}) + \underline{\theta}$, attracts all consumers to policy H at a price above the cost of serving

them, since

$$\widehat{P}_H = AC_L(\underline{\Delta P}^{BE}) + \underline{\theta} \geq \underline{AC}_L + \underline{\theta} > \underline{AC}_H,$$

where the last inequality holds because $\Delta AC(\underline{\theta}) = \underline{AC}_H - \underline{AC}_L < \underline{\theta}$. Moreover, we show in the appendix that the worst possible safe reaction to this deviation is an offer of policy L at a price that breaks even given \widehat{P}_H ; i.e., a $\underline{P}_L = AC_L(\widehat{P}_H - \underline{P}_L)$. Since we have $\Delta AC(\Delta P) < \Delta P$ for all $\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE})$ when $\Delta AC(\underline{\theta}) < \underline{\theta}$, this implies that $\widehat{P}_H > AC_H(\widehat{P}_H - \underline{P}_L)$, so the reaction can't make the deviator incur losses. On the other hand, when $\Delta AC(\underline{\theta}) > \underline{\theta}$, 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.

Note that any Nash equilibrium (NE) must be a RE since the set of deviations that are considered profitable under NE contains the set of Riley profitable deviations. Thus, Proposition 1 also describes NE, should they exist. However, while RE always exists in our model, NE need not. When $\Delta AC(\underline{\theta}) < \underline{\theta}$, the all-in-H RE outcome is also a NE (in fact the unique one) since, as noted above, no cream-skimming deviation is then profitable. However, when $\Delta AC(\underline{\theta}) > \underline{\theta}$, the RE — which has positive sales of policy L — need not be a NE. In particular, we show in Appendix A 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 $\max_{\widehat{P}_H \leq P_H^*} \Pi(\widehat{P}_H, P_L^*) = 0$. 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 there is only one privately-supplied policy over which competition occurs. This yields a Nash equilibrium at the lowest price P at which $P = AC$, where AC is the average cost of those consumers who purchase the policy.¹³ Their model can apply when there is only one possible type of insurance coverage, or when a higher coverage level is achieved through purchase of a privately-supplied 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.¹⁴ 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).

In contrast, in our model competition occurs over two policies, and equilibrium when both policies are purchased involves both breaking even, yielding the lowest ΔP at which $\Delta P = \Delta AC$, where ΔAC is the difference in the average costs of the two plans, given the consumers who purchase each plan. In

¹²We also discuss, in Appendix A, 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.

¹³While 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].

¹⁴The 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.

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, a possibility 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 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.¹⁶

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 (“loss” and “no loss”) 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 (bounded away from zero). Consistent with this result, in our model, when the low coverage involves no insurance, some consumers must purchase high coverage in the RE.¹⁷ 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.

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.¹⁸

Consider a single-period setting, in which a consumer’s medical expenses are $\tilde{m} = \phi\tilde{\varepsilon}_b + (1 - \phi)\tilde{\varepsilon}_a$, where $\tilde{\varepsilon}_b$ and $\tilde{\varepsilon}_a$ are both independently drawn from some distribution H , and $\phi \in [0, 1]$. The realization of ε_b occurs before contracting, while that of ε_a occurs after. With pure community rating, health status — the realization of ε_b — cannot be priced, while with health-based pricing it can. The parameter ϕ captures how much information about health status is known at the time of contracting. (As we will see

¹⁵Note that profitable cream-skimming deviations that reduce P_{60} involve *increases* in ΔP , while in the EFC model only reductions in P can attract consumers.

¹⁶Specifically, in the case of an add-on policy (so policy H is then the combined add-on and government policies), the EFC equilibrium condition is $\Delta P = AC_H(\Delta P) - \widehat{AC}_L(\Delta P)$, where $\widehat{AC}_L(\Delta P)$ is the average cost of policy L for the population who chooses policy H given ΔP . In contrast, our (interior) equilibrium condition is $\Delta P = AC_H(\Delta P) - AC_L(\Delta P)$. Since adverse selection implies that $\widehat{AC}_L(\Delta P) > AC_L(\Delta P)$, when $\Delta AC(\underline{\theta}) > \underline{\theta}$ the lowest ΔP satisfying our equilibrium condition is above the lowest satisfying the EFC condition, implying more unraveling in our setting of two privately-provided policies. In fact, Weyl and Veiga (2014) show that the equilibrium in the EFC data using our condition involves complete unraveling.

¹⁷To see this, observe that in that case the average cost of 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.

¹⁸The lifetime calculation we do later can be viewed as a sequence of static markets.

in the next section, in our data this ranges between 0.18 and 0.29, depending on the age cohort.) With community rating, there is an adverse selection problem, as consumers know their ε_b realization. In contrast, under perfect health-based pricing, a consumer faces insurance prices that perfectly reflect the realization of ε_b . Consumers are therefore able to perfectly insure the risk in ε_a , but end up bearing all of the risk in ε_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 ϕ with perfect health-based pricing.¹⁹

Figure 2 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 constant absolute risk aversion (CARA) 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.²⁰ Each panel plots three curves. The horizontal axis measures the share ϕ of medical risk that is realized before contracting. For each ϕ , 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.

Comparing the four panels in Figure 2, we see that the greater is s_L (the coverage in the low-coverage 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 ϕ .²¹ 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 ε_b is priced with perfect health-based pricing. Between these two extremes for ϕ , when $s_L = 0$ health-based pricing is better at high ϕ at which the market nearly fully unravels with community rating, but worse at low ϕ where all consumers get high coverage. A similar pattern

¹⁹This is only a rough statement, because $\tilde{\varepsilon}_b$ and $\tilde{\varepsilon}_a$ are drawn independently, which reduces the risk under community rating relative to that in health-based pricing.

²⁰Our 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.

²¹Although it cannot be detected in the figures, when $s_L = 0$, there are some consumers in the high-coverage 90 policy at all $\phi < 1$.

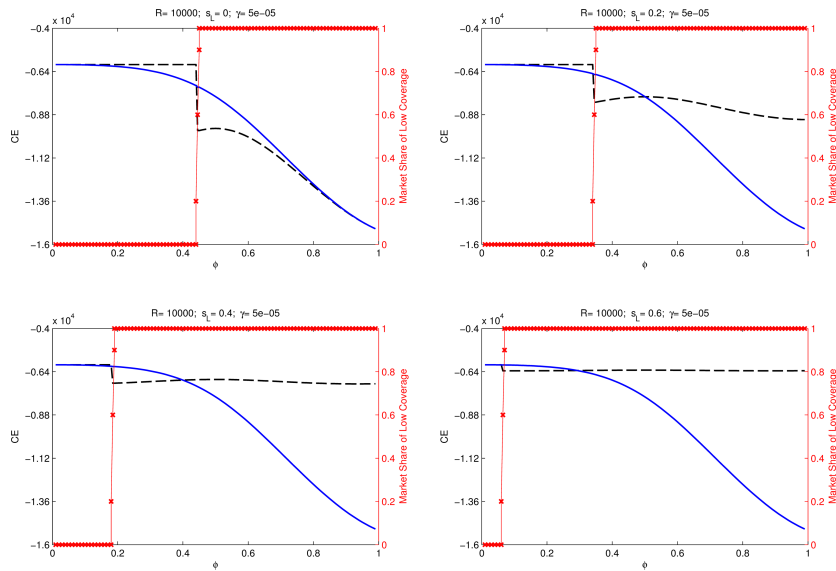


Figure 2: Adverse selection vs. reclassification risk, $R = 10,000$. X curve: market share of low coverage plan; dashed curve: certainty equivalent with pure community rating; solid curve: certainty equivalent with perfect health-based pricing.

emerges at higher levels of s_L except that full unraveling (which happens with pure community rating 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 ϕ at which the market unravels.²² Our empirical work, which we now turn to, explicitly quantifies ϕ , R , and the other key parameters described here and uses these inputs to study the trade-off between adverse selection and reclassification risk induced by different pricing and contract regulations.

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).

²²In Online Appendix H, we show a similar figure for a case with greater medical risk ($R = 30,000$). Unraveling happens at higher ϕ in that case, reflecting consumers' greater reluctance to choose a low coverage plan.

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 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: PPO₂₅₀, PPO₅₀₀, and PPO₁₂₀₀. 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), PPO₂₅₀ is approximately a 90% actuarial equivalence value plan (for our sample) while PPO₁₂₀₀ is approximately a 73% actuarial equivalence value plan (PPO₅₀₀ is about halfway between PPO₂₅₀ and PPO₁₂₀₀). 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. See Figure 2 in Handel (2013) for specific detail on the within-sample premium variation, which primarily reflects (i) variation in the average costs of the pool enrolling in each plan (ii) number of dependents covered (iii) employee income and (iv) the firm's rule for subsidizing coverage.

We restrict the final sample used in choice model estimation to those individuals / families that (i) enroll in a PPO option at the firm and (ii) are present in all years from t_{-1} , the year before the menu change, through at least t_1 . 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

Sample Demographics			
	All Employees	PPO Ever	Final Sample
N - Employee Only	11,253	5,667	2,023
N - All Family Members	20,963	10,713	4,544
Mean Employee Age (Median)	40.1 (37)	40.0 (37)	42.3 (44)
Gender (Male %)	46.7%	46.3%	46.7%
Income			
Tier 1 (< \$41K)	33.9%	31.9%	19.0%
Tier 2 (\$41K-\$72K)	39.5%	39.7%	40.5%
Tier 3 (\$72K-\$124K)	17.9%	18.6%	25.0%
Tier 4 (\$124K-\$176K)	5.2%	5.4%	7.8%
Tier 5 (> \$176K)	3.5%	4.4%	7.7%
Family Size			
1	58.0 %	56.1 %	41.3 %
2	16.9 %	18.8 %	22.3 %
3	11.0 %	11.0 %	14.1 %
4+	14.1 %	14.1 %	22.3 %
Staff Grouping			
Manager (%)	23.2%	25.1%	37.5%
White-Collar (%)	47.9%	47.5%	41.3%
Blue-Collar (%)	28.9%	27.3%	21.1%
Additional Demographics			
Quantitative Manager	12.8%	13.3%	20.7%
Job Tenure Mean Years (Median)	7.2 (4)	7.1 (3)	10.1 (6)

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) enroll in the PPO option at the firm in t_{-1} and (ii) remain enrolled in one of the three new PPO options at the firm through at least t_1 .

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 and Cost Model

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 expenses for the upcoming year at each point in time.²³ We denote these ex ante predictions of the next year’s expected medical expenditures by λ and compute these measures for each individual in the sample (including dependents as well as employees). We refer to λ_{it} as individual i ’s “health status” at time t . Figure H1 in Online Appendix H presents the distribution of λ for individuals in the data, as predicted for year t_1 , for any individuals in the data (including dependents) present at both t_0 and t_1 . The average predicted yearly expenditures for an individual are \$4,878 and as is typical in the health care literature, the distribution is skewed with a large right tail. See Table 3 later in this section and Table H1 in Online Appendix H for additional detailed information on the distribution of health spending for our primary sample of interest.

The health status variable λ 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 $H_k(X_{jt}|\lambda_{jt}, \mathbf{Z}_{jt})$. Here, λ_{jt} is the vector of λ_{it} for all i in family j , \mathbf{Z}_{jt} are family demographics, 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 Online 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, λ_{it} , 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 λ_{it} . 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.

²³The 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.

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, $H_k(X_{jt}|\boldsymbol{\lambda}_{jt}, \mathbf{Z}_{jt})$, 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.²⁴ To support these assumptions, we run a ‘‘correlation test’’ in the spirit of Chiappori and Salanie (2000) that investigates whether the choice of higher coverage predicts higher ex post total spending (due to either moral hazard or selection on private information). The test reveals that choice of more comprehensive coverage does not predict higher ex post expenditures, controlling for other observable information used in our choice model.²⁵

3.3 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 $H_k(X_{jt}|\boldsymbol{\lambda}_{jt}, \mathbf{Z}_{jt})$. Specifically, the utility of plan k for household j at time t is

$$U_{jkt} = \int_0^\infty u_j(M_{jkt}(X_{jt}, \mathbf{Z}_{jt}))dH_k(X_{jt}|\boldsymbol{\lambda}_{jt}, \mathbf{Z}_{jt}) \quad (2)$$

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 . \mathbf{Z}_{jt} are individual-level observables (described shortly) and M_{jkt} is the effective household consumption, given by

$$M_{jkt} = W_j - P_{jkt} - X_{jt} + \eta(\mathbf{Z}_j^B)\mathbf{1}_{jk,t-1} + \delta_j(A_j)\mathbf{1}_{1200} + \alpha HTC_{j,t-1}\mathbf{1}_{250} + \varepsilon_{jkt}(A_j) \quad (3)$$

²⁴Pregnancies, 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.

²⁵We perform this analysis for the set of families in our estimation sample for the year t_0 , when all of these families make an active plan choice. We estimate a robust standard-error OLS specification with total family spending during t_0 as the dependent variable, and indicator variables for choice of PPO_{250} and PPO_{500} for t_0 on the right-hand side, which also contains observable information such as ex ante predicted family mean spending, past costs, age, income, and other factors that enter our predictive cost model. The coefficient on PPO_{250} is \$839 (T = 0.78) and on PPO_{500} is -\$531 (T = -0.52) implying that family plan choice is not predictive of residual spending at t_0 above and beyond our rich observable measures (though because of the noise inherent to medical spending, a medium-sized effect of private information cannot be ruled out).

where W_j denotes household wealth, P_{jkt} is the premium contribution for plan k at time t and $\mathbf{1}_{jk,t-1}$ is an indicator that equals one if plan k is the incumbent plan (default option) at choice year t . This variable captures consumer inertia, which may be present for years with a default option (when the consumer may incur cost η to switch).²⁶ $\delta_j(A_j)$ is a random coefficient, with distribution estimated conditional on family status A_j (single or covering dependents), that captures permanent horizontal preferences for PPO₁₂₀₀ arising from the Health Savings Account linked to this plan option. Parameter α captures preferences for very high-expenditure consumers, who almost exclusively choose PPO₂₅₀ 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 ε_{jkt} known to the decision-maker, with variance σ_ε to be estimated conditional on family status A_j .

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

$$u_j(M_{jkt}) = -\frac{1}{\gamma_j} e^{-\gamma_j M_{jkt}} \quad (4)$$

Parameter γ_j is a household-specific CARA risk preference parameter unobserved by the econometrician. We estimate a random-coefficient distribution of γ_j that is assumed to have mean $\mu_\gamma(\mathbf{Z}_j^A, \boldsymbol{\lambda}_j)$ and be normally distributed with variance σ_γ^2 .²⁷ Note that observable heterogeneity impacts risk preference estimates through a shift in μ_γ , while the level of unobserved heterogeneity measured by σ_γ^2 is assumed constant for the entire population. We use the following specification for $\mu_\gamma(\mathbf{Z}_j^A, \boldsymbol{\lambda}_j)$:

$$\mu_\gamma(\mathbf{Z}_j^A, \boldsymbol{\lambda}_j) = \beta_0 + \beta_1 \log(\sum_{i \in j} \lambda_i) + \beta_2 age_j + \beta_3 \log(\sum_{i \in j} \lambda_i) * age_j + \beta_4 1_{mj} + \beta_5 1_{mj} \hat{v}_{mj} + \beta_6 1_{nmj} \hat{v}_{nmj} \quad (5)$$

In addition to expected household health expenditures ($\sum_{i \in j} \lambda_i$), risk preferences depend on the 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} . \hat{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:

$$Income_j = \alpha_0 + \alpha_1 age_j + \alpha_2 age_j^2 + v_j \quad (6)$$

The residual \hat{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 , together with the assumption that risk preferences are

²⁶ η depends on \mathbf{Z}_j^B , a subset of demographic variables and linked choices. See Table D1 in Online Appendix D for a list of the variables included in \mathbf{Z}_j^B and Handel (2013) for a discussion of heterogeneity in inertia.

²⁷ The left tail of this normal distribution is truncated at a value just above 0, as is required in the CARA model. This truncation has a very minimal impact empirically.

constant within family over time. 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 using the price variation that exists across income tiers, coverage tiers (number of family members covered) and over time, combined with the changes to household expected medical spending over time [see Figure 2 in Handel (2013), and the related discussion in the text for further discussion of this variation]. 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 Online Appendix D.

3.4 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 σ_ε), for simplicity we present and discuss the rest of the estimated parameters in Online Appendix D (e.g., inertia estimates, PPO_{1200} random coefficients, ε_{jkt} standard deviations, and income regressions). Parameter standard errors, which are generally quite small, are also presented in Online Appendix D.

For the primary specification, the population mean for μ_γ , the household mean risk-aversion level, is $4.39 * 10^{-4}$. The standard deviation for μ_γ (or the standard deviation in risk preferences based on observable heterogeneity) equals $6.63 * 10^{-5}$. The standard deviation of unobservable heterogeneity in risk preferences, σ_γ equals $1.24 * 10^{-4}$. See the results in the bottom section of Table 2 for interpretations of these risk preference estimates in the context of simple hypothetical gambles.²⁸

²⁸The bottom rows in Table 2 interpret the mean of the average estimated risk aversion μ_γ , as well as several quantiles surrounding that average μ_γ . 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 μ_γ 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

Empirical Model Results

	(1)	(2)	(3)	(4)
Parameter / Model	Primary Model	Robustness 1	Robustness 2	Robustness 3
Risk Preference Estimates				
μ_γ - Intercept, β_0	$1.21 * 10^{-3}$	$1.63 * 10^{-4}$	$1.06 * 10^{-3}$	$2.54 * 10^{-4}$
μ_γ - $\log(\sum_{i \in j} \lambda_i)$, β_1	$-1.14 * 10^{-4}$	-	$-1.21 * 10^{-4}$	-
μ_γ - age, β_2	$-5.21 * 10^{-6}$	$3.60 * 10^{-6}$	$-4.69 * 10^{-6}$	$3.99 * 10^{-6}$
μ_γ - $\log(\sum_{i \in j} \lambda_i) * \text{age}$, β_3	$1.10 * 10^{-6}$	-	$1.01 * 10^{-6}$	-
μ_γ - Manager, β_4	$4.3 * 10^{-5}$	$7.45 * 10^{-5}$	$5.3 * 10^{-5}$	$5.4 * 10^{-5}$
μ_γ - Manager ability, β_5	$1.4 * 10^{-5}$	$4.49 * 10^{-5}$	-	-
μ_γ - Non-manager ability, β_6	$7.5 * 10^{-6}$	$3.24 * 10^{-5}$	-	-
μ_γ - Nominal Income, β_7	-	-	$3.0 * 10^{-5}$	-
μ_γ - Population Mean	$4.39 * 10^{-4}$	$3.71 * 10^{-4}$	$4.33 * 10^{-4}$	$4.73 * 10^{-4}$
μ_γ - Population σ	$6.63 * 10^{-5}$	$7.45 * 10^{-5}$	$8.27 * 10^{-5}$	$6.30 * 10^{-5}$
σ_γ - γ standard deviation	$1.24 * 10^{-4}$	$1.14 * 10^{-4}$	$1.40 * 10^{-4}$	$1.20 * 10^{-4}$
Gamble Interp.:				
μ_γ Mean	693	728	696	676
μ_γ Mean + 25th Quantile σ_γ	736	772	748	717
μ_γ Mean + 75th Quantile σ_γ	653	688	651	640
μ_γ Mean + 95th Quantile σ_γ	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, PPO₁₂₀₀ random coefficients, and ε_{jkt} standard errors) and the standard errors for all parameters are provided in Online Appendix D. 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 / ability and risk preferences add richness.

In terms of observable heterogeneity, risk preferences are negatively correlated with mean health risk: a one point increase in $\log(\sum \lambda_i)$ reduces μ_γ by $8.10 * 10^{-5}$ for a 30-year old.²⁹ While a negative correlation between mean risk (expected total medical expenses) and risk aversion may suggest less adverse selection than when these factors are independent, Veiga and Weyl (2013) 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, which is the appropriate measure of insurance value under some assumptions. In our case, the correlation between insurance value and mean expected risk is positive, exacerbating adverse selection. Managers and those with higher ability are slightly more risk averse. With a log expected total health spending value of 9 (around the median for a household) risk aversion is increasing in age by $4.69 * 10^{-6}$ 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).

3.5 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.³⁰ 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 values are decreasing because they decrease as γ increases).

²⁹The 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.

³⁰For 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 λ . 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.

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. Table H1 in Online Appendix H describes some key descriptive variables 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, similarly to what we see in the data overall, the simulation sample covers the range of ages from 25-65 fairly evenly: this is relevant to our upcoming welfare analysis, which assumes that the population is in a steady state.

Table 3 shows the distribution of expenses for the simulation sample. The first two columns shows 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 (i.e., the mean of squared deviations from the individual means). The last two columns show what we denoted as R and ϕ in Section 2.2. R is defined as the variance of health expenses divided by the mean expenses, while ϕ 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, ϕ decreases in age. Namely, a lower proportion of the uncertainty is revealed prior to contracting for older groups.³¹ Moreover, the majority of the variance in expenses remains to be resolved after contracting. Viewed in the context of the model in Section 2.2, these quantities have direct implications for the empirical trade-off between adverse selection and reclassification risk as a function of the different pricing, contract, and market regulations that we investigate for the remainder of the paper.

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 two policies. We assume here that 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) and 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.

³¹However, comparing R (the ratio of the variance to mean medical expenses) and mean medical expenses, we see that the overall variance of medical expenses is roughly four times larger in age group 60-65 than in age group 25-30. Thus, the total amount of information known prior to contracting (measured by its variance) is larger in the former group, despite the fact that ϕ is decreasing in age.

Final Sample Total Health Expenditure Statistics						
Ages	Mean	S. D.	S. D. of mean	S. D. around mean	R	ϕ
All	6,099	13,859	6,798	9,228	31,369	0.24
25-30	3,112	9,069	4,918	5,017	26,429	0.29
30-35	3,766	10,186	5,473	5,806	27,550	0.29
35-40	4,219	10,753	5,304	6,751	27,407	0.24
40-45	5,076	12,008	5,942	7,789	28,407	0.25
45-50	6,370	14,095	6,874	9,670	31,149	0.24
50-55	7,394	15,315	7,116	11,092	31,722	0.22
55-60	9,175	17,165	7,414	13,393	32,113	0.19
60-65	10,236	18,057	7,619	14,366	31,854	0.18

Table 3: 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.

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 λ discussed in the previous section. For a given λ , we take 100 draws from the estimated distribution of γ (conditional on λ 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 ε is distributed $N(0, \sigma_\varepsilon^2)$. 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 ε for the single population for PPO₁₂₀₀ relative to PPO₂₅₀. As we report below, our results are robust to medium-sized changes in σ_ε .

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 $\lambda_{it} - E[X_{it}|\lambda_{it}, Z_{it}]$, aggregating over all individuals associated with each θ , while $AC_{90}(\theta)$ and $AC_{60}(\theta)$ are determined by aggregating these costs over the θ 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 3 shows that AC_{90} and AC_{60} are increasing in ΔP for each policy, and that AC_{90} exceeds AC_{60} at all ΔP .

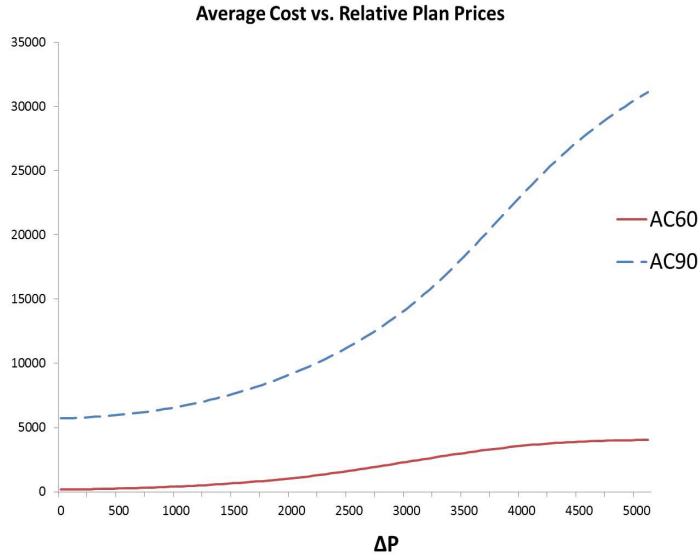


Figure 3: Plot of average costs vs. the price difference ΔP . Average costs are increasing in this price difference, and are larger for the 90 policy at each ΔP , consistent with the Adverse Selection Property maintained to derive our theoretical results.

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.

The first step towards finding equilibria involves checking whether all consumers pooling in the 90 plan is an equilibrium. Figure 4, which plots $\Delta AC(\Delta P)$, shows that $\Delta AC(\theta) > \underline{\theta}$, which implies that there is a profitable cream-skimming deviation from all-in-90 that attracts the healthiest customers to the 60 policy.³² 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 ΔP , $\underline{\Delta P}^{BE}$; i.e., the lowest interior ΔP at which $\Delta P = AC_{90}(\Delta P) - AC_{60}(\Delta P)$, if any exist, or $\Delta P = \bar{\theta}$ otherwise. This is then the RE ΔP .

Figure 4 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.

³²Figures 4 and 5 present $\Delta AC(\Delta P)$ for only $\Delta P > 0$, even though empirically a very small proportion of consumers have $\theta < 0$ because they are both healthy and have negative draws of the idiosyncratic preference shock ε . The values for $\Delta AC(\theta)$ are essentially identical to those for $\Delta AC(0)$ depicted in both figures.

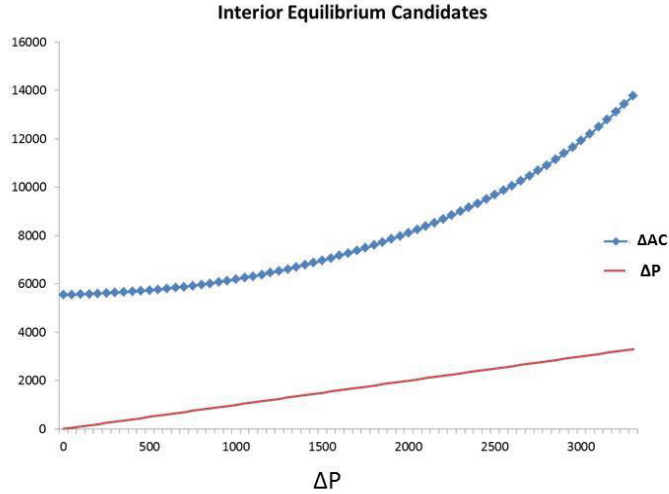


Figure 4: Plot of the average cost difference $\Delta AC(\Delta P)$ and the price difference ΔP .

All-in-60 is not a Nash Equilibrium as a price cut in P_{90} in conjunction with an infinitesimal reduction of P_{60} is profitable.³³ The top section of Table 4 summarizes these findings for the case of a pure community rating pricing 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 λ : 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 based on health status. 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.

³³This type of deviation is profitable in every all-in-60 RE we report throughout in the paper. Appendix A also discusses Nash equilibria when firms can only 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).

Equilibria without Pre-existing Conditions							
	Equilibrium Type	P ₆₀	S ₆₀	AC ₆₀	P ₉₀	S ₉₀	AC ₉₀
	RE	4,051	100.0	4,051	-	0	-
	NE	Does not exist					

Equilibria with Health Status-based Pricing							
Market	Equilibrium Type	P ₆₀	S ₆₀	AC ₆₀	P ₉₀	S ₉₀	AC ₉₀
Quartile 1	RE/NE	289	64.8	289	1,550	35.2	1,550
Quartile 2	RE	1,467	100.0	1,467	-	0	-
Quartile 3	RE	4,577	100.0	4,577	-	0	-
Quartile 4	RE	9,802	100.0	9,802	-	0	-

Table 4: 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 in which 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.

Figure 5 shows that, as in the pure community rating case, $\Delta AC(\underline{\theta}) > \underline{\theta}$, implying that all-in-90 is not an equilibrium.

The second step is to look for interior equilibrium candidates. Figure 5 shows two interior break-even ΔP s. By Proposition 1 the lowest ΔP , the one with the largest share of customers in the 90 policy, is the RE. In this equilibrium, 35.2 percent of quartile 1 consumers obtain high coverage.

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 4. The bottom section of Table 4 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, consumers 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 reclassification risk, we also 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 5 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

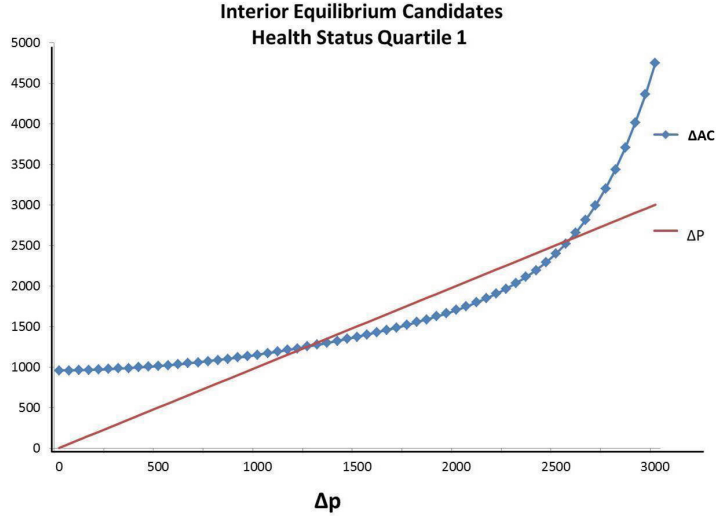


Figure 5: Plot of the average cost difference $\Delta AC(\Delta P)$ and price difference ΔP for the healthiest quartile.

Equilibria Welfare Loss from Health Status-based Pricing: Varying Regulation				
# of Health Buckets	S_{60}	$y_{HBx,PCR}$		$y_{HBx,PCR}$
		Fixed Income	Non-Manager Income path	Manager Income Path
2	100.0	1,920	710	-102
4	90.0	3,082	1,821	-886
6	82.0	3,951	2,377	-232
8	85.1	4,649	2,084	-1,510
10	83.2	5,357	2,269	-1,364
20	81.4	8,590	4,621	-393
50	63.2	11,578	7,302	2,359
∞	27.0	14,733	9,944	2,399

Table 5: Equilibria and long-run welfare comparison between the pricing regulations that allow some pricing based on health status and the case in which 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 pure community 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 ∞ is full risk rating. The results presented are for Riley Equilibria and $\gamma = 0.0004$.

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.³⁴ (The welfare numbers in columns 3-5 of Table 5 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 (λ) and risk aversion (γ), 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 (λ, γ) 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 γ 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' :

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

or

$$y_{x,x'}(\gamma) = -\frac{1}{\gamma} \ln \left(\frac{\sum_{t=25}^{65} \delta^t E[-e^{-\gamma\{I_t - CE_{x'}(\lambda_t, \gamma)\}}]}{\sum_{t=25}^{65} \delta^t E[-e^{-\gamma\{I_t - CE_x(\lambda_t, \gamma)\}}]} \right). \quad (7)$$

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 γ at age 25. If risk was independent of risk aversion the computation would be straightforward. In a steady state, 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.³⁵

However, our estimates imply that health and risk aversion are correlated, with more risk averse individuals being healthier on average. Table H2 in Online Appendix H shows, for various risk aversion

³⁴With no ε preference shock, with full risk-rating all consumers would enroll in the 90% plan. Here, with the estimated ε standard deviation incorporated, the first-best allocation has 73% of consumers in the 90% plan, since some choose the 60% plan due to this preference shock.

³⁵Recall that the age distribution in our sample is close to uniform, as it should be in a steady state population.

levels γ , 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 γ .

To identify the stochastic health outcomes a 25-year old with a given risk aversion γ foresees at any given future age t , we isolate those individuals in our simulation sample of age t whose risk-aversion γ_t falls into a band around the level expected based on our estimates of equation (5), for individuals with risk aversion level γ at age 25.³⁶ For a given discount factor $\delta \leq 1$ and regime x , we calculate $\sum_t \delta^t E[-e^{-\gamma\{I_t - CE_x(\lambda_t, \gamma)\}}]$ as follows: first, we generate the value of $e^{-\gamma\{I_t - CE_x(\lambda_t, \gamma)\}}$ that each individual of age t in the band associated with γ would have if he chose between the 60 and 90 policies facing the equilibrium prices in regime x and having risk aversion parameter γ .³⁷ The income level I_t is either held fixed (in which case, with CARA preferences, its level doesn't matter) or comes from the regression in equation (6) and is estimated separately for managers and non-managers.³⁸ We then derive $E_{x_t}[-e^{-\gamma\{I_t - CE_x(\lambda_t, \gamma)\}}]$ by calculating the sample mean of those values for age t individuals in the γ band. We then discount and add these values over t to get $\sum_t \delta^t E_{x_t}[-e^{-\gamma\{I_t - CE_x(\lambda_t, \gamma)\}}]$. We proceed similarly for regime x' .

In our primary analysis, we do not allow consumers to borrow and save over the course of their lifetimes to self-insure against health shocks. We assume this because (i) we don't observe the extent to which agents are able to save and borrow in practice and (ii) integrating borrowing and saving into our full welfare model introduces substantial computational complexity. Our main analysis allows for two types of consumer income paths. The first assumes that income is fixed at the same level over time (perfect income smoothing prior to health spending) while the second allows for increasing income paths (as observed in our data) without the possibility of borrowing or saving. In the latter case we provide a calculation separately for managers and non-managers, whose expected incomes paths differ. We note that, since self-insurance through borrowing and/or saving has the potential to impact our main conclusions, in Section 6.3 we study a simplified extension of our primary welfare model that allows for dynamic borrowing and saving decisions over the course of a consumer's lifetime.

We first compare two regimes: ACG-quartile pricing and pure community rating. The latter eliminates reclassification risk but exacerbates adverse selection. Health-based pricing also involves some intertemporal 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 6

³⁶We use a band radius of 0.00005.

³⁷Thus, we evaluate the welfare of an individual who at age 25 does not foresee his risk aversion changing.

³⁸For 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 Online Appendix D for more details.

Welfare Loss from Health Status-based Pricing in RE/sp-NE (\$/year)			
γ	$y_{HB4,PCR}(\gamma)$ Fixed Income	$y_{HB4,PCR}(\gamma)$ Non-Manager Income path	$y_{HB4,PCR}(\gamma)$ Manager Income Path
0.0002	2,220	1,499	-384
0.0003	2,693	1,688	-613
0.0004	3,082	1,821	-886
0.0005	3,399	1,764	-973
0.0006	3,626	2,115	-891

Table 6: Long-run welfare comparison between the two pricing regulations of (i) pricing based on health status quartiles ($x = \text{“}HB4\text{”}$) and (ii) pure community rating ($x' = \text{“}PCR\text{”}$). The table presents the values for $y_{HB4,PCR}(\gamma)$, the annual payment required under regime $HB4$ to make consumers indifferent between $HB4$ and PCR . The results presented are based on the RE outcomes presented in Table 4. We present results for the differing cases of (i) fixed income (ii) the non-manager income path, and (iii) the manager income path. The assumed discount rate is $\delta = 0.975$.

shows the values of $y_{x,x'}(\gamma)$ comparing pricing based on ACG-quartiles ($x = \text{“}HB4\text{”}$) and community rating ($x' = \text{“}PCR\text{”}$) for $\delta = 0.975$.

With a fixed income, the welfare gains from eliminating reclassification through community rating 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 51% of the \$6,099 annual average total expenses in the population (see Table H1 in Online Appendix H). 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 $P_{90} = \underline{AC}_{90}$ 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.

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 38), 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. Section 6.3 investigates a model where consumers can self-insure via dynamic borrowing and saving, and reveals that our main conclusions about the importance of reclassification risk relative to adverse selection are unchanged once self-

insurance is possible.

We revisit Table 5 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 for risk aversion value $\gamma = 0.0004$. 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.^{39 40}

6 Extensions

In this section we study several extensions to our primary analysis. First, we investigate how market equilibria and the welfare trade-off between adverse selection and reclassification risk depend on the actuarial values of the contracts the regulator allows insurers to offer. Second, we allow for age-based pricing.⁴¹ Third, we incorporate self-insurance through saving and borrowing into the analysis. The ability to borrow after a health shock, or save in anticipation of future shocks, could in theory alter our conclusions by substantially reducing the costs of reclassification risk. Fourth, we study the impact of insurer risk-adjustment transfers, whereby insurers are at least partially compensated when enrolling ex ante sicker consumers. Finally, in Online Appendices F and G we present two additional extensions: (i) endogenous consumer exchange participation and (ii) an alternative weighting of our sample designed to reflect representative U.S. demographics.

6.1 Alternative Contracts and Contract Design

So far we have studied pricing regulation for a given set of contracts. In practice, exchange designers also regulate contract configuration. In this section, we replicate our analysis of adverse selection

³⁹In 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.

⁴⁰One caveat to these results is that they rely on our estimated risk preferences being appropriate for evaluating reclassification risk. With fine pricing of health status consumers can face very large monetary losses from reclassification, and the implied certainty equivalents for risk averse consumers can become implausibly large in magnitude for the reasons noted by Rabin (2000).

⁴¹Age-based pricing is commonly found in health exchanges in practice, including the state exchanges set up under the ACA. We note that age-based pricing will not impact the extent of reclassification risk, since age is deterministic over one's lifetime.

Equilibrium for Alternative Insurance Contract Designs									
Contracts	90% and 80%			90% and 40%			90% and 20%		
	P_{90}	P_{80}	S_{80}	P_{90}	P_{40}	S_{40}	P_{90}	P_{20}	S_{20}
All	-	4800	100	-	2413	100	7345	31	28
Q1	1434	652	71	1253	4	21	1252	0	20
Q2	-	2114	100	2855	76	10	2840	6	9
Q3	-	5491	100	7519	895	26	6794	142	8
Q4	-	10945	100	-	6224	100	13343	685	12

Table 7: RE results for the cases of (i) community rating and (ii) pricing on health status quartiles for a range of actuarial contract values allowed in the marketplace by the regulator.

and reclassification risk for a range of alternative contract configurations. Specifically, we investigate configurations that hold the high coverage contract at an actuarial value of 90, and set the low coverage contract at 80, 40, and 20, respectively.

Table 7 shows market equilibrium results for these alternative contract configurations. 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, spiralling 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 subsection of Table 8 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 the entry for pure community rating under fixed income. 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. 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 managers (who have a steeper income growth), but not non-managers, may prefer to pool at 60 rather than at 80 in order to reduce premiums earlier in life when income is lower. In addition, under community rating, only managers prefer the RE in 90-20 to pooling in 60 specifically because enrolling in the 20 plan is relatively less costly for them due to their steeper income profile. Both non-managers and managers prefer pooling in 60 to pooling in 40 (the RE outcome for the 90-40 configuration).

Next we look at the impact of allowing health-based pricing for different contract configurations. The first column of each configuration in Table 8 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 choose the 90 policy. However, as trade increases with more partitions only managers benefit. Namely, as in Section 5, if income growth is not steep, the gains from reducing adverse selection are smaller than the additional losses from reclassification risk. This is also true, in most cases, for managers, who are most likely to prefer discrimination because of their relatively steep income paths.

6.2 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 [see, e.g., Ericson and Starc (2013) for a lengthier discussion].

We group consumers into five-year age bins as usually done in practice, for example in the Massachusetts Connector. Table 3 (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 first consider whether age-based pricing ameliorates the extent of adverse selection. As we saw in Section 4, by allowing some health status based pricing, additional trade was generated for the healthiest quartile of the population. Because age — as shown in column 1 — is a proxy for health type, we may expect 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 and risk preferences still imply that, even for the younger age groups, full unraveling occurs in equilibrium.⁴²

Finally, we consider the simultaneous pricing of age and health status. The exercise is interesting for at least two reasons. First, health-based 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 impact of health-based pricing, age-based pricing may neutralize the benefits associated with consumption smoothing, by reducing the transfer from young to old that health-based pricing otherwise induces.

Table 9 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

⁴²We note that these results are robust to medium-sized changes in σ_ε , even though this shock to preferences introduces a source of willingness to pay for coverage unrelated to risk type.

Welfare Losses from Health-based Pricing: Varying Contract Designs				
90% and 80%				
# of Health Buckets	S_{80}	Fixed Income	Non-Manager Income path	Manager Income Path
Community Rating	100.0	-278	-83	194
4	92.2	3,265	1,987	-896
10	90.8	5,585	2,974	-1,343
20	87.4	8,920	5,280	-491
50	85.1	11,895	7,409	2,323
500 (∞)	31.0	18,166	13,035	4,940
90% and 40%				
# of Health Buckets	S_{40}	Fixed Income	Non-Manager Income path	Manager Income Path
Community Rating	100.0	4,472	3,243	2,098
4	45.2	6,664	4,790	953
10	42.5	8,552	5,640	429
20	32.8	11,317	7,396	1,538
50	36.6	14,010	9,491	4,247
500 (∞)	3.0	19,986	16,022	9,112
90% and 20%				
# of Health Buckets	S_{20}	Fixed Income	Non-Manager Income path	Manager Income Path
Community Rating	28.0	572	573	-45
4	11.8	3,635	2,404	-487
10	18.3	14,885	11,355	3,487
20	13.4	17,125	12,749	6,075
50	12.4	19,399	14,715	9,957
500 (∞)	2.0	20,893	17,550	11,861

Table 8: 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											
	Q1 (Healthy)			Q2			Q3		Q4 (Sick)		Avg.
Ages	S_{60}	P_{60}	P_{90}	S_{60}	P_{60}	P_{90}	S_{60}	P_{60}	S_{60}	P_{60}	S_{60}
25-30	37	126	616	75	375	1,935	100	930	100	5,520	78
30-35	37	156	676	58	337	1,597	100	1,411	100	6,855	74
35-40	48	189	966	50	608	2,028	100	1,867	100	7,246	75
40-45	62	299	1,489	100	1,257	-	100	3,180	100	8,141	90
45-50	37	492	1,592	82	1,574	4,044	100	3,891	100	10,138	80
50-55	73	946	2,936	100	2,304	-	100	5,847	100	10,858	93
55-60	67	1,477	3,617	100	5,159	-	100	6,733	100	11,702	92
60-65	100	2,200	-	100	5,824	-	100	7,666	100	13,321	100

Table 9: RE for pricing regulation that allows insurers to price based on health status quartiles and age.

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 H3 in Online Appendix H 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 (the result of pure age-based pricing). Once age is priced, health-based pricing, which appealed to individuals with steeply increasing income, is no longer preferred by those consumers. The benefit of health-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 across the range of risk aversion types and for the different income path models studied.⁴³

6.3 Self Insurance: Saving and Borrowing

Our core analysis investigates several models for consumer lifetime income paths, but does not allow for consumers to either borrow when they receive negative health shocks or save in advance of such shocks. Such precautionary savings and borrowing could, in theory, mitigate the welfare losses from risky health shocks, especially in environments in which they lead to significant reclassification risk. To illustrate the potential impact of savings and borrowing, and study the robustness of our main findings, we study an extension that embeds our basic model into a stylized life-cycle model with capital markets. As in our main analysis, the consumer has an income flow, and stochastic health expenses (including premiums) that may depend on age and health status. We add on top of this a model of health

⁴³Although we do not do so here, one can also examine the welfare effects of allowing age-based pricing versus pure community rating. Age-based pricing may, in general, affect the extent of unraveling. Even when it doesn't, it may generate intertemporal gains. This is true even when consumers can borrow and lend (as in the next subsection) because it effectively allows borrowing at a zero interest rate (given the break-even condition).

status transitions, which we estimate with our data, and a model for borrowing and saving that allows consumers to insulate themselves from health shocks. We describe the important aspects of this model here, and present the full model in Online Appendix E.

Specifically, we modify the model as follows. First, we make the simplifying assumption that each period in the model corresponds to a five-year age bin (25-30, 30-35,..., 60-65). This is done both to simplify the dynamic computation and to have large enough sample sizes for age-specific health transition matrices.⁴⁴ In each period the consumer chooses an insurance policy based on their ex ante information, and then during the period realizes their in-period health expenses and updated health status. Their updated health status determines (i) the distribution of their health expenses for the next period (ii) premiums for the next period (if health status can be priced) and (iii) the future evolution of their health status. We assume that period t saving or borrowing is decided after observing health expenses for that period. This assumption represents a fluid financial market where, e.g., individuals can take a last minute loan if they were unlucky during the period.⁴⁵ We note that within each period, consumers experience five years of identical health claims in the insurance contract they chose for that period, appropriately discounted. For each age bin, health status, and regulatory pricing regime, we use the static market equilibrium outcomes from our primary analysis and determine the actual choice each individual makes in each period, yielding her premiums and out of pocket expenses.⁴⁶ We assume consumers have flat income profiles over time (as in the first column of Table 6) in order to neutralize the other channels through which savings could impact welfare. We consider a consumer with risk aversion coefficient $\gamma = 0.0004$.

Solving the dynamic life cycle savings problem requires modeling transitions across health states, which we estimate from our sample using empirical year-to-year transitions in consumers' ACG indices λ_{it} . To this end, we divide the population into 7 cells reflecting different health status levels based on ACG index, and non-parametrically estimate a 7-by-7 transition matrix. We estimate a separate transition matrix for each of 8 five-year age groups. Using these ingredients, we solve an 8-period dynamic optimization problem where individuals transition over 7 health types as they age and can save and borrow in each period. We solve the consumer's dynamic problem using backwards induction, determine each consumer's lifetime value for each possible starting state in period 1, and then compute the ex-ante certainty equivalent of regulatory pricing regime x for an unborn individual who does not yet know her type (as in Section 5).

⁴⁴As seen in the results below, this simplified framework yields welfare results that are similar in magnitude to the model without borrowing or saving presented in our primary analysis.

⁴⁵Access to capital, especially when a health condition develops, may not be this fluid in practice. To the extent that true credit markets have frictions we don't capture, we likely overstate the positive impact of borrowing in mitigating the welfare loss from reclassification risk.

⁴⁶Market outcomes are assumed to be the same as those in our primary equilibrium analysis. They thus do not account for the potential effect that borrowing and saving could have on consumer insurance choices. Accounting for these dynamic effects would likely push consumers more towards lower insurance, and would therefore likely not have a large impact on equilibrium outcomes.

Welfare Loss with Borrowing and Saving (\$/year)		
Savings Case	$y_{PCR,90}$	$y_{HB4,PCR}$
<i>Any S</i>	269	1,540
$S \geq 0$	391	1,977
$S \leq 0$	337	2,480
$S = 0$	765	3,352

Table 10: This table presents the long-run welfare results when consumers are allowed to (i) borrow ($S \leq 0$) (ii) save ($S \geq 0$) or (iii) borrow and save (*Any S*). We investigate these models for the cases of (i) pure community rating and (ii) health status quartile based pricing examined in our primary analysis ($S = 0$). The results presented are based on the RE outcomes for each of the two pricing regulations. The assumed discount rate is $\delta = 0.975$ and the consumer's risk aversion coefficient is $\gamma = 0.0004$.

We use this framework to compare three regimes: (i) all-in-90 (ii) the Riley equilibrium with pure community rating (*PCR*) and (iii) the Riley equilibrium under pricing health quartiles (*HB4*).⁴⁷ The welfare results are presented in Table 10. The first column shows the welfare loss from adverse selection for the case of pure community rating relative to all-in-90. The second column shows the relative welfare loss from (i) reduced adverse selection but (ii) increased reclassification risk moving from pure community rating to health status quartile pricing (analogous to Table 6). The results show that, as expected, access to capital markets lowers the welfare losses for both of these comparisons. Without the possibility of saving or borrowing (" $S = 0$ "), the welfare loss from health status quartile-based pricing relative to community rating is \$3,352 per person per year, while when full borrowing and saving are allowed ("*Any S*"), the loss is reduced to \$1,540 per person per year. The corresponding losses from community rating relative to all-in-90 are \$765 and \$269 respectively. Thus, while allowing for saving and borrowing improves consumer welfare in all pricing regimes, the welfare losses from reclassification risk in health status quartile-based pricing still far outweigh the welfare gains from reduced adverse selection, relative to the case of pure community rating.

We also examine the two cases where consumers are only allowed to borrow (" $S \leq 0$ ") or only allowed to save (" $S \geq 0$ ") in order to decompose their effects. While both cases are clearly preferred by the consumer to the case where neither borrowing nor saving is allowed, borrowing is less helpful in contending with reclassification risk under health status quartile pricing.

⁴⁷The welfare loss from pricing health status quartiles, relative to pure community rating, under flat income is \$3,082 per consumer per year, in our primary analysis (see Table 6). Here, this value is slightly larger, equal to \$3,352, because our model with saving and borrowing makes some necessary simplifications relative to our primary specification. The primary simplification is modeling health status transitions across seven possible health states (and for five year age bins) rather than assuming a continuous health state and steady state population.

6.4 Risk Adjustment

Risk adjustment transfers are a key policy implemented in many health insurance markets in order to ameliorate adverse selection. 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 in each plan equal to the average cost of the plan if there was no selection (i.e., equal to the population average cost in that plan), thereby eliminating the impact of selection on cost. However, even if the government were to accomplish this, so that $\Delta P = \underline{AC}_H - \overline{AC}_L$, an efficient outcome will result only if $\underline{\theta} \leq \underline{AC}_H - \overline{AC}_L$, as otherwise the consumers with willingness to pay below $\underline{AC}_H - \overline{AC}_L$ will still choose to purchase policy L. Moreover, doing so can result in the government running a deficit. Still, risk adjustment can reduce the losses from adverse selection.

In this subsection, to illustrate how our framework can incorporate risk adjustment transfers, and the impact of these transfers 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.⁴⁸ In practice risk adjustment can lead to a number 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.

The HHS risk-adjustment policy is designed to always break even. It provides a transfer payment per member to each plan i equal to

$$T_i = \left\{ \left(\frac{R_i}{\sum_i s_i R_i} \right) - \left(\frac{AV_i}{\sum_i s_i AV_i} \right) \right\} \bar{P}, \quad (8)$$

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., 0.60 or 0.90 in our model), s_i is plan i 's market share, and \bar{P} is the average premium in the market. Intuitively, if the average cost of the 90 policy was 50% more than of the 60 policy, as it would be if each had a random sample of consumers, transfers would be zero. When the average cost in the 90 policy is more than 50% greater than that of the 60 policy, transfers flow to the 90 plan. 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:⁴⁹

$$\bar{P} = \overline{AC}(\Delta P) \equiv s_{90}(\Delta P)AC_{90}(\Delta P) + s_{60}(\Delta P)AC_{60}(\Delta P).$$

⁴⁸See the concurrent work of Glazer et al. (2014) and Mahoney and Weyl (2014) for further discussions of insurer risk-adjustment transfers and their impact on equilibria in insurance markets.

⁴⁹Formally, 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 $\bar{P} = s_{90}(\Delta P)P_{90} + s_{60}(\Delta P)P_{60} = \overline{AC}(\Delta P)$.

Plan i 's risk score is $R_i = AC_{90}(\Delta P)/\overline{AC}(\Delta P)$. Substituting into (8), we get

$$\begin{aligned} T_{90}(\Delta P) &= \left\{ \left(\frac{AC_{90}(\Delta P)}{\overline{AC}(\Delta P)} \right) - \left(\frac{0.9}{\overline{AV}(\Delta P)} \right) \right\} \overline{AC}(\Delta P) \\ &= AC_{90}(\Delta P) - \overline{AC}(\Delta P) \left(\frac{0.9}{\overline{AV}(\Delta P)} \right) \end{aligned}$$

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 ΔP), while the market prices depend on the transfer rule. Thus, the equilibrium prices are determined as a fixed point. Specifically, 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 ΔP :

$$\Delta P = \overline{AC}(\Delta P) \left(\frac{0.3}{\overline{AV}(\Delta P)} \right). \quad (9)$$

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 $P_{60} = 4,139$ (so $\Delta P = 2,050$), and the 90 policy capturing a 49% market share for the whole population.⁵⁰

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 H4 in Online Appendix H shows the yearly amount $y_{PCR,risk-adj}$ an individual would need to receive with pure community rating to be as well off as when risk adjustment occurs. The risk adjustment outcome is preferred, reflecting the reduction in adverse selection compared to the case with no insurer transfers. For example, an individual with fixed income and $\gamma = 0.0004$ would need to receive \$349 per year under pure community rating to be as well off as when risk adjustment occurs.

7 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

⁵⁰In contrast, if the government were to instead implement risk adjustment transfers that result in price difference $\Delta P = \underline{AC}_H - \overline{AC}_L = 1,571$ in this market, 66% of consumers would purchase the 90 policy and the government would run a deficit of \$274 per consumer (on average), losing \$2,139 per consumer in the 90 policy and gaining \$3,348 per consumer in the 60 policy.

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 health-based pricing on market outcomes and welfare for a population of employees at a large employer. While allowing even partial health-based pricing increases coverage compared to the full unraveling that arises under pure community rating, if consumers can smooth their income over time or if pricing based on age is also allowed (eliminating any consumption smoothing benefit of health-based pricing), the welfare loss from the 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 issues, such as the effect of varying the coverage levels of available plans, age-based pricing, self-insurance through consumer saving and borrowing, and insurer risk adjustment transfers.

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. Incorporating product differentiation, and, additionally, the possibility of imperfect competition, could enrich both 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, limited consumer information, or issues of consumer choice adequacy, all of which prior research has demonstrated may be important factors in insurance markets.

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

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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 \widehat{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).⁵¹

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 a $\widehat{P}_L < P_L''$ 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 $AC_L(\widehat{P}_H - P_L'') \leq AC_L(P_H - P_L'') \leq P_L''$. \square

Definition 2. The *lowest safe policy L price given P_H* is $\underline{P}_L(P_H) \equiv \min\{P_L'' : \Pi_L(P_H, P_L'') \geq 0\}$.

⁵¹In fact, it suffices to restrict attention to deviations by potential entrants.

Remark 1. The lowest safe price given P_H is given by

$$\underline{P}_L(P_H) = \left\{ \begin{array}{ll} P_H - \underline{\theta} & \text{if } P_H \leq \underline{AC}_L + \underline{\theta} \\ \tilde{P}_L(P_H) & \text{if } P_H \in (\underline{AC}_L + \underline{\theta}, \overline{AC}_L + \bar{\theta}) \\ \overline{AC}_L & \text{if } P_H \geq \overline{AC}_L + \bar{\theta} \end{array} \right\}$$

where $\tilde{P}_L(P_H) \equiv \{ \tilde{P}_L : \tilde{P}_L = AC_L(P_H - \tilde{P}_L) \}$. When $P_H \leq \underline{AC}_L + \underline{\theta}$, all consumers buy policy H at prices $(P_H, \underline{P}_L(P_H))$; when $P_H \in (\underline{AC}_L + \underline{\theta}, \overline{AC}_L + \bar{\theta})$ there are positive sales of both policies at prices $(P_H, \underline{P}_L(P_H))$; and when $P_H \geq \overline{AC}_L + \bar{\theta}$ all consumers buy policy L at prices $(P_H, \underline{P}_L(P_H))$. Note that for $P_H \in (\underline{AC}_L + \underline{\theta}, \overline{AC}_L + \bar{\theta})$, the price $\underline{P}_L(P_H)$ and price difference $P_H - \underline{P}_L(P_H)$ are both continuous and strictly increasing in P_H . [The price difference $P_H - \underline{P}_L(P_H)$ must increase if $\underline{P}_L(P_H)$ does since $\underline{P}_L(P_H) = AC_L(P_H - \underline{P}_L(P_H))$ for P_H in this range.]

Remark 2. Observe that if a two-policy reaction (P_H'', P_L'') is safe and causes the profitable single-policy deviation P_H' to instead make losses, then the single-policy reaction P_L'' is also safe and causes the single-policy deviation P_H' to make losses. To see why, note first that it cannot be that $P_H'' < P_H'$ (otherwise the deviator's profit would not be strictly negative). The result is immediate if $P_H'' > P_H'$. So suppose that $P_H'' = P_H'$. Since the firms make losses on policy H and the reaction is safe, we must have $\Pi_L(P_H', P_L'') \geq 0$. But then Lemma 1 implies that the single-policy reaction P_L'' is safe and clearly also causes the deviating firm to make losses. Hence, in looking at safe reactions to single-policy deviations in P_H , we can restrict attention to single-policy safe reactions in P_L .

Lemma 2. If at $(P_H, \underline{P}_L(P_H))$ we have positive sales of policy H and $\Pi_H(P_H, \underline{P}_L(P_H)) \geq 0$, then $\Pi_H(P_H, P_L) \geq 0$ at all $P_L > \underline{P}_L(P_H)$.

Proof. Since there are positive sales of policy H, it follows that $P_H \geq AC_H(P_H - \underline{P}_L(P_H)) \geq AC_H(P_H - P_L)$ for any $P_L > \underline{P}_L(P_H)$, where the second inequality follows from that fact that increases in P_L weakly lower AC_H . \square

Remark 3. In light of Remark 2, Lemma 2 implies that a profitable single-policy deviation to P_H' can be rendered unprofitable by a safe reaction if and only if it is rendered unprofitable by a single-policy reaction to $\underline{P}_L(P_H')$.

A.2 RE and NE Characterizations

We first establish three properties shared by RE and NE: (i) both policies break even; (ii) all-in-H is an equilibrium if and only if $\Delta AC(\underline{\theta}) \leq \underline{\theta}$, (iii) if $\Delta AC(\underline{\theta}) > \underline{\theta}$, then the equilibrium price difference must be $\underline{\Delta P}_{BE}$.

Lemma 3. If (P_H^*, P_L^*) is a RE (resp. NE), then $\Pi_H(P_H^*, P_L^*) = \Pi_L(P_H^*, P_L^*) = 0$.

Proof. Since any NE is a RE, we establish the result by showing it for RE. We first show that $\Pi_L(P_H^*, P_L^*) \leq 0$. Suppose otherwise, so that $\Pi_L(P_H^*, P_L^*) > 0$. Then for small $\varepsilon > 0$ we would

have $\Pi_L(P_H^*, P_L^* - \varepsilon) > 0$. By Lemma 1, a single-policy deviation that offers $P_L^* - \varepsilon$ would then be safe, and there would therefore be no reaction that could render it unprofitable. But then (P_H^*, P_L^*) would not be a RE, a contradiction.

We next show that $\Pi_H(P_H^*, P_L^*) \leq 0$. The result is immediate if policy H makes no sales at (P_H^*, P_L^*) . So suppose that $\Delta P^* < \bar{\theta}$ and that contrary to the claim (P_H^*, P_L^*) is a RE with $\Pi_H(P_H^*, P_L^*) > 0$. If $\underline{P}_L(P_H^*) > P_L^*$, then a single-policy deviation to $P_H^* - \varepsilon$ for small enough $\varepsilon > 0$ would be a profitable Riley deviation as no safe reaction in P_L could render it unprofitable. So we must have $\underline{P}_L(P_H^*) \leq P_L^*$. Now if $\underline{P}_L(P_H^*) < P_L^*$, then there can be no policy L sales at (P_H^*, P_L') for any $P_L' \in [\underline{P}_L(P_H^*), P_L^*)$, since otherwise a single-policy deviation to $P_L' + \varepsilon$ for sufficiently small $\varepsilon > 0$ would be strictly profitable and safe. Thus, $\underline{P}_L(P_H^*) \leq P_L^*$ implies that $\Pi_H(P_H^*, \underline{P}_L(P_H^*)) = \Pi_H(P_H^*, P_L^*) > 0$. By continuity, we then have that $\Pi_H(P_H^* - \varepsilon, \underline{P}_L(P_H^* - \varepsilon)) > 0$ for small enough $\varepsilon > 0$, so a single-policy deviation to such a $P_H^* - \varepsilon$ cannot be rendered unprofitable by any safe reaction, yielding a contradiction.

Thus, we have $\Pi_L(P_H^*, P_L^*) \leq 0$ and $\Pi_H(P_H^*, P_L^*) \leq 0$. But if either is strictly negative, then some firm must be earning strictly negative profits, and would do better by dropping all of its policies. The result follows. \square

Lemma 4. *There is a RE (resp. NE) in which all consumers buy policy H if and only if $\Delta AC(\underline{\theta}) \leq \underline{\theta}$.*

Proof. By Lemma 3, $P_H^* = \underline{AC}_H$ in any all-in-H equilibrium. Suppose that $\Delta AC(\underline{\theta}) > \underline{\theta}$, so that $\underline{AC}_H - \underline{\theta} > \underline{AC}_L$. Then a single-policy deviation offering $\hat{P}_L = \underline{AC}_H - \underline{\theta} - \varepsilon$ for small enough $\varepsilon > 0$ attracts a positive measure of consumers at an average cost close to \underline{AC}_L and thus makes positive profits: i.e., $\Pi_L(\underline{AC}_H, \underline{AC}_H - \underline{\theta} - \varepsilon) > 0$. Moreover, this deviation is safe, so cannot be made unprofitable by any reactions. Hence, all-in-H is not an RE, and hence not a NE.

Now suppose that $\Delta AC(\underline{\theta}) \leq \underline{\theta}$. Let $P_H^* = \underline{AC}_H$ and $P_L^* \geq \underline{AC}_H - \underline{\theta}$ be offered by more than one firm. We show that there are then no profitable deviations, even before considering any reactions, implying that all-in-H is a RE and NE. Consider any deviation $(\hat{P}_H, \hat{P}_L) \leq (\underline{AC}_H, P_L^*)$. To be profitable, some consumers must buy policy L in the deviation, so $\hat{P}_L < \underline{AC}_H - \underline{\theta}$ and $\Delta \hat{P} > \Delta P^*$. But the most profitable such deviation has \hat{P}_H equal to or arbitrarily close to P_H^* . (Otherwise, both \hat{P}_H and \hat{P}_L could be raised by a small and equal amount.) But, since the reduction in P_L makes policy H at price P_H^* either strictly unprofitable or have no sales, this deviation is weakly less profitable than a single-policy deviation to \hat{P}_L . But since $\hat{P}_L < \underline{AC}_H - \underline{\theta} \leq \underline{AC}_L$, this single-policy deviation is unprofitable. \square

Lemma 5. *Among all price pairs (P_H, P_L) at which both policies break even and there are positive sales of policy L, only the one with the lowest sales of policy L (i.e., having $\Delta P = \underline{\Delta P}^{BE}$) can be a RE (resp. NE).*

Proof. Suppose that at price configurations $P' = (P'_H, P'_L)$ and $P'' = (P''_H, P''_L)$ both policies break even, $\min\{\Delta P', \Delta P''\} > \underline{\theta}$, and there is a larger share for policy L in P'' than in P' . Then $\Delta P' < \Delta P''$

and there are positive sales of policy H at P' .⁵² In addition, $P'_L = AC_L(\Delta P') < AC_L(\Delta P'') = P''_L$. Starting at price configuration P'' , consider an entrant deviation offering price $P'_H = AC_H(\Delta P') < AC_H(\Delta P'') = P''_H$. Since $P'_H - P'_L < \Delta P'$, after the deviation the share of policy H is positive and moreover $P'_H - AC_H(P'_H - P'_L) > 0$. Thus, the deviation is profitable. Now, observe that the lowest safe policy L price given P'_H is P'_L ; i.e., $\underline{P}_L(P'_H) = P'_L$, so $\Pi_H(P'_H, \underline{P}_L(P'_H)) = 0$. Hence, there are no safe reactions that make the deviator incur a loss (Remark 3). This implies that (P''_H, P''_L) is not a RE, which is a contradiction. Since it is not a RE, it also cannot be a NE. \square

Remark 4. *Note that in the proofs of the above results, all profitable deviations were single-policy deviations. Thus, the same properties hold for NE in which firms can offer only a single policy.*

We now separately complete the characterization of RE and NE. We first note the following fact about RE:

Lemma 6. *Suppose that at $P^* = (P^*_H, P^*_L)$ there are positive sales of policy L (so $\Delta P^* \in (\theta, \bar{\theta}]$) and both policies break even. Then P^* is a RE if and only if there are no single-policy Riley profitable deviations in P_H .*

Proof. Consider a multi-policy profitable Riley deviation $P' = (P'_H, P'_L)$. We will show that we necessarily have $\Pi_H(P'_H, P^*_L) > 0$ and $\Pi_H(P'_H, \tilde{P}_L) \geq 0$ for all $\tilde{P}_L \in [\underline{P}_L(P'_H), P^*_L]$. Thus, a single-policy deviation to P'_H would be a profitable Riley deviation.

The claim is immediate if $P'_L > P^*_L$ since then dropping offer P'_L would affect neither the deviation profit, nor the deviator's profit after any reaction. So henceforth we shall assume that $P'_L \leq P^*_L$. Moreover, we must have $P'_H \leq P^*_H$: otherwise the deviator can sell only policy L at price $P'_L \leq P^*_L = AC_L(\Delta P^*) \leq AC_L(\Delta P')$, contradicting P' being a profitable Riley deviation. So $P' \leq P^*$.

Next, observe that we must have $\Delta P' < \Delta P^*$ and an increased share of policy H being purchased. If not, then since the average costs of both policies would be no lower than they were before the deviation, and both deviation prices would be weakly lower, the deviation could not generate a strictly positive profit. Note that this also implies that we must have $P'_H < P^*_H$.

Suppose, first, that $\underline{P}_L(P'_H) < P'_L$. If $\Pi_H(P'_H, \underline{P}_L(P'_H)) < 0$, then the safe single-policy reaction to $\underline{P}_L(P'_H)$ makes the deviator incur losses, in contradiction to the assumption that P' is a profitable Riley deviation. So in this case we must have $\Pi_H(P'_H, \underline{P}_L(P'_H)) \geq 0$. Moreover, there must be positive sales of policy H at prices $(P'_H, \underline{P}_L(P'_H))$ because, if not, then (see Remark 1) $\underline{P}_L(P'_H) = \overline{AC}_L \geq P^*_L \geq P'_L$. Thus, $\Pi_H(P'_H, \tilde{P}_L) > 0$ for all $\tilde{P}_L \in (\underline{P}_L(P'_H), P^*_L]$, implying that the single-policy deviation to P'_H is a profitable Riley deviation.

On the other hand, if $\underline{P}_L(P'_H) \geq P'_L$, then $\Pi_L(P'_H, P'_L) \leq 0$, which implies that $\Pi_H(P'_H, P'_L) > 0$ (since the deviation to P' is profitable). This, in turn, implies that $\Pi_H(P'_H, \tilde{P}_L) > 0$ for all $\tilde{P}_L \in [\underline{P}_L(P'_H), P^*_L]$, which establishes the result. \square

⁵²Note that we may have $\Delta P'' = \bar{\theta}$.

With these results in hand, we now prove Proposition 1:

Proof. of Proposition 1: Suppose, first, that $\Delta AC(\underline{\theta}) \leq \underline{\theta}$. By Lemma 4 we know that there is an all-in-H RE (and any such RE has a unique outcome, with $P_H^* = \underline{AC}_H$). We now show that if $\Delta AC(\underline{\theta}) < \underline{\theta}$, then this is the unique RE outcome. By Lemma 5 we know that any RE involving positive sales of policy L must involve the lowest break-even price difference, $\underline{\Delta P}_{BE}$. Let $(P_H^{**}, P_L^{**}) = (AC_H(\underline{\Delta P}_{BE}), AC_L(\underline{\Delta P}_{BE}))$ denote the corresponding break-even prices. Consider a single-policy deviation to $\hat{P}_H = P_L^{**} + \underline{\theta}$, which will attract all consumers to policy H. Since $\hat{P}_H > \underline{AC}_L + \underline{\theta} > \underline{AC}_H$, this is a profitable deviation absent any reaction. Since $\hat{P}_H \in (\underline{AC}_L + \underline{\theta}, \overline{AC}_L + \bar{\theta})$, we know that $\underline{P}_L(\hat{P}_H) = AC_L(\hat{P}_H - \underline{P}_L(\hat{P}_H))$ (see Remark 1). Since $\Delta AC(\Delta P) \leq \Delta P$ for all $\Delta P \in [\underline{\theta}, \underline{\Delta P}_{BE})$, this implies that $\hat{P}_H > AC_H(\hat{P}_H - \underline{P}_L(\hat{P}_H))$, so by Remark 3 no safe reaction can make the deviation unprofitable.

Suppose, instead, that $\Delta AC(\underline{\theta}) > \underline{\theta}$. By Lemma 5 we know that the only candidate for a RE involves the lowest break-even price difference with positive sales of policy L, $\underline{\Delta P}_{BE}$. Again, let $(P_H^{**}, P_L^{**}) = (AC_H(\underline{\Delta P}_{BE}), AC_L(\underline{\Delta P}_{BE}))$ denote the corresponding break-even prices. By Lemma 6 we need only consider single policy deviations in P_H to verify that this is an equilibrium. Any such deviation \hat{P}_H that is strictly profitable must have $\hat{P}_H < \min\{P_H^{**}, P_L^{**} + \underline{\theta}\}$ and $\hat{P}_H > AC_H(\hat{P}_H - P_L^{**})$. By the latter inequality, $\hat{P}_H > \underline{AC}_H > \underline{AC}_L + \underline{\theta}$. Then, by Remark 1, the lowest safe reaction in P_L has $\underline{P}_L(\hat{P}_H) = AC_L(\hat{P}_H - \underline{P}_L(\hat{P}_H))$ and results in positive sales of policy H. Since $\Delta AC(\Delta P) > \Delta P$ for all $\Delta P \in [\underline{\theta}, \underline{\Delta P}_{BE})$, this implies that $\hat{P}_H < AC_H(\hat{P}_H - \underline{P}_L(\hat{P}_H))$, so the deviation is unprofitable. \square

We now turn to NE:

Lemma 7. *If $\Delta AC(\underline{\theta}) < \underline{\theta}$ there is a unique NE outcome and it involves all consumers purchasing policy H. If $\Delta AC(\underline{\theta}) > \underline{\theta}$, there is a unique NE outcome and it involves the break-even prices $(\underline{P}_H^{BE}, \underline{P}_L^{BE})$ corresponding to the lowest break-even price difference with positive sales of policy L ($\underline{\Delta P}_{BE}$), iff $\Pi(\underline{P}_H^{BE}, \underline{P}_L^{BE}) = 0 = \max_{\hat{P}_H \leq P_H^*} \Pi(\hat{P}_H, \underline{P}_L^{BE})$, that is, if there is no profitable multi-policy deviation by an entrant that reduces P_H and lowers P_L slightly to capture all consumers.*

Proof. Since any NE is a RE, the uniqueness result for $\Delta AC(\underline{\theta}) < \underline{\theta}$ follows directly from Proposition 1. Suppose, instead, that $\Delta AC(\underline{\theta}) > \underline{\theta}$. By our previous results for RE, any NE outcome must involve price configuration $(\underline{P}_H^{BE}, \underline{P}_L^{BE})$. Observe, first, that no deviation from $(\underline{P}_H^{BE}, \underline{P}_L^{BE})$ that raises ΔP (including single-policy deviations in P_L) can be profitable, as this raises the average costs of both policies.

Now consider deviations that lower ΔP . A single-policy deviation offering policy H at price $\hat{P}_H < \underline{P}_H^{BE}$, since it makes policy L at price \underline{P}_L^{BE} earn strictly positive profits, is less profitable than the multi-policy deviation $(\hat{P}_H, \underline{P}_L^{BE} - \varepsilon)$ for sufficiently small $\varepsilon > 0$, as this captures the entire market. However, any multi-policy deviation $(\hat{P}_H, \hat{P}_L) \ll (\underline{P}_H^{BE}, \underline{P}_L^{BE})$ is dominated by a deviation $(\hat{P}_H + \delta, \hat{P}_L + \delta)$ for some $\delta > 0$. As $\Delta \hat{P} < \Delta P_{BE}$, the supremum of deviation profits is therefore $\max_{\hat{P}_H \leq \underline{P}_H^{BE}} \Pi(\hat{P}_H, \underline{P}_L^{BE})$. \square

Remark 5. If firms can only offer one policy, the only change to Lemma 7 would be that if $\Delta AC(\underline{\theta}) > \underline{\theta}$, then there is a NE at the break-even prices $(\underline{P}_H^{BE}, \underline{P}_L^{BE})$ corresponding to the lowest break-even price difference with positive sales of policy L ($\Delta \underline{P}_{BE}$), if and only if $\Pi(\underline{P}_H^{BE}, \underline{P}_L^{BE}) = 0 = \max_{\hat{P}_H \leq \underline{P}_H^{BE}} \Pi_H(\hat{P}_H, \underline{P}_L^{BE})$, that is, if there is no profitable single-policy deviation in P_H by an entrant.

Although it will not play a role in our analysis, we note the following result:

Lemma 8. If $\theta > C_H(\theta) - C_L(\theta)$ for all $\theta \in [\underline{\theta}, \bar{\theta}]$, then some consumers must be buying policy H in any NE.

Proof. Suppose all consumers are purchasing policy L. Then, by Lemma 3, $P_L^* = \overline{AC}_L$ and $P_H^* = P_L^* + \bar{\theta}$. Now consider a deviation to $(P_H^* - \varepsilon, P_L^*)$. We will show that for small $\varepsilon > 0$, aggregate profits are strictly positive. Aggregate profits equal

$$\psi(\varepsilon) \equiv \Pi(P_H^* - \varepsilon, P_L^*) = \int_{\bar{\theta} - \varepsilon}^{\bar{\theta}} [P_H^* - \varepsilon - C_H(\theta)] f(\theta) d\theta + \int_{\underline{\theta}}^{\bar{\theta} - \varepsilon} [P_L^* - C_L(\theta)] f(\theta) d\theta.$$

Now

$$\psi'(\varepsilon) = [P_H^* - \varepsilon - C_H(\bar{\theta} - \varepsilon)] f(\bar{\theta} - \varepsilon) - [P_L^* - C_L(\bar{\theta} - \varepsilon)] f(\bar{\theta} - \varepsilon) - [1 - F(\bar{\theta} - \varepsilon)],$$

so

$$\begin{aligned} \psi'(0) &= [P_H^* - C_H(\bar{\theta})] f(\bar{\theta}) - [P_L^* - C_L(\bar{\theta})] f(\bar{\theta}) \\ &= f(\bar{\theta}) \{ \bar{\theta} - [C_H(\bar{\theta}) - C_L(\bar{\theta})] \} > 0. \end{aligned}$$

Since, by Lemma 3, $\psi(0) = \Pi(P_H^*, P_L^*) = 0$, this implies that for small $\varepsilon > 0$ aggregate profit is strictly positive. As a result, there is a $\delta > 0$ such that $(P_H^* - \varepsilon, P_L^* - \delta)$ is a profitable deviation. \square

The assumption that $\theta > C_H(\theta) - C_L(\theta)$ for all $\theta \in [\underline{\theta}, \bar{\theta}]$ is an implication of risk aversion; it says that all consumers prefer the greater coverage of policy H if it is priced at fair odds (for that consumer). However, in our analysis the presence of a (behavioral) idiosyncratic preference shock for each policy could mean that consumers do not satisfy this condition.

B Online Appendix: Wilson Equilibria

B.1 Characterization of Wilson Equilibria

A price configuration $P = (P_H, P_L)$ is a Wilson equilibrium (WE) if there is no deviation by an entrant to a price pair that is strictly profitable once any offers are withdrawn that make losses after the deviation.⁵³ We will say that a deviation from price configuration P that is strictly profitable after

⁵³Note that since at least one of P_H and P_L is undercut by any profitable entrant deviation, there is no ambiguity about which policies to withdraw in the event that one of the offers in the price configuration makes losses.

any such withdrawals is a “profitable Wilson deviation.”⁵⁴ Note that no policy L offers will ever be withdrawn after a deviation, because a reduction in P_H can never cause a P_L offer to make losses (since a reduction in P_H lowers AC_L).

We establish the following result, which we use to identify WE in our data:

Proposition 2. *Let $(\underline{P}_H^{BE}, \underline{P}_L^{BE})$ be the break-even price configuration associated with $\underline{\Delta P}^{BE}$, and let $\Delta P^w \in \text{Arg max}_{\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]} \Pi(\underline{P}_L^{BE} + \Delta P, \underline{P}_L^{BE})$. If $\Delta AC(\underline{\theta}) > \underline{\theta}$, then the break-even price configuration (P_H^w, P_L^w) associated with price difference ΔP^w is a WE, and is the unique WE whenever $\Delta P^w = \text{Arg max}_{\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]} \Pi(\underline{P}_L^{BE} + \Delta P, \underline{P}_L^{BE}) \in (\underline{\theta}, \underline{\Delta P}^{BE})$. If instead $\Delta AC(\underline{\theta}) < \underline{\theta}$, then the unique WE outcome has all consumers purchasing policy H at price $P_H^* = \underline{AC}_H$.*

We establish Proposition 2 through a series of lemmas. First, we identify some properties that any WE must satisfy:

Lemma 9. *If $P^w = (P_H^w, P_L^w)$ is a WE price configuration, then*

- (a) $\Pi(P_H^w, P_L^w) = 0$;
- (b) $\Pi_H(P'_H, P_L^w) \leq 0$ for all $P'_H \leq P_H^w$;
- (c) $\Delta P^w = (P_H^w - P_L^w) \leq \underline{\Delta P}^{BE}$, the lowest break-even ΔP with positive sales of policy L.

Proof. (a) If $\Pi(P_H^w, P_L^w) < 0$, then some firm would be better off dropping its offers, while if $\Pi(P_H^w, P_L^w) > 0$ then an entrant could profit by offering $(P_H^w - \varepsilon, P_L^w - \varepsilon)$ for sufficiently small $\varepsilon > 0$. (b) If this is violated at P'_H , then $\Pi_H(P'_H - \varepsilon, P_L^w) > 0$ for sufficiently small $\varepsilon > 0$. A entrants’ offering of $P'_H - \varepsilon$ would be a profitable Wilson deviation. (c) This is immediate if $\underline{\Delta P}^{BE} = \bar{\theta}$. So suppose that $\underline{\Delta P}^{BE} < \bar{\theta}$ and that $\Delta P^w > \underline{\Delta P}^{BE}$, which implies that there are positive sales of policy L at P^w . Since both policies break even at $\underline{\Delta P}^{BE}$, and $\Pi_L(P_H^w, P_L^w) \geq 0$ by parts (a) and (b), it must be that the break-even price configuration associated with $\underline{\Delta P}^{BE}$, $(\underline{P}_H^{BE}, \underline{P}_L^{BE})$, has $\underline{P}_L^{BE} = AC_L(\underline{\Delta P}^{BE}) < AC_L(\Delta P^w) \leq P_L^w$. Since $\underline{P}_L^{BE} < P_L^w$ and $\underline{\Delta P}^{BE} < \Delta P^w$, we also have $\underline{P}_H^{BE} < P_H^w$. So an entrant’s offer of $(\underline{P}_H^{BE} + \varepsilon, \underline{P}_L^{BE} + \varepsilon)$ for sufficiently small $\varepsilon > 0$ is a profitable Wilson deviation. \square

Consider the following problem:

$$\begin{array}{ll}
 \min_{(P_H, P_L)} & P_L \\
 \text{s.t.} & \text{(i) } \Pi(P_H, P_L) = 0 \\
 & \text{(ii) } \Pi_H(P'_H, P_L) \leq 0 \text{ for all } P'_H \leq P_H \\
 & \text{(iii) } P_H - P_L \in [\underline{\theta}, \underline{\Delta P}^{BE}]
 \end{array} \tag{10}$$

Lemma 10. *Any $P^* = (P_H^*, P_L^*)$ that solves problem (10) is a WE price configuration.*

⁵⁴Note that, in principle, a NE need not be a WE, as a profitable Wilson deviation may not be profitable if no policies are withdrawn.

Proof. We construct an equilibrium in which all prices $P \geq P^*$ are offered by multiple firms and each firm has an equal share of sales of both policies. Thus, all active firms earn zero, and we need only consider deviations by entrants.

To begin, it follows from constraint (ii) of problem (10), and the fact that L offers are never withdrawn, that there is no profitable Wilson deviation in which an entrant makes sales only of the H policy (which would require a price $\hat{P}_H < P_H^*$).

Next, there is no profitable Wilson deviation in which an entrant makes sales only of policy L. Suppose there were and let the deviation price be $\hat{P}_L < P_L^*$. If everyone buys policy L at prices (P_H^*, \hat{P}_L) then no policy H offers will be withdrawn and $\hat{P}_L > \overline{AC}_L$. But then prices (P_H^*, \overline{AC}_L) would be feasible in problem (10) and attain a lower value of P_L than P_L^* , contradicting P^* being a solution. Suppose instead that some consumers still buy policy H at prices (P_H^*, \hat{P}_L) . Then $\Pi_H(P_H^*, \hat{P}_L) < 0$, which implies that offer P_H^* will be withdrawn, as will every P_H up to the lowest \overline{P}_H above P_H^* such that $\Pi_H(\overline{P}_H, \hat{P}_L) = 0$. The entrant's profit will therefore be $\Pi_L(\overline{P}_H, \hat{P}_L)$. However, it cannot be that $\Pi_L(\overline{P}_H, \hat{P}_L) > 0$: if so then we have $\Pi(\overline{P}_H, \hat{P}_L) > 0$. But this would imply that there is an $\delta > 0$ such that price pair $(\overline{P}_H - \delta, \hat{P}_L - \delta)$ is feasible in problem (10) and achieves a lower P_L than P_L^* , a contradiction to P^* solving problem (10).⁵⁵

Finally, suppose that there is a profitable Wilson deviation for an entrant offering $\hat{P} = (\hat{P}_H, \hat{P}_L)$, in which the entrant makes sales of both policies. Then since offers for policy L are never withdrawn, $\hat{P}_L \leq P_L^*$. We first argue that $\Pi_H(P_H, \hat{P}_L) \leq 0$ for all $P_H \leq \hat{P}_H$. If $\hat{P}_H < P_H^*$, then this follows because P^* satisfies constraint (ii) and $\hat{P}_L \leq P_L^*$. If, instead, $\hat{P}_H > P_H^*$, then it follows because the entrant can make sales of the H policy only if $\Pi_H(P_H, \hat{P}_L) < 0$ for all $P_H < \hat{P}_H$, so that rivals' offers are withdrawn. Next, observe that if $\Pi_H(\hat{P}_H, \hat{P}_L) \leq 0$ and $\Pi(\hat{P}_H, \hat{P}_L) > 0$, then for some $\delta > 0$ price pair $(\hat{P}_H - \delta, \hat{P}_L - \delta)$ is feasible in problem (10) and achieves a lower P_L than P_L^* , a contradiction to P^* solving problem (10). \square

To solve for the Wilson equilibrium, we examine a relaxed version of problem (10). For $\Delta P \in [\underline{\theta}, \overline{\theta}]$, we first define $P_L^{BE}(\Delta P)$ by

$$[P_L^{BE}(\Delta P) - AC_L(\Delta P)]F(\Delta P) + [P_L^{BE}(\Delta P) + \Delta P - AC_H(\Delta P)][1 - F(\Delta P)] = 0,$$

and $P_H^{BE}(\Delta P) \equiv P_L^{BE}(\Delta P) + \Delta P$. Note that $P_L^{BE}(\Delta P)$ and $P_H^{BE}(\Delta P)$ are continuous functions. Note as well that, for $\Delta P \in [\underline{\theta}, \overline{\theta}]$, $[P_L^{BE}(\Delta P) - AC_L(\Delta P)] \geq 0$ if and only if $\Delta AC(\Delta P) \geq \Delta P$.⁵⁶

We will consider the relaxed problem

$$\min_{\Delta P \in [\underline{\theta}, \Delta P^{BE}]} P_L^{BE}(\Delta P) \tag{11}$$

⁵⁵This δ would set $\Pi(\overline{P}_H - \delta, \hat{P}_L - \delta) = 0$, and would satisfy constraint (ii) of problem (10) since $\Pi_H(P_H, \hat{P}_L - \delta) \leq 0$ for all $P_H \leq \overline{P}_H$.

⁵⁶This follows because

$$\Delta AC(\Delta P) \geq \Delta P \Leftrightarrow P_L^{BE}(\Delta P) - AC_L(\Delta P) \geq P_H^{BE}(\Delta P) - AC_H(\Delta P).$$

Note that in problem (11) the constraint set is closed and bounded, and the objective function is continuous, so a solution exists. In Lemma 11, we show the equivalence of this problem when $\Delta AC(\underline{\theta}) > \underline{\theta}$ to the problem of finding the profit-maximizing multi-policy Nash deviation from price configuration $(\underline{P}_H^{BE}, \underline{P}_L^{BE})$:

$$\max_{\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]} \Pi(\underline{P}_L^{BE} + \Delta P, \underline{P}_L^{BE}) \quad (12)$$

Lemma 11. *Suppose that $\Delta AC(\underline{\theta}) > \underline{\theta}$. Then $\text{Arg min}_{\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]} P_L^{BE}(\Delta P) = \text{Arg max}_{\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]} \Pi(\underline{P}_L^{BE} + \Delta P, \underline{P}_L^{BE})$.*

Proof. Letting $\delta(\Delta P) \equiv \underline{P}_L^{BE} - P_L^{BE}(\Delta P)$, we have

$$\begin{aligned} \Pi(\underline{P}_L^{BE} + \Delta P, \underline{P}_L^{BE}) &= \Pi(P_L^{BE}(\Delta P) + \Delta P + \delta(\Delta P), P_L^{BE}(\Delta P) + \delta(\Delta P)) \\ &= \Pi(P_L^{BE}(\Delta P) + \Delta P, P_L^{BE}(\Delta P)) + \delta(\Delta P) \\ &= \underline{P}_L^{BE} - P_L^{BE}(\Delta P), \end{aligned}$$

so for any ΔP and $\Delta P'$ we have

$$\Pi(\underline{P}_L^{BE} + \Delta P, \underline{P}_L^{BE}) - \Pi(\underline{P}_L^{BE} + \Delta P', \underline{P}_L^{BE}) = P_L^{BE}(\Delta P') - P_L^{BE}(\Delta P).$$

□

Thus, the solution to the relaxed problem (12) is exactly the $\Delta P \leq \underline{\Delta P}^{BE}$ that maximizes the multi-policy deviation profits from $\underline{\Delta P}^{BE}$. By Lemma 10, any solution to problem 12 for which there is a price configuration (P_H, P_L) with $P_H - P_L = \Delta P$ that is feasible in problem 10 is a WE. This is the case whenever the solution to problem 12 is $\Delta P = \underline{\Delta P}^{BE}$.

The usefulness of the relaxed problems (11) and (12) also stems from the following result:

Lemma 12. *Suppose that $\Delta AC(\underline{\theta}) > \underline{\theta}$ and that $\Delta P^* = \arg \min_{\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]} P_L^{BE}(\Delta P)$. Then the price configuration $(P_H^{BE}(\Delta P^*), P_L^{BE}(\Delta P^*))$ is the unique solution to problem (10).*

Proof. By Lemma 11, we need only show that $(P_H^{BE}(\Delta P^*), P_L^{BE}(\Delta P^*))$ is feasible in problem (10). By construction $(P_H^{BE}(\Delta P^*), P_L^{BE}(\Delta P^*))$ satisfies constraints (i) and (iii) of problem (10). We therefore need only show that $(P_H^{BE}(\Delta P^*), P_L^{BE}(\Delta P^*))$ satisfies constraint (ii). Observe that when $\Delta AC(\underline{\theta}) > \underline{\theta}$, at any $\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]$ we have $\Delta AC(\Delta P) > \Delta P$. This implies that for all $\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]$

$$\Pi_H(P_H^{BE}(\Delta P), P_L^{BE}(\Delta P)) \leq 0.$$

Since $P_L^{BE}(\Delta P^*) \leq P_L^{BE}(\Delta P)$ for all $\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]$ by virtue of ΔP^* being the solution to problem (11), we therefore have $\Pi_H(P_H^{BE}(\Delta P), P_L^{BE}(\Delta P^*)) \leq 0$ for all $\Delta P \in [\underline{\theta}, \underline{\Delta P}^{BE}]$. Continuity of $P_H^{BE}(\Delta P)$ in ΔP then implies that

$$\Pi_H(P_H, P_L^{BE}(\Delta P^*)) \leq 0 \text{ for all } P_H \in [\underline{AC}_H, P_H^{BE}(\Delta P^*)].$$

Since we also have that

$$\Pi_H(P_H, P_L^{BE}(\Delta P^*)) \leq 0 \text{ for all } P_H \leq \underline{AC}_H,$$

$(P_H^{BE}(\Delta P^*), P_L^{BE}(\Delta P^*))$ satisfies constraint (ii) of problem (10). \square

We next show that, when $\Delta AC(\underline{\theta}) \neq \underline{\theta}$, a unique solution P^* to problem (10) is the *only* WE whenever $\Delta P^* \in (\underline{\theta}, \underline{\Delta P}^{BE})$.

Lemma 13. *Suppose that $\Delta AC(\underline{\theta}) > \underline{\theta}$, there is a unique solution P^* of problem (10), and that $\Delta P^* \in (\underline{\theta}, \underline{\Delta P}^{BE})$. Then P^* is the unique WE price configuration.⁵⁷*

Proof. Lemma 9 shows that any WE price configuration must satisfy the constraints of problem (10). We next argue that when P^* is the unique solution to problem (10), any price configuration $\tilde{P} = (\tilde{P}_H, \tilde{P}_L)$ that satisfies the constraints but is not a solution cannot be a WE price configuration. By definition, $P_L^* < \min\{\underline{AC}_H - \underline{\theta}, \tilde{P}_L\}$.⁵⁸

If $(P_H^*, P_L^*) \ll (\tilde{P}_H, \tilde{P}_L)$ then at price configuration $(\tilde{P}_H, \tilde{P}_L)$ an entrant has a profitable Wilson deviation to $(P_H^* + \varepsilon, P_L^* + \varepsilon)$ for small $\varepsilon > 0$. So, for the rest of the proof, suppose instead that $P_H^* \geq \tilde{P}_H$, which also implies that $\Delta \tilde{P} < \Delta P^*$ since $P_L^* < \tilde{P}_L$.

We will show that

$$\Pi_H(P_H, P_L^*) < 0 \text{ for all } P_H \in (\tilde{P}_H, P_H^*] \quad (13)$$

which will imply that at \tilde{P} an entrant has a profitable Wilson deviation offering prices $(P_H^* + \varepsilon, P_L^* + \varepsilon)$ for $\varepsilon > 0$ such that $\Pi_H(P_H', P_L^* + \varepsilon) < 0$ for all $P_H' \in [\tilde{P}_H, P_H^* + \varepsilon]$ and $P_L^* + \varepsilon < \tilde{P}_L$, which results in all H policy offers in $[\tilde{P}_H, P_H^* + \varepsilon]$ being withdrawn.

Condition (13) follows immediately if $P_H^* \leq \underline{AC}_H$, since $P_H - P_L^* < \Delta P^*$ for all $P_H \leq P_H^*$ implies that there are positive sales of policy H at price configuration (P_H, P_L^*) . So suppose henceforth that $P_H^* > \underline{AC}_H$.

Because $\Delta AC(\underline{\theta}) > \underline{\theta}$, we have $\Delta AC(\Delta P) > \Delta P$ for all $\Delta P \in (\underline{\theta}, \underline{\Delta P}^{BE})$, which implies that $\Pi_H(P_H^{BE}(\Delta P), P_L^{BE}(\Delta P)) < 0$ for all $\Delta P \in (\underline{\theta}, \underline{\Delta P}^{BE})$. Moreover, continuity of $P_H^{BE}(\cdot)$ implies that for each $P_H \in [\underline{AC}_H, P_H^*]$, there is a $\Delta P' \in (\underline{\theta}, \underline{\Delta P}^{BE})$ such that $P_H^{BE}(\Delta P') = P_H$. Thus, we have

$$\Pi_H(P_H, P_L^*) < 0 \text{ for all } P_H \in (\underline{AC}_H, P_H^*] \quad (14)$$

since there are positive sales of policy H at price configuration (P_H, P_L^*) and

$$P_H = P_H^{BE}(\Delta P') < AC_H(P_H^{BE}(\Delta P') - P_L^{BE}(\Delta P')) < AC_H(P_H^{BE}(\Delta P') - P_L^*) = AC_H(P_H - P_L^*),$$

[the first inequality follows because $\Pi_H(P_H^{BE}(\Delta P'), P_L^{BE}(\Delta P')) < 0$ and the last inequality follows because P^* being the solution to problem (10) implies that $P_L^* < P_L^{BE}(\Delta P')$]. If $\tilde{P}_H > \underline{AC}_H$, then this establishes (13).

⁵⁷We conjecture, but have not proven, that the result extends to cases in which $\Delta P^* = \underline{\Delta P}^{BE}$.

⁵⁸The inequality $P_L^* < \underline{AC}_H - \underline{\theta}$ holds because the price configuration $(\underline{AC}_H, \underline{AC}_H - \underline{\theta})$, which results in all consumers choosing policy H, is feasible in problem (10), but is not the solution.

Finally, suppose that $\tilde{P}_H \leq \underline{AC}_H$. Then

$$\Pi_H(P_H, P_L^*) < 0 \text{ for all } P_H \in [\tilde{P}_H, \underline{AC}_H] \quad (15)$$

since $P_H - P_L^* < \Delta P^*$ implies that there are positive sales of policy H at price configuration (P_H, P_L^*) and $P_H - P_L^* > \bar{\theta}$ if $P_H = \underline{AC}_H$ (since $P_L^* < \underline{AC}_H - \underline{\theta}$) implies that there are positive sales of policy L at price configuration $(\underline{AC}_H, P_L^*)$. Then (14) and (15) together imply (13). \square

Finally, for the case where $\Delta AC(\underline{\theta}) < \underline{\theta}$ we have the following result:

Lemma 14. *Suppose that $\Delta AC(\underline{\theta}) < \underline{\theta}$. Then the unique WE outcome has all consumers purchasing policy H at price $P_H^* = \underline{AC}_H$.*

Proof. In Lemma 4 we established that all-in-90 is a RE when $\Delta AC(\underline{\theta}) < \underline{\theta}$ by arguing that when $P_H^* = \underline{AC}_H$ and $P_L^* > \underline{AC}_H - \underline{\theta}$, there was no profitable single-policy deviation in P_L . Since the exit of policy H cannot make policy L profitable (it would raise AC_L), there are also no profitable Wilson single-policy deviations in P_L . It is also immediate that there are no profitable Wilson deviations in only P_H or in both prices. The proof of uniqueness follows much as in the proof of Proposition 1: Now any WE P^{**} must have $P_L^{**} \geq AC_L(\Delta P^{**})$ by Lemma 9. A single policy deviation to $\hat{P}_H = P_L^{**} + \underline{\theta}$ attracts all consumers to policy H. Since $\hat{P}_H > AC_L(\Delta P^{**}) + \underline{\theta} > \underline{AC}_L + \underline{\theta} > \underline{AC}_H$ it is profitable absent any exit of policy L, and policy L will not exit since it does not make losses (and could not make policy H unprofitable even if it did exit). \square

Remark 6. *Proposition 2 implies that [provided that $\Delta AC_H(\underline{\theta}) \neq \underline{\theta}$] any NE is a WE, and that whenever WE and RE outcomes coincide, they are also a NE outcome. Another implication of our discussion is that WE outcomes weakly Pareto dominate RE outcomes. In particular, when $\Delta AC(\underline{\theta}) < \underline{\theta}$ and $\Delta P^w < \underline{\Delta P}^{BE}$, we have $P_L^w < \underline{P}_L^{BE}$ (by Lemma 12) and $P_L^w < \underline{P}_L^{BE}$ (since $P_L^w < \underline{P}_L^{BE}$ and $\Delta P^w < \underline{\Delta P}^{BE}$).*

Wilson Equilibria: Community Rating and Health Status-based Pricing (Quartiles)						
Market	P ₆₀	S ₆₀	AC ₆₀	P ₉₀	S ₉₀	AC ₉₀
Full Population	4,006	83.7	2,477	7,105	16.3	14,961
Quartile 1	302	60.2	290	1,502	39.8	1,519
Quartile 2	1,307	64.7	1,155	3,307	35.3	3,586
Quartile 3	4,443	70.0	3,337	7,193	30.0	9,648
Quartile 4	9,704	73.6	7,259	13,204	26.4	20,007

Table B1: Equilibrium results for Wilson solution concept for (i) pure community rating (no pre-existing conditions) and (ii) health-based pricing with quartiles.

Welfare Loss from Health-Status-based Pricing (Quartiles) in Wilson Equilibrium (\$/year)			
γ	$y_{HB4,no-pre}(\gamma)$ Fixed Income	$y_{HB4,no-pre}(\gamma)$ Non-Manager Income path	$y_{HB4,no-pre}(\gamma)$ Manager Income Path
0.0002	2,101	1,390	-468
0.0003	2,577	1,592	-682
0.0004	2,964	1,711	-950
0.0005	3,277	1,628	-1,076
0.0006	3,506	1,923	-1,050

Table B2: Long-run welfare based on the Wilson Equilibrium results. Compares the two pricing regulations of (i) pricing based on health status quartiles ($x = \text{“}HB4\text{”}$) and (ii) pure community rating / no pre-existing conditions ($x' = \text{“}no - pre\text{”}$).

B.2 Empirical Results for Wilson Equilibria

We identify WE using Proposition 2, focusing on our baseline case of a 90 and a 60 policy. When $\Delta AC(\underline{\theta}) > \underline{\theta}$ (which is the case in our data), the price difference that maximizes the profit from a multi-policy deviation from $(\underline{P}_{90}^{BE}, \underline{P}_{60}^{BE})$, the break-even price configuration associated with $\underline{\Delta P}^{BE}$, is a WE.⁵⁹ Table B1 shows the equilibria with community rating and with health status quartile pricing. Wilson equilibrium policies break even in total, but they do so allowing the policy L to cross-subsidize policy H. The cross-subsidization can be seen by comparing the prices to the average costs for each policy. We see that in every population the WE has a positive share of consumers purchasing the 90 policy, in contrast to the RE/sp-NE of Section 4.

Table B2 shows welfare results for WE, which are of a similar order of magnitude to those for RE.

⁵⁹As noted above, this is the unique Wilson equilibrium when $\Delta P^w \in (\underline{\theta}, \underline{\Delta P}^{BE})$. We conjecture, but have not proven that the same is true if $\Delta P^w \in \{\underline{\theta}, \underline{\Delta P}^{BE}\}$.

C Online Appendix: Cost Model Setup and Estimation

This appendix describes the details of the cost model, which is summarized at a high-level in Section 3, and similar to that used in Handel (2013). The output of this model, F_{jkt} , is a family-plan-time-specific distribution of predicted out-of-pocket expenditures for the upcoming year. This distribution is an important input into the empirical choice model, where it enters as a family’s predictions of its out-of-pocket expenses at the time of plan choice, for each plan option. We predict this distribution in a sophisticated manner that incorporates (i) past diagnostic information (ICD-9 codes) (ii) the Johns Hopkins ACG predictive medical software package (iii) a non-parametric model linking modeled health risk to total medical expenditures using observed cost data and (iv) a detailed division of medical claims and health plan characteristics to precisely map total medical expenditures to out-of-pocket expenses. The level of precision we gain from the cost model leads to more credible estimates of the choice parameters of primary interest (e.g., risk preferences and health risk). Crucially, the cost model output is also used to predict consumer expected average costs for the upcoming year, λ , which is used to determine plan costs (as a function of who selects which plans) in our equilibrium analyses.

In order to predict expenses in a precise manner, we categorize the universe of total medical claims into four mutually exclusive and exhaustive subdivisions of claims using the claims data. These categories are (i) hospital and physician services (ii) pharmacy (iii) mental health and (iv) physician office visits. We divide claims into these four specific categories so that we can accurately characterize the plan-specific mappings from total claims to out-of-pocket expenditures since each of these categories maps to out-of-pocket expenditures in a different manner. We denote this four dimensional vector of claims \mathbf{C}_{it} and any given element of that vector $C_{d,it}$ where $d \in D$ represents one of the four categories and i denotes an individual (employee or dependent). After describing how we predict this vector of claims for a given individual, we return to the question of how we determine out-of-pocket expenditures in plan k given \mathbf{C}_{it} .

Denote an individual’s past year of medical diagnoses and payments by ξ_{it} and the demographics age and sex by ζ_{it} . We use the ACG software mapping, denoted A , to map these characteristics into a predicted mean level of health expenditures for the upcoming year, denoted θ :

$$A : \xi \times \zeta \rightarrow \theta$$

In addition to forecasting a mean level of total expenditures, the software has an application that predicts future mean pharmacy expenditures. This mapping is analogous to A and outputs a prediction κ for future pharmacy expenses.

We use the predictions θ and κ to categorize similar groups of individuals across each of four claims categories in vector in \mathbf{C}_{it} . Then for each group of individuals in each claims category, we use the actual ex post realized claims for that group to estimate the ex ante distribution for each individual under the assumption that this distribution is identical for all individuals within the cell. Individuals are categorized into cells based on different metrics for each of the four elements of \mathbf{C} :

Pharmacy:	κ_{it}
Hospital / Physician (Non-OV):	θ_{it}
Physician Office Visit:	θ_{it}
Mental Health:	$C_{MH,i,t-1}$

For pharmacy claims, individuals are grouped into cells based on the predicted future mean pharmacy claims measure output by the ACG software, κ_{it} . For the categories of hospital / physician services (non office visit) and physician office visit claims individuals are grouped based on their mean predicted total future health expenses, θ_{it} . Finally, for mental health claims, individuals are grouped into categories based on their mental health claims from the previous year, $C_{MH,i,t-1}$ since (i) mental health claims are very persistent over time in the data and (ii) mental health claims are generally uncorrelated with other health expenditures in the data. For each category we group individuals into a number of cells between 8 and 10, taking into account the tradeoff between cell size and precision. The minimum number of individuals in any cell is 73 while almost all cells have over 500 members. Thus, since there are four categories of claims, each individual can belong to one of approximately 10^4 or 10,000 combination of cells.

Denote an arbitrary cell within a given category d by z . Denote the population in a given category-cell combination (d, z) by I_{dz} . Denote the empirical distribution of ex-post claims in this category for this population $G_{I_{dz}}^{\wedge}(\cdot)$. Then we assume that each individual in this cell has a distribution equal to a continuous fit of $G_{I_{dz}}^{\wedge}(\cdot)$, which we denote G_{dz} :

$$\varpi : G_{I_{dz}}^{\wedge}(\cdot) \rightarrow G_{dz}$$

We model this distribution continuously in order to easily incorporate correlations across d . Otherwise, it would be appropriate to use $G_{I_{dz}}$ as the distribution for each cell.

The above process generates a distribution of claims for each d and z but does not model correlation over D . It is important to model correlation across claims categories because it is likely that someone with a bad expenditure shock in one category (e.g., hospital) will have high expenses in another area (e.g., pharmacy). We model correlation at the individual level by combining marginal distributions $G_{idt} \forall d$ with empirical data on the rank correlations between pairs (d, d') .⁶⁰ Here, G_{idt} is the distribution G_{dz} where $i \in I_{dz}$ at time t . Since correlations are modeled across d we pick the metric θ to group people into cells for the basis of determining correlations (we use the same cells that we use to determine group people for hospital and physician office visit claims). Denote these cells based on θ by z_{θ} . Then for each cell z_{θ} denote the empirical rank correlation between claims of type d and type d' by $\rho_{z_{\theta}}(d, d')$.

⁶⁰It is important to use rank correlations here to properly combine these marginal distribution into a joint distribution. Linear correlation would not translate empirical correlations to this joint distribution appropriately.

Then, for a given individual i we determine the joint distribution of claims across D for year t , denoted $H_{it}(\cdot)$, by combining i 's marginal distributions for all d at t using $\rho_{z_{\theta}}(d, d')$:

$$\Psi : G_{iDt} \times \rho_{z_{\theta_{it}}}(D, D') \rightarrow H_{it}$$

Here, G_{iDt} refers to the set of marginal distributions $G_{idt} \forall d \in D$ and $\rho_{z_{\theta_{it}}}(D, D')$ is the set of all pairwise correlations $\rho_{z_{\theta_{it}}}(d, d') \forall (d, d')^2$. In estimation we perform Ψ by using a Gaussian copula to combine the marginal distribution with the rank correlations, a process which we describe momentarily.

The final part of the cost model maps the joint distribution H_{it} of the vector of total claims C over the four categories into a distribution of out of pocket expenditures for each plan. For each of the three plan options we construct a mapping from the vector of claims C to out-of-pocket expenditures X_k :

$$\Omega_k : C \rightarrow X_k$$

This mapping takes a given draw of claims from H_{it} and converts it into the out-of-pocket expenditures an individual would have for those claims in plan k . This mapping accounts for plan-specific features such as the deductible, co-insurance, co-payments, and out-of-pocket maximums described in the text. We test the mapping Ω_k on the actual realizations of the claims vector C to verify that our mapping comes close to reconstructing the true mapping. Our mapping is necessarily simpler and omits things like emergency room co-payments and out of network claims. We constructed our mapping with and without these omitted categories to insure they did not lead to an incremental increase in precision. We find that our categorization of claims into the four categories in C passed through our mapping Ω_k closely approximates the true mapping from claims to out-of-pocket expenses. Further, we find that it is important to model all four categories described above: removing any of the four makes Ω_k less accurate. See Handel (2013) for figures describing this validation exercise with the data used in this paper.

Once we have a draw of X_{ikt} for each i (claim draw from H_{it} passed through Ω_k) we map individual out-of-pocket expenditures into family out-of-pocket expenditures. For families with less than two members this involves adding up all the within family X_{ikt} . For families with more than three members there are family level restrictions on deductible paid and out-of-pocket maximums that we adjust for. Define a family j as a collection of individuals i_j and the set of families as J . Then for a given family out-of-pocket expenditures are generated:

$$\Gamma_k : X_{i_j, kt} \rightarrow X_{jkt}$$

To create the final object of interest, the family-plan-time specific distribution of out of pocket expenditures $F_{jkt}(\cdot)$, we pass the claims distributions H_{it} through Ω_k and combine families through Γ_k . $F_{jkt}(\cdot)$ is then used as an input into the choice model that represents each family's information set over future medical expenses at the time of plan choice. Eventually, we also use H_{it} to calculate total plan cost when we analyze counterfactual plan pricing based on the average cost of enrollees.

We note that the decision to do the cost model by grouping individuals into cells, rather than by specifying a more continuous form, has costs and benefits. The cost is that all individuals within a given cell for a given type of claims are treated identically. The benefit is that our method produces local cost estimates for each individual that are not impacted by the combination of functional form and the health risk of medically different individuals. Also, the method we use allows for flexible modeling across claims categories. Finally, we note that we map the empirical distribution of claims to a continuous representation because this is convenient for building in correlations in the next step. The continuous distributions we generate very closely fit the actual empirical distribution of claims across these four categories.

Cost Model Identification and Estimation. The cost model is identified based on the two assumptions of (i) no moral hazard / selection based on private information and (ii) that individuals within the same cells for claims d have the same ex ante distribution of total claims in that category. Once these assumptions are made, the model uses the detailed medical data, the Johns Hopkins predictive algorithm, and the plan-specific mappings for out of pocket expenditures to generate the final output $F_{jkt}(\cdot)$. These assumptions, and corresponding robustness analyses, are discussed at more length in the main text and in Handel (2013).

Once we group individuals into cells for each of the four claims categories, there are two statistical components to estimation. First, we need to generate the continuous marginal distribution of claims for each cell z in claim category d , G_{dz} . To do this, we fit the empirical distribution of claims $G_{I_{dz}}$ to a Weibull distribution with a mass of values at 0. We use the Weibull distribution instead of the lognormal distribution, which is traditionally used to model medical expenditures, because we find that the lognormal distribution overpredicts large claims in the data while the Weibull does not. For each d and z the claims greater than zero are estimated with a maximum likelihood fit to the Weibull distribution:

$$\max_{(\alpha_{dz}, \beta_{dz})} \prod_{i \in I_{dz}} \frac{\beta_{dz}}{\alpha_{dz}} \left(\frac{c_{id}}{\alpha_{dz}} \right)^{\beta_{dz}-1} e^{-\left(\frac{c_{id}}{\alpha_{dz}} \right)^{\beta_{dz}}}$$

Here, $\hat{\alpha}_{dz}$ and $\hat{\beta}_{dz}$ are the shape and scale parameters that characterize the Weibull distribution. Denoting this distribution $W(\hat{\alpha}_{dz}, \hat{\beta}_{dz})$ the estimated distribution \hat{G}_{dz} is formed by combining this with the estimated mass at zero claims, which is the empirical likelihood:

$$G_{dz}^{\hat{}}(c) = \begin{cases} G_{I_{dz}}(0) & \text{if } c = 0 \\ G_{I_{dz}}(0) + \frac{W(\hat{\alpha}_{dz}, \hat{\beta}_{dz})(c)}{1 - G_{I_{dz}}(0)} & \text{if } c > 0 \end{cases}$$

Again, we use the notation \hat{G}_{iDt} to represent the set of marginal distributions for i over the categories d : the distribution for each d depends on the cell z an individual i is in at t . We combine the distributions \hat{G}_{iDt} for a given i and t into the joint distribution H_{it} using a Gaussian copula method for the mapping Ψ . Intuitively, this amounts to assuming a parametric form for correlation across \hat{G}_{iDt} equivalent

to that from a standard normal distribution with correlations equal to empirical rank correlations $\rho_{z_{\theta_{it}}}(D, D')$ described in the previous section. Let $\Phi_{1|2|3|4}^i$ denote the standard multivariate normal distribution with pairwise correlations $\rho_{z_{\theta_{it}}}(D, D')$ for all pairings of the four claims categories D . Then an individual's joint distribution of non-zero claims is:

$$H_{i,t}^{\hat{}}(\cdot) = \Phi_{1|2|3|4}(\Phi_1^{-1}(G_{id_1t}^{\hat{}}), \Phi_2^{-1}(G_{id_2t}^{\hat{}}), \Phi_3^{-1}(G_{id_3t}^{\hat{}}), \Phi_4^{-1}(G_{id_4t}^{\hat{}}))$$

Above, Φ_d is the standard marginal normal distribution for each d . $\hat{H}_{i,t}$ is the joint distribution of claims across the four claims categories for each individual in each time period. After this is estimated, we determine our final object of interest $F_{jkt}(\cdot)$ by simulating K multivariate draws from $\hat{H}_{i,t}$ for each i and t , and passing these values through the plan-specific total claims to out of pocket mapping Ω_k and the individual to family out of pocket mapping Γ_k . The simulated $F_{jkt}(\cdot)$ for each j , k , and t is then used as an input into estimation of the choice model.

Table C1 presents summary results from the cost model estimation for the final choice model sample, including population statistics on the ACG index θ , the Weibull distribution parameters $\hat{\alpha}_{dz}$ and $\hat{\beta}_{dz}$ for each category d , as well as the across category rank correlations $\rho_{z_{\theta_{it}}}(D, D')$. These are the fundamentals inputs used to generate F_{jkt} , as described above, and lead to accurate characterizations of the overall total cost and out-of-pocket cost distributions (validation exercises which are not presented here).

Final Sample				
Cost Model Output				
	Overall	PPO ₂₅₀	PPO ₅₀₀	PPO ₁₂₀₀
Individual Mean (Median)				
Unscaled ACG Predictor				
Mean		1.42	0.74	0.72
Median		0.83	0.37	0.37
Pharmacy: Model Output				
Zero Claim Pr.	0.35 (0.37)	0.31 (0.18)	0.40 (0.37)	0.42 (0.37)
Weibull α	1182 (307)	1490 (462)	718 (307)	596 (307)
Weibull β	0.77 (0.77)	0.77 (0.77)	0.77 (0.77)	0.77 (0.77)
Mental Health				
Zero Claim Pr.	0.88 (0.96)	0.87 (0.96)	0.90 (0.96)	0.90 (0.96)
Weibull α	1422 (1295)	1447 (1295)	1374 (1295)	1398 (1295)
Weibull β	0.98 (0.97)	0.99 (0.97)	0.98 (0.97)	0.98 (0.97)
Hospital / Physician				
Zero Claim Pr.	0.23 (0.23)	0.21 (0.23)	0.26 (0.23)	0.26 (0.23)
Weibull α	2214 (1599)	2523 (1599)	1717 (1599)	1652 (1599)
Weibull β	0.58 (0.55)	0.59 (0.55)	0.55 (0.55)	0.55 (0.55)
(> \$40,000) Claim Pr.	0.02 (0.01)	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)
Physician OV				
Zero Claim Pr.	0.29 (0.20)	0.26 (0.20)	0.33 (0.46)	0.34 (0.46)
Weibull α	605 (553)	653 (553)	517 (410)	529 (410)
Weibull β	1.15 (1.14)	1.15 (1.14)	1.15 (1.14)	1.14 (1.14)
Correlations				
Rank Correlation Hospital-Pharm.	0.28 (0.34)	0.26 (0.32)	0.31 (0.34)	0.32 (0.34)
Rank Correlation Hospital-OV	0.73 (0.74)	0.72 (0.74)	0.74 (0.74)	0.74 (0.74)
Rank Correlation Pharm.-OV	0.35 (0.41)	0.33 (0.37)	0.38 (0.41)	0.39 (0.41)

Table C1: This table describes the output of the cost model in terms of the means and medians of individual level parameters, classified by the plan actually chosen. These parameters are aggregated for these groups but have more micro-level groupings, which are the primary inputs into our cost projections in the choice model. Weibull α , Weibull β , and Zero Claim Probability correspond to the cell-specific predicted total individual-level health expenses as described in more detail in Appendix C.

D Online Appendix: Choice Model Estimation Algorithm Details and Additional Results

This appendix describes the details of the choice model estimation algorithm. The corresponding section in the text provided a high-level overview of this algorithm and outlined the estimation assumptions we make regarding choice model fundamentals and their links to observable data. In addition, after the presentation of the estimation algorithm, we discuss further specification details and results for our primary choice model.

We estimate the choice model using a random coefficients simulated maximum likelihood approach similar to that summarized in Train (2009). The simulated maximum likelihood estimation approach has the minimum variance for a consistent and asymptotically normal estimator, while not being too computationally burdensome in our framework. Since we use panel data, the likelihood function at the family 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 choice made in the previous period. The maximum likelihood estimator selects the parameter values that maximize the similarity between actual choices and choices simulated with the parameters.

First, the estimator simulates Q draws from the distribution of health expenditures output from the cost model, F_{jkt} , for each family, plan, and time period. These draws are used to compute plan expected utility conditional on all other preference parameters. It then simulates S draws for each family from the distributions of the random coefficients γ_j and δ_j , as well as from the distribution of the preference shocks ϵ_k . We define the set of parameters θ as the full set of ex ante model parameters (before the S draws are taken):

$$\theta \equiv (\mu, \beta, \sigma_\gamma^2, \mu_\delta(A_j), \sigma_\delta(A_j), \alpha, \mu_{\epsilon_K}(A_j), \sigma_{\epsilon_K}(A_j), \eta_0, \eta_1).$$

We denote θ_{sj} one draw derived from these parameters for each family, including the parameters constant across draws:

$$\theta_{sj} \equiv (\gamma_j, \delta_j, \alpha, \epsilon_{KT}, \eta_0, \eta_1)$$

Denote θ_{Sj} the set of all S simulated draws for family j . For each θ_{sj} the estimator then uses all Q health draws to compute family-plan-time-specific expected utilities U_{sjkt} following the choice model outlined in earlier in Section 3. Given these expected utilities for each θ_{sj} , we simulate the probability of choosing plan k in each period using a smoothed accept-reject function with the form:

$$Pr_{sjt}(k = k^*) = \frac{\left(\frac{\frac{1}{-U_{sjk^*t}(\cdot)}}{\sum_K \frac{1}{-U_{sjkt}(\cdot)}} \right)^\tau}{\sum_k \left(\frac{\frac{1}{-U_{sjkt}(\cdot)}}{\sum_K \frac{1}{-U_{sjkt}(\cdot)}} \right)^\tau}$$

This smoothed accept-reject methodology follows that outlined in Train (2009) with some slight modifications to account for the expected utility specification. In theory, conditional on θ_{sj} , we would want to pick the k that maximizes U_{jkt} for each family, and then average over S to get final choice probabilities. However, doing this leads to a likelihood function with flat regions, because for small changes in the estimated parameters θ , the discrete choice made does not change. The smoothing function above mimics this process for CARA utility functions: as the smoothing parameter τ becomes large the smoothed Accept-Reject simulator becomes almost identical to the true Accept-Reject simulator just described, where the actual utility-maximizing option is chosen with probability one. By choosing τ to be large, an individual will always choose k^* when $\frac{1}{-U_{jk^*t}} > \frac{1}{-U_{jkt}} \forall k \neq k^*$. The smoothing function is modified from the logit smoothing function in Train (2009) for two reasons (i) CARA utilities are negative, so the choice should correspond to the utility with the lowest absolute value and (ii) the logit form requires exponentiating the expected utility, which in our case is already the sum of exponential functions (from CARA). This double exponentiating leads to computational issues that our specification overcomes, without any true content change since both models approach the true Accept-Reject function.

Denote any sequence of three choices made as k^3 and the set of such sequences as K^3 . In the limit as τ grows large the probability of a given k^3 will either approach 1 or 0 for a given simulated draw s and family j . This is because for a given draw the sequence (k_1, k_2, k_3) will either be the sequential utility maximizing sequence or not. This implicitly includes the appropriate level of inertia by conditioning on previous choices within the sequential utility calculation. For example, under θ_{sj} a choice in period two will be made by a family j only if it is optimal conditional on θ_{sj} , other preference factors, and the inertia implied by the period one choice. For all S simulation draws we compute the optimal sequence of choices for k with the smoothed Accept-Reject simulator, denoted k_{sj}^3 . For any set of parameter values θ_{Sj} the probability that the model predicts k^3 will be chosen by j is:

$$P_j^{\hat{k}^3}(\theta, F_{jkt}, \mathbf{Z}_j^A, \mathbf{Z}_j^B, H_j, A_j) = \sum_{s \in S} \mathbf{1}[k^3 = k_{sj}^3]$$

Let $\hat{P}_j^{\hat{k}^3}(\theta)$ be shorthand notation for $P_j^{\hat{k}^3}(\theta, F_{jkt}, Z_j^A, Z_j^B, H_k, A_j)$. Conditional on these probabilities for each j , the simulated log-likelihood value for parameters θ is:

$$SLL(\theta) = \sum_{j \in J} \sum_{k^3 \in K^3} d_{jk^3} \ln \hat{P}_j^{\hat{k}^3}$$

Here d_{jk^3} is an indicator function equal to one if the actual sequence of decisions made by family j was k^3 . Then the maximum simulated likelihood estimator (MSLE) is the value of θ in the parameter space Θ that maximizes $SLL(\theta)$. In the results presented in the text, we choose $Q = 100$, $S = 50$, and $\tau = 6$, all values large enough such that the estimated parameters vary little in response to changes.

D.1 Specification for Inertia

In the main text we did not describe the details for our specification for consumer inertia. The model for inertia, which is similar to that in Handel (2013), specifies an inertial cost $\eta(\mathbf{Z}_j^B)$ that is linearly related to consumer characteristics and linked choices, \mathbf{Z}_j^B :

$$\eta(\mathbf{Z}_j^B) = \eta_0 + \eta_1 Z_{jt}^B$$

The characteristics in \mathbf{Z}_j^B include family status (e.g., single or covering dependents), income, several job status measures, linked choice of Flexible Spending Account (FSA), and whether the family has any members with chronic medical conditions (and, if so, how many chronic conditions total in the family).

D.2 Additional Results

In the interest of space, the text only presented the risk preference parameter estimates from our primary specification, since this was the key object of interest recovered there for our equilibrium analysis of insurance exchange pricing regulations. Here, for completeness, in Tables D1 and D2 we include the full set of estimates in the primary model for reference, including inertia parameters, PPO_{1200} random coefficients, and ε standard deviations. Overall, the parameters not discussed in the text have similar estimates to those in Handel (2013), though the risk preference estimates differ here because they are linked explicitly to health risk to estimate correlations between those two micro-foundations.

Empirical Model Results		
Parameter / Model	(1) Primary Model	Parameter Standard Error
Risk Preference Estimates		
μ_γ - Intercept, β_0	$1.21 * 10^{-3}$	$5.0 * 10^{-5}$
μ_γ - $\log(\sum_{i \in j} \lambda_i)$, β_1	$-1.14 * 10^{-4}$	$9.8 * 10^{-6}$
μ_γ - age, β_2	$-5.21 * 10^{-6}$	$1.0 * 10^{-7}$
μ_γ - $\log(\sum_{i \in j} \lambda_i) * \text{age}$, β_3	$1.10 * 10^{-6}$	$1.3 * 10^{-7}$
μ_γ - Manager, β_4	$4.3 * 10^{-5}$	$5.2 * 10^{-5}$
μ_γ - Manager ability, β_5	$1.4 * 10^{-5}$	$1.2 * 10^{-5}$
μ_γ - Non-manager ability, β_6	$7.5 * 10^{-6}$	$2.4 * 10^{-6}$
μ_γ - Population Mean	$4.39 * 10^{-4}$	-
μ_γ - Population σ	$6.63 * 10^{-5}$	-
σ_γ - γ standard deviation	$1.24 * 10^{-4}$	$3.5 * 10^{-5}$
Inertia Estimates		
η_0 , Intercept	1,336	76
η_1 , Family	2,101	52
η_1 , FSA Enroll	-472	44
η_1 , Income	96	15
η_1 , Quantitative	6	27
η_1 , Manager	162	34
η_1 , Chronic Condition	108	24

Table D1: This table presents the first half of the full set of primary choice model estimates: the set of estimates relevant for our analysis of exchange pricing regulation is presented and interpreted in much more detail in the main text. Standard errors are presented in column 2.

Empirical Model Results		
Parameter / Model	(1) Primary Model	Parameter Standard Error
PPO₁₂₀₀ Preferences		
μ_δ : Single	-2,504	138
σ_δ : Single	806	47
μ_δ : Family	-2,821	424
σ_δ : Family	872	48
Other		
α , High-Cost, PPO ₂₅₀	-805	79
ε_{500} , σ_ε , Single	50	340
ε_{1200} , σ_ε , Single	525	180
ε_{500} , σ_ε , Family	141	56
ε_{1200} , σ_ε , Family	615	216

Table D2: This table presents the second half of the full set of primary choice model estimates: the set of estimates relevant for our analysis of exchange pricing regulation is presented and interpreted in much more detail in the main text. Standard errors are presented in column 2.

E Online Appendix: Self-Insurance Model

Section 6.3 describes our extension that allows for consumers to save and borrow to self-insure against health shocks. That section in the main text describes the key features of our model of saving and borrowing as well as the results from that model. In this section we provide some additional details on this model and present a more formal treatment of it.

We allow for borrowing and saving by solving a finite horizon dynamic problem. To clarify notation and timing, we define the following terms:

- $W_t \equiv$ income in period t
- $p_{it} \equiv$ price of policy i in period t
- $m_t \equiv$ medical expenses in period t
- $\lambda_t \equiv$ ACG health status realization for period t (realized in period $t - 1$)
- $O_i(m) \equiv$ out of pocket expense for policy i with medical expenses outcome m
- $S_t \equiv$ savings chosen in period t
- $\bar{W}_t \equiv W_t + (1 + r)S_{t-1}$ are funds available in period t
- $c(m|i_t) = p_{i_t} + O_{i_t}(m)$ is the consumer's total medical expenses under policy i_t given m

Timing:

In each period t , the consumer chooses an insurance policy, (λ_{t+1}, m_t) is realized, and then a savings decision, S_t , is made. Given λ_{t+1} , m_{t+1} is then drawn in period $t + 1$ from a distribution $F_{t+1}(m_{t+1}|\lambda_{t+1})$. Thus, period t savings are decided after observing health expenses for period t and period $t + 1$'s health status. This assumption reflects a fluid financial market where individuals can take a last minute loan if they were unlucky or deposit extra cash if they were healthier than expected.

Solving the model:

We start in period T and solve for optimal savings backward. In period T given realization λ_T and starting savings plus income \bar{W}_T consumer expected utility is:

$$-E[e^{-\gamma(\bar{W}_T - c(m_T|i_T))}|\lambda_T] = -E[e^{-\gamma(W_T - c(m_T|i_T))}|\lambda_T]e^{-\gamma(1+r)S_{T-1}}$$

Given that $i_T^*(\lambda_T)$ is the consumer's policy choice at T when he has health status λ_T , expected period T utility is:

$$-E[e^{-\gamma(W_T - c(m_T|i_T^*(\lambda_T)))}|\lambda_T]e^{-\gamma(1+r)S_{T-1}}$$

which is a function of λ_T and S_{T-1} . We can thus denote the value function in period T as a function of the state, $V_T(\lambda_T, S_{T-1})$. Optimal period $T - 1$ saving S_{T-1} (saving for period T) solves:

$$\max_{S_{T-1}, i_{T-1}} -E[e^{-\gamma[\bar{W}_{T-1} - c(m_{T-1}|i_{T-1})]}|\lambda_{T-1}]e^{\gamma S_{T-1}} + \delta V_T(\lambda_T, S_{T-1})$$

which in turn delivers $V_{T-1}(\lambda_{T-1}, S_{T-2})$.

In this manner, we recursively solve the optimal savings level all the way backwards to period 1 for every possible history. Once we have $V_1(\lambda_1, 0)$ we compute the ex-ante welfare of an unborn individual who does not yet know her future λ_1 as:

$$W_0(W) = E_{\lambda_1}(V_1(\lambda_1, 0)).$$

The ex-ante welfare depends on the income profile $W = [W_1, W_2, \dots, W_T]$, on the initial distribution of types, and on the regulatory pricing regimes we want to evaluate. A pricing regime affects expected welfare through both the out of pocket expenses $O_i(m_t)$ as well as the premium paid, $p_i(\lambda_t)$. We translate the ex ante welfare difference between pricing regimes into yearly certainty equivalent values as in Section 5 in the main text.

E.1 Computation

To implement the dynamic problem we need assumptions about the evolution of the state variable. Unlike the primary welfare analysis in the paper (which assumed a steady state population) the computation here requires transitions across health states (predictive ACG index) over time. Namely, at any point in time, we need to compute the expected evolution of the future uncertainty, to figure out optimal savings.

We estimate health state transitions using the observed transitions in our sample. So that we have enough sample size to non-parametrically estimate this transition matrix, we divide the population into 7 groups based on health status and compute a 7-by-7 transition matrix for each of 8 five year age bins (25-30, 30-35,...). We assume that the estimated transition matrix for each five year age bin reflects the transition probabilities for consumers in that five year age bin transitioning to a given health status level for the next five year age bin. Within each period, consumers experience five years of identical health claims in the insurance contract they chose for that period, appropriately discounted. For each age bin, health type, and regulatory pricing regime, we use the static market equilibrium outcomes from our primary analysis $i^*(\lambda)$ and determine the actual choice each individual makes in each period, yielding her premia and out of pocket expenses.⁶¹ We assume consumers have flat income profiles over

⁶¹Market outcomes are assumed to be the same as those in our primary equilibrium analysis. They thus do not account for a potential effect that borrowing and saving would have on consumer insurance choices. Accounting for these dynamic effects would likely push consumers more towards lower insurance, and thus likely not have a large impact on equilibrium outcomes. This reflects the goal of this section, which is to quantify the impact of savings on the welfare numbers, keeping other things (including static market equilibrium outcomes) equal. In that spirit we keep the equilibrium prediction unchanged, as described in the paper for each pricing regime, and see how a representative individual's welfare would change if she is allowed to borrow or save.

time ($W_t = W$) (as in the first column of Table 6) in order to neutralize the other channels through which savings could impact welfare.

Given this setup, we solve the 8-period dynamic problem as described above. Once we recover the value function for an unborn individual (prior to age 25) for each possible realization of the initial health state, we compute the certainty equivalent of each regime x as:

$$-\sum_t^{T=8} \beta^t e^{-\gamma C E_x} = -\sum_j^7 p_j e^{-\gamma V_1(\lambda_j, 0)}.$$

The results from this model are presented and discussed in Section 6.3.

F Online Appendix: Exchange Participation

Our market analysis in the main text assumed full participation in the market. This could result from, for example, a legally enforced individual mandate (as in the ACA) with a large penalty, or, alternatively, an employer requiring all workers to remain in the insurance pool of a private exchange. In reality, such a requirement may be difficult to enforce, or the penalty for not purchasing insurance may be small, leading to a scenario where certain consumers, especially healthy ones, may prefer to opt out of the market.

To understand the role of mandated participation, we investigate the case where individuals can opt out of the exchanges should their expected utility from being uninsured be higher than joining their favorite insurance plan in the 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 in the market. We find equilibria allowing individuals to opt out without any penalty.⁶²

Recall that equilibria without age-based pricing unraveled to all-in-60. The column “Better-off In” in the “Community Rating” section of Table F1 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 $4.26 * 10^{-4}$ versus $4.03 * 10^{-4}$ 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 with a RE premium of \$5,339 when no more individuals want to drop out (that is, the RE for the remaining pool has $P_{60} = \$5,339$). The equilibrium without the mandate involves full unraveling 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 [$= 0.743(1,271) - 0.257(1,972)$] per person. On the right side of Table F1 we show the corresponding numbers for age-based pricing. As we saw in Section 6.2, all the equilibria under the mandate (with no opting out) for the different age groups

⁶²More 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.

Implications of Individual Mandate						
Ages	Community Rating		Age-Based Pricing			
	Mandate:	No Mandate:	Mandate:		No Mandate:	
	Better-Off In	Participation	Premium	Better-Off In	Premium	Participation
All	78.3%	74.3%	-	80.7%	-	77.0%
25-30	55.8%	50.6%	1,786	70.1%	2,732	63.1%
30-35	59.6%	54.1%	2,215	70.0%	3,409	62.5%
35-40	68.7%	62.2%	2,542	75.9%	3,476	70.8%
40-45	75.1%	70.9%	3,242	77.7%	4,233	74.5%
45-50	82.5%	79.3%	4,103	82.9%	4,976	80.6%
50-55	90.6%	87.2%	5,038	88.6%	5,714	86.9%
55-60	94.7%	92.5%	6,304	92.1%	6,927	89.9%
60-65	95.8%	93.9%	7,259	91.6%	7,959	90.2%

Table F1: Implications of the individual mandate for equilibrium prices and market participation.

involve unravelling to 60. At the equilibrium premium, reported in the “Mandate: Premium” column, only some 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 or penalty levels (analysis available upon request).

G Online Appendix: Population Re-Weighting

The analysis in the main text uses 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 rough sense of how our results could change under a population more similar to that enrolling 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 G.1 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 an “ACA relevant” sample composed of individuals in the MEPS data who are (i) between the ages of 25-65 and (ii) either uninsured or covered by a plan on the individual market ($N = 21,856$). This sample is similar in spirit to the sample that actually enrolls in the state insurance exchanges proposed under the ACA (which contain few people who already have access to existing public or employer-sponsored insurance). We note that, in addition to this “ACA relevant” MEPS sample, we also perform our equilibrium and welfare analysis for a second, broader, sample composed of all individuals in MEPS between the ages of 25 and 65, including those with employer sponsored or public insurance (Column 2 in Table G.1, $N = 81,733$). For the remainder of this section, we focus on the “ACA relevant” MEPS sample, our primary sample of interest.

Our analysis matches individuals in the employer data used throughout our analysis to the MEPS “ACA relevant” population and creates a new simulation sample with demographic weights similar to the MEPS sample but with detailed health and risk preference data from our estimates.⁶³ 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 sample, 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 survey sample weights in the MEPS data, which are intended to correct for sampling and response issues. Table G.2 describes the non-parametric age, income, and gender cell multivariate cell weights

⁶³We 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.

for this MEPS sample.⁶⁴ ⁶⁵

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 G.4 presents the main results for this sample, and can be directly compared to Table 4 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 \$4,051 while in the latter they are \$3,901.⁶⁶ 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.⁶⁷ Table G.5 and G.6 present, respectively, the demographics and equilibrium results for the broader sample of all individuals in MEPS between the ages of 25 and 65, including those with employer sponsored or public insurance within-sample.

⁶⁴We 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 and tables below show that average costs conditional on demographic bins are similar in our data and in the MEPS data. Table G.3 provides more detail on the health risk for both MEPS samples.

⁶⁵We note that Table G.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 G.1.

⁶⁶Though 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.

⁶⁷The 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)].

	Entire MEPS (1)	All Ind. 25-65 (2)	25-65 Unins/Ind (3)
N - Individual-Year Obs.	166,539	81,733	21,856
N - Individuals in Panel	105,353	51,922	13,804
N - Family-Year Obs.	58,647	-	-
N - Families in Panel	36,317	-	-
Avg. Family Members	2.90	-	-
Age-Individual			
Mean	33.82	43.15	42.6
10th Qtile	5	28	27
25th Qtile	14	34	32
Median	32	43	42
75th Qtile	51	52	52
90th Qtile	66	59	60
Gender-Individual			
Male %	47.7%	46.6%	50.2%
Total Income-Family-Year* **			
Mean	53613	64058	42746
10th Qtile	9240	12733	8000
25th Qtile	19000	26000	17068
Median	39080	50000	31114
75th Qtile	72375	85584	54995
90th Qtile	115086	131080	89600
Wage Income-Family-Year**			
Mean	44583	59945	38882
10th Qtile	0	7348	300
25th Qtile	8000	24000	14280
Median	32000	48300	30000
75th Qtile	65000	83753	52000
90th Qtile	104438	124996	82680
Region-Individual			
Northeast	14.5%	15.0%	10.1%
Midwest	19.2%	19.6%	15.0%
South	38.3%	38.7%	46.3%
West	26.9%	26.8%	28.7%

Table G1: This table describes demographic data for key samples of interest in the MEPS data, for the pooled data from 2004-2008. A more detailed description of each column's sample is contained in the text.

*In individual samples, a given family's income may count twice since two individuals can be from same family.

MEPS Weights Incorporated**All 25-65 Sample**

Age Bucket / Fam. Wages	0-\$35,000	\$35,000-\$70,000	\$70,000-\$105,000	≥ 105,000	Total
25-29	4.1%	4.5	2.7	1.9	13.1%
30-34	3.3%	4.4	2.6	1.9	12.3%
35-39	3.5%	4.2	2.8	2.3	12.9%
40-44	3.6%	4.5	3.0	2.8	13.9%
45-49	3.5%	4.2	3.0	3.1	13.9%
50-54	3.5%	3.8	2.8	2.9	13.1%
55-59	3.8%	3.2	2.3	2.3	11.7%
60-64	4.4%	2.3	1.3	1.2	9.2%
Total	29.7%	31.1%	20.5%	18.4%	100%
% Male by Income*	45.6%	49.9%	50.3%	51.4%	

25-65 Unins./ Private

Age Bucket / Fam. Wages	0-\$35,000	\$35,000-\$70,000	\$70,000-\$105,000	≥ 105,000	Total
25-29	7.4%	5.0	1.9	1.6	15.9%
30-34	6.0%	4.4	1.3	0.7	12.4%
35-39	6.4%	3.5	1.1	0.6	11.6%
40-44	6.1%	4.0	1.4	0.8	12.2%
45-49	6.2%	3.1	1.6	0.9	10.8%
50-54	5.9%	2.9	1.1	0.9	10.8%
55-59	7.0%	2.5	1.1	0.8	11.4%
60-64	10.1%	2.3	0.8	0.8	14.0%
Total	55.1%	27.7%	10.3%	7.1%	100%
% Male by Income*	51.4%	56.2%	55.4%	56.8%	

Table G2: This table describes the discrete age probabilities for different age / gender / income categories for (i) all individuals in MEPS, age 25-65, and (ii) all uninsured / individual market insured individuals in MEPS, age 25-65. These weights incorporate MEPS sample weights as well, as an additional weighting factor.

*Percentages of gender across age are essentially constant conditional on income, which is why those figures are not presented here.

MEPS Weights Incl.							
All 25-65 Sample							
Age Bucket / Quantile	10th	25th	50th	75th	90th	95th	Mean
25-29	0 (0)	0 (203)	125 (843)	620 (2833)	2109 (7638)	4155 (12007)	997 (2820)
30-34	0 (0)	0 (241)	224 (940)	922 (3179)	2815 (9040)	5582 (13122)	1376 (3146)
35-39	0 (0)	0 (239)	331 (925)	1314 (2928)	3499 (8158)	6333 (13595)	1696 (3126)
40-44	0 (0)	25 (258)	450 (967)	1669 (2955)	4513 (7844)	9099 (13843)	2235 (3544)
45-49	0 (0)	115 (365)	703 (1342)	2425 (3827)	6423 (9143)	12125 (15505)	3016 (3838)
50-54	0 (90)	221 (563)	1114 (1860)	3385 (4744)	8562 (10683)	16271 (17135)	4187 (4551)
55-59	0 (102)	410 (781)	1837 (2437)	4953 (5820)	11929 (13615)	21069 (22741)	5315 (6129)
60-64	71 (255)	707 (1109)	2337 (2906)	5916 (6771)	15261 (14493)	27033 (24997)	6790 (6666)

25-65 Unins./ Private							
Age Bucket / Quantile	10th	25th	50th	75th	90th	95th	Mean
25-29	0 (0)	0 (0)	0 (166)	173 (758)	819 (2959)	1824 (5502)	391 (952)
30-34	0 (0)	0 (0)	0 (180)	254 (852)	1062 (3234)	2024 (6095)	608 (1322)
35-39	0 (0)	0 (0)	0 (174)	328 (1024)	1650 (3187)	3164 (5748)	744 (1223)
40-44	0 (0)	0 (0)	50 (308)	750 (1459)	2929 (3966)	4500 (6908)	1381 (2449)
45-49	0 (0)	0 (0)	120 (425)	857 (1846)	3108 (4566)	6719 (9658)	2089 (1967)
50-54	0 (0)	0 (144)	340 (798)	1576 (2866)	5590 (7462)	11851 (12952)	2474 (3085)
55-59	0 (0)	24 (176)	1076 (1312)	3565 (3996)	9290 (9990)	16419 (19459)	3898 (4941)
60-64	0 (60)	449 (732)	1966 (2398)	5166 (5730)	13749 (12017)	24157 (21839)	6003 (6043)

Table G3: This table describes the expenditure quantiles for (i) all individuals in MEPS age 25-65 (top panel) and (iii) all uninsured / individual market insured individuals in MEPS, age 25-65 (bottom panel). Female numbers presented in parantheses, male numbers are not.

MEPS Unins. Weighted: Equilibria without Pre-existing Conditions							
	Equilibrium Type	P ₆₀	S ₆₀	AC ₆₀	P ₉₀	S ₉₀	AC ₉₀
	RE	3,901	100.0	3,901	-	0	-
	NE	Does not exist					

MEPS Unins. Weighted: Equilibria with Health Status-based Pricing (Quartiles)							
Market	Equilibrium Type	P ₆₀	S ₆₀	AC ₆₀	P ₉₀	S ₉₀	AC ₉₀
Quartile 1	RE	311	57.5	311	1,476	42.5	1,476
Quartile 2	RE	1,128	69.6	1,128	3,228	30.4	3,228
Quartile 3	RE	4,121	100.0	4,121	-	0	-
Quartile 4	RE	9,751	100.0	9,751	-	0	-

Table G4: 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.

	Entire MEPS (1)	All Ind. 25-65 (2)	25-65 Unins/Ind (3)
Family-Year: Coverage Type*			
Private (Employer or Ind.)	66.3%	73.3%	41.0%
Medicaid (someone)	30.7%	33.4%	45.4%
Medicare (someone)	29.01%	14.0%	16.4%
Uninsured** (someone)	26.7%	35.0%	84.7%
Only Public in Fam	22.5 %	15.1%	0%
Always Offered Employer (someone)	48.8 %	62.1%	–
Offered Employer Sometimes (someone)	62.0%	76.1%	–
Family Member Emp. Always	69.7%	84.7%	76.2%
Family Member Emp. Once	77.5%	92.3%	87.4%
Individual-Year: Coverage Type*			
Private (Employer or Ind.)	54.5%	64.0%	16.8%
Medicaid	25.4%	12.4%	0.72%
Medicare	13.4%	3.9% 1	.25%
Uninsured**	16.6%	22.3%	83.2%
Only Public	27.6%	12.7%	0%
Always Offered Employer	21.3 %	38.9%	–
Offered Employer Sometimes	32.5%	55.0%	–
Individual Emp. Always	37%	65.4%	37.5%
Individual Emp. Once	48%	78.3%	48.0%

Table G5: This table describes insurance coverage, expenditures, and other statistics in the MEPS data for the pooled data from 2004-2008. A more detailed description of each column's sample is contained in the text.

*Coverage type reflects whether a family ever had this kind of coverage (for any member) throughout the year, so these numbers add to more than 100%.

**Uninsured variable occurs when none of other coverage types are held, and the family is uninsured for whole year.

MEPS Weighted: Equilibria without Pre-existing Conditions							
	Equilibrium Type	P ₆₀	S ₆₀	AC ₆₀	P ₉₀	S ₉₀	AC ₉₀
	RE	3,852	100.0	4,051	-	0	-
	NE	Does not exist					

MEPS Weighted: Equilibria with Health Status-based Pricing (Quartiles)							
Market	Equilibrium Type	P ₆₀	S ₆₀	AC ₆₀	P ₉₀	S ₉₀	AC ₉₀
Quartile 1	RE	321	60.2	321	1,521	39.8	1,521
Quartile 2	RE	1,445	100.0	1,445	-	0	-
Quartile 3	RE	4,239	100.0	4,239	-	0	-
Quartile 4	RE	9,347	100.0	9,347	-	0	-

Table G6: This table presents the analogous table to Table 5 on equilibrium outcomes, applied to the sample reweighted by characteristics of the MEPS full population, as 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.

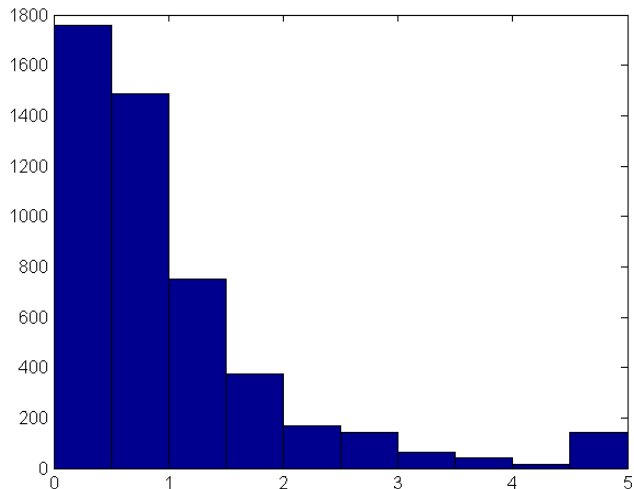


Figure H1: This figure presents the distribution of λ predicted for t_1 , for all individuals in the data (including dependents) present during both t_0 and t_1 . Predicted expected expenses are normalized by the average in this sample of \$4,878 (thus equal to 1 in this chart). The distribution presented is truncated at 5 times for this chart, but not in estimation / analysis.

H Online Appendix: Additional Analysis

This appendix contains several additional figures and tables discussed in the text. Figure H1 presents the distribution of λ 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 this sample 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. See Handel (2013) for additional detailed analysis of expected expenditures for employees at dependents at the firm we study.

Table H1 presents descriptive statistics for the pseudo-sample of individuals used in our insurance exchange simulations. The sample has a risk preference mean and standard deviation similar to those of the choice model estimation sample. Moreover, the distribution of income and health status are similar to those in the estimation sample and in the general population. The table just below in the text here illustrates that the simulation sample (as in our data overall) has a fairly uniform distribution of age between 25 and 65, consistent with our assumption of a steady state population in the welfare analysis. See Section 3.6 for further details on the sample used in our counterfactual analyses.

Quantile	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
Age	26	28	33	37	41	45	49	52	56	60	62

Table H2 shows average costs as a function of age 25 risk preferences, to illustrate the relationship between risk preferences and age that exists in our welfare framework. Following the choice model

estimates, costs are negatively related to risk aversion conditional on age. See Section 5 in the main text for more details.

Table H3 supports the analysis in our age-based pricing extension in Section 6 in the main text. The table 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 (the result of pure age-based pricing). Once age is priced, health-based pricing, which appealed to individuals with steeply increasing income, is no longer preferred by those consumers. The benefit of health-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 across the range of risk aversion types and for the different income path models studied.

Table H4 presents the long-run welfare implications of allowing for insurer risk-adjustment transfers, as specified in the HHS risk adjustment formula, described in Section 6 in the main text. Risk adjustment transfers partially reduce the extent of adverse selection under pure community rating, improving consumer welfare.

Figure H2 presents an additional calibration of the framework developed in Section 2 that highlights the tradeoff between adverse selection and reclassification risk, as a function of the fraction of health risk information known by consumers at the time of contracting. This is similar to a figure in that section, but calibrated so that consumers face more health risk. ($R = 30,000$). Unraveling occurs at higher ϕ 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 the figure in the appendix there is a smaller range of ϕ over which health-based pricing is better than community rating.

Simulation Sample	
	Simulation Sample
N - Families	-
N - Individuals 25-65	10,372
Mean Age	44.5
Median Age	45
Gender (Male %)	45
Income	
Tier 1 (< \$41K)	20%
Tier 2 (\$41K-\$72K)	40%
Tier 3 (\$72K-\$124K)	24%
Tier 4 (\$124K-\$176K)	8%
Tier 5 (> \$176K)	8%
Predicted Mean Total Expenditures	
Mean	\$6,099
25th quantile	\$1,668
Median	\$3,654
75th quantile	\$8,299
90th quantile	\$13,911
95th quantile	\$18,630
99th quantile	\$34,008
Risk Preferences	
Mean μ_γ	$4.28 * 10^{-4}$
Standard Deviation μ_γ	$7.50 * 10^{-5}$

Table H1: 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.

Average Costs at Various Ages Conditional on Age 25 Risk Aversion			
γ	30-35	45-50	55-60
0.0002	5,586	7,196	10,857
0.0003	4,212	6,390	10,319
0.0004	3,100	5,687	9,767
0.0005	2,328	4,911	9,271
0.0006	1,775	4,373	8,813

Table H2: 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.

Welfare Loss from Health Status-quartile Age-based pricing (\$/year)			
γ	$y_{HB4+age,age}(\gamma)$ Fixed Income	$y_{HB4+age,age}(\gamma)$ Non-Manager Income path	$y_{HB4+age,age}(\gamma)$ Manager Income Path
0.0002	2,111	2,129	1,100
0.0003	2,911	2,028	920
0.0004	3,707	1,842	778
0.0005	4,510	1,646	1,353
0.0006	5,137	1,612	1,876

Table H3: Long-run welfare comparison between the two pricing regulations of (i) pricing based on health status quartiles by age ($x = "HB4 + age"$) 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 $\delta = 0.975$.

Welfare Benefit of Risk-Adjustment Transfers: RE (\$/year)			
γ	$y_{PCR,risk-adj}(\gamma)$ Fixed Income	$y_{PCR,risk-adj}(\gamma)$ Non-Manager Income path	$y_{PCR,risk-adj}(\gamma)$ Manager Income Path
0.0001	316	261	106
0.0002	327	202	27
0.0003	336	139	18
0.0004	349	84	0
0.0005	368	36	38
0.0006	386	23	72

Table H4: Long-run welfare implications of insurer risk adjustment regulation (transfers based on the HHS risk adjustment formula).

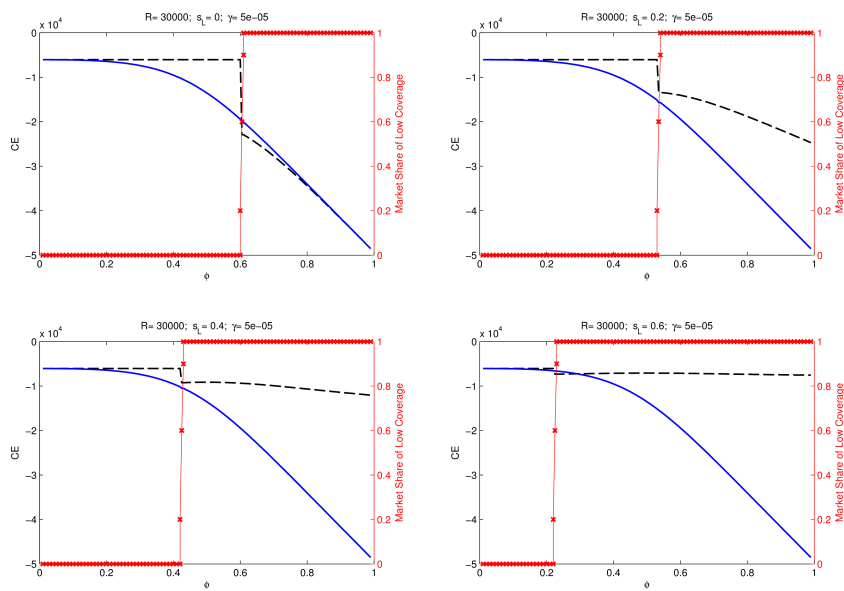


Figure H2: Adverse selection vs. reclassification risk, $R = 30,000$. X curve: market share of low coverage plan; dashed curve: certainty equivalent with pure community rating; solid curve: certainty equivalent with perfect health-based pricing.