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ABSTRACT

We evaluate reclassification risk in the small group health insurance market from a period before ACA community rating regulations. Reclassification risk in this setting is of key policy relevance and also a matter of debate. We use detailed claims and premiums data from a large insurance company and control non-parametrically for selection. We find a pass through of 16% from changes in health risk to changes in premiums, with a stronger equilibrium relationship between premiums and risk. This pattern is consistent with the insurer implicitly offering "guaranteed renewability" contracts with one-sided pricing commitment. We further find that groups whose health risk decreases have premiums that are more responsive to risk, which the guaranteed renewability model attributes to ex post renegotiation. The observed pricing policy adds 60% of the consumer welfare gain from community rating relative to experience rating. The welfare gains are limited because employers and employees switch coverage frequently.

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1 Introduction

One of the most important concerns in designing health insurance markets is reclassification risk, which occurs when an adverse and persistent health shock leads to higher future premiums or worse coverage. Reclassification risk has the potential to lead to market failure by limiting the long-run risk protection from insurance. A main goal of the 2010 Affordable Care Act (ACA) was to reduce reclassification risk—in the individual and small group markets—through community rating provisions.

This paper considers reclassification risk in the context of the small group health insurance market. This market provides insurance to individuals at employers with 2 to 50 employees.[1] In 2013, this market covered 18 million people in the U.S. (Kaiser Family Foundation, 2013), representing about $100 billion in revenues.[2] Our study brings novel data to bear on this understudied market. Reclassification risk is particularly salient for this market because of the small sizes of the employers. To illustrate, consider an individual who works for an employer with 5 employees with an annual health insurance contract.[3] Suppose that the individual or her co-worker is diagnosed with a serious illness, perhaps diabetes, with an expected cost of $25,000 per year going forward. A market that fully passes through risk to the employer—such as a competitive insurance market without long run contracts—will increase premiums to this employer by $25,000, which raises per-employee costs by $5,000.

The extent of reclassification risk in the small group market prior to the ACA is unclear. On the one hand, a number of influential studies have documented substantial variation in premiums across employers in this market (Cutler, 1994; Cebul et al., 2011; Bundorf et al., 2012). A plausible cause of this premium variation is reclassification risk, i.e., from employers with higher health risks facing higher premiums (Gruber, 2000). On the other hand, using survey data, Pauly and Herring (1999) find that premiums did not corre-

[1]Prior to the ACA, the small group market included groups with 1 to 50 members. The ACA originally mandated a change in the market definition to include groups with up to 100 members. This change was eliminated in the 2015 Protecting Affordable Coverage for Employees (PACE) Act, so that the federal definition remains 1-50 members. However, four states use the 100 members maximum in their definition (Jost, 2015).

[2]Authors' calculation using premium information from Blavin et al. (2014).

[3]Annual insurance contracts are typical in this market.

late much with health risk in either the individual and small group insurance markets. Herring and Pauly (2006) attribute this to the market providing protection from reclassification risk in the pre-ACA era in the form of "guaranteed renewability" contracts that do not increase rates in response to health risk increases. Given these mixed findings and the relevance to the ACA, we believe that understanding how much reclassification risk existed in this market, and why it existed, is important to understanding the value of what is one of the largest reforms to healthcare policy in the history of the U.S.

This paper has three main goals related to health insurance in the small group market. The first goal is to examine the extent of reclassification risk in this market. The second goal is to evaluate the mechanisms underlying our findings on reclassification risk. The third goal is to understand the welfare consequences of alternative pricing policies, such as community rating and full experience rating, relative to the current environment.

Our study uses data on the small group insurance market from a large health insurance company, which we refer to as the United States Insurance Company, or USIC. These data include a panel of claims and premiums for USIC's small group market products in 10 states over the period 2012-15, containing information on over 300,000 USIC enrollees at more than 12,000 employers.[4] Crucially, this database allows us to observe healthcare costs and premiums for each employer, which we use to directly evaluate reclassification risk. Our study is unique in having access to a large database on the small group market with this information.[5]

To motivate our empirical specifications, we first develop a simple two-period model of insurance in the small group market. Our model specifies that USIC offers health insurance to a small employer, charging premiums that are potentially based on the health risk (or equivalently, the expected claims cost) of the employer. Potential enrollees decide whether or not to enroll in insurance if offered, given their health risk and the premium

[4]This time period was immediately before most of the ACA regulations for the small group market were effective. For the time period and states in our sample, insurers could experience rate small employers without significant regulatory restrictions.

[5]Related to our study, Buchmueller and DiNardo (2002) investigated whether the implementation of community rating in New York led to adverse selection, while Cutler and Reber (1998); Bundorf et al. (2012); Einav et al. (2010), and Kowalski (2015) study reclassification risk for employees who could choose from a menu of plans offered by their employer, and Atal et al. (2019) study guaranteed renewability contracts in Germany.

charged. The welfare loss from reclassification risk is increasing in the pass through from changes in mean health risk at an employer to changes in premiums. We highlight three benchmark cases: full experience rating—where an increase in health risk at an employer is fully passed through in the form of higher premiums; community rating—where pass through is zero; and USIC's actual pass-through rate.

We evaluate the extent of reclassification risk by estimating the pass-through from changes in health risk at an employer in a year to changes in its per-enrollee premiums. We compute health risk for each individual as the ACG score, using the previous year's claims data.[6] Because there is frequent movement in and out of small group insurance, our estimation controls for selection with a non-parametric correction (Newey, 2009). Our fixed effects estimates are identified by the extent to which changes in health risk at an employer translate into changes in premiums, conditioning non-parametrically for the probability of being in the sample. Individual risk and industrial sector provide useful exclusion restrictions in the premium setting (treatment) equation that help identify the probability of being in the sample.

Overview of findings. We find that a unit increase in mean ACG score for an employer increases its mean annual claims cost by \$4003.[7] Our base estimates—with enrollee fixed effects and controls for selection—show that this unit increase causes premiums to rise by \$624. Thus, our estimated pass through from expected claims to premiums is 16%. Our results that do not control for fixed effects, but still control for selection, show a much higher relation between health risk and premiums, of \$2811, or 70% of health risk. The difference between the fixed effects and non-fixed effects estimates suggests that USIC prices new accounts based on their health risk and then updates premiums for existing accounts with much less regard to health risk.

Given the Herring and Pauly (2006) view that insurers typically offered guaranteed renewability contracts in the individual insurance market prior to the ACA, we seek to understand whether these contracts can explain our fixed effects findings. Under these

[6]The ACG score, which was developed by Johns Hopkins University, is widely used in this context (see, for instance Gowrisankaran et al., 2013; Handel, 2013; Ghili et al., 2019), and similar to USIC's proprietary risk score.

[7]An ACG score of 1 is the population mean score, so a unit increase would occur from an employer having double the expected health cost of the population mean.

contracts, insurers commit to a long-run premium schedule that is invariant to updates in health risk, but enrollees can let their insurance lapse and potentially buy a new policy. Handel et al. (2019) and Ghili et al. (2019) consider the optimal guaranteed renewability contract accounting for enrollee liquidity constraints. Under such contracts, insurers will partly front load premiums to avoid lapsation but will balance the front loading against consumption smoothing. In equilibrium, groups with decreases in risk score will renegotiate their contracts and obtain lower premiums.

The guaranteed renewability model with liquidity constraints has main three testable implications relevant to our setting. First, it implies positive, but incomplete, pass through from health risk to premiums. Second, it implies that the marginal impact of health risk on premiums will be greater for groups whose risk scores decrease than for groups whose risk scores increase. Finally, it implies that groups with initially higher risk scores will face greater pass through from health risk to premiums than other groups, since there is more scope for their premiums to decrease.

We simulated data from Handel et al. and show that these three implications hold for their optimal contracts. We test these three implications in the USIC data and find that they hold in our setting, though the exact numbers differ from Handel et al. due to institutional differences. Focusing on the USIC data, our above finding of a pass through of 16% is consistent with the first implication. Regarding the second implication, a unit increase in the ACG score caused only a $44 increase in premiums, while a unit decrease caused a $795 reduction in premiums, relative to a group with unchanged risk scores. Regarding the third implication, groups with above average initial risk scores faced a point estimate of an average increase of $413 from a unit increase in risk score while the figure is $378 for groups with below average initial risk scores. These results suggest that USIC may implicitly provide reclassification risk protection similar to guaranteed renewability contracts.

We then simulate counterfactuals to evaluate the extent to which the insurance provided by USIC provides value in the form of protection from reclassification risk in the small group market. We non-parametrically simulate the evolution of health risk over a ten-year horizon to evaluate how this would translate into financial risk for individuals.

Given that our specifications with enrollee fixed effects uncover USIC's pass through for existing employers, we assume that when individuals remain in USIC insurance with a given employer, they receive a new premium based on the new employer risk and the estimated coefficient from the model with enrollee fixed effects and the selection correction. Given that our non-fixed-effects specifications may reflect risk-based pricing for new accounts, we further assume that when individuals leave USIC insurance with the same employer, they work at an employer of a similar size and risk and receive a premium based on the coefficient estimated without enrollee fixed effects. We calculate the certainty equivalent loss in income from financial risk, using a CARA functional form and estimated risk preferences from the literature (Handel, 2013).

We find that USIC's current policies result in a mean annual certainty equivalent loss from financial risk of $3,050 over the ten years after the initial period. Even though our estimates with enrollee fixed effects show low pass through similar to community rating, the reclassification risk protection of these contracts is limited by employees in this market frequently switching insurance coverage and by substantial out-of-pocket costs. With community rating, we find a mean certainty equivalent loss of $1,950, all of which is due to the financial risk from out-of-pocket costs. The certainty equivalent income loss is $4,500 under full experience rating, implying that USIC's current pricing policy generates about 60% of the certainty equivalent gains in risk protection of community rating regulations relative to full experience rating.

Finally, we evaluate the extent to which pooling in the small group market adds value relative to an individual market with identical guaranteed renewability contracts and selection. We find that individuals in such a market would have a certainty equivalent loss of $3,650 over the ten year horizon, implying that pooling across beneficiaries within a small employer adds an average of $600 in risk protection annually.

The remainder of our paper is organized as follows. Section 2 describes our model of enrollee choice, risk, and selection. Section 3 describes our data sources and estimation sample. Section 4 describes our empirical approach. Section 5 describes our estimation results, Section 6 presents our counterfactuals, and Section 7 concludes.

2 Model

2.1 Enrollee utility and choice

We develop a simple and stylized model of reclassification risk and selection in the health insurance industry. The model has two time periods, periods 1 and 2. Period 2 payoffs are discounted at the rate δ. A period is meant to represent a year, the typical length of a health insurance contract.[8] We consider potential enrollees who can obtain health insurance through a small group employer.[9] Denote the potential enrollee by i, the employer by j, the time period by t, and the number of potential enrollees at employer j by I_j.

Each potential enrollee starts each period with risk score r_{ijt}. The risk score is based on her previous year's healthcare claims, is proportional to her total expected costs of healthcare at period t, is normalized to 1 for the mean individual in the population, and is observable to both the potential enrollee and the insurer. Let $H \sim dF_H(r_{ijt})$ denote the period t health shock as a function of risk score and $c(H)$ denote the claims cost given health shock H. We separate costs into the portion that the insurer pays, $c^{ins}(H)$, and the portion that the enrollee pays out of pocket, $c^{oop}(H)$. Insurer-paid claims satisfy

$$E[c^{ins}(H)] = \gamma r_{ijt} \tag{1}$$

where γ is a constant of proportionality.[10] The individual risk scores imply that the employer mean risk score over its population of potential enrollees is $R_{jt} \equiv \frac{1}{I_j}\sum_{i=1}^{I_j} r_{ijt}$.

The timing in our model is as follows. In period 1, employer j forms with some exogenous set of employees. In both periods, the insurer first observes R_{jt} and then decides on the per-person premium, $p_{jt}(R_{jt})$, which is the total premium for employer j divided by the number of enrollees at employer j. This premium is potentially based on both R_{jt} and the employer's history with the insurer. Following this, the employer decides whether to offer insurance. Potential enrollees then decide whether to take up the insurance if

[8]We make this assumption for ease of notation. Our empirical work allows for more than two periods.

[9]Our theoretical analysis does not distinguish between potential enrollees who are employees and dependents.

[10]While risk scores typically concern overall costs, we assume here that the proportional relationship holds for the costs borne by the insurer.

offered. Finally, the health shocks H are realized.

We now exposit the utility at each period. We assume that utility is additively separable across the time periods. We denote the per-period utility from obtaining insurance when offered as $U^A_{ij}(r_{ijt}, p_{jt}(R_{jt}))$. This utility is a function of the potential enrollee's income Y_{ijt}, her employer's premium, and her out-of-pocket health costs:

$$U^A_{ij}(r_{ijt}, p_{jt}(R_{jt})) = \int u_{ij} \left[Y_{ijt} - p_{jt}(R_{jt}) - c^{oop}(H)\right] dF_H(r_{ijt}), \tag{2}$$

where $u_{ij}(\cdot)$ is her money utility function. We assume that, through adjustments to premium or wage, the potential enrollee pays her employer the full cost of her health premium,[11] and that enrollees are risk averse.

We denote the per-period utility from not having insurance as $U^N_{ij}(r_{ijt})$. Without insurance, the individual bears the full cost of her health expenditures:

$$U^N_{ij}(r_{ijt}) = \int u \left[Y_{ijt} - c(H)\right] dF_H(r_{ijt}). \tag{3}$$

Combining the utility from both choices, the potential enrollee's per-period utility is then:

$$U_{ij}(r_{ijt}, p_{jt}(R_{jt})) = \max\{U^A_{ij}(r_{ijt}, p_{jt}(R_{jt})), U^N_{ij}(r_{ijt})\}. \tag{4}$$

Finally, the discounted value of the potential enrollee over the two periods is:

$$V_{ij}(\vec{r}_{j1}) = U_{ij}(r_{ij1}, p_{j1}(R_{j1})) + \delta \int U_{ij}(r_{ij2}, p_{j2}(R_{j2})) dF_{R,r}(R_{j2}, r_{ij2}|\vec{r}_{j1}), \tag{5}$$

where $\vec{r}_{1j1}$ is the vector of period 1 risk scores and $dF_{R,r}(R_{j2}, r_{ij2}|\vec{r}_{j1})$ is the joint conditional risk score distributions at period 2, for the potential enrollee and her employer.

[11]The literature has shown positive but sometimes incomplete pass through from higher premiums to lower wages (Baicker and Chandra, 2006; Bhattacharya and Bundorf, 2009). We model complete pass through for simplicity but our empirical findings are robust to incomplete pass through.

2.2 Risk rating and reclassification risk

Reclassification risk can enter in our model because a bad and persistent health shock at period 1 for the individual or her coworker will raise R_{j2}. With experience rating, this will in turn raise per-person premiums at employer j. The extent of reclassification risk depends on the distribution of F_R and on $p_{j2}(\cdot)$. If the individual were in a large risk pool, then reclassification risk would not be a substantial issue because the distribution of F_R would be very concentrated and degenerate to a point in the limit. Even if the individual were in a small risk pool, if $p_{jt}(R_{jt})$ did not vary much in response to R_{jt}, then she would not face much reclassification risk. Thus, individuals employed by large employers or in settings without much experience rating do not face much reclassification risk. In contrast, individuals in small risk pools without significant restrictions on experience rating—i.e., individuals in our sample—may be faced with significant reclassification risk.

We now consider the impact of different risk rating policies, focusing on the case where potential enrollees take up insurance. For ease of notation, we assume that the insured have no out-of-pocket costs.[12] This implies that $E[c(H(r_{ijt}))] = E[c^{ins}(H(r_{ijt}))] = \gamma R_{jt}$.

First, we examine full experience rating. In this case, the insurer sets premiums exactly equal to expected equilibrium insured risk, so that $p_{jt}(R) = \gamma R$. Suppressing dependencies on variables that no longer enter, equation (5) specializes to:

$$V_{ij}(\vec{r}_{j1}) = U_{ij}^A(\gamma R_{j1}) + \delta \int U_{ij}^A(\gamma R_{j2}) dF_R(R_{j2}|\vec{r}_{j1}). \tag{6}$$

Individuals here are faced with reclassification risk: an increase in the expected equilibrium mean risk score among the insured in period 2, R_{j2}, is passed through into an increase in expected insurance costs at the employer in period 2. This occurs even though contracts are actuarially fair.

Next, we consider long-run contracts with a binding commitment to future premiums. Consider such a contract with a period 1 premium of $p_{j1} = \gamma R_{j1}$ and a period 2 premium of $p_{j2} = \gamma E[R_{j2}|\vec{r}_{j1}]$. This contract would have premium equal to expected marginal cost and would eliminate reclassification risk. Given our assumption that consumers are risk

[12] Our empirical work accounts for out-of-pocket costs.

averse,

$$\int U^A_{ij}(Y_{ij2} - \gamma R_{j2}) dF_R(R_{j2}|\vec{r}_{j1}) < U^A_{ij}(Y_{ij2} - \gamma E[R_{j2}|\vec{r}_{j1}),$$

implying that such a contract would improve enrollee welfare for individuals who take-up insurance over state-contingent one-period contracts of the same actuarial value. Consider further the case where income and mean risk are the same across periods, so that $Y_{ij1} = Y_{ij2},\ \forall i$, and $E[R_{j2}|\vec{r}_{j1}] = R_{j1}$. In this case, the above contract would maximize U^A among long-run break-even contracts. This implies that a competitive insurance industry with full take-up would result in employers signing these two-period contracts.

Note further that this two-period contract is approximately equivalent to a community rating provision (provided the rating pool includes a large number of people) in that there is no pass through from health risk to premiums. However, it is likely different from community rating in that the initial premiums might vary based on employer characteristics. In particular, with binding contracts and competition, new employers would get risk rated while continuing accounts would not. This would result in the initial premiums, p_{j1}, being larger with a higher R_{j1}, which would not occur under community rating.

Finally, we consider the general case with different levels of pass through. A simple functional form for premiums here is:

$$p_{jt} = c_{jt} + \beta R_{jt}, \tag{7}$$

for some constant c_{jt}, which reflects baseline prices at period t, and might vary due to changes in healthcare provider prices or general expected increases in health risk over time. If $\beta = \gamma$, then this is the full experience rating case. Under community rating or binding two-period contracts, we would have $\beta = 0$. For $0 < \beta < \gamma$, there will be positive but incomplete pass through from changes in risk to changes in premiums. Given that preferences are risk averse, for $\beta' < \tilde{\beta}$,

$$\begin{aligned} &\int U^A_{ij}(Y_{ij2} - p_{j1} - c - \tilde{\beta}(R_{j2} - E[R_{j2}|\vec{r}_{j1}]) dF_R(R_{j2}|\vec{r}_{j1})) \\ &< \int U^A_{ij}(Y_{ij2} - p_{j1} - c - \beta'(R_{j2} - E[R_{j2}|\vec{r}_{j1}]) dF_R(R_{j2}|\vec{r}_{j1})), \end{aligned} \tag{8}$$

implying that actuarially equivalent contracts with a lower β increases utility.

In a regression based on (7) with employer and year fixed effects to proxy for c_{jt}, β would indicate the pass through from changes in health risk to changes in premiums. In a similar regression without employer fixed effects, the analogous coefficient would indicate this pass through plus the risk-based portion of the initial premium in c_{j1}.

Since utility is decreasing in β, β is a sufficient statistic to evaluate the reclassification risk from a contract, conditional on preferences and the distribution of health shocks scaled in dollars using γ. In the tradition of Chetty (2009) and Einav et al. (2010), our empirical analysis will estimate β and use it to characterize reclassification risk in this market. This does not require us to specify or estimate all preferences parameters. To understand welfare under the observed and counterfactual environments, we then combine our estimates of β with risk preference parameters from the literature, the estimated distribution of health shocks scaled in dollars, and models of selection into insurance.

An important empirical question regards the β we would expect to occur in our data. Since insurers can create value for risk averse individuals by offering a high c and a low β relative to other actuarially equivalent policies, the market may evolve to have such features. Nonetheless, this is not certain to occur, since a market without multi-period contracts will have full experience rating, i.e. $\beta = \gamma$, and it is very difficult to enforce enrollee commitment to binding multi-period contracts. However, one-sided commitment by insurers may have existed in the individual and even small group insurance markets during our sample period (Pauly and Lieberthal, 2008). When one-sided commitment is allowed and there are liquidity constraints, a competitive insurance market will result in these contracts occurring (Harris and Holmstrom, 1982).

Under the optimal one-sided commitment contracts with a competitive market, we would expect positive but limited pass through from changes in health risk to changes in premiums (Ghili et al., 2019).[13] This would result in a relatively low β in regressions of premiums on health risk with employer and year fixed effects based on (7). Since one-sided

[13]The small group insurance market, which has few insurance companies active in most states, is best characterized as an oligopoly rather than a competitive market (Kaiser Family Foundation, 2013). For this reason, the real world impact of one-sided commitment contracts in this market may be somewhat different from the theory. However, we would still expect the general patterns from the theoretical literature to hold.

commitment contracts do not solve the problem of risk-based pricing for new accounts, we would expect a stronger relationship between health risk and premiums in analogous regressions without employer fixed effects. We will return to the difference between our results with and without employee/employer fixed effects in Section 5.3.

2.3 Selection of enrollees

Our above results deal with the case where enrollees choose USIC insurance in both periods. In the real world, take-up of insurance is limited and employers and enrollees start and stop coverage frequently. We now discuss selection of potential enrollees into insurance. We model the combined offer and take-up decision for the employer and enrollee as:

$$D_{ijt} = \mathbb{1}\{f(R_{jt}, r_{ijt}, x_{ijt}) + \varepsilon^s_{ijt} > 0\} \tag{9}$$

where $D_{ijt} = 1$ indicates offer and take-up of insurance, $f(\cdot)$ is a flexible mean utility function to be estimated, and ε^s_{ijt} is an unobservable. Starting with (7) we then model premiums as:

$$p_{ijt} = \bar{c}_{jt} + \beta R_{jt} + \varepsilon^p_{ijt}, \tag{10}$$

where we are now indexing p by 'i', $\bar{c}_{jt}$ is the mean average pass through given characteristics of employer j and period t, and ε^p_{ijt} is also an unobservable, capturing idiosyncratic premium risk unexplained by other factors and uncorrelated with risk, for instance due to variation in employer or insurance broker bargaining ability.

Our data contain premiums only for individuals who take up insurance and hence for whom $D_{ijt} = 1$. Hence, (9) is our selection equation while (10) is our treatment equation. As is typical in selection models, we allow for correlations between ε^s_{ijt} and ε^p_{ijt} for a given i. We generally expect that there would be a negative correlation between the two unobservables since individuals who received a higher premium than expected given observables would also be less likely to select into insurance than expected given observables. Note also that ε^p_{ijt} will be highly correlated for individuals at the same employer and year since individuals at a given employer and year pay the same premium.

Our estimation seeks to recover consistent treatment effects for β in (10) in the presence of selection. Specifically, we non-parametrically control for selection in (10) using the methods of Newey (2009).

3 Data and Estimation Sample

3.1 Data

Our principal data are from employers who purchase health insurance for employee and dependent coverage from "United States Insurance Company" (USIC) in the small group market during the years 2012 to 2015. USIC provided us with data from 10 different states: AR, DE, IL, PA, OK, MO, TN, TX, WI, and WY. USIC further classified the data into 19 different geographic markets, e.g., Texas is divided into Central Texas, Dallas, Houston, North Texas, and South Texas. Employers in our sample purchased fully-insured insurance products from USIC, not third-party administrative services. Figure A.1 in On-Line Appendix A provides a map of the states in our estimation sample.

While all states regulate small group insurance, they vary in the degree of their regulation. The states that we use were all lightly regulated prior to the ACA. For instance, none of the states had community rating regulations during this period. One measure of state regulation is the extent to which premiums are allowed to vary across groups for all reasons apart from plan generosity, which are known as ratings bands. Prior to the start of ACA regulations on this market, DE, PA, TX, IL, WI, and WY allowed premiums to range across groups by a ratio of 25-to-1 or greater (a total of 12 states had bands this large); MO and OK had rating bands between 19- and 25-to-1; and AR and TN had rating bands between 13- and 19-to-1.[14] During this period, all states had provisions that essentially implied that USIC would not be able to cancel a group's policy even if the mean health risk for the group rose substantially.

The ACA implemented community rating regulations for the small group market—specifically a ban on health status underwriting and a requirement that plans in the market have a common small group risk pool—that were originally supposed to start in January,

[14]See http://www.naic.org/documents/topics_health_insurance_rate_regulation_brief.pdf.

2014. However, almost all small group plans were exempt from the ACA market reforms during our sample period, for two reasons. First, some of these plans were "grandfathered," meaning that the ACA included a clause that allowed consumers to keep their existing health plans, conditional on the plan not significantly changing its benefits.[15] Second, a transitional rule let states allow "grandmothered" plans in the small group market, meaning that they could permit insurers to continue offering non-ACA compliant plans to small employers. The great majority of states opted to allow the sale of grandmothered plans past our sample period, and indeed through 2018.[16] Importantly for our analysis, both grandmothered and grandfathered plans are exempt from the ACA's community rating regulations noted above.

Our data include information at both the enrollee-year (employee or dependent) and employer-year levels. At the employer-year level, for all the employers that contract with USIC, we observe the total number of employees that are eligible for health coverage, the number of health insurance plans available to their enrollees in each year, the characteristics of each plan, and the total premium paid by the employer to the insurer for each plan in each month of each year.

We observe data for each enrollee that takes up insurance in each year. Specifically, we observe age, gender, the health plan chosen, the relationship of the enrollee to the employee (e.g., self, spouse, child), and information to link enrollees to the employer and to the employee with employer-sponsored coverage. We also observe claim-level data—for both medical and pharmaceutical claims—for every healthcare encounter. These data provide diagnosis, procedure, date of service, and premium information and are linked to the enrollee identifier.

We calculate a per-enrollee premium by dividing the total premium paid by the employer to USIC in a year for a plan by the number of enrollees (employees and dependents) at that employer and plan during that year. We use the January premium and enrollee information for this calculation and multiply the monthly premium by twelve to annualize

[15]The concept of grandfathering of health plans was popularized by President Obama's statement that "if you like your health plan, you can keep your health plan."

[16]See Jost (2017) and CMS (2017) for further details on this discussion.

it.[17]

To measure the predicted health expenditure risk for each enrollee, we use the ACG risk prediction software developed at Johns Hopkins Medical School. The software outputs an "ACG score" for each enrollee in each year, which corresponds to r_{ijt} in our model. The ACG score indicates the predicted relative healthcare cost for the individual over the year, and has a mean of 1 in a reference group chosen by ACG. The ACG score is based on past diagnostic codes, expense, prescription drug consumption (code and length of consumption), age, and gender for each individual. In our case, we use the twelve months of data from the previous year to generate the ACG score for a given year. Similarly to the ACG score, USIC also uses a proprietary system to derive a risk score for each enrollee. While we do not have access to the USIC scores, the ACG and USIC scores are very similar (as we further show in On-Line Appendix B using a subsample of enrollees for whom we have both scores).

For new groups, USIC did not generally use their proprietary risk scores, because this would have required obtaining and processing claims information from the previous insurer for each enrollee. Instead, USIC typically obtained information on health risk from a health questionnaire. This questionnaire requested information regarding 15 conditions, including cancer, diabetes, and heart disease, and asked potential enrollees to list any claims in excess of $5,000.

Since our risk score measures are calculated using the previous year claims data, we need to observe an employer or individual for two consecutive years in order to have a complete observation where we can observe the risk score and the premium. Thus, for instance if we observed an employer in 2012 and 2013, this would allow us to compute the 2013 premium and mean risk score for the employer, where the risk score was computed from 2012 data.

Most of our regressions use employer or enrollee fixed effects. Since we obtain the risk score calculation from the previous year, we need three continuous years of data (which

[17]Because individuals typically make enrollment decisions annually with contracts starting in January, the total premiums paid by the employer to USIC in January is a good representation of annual per-person premiums charged by USIC. We also computed per-enrollee premiums using the mean and mode of the monthly premiums paid by the employer over different months, and obtained similar results with these alternative measures.

generates two years with complete observations) to compute an employer/enrollee fixed effect. For comparability across estimates, we drop employers/enrollees for which we observe fewer than three continuous years of data for all our specifications, even those without employer/enrollee fixed effects.[18]

As an additional source to evaluate selection, we use data from the Medical Expenditure Panel Survey (MEPS), which is a nationally representative survey regarding individual insurance decisions and health care expenditures. The MEPS data allow us to understand selection into the small group market since it has information about individuals that did not take up insurance. We construct the sample by using panel 18 from the consolidated database for years 2013 and 2014. To select individuals who could participate in the small group market, we select individuals that were (a) working but not self-employed at the beginning of the period, (b) who worked at an establishment size less than or equal to 50 individuals, and (c) were offered insurance via their employer. We use age, gender, and health conditions of individuals and establishment size and industrial sector as characteristics to predict the probability of taking up insurance.

3.2 Summary statistics on estimation sample

Table 1 provides summary statistics on the enrollees in our estimation sample. Our full sample includes approximately 330,000 unique individuals and 650,000 observations.

We first analyze enrollee turnover. To do this, we characterize enrollees based on whether they have joined or quit available USIC coverage during our sample. A "joiner" is an enrollee for whom we did not have a complete observation in the first year but for whom we had a complete observation in a later year and whose employer was in the sample prior to her being there. A "quitter" is the opposite: an enrollee for whom we did not have a complete observation in the last year but for whom we had a complete observation in an earlier year and whose employer remained in the sample after she was no longer there. A "stayer" is an enrollee for whom we have three complete observations. Note that an individual can be both a joiner and a quitter, which would occur if she were in our data in the middle two years only. Also, note that enrollees whom we do not observe for two consecutive years would not fit any of these three categories.

[18] We also drop employers with missing information for premiums, plan characteristics, or enrollment.

Table 1: Descriptive statistics on estimation sample at the enrollee-year level

	Full Sample	Stayers	Joiners	Quitters
Unique individuals	336,755	80,031	87,107	113,124
Observations	646,904	240,093	176,163	186,012
Relation (%)				
Employees	56.57	56.25	56.19	56.46
Spouses	15.50	16.18	15.28	15.49
Children	27.56	27.35	28.12	27.78
Others	0.37	0.22	0.41	0.28
Age	38 (18)	40 (18)	36 (18)	38 (18)
Female (%)	47	46	47	48
In dollars:				
Lagged paid total claims	3,388 (17,468)	3,778 (16,251)	3,287 (18,250)	3,272 (17,839)
Lagged out-of-pocket claims	902 (1,854)	1,009 (1,881)	894 (1,844)	845 (1,918)
Annual premiums	5,219 (1,955)	5,493 (2,028)	4,977 (1,698)	5,105 (2,106)
Health risk, r_{ijt}	1.00 (1.46)	1.01 (1.41)	0.92 (1.40)	1.05 (1.58)
$r_{ijt} - r_{ij,t-1}$	0.05 (1.07)	0.05 (1.03)	0.06 (1.04)	0.06 (1.19)
Conditions (%)				
Cancer	2.47	2.57	2.03	2.60
Acute myocardial infarction	0.16	0.16	0.16	0.17
Transplant	0.14	0.15	0.12	0.16
Diabetes	5.57	5.66	4.90	5.90
Hypertension	14.12	14.64	12.26	14.55
Heart disease	0.39	0.38	0.34	0.43
Chronic kidney disease	0.48	0.49	0.43	0.51
Asthma	3.38	3.27	3.35	3.59

Note: each observation in table is one enrollee during one year, 2013-15. Table reports mean values with standard deviations in parentheses. "Stayers" are enrollees always in sample; "joiners" are enrollees with one or more full observation but without a full observation in 2013; and "quitters" are enrollees with one or more full observation but without a full observation in 2015.

We find a lot of enrollee turnover. Only 37% of observations in our sample are for stayers. Approximately 27% of observations are for joiners while 29% of observations are for quitters.

Overall, there is a clear though moderate pattern of differences between the groups, where joiners have lower health risk than stayers who have lower health risk than quitters. Specifically, joiners have a mean ACG score—or expected claims cost—of 0.92, compared to 1.01 for stayers, and 1.05 for quitters. Consistent with this, joiners are on average two years younger than quitters, though stayers are older than either group, suggesting that age affects insurance lapsation for reasons other than health risk.

On average, people paid \$5,219 in annual premiums, had \$3,388 in total claims, and \$902 in out-of-pocket claims. We measure a number of chronic conditions from the claims data. The most prevalent is hypertension, occurring in 14% of observations. The next most common is diabetes, which occurs in 6% of enrollees.

Table 2: Descriptive statistics at the employer-year level

	Full Sample	Stayers	Joiners	Quitters
Employers	12,242	6,560	2,281	3,401
Observations	31,044	19,680	4,562	6,802
Subscribers	21 (27)	21 (26)	23 (27)	20 (28)
Take up rate (%)	54 (22)	54 (22)	57 (21)	53 (23)
Relation (%)				
Employees	64.80	64.45	63.90	66.40
Spouses	12.82	13.01	13.08	12.12
Children	22.17	22.32	22.85	21.28
Others	0.21	0.21	0.18	0.21
Age	41 (9)	41 (9)	39 (8)	41 (10)
Female (%)	46	46	46	47
In dollars:				
Lagged paid total claims	4,076 (8,456)	4,003 (8,272)	3,775 (6,951)	4,490 (9,783)
Lagged out-of-pocket claims	1,092 (889)	1,051 (812)	1,061 (835)	1,232 (1,098)
Annual premiums	6,162 (2,837)	6,248 (2,689)	5,385 (2,067)	6,433 (3,529)
2013	5,954 (2,839)	5,881 (2,711)		6,095 (3,066)
2014	6,276 (3,103)	6,394 (2,808)	5,196 (2,157)	6,772 (3,908)
2015	6,238 (2,402)	6,469 (2,499)	5,574 (1,955)	
Health risk for enrolled, R_{jt}	1.07 (0.72)	1.05 (0.70)	0.97 (0.59)	1.17 (0.82)
$R_{jt} - R_{j,t-1}$	0.02 (0.51)	0.01 (0.49)	0.04 (0.45)	0.05 (0.62)
Conditions (%)				
Cancer	3.02	3.04	2.40	3.38
Acute myocardial infarction	0.18	0.17	0.17	0.21
Transplant	0.19	0.21	0.10	0.19
Diabetes	6.15	5.95	5.29	7.33
Hypertension	15.67	15.43	14.15	17.39
Heart disease	0.46	0.45	0.40	0.52
Chronic kidney disease	0.57	0.55	0.54	0.66
Asthma	3.34	3.28	3.18	3.61

Note: each observation in table is one small group employer during one year, 2013-15. Table reports mean values with standard deviations in parentheses. “Stayers” are employers always in sample; “joiners” are employers with one or more full observation but without a full observation in 2013; and “quitters” are employers with one or more full observation but without a full observation in 2015.

Table 2 provides summary statistics on the employers in our estimation sample. Our sample includes 12,242 employers. Similarly to Table 1, we report the employers which are stayers, joiners, or quitters. We define an employer to be a stayer if it had at least one enrollee with complete data in each year; a joiner if it had no enrollee with complete data in 2013 but enrollee with complete data in 2014 and 2015 and a quitter if it had no enrollee with complete data in 2015 but enrollees with complete data in 2013 and 2014. Roughly half the employers in our sample, 54%, were stayers and hence present throughout the sample period, with complete observations from 2013-15. Similarly to at the individual level, more employers quit than joined coverage.

On average, employers in our sample have 21 subscribers. Eligible potential enrollees include employees, spouses, children, and other family members. Employees constitute 65% of covered lives. The mean take-up rate among eligible employees was 54%.

We observe a similar pattern of selection at the employer level to at the enrollee level. The mean of the employer mean risk scores, R, is 0.97 for joiners, 1.05 for stayers, and 1.17 for quitters. We also observe a substantial standard deviation in the *change* in R over time. This variation will provide us with power to identify the USIC's pass through, in our models with employer or enrollee fixed effects.

Table 2 also presents the same statistics on enrollees that we reported in Table 1, but at the employer-year level. We find similar values of the statistics regarding age, gender, premiums, claims, and out-of-pocket costs using this measure. Premiums in this market rose a moderate 5% over our two-year sample period.

Finally, Table 2 presents the mean incidence of eight chronic conditions at an employer—cancer, transplants, acute myocardial infarctions (heart attacks), diabetes, hypertension, heart disease, chronic kidney disease, and asthma—defined as the percentage of enrollees with a diagnosis of the condition during the year. In On-Line Appendix B, we use the presence of these chronic conditions at the employer as a robustness check. While the incidence of transplants and AMI is less than 1%, the mean incidence of cancer is 3% and diabetes is 6%.

Overall, the previous tables show lots of movement in and out of USIC insurance. The small businesses that are in this market frequently start and stop coverage with USIC. Potential enrollees at these businesses also frequently start and stop insurance take-up. This movement is driven by at least three different factors. First, businesses may open or close for reasons orthogonal to health insurance premiums. Second, individuals can also change jobs for reasons that are orthogonal to premiums. Both of these factors are likely to be true given that small businesses enter and exit frequently and also change employees frequently. Third, there can be selection of health insurance based on premiums. Our results show moderate evidence of selection based on health risk, e.g., quitter employers have 9% higher expected costs than stayer employers, while quitter enrollees have 4% higher expected costs than stayer enrollees. This selection based on risk suggests that there may be selection based on premiums, which would bias our estimates of the pass-through coefficient β. In order to address this potential selection, our estimates control for the effect of selection and our counterfactuals model a different impact of health risk on premiums for individuals who leave the sample.

Table 3: Persistence in health risk over time

	(1)	(2)	(3)
Panel A: dependent variable individual risk (r_{ijt})			
Enrollee ACG score, $r_{ij,t-1}$	0.733***	0.718***	0.561***
	(0.005)	(0.007)	(0.010)
Lagged enrollee ACG score, $r_{ij,t-2}$			0.241***
			(0.010)
Sample	2013-15	2014-15	2014-15
Market FE	Yes	Yes	Yes
Observations	523,679	264,153	264,153
Panel B: dependent variable employer risk (R_{jt})			
Health risk for enrolled, $R_{j,t-1}$	0.667***	0.630***	0.506***
	(0.003)	(0.004)	(0.006)
Lagged health risk for enrolled, $R_{j,t-2}$			0.193***
			(0.007)
Sample	2013-15	2014-15	2014-15
Employer FE	Yes	Yes	Yes
Observations	31,044	18,802	18,802

Note: for panel A (B), each observation is one enrollee (employer) during one year. We cluster standard errors at the employer level. Markets are defined by USIC and roughly represent an MSA or state. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

We next present the patterns of persistence over time for the ACG risk, in Table 3. Panel A presents the results at the individual level for an AR(1) process in columns 1 and 2 and an AR(2) process in column 3. Column 1 reports the AR(1) process for the full sample while column 2 reports the AR(1) process for the same sample as in column 3. Mean health risk exhibits substantial persistence but at the same time a reversion to the mean. For instance, in the specification with only one lag, the autocorrelation coefficient is 0.733. In the specification with two lags, reported in column 3, the autocorrelation coefficients sum to 0.802. Thus, all the autocorrelated models are stationary. Moreover, the sum of the coefficients when we include two lags is similar to the results when we include only one lag, although these two processes imply different risk effects over time.

Panel B presents the autocorrelation results at the employer level. The results show that the AR(1) and AR(2) processes are stable but also relatively persistent. The fact that persistence at the employer level is smaller than at the individual level implies that the shocks for different enrollees are not completely correlated, so they partially cancel each other out over time.

Finally, Table 4 reports descriptive statistics on the MEPS sample. From the full sample of people offered insurance, 72% of individuals choose insurance through the employer. The average age of these individuals is 42 years old and 52% of them are females. The average employer size is

Table 4: Descriptive statistics for MEPS sample

	Choose insurance	Age	Female	Employer size
Mean	0.72	41.77	0.52	21.47
Standard deviation	0.45	12.91	0.50	14.66
Observations	1,355	1,355	1,355	1,355

Note: each observation in table is one individual in the consolidated Panel 18 for years 2013 and 2014 in MEPS. We selected working individuals not self-employed, who worked in establishments with less than 50 individuals and were offered health insurance via the employer.

21 which is similar but somewhat larger than the average employer size in our USIC sample. Not reported in the table, the incidence of health conditions in the MEPS data are similar to in the USIC sample.

4 Empirical Approach

The primary goal of our estimation is to recover γ, the impact of risk score on expected insurer costs ($dE[c^{ins}]/dR$), and β, the impact of employer mean insured risk on premiums (dp/dR). We use these parameters together to understand the pass through from insurer costs to premiums, $dp/dE[c^{ins}]$:

$$\frac{dp}{dE[c^{ins}]} = \frac{\frac{dp}{dR}}{\frac{dE[c^{ins}]}{dR}} = \frac{\frac{dp}{dR}}{\frac{dE[c^{ins}]}{dr}} = \frac{\beta}{\gamma}. \tag{11}$$

We also use these parameters separately in our counterfactual analysis. Note that these parameters regard insurer behavior; we do not estimate any utility parameters and our estimation algorithm does not impose utility maximization.

We now discuss our estimation of γ, which is the parameter that scales risk scores into dollar costs. Following (1), we estimate regressions that take the form:

$$c_{ijt}^{ins} = \gamma r_{ijt} + \gamma_2 x_{jt} + \varepsilon_{ijt}^{r}, \tag{12}$$

where c_{ijt}^{ins} measures the total dollar value of claims for the individual over the year. Equation (12) considers the impact of the individual's current risk score—estimated using the previous year's claims—on current claims to the insurer. Comparing equations (12) and (1), the empirical specification uses the actual insurer costs while the theoretical model is based on the expectation of costs. Thus, ε_{ijt}^{r} in equation (12) will capture the difference between actual claims and expected claims for an individual in a year.[19]

The empirical specification also includes controls x_{jt}. We include market fixed effects here (using USIC's market definition) to control for different provider prices across markets. Unless individuals at different employers systematically use different-cost providers for the same conditions in a way that correlates with the risk at that employer, we do not need to include employer or enrollee fixed effects. We estimate γ using only data from 2014, to not have to worry about changes in provider prices over time.[20]

We now discuss our estimation of β, the impact of employer mean risk score on premiums. Following Newey (2009), we estimate a two-step semi-parametric selection model. Specifically, we first estimate the following selection equation:

$$D_{ijt} = \mathbb{1}\{f(R_{jt}, r_{ijt}, x_{ijt}) + \varepsilon^{s}_{ijt} > 0\} \tag{13}$$

where R_{jt} and r_{ijt} are the risk scores for the employer and the individual respectively, x_{ijt} are time-varying individual characteristics, and ε^{s}_{ijt} is an unobservable component to the utility from selection into the sample. We estimate (13) using a probit specification and a flexible functional form for $f(\cdot)$.

We estimate two different specifications for the selection equation $f(\cdot)$. The first specification uses USIC data. Since our USIC data only tracks individuals insured by USIC, observations at period t include both individuals who left USIC after period $t-1$ and those who were with USIC at period $t-1$ and remained at period t. These observations cannot include people who joined USIC at period t and hence this estimation controls for dropped coverage but not new take-up of insurance. In this specification, we include industry fixed effects, employer size, age, and gender in x_{ijt}. The main advantage of this specification is that the inclusion of R_{jt} increases the accuracy of the selection equation. The main disadvantage is that it only controls for individuals who left USIC.

Our second specification for our selection equation uses the MEPS data. In this specification, we include in $f(\cdot)$ proxies to approximate r_{ijt}, industry fixed effects, employer size, age, and gender. The proxies for risk are indicators for hypertension, heart disease, AMI, ischemic stroke, respiratory failure, cancer, diabetes, and asthma, and are observable in both the MEPS data and in the USIC data. In this specification we include fewer regressors but we are able to control for

[19]We also estimate empirical specifications with $c^{oop}(H(r_{ijt}))$ as the dependent variable.
[20]We also investigated estimating γ using other years in our sample and obtained similar results.

everyone who is offered insurance. Using the estimated parameters of (13), we define

$$S_{ijt} \equiv Pr(f(R_{jt}, r_{ijt}, x_{ijt}) + \varepsilon^s_{ijt} > 0). \tag{14}$$

We compute S_{ijt} using the predictions from our estimates of (13).

We use S_{ijt} as a control in the second stage treatment effects equation. The treatment effects equation is:

$$p_{ijt} = \beta R_{jt} + \alpha x_{jt} + \overline{FE}_i + FE_t + g(S_{ijt}) + \varepsilon_{ijt} \tag{15}$$

where p_{ijt} is the premium charged to enrollee i working at employer j at period t and R_{jt} is the employer mean ACG risk score among enrollees who take up insurance at period t. In equation (15), $\overline{FE}_i$ are enrollee fixed effects, FE_t are year dummies, and x_{jt} are time-varying enrollee attributes, and ε_{ijt} is the econometric unobservable. The non-parametric selection correction $g(S_{ijt})$ (using power series approximation) approximates the inverse Mills ratio from Heckman (1979). Comparing (10) to (15), $\varepsilon^p_{ijt} = g(S_{ijt}) + \varepsilon_{ijt}$. While equation (15) specifies premium as the dependent variable, we also report specifications where plan characteristics are the dependent variables.

We adjust our standard errors of β in (15) for the fact that we estimated β with a two-step estimator, by modifying the formula proposed by Newey (2009). Newey accounts for the standard errors of the selection parameters on the second stage variance formula; we modify his formula to two-way cluster the standard errors, by employer and year.

Finally, we discuss identification. To obtain consistent estimates for the parameters of interest, identification of both the selection equation (13) and the treatment equation (15) is required. It is well understand that selection models are most credibly identified with exclusion restrictions in the treatment equation. In our case, enrollee risk and industry fixed effects provide useful exclusion restrictions. In particular, we assume that individual risk and variation across industries in employment turnover rates affect the probability of leaving the sample, but do not affect the pass through given the set of controls in the second stage. We also use multiple data sources to evaluate the robustness of our selection equation to specification.

Note further that our treatment equations include employer or enrollee fixed effects in most specifications. In this case, our identification of β is based on changes in p_{jt} following changes in R_{jt}. The selection correction further non-parametrically corrects β to estimate its value if everyone selected into USIC insurance. Because we control for the baseline health status with fixed effects and also control for selection, we believe that it is reasonable to consider changes in the risk score—which reflect changes in expected health expenditure for the population of potential enrollees conditional on the base level—to be exogenous.

5 Estimation Results

We now present our estimation results, starting with our results on the impact of health risk on claims costs and on the determinants of sample selection. We then discuss our main results, which are the impact of health risk on premiums and evidence regarding the mechanism of guaranteed renewability contracts.

5.1 Impact of health risk on claims costs

Table 5: Impact of expected risk on claims

	Dependent variable:		
	Paid amount ($)	Allowed amount ($)	OOP amount ($)
Regressor:	(1)	(2)	(3)
Enrollee ACG score, r_{ijt}	4,003***	4,483***	480***
	(129)	(131)	(9)
Market FE	Yes	Yes	Yes
Observations	204,913	204,913	204,913

Note: each observation is one enrollee during one year. The dependent variables indicate three measures of the total claims amount for that enrollee. The sample is covered individuals with an ACG score in 2014 only. Markets are defined by USIC and roughly represent an MSA or state. We cluster standard errors at the employer level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 5 presents the estimated relationship between health risk and claims, which is γ. From column 1, we find that an increase in ACG score of 1—which would mean doubling the score relative to the population mean—would lead to an expected increase in USIC-paid claims of $\gamma =$\$4,003. From column 2, an increase in ACG score increases the allowed amount of the claims by $4,483. This latter figure includes the portion for which payment is the responsibility of the enrollee as well as the amount that USIC expects to pay for the claim. Not surprisingly, the coefficient on the out-of-pocket amount—which is reported in column 3—at $480, is the difference between these two coefficients.

Robustness. On-Line Appendix A provides robustness on the evidence presented in Table 5 by using splines. These results are very similar to our base results, though with some non-linearity. Our takeaway is that our base coefficient of $4,003 is a reasonable approximation of the impact of risk score on expected claims.

5.2 Selection equation estimates

Table 6 presents the results of the sample selection equations that we then use to estimate β. Columns 1 and 2 present the average marginal effects and the standard errors, respectively, of the selection equation estimated using the USIC sample. Consistent with the findings that quitters had a higher R in Table 2, R here also positively predicts leaving the USIC sample. Enrollee age, employer size, and the industry fixed effects are also statistically significant.

Columns 3 and 4 of Table 6 present the average marginal effects and the standard errors, respectively, of the selection equation with the MEPS sample. Enrollee age and the industry fixed effects are the only variables that are statistically significant here. The lack of significance may be due to the MEPS sample size being much smaller.[21]

5.3 Impact of health risk on premiums

We now investigate our main parameter of interest, the pass through from health risk to premiums, which is β. Table 7, Panel A provides results with employer or enrollee fixed effects, indicating how *changes* in the employer mean ACG score among the insured, R, result in changes in the mean per-enrollee premium for the employer, p. We expect that we will obtain similar results when we include either employer or enrollee fixed effects. Both specifications will identify β from the impact of a change in health risk at the employer on a change in premiums. However, enrollee fixed effects allow for us to more appropriately implement our selection correction, given that we model selection at the enrollee level. For this reason, we use enrollee fixed effects in our specifications that control for selection.

Panel A, column 1 regresses p on R at the employer/year level, including employer fixed effects, without controls for selection. In this specification, a unit increase in employer mean ACG risk score for an employer results in a \$188 increase in premiums. Column 2 presents a similar specification without selection correction but at the enrollee/year level and including enrollee fixed effects. As we expected, this specification with enrollee year fixed effects reports similar results: a unit increase in enrollee mean ACG risk score for an employer results in a \$195 increase in

[21] The health conditions that we observe in the MEPS data are similar to those that USIC included in its questionnaires for new enrollees.

Table 6: Selection equation estimates using USIC and MEPS samples

	Sample USIC		Sample MEPS	
Dependent variable:	*Drop coverage*$_{ijt}$		*Decline insurance*$_{ijt}$	
	(1)	(2)	(3)	(4)
	Average marginal effect	Standard error	Average marginal effect	Standard error
Health risk for enrolled, R_{jt}	0.067***	(0.009)		
Individuals ACG score, $r_{ij,t}$	0.008	(0.008)		
Age$_{ijt}$	-0.001***	(0.0001)	0.005***	(0.001)
Female$_{ijt}$	0.003	(0.003)	-0.039	(0.261)
Employer size$_{jt}$	0.001***	(0.0002)	0.001	(0.001)
Hypertension$_{j,t-1}$			-0.001	(0.030)
Heart disease$_{j,t-1}$			0.089	(0.092)
AMI$_{j,t-1}$			-0.177	(0.121)
Ischemic stroke$_{j,t-1}$			-0.116	(0.124)
Respiratory failure$_{j,t-1}$			0.064	(0.063)
Cancer$_{j,t-1}$			-0.054	(0.061)
Diabetes$_{j,t-1}$			0.019	(0.051)
Asthma$_{j,t-1}$			0.027	(0.041)
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	204,913		1,355	

Note: in the USIC sample each observation is one enrollee during one year. "Drop coverage$_{ijt}$" indicates that individual was in sample in period t but not $t+1$. In the MEPS sample each observation is one individual in the consolidated panel 18 for 2013-14. "Decline insurance$_{ijt}$" indicates that the individual was offered insurance through the employer and declined this insurance coverage. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. We cluster standard errors at the employer level. *** indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level.

premiums.

Panel A, columns 3 and 4 present results similar to column 2 but where we control for sample selection by specifying first- and sixth-order polynomials for $g(S_{ijt})$, respectively. The estimates of β are $663 for the first-order polynomial and $624 for the sixth-order polynomial, higher than the uncorrected estimate. This implies that enrollees disproportionately quit USIC insurance if they receive a high pass through from claims to premiums, which fits with our priors. It is also consistent with our finding that higher risk people disproportionately quit USIC insurance. While the sample selection controls increase the estimate of β, the coefficients are between 16% and 17% of γ, still indicating that pass through from expected claims to premiums is very far from full experience rating.

Table 7: Impact of risk on premiums with USIC sample correction

	Observation level:			
	Employer/year	Enrollee/year	Enrollee/year	Enrollee/year
	No selection correction		With selection correction	
	(1)	(2)	(3)	(4)
Panel A: specifications with employer/enrollee fixed effects				
Health risk for enrolled, R_{jt}	188**	195***	663***	624***
	(87)	(82)	(132)	(121)
Panel B: specifications without employer/enrollee fixed effects				
Health risk for enrolled, R_{jt}	1,749***	2,263***	2,594***	2,811***
	(120)	(88)	(174)	(116)
Year FE	Yes	Yes	Yes	Yes
Polynomial Order	No	No	1^{st}	6^{th}
Observations	31,044	448,259	448,259	448,259

Note: each observation is either one employer or enrollee during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Column (1) in Panel A includes employer fixed effects. Columns (2) to (4) in Panel A include enrollee fixed effects. Panel B includes market fixed effects. Columns (3) and (4) control non-parametrically for selection with polynomial of the selection probability. Markets are defined by USIC and roughly represent an MSA or state. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 7, Panel B presents analogous results to panel A but without employer/enrollee fixed effects (though with market fixed effects, using USIC's market definitions). Given that we do not include employer/enrollee fixed effects, the results from this panel indicate the equilibrium relation between health risk and premiums rather than the pass through from changes in health risk to changes in premiums. As we discussed in Section 2.2, this specification captures the equilibrium relationship between health risk and premiums, which includes the pass-through plus the risk rated part of the initial premium. [22] Analogously to Panel A, column 1 is at the employer/year level, all the other columns are at the enrollee/year level, and columns 3 and 4 include sample selection corrections.

The estimates show a substantially larger relationship between health risk and premiums than does Panel A. The enrollee/year level coefficient in column 2 is \$2,263 and increases to \$2,594 or \$2,811 with controls for sample selection. Thus, the selection correction changes the estimate of β in the same direction as in the enrollee fixed effects specification. The coefficients here show that equilibrium premiums reflect between 44% and 70% of expected claims. This indicates that the equilibrium does not reflect full experience rating, though it does reflect a much stronger relation between expected claims and premiums than the pass through coefficients in Panel A.

While our Panel B results show the equilibrium relationship between health risk and premiums, we interpret them as being similar to the amount of risk rating that USIC would impose on new enrollees. To verify this, we estimated a specification analogous to Panel B, column 4 on the sample of 2014 joiners (who started coverage in 2013) for the year 2014. We estimate a coefficient on R_{jt} of \$2,566, which is very similar to our Panel B value of \$2,811. Together, our results show that USIC passes through very little risk for existing customers into premiums, while new customers receive premiums that are more based on their risk.

Robustness. We also analyze the robustness of our estimates of the impact of health risk on premiums to several factors. We use MEPS as an alternative source of data for selection correction; we verify the robustness of our health risk to measurement error; we include indicators for specific chronic conditions; and we examine changes in plan characteristics following changes in health risk. In all cases, we find very similar results to the baseline. We also show that the low pass-through cannot be explained by the planned roll-out of community rating regulations under the ACA and that the pass-through is similar across employer size. On-Line Appendix B provides the details.

5.4 Evidence of guaranteed renewability contracts

We find much less reclassification risk in the small group market than in the simple model with full experience rating, particularly among groups continuously enrolled with USIC. This is different

[22] For comparability, we use the same sample for Panel A and Panel B of Table 7. We find similar results for Panel B when we include all observations.

from what many observers thought was likely occurring in this market (Gruber, 2000).[23] However, it is broadly consistent with the Herring and Pauly (2006) view that the individual insurance market mostly operated with "guaranteed renewability" dynamic insurance contracts in the pre-ACA era.

We further investigate the possibility that our results are driven by USIC implicitly offering guaranteed renewability contracts. Under these contracts, insurers operating in a competitive market commit to a long-run premium schedule (Pauly et al., 1995).[24] The commitment is one-sided: while insurers promise to offer insurance at set rates in future periods, enrollees do not commit to renew their contracts. Although the contracts underlying our data do not explicitly include guaranteed renewability provisions, our conversations with USIC suggest that their actual practices resembled guaranteed renewability during our sample period.[25]

Guaranteed renewability contracts add value relative to full experience rating by providing protection against reclassification risk. In many models with guaranteed renewability contracts, the equilibrium risk protection is only partial (Harris and Holmstrom, 1982; Ghili et al., 2019).[26] In these models, enrollees with relative drops in risk scores would be able to obtain a new insurance plan from the market at a rate that is lower than with their existing contract. Insurers then offer to renegotiate insurance contracts for these enrollees at cheaper rates, to avoid lapsation and recontracting.

The only way to avoid this equilibrium renegotiation would be to substantially front load premiums but, in the presence of liquidity constraints, this would lower welfare by reducing consumption for the young. Thus, the equilibrium with a competitive market of insurers when one-sided commitment is allowed has guaranteed renewability contracts with ex post renegotiation, where the level of front loading optimally balances risk protection against consumption smoothing (Harris and Holmstrom, 1982; Ghili et al., 2019).

We test three principal empirical implications of the guaranteed renewability model with ex post renegotiation. First, the model implies an incomplete pass through from health risk to premi-

[23]Low pass through from costs to prices are observed in a variety of contexts, including energy costs (Ganapati et al., 2016), tariffs (De Loecker et al., 2016), and beverage taxes (Cawley et al., 2018).

[24]Relatedly, Cochrane (1995) proposed a scheme where enrollees would be compensated based on changes in their risk score.

[25]For instance, they indicated to us that they typically did not re-underwrite existing accounts. Pauly and Lieberthal (2008) notes that the individual insurance typically operated in this manner in the pre-ACA era.

[26]Harris and Holmstrom (1982) model labor markets with symmetric learning. Insurance models with one-sided commitment build on their framework. Hendel and Lizzeri (2003) also model one-sided commitment contracts for life insurance.

ums, i.e. $0 < \beta < \gamma$. This property is exactly why guaranteed renewability contracts add value: they lower equilibrium reclassification risk. Second, the marginal impact of an increase in health risk on premiums is lower for groups with relative increases in health risk than for groups with relative decreases. The reason for this is that groups whose health risk increase sufficiently will simply obtain the guaranteed premium after the first period. The other groups will obtain reductions in their premiums through the threat of renegotiation, with higher reductions the greater is their decrease in risk. Third, groups with high ex ante risk will face more reclassification risk, because they have a higher probability of having their health risk drop, and health risk drops lead to renegotiation, which leads to reclassification risk. Note that these implications are specific to a model with ex post renegotiation of contracts, such as Ghili et al. (2019).

We demonstrate that these implications hold in calibrated guaranteed renewability contracts and then test them by evaluating whether they hold in the USIC data. Specifically, we simulate data using Handel et al. (2019)'s reported figures on risk score transitions and equilibrium premiums from guaranteed renewability contracts.[27] These figures report actual risk score transitions and calibrated guaranteed renewability contracts for a variety of counterfactual scenarios. We created our simulated data using the reported initial health status distribution and health status transitions for ages 30-35. The Handel et al. equilibrium long-term contracts depend on the year relative to the contract start, age of the individual, and income profile. We use contracts for individuals with "flat net income" and aged 25 (as Handel et al. do not report contracts for ages 30-35).

To demonstrate the first implication in the calibrated contracts, we consider pass through from risk to premiums by performing regressions analogous to Table 7, Panel A from the Handel et al. simulated data. We find that β = \$1,821 with a standard error of \$410, indicating positive but incomplete pass through. In particular, the pass through in this simulation is larger than with our fixed effects estimator but much smaller than under full experience rating. Moreover, the figures reported in this part of Handel et al. do not incorporate switching costs (though they do consider switching costs in other parts of the paper). Switching costs would lower pass through by decreasing the ability of healthy enrollees to renegotiate and have been found to exist in similar settings (Handel, 2013).

To examine the second implication, Table 8, Panel A presents results from regressions of pass through of a spline of the change in risk, for both the Handel et al. simulated data and the USIC

[27] Handel et al. (2019) is an older version of Ghili et al. (2019) with calculations from a different database; Handel et al. (2019) report the data necessary for this calculation but Ghili et al. (2019) do not.

Table 8: Impact of risk on premiums using splines, with simulated guaranteed renewability data and USIC data

Panel A: specifications with enrollee fixed effects				
Dependent variable: change in annual employer mean premium, p_{jt}				
Sample:	HHW	USIC		
	(1)	(2)	(3)	(4)
Spline, $\Delta R_{jt} \leq 0$	3,612***	465***	752***	795***
	(88)	(82)	(99)	(30)
Spline, $\Delta R_{jt} > 0$	172***	-275***	12	44
	(26)	(71)	(85)	(29)
Enrollee FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Polynomial Order		No	1^{st}	6^{th}
Observations		90,826	90,826	90,826
Panel B: specifications without enrollee fixed effects				
Dependent variable: annual employer mean premium, p_{jt}				
Spline, $R_{jt} \leq 1$	2,973***	3,203***	3,669***	3,532***
	(742)	(136)	(126)	(123)
Spline, $R_{jt} > 1$	1,638***	1,887***	2,212***	2,480***
	(478)	(181)	(187)	(223)
Enrollee FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Polynomial Order		No	1^{st}	6^{th}
Observations		181,652	181,652	181,652

Note: each observation is one enrollee for which we have a complete observation for years 2014 and 2015. Column (1) uses simulated data from Handel et al. (2019). In Columns (2) to (4), the dependent variable is the premium charged the employer by USIC divided by the number of covered lives. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Columns (3) and (4) control non-parametrically for selection with polynomial of the selection probability. Markets are defined by USIC and roughly represent an MSA or state. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

data. For the USIC data, we use the last two years of our sample, 2014 and 2015—and individuals with complete observations during these years—in order to have a uniquely defined measure of the change in risk.

The Handel et al. results verify that their simulated guaranteed renewability contracts imply substantial equilibrium pass through for individuals whose risk score decreases, and positive, but much lower, pass through at the margin for individuals whose risk scores increase. We find the same qualitative pattern with the USIC data. For instance, column (4), which corrects for selection, reports a pass through of $795 on the spline for decreases in risk score, with a coefficient of $44 on the spline for increases in risk score. While the overall levels of pass through are different across the two samples, this again may reflect the presence of switching costs in the real world, as well as other institutional differences.[28]

Panel B shows specifications without enrollee fixed effects where we again examine the relation between premiums and risk scores using splines. For this panel, we now base the spline on risk, not change in risk, and use a cut point of $R = 1$ (the overall population mean risk score).[29] These specifications capture the equilibrium effect of risk score on premiums, rather than the pass through from a change in risk score on a change in premiums. Once again, both the Handel et al. simulated data and the USIC data show a similar pattern: the equilibrium relation between risk and premiums at the margin is larger for low risk and smaller for high risk groups.

To examine the third implication, Table 9, Panel A presents results from regressions of pass through from expected health risk to premiums, stratifying by the period 1 health risk. We again choose the population mean of $R = 1$ as the cut point. For the Handel et al. simulated data, we find that the large β, and hence the bulk of the reclassification risk, is largely occurring for individuals with $R > 1$, who were less healthy than average in the initial period. The USIC data shows a consistent, though weaker, pattern. For instance, in the selection corrected results in column 4, the pass through coefficient β for groups with initially below average risk is \$378, while it is \$413 for groups with initially above average risk.[30]

Panel B presents analogous results without enrollee fixed effects, stratifying based on the period 1 risk score. The results are again broadly consistent between the Handel et al. simulated data and the USIC data. They show a stronger equilibrium relation between expected health risk and premiums for groups with a higher period 1 risk score.

In sum, our tests show that the main implications of the guaranteed renewability model hold in our data.[31] In particular, we find that there is partial pass through from changes in health risk to changes in premiums. Groups with decreases in risk score faced a larger marginal impact of expected health risk on premiums, while groups with increases in risk score were not very exposed to reclassification risk at the margin. Similarly, groups with higher risk scores, which had a greater

[28]Three features of our setting differ from Handel et al.. First, the small group insurance market is best characterized as an oligopoly while they model competition. Second, individuals frequently select out of USIC insurance for reasons such as switching employers, while they do not allow for this behavior. Finally, we model the small group market while they consider individual insurance.

[29]For comparability, we use the same sample as in Panel A, but the results using all complete observations during our sample period are similar.

[30]This is also consistent with our finding of higher initial risk scores for quitters in Tables 1 and 2, as some of these groups may be obtaining insurance from a different insurer instead of renegotiating with USIC.

[31]On-Line Appendix C verifies that these results also hold when we use the sample of 2013 joiners. We do not use this sample as our base sample because it has fewer observations. However, it is more similar to our Handel et al. simulations, which consider the first year of guaranteed renewability contracts.

Table 9: Impact of risk on premiums heterogeneity stratifying on initial risk, with simulated guaranteed renewability data and USIC data

Panel A: specifications with enrollee fixed effects				
Dependent variable: change in annual employer mean premium, p_{jt}				
Sample:	HHW	USIC		
	(1)	(2)	(3)	(4)
$1\{R_{j1} \leq 1\} \times \Delta R_{jt}$	279***	39	337***	378***
	(91)	(63)	(87)	(33)
$1\{R_{j1} > 1\} \times \Delta R_{jt}$	2,798***	65	346***	413***
	(491)	(64)	(87)	(27)
Enrollee FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Polynomial Order		No	1^{st}	6^{th}
Observations		90,826	90,826	90,826
Panel B: specifications without enrollee fixed effects				
Dependent variable: annual employer mean premium, p_{jt}				
$1\{R_{j1} \leq 1\} \times R_{jt}$	615***	1,313***	1,692***	1,978***
	(205)	(106)	(119)	(18)
$1\{R_{j1} > 1\} \times R_{jt}$	3,181***	2,002***	2,337***	2,554***
	(209)	(70)	(81)	(12)
Enrollee FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Polynomial Order		No	1^{st}	6^{th}
Observations		181,652	181,652	181,652

Note: each observation is one enrollee for which we have a complete observation for years 2014 and 2015. Column (1) uses simulated data from Handel et al. (2019). In Columns (2) to (4), the dependent variable is the premium charged the employer by USIC divided by the number of covered lives. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Columns (3) and (4) control non-parametrically for selection with polynomial of the selection probability. Markets are defined by USIC and roughly represent an MSA or state. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

possibility of a decrease in risk score, were also more exposed to equilibrium reclassification risk. This suggests that USIC may be offering contracts with an implicit promise of guaranteed renewability for existing accounts, with ex post renegotiation for groups with drops in risk score.

Robustness. We also consider three other different explanations for our findings: (1) oligopoly power by USIC; (2) USIC potentially passing on expected health risk to premiums slowly over time; and (3) consumer search. We find little support for any of these explanations. See On-Line Appendix D for details.

6 Counterfactuals and Welfare

6.1 Simulation of counterfactuals

Using our estimates, we now examine the extent of reclassification risk and the resulting welfare loss under the current pricing environment and counterfactual environments, over a 10-year horizon after the initial insurance enrollment. We base our counterfactuals on the idea that enrollees obtain the fixed-effects pass through coefficient when they stay with USIC insurance, as this coefficient indicates the impact of changes in health risk on changes in premiums. When they leave USIC insurance, they work at another small employer with similar employees and obtain premiums that are determined by the non-fixed-effects coefficient in this case.

We calculate our counterfactuals with three steps. First, we iteratively construct the future distribution of enrollee health risk and mean employer health risk to which an enrollee is exposed, over a 10-year renewal period following the initial insurance enrollment. Following Table 3, which shows that two lags of risk scores are predictive of the current score, we predict the health risk using two lags of the score. Rather than using the coefficients from Table 3, we simulate future risk scores and out-of-pocket expenditures non-parametrically for each individual, using enrollees with similar ACG scores for the two previous periods, for each enrollee.[32]

Second, we evaluate how changes in risk translate into changes in future premiums and out-of-pocket costs. This reclassification risk occurs through two mechanisms. First, health shocks (for the enrollee or others in her group) result in enrollees facing higher premiums; second, enrollees may drop health coverage due to the higher premiums caused by these health shocks. Since both of these sources of risk are potentially important, our counterfactuals capture both sources. Specifically, to evaluate reclassification risk under the observed environment, after simulating the new risk scores R_{ijt} and r_{ijt} each period, we simulate a joint draw from the estimated ε^s and ε^p distributions. We then use ε^s to simulate whether the individual selects into insurance. If so, she receives new premiums based on the estimated β from our specification with enrollee fixed effects and selection correction in Table 7, panel A, column 4 (and using the draws of ε^s and ε^p).[33] If she selects out of her current insurance, we assume that she receives new premiums based on β estimated without employer/enrollee fixed effects or selection corrections (Table 7, panel B, column

[32] We use a uniform kernel and choose the bandwidth based on Silverman's rule (Hansen, 2018).

[33] Although Section 5.4 shows evidence of heterogeneity of pass through based on the changes in risk score, given the small pass through overall, we use the mean pass through coefficient here for simplicity.

2) and a draw from the unconditional estimated distribution of ε^p.

Third, we examine how this distribution of premiums and out-of-pocket costs translates into a certainty equivalent income level. We use a CARA functional form for our money utility function $u_{ij}(\cdot)$. We do not estimate the CARA risk aversion parameter, but instead use 0.000428, the value from Handel (2013), who estimates risk in a similar context of health insurance choice.[34]

6.2 Counterfactual results

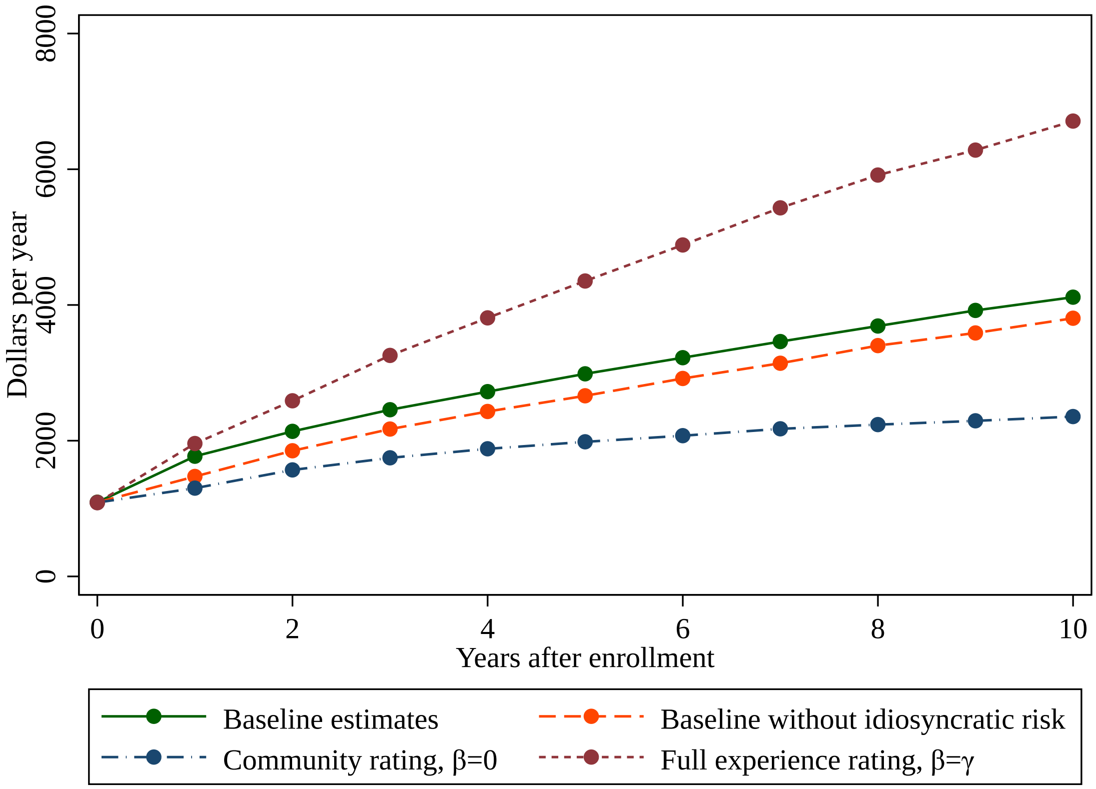
We consider four different pricing environments. First, as the baseline, we examine the observed pricing environment, using our simulation methods described above. Second, we examine the baseline but without idiosyncratic premium risk. In this case, we follow the same procedure as in the baseline, but we set $\varepsilon^p = 0$. Third, we examine community rating, where $\beta = 0$. Finally, we examine full experience rating, under which $\beta = \gamma$.

Figure 1 reports the mean across individuals in the certainty equivalent loss from risk across these pricing environments. The baseline estimates show a mean annual certainty equivalent loss from risk of $3,050 in the ten years after the initial enrollment. Some of this is caused by idiosyncratic premium risk. Without idiosyncratic risk, the mean certainty equivalent loss from risk drops to $2,750. Under community rating, the mean annual certainty equivalent income loss is $1,950, while it is $4,500 under full experience rating. Thus, USIC's observed pricing policy provides approximately 60% of the consumer welfare protection from reclassification risk as does community rating, relative to full experience rating. Even though USIC's pricing policy for existing customers exhibits very little experience rating, turnover in this market is large, which limits this protection. In addition, even under community rating, the possibility of large out-of-pocket expenditures generates a substantial certainty equivalent loss from risk, particularly later in the sample.

Figures 2 and 3 report the mean standard deviation in premiums and total health spending, respectively. The numbers here follow Figure 1 pretty close here, with the baseline policy without idiosyncratic risk having about half of the standard deviation in premiums of the full experience rating case relative to the community rating case. Consistent with the welfare loss from out-of-pocket costs in Figure 1, the standard deviation on total healthcare expenditures is $1,300 in the initial year, stemming exclusively from out-of-pocket expenditures. This rises gradually over time

[34] With the CARA utility function, the certainty equivalent income loss of a lottery does not depend on the base income level, and hence we do not specify the income for each enrollee. We also examine robustness using the CARA parameter of 0.00008, which is also used by Ghili et al. (2019).

Figure 1: Simulated mean certainty equivalent loss from risk across pricing policies



Note: Figure based on authors' calculations as described in paper.

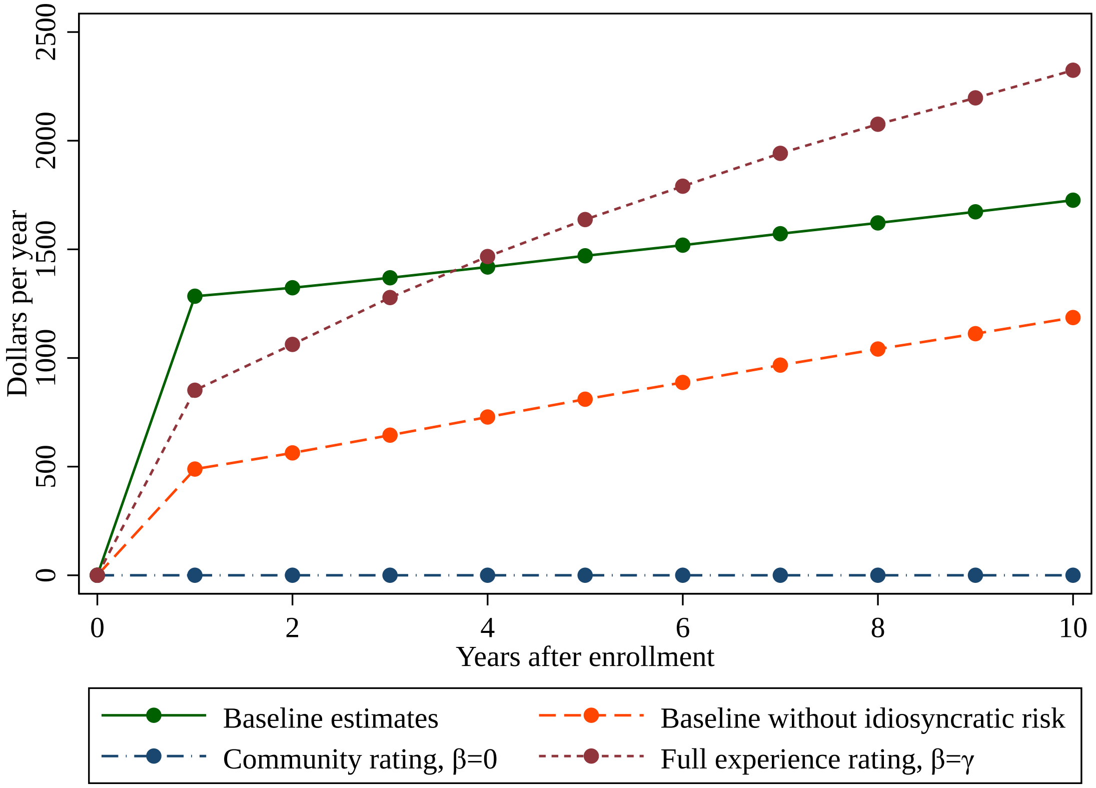
under all of the four scenarios.

One difference here is that the baseline policy has a greater standard deviation in the early years than other policies. But, because this risk is $i.i.d.$, this standard deviation does not generate as big a welfare impact over time as the premium risk from experience rating.

Finally, Figure 4 examines the extent to which pooling in the small group market adds value. Specifically, it performs a simulation similar to our baseline estimate but where each individual's premiums are based on her risk scores, r_{ijt}, rather than on her employer's mean risk scores, R_{jt}. We find that the value generated by pooling in the small group market is moderate. Specifically, we find that the mean difference in the certainty equivalent income loss from being exposed to USIC's current pricing policies and being in a small group versus being exposed to the same pricing policies but purchasing individual insurance is $600 per year over the 10-year horizon.

In sum, our results show that USIC offer insurance contracts with characteristics similar to guaranteed renewability. However, employees switching jobs and employers starting and stop-

Figure 2: Simulated mean standard deviation in premiums across pricing policies



Note: Figure based on authors' calculations as described in paper.

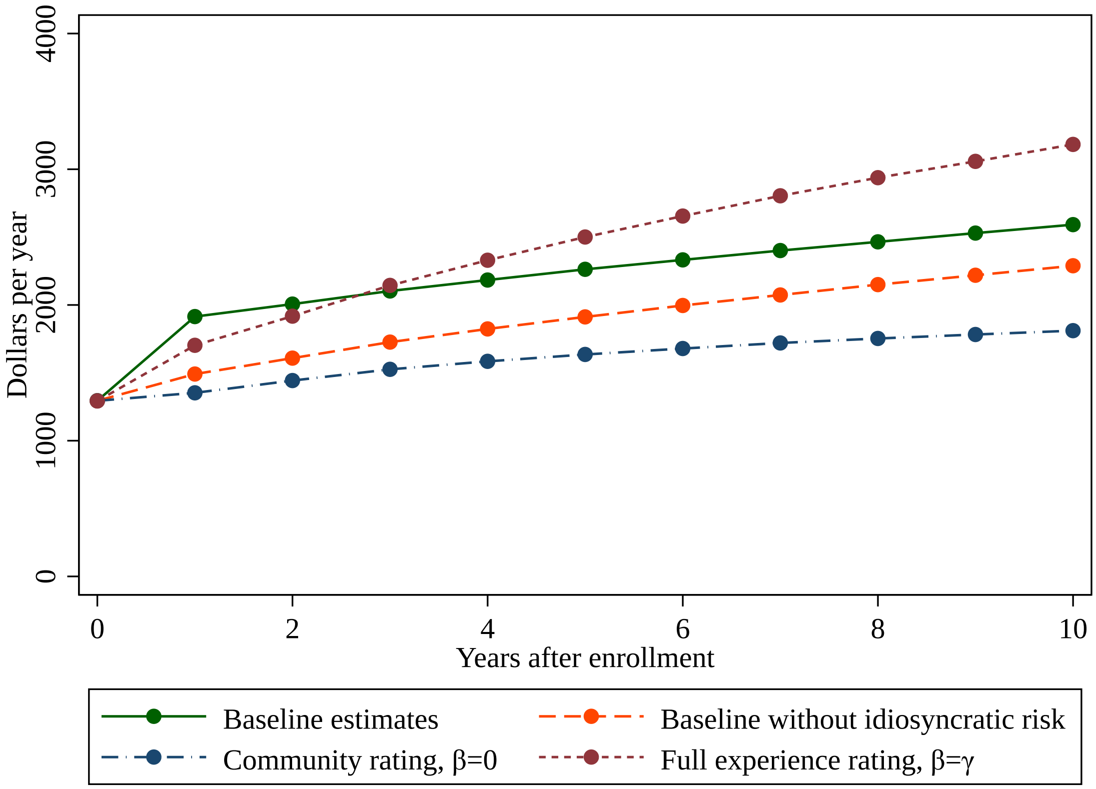
ping coverage likely due to shutting down limits the consumer welfare gains from these contracts well below the first best level.

Robustness. On-Line Appendix E provides robustness results with a different risk aversion coefficient. Although the magnitude of the welfare losses differs with different risk aversion parameters, the pattern of the results is similar to the baseline.

7 Conclusion

In this paper, we seek to understand the extent and causes of reclassification risk in the small group insurance market from a period before ACA community rating regulations were effective. The ACA was designed, in part, to reduce reclassification risk in the individual and small group markets. Studies from the pre-ACA era assessed very different priors on the extent of reclassification risk in this market (Cutler, 1994; Pauly and Herring, 1999; Gruber, 2000; Herring and Pauly,

Figure 3: Simulated mean standard deviation in healthcare expenditures across pricing policies



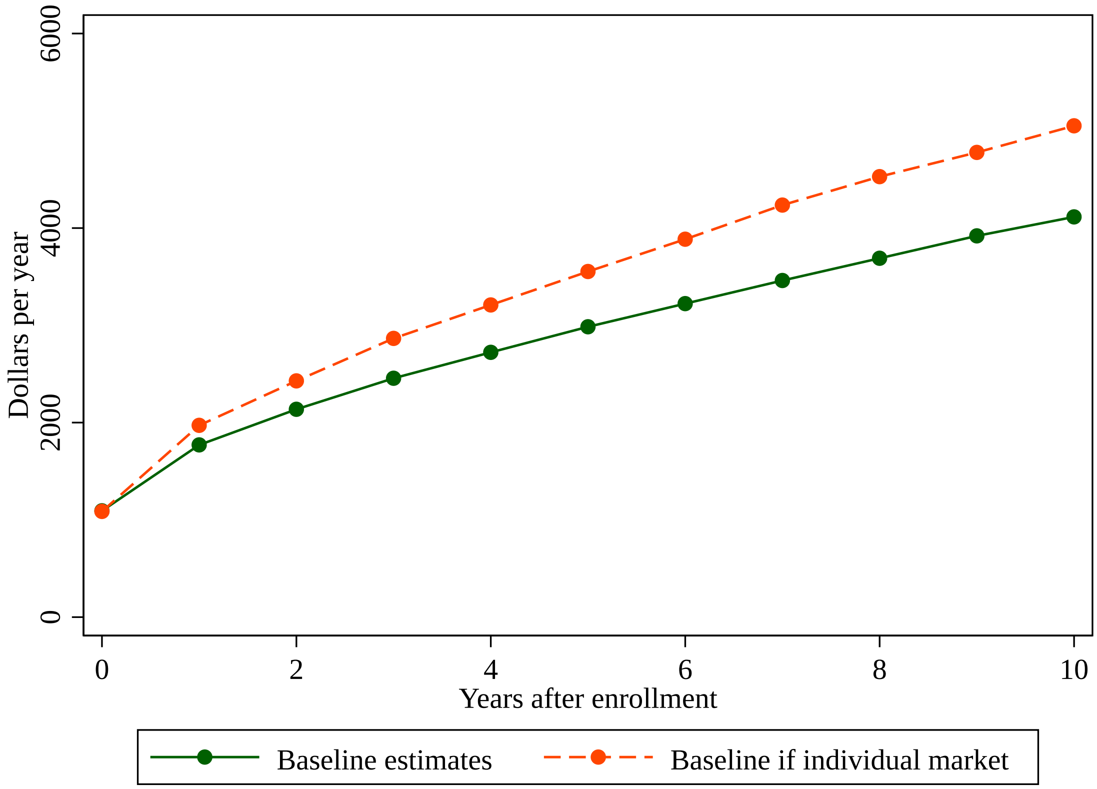
Note: Figure based on authors' calculations as described in paper.

2006). Our study makes use of a unique database from a large U.S. health insurer, "United States Insurance Company" (USIC), with premium information on over 12,000 employers, and claims data from more than 300,000 enrollees at these employers. Our data allow us to obtain direct evidence on the relationship between health risk and claims in this market.

We first develop a simple two-period model of insurer pricing and employer/employee offer/take-up. Our model allows for the premiums to each employer to be based on the expected claims cost of the employer and for enrollees to select insurance based on their premiums and risk scores. We show that the pass through from changes in health risk to changes in premiums, which we denote β, is a sufficient statistic to understand reclassification risk in this market, under some conditions. In the tradition of Chetty (2009) and Einav et al. (2010), we estimate β and use it to characterize reclassification risk in this market, but do not estimate preference parameters.

We find that the pass through from changes in expected claims to changes in premiums is 16%

Figure 4: Simulated mean certainty equivalent loss with no pooling within group



Note: Figure based on authors' calculations as described in paper.

with enrollee fixed effects and non-parametric selection controls, which is much closer to binding long-run contracts or community rating than experience rating. Without enrollee fixed effects or selection controls, the relation is larger, with a dollar in higher expected claims associated with 44 cents higher premiums. Together, these results suggest that USIC prices new accounts based on health risk but then does not adjust premiums for existing accounts much in response to changes in health risk.

This limited reclassification risk for existing accounts is consistent with USIC offering "guaranteed renewability" one-sided commitment contracts where the insurer imposes little risk rating on existing customers. We further test two additional implications of the optimal guaranteed renewability contracts with liquidity constraints and find that they hold in our setting. First, we find that health risk reductions lead to relatively large drops in premiums compared to health risk increases, which the guaranteed renewability model attributes to ex post renegotiation by groups with drops in health risk. Second, we find higher reclassification risk for groups with ex ante higher risk, which follows because they are more likely to revert to lower risks and renegotiate ex post. Additionally, we show that the limited reclassification risk that we observe cannot be explained by alternative hypotheses such as slow pass through over time, market power, or search frictions.

Finally, we simulate counterfactuals to evaluate the extent to which USIC insurance provided value in the form of protection from reclassification risk in the small group market. To compute this, we non-parametrically simulate the evolution of health risk for an employer over a ten-year horizon and evaluate how this would translate into selection into and out of insurance and a welfare loss from financial risk. We use a CARA risk aversion parameter taken from the literature and our estimated pass-through, extent of selection, and health risk transitions. We find that the observed USIC policy adds about 60% of the difference in consumer welfare between full experience rating and community rating. The high turnover of enrollees limits the value from the guaranteed renewability feature of USIC's contracts. Substantial out-of-pocket costs in this market also generate significant welfare loss. The value from pooling within a small group is relatively small, at $600 per year under the baseline policy.

Overall, our findings are consistent with the existence of optimal guaranteed renewability contracts in the sense of Ghili et al. (2019) in the small group market before the ACA regulations. This finding is different from what many observers thought was likely occurring in this market before the ACA (Gruber, 2000), although broadly consistent with the analysis of Herring and Pauly (2006). Finally, and although these contracts improve consumer welfare substantially, there are limitations to their value. These occur because of significant out-of-pocket costs from the small group insurance products that we observe and because employees and employers switch insurance companies frequently, likely due to business creation and destruction and job switching.

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On-Line Appendices

A On-Line Appendix A: Extra exhibits on data

Figure A.1: States in our estimation sample

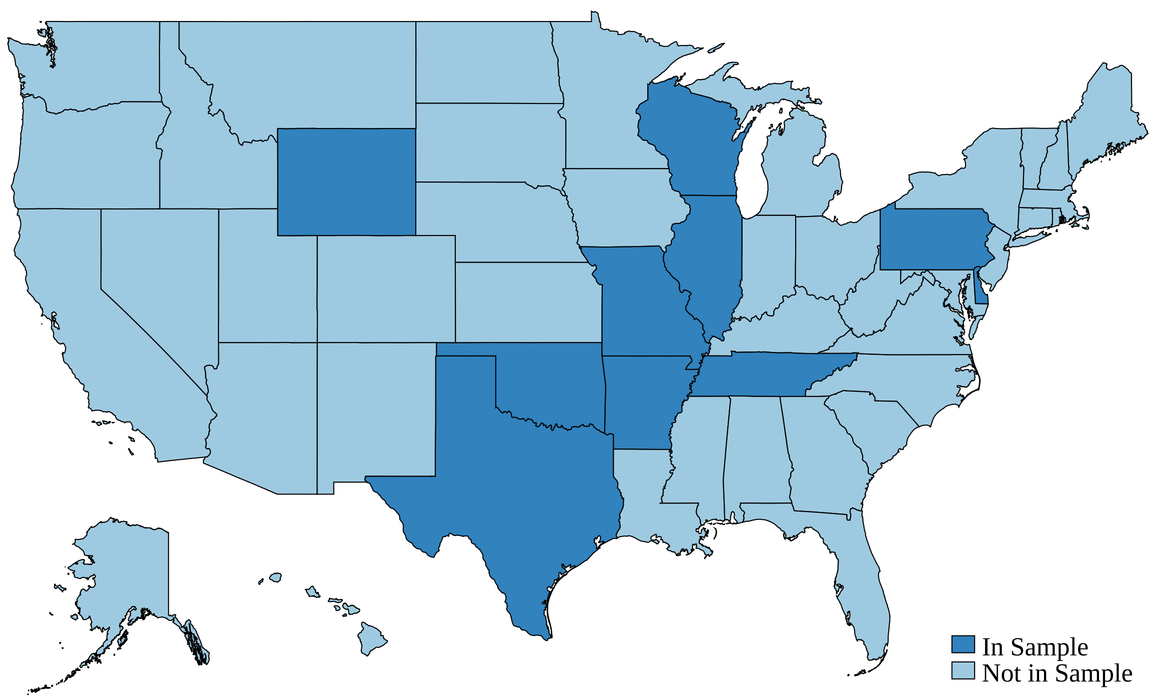


Table A.1: Impact of expected risk on claims using splines

	Dependent Variable: Paid amount ($)			
Regressor:	(1)	(2)	(3)	(4)
Spline enrollee ACG score, $r_{ijt} \in [0, 1)$	2,746***	2,836***		
	(94)	(96)		
Spline enrollee ACG score, $r_{ijt} \in [1, 2.5)$	3,174***	3,190***		
	(151)	(151)		
Spline enrollee ACG score, $r_{ijt} \in [2.5, 5)$	4,284***	4,282***		
	(361)	(361)		
Spline enrollee ACG score, $r_{ijt} \in [5, \infty)$	4,692***	4,689***		
	(398)	(398)		
Spline enrollee ACG score, $r_{ijt} \in [0, .32)$			2,503***	2,633***
			(559)	(563)
Spline enrollee ACG score, $r_{ijt} \in [.32, .57)$			3,756***	3,814***
			(411)	(411)
Spline enrollee ACG score, $r_{ijt} \in [.57, 1.13)$			1,189***	1,289***
			(421)	(420)
Spline enrollee ACG score, $r_{ijt} \in [1.13, \infty)$			4,345***	4,344***
			(185)	(185)
Market FE	No	Yes	No	Yes
Splines	Fixed cut points	Fixed cut points	Quartiles	Quartiles
Observations	204,913	204,913	204,913	204,913

Note: each observation is one enrollee during one year. The dependent variable indicates the total claims amount paid by USIC for that enrollee. The sample is covered individuals with an ACG score in 2014 only. Markets are defined by USIC and roughly represent an MSA or state. We cluster standard errors at the employer level. *** indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level.

B On-Line Appendix B: Robustness to results of impact of health risk on premiums

We consider a number of robustness checks of our results on the impact of health risk on premiums. First, we examine robustness to our selection correction. Table B.1 presents the results of our main estimates when we control for selection using the MEPS sample instead of the USIC sample, with analogous specifications to Table 7. The estimates of the pass through are smaller than in Table 7 for both the fixed-effects and the non-fixed-effects specifications. Overall, the estimates using the MEPS sample correction show a very similar pattern to the main estimates.

Table B.1: Impact of risk on premiums using MEPS sample correction

	Observation level:			
	Employer/year	Enrollee/year	Enrollee/year	Enrollee/year
	No selection correction		With selection correction	
	(1)	(2)	(3)	(4)
Panel A: specifications with employer/enrollee fixed effects				
Health risk for enrolled, R_{jt}	188**	195***	195	196
	(87)	(82)	(84)	(102)
Panel B: Estimations with market fixed effects				
Health risk for enrolled, R_{jt}	1,749***	2,263***	2,210**	2,175***
	(120)	(88)	(94)	(272)
Year FE	Yes	Yes	Yes	Yes
Polynomial Order	No	No	1^{st}	6^{th}
Observations	31,044	448,259	448,259	448,259

Note: each observation is either one employer or enrollee during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Column (1) in Panel A includes employer fixed effects. Columns (2) to (4) in Panel A include enrollee fixed effects. Panel B includes market fixed effects. Columns (3) and (4) control non-parametrically for selection with polynomial of the selection probability. Markets are defined by USIC and roughly represent an MSA or state. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Second, we consider the bias from measurement error from the fact that we use the ACG risk score instead of USIC's risk score. For a subset of 3,759 enrollees in 2013, we have USIC's own risk score.[35] We found a high correlation between the USIC score and the ACG score for this subsample. In particular, the linear (Pearson) correlation between the ACG risk score and the USIC risk score is 0.835 and the rank Spearman correlation is 0.881.[36] We then computed the size of the true pass-through coefficient assuming that the measurement error is uncorrelated with the

[35]USIC develops this score in-house for use in its risk rating decisions. USIC was unable to recover their risk score for the rest of the sample.

[36]We also estimated β for this subsample using USIC's risk score instead of the ACG score and we found a result that is not statistically different from our main result.

regressors,[37] using $\beta^{estimate} = \beta^{true} \frac{\sigma_{RR}}{\sigma_{RR}+\sigma_{\omega\omega}}$ (Wooldridge, 2010, p. 75), where $\sigma_{\omega\omega}$ is the variance of the measurement error and σ_{RR} is the variance of the (USIC) true risk score. We calculated $\sigma_{RR} = 1.92$ for our estimation sample and estimated $\sigma_{\omega\omega}$ as the standard deviation of the residual from a regression of the ACG score on the USIC score, obtaining 0.74, which yields $\beta^{true} = \$863$. Thus, the measurement error here can only explain a very small part of the pricing relative to full experience rating. We also constructed our own risk score (ORS) measure using a random forest algorithm, and instrumented for the USIC risk score with ORS. We find a pass through that is smaller than the estimated using the ACG score that is not statistically different from zero.

Third, Table B.2 presents similar specifications to our main results in Table 7, panel A, column 4 but with the addition of the percent of enrollees with specific chronic diseases. We chose cancer, transplants, AMIs (heart attacks) and diabetes (in Panel A), and hypertension, heart failure, kidney chronic disease and asthma (in Panel B), as these diseases result in persistent increases in the costs of healthcare, and they may serve as markers that insurers use to price risk. The pass through from the risk score to premiums is very similar, ranging from \$625 to \$648, which are not very different from our main estimate of \$624. While increases in the percent of enrollees with cancer and heart failure increase premiums, we do not find significantly significant and positive effects for the other conditions. Our takeaway from this is that the pass through from expected claims to premiums is very stable to the inclusion of these chronic diseases.

[37]The measurement error here is likely uncorrelated, since the point estimate of β does not change in different specifications when we add different controls.

Table B.2: Impact of expected risk on premiums, with chronic conditions

Dependent Variable: Annual employer mean premium, p_{jt}					
Panel A: Effect controlling for chronic conditions					
Regressor:	(1)	(2)	(3)	(4)	(5)
Health risk for enrolled, R_{jt}	624**	648**	626**	625**	628**
	(116)	(117)	(135)	(124)	(116)
Lag % cancer at employer		2**			
		(4)			
Lag % transplant at employer			2		
			(2)		
Lag % AMI at employer				1	
				(0.5)	
Lag % diabetes at employer					1
					(0.3)
Year FE	Yes	Yes	Yes	Yes	Yes
Enrollee FE	Yes	Yes	Yes	Yes	Yes
Polynomial Order	6^{th}	6^{th}	6^{th}	6^{th}	6^{th}
Observations	448,259	448,259	448,259	448,259	448,259
Panel B: Effect controlling for chronic conditions					
Health risk for enrolled, R_{jt}	624**	627**	633**	627**	625**
	(116)	(120)	(119)	(116)	(119)
Lag % hypertension at employer		0.2			
		(0.1)			
Lag % heart failure at employer			2**		
			(0.4)		
Lag % kidney disease at employer				0.7	
				(0.3)	
Lag % asthma at employer					0.2
					(0.1)
Year FE	Yes	Yes	Yes	Yes	Yes
Enrollee FE	Yes	Yes	Yes	Yes	Yes
Polynomial Order	6^{th}	6^{th}	6^{th}	6^{th}	6^{th}
Observations	448,259	448,259	448,259	448,259	448,259

Note: each observation is either one employer or enrollee during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Column (1) in Panel A includes employer fixed effects. Columns (2) to (4) in Panel A include enrollee fixed effects. Panel B includes market fixed effects. Columns (3) and (4) control non-parametrically for selection with polynomial of the selection probability. Chronic disease regressors indicate the mean percent of enrollees with a claim for the disease in the previous year. Markets are defined by USIC and roughly represent an MSA or state. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Fourth, in Table B.3 we examine whether changes in health risk lead to changes in the plan benefits that the employer chooses, again using similar specifications to our main results. We consider three measures of plan benefits: the out-of-pocket maximum, the coinsurance rate, and the in-network deductible. For each of our benefit measures, the estimated coefficient on health risk is small and not statistically significant, suggesting that employers do not systematically substitute to plans with different benefit structures following health risk shocks.

Table B.3: Impact of expected risk on benefits

	Dependent variable		
	In-network maximum OOP ($)	Coinsurance rate (%)	In-network deductible ($)
Regressor:	(1)	(2)	(3)
Health risk for enrolled, R_{jt}	303	-0.43	159
	(113)	(0.57)	(58)
Year FE	Yes	Yes	Yes
Enrollee-plan FE	Yes	Yes	Yes
Polynomial Order	6^{th}	6^{th}	6^{th}
Observations	448,259	448,259	448,259

Note: each observation is one enrollee during one year. Each dependent variable is a measure of plan benefits. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Column (1) in Panel A includes employer fixed effects. Columns (2) to (4) in Panel A include enrollee fixed effects. Panel B includes market fixed effects. Columns (3) and (4) control non-parametrically for selection with polynomial of the selection probability. Markets are defined by USIC and roughly represent an MSA or state. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Fifth, we consider whether the low pass through may be due to the planned roll-out of community rating regulations, that may have affected insurers' pass through. We checked whether there was a change in the pass-through coefficient between 2013-2014 and 2014-2015, because of the gradual phase-in of ACA regulations. We present the results from our base specification but with the two different samples in Table B.4. The estimated coefficient of pass through for the first period is somewhat smaller than in our main specification but not statistically significant from our main estimate. The point estimate for the 2014-2015 sample is lower, and not statistically different from the estimate for the first period. Overall, the evidence does not suggest that our estimated passthrough is affected by changes in regulations after 2014.

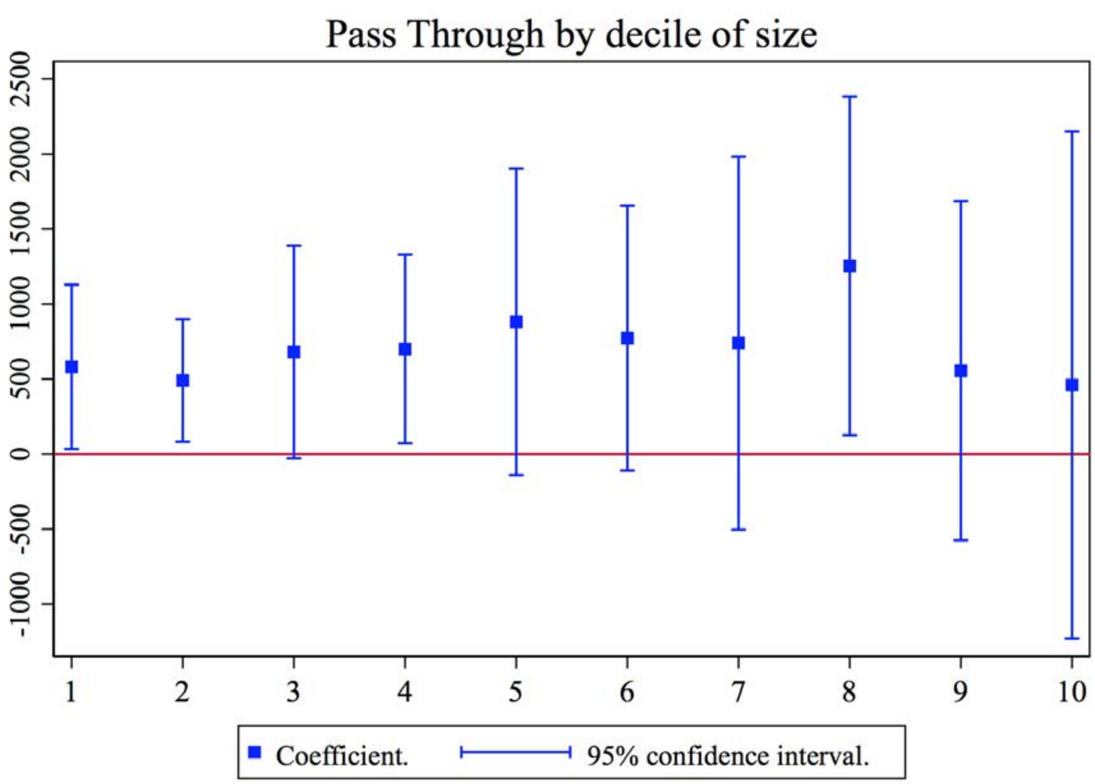
Finally, our analysis suggest that there are not large differences in the pass-through results by employer size. To analyze this, we split the sample based on deciles of the distribution of employers size. Figure B.1 presents the results for our base specification but where we split the pass-through coefficient by deciles. The pass through remains stable across the size distribution.

Table B.4: Impact of risk on premiums with heterogeneity by different periods

Dependent variable: annual employer mean premium, p_{jt}				
	(1)	(2)	(3)	(4)
Health risk for enrolled, R_{jt}	568*	2,903**	440*	2,766***
	(85)	(74)	(68)	(189)
Sample Years	2013-14	2013-14	2014-15	2014-15
Enrollee FE	Yes	No	Yes	No
Market FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Polynomial Order	6^{th}	6^{th}	6^{th}	6^{th}
Observations	281,932	325,080	246,358	307,293

Note: each observation is one enrollee during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Markets are defined by USIC and roughly represent an MSA or state. All estimates control non-parametrically for selection with a 6th order polynomial of the selection probability. SWe two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Figure B.1: Effect of risk on premium by employer size



Note: Coefficients from our preferred specifications allowing different effects by size.

C On-Line Appendix C: Robustness evidence on guaranteed renewability contracts using joiners sample

Table C.1: Impact of risk on premiums using splines, with simulated guaranteed renewability data and USIC data

Panel A: specifications with enrollee fixed effects				
Dependent variable: change in annual employer mean premium, p_{jt}				
Sample:	HHW	USIC		
	(1)	(2)	(3)	(4)
Spline, $\Delta\ R_{jt} \leq 0$	3,612***	374***	733***	749***
	(88)	(129)	(159)	(78)
Spline, $\Delta\ R_{jt} > 0$	172***	-164***	211	212
	(26)	(142)	(162)	(79)
Enrollee FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Polynomial Order		No	1^{st}	6^{th}
Observations		10,795	10,795	10,795
Panel B: specifications without enrollee fixed effects				
Dependent variable: annual employer mean premium, p_{jt}				
Spline, $R_{jt} \leq 1$	2,973***	3,265***	3,512***	3,489***
	(742)	(239)	(194)	(185)
Spline, $R_{jt} > 1$	1,638***	2,240***	2,370***	2,508***
	(478)	(160)	(166)	(199)
Enrollee FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Polynomial Order		No	1^{st}	6^{th}
Observations		21,590	21,590	21,590

Note: each observation is a joiner in 2013 for which we have a complete observation for years 2014 and 2015. Column (1) uses simulated data from Handel et al. (2019). In Columns (2) to (4), the dependent variable is the premium charged the employer by USIC divided by the number of covered lives. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Columns (3) and (4) control non-parametrically for selection with polynomial of the selection probability. Markets are defined by USIC and roughly represent an MSA or state. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table C.2: Impact of risk on premiums heterogeneity stratifying on initial risk, with simulated guaranteed renewability data and USIC data

Panel A: specifications with enrollee fixed effects				
Dependent variable: change in annual employer mean premium, p_{jt}				
Sample:	HHW	USIC		
	(1)	(2)	(3)	(4)
$1\{R_{j1} \leq 1\} \times \Delta R_{jt}$	279***	-20	364***	357***
	(91)	(129)	(148)	(83)
$1\{R_{j1} > 1\} \times \Delta R_{jt}$	2,798***	170	532***	537***
	(491)	(110)	(143)	(70)
Enrollee FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Polynomial Order		No	1^{st}	6^{th}
Observations		10,795	10,795	10,795
Panel B: specifications without enrollee fixed effects				
Dependent variable: annual employer mean premium, p_{jt}				
$1\{R_{j1} \leq 1\} \times R_{jt}$	615***	1,448***	1,603***	1,721***
	(205)	(166)	(201)	(51)
$1\{R_{j1} > 1\} \times R_{jt}$	3,181***	2,254***	2,395***	2,490***
	(209)	(124)	(138)	(35)
Enrollee FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Polynomial Order		No	1^{st}	6^{th}
Observations		21,590	21,590	21,590

Note: each observation is a joiner in 2013 for which we have a complete observation for years 2014 and 2015. Column (1) uses simulated data from Handel et al. (2019). In Columns (2) to (4), the dependent variable is the premium charged the employer by USIC divided by the number of covered lives. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Columns (3) and (4) control non-parametrically for selection with polynomial of the selection probability. Markets are defined by USIC and roughly represent an MSA or state. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

D On-Line Appendix D: Alternative explanations for findings

We consider three explanations for our findings beside USIC offering guaranteed renewability contracts: (1) oligopoly power by USIC; (2) USIC potentially passing on expected health risk to premiums slowly over time; and (3) consumer search.

First, our results may be driven by USIC having pricing power and choosing pass through to maximize revenues based on this pricing power. Suppose that the insurer set premiums as a single firm maximizing static profits. In this case, we would expect that its price in each market would vary with its residual demand in that market. While it would be difficult to estimate USIC's residual demand across markets, we believe that residual demand would likely vary based on the market concentration in a particular area. Thus, we test whether our results may be generated by static pricing power by evaluating whether USIC's pricing policies vary across markets based on measures of concentration. Table D.1 interacts the pass-through coefficient with three different measures of market concentration, specifically the Herfindahl Index (HHI), the market share of the leader insurer, and the number of insurers with more than 5% of market share, in panels A, B and C, respectively.[38]

In all cases, the interaction measures are not statically significant. Thus, we do not find evidence that the low levels of pass through that we estimate are driven by insurer pricing power. Additionally, Figure D.1 present the variation across different states. We find no significant pattern in the variation of pass through across states.

Second, it is possible that when an employer has an increase in R, its average risk score, USIC passes through the expected costs to premiums slowly over time, rather than immediately. In order to test this proposition, Table D.2 reports the pass through using the current and lagged ACG scores, with specifications analogous to our main specifications with and without fixed effects (which are repeated in columns 1 and 3, respectively). Our fixed-effects specification with a lagged risk score in column 2 shows no evidence that employers raise their premiums based on the lagged risk score. In contrast, our specification in column 4 without fixed effects shows a positive and significant estimate on lagged risk score, with the sum of the coefficients adding up roughly to the unique risk score coefficient in column 3. Our interpretation is again that employers that are new to USIC face a premium that is relatively risk based while employers with existing USIC accounts do not see much variation in premiums as their risk changes.

[38] We define these indices at the state level using Kaiser Family Foundation data for 2013-15.

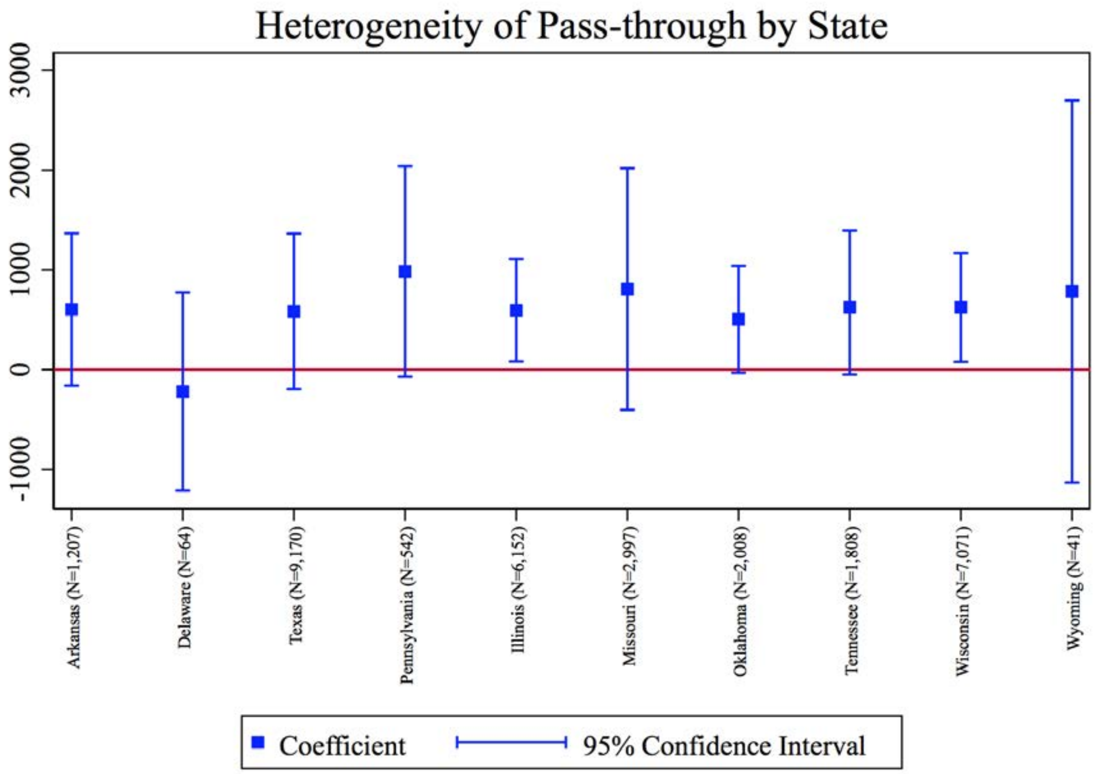
Table D.1: Impact of expected risk on premiums by market concentration

Dependent variable: annual employer mean premium, p_{jt}			
	(1)	(2)	(3)
Panel A: market HHI			
Health risk for enrolled, R_{jt}	624** (121)	617** (146)	700** (116)
HHI		0.035*** (0.008)	0.057 (0.032)
R_{jt} × HHI			−0.023 (0.057)
Enrollee FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	448,259	448,259	448,259
Panel B: share of largest insurer			
Health risk for enrolled, R_{jt}	624** (121)	617** (87)	711** (101)
Share of leader insurer		280** (58)	447** (245)
R_{jt} × Share of leader insurer			−174 (228)
Enrollee FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Polynomial Order	6^{th}	6^{th}	6^{th}
Observations	448,259	448,259	448,259
Panel C: number of insurers with 5% or larger market share			
Health risk for enrolled, R_{jt}	624** (121)	615** (116)	605 (231)
Number of insurers with 5%+ share		−58 (19)	− 60 (73)
R^p_{jt} × Number of insurers with 5%+ share			2.5 (61)
Enrollee FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Polynomial Order	6^{th}	6^{th}	6^{th}
Observations	448,259	448,259	448,259

Note: each observation is one enrollee during one year. Markets are defined by USIC and roughly represent an MSA or state. We define HHI, share of leader insurer, and number of insurers with 5%+ market share using the Kaiser Family Foundation State Health Facts database. All estimates control non-parametrically for selection with a 6th order polynomial of the selection probability. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Third, our results may be driven by consumer search. To understand the size of the effect of consumer search on pass through, we calculate a back-of-the-envelope estimate of the potential pass through from search frictions using Cebul et al. (2011)'s estimated model of search frictions for health insurance. In equation (13), Cebul et al. define average premiums as $\bar{p} = c + \frac{\gamma}{1+\gamma}(p^R - c)$, where c is marginal cost, p^R is the maximum willingness to pay for insurance, and γ is the "market friction parameter." Using this equation and their estimated $\gamma = 0.153$ from Panel A of Table 12, the pass through can be expressed as: $\frac{\Delta \bar{p}}{\Delta c} = \frac{1}{1+\gamma}$=86.7%. Therefore, their estimated search model implies that about 87% of a cost increase would be passed through to the mean small group employer. Given our pass-through estimate of 16% in the fixed effects specification, our results are also unlikely to be mostly explained by search frictions.

Figure D.1: Effect of risk on premium by state



Note: Coefficients from our preferred specifications allowing different effects by state.

Table D.2: Impact of risk on premiums with lagged risk score

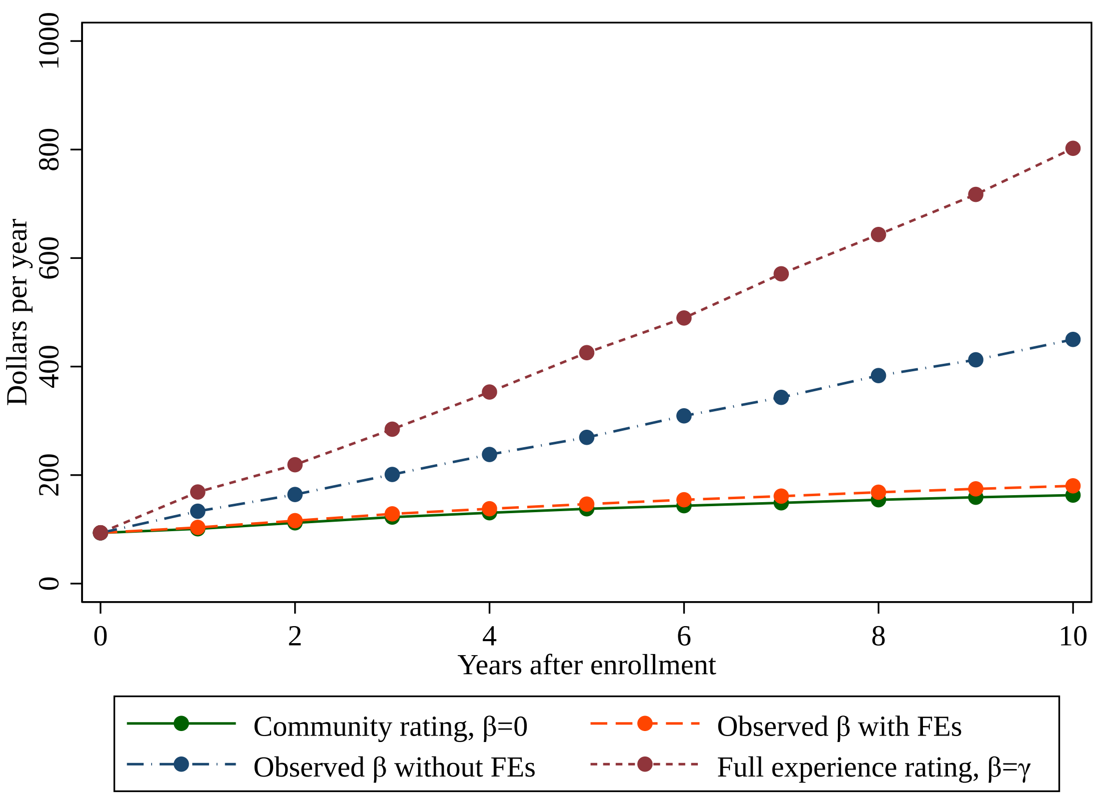
Dependent variable: annual employer mean premium, p_{jt}				
Regressor:	(1)	(2)	(3)	(4)
Health risk for enrolled, R_{jt}	624**	450	2,811***	1,822**
	(121)	(92)	(127)	(112)
Lagged health risk for enrolled, $R_{j,t-1}$		218		1,311**
		(54)		(98)
Year FE	Yes	Yes	Yes	Yes
Enrollee FE	Yes	Yes	No	No
Market FE	No	No	Yes	Yes
Polynomial Order	6^{th}	6^{th}	6^{th}	6^{th}
Observations	448,259	160,062	448,259	264,145

Note: each observation is one enrollee during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. We calculate R_{jt} based on individuals that worked in the employer in the previous year and had an ACG score. Markets are defined by USIC and roughly represent an MSA or state. All estimates control non-parametrically for selection with a 6th order polynomial of the selection probability. We two-way cluster standard errors at the enrollee and year levels. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

E On-Line Appendix E: Additional counterfactual simulations

Figure E.1 replicates Figure 1, considering the certainty equivalent income loss with the lower CARA risk aversion coefficient of 0.00008 used by Ghili et al. (2019). The same relative pattern of certain equivalent losses hold as in Figure 1. However, the dollar values of the certainty equivalent income losses are much smaller. For instance, there is a $200 mean annual loss under the baseline instead of $3,050 with the base risk aversion parameter.

Figure E.1: Simulated mean certainty equivalent loss from risk, with lower risk aversion



Note: Figure based on authors' calculations as described in paper. The CARA risk aversion parameter is 0.00008.