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Working Paper 24663
http://www.nber.org/papers/w24663

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2018

We thank Steve Berry, Jan De Loecker, Tim Dunne, Josh Gottlieb, Matt Grennan, Ben Handel, Neale Mahoney, Daniel Prinz, Jim Rebitzer, Bob Town, Erin Trish, and numerous seminar and conference participants for helpful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w24663.ack

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NBER Working Paper No. 24663
May 2018
JEL No. D25,I13,L13

ABSTRACT

We evaluate reclassification risk and adverse selection in the small group insurance market from a period before ACA community rating regulations. Using detailed individual-level data from a large insurer, we find a pass through of 5-43% from expected health risk to premiums. This limited reclassification risk cannot be explained by market power or search frictions but may be due to implicit long-term contracts. We find no evidence of adverse selection generated by reclassification risk. The observed pricing policy adds $2,346 annually in consumer welfare over 10 years relative to experience rating. Community rating would not increase consumer welfare substantially.

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1 Introduction

Two of the most important concerns in designing markets for health insurance are reclassification risk and adverse selection. Reclassification risk occurs when an adverse and persistent health shock leads to higher future premiums or worse coverage. Adverse selection occurs when the market only serves high cost individuals. Both reclassification risk and adverse selection have the potential to lead to market failure. However, regulations to limit reclassification risk may increase adverse selection, implying potential tradeoffs between them (Handel et al., 2015). The 2010 Affordable Care Act (ACA) sought to reduce reclassification risk and adverse selection—for individuals purchasing health insurance on their own or through small employers—through community rating provisions and the individual mandate.

This paper considers reclassification risk and adverse selection in the context of the small group health insurance market. This market provides insurance to individuals at employers with 2 to 50 covered lives.[1] In 2013, this market covered 18 million people in the U.S. (Kaiser Family Foundation, 2013), representing about \$100 billion in revenues.[2] 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 each employer will increase the premiums to this employer by \$25,000, which will in turn raise per-employee costs by \$5,000 per year. In addition, this market also displays evidence consistent with market failure from adverse selection, with fewer than 50 percent of small employers offering health insurance (MEPS, 2013).

A number of influential studies have documented substantial variation in premiums across employers in the small group market (Cutler, 1994; Cebul et al., 2011; Bundorf et al., 2012). Using an employer survey, Cutler finds that the 90th percentile of premiums is 2.74 times

[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.

the 10th percentile for this market. Due to data limitations, Cutler did not explicitly tie the variation in premiums to health risk. Nonetheless, many researchers viewed Cutler's findings as suggesting that the premium variation in this market is mostly due to reclassification risk from experience rating, i.e., from employers with higher expected health risks facing higher premiums (Gruber, 2000). Despite this suggestive evidence, we believe that the question of how much reclassification risk exists in this market is still open, with better data crucial to obtaining more definitive evidence.

This paper has two main goals related to health insurance in the small group market. Our first goal is to examine the extent of reclassification risk in this market and quantify the resulting welfare loss. Our second goal is to understand the extent of advantageous or adverse selection that occurs from experience rating affecting potential enrollee take-up in this market.

Our study makes use of a unique dataset on the small group insurance market provided to us by a large health insurance company, which we refer to as the United States Insurance Company, or USIC. USIC provided us with a panel of claims and premiums for their small group market products in 10 states over the period 2012-15.[4] Our analysis data contain information on over 300,000 USIC enrollees at more than 12,000 employers. Our study is unique in having access to a large dataset on the small group market that includes both claims and premiums at the individual level. This dataset allows us to estimate how USIC responds to shocks across the small employers which it serves.

To evaluate reclassification risk and selection with our data, 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 expected claims risk of the employer. Potential enrollees decide whether or not to enroll in insurance, given their health risk and the premium charged. Our model shows that the welfare loss from reclassification risk is increasing in the pass through from changes in mean equilibrium health risk among potential enrollees who take-up insurance at an employer to changes in premiums. Thus, this pass through coefficient forms a sufficient statistic for

[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.

understanding reclassification risk in this market. In the spirit of Chetty (2008, 2009); Chetty and Saez (2010) and Einav et al. (2010), we can understand the extent of reclassification risk in the market by estimating this coefficient, instead of fully specifying and estimating the structural model.

We estimate USIC's pass through by evaluating the extent to which mean expected health risk for enrollees at an employer in a year translates into premiums for the employer. In our regressions with employer fixed effects, our identifying assumption is that changes in the mean expected health risk among the eligible enrollees for an employer are not correlated with any unobservable changes in the premiums that would have occurred in the absence of the health shock.[5] We compute expected health risk as the ACG score, using the previous year's claims data.[6] Using our data and estimated parameters, we calculate how alternative rate-setting policies would affect reclassification risk in this market. We highlight three cases: full experience rating—where expected 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.

The estimated pass through coefficient incorporates two channels. First, there is the pass through that would occur if selection by potential enrollees into health insurance did not change following a premium change. Second, there is the pass through that is driven by selection, i.e., adverse (advantageous) selection is when bad health shocks cause premiums to rise, in turn causing the healthy (sick) to stop taking-up insurance, in turn raising (lowering) the insured risk. We show that we can test for adverse selection by evaluating whether an increase in expected health risk among eligible enrollees increases the expected health risk among enrollees who take up insurance, relative to expected health risk among the eligible. We test for adverse and advantageous selection and quantify their magnitudes by evaluating the extent to which selection affects reclassification risk in this market.

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] In contrast, the unit increase causes

[5]In most specifications, we instrument for the health risk of individuals who take up insurance with the health risk among those eligible to take-up insurance.

[6]The ACG score, which was developed by Johns Hopkins University, is widely used in this context (Gowrisankaran et al., 2013; Handel, 2013; Handel et al., 2016).

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

premiums to rise by only \$213 with employer fixed effects or \$1,709 without employer fixed effects.

This implies that the pass through from expected claims to premiums ranges from 5 to 43%. Thus, USIC's pass through is a small fraction of the 100% pass through that would occur with full experience rating.[8] This empirical finding is in contrast to the view that this market likely reflected substantial experience rating (Gruber, 2000), though it is consistent with some previous survey-based cross-sectional evidence.[9]

Having found evidence that the amount of pass through is much closer to community rating than to experience rating, we seek to understand what model of behavior by USIC can generate this pattern. We propose four candidate explanations.

First, it is possible that USIC passes through an expected health shock to an employer slowly over time. However, in this case, we should see that the coefficient on the lag of the risk score should be positive, in a specification with employer fixed effects. We consider specifications where the risk score and lagged risk score are both allowed to affect premiums and do not find any significance on the lagged risk score.

Second, our results may be due to static pricing power. In particular, an oligopolist's pass through of a cost shock is different from the competitive case of full pass through and depends on the curvature of the residual demand curve (Weyl and Fabinger, 2013). We show that a similar—though more complicated—pass through formula exists in our model, implying that low pass through may be supportable by oligopoly profit maximization. In this case, we would expect pass through to vary based on insurer market concentration, since concentration should affect the shape of the residual demand curve. We interact our pass through across markets with several different measures of market concentration and never find that market concentration is a significant predictor of pass through. Thus, we do not find evidence in favor of this explanation.[10]

Third, it is possible that the limited pass through is driven by search frictions. Applying

double the expected health cost of the population mean.

[8]There is also no significant effect of extra risk on plan benefits.

[9]Using survey data from 1987-88 and a cross-sectional design, Pauly and Herring (1999) found that the elasticity of premiums with respect to expected costs ranged from -0.06 to 0.44 for the individual and small-group markets.

[10]The small level of pass through that we find also seems unlikely to be driven by this explanation.

the search model estimates from Cebul et al. (2011), approximately 87% of expected claims costs would be passed through as higher premiums. Given that our upper bound of pass through is only 43%, which is about half this figure, our results are also unlikely to be explained by search frictions.

Fourth, we consider the possibility that USIC chooses implicit dynamic contracts with low pass through. The strategy of choosing such contracts to mitigate reclassification risk has been discussed by Cutler (1994); Pauly and Herring (1999) and Herring and Pauly (2006). Such contracts may add value and be profitable if employers and enrollees are inertial, so that the healthy do not switch health plans often even when they could lower premiums by switching.[11]

We next consider the impact of take-up on selection. We find no evidence of adverse selection and limited evidence of advantageous selection. In particular we find that a unit change in health risk for eligibles increases health risk among the enrolled by 88.1%, which is less than 100% and hence consistent with advantageous selection, though statistically significant only at the 10% level. With this coefficient, if USIC kept the pass through for the set of individuals who take up insurance constant but existed in a world where there was no advantageous selection, it would increase pass through on the insured by about 12% of our base pass-through estimate, which is 0.6% of the expected claims cost. This implies that advantageous selection explains, at best, only a small part of our low estimated pass through.

Finally, we 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.[12] We non-parametrically simulate the evolution of health risk for an employer over a ten-year horizon to evaluate how this would translate into financial risk for individuals. Using our estimates with fixed effects, we find that the standard deviations of expected premiums are very low, at $46 annually in the first year after obtaining insurance and $125 annually in the tenth year. The small reclassification risk implies that the welfare gain from community rating is also small. Even using our largest pass through coefficient of 43% of expected claims cost, the certainty equivalent income loss caused by USIC's pricing policy is only $157 in the

[11]Enrollees have been shown to be inertial in their choice of health plans in related contexts (Handel, 2013).

[12]Given our small estimated selection effects, our counterfactuals consider individuals who take-up USIC insurance continuously.

year after the initial insurance enrollment and $969 in the tenth year after enrollment. In contrast, the gains relative to full experience rating are much larger, at $644 in the year after the initial insurance enrollment and $3,885 in the tenth year after enrollment. Thus, community rating regulations in this market can only add limited value.[13]

Relation to literature. Our paper builds on a substantial literature that analyzes reclassification risk (see Cutler, 1994; Cutler and Reber, 1998; Pauly and Herring, 1999; Gruber, 2000; Buchmueller and DiNardo, 2002; Herring and Pauly, 2006; Einav et al., 2010; Cebul et al., 2011; Bundorf et al., 2012; Handel, 2013; Handel et al., 2015; Kowalski, 2015). Cutler and Reber (1998); Einav et al. (2010); Handel (2013) and Kowalski (2015) examine large employers, evaluating the premiums that they charge their employees for the different plans that they offer and the resulting adverse selection and reclassification risk. Buchmueller and DiNardo (2002) consider the impact of community rating on the small group and individual markets, using New York's implementation of community rating in these markets as the treatment. Bundorf et al. (2012) focus on the small group market, evaluating the welfare impact of employee choice of plans under different premium pass through mechanisms from employers to enrollees. On the individual market, Handel et al. (2015) evaluate the equilibrium adverse selection and reclassification risk from a competitive market of exchange firms, while Handel et al. (2016) examine reclassification risk in a competitive market of long-term contracts with one-sided commitment.

We add to this literature in two ways. First, our data are unique and allow us to identify the extent to which experience-rated health insurance creates reclassification risk and selection in the real world. Specifically, we recover how much expected future claims are passed through into future premiums, in a context in which this is permitted. We are not aware of any other study that has attempted to empirically quantify the reclassification risk from experience rating in the small group market. We believe that our results here are important, particularly in light of the presumption by other scholars that reclassification risk in this segment was much higher than the levels that we found.

[13] In contrast, enrollees in our sample face substantial financial risk from having an adverse health shock result in high *out-of-pocket* costs. We find that out-of-pocket expenditures cause $1,511 in certainty equivalent income loss in the year of initial enrollment and $5,372 in the eleventh year of insurance coverage, even with community rating regulations.

Second, we develop a simple theoretical framework that allows us to estimate sufficient statistics for reclassification risk and selection in this market. We believe that this framework may be useful in evaluating these issues for other markets.

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.[14] We consider potential enrollees who can obtain health insurance through a small-group employer.[15] Denote the potential enrollee by i, the employer by j, the time period by t, and the number of potential enrollees at employer j as I_j.

Each potential enrollee starts each period with an expected risk score r_{ijt}, which is based on her previous year's healthcare claims. The risk score 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. The employer is faced with a per-person premium amount, $p_{jt}(R^p_{jt}, j)$, which is based on the mean risk score over its population of potential enrollees, $R^p_{jt} \equiv \frac{1}{I_j}\sum_{i=1}^{I_j} r_{ijt}$, and its history with the insurer. Thus, we can write $p_{jt} = p(R^p_{jt}, j)$. For the remainder of this section, we consider one small employer, and hence we drop the j subscript.

Each period, each potential enrollee is faced with a distribution of potential health shocks, which is a function of her current risk score. Let the random variable $H(r_{it})$ denote the period t health shock and let the function $c(H(r_{it}))$ denote the claims cost for an individual with

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

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

health shock $H(r_{it})$. We separate costs into the portion that the insurer pays, $c^{ins}(H(r_{it}))$, and the portion that the enrollee pays out of pocket, $c^{oop}(H_{it}(r_{it}))$. Our model allows for a costly health shock in period 1 to increase the period 2 risk score, which will correlate with costly health shocks in period 2.

Since the potential enrollee's period 2 expected health risk is a function of her period 1 realized health shock, we can write $r_{i2} = f(H_{i1})$. We assume that the potential enrollee and insurer learn the realization of H_{i1} during period 1 from the potential enrollee's health claims and determine p_2 in part using the mean realized values of r_{i2}. Since the expected costs are proportional to the risk score, we can write

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

where γ is the constant of proportionality.[16]

We now exposit the utility at each period prior to the realization of the period health shock. We assume that utility is additively separable across the time periods. Each period, potential enrollees have the option of taking-up or not taking-up insurance.

Consider first the per-period utility from taking-up the employer's insurance, which we denote $U^I(r_{it}, p(R_t^p))$. This utility is a function of the potential enrollee's income Y_{it}, her premium, and her out-of-pocket health costs:

$$U^I(r_{it}, p(R_t^p)) = \int u\left[Y_{it} - p(R_t^p) - c^{oop}(H(r_{it}))\right] dF_H(H(r_{it})), \tag{2}$$

where $dF_H(H(r_{it}))$ is the distribution of health shocks conditional on a risk score and $u(\cdot)$ is the utility conditional on a particular health shock realization.

We assume that $u(\cdot)$ follows a CARA functional form, so that:

$$u(x) = -\frac{1}{\sigma}\exp\left(-\sigma x\right), \tag{3}$$

where x is income net of health expenditures (so that $x = Y_{it} - p(R_t^p) - c^{oop}(H(r_{it}))$ in the

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

case of insurance enrollment).[17] We further assume that each potential enrollee pays the full cost of her health premium to her employer, in the form of higher actual premiums or lower wages.[18]

Consider now the per-period utility from not having insurance, which we denote $U^N(r_{it})$. Without insurance, the individual bears the full cost of her health expenditures:

$$U^N(r_{it}) = \int u\left[Y_{it} - c(H(r_{it}))\right] dF_H(H(r_{it})), \tag{4}$$

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

$$U(r_{it}, p(R_t^p)) = \max\{U^I(r_{it}, p(R_t^p)), U^N(r_{it})\}. \tag{5}$$

Having discussed the per-period utility function, we exposit the discounted value of the potential enrollee over the two periods as:

$$V(r_{11}, \ldots, r_{I1}, i) = U(r_{i1}, p(R_1^p)) + \delta \int U(r_{i2}, p(R_2^p)) dF_{R^p,r}(R_2^p, r_{i2} | r_{11}, \ldots r_{I1}), \tag{6}$$

where $dF_{R^p,r}(R_2^p, r_{i2}|r_{11}, \ldots r_{I1})$ is the conditional risk score distribution at period 2, for the potential enrollee and her employer, given the period 1 risk scores.

To understand how reclassification risk enters into our model, consider an individual at period 1. A bad and persistent health shock at period 1 for herself or her coworker will raise R_2^p. With experience rating, this will in turn raise premiums for the individual. The extent of reclassification risk depends on the distributions of F_R^p and $p(\cdot)$. If the individual were in a large risk pool, then reclassification risk would not be a substantial issue because the distribution of F_R^p would be very concentrated and degenerate to a point in the limit. Even if the individual were in a small risk pool, if the premium did not vary much in response to R^p, then she would not be faced with 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

[17] The CARA functional form is often used to model health expenditures (see, e.g., Handel, 2013).

[18] The literature has shown positive but sometimes incomplete pass through from higher premiums to lower wages (Baicker and Chandra, 2006; Bhattacharya and Bundorf, 2009).

rating—i.e., individuals in our sample—may be faced with significant reclassification risk.

We now turn to the insurance enrollment decision and how this may create selection based on risk. Enrollee optimization results in a take-up rate among potential enrollees at employer j. Let $Q(p(R^p), R^p)$ denote the take-up rate, or equivalently, the per-person demand curve specific to employer j. Because it is a take-up rate, $Q(p(R^p), R^p) \in [0, 1]$. For ease of analysis, we omit the direct dependence of the take-up rate on R^p so that we can write $Q(p(R^p))$.

We also can think of which individuals enroll in insurance as a function of Q. Denote the insured risk as R. We can write:

$$R = R(R^p, Q(p(R^p))). \tag{7}$$

From (7), population risk R^p for an employer is exogenous, but the insured risk R is endogenous, responding to premiums and R^p, and potentially generating adverse or advantageous selection.

2.2 Risk rating and reclassification risk

We now consider the impact of potential risk rating policies. For ease of notation, in this subsection we assume that taking up insurance implies no out-of-pocket costs.[19] With no out-of-pocket costs, we have that $E[c(H(r_{it}))] = E[c^{ins}(H(r_{it}))] = \gamma R_t$; also, U^I is no longer a function of individual risk r_{it}.

First, we consider the case of full experience rating. This case implies that USIC sets premiums exactly equal to expected equilibrium insured risk, so that $p(R_t) = \gamma R_t$. Consider an individual who takes up insurance in both periods. In this case, equation (6) specializes to:

$$V(r_{11}, \ldots, r_{I1}, i) = U^I(\gamma R_1) + \delta \int U^I(\gamma R_2) dF_R(R_2 | r_{11}, \ldots r_{I1}). \tag{8}$$

Individuals here are faced with reclassification risk: an increase in the expected equilibrium mean risk score among the insured in period 2, R_2, is passed through into an increase in expected insurance costs at the employer in period 2. This occurs even though the insured here pay premiums equal to the expected mean costs of their risk pool.

[19] Our empirical work does account for out-of-pocket costs.

Next, we consider the long-run contracts with binding commitment to future premiums. Consider such a contract with a period 1 premium of $p_1 = \gamma R_1$ and a period 2 premium of $p_2 = \gamma E[R_2|r_{11}, \ldots r_{I1}]$. This contract would have premium equal to expected marginal cost and would eliminate reclassification risk. Because of this, with CARA utility,

$$\int U^I(Y_{i2} - \gamma R_2) dF_R(R_2|r_{11}, \ldots r_{I1}) < U^I(Y_{i2} - \gamma E[R_2|r_{11}, \ldots r_{I1}]),$$

implying that such a contract would improve enrollee welfare for individuals who take-up insurance over the state-contingent one-period contracts considered above. Consider further the case where income and mean risk are the same across periods, so that $Y_{i1} = Y_{i2}$, $\forall i$ and $E[R_2|r_{11}, \ldots r_{I1}] = R_1$. In this case, the take-up rate would be $Q_1 = Q_2 = 1$ since individuals are risk averse and would want to take-up insurance given the symmetry across periods. Thus, under these assumptions, this contract would be the utility-maximizing contract among long-run break-even contracts. This implies that a perfectly competitive insurance industry would result in the employer always signing this two-period contract.[20]

Finally, we consider the general case where expected equilibrium claims risk may be partially passed through. A simple functional form for the pass through from period 2 expected equilibrium risk to period 2 premium is:

$$p_2 - p_1 = c_2 + \beta(R_2 - E[R_2|r_{11}, \ldots, r_{I1}]), \tag{9}$$

for some constant c_2. Note that the period 1 expectation of the period 2 premium increase is simply c_2, and thus this term would include any extra costs or markups in period 2.

If $\beta = \gamma$, then the insurer fully experience rates the health risk R_2. For $0 < \beta < \gamma$, there will be positive but incomplete pass-through from expected risk to premiums. Under community rating or binding two-period contracts as discussed above, we would have $\beta = 0$.

[20] In the real world, it is difficult to enforce long-run contracts with commitment on both sides. Without such enforcement, a competitive insurance industry might provide partial protection against reclassification risk (Handel et al., 2016).

It is also easy to see that, for $\beta' < \beta$,

$$\int U(Y_{i2} - p_1 - c_2 - \beta(R_2 - E[R_2|r_{11}, \ldots, r_{I1}]))dF_R(R_2|r_{11}, \ldots r_{I1})$$
$$< \int U(Y_{i2} - p_1 - c_2 - \beta'(R_2 - E[R_2|r_{11}, \ldots, r_{I1}]))dF_R(R_2|r_{11}, \ldots r_{I1}),$$

since the left side is a mean-preserving spread of the right side for individuals who take-up insurance, and the left and right sides are the same for individuals who do not take up insurance. Since utility is higher the lower is β, an insurer with an incomplete ability to enforce two-period contracts may try to have a low β to maximize consumer welfare and a high c_2 to capture some of this welfare. Since individuals with CARA preferences are willing to pay higher premiums up-front to reduce reclassification risk in the future, USIC will be incentivized to offer such contracts, to the extent that they are feasible.

The principal goal of our empirical analysis is to estimate γ and β.[21] The higher is β relative to γ, the greater is the reclassification risk for a given risk preference parameter, σ. Together with the empirical distribution of health shocks, we can use these coefficients to understand reclassification risk and the certainty equivalent welfare loss from reclassification risk, under both the current pricing environment and counterfactual environments. Thus, these parameters form sufficient statistics for evaluating reclassification risk. In the tradition of Chetty (2009) and Einav et al. (2010), this evaluation does not require specifying or estimating all structural parameters.

2.3 Selection of enrollees

We next consider selection of potential enrollees into insurance based on their risk. Equation (7) expresses the insured risk for the employer as a function of the population risk. We decompose this function, in order to understand the extent to which selection might drive our results as to reclassification risk. We differentiate (7) to obtain:

$$\alpha \equiv \frac{dR}{dR^p} = \underbrace{\frac{\partial R}{\partial R^p}}_{\text{risk change for individuals in pool}} + \underbrace{\frac{\partial R}{\partial Q}\frac{dQ}{dp}\frac{\partial p}{\partial R^p}}_{\text{risk change from selection}} . \tag{10}$$

[21]We take σ from the literature.

From (10), the first term is the impact of a change in population risk on actual risk, holding constant take-up. Assuming that an increase in the population risk translates evenly across all individuals in the pool, this is 1. The second term is he impact of selection. It indicates the amount that population risk would raise insured risk, beyond the unit increase that we would expect without selection. Thus, if the second term of (10) is positive, this will indicate adverse selection; if it is negative, this will indicate advantageous selection. Given this, our empirical work on selection will estimate α, with the finding of adverse selection if $\alpha > 1$ and advantageous selection if $\alpha < 1$. .

In addition to characterizing whether selection is adverse or advantageous, we can also decompose reclassification risk into the component that is due to selection and the component that is not. If we assume that USIC's policy is to provide a coefficient of β on insured risk, we can define the impact of selection on reclassification risk as the difference—with and without selection—in the pass through from expected claims to premiums, which we call IS. Without any selection, the mean expected insured risk R would equal the population risk. Thus, IS can be expressed as:

$$IS = \frac{dp}{dR} - \frac{dp}{dR^p} = \frac{\frac{dp}{dR^p}}{\frac{dR}{dR^p}} - \frac{dp}{dR^p} = (1 - \frac{dR}{dR^p})\beta = (1 - \alpha)\beta \tag{11}$$

If IS is positive, then there is advantageous selection and IS indicates the decrease in reclassification risk from advantageous selection. If IS is negative, then there is adverse selection and $|IS|$ indicates the increase in reclassification risk from adverse selection.

3 Data and Estimation Sample

3.1 Data

Our 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 markets, e.g., Texas is divided into Central Texas, Dallas, Houston, North Texas, and South

Texas. Employers in this market purchase fully-insured insurance products from USIC, not third-party administrative services. Figure A1 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.[22] All states had guaranteed renewability of small group policies during this time period, implying that USIC would not be able to cancel a group's policy even if the increased 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, 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.[23] 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.[24] 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

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

[23]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."

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

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 employees 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 it.[25]

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, we believe that the ACG and USIC scores are very similar. For new groups, information on enrollee health is generally, if imprecisely, obtained via questionnaire.

Since our risk score measures are calculated using the previous year claims data, we need

[25]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.

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 fixed effects. Since we obtain the risk score calculation from the previous year, we need three continuous years of data (which generates two years with complete observations) to compute an employer fixed effect. For comparability across estimates, we drop employers for which we observe fewer than three continuous years of data for all our specifications, even those without employer fixed effects.[26]

We can characterize potential enrollees and employers based on whether they have joined or quit coverage during our sample. A "joiner" is a potential enrollee or employer for which we did not have a complete observation in the first year but for which we had a complete observation in a later year. A "quitter" is the opposite: a potential enrollee or employer for which we did not have a complete observation in the last year but for which we had a complete observation in an earlier year. A "stayer" is a potential enrollee or employer for which we have three complete observations. Note that an employer or individual can be both a joiner and a quitter, which would occur if it were in our data in the middle two years only. Also, note that enrollees or employers which we do not observe for two consecutive years would not fit any of these three categories.

3.2 Summary statistics on estimation sample

Table 1 provides summary statistics on the enrollees in our estimation sample. Our full sample includes about 650,000 observations. There is a lot of enrollee turnover in this market. Only 37% of observations in our sample are for individuals who enrolled in a small group plan with USIC for four years. Approximately 27% of observations are for joiners while 29% of observations are for quitters. Some observations in the full sample are for individuals without consecutive years of data, who then do not fall into any of the categories of stayers, joiners, or quitters. The turnover in our data may be due to individuals switching jobs, small businesses closing and opening, and

[26]We 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.

individuals dropping or adding health coverage conditional on staying at a job. We further analyze the impact of risk on turnover below.

Overall, the three samples of employees who are joiners, quitters, and stayers are quite similar, though not identical. On average, joiners are two years younger than quitters, who are themselves two years younger than stayers. In addition, joiners have a 9% lower ACG score—or expected claims cost—than stayers, reflecting 9% lower expected claims costs. Stayers have a 4% lower ACG score than quitters. While the mean in change in health risk r from year to year is quite modest, the standard deviation in this value is quite large, indicating that health risk can change suddenly.

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}	1.11 (0.79)	1.09 (0.78)	1.01 (0.65)	1.22 (0.89)
$R_{jt} - R_{j,t-1}$	0.03 (0.61)	0.02 (0.60)	0.03 (0.53)	0.06 (0.70)
Health risk for eligibles, R^p_{jt}	1.07 (0.72)	1.05 (0.70)	0.97 (0.59)	1.17 (0.82)
$R^p_{jt} - R^p_{j,t-1}$	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 enrollees with one or more full observation but without a full observation in 2015.

Table 2 characterizes the employers in our estimation sample and the enrollees at these employers. Our sample includes 12,242 employers. Similarly to Table 1, we report the employers which are stayers, joiners, or quitters. The majority of 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 sometimes other family members. Employees constitute 65% of covered lives. The mean take-up rate among eligible employees was 54%.

The mean health risk among enrollees, R, is 1.11 in the full sample, a little lower among employers that are joiners and stayers, and higher among employers that are quitters. This health risk is calculated based only on people who were enrolled in the prior period and continued to stay enrolled. The health risk among enrollees who were enrolled in the prior period, R^p is about 4-5% lower than the health risk among enrollees, R. Moreover, the 4-5% difference between R and R^p is stable across employers who are joiners, stayers, quitters, and overall.

The changes in the mean health risks R and R^p over time are also stable across employers that are joiners, stayers, quitters, and overall. In addition, there is a substantial standard deviation in the change in these variables over time. This variation will provide us with power to identify the rating behavior that USIC uses, even with employer 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 Section 5, 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%.

We 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. All the autocorrelated models are stationary, with stable mean and variance. 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.

Table 3: Persistence in risk over time

	(1)	(2)	(3)
Panel A: dependent variable individual risk (r_{ijt})			
Individuals ACG score, $r_{ij,t-1}$	0.733***	0.718***	0.561***
	(0.005)	(0.007)	(0.010)
Lagged individual 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^p_{jt})			
Health risk for eligibles, $R^p_{j,t-1}$	0.667***	0.630***	0.506***
	(0.003)	(0.004)	(0.006)
Lagged health risk for eligibles, $R^p_{j,t-2}$			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 employee (employer) during one year. Standard errors are clustered at the employer level. Markets are defined by USIC and roughly represent an MSA or state. *** indicates significance at the 1% level and ** indicates significance at the 5% level.

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

Table 4: Exit of individuals and employers, by risk score

	(1)	(2)
Dependent variable:	Individual-level exit	Employer-level exit
Individual risk (r_{ijt})	-0.014^{***}	
	(0.002)	
Health risk for eligibles, R^p_{jt}	-0.125^{***}	0.024***
	(0.003)	(0.008)
$R^p_{jt} \times r_{ijt}$	0.006***	
	(0.001)	
Employer FE	Yes	No
Market FE	No	Yes
Industry FE	No	Yes
Observations	329,806	9,961

In column 1 (2), each observation is one enrollee (employer) during one year. Markets are defined by USIC and roughly represent an MSA or state. Industry FE represent different economic activities form the two-digit ISIC classification. Standard errors are clustered at the employer level. *** indicates significance at the 1% level and ** indicates significance at the 5% level.

Finally, we analyze selection out of our sample, by individuals and employers. Table 4 regresses individual and employer exits on risk scores. Focusing on column 1, an individual-level exit in a year is defined by an individual who drops coverage after that year even though her employer is still in the sample. We control for employer fixed effects in this regression. We find a positive and significant interaction term between R^p and r. This means that when employers see an adverse health shock, the people who drop coverage tend to be the sicker ones. If adverse health shocks lead to increases in premiums which lead to lower lower take-up, then this is evidence of advantageous selection: that lower take-up leads to the relatively sick dropping out of the market when employer risk increases. We return to this point with formal estimates of the selection parameters of our model in Section 5.3.

Column 2 of Table 4 considers employer exit, defined as an employer offering coverage in some year but no longer offering coverage through USIC after that year. We cannot control for employer fixed effects here since we observe at most one exit per employer. Nonetheless, we control for market and sector fixed effects. We find that employers with higher risk scores have a small but significantly higher probability of exit. In particular, an increase of the risk score from the population average of 1 to 2 increases the probability of employer exit by 2.4 percentage points. This effect may be due to many factors, such as small employers with sick employees closing their business. Unlike with employee selection, we do not model employer selection in our formal results below since we do not know anything about what the premiums would have been for employers that exited. Nonetheless, it is worth noting that the impact of expected health risk on employer exit appears to be reasonably small.

4 Empirical Approach

The primary goal of our estimation is to recover the impact of risk score on expected insurer costs ($dE[c^{ins}]/dR$), which is γ from equation (1), and the impact of employer mean insured risk on premiums (dp/dR), which is β from equation (9). We are interested in these parameters for two principal reasons. First, we use them together to understand the pass through from insurer costs to premiums, $dp/dE[c^{ins}]$:

$$\frac{dp}{dE[c^{ins}]} = \frac{\frac{dp}{dR}}{\frac{dE[c^{ins}]}{dR}} = \frac{\frac{dp}{dR}}{\frac{dE[c^{ins}]}{dr}} = \frac{\beta}{\gamma}. \tag{12}$$

Second, we use these parameters separately in our counterfactual analysis, in order to understand the reclassification risk and welfare from different rating mechanisms. Note that these parameters regard insurer behavior; we do not estimate any enrollee utility parameters and our estimation algorithm does not impose potential enrollee utility maximization.

The remainder of this section discusses our estimation of the impact of risk score on healthcare costs and premiums, the estimation of our selection parameters, and our simulation of counterfactuals.

4.1 Estimation of impact of risk score on healthcare costs

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

$$c_{ijt}^{ins} = \gamma r_{ijt} + \gamma_2 x_{jt} + \varepsilon_{ijt}^{A}, \tag{13}$$

where $c^{ins}(H(r_{ijt}))$ is measured as the total dollar value of claims for the individual over the year. Equation (13) considers the impact of the individual's current risk score—estimated using the previous year's claims—on current claims to the insurer. Comparing equation (13) to equation (1), the empirical specification uses the actual insurer costs while the theoretical model is based on the expectation of costs. Thus, ε_{ijt}^{A} in equation (13) will capture the difference between actual claims and expected claims for an individual in a year.[27]

The risk score is meant to be a causal and proportional predictor of healthcare usage. Thus, we should expect a roughly linear relationship between r_{ijt} and $c^{ins}(H(r_{ijt}))$, given a constant set of provider prices. We include market fixed effects 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 fixed effects. We further estimate γ using only data from 2014, to not have to worry about changes in provider prices over time.[28]

[27] We also estimate empirical specifications with $c^{oop}(H(r_{ijt}))$ as the dependent variable.

[28] We also investigated estimating γ using other years in our sample and obtained similar results.

4.2 Estimation of impact of risk score on premiums

We now discuss our estimation of the impact of employer mean risk score on premiums. Here, we estimate empirical analogs to the pricing equation given in equation (9). Specifically, we estimate regressions of the form:

$$p_{jt} = \beta R_{jt} + \beta_2 x_{jt} + \overline{FE}_j + FE_t + \varepsilon_{jt}^B, \tag{14}$$

where p_{jt} is the premium charged to 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 (14), $\overline{FE}_j$ are employer fixed effects, FE_t are year dummies, x_{jt} are time-varying employer attributes, and ε_{jt}^B is the unobservable. The unobservable captures changes in premiums unexplained by other factors, for instance due to variation in employer or insurance broker bargaining ability. While equation (14) specifies premium as the dependent variable, we also report specifications where plan characteristics are the dependent variables.

With two periods of data, our estimating equation (14) is equivalent to our theoretical model in (9) with:

$$c_{j2} = FE_2 - FE_1 + \beta_2(x_{j2} - x_{j1}) + \beta(E[R_{j2}|r_{1j1}, \ldots, r_{I_j j1}] - R_{j1}) + \varepsilon_{j2}^B - \varepsilon_{j1}^B. \tag{15}$$

In this case, the interpretation is that c_{j2} is the amount that premiums to employer j would have risen if insured risk remained at its expected level given R_{j1}, while $\beta(R_{j2} - E[R_{j2}|r_{1j1}, \ldots, r_{I_j j1}])$ is the increase in premiums that is caused by the risk change.[29]

Note that (14) regresses mean expected risk among the actual enrollees R_{jt} on premiums p_{jt}, even though both are endogenous in our model and R_{jt} is a function of p_{jt}, as in equation (7). Hence, a least squares estimation of p_{jt} on R_{jt} may yield inconsistent estimates, stemming from this reverse causality. Using (7), we can express both terns as a function of the exogenous R_{jt}^p, which is the risk among the eligible enrollees at the employer:

$$\beta = \frac{dp}{dR} = \frac{\frac{dp}{dR^p}}{\frac{dR}{dR^p}}. \tag{16}$$

Equation (16) expresses the structural $\frac{dp}{dR}$ relationship as the reduced form divided by the first stage. Following the logic of ((16), in most specifications, we instrument for R_{jt} with R_{jt}^p in (14).

[29] With more than two periods of data, the estimating equation is a difference relative to the within-firm mean, rather than a first difference.

Recall that our period t risk scores are calculated from claims data in the previous year. Because our data do not track individuals once they leave USIC, we do not have full information on R_{jt} and R^p, and need to approximate them with imperfect data. Specifically, R_{jt} ideally should be the mean risk scores for all enrollees taking up insurance at period t. However, we need to exclude individuals who are new in period t: we do not know their risk score since we do not have their period $t-1$ claims data. Similarly, R^p_{jt} should ideally include the risk scores for all individuals who are eligible for insurance at period t. However, we exclude individuals who did not take up insurance at period $t-1$ (as we do not have their risk score) and we also include enrollees who took up insurance at period $t-1$ but were no longer eligible for insurance at period t (e.g., due to leaving employment at employer j).

Our main identifying assumption in equation (14) is that R^p_{jt} is exogenous conditional on employer and time fixed effects and other characteristics, or equivalently, that the change in employer j's mean risk score between years is mean independent from changes in unobservable factors that affect the premiums that employer j pays for insurance from USIC. Because we control for the baseline health status with employer fixed effects, 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.

4.3 Estimation of selection parameters

We now consider our estimation of the extent and impact of selection in this market. From equation (10), we can test for the presence of adverse or advantageous selection in this market by evaluating dR_{jt}/dR^p_{jt}. If $dR_{jt}/dR^p_{jt} > 1$, this indicates the presence of adverse selection, and if $dR_{jt}/dR^p_{jt} < 1$, this indicates the presence of advantageous selection. With adverse selection, an adverse health shock among the potential enrollees for an employer raises premiums, which causes relatively healthy people to not take-up insurance, thereby increasing the expected risk among the actual enrollees. This exacerbates the effect of reclassification risk among the people who continue to take-up insurance, by making them pool with a less healthy population. With advantageous selection, the increase in premiums causes the relatively sick people to not take-up health insurance, thereby decreasing the expected risk among the actual enrollees. In this case, selection diminishes the effect of reclassification risk among the individuals who take-up health insurance, by making them pool with more healthy people.

To evaluate dR_{jt}/dR^p_{jt}, we estimate specifications where we regress R_{jt} on R^p_{jt}:

$$R_{jt} = \alpha R^p_{jt} + \overline{FE}_j + FE_t + \varepsilon^C_{jt}. \tag{17}$$

As with (14), we estimate specifications with employer fixed effects and ones without employer fixed effects.

Noting from equation (10) that the selection component of dR_{jt}/dR^p_{jt} is driven in part by the premium elasticity, we also estimate dQ_{jt}/dp_{jt} using specifications similar to (17). Finally, we can evaluate IS from (11) by combining our estimate of α from (17) with our estimate of β from (14).

4.4 Simulation of counterfactuals

We now discuss our simulation of counterfactual outcomes and welfare. Consumer reclassification risk in our framework 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. Our counterfactuals focus on the first mechanism and do not account for any change in the coverage decision by the employer or potential enrollee following a health shock. We make this simplification because we do not have any information on the health insurance coverage that employers or potential enrollees receive upon terminating coverage with USIC.

Our estimation recovers both γ and β. Using these estimates and the empirical transitions of risk scores, we examine the extent of reclassification risk in our sample and the utility loss from this risk. We then compare the estimated level of reclassification risk and welfare to counterfactual environments, notably community rating and full experience rating. We display risk by year over a 10-year period, under these different environments.

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. Second, we evaluate how the distribution of future risk translates into a distribution of future premiums and out-of-pocket costs. Third, we examine how this distribution of premiums and out-of-pocket costs translates into a certainty equivalent income level. We now discuss these three parts of our analysis in turn.

First, to construct the distribution of enrollee health risk, we start with two periods of ACG scores for each individual. Given the evidence in Table 3 that two lags of scores are predictive of the current score, we predict the following year scores using two years of scores. Rather than using the coefficients from Table 3, we simulate future risk scores and out-of-pocket expenditures for each individual, using enrollees with similar ACG scores for the two previous periods, for each enrollee.[30] We perform our simulation process iteratively for 10 years after the initial insurance enrollment and use 500 paths of simulation draws for each enrollee. From our simulated enrollee risk scores, we derive simulated employer risk scores by taking the mean over all enrollees at the employer.

Second, to evaluate how employer risk scores translate into premiums, we use our estimate of β. We use the simulation draws calculated in step 1 that provide distributions of mean employer risk scores for each enrollee. We then sum the financial risks imposed by the distribution of higher premiums and by the out-of-pocket costs to derive the period 2 distribution of healthcare/insurance expenditures. We also replicate this step with counterfactual exposures to reclassification risk. Specifically, we examine full experience rating, by setting $\beta = \gamma$, and community rating, by setting $\beta = 0$. In these counterfactual simulations, we assume that the insurance plan characteristics other than premiums, and hence out-of-pocket costs, would remain the same as in the baseline.

Third, we consider the standard deviation in net income and the certainty equivalent income loss from the healthcare and health insurance expenditure risk borne by individuals, under different pricing environments. As in equation (3), we use a CARA functional form for our utility calculations. We do not estimate the CARA parameter σ, but instead use $\sigma = 0.000428$ from Handel (2013), who estimates risk in a similar context of health insurance choice. Step 2 provides us with simulation draws from the distributions of $p(R_{jt,t})$ and r_{jt} (which we use to calculate out-of-pocket costs) for every individual under the observed and counterfactual risk rating environments. 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. Our simulations report the loss in certainty equivalent income by year under the different pricing environments.

5 Estimation Results

In this section we present our estimation results. We start with the impact of expected health risk on claims costs, then exposit our results on the impact of expected health risk on premiums, and finally discuss our results on selection.

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

5.1 Impact of expected risk on claims costs

Table 5: Pass through from expected risk to 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. Standard errors are clustered at the employer level. *** indicates significance at the 1% level.

Table 5 presents the estimated relationship between expected 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 increase in USIC-paid claims for the enrollee 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. Table A1 in On-line Appendix A provides robustness on the evidence presented in Table 5 by using splines. Columns 1 and 2 use splines with cut points of 1, 2.5, and 5, chosen as round numbers that differentiate enrollees with serious chronic diseases from others. These results are very similar to our base results. Columns 3 and 4 use splines defined by quartiles of our in-sample ACG score distribution. The results here show more non-linearity, which might be due to a small number of outliers with high medical costs. Overall, 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 Main results: impact of expected risk on premiums

We now investigate our main parameter of interest, the pass through from expected risk to premiums, which is β. These regressions are at the employer/year level and based on equation (14). Recall that our sample is employers with at least two complete observations.

The baseline results are given in Table 6, column 1. This specification regresses the employer

Table 6: Pass through from risk to premiums

Dependent variable: annual employer mean premium, p_{jt}						
	Panel A: base specification					
Regressor:	(1)	(2)	(3)	(4)	(5)	(6)
Health risk for enrolled, R_{jt}	213**	254***		1,709***	1,494***	
	(93)	(76)		(91)	(96)	
Health risk for eligibles, R^p_{jt}			188**			1,725***
			(79)			(76)
Instrument	R^p_{jt}	No	No	R^p_{jt}	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer FE	Yes	Yes	Yes	No	No	No
Market FE	No	No	No	Yes	Yes	Yes
Observations	31,044	31,044	31,044	31,044	31,044	31,044

Note: each observation is one employer during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. R_{jt} is calculated based on individuals that stay in the employer with an ACG score from last year. Standard errors are clustered at the employer level. *** indicates significance at the 1% level and ** indicates significance at the 5% level.

mean ACG score among the insured, R, on the mean per-enrollee premium for the employer, instrumenting for R with the mean risk score among the population, R^p. It includes employer and year fixed effects. We find that a unit increase in employer mean ACG risk score for an employer results in a \$213 increase in premiums.[31] These results are largely robust across specifications with employer fixed effects: the specification without instruments shows a coefficient of \$254, while our reduced-form specification of premiums regressed on R^p shows a coefficient of \$188.

Our results without employer fixed effects show substantially higher pass through than our estimates with FE estimates. Here again, our three coefficients are quite similar: our OLS pass through coefficient is \$1,494, our IV pass through coefficient is \$1,709, and our first-stage pass through coefficient is \$1,725.

In all the cases from Table 6, the pass-through is much smaller than the impact of mean risk on claims costs of \$4,003. In particular, among our four coefficients, the pass through from premiums to costs ranges from 5 to 43% of the expected risk. This compares to 100% pass through under our benchmark model with full experience rating. Particularly since the FE model is a more credible measure of pass through, it is also different than the prevalent view that this market market likely reflected substantial experience rating.

Robustness. We consider a number of robustness checks of our main results, with tables and figures in On-line Appendix A. First, Table A2, columns 1 and 2 present the results when we consider

[31] We do not report first stage F statistics since they are very large: 210.2 for column 1 and 2229.7 for column 4.

a linear spline relationship between the risk score and claims, also instrumenting for R with R^p. The results generally show a roughly linear relationship between risk scores and premiums, which is somewhat lower for employers with higher risk scores. Table A2, columns 3 and 4 present the same relationship, but stratified across smaller and larger employers. The results here are very similar to the results with all employers.

Table A3 presents similar specifications to our baseline specification in column 1 of Table 6 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. In our specifications with employer and year fixed effects and risk scores, the pass through from risk to premiums is very similar, ranging from \$169 to \$222, which are not very different from our main estimate of \$213. Additionally, increases in the percent of enrollees with cancer, hypertension and diabetes increase premiums. We do not find significantly significant and positive effects for the other conditions and indeed, we find a negative and statistically significant effect for asthma. Our takeaway from this is that the pass through from expected claims to premiums is very stable to the inclusion of these chronic diseases.

We also perform a robustness check where we explore the size of the pass through coefficient when we include the presence of a large claim in the last period. The idea is that USIC may only adjust premiums following a very large claims due to some perceived fixed cost of adjustment. In estimates not reported in the paper we add variables that indicates claims larger than \$50,000, \$75,000 and \$100,000 to our base specification. In all these specifications, the pass through coefficient is very similar to in our preferred specifications. As another unreported robustness check, we include the variance of risk across enrollees, to check if there is any conditional response of premiums to the variance. Here again we find that the pass through coefficient from premiums to risk does not change in a statistically significant way.

In Table A4 we examine whether changes in expected risk lead to changes in the plan benefits that the employer chooses. Here, our unit of observation is one employer/plan during one year, rather than one employer during one year. Most employers in our sample choose one plan but some choose more than one plan, resulting in 35,210 observations here instead of 31,044 in the employer/year sample. We consider three measures of plan benefits and we estimate these benefits on health risk for the enrolled, R, instrumenting with R^p and including the same fixed effects as in our base estimation. For each of our benefit measures, the estimated coefficient on risk is very small and not statistically significant. The negative signs of the coefficients for the out-of-pocket dollar maximum for in-network services and the coinsurance rate suggest that premium increases might be slightly mitigated by better plans benefits. However, the coefficient of the effect on in-network deductible is positive, suggesting worse plan benefits.

A different concern about the low pass through may be the roll-out of regulations, related to the ACA or other regulations, that may restrict the ability of insurers to pass through the risk increases to premiums. As mentioned above, our sample consists of states which imposed little binding regulation on the amount of risk at a small group that could be translated into premiums. However, it is useful to check if there is a change in the pass through coefficient between 2013-2014 and 2014-2015, because of the gradual phase-in of ACA regulations. The results from our base specification but with the two different samples are presented in Table A5. The estimated coefficient of pass through for the first period is somewhat larger than in our main specification. However, the standard errors are much larger because of the smaller sample and therefore this estimate is not statistically significant. The point estimate for the 2014-2015 sample is lower, and also not statistically significant. 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 A3 presents the results for our base sample but where we split the pass through coefficient by deciles. Overall, pass through remains stable across the size distribution.

Interpretation. Our effects paint a very different picture from the benchmark model of competition. We find much less reclassification risk in the small group market than this model, particularly among groups continuously enrolled with USIC. This is also quite different from what many observers thought was occurring in this market (Gruber, 2000).

We consider a number of different explanations for our findings, with tables and figures in Online Appendix A. First, given the difference in magnitude between the estimates with and without employer fixed effects, one possibility is that when an employer has an increase in R, USIC passes through the expected costs to premiums slowly over time, rather than immediately. In order to test this proposition, Table 7 reports the pass through using the current and lagged ACG scores.[32] Across our three fixed effects specifications, we find no evidence that employers raise their premiums

[32] We do not instrument for $R_{j,t-1}$ since it is not a function of current premiums p_{jt}, unlike R_{jt}.

Table 7: Pass through from risk to premiums with lagged risk score

Dependent variable: annual employer mean premium, p_{jt}						
Regressor:	(1)	(2)	(3)	(4)	(5)	(6)
Health risk for enrolled, R_{jt}	-5	224**		1,080***	848***	
	(61)	(100)		(141)	(143)	
Health risk for eligibles, R^p_{jt}			-4			1,098***
			(56)			(120)
Lagged health risk for enrolled, $R_{j,t-1}$	38	85	39	724***	902***	737***
	(56)	(74)	(54)	(97)	(100)	(87)
Instrument	R^p_{jt}	No	No	R^p_{jt}	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer FE	Yes	Yes	Yes	No	No	No
Market FE	No	No	No	Yes	Yes	Yes
Observations	13,120	13,120	13,120	18,802	18,802	18,802

Note: each observation is one employer during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. R_{jt} is calculated based on individuals that stay in the employer with an ACG score from last year. Standard errors are clustered at the employer level. *** indicates significance at the 1% level and ** indicates significance at the 5% level.

based on the lagged risk score. In contrast, our specifications without fixed effects all show positive and significant estimates on lagged risk score, with the sum of the coefficients adding up roughly to the unique risk coefficient from Panel A. Our interpretation is that employers that are new to USIC face a premium that is relatively risk based while employers with existing USIC accounts do not experience much variation in premiums as their risk changes.

Second, 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. We can write the expected profits for the insurer from premium p with risk score R^p as:

$$\pi(p, R^p) = \left(p - \gamma R(\underbrace{R^p}_{\text{fixed take-up term}}, \underbrace{Q(p)}_{\text{selection term}})\right)Q(p) \tag{18}$$

where (18) uses (7), suppressing the dependence of p on R^p and explicitly noting the selection term and the term that would occur even if take-up were fixed. We can then express the first order condition for profit maximization as:

$$\frac{\partial \pi}{\partial p} : \left[1 - \gamma \frac{\partial R}{\partial Q}\frac{dQ}{dp}\right]Q(p) + \left[p - \gamma R(R^p, Q(p))\right]\frac{dQ}{dp} = 0. \tag{19}$$

Implicitly differentiating (19), we can then exposit the pass through from R^p to p as:

$$\frac{dp}{dR^p} = \frac{\overbrace{\gamma\frac{dQ}{dp}\frac{\partial R}{\partial R^p}}^{\text{fixed take-up term}} + \overbrace{\frac{\partial^2 R}{\partial Q \partial R^p}\left(\gamma\frac{dQ}{dp}Q(p)\right)}^{\text{selection term}}}{\underbrace{2\frac{dQ}{dp} + \frac{d^2Q}{dp^2}\left(p - \gamma R\right)}_{\text{fixed take-up term}} - \underbrace{\frac{\partial R}{\partial Q}\left(2\gamma\frac{dQ}{dp}\left(\frac{dQ}{dp} + \frac{1}{2}\frac{\partial^2 R}{\partial Q^2}Q(p)\frac{dQ}{dp}\right) + \gamma\frac{d^2Q}{dp^2}Q(p)\right)}_{\text{selection term}}}, \tag{20}$$

where (20) again explicitly notes which terms are due to selection and which terms would occur even if selection were fixed.[33]

Since equation (20) is relatively involved, it is worth considering a simple special case as a benchmark. Assume that that demand is linear, so $\frac{\partial^2 Q_j}{\partial p^2} = 0$, and that there is no selection, so that $\frac{\partial R}{\partial Q} = 0$. Under these assumptions, (20) specializes to $\frac{dp}{dR} = \frac{1}{2}\gamma$. This simple result is analogous to the well-understood result that a monopolist with linear demand would pass through one-half of an expected cost increase to consumers.

Recall that full experience rating—or equivalently full pass-through from expected risk to premiums—implies that $\frac{dp}{dR} = \gamma$. Since the above example implies that pass-through is only one-half of the expected risk, here the insurer with pricing power provides partial reclassification risk protection. However, it is possible to construct other examples where the insurer with pricing power passes through more than the full amount. These can stem from either a different curvature of residual demand with respect to premium increases (Weyl and Fabinger, 2013) or from a non-zero response of expected quantity to a change in employer mean risk score.

While it would be difficult to estimate the insurer's residual demand, we do believe that residual demand would likely vary based on the market concentration in a particular area. Accordingly, Table 8 interacts the pass-through coefficient with 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. 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, we present the variation across different states in Figure A2 in On-line Appendix A. We find no significant pattern in the variation of pass through across states.

Third, our results may be driven by consumer search. To understand the size of the effect of

[33] We have also derived $\frac{dp}{dR^p}$ for the general case where Q is a function of both p and R^p and can provide it upon request.

Table 8: ACG score and claims pass-through to 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}	213** (93)	213** (94)	394 (246)
HHI		−0.001 (0.010)	0.051 (0.045)
R_{jt} × HHI			−0.048 (0.045)
Instrument for R_{jt}	R^p_{jt}	R^p_{jt}	R^p_{jt}
Instrument for $R_{jt} \times HHI$			R^p_{jt} × HHI
Employer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	31,044	31,044	31,044
Panel B: share of largest insurer			
Health risk for enrolled, R_{jt}	213** (93)	213** (94)	436 (283)
Share of Leader Insurer		29 (78)	458 (379)
R^p_{jt} × Share of Leader Insurer			−404 (379)
Instrument for R_{jt}	R^p_{jt}	R^p_{jt}	R^p_{jt}
Instrument for $R_{jt} \times Leader$			R^p_{jt} × Leader
Employer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	31,044	31,044	31,044
Panel C: number of insurers with 5% or larger market share			
Health risk for enrolled, R_{jt}	213** (93)	213** (93)	219 (231)
Number of insurers with 5%+		−11 (15)	−9 (71)
R^p_{jt} × Number of insurers with 5%+			−2 (72)
Instrument for R_{jt}	R^p_{jt}	R^p_{jt}	R^p_{jt}
Instrument for $R_{jt} \times Number$			R^p_{jt} × Number
Employer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	31,044	31,044	31,044

Note: each observation is one employer during one year. Markets are defined by USIC and roughly represent an MSA or state. HHI indexes, share of leader insurer and number of insurer with 5%+ market share are taken from Kaiser Family Foundation State Health Facts database. Standard errors are clustered at the employer level. *** indicates significance at the 1% level and ** indicates significance at the 5% level.

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 that our upper bound of pass through is at most 43%, which is less than half this figure, our results are also unlikely to be mostly explained by search frictions.

Fourth, our results may be driven by implicit commitment. Insurers may offer an implicit commitment to not raise premiums much to an employer when its expected health risk rises, as this may add value to its enrollees (as we showed in Section 2.2).[34] This can mimic a long-run contract to the extent that employers do not switch insurers. However, in the absence of formal long-run contracts, employers *without* adverse health shocks may switch insurers if the insurer raises their rates by pooling across employers. Why would the employers with below average expected health costs not switch plans? One possibility is inertia. Inertia is generally believed to exist in individual health plan choice (Handel, 2013) and may also exist for small employers' choices of health plans for their enrollees. Inertia provides implicit commitment on the part of the employer to not switch insurers. Given that our other three explanations do not seem to explain the low pass through that we observe, we believe that inertia and implicit long-run commitments may be a relevant explanation for this market.

5.3 Estimates of selection

Table 9: Impact of risk and price on take-up and selection

	(1)	(2)	(3)	(4)
	Dependent variable			
	Health risk for enrolled, R_{jt}		Take-up among employees, Q_{jt}	
Health risk for eligibles, R^p_{jt}	0.881***	1.001***		
	(0.061)	(0.021)		
Mean premiums			−.0002***	−.0006**
			(0.000)	(0.000)
Year FE	Yes	Yes	Yes	Yes
Employer FE	Yes	No	Yes	No
Market FE	No	Yes	No	Yes
Observations	31,044	31,044	31,044	31,044

Note: each observation is one employer during one year. The dependent variable in Columns (1) and (2) is the health risk for enrolled, R_{jt}. The dependent variable for Columns (2) and (4) is the take-up rate (in percentage points) among employees. The health risk for eligibles, R^p_{jt}, is calculated based on individuals that where in the employer with an ACG score last year. Standard errors are clustered at the employer level. *** indicates significance at the 1% level and ** indicates significance at the 5% level.

[34] All policies in the small-group market have guaranteed renewability, which provides some one-sided commitment (Pauly and Herring, 1999), though this does not preclude insurers from experience rating.

The first two columns of Table 9 present the estimated relationship between health risk for eligibles and health risk for the enrolled, which is α. Column 1 presents the results for a specification with employer fixed effects. The estimated coefficient is 0.881 with a standard error of 0.061.

Recall that an estimated $\frac{dR}{dR^p} < 1$ reflects advantageous selection, i.e., that the increase in premiums causes the relatively sick people to not take-up health insurance, in turn causing a decrease in the expected risk of the actual enrollees. Thus, our results are consistent with advantageous selection, though only significantly different from 1 at the 10% (and not 5%) level. However, our estimated coefficient without employer fixed effects is not significantly different than 1 and in fact, is slightly larger than 1. Given these findings, we believe that our estimates point to suggestive, but not definitive, evidence of advantageous selection.

Using our estimated coefficients from Tables 6 and 9 with employer fixed effects, we also calculate the impact of selection, $IS = (1 - \alpha)\beta = \$25$. This number implies that pass-through from a unit increase in risk score would be about \$25 larger if there were no selection and USIC used the same pass through from expected risk to premiums with respect to the enrolled as it currently does. This \$25 represents only 0.6% of the total extra expected costs from a unit increase in risk score. Thus, the impact of selection on reclassification risk is very modest.

Finally, it is worth evaluating why the impact of selection is so small. Recall that the effect of selection is composed of three components, $\frac{\partial R}{\partial Q}$, $\frac{dQ}{dp}$, and $\frac{\partial p}{\partial R^p}$, which are multiplied together. Therefore, if enrollees are very price inelastic, the effects of selection will be small. To evaluate this hypothesis, Table 9, columns 3 and 4 present results of regressions of the take-up rate among employees, Q_{jt} (our proxy for health insurance demand), on premiums, p_{jt}. In our specification with fixed effects, presented in column 3, the estimated coefficient is negative, as expected, and statistically significant at the 1% level. However, the coefficient is very small at -0.0002. Using the mean premiums and take-up rates from Table 2, this implies an elasticity of demand of -0.022.[35] While the coefficient without fixed effects—and hence the accompanying elasticity—is three times as large, all the numbers paint a picture of employees with a very low price elasticity of demand.

[35] In related work, we evaluate the elasticity of demand for insurance from USIC using discrete choice models and find price elasticities ranging from -0.05 to -0.07 (Fleitas et al., 2018).

6 Counterfactuals and Welfare

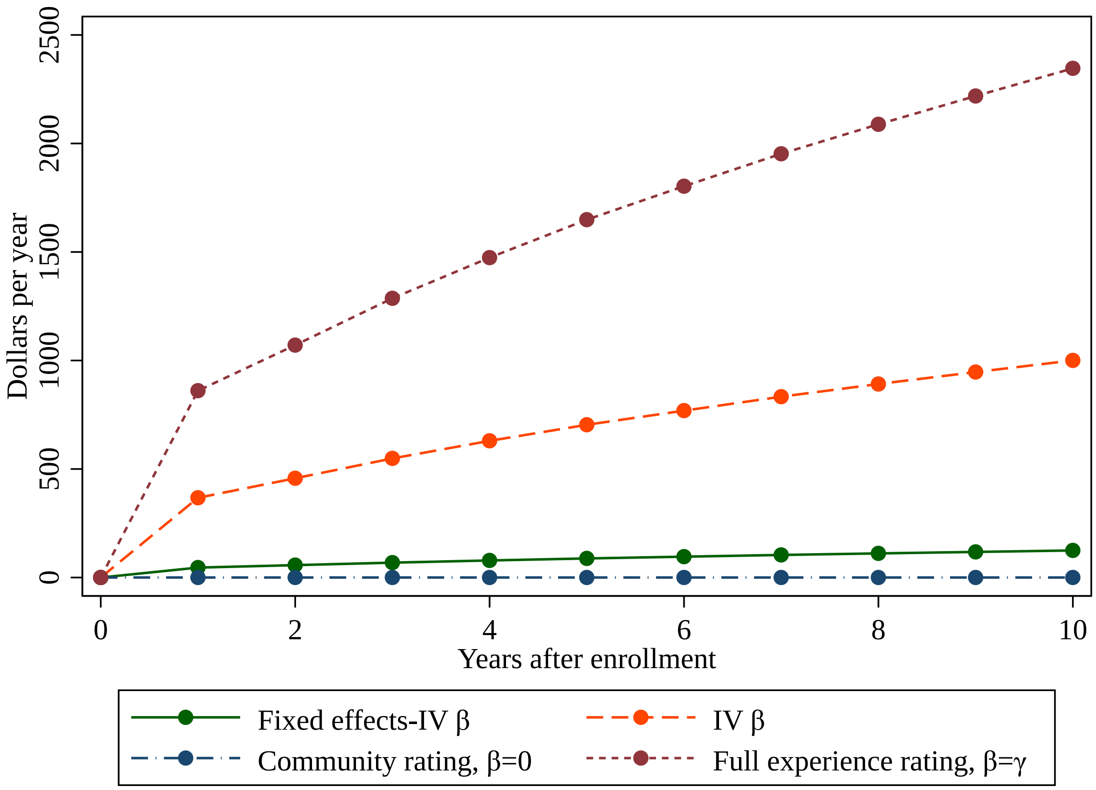
Using our estimates, we now examine the extent of reclassification risk and the resulting welfare loss under the current pricing environment and counterfactual environments, over a 10-year horizon after the initial insurance enrollment. Recall that our counterfactuals do not consider selection out of insurance and instead calculate risk assuming that the take-up rate $Q_{jt} = 1$.

We consider four different pricing environments. First, we consider community rating, where the change in rates is not a function of the increase in health risk and hence $\beta = 0$. Second, we consider risk pricing using our baseline estimate of β with employer fixed effects, in Table 6, column 1. Third, we present results from our estimate of β without employer fixed effects, in Table 6, column 3. Because it appears that USIC's pricing policy incorporates more risk rating for new employers, these estimates provide a useful upper bound to the experience rating from USIC's pricing policy. For instance, this level of pass through might conceivably occur if, each year, the employee switched to an employer which started a new account with USIC. Finally, we present results from the case of full experience rating, under which $\beta = \gamma$.

Figure 1 reports the mean across individuals in the standard deviation in annual premiums, for the four pricing policies described above. By construction, the standard deviation in premiums is 0 in the year of initial insurance enrollment, across the four pricing policies. For all the cases except community rating, the standard deviation in premiums is increasing over time, reflecting the greater uncertainty in health risk as one considers years further in the future. However, the standard deviation for premiums using our baseline estimates with fixed effects at the employer level is extremely low—at \$125 even after 10 years, consistent with our low estimated β. Even using our estimates without employer fixed effects, the standard deviation after 10 years, at \$1,000, is much smaller than the value of \$2,346 with full experience rating.

Figure 2 adds in the risk from out-of-pocket spending to the premium risk from Figure 1, to obtain a more complete picture of the total risk in healthcare spending faced by enrollees over time. This figure shows that there is substantial risk in healthcare spending, even with community rating. In particular, even the community rating case will result in a spending standard deviation of \$2,034, 10 years after the initial enrollment. Comparing the community rating case to the estimated pass through without employer fixed effects, we can see that, even with this higher estimate to pass through, USIC's pricing policy leaves individuals with a level of risk that is much closer to community rating—with a standard deviation of \$2,410 after 10 years—than to full experience rating—which

Figure 1: Simulated mean standard deviation in premiums across pricing policies



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

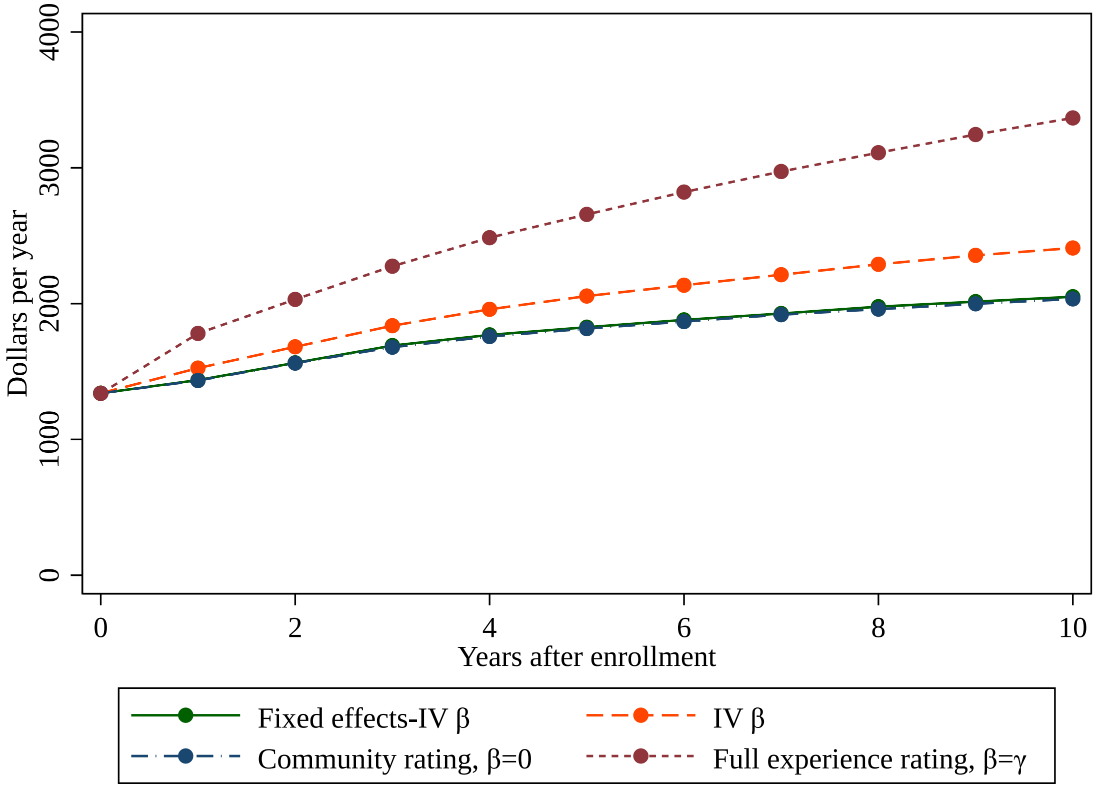
has a standard deviation of $3,367 after 10 years.

Finally, Figure 3 calculates the certainty equivalent income loss from the risk borne by individuals (using the risk aversion estimate from Handel, 2013). In general, Figure 3 tracks the general pattern from Figure 2, but with greater non-linearity. The greater non-linearity is due to the convexity of the certainty equivalent income loss in the size of the lotteries, given CARA preferences.

Considering the year in which the individual first enrolls in insurance, there is a substantial welfare loss from risk, of $1,510, which is driven exclusively by out-of-pocket expenses. In other words, individuals would be willing to pay a mean of $1,510 to be given their same expected income level, but with certainty.

Tracking the standard deviation numbers from Figure 2, the welfare loss from the out-of-pocket expenses under community rating grows over time, and is $5,372 10 years after the initial enrollment. On average over the 11 years starting with the year of initial insurance enrollment, the welfare loss from out-of-pocket expenses under community rating is $4,161 per year.

Figure 2: Simulated mean standard deviation in healthcare expenditures across pricing policies



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

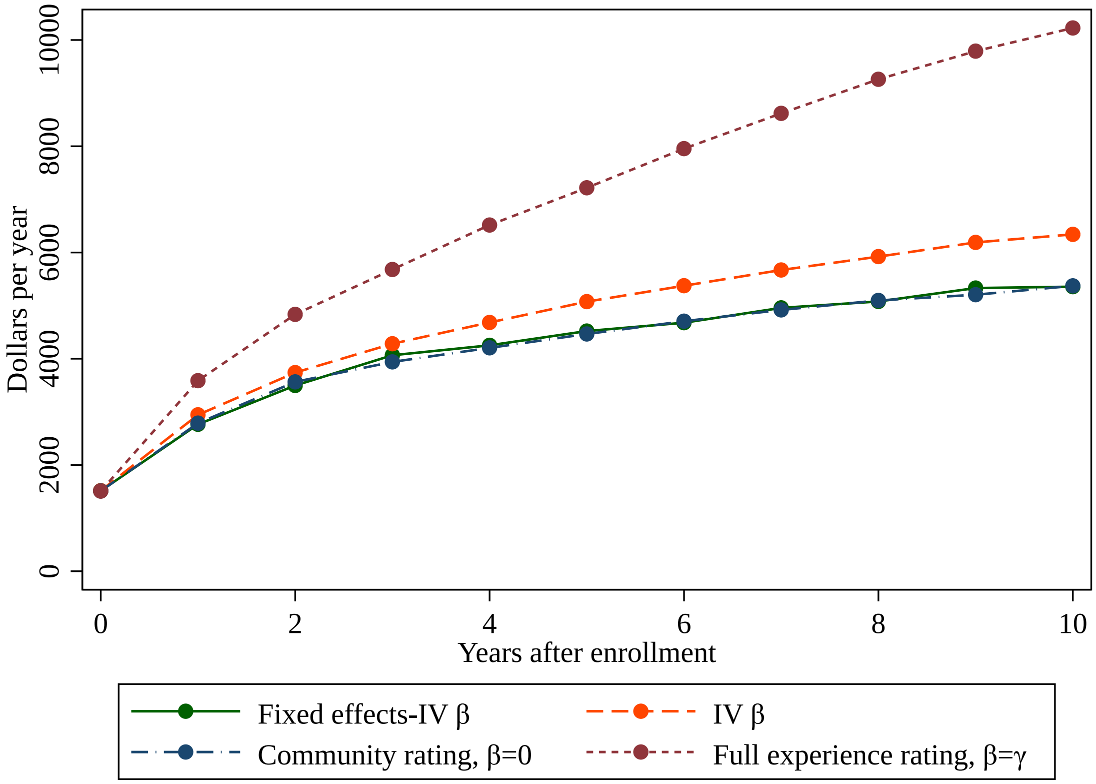
Despite the welfare loss from out-of-pocket expenses, the pricing policy of USIC generates little welfare loss from reclassification risk relative to community rating. In particular, even using the higher estimate of pass through, the welfare loss relative to community rating is only \$985 annually 10 years after the initial enrollment, or an average of \$572 per year over the 10 year horizon.

In contrast, USIC's pricing policy appears to provide considerable risk protection over full experience rating, even using the higher estimate of pass through. In particular, 10 years after the initial enrollment, the risk protection from USIC's pricing policy is \$3,885 relative to full experience rating and this policy adds a mean of \$2,346 in certainty equivalent income annually over the 10 year period following the initial enrollment.

Similarly to Figure 3, Figure A4 in On-line Appendix A considers the certainty equivalent income losses from the four different pricing environments, but for the case of the smaller employers in our sample, those with 13 or fewer covered lives during the entire sample period.[36] Due to the

[36]We choose this cutoff because it is the median employer size in our sample.

Figure 3: Simulated mean certainty equivalent loss from risk



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

fact that the risk sharing here is over a much smaller number of enrollees, the results from Figure 3 are magnified. Thus, for this subgroup, the risk protection provided by USIC's pricing policy adds a mean of $8,156 annually over the 10 year horizon relative to full experience rating, which is over twice the number in the full sample.

7 Conclusion

In this paper, we seek to understand the extent of reclassification risk and adverse selection in the small group insurance market from a period before ACA community rating regulations. We develop a simple two-period model of insurance in the small group market. Our model considers employees who can choose whether or not to buy employer-sponsored health insurance from an insurer. We allow for the insurer's pricing to each employer to potentially be based on the expected claims risk of the employer. The model highlights how the pass through from expected claims cost to premiums forms a sufficient statistic for understanding reclassification risk in this market. It also allows us to evaluate whether experience rating in this market leads to adverse or advantageous selection.

To estimate the pass through coefficient, we use a unique dataset 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. We find that the pass through from mean health risk to premiums ranges from 5 to 43%, depending on whether we include employer fixed effects in our specification. This limited reclassification risk cannot be explained by slow pass through over time, market power, or search frictions. It may be due to implicit long-term contracts. There is also little evidence that plan benefits change in response to changes in expected health risk.

We find no evidence of adverse selection and limited evidence of advantageous selection. In particular we find that a unit change in health risk for eligibles increases health risk among the enrolled by 88.1%, which is less than 100% and hence consistent with advantageous selection, though statistically significant only at the 10% level. However, advantageous selection explains, at best, only a small part of our low estimated pass through: pass through would be 0.6% higher if there was no advantageous selection but USIC followed the same pass through policy from claims risk on the insured to premiums.

Finally, we simulate counterfactuals to evaluate the extent to which the insurance provided by USIC 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 to evaluate how this would translate into financial risk for individuals using our estimated parameters and a risk aversion parameter taken from the literature. We find that the observed policy of USIC adds $2,346 annually in consumer welfare over the 10 years after insurance enrollment relative to full experience rating, even in the worst case where we assume that USIC passes through 43% of risk to consumers. Community rating would not increase consumer welfare substantially. Out-of-pocket costs are a substantial contributor to financial risk, even for individuals who buy community-rated health insurance, contributing $4,161 annually in equivalent loss over the same horizon.

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A Appendix

Figure A1: States in our estimation sample

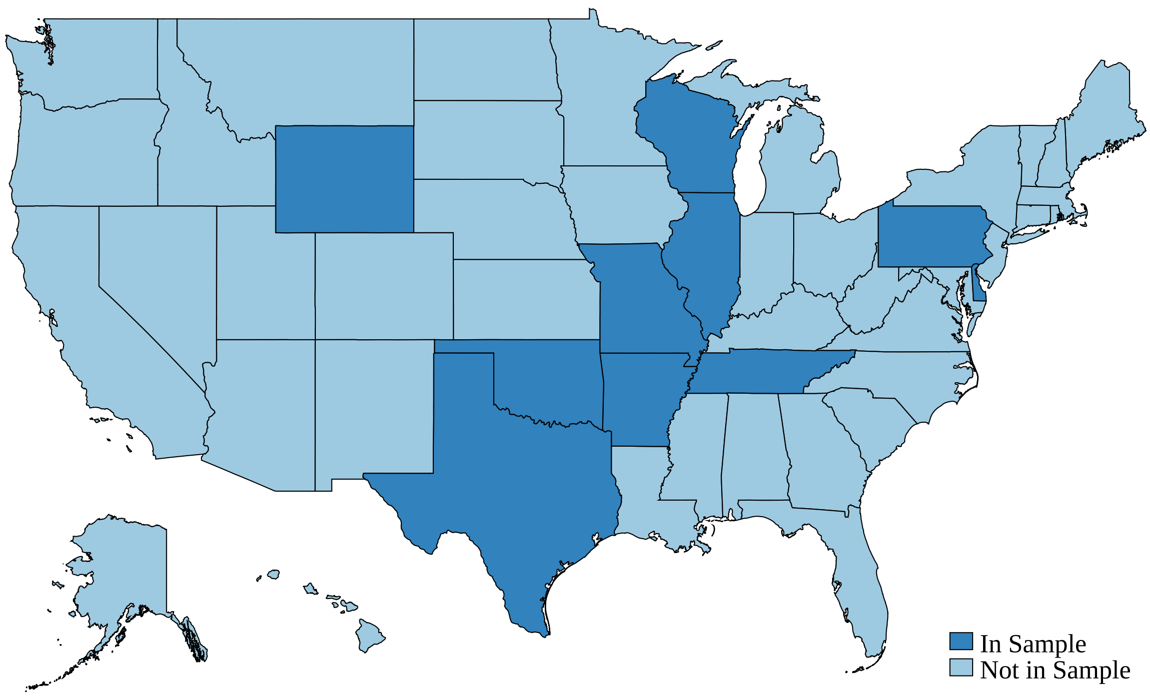
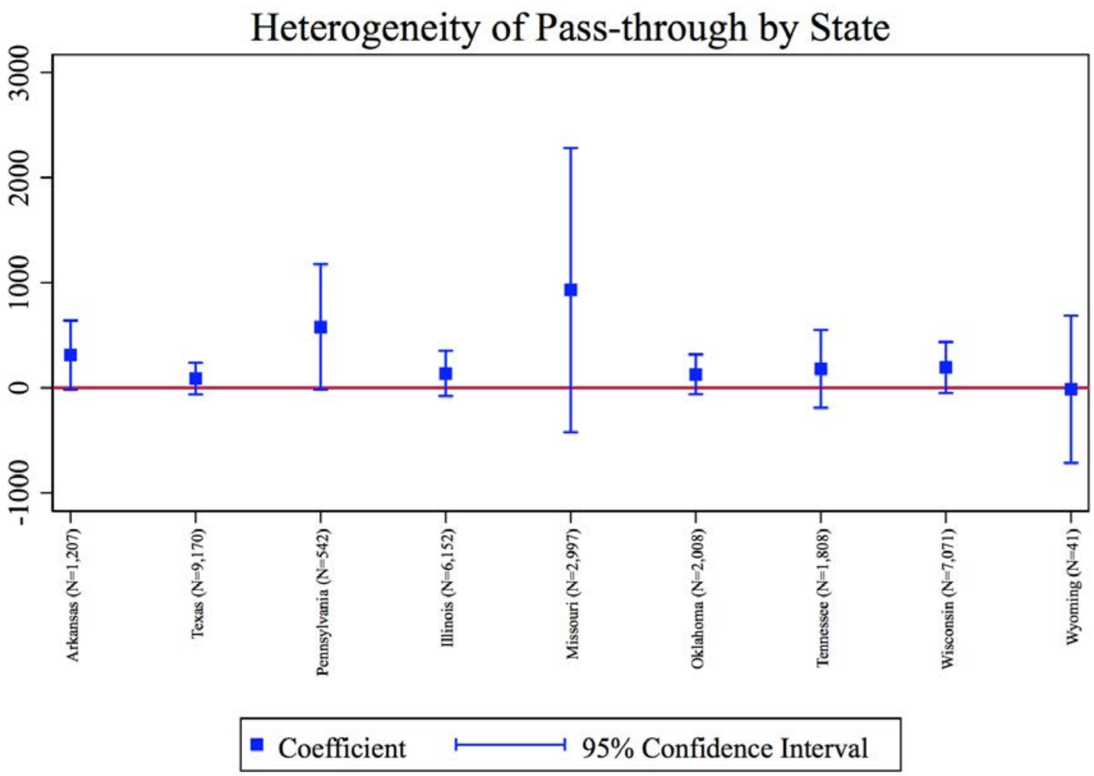
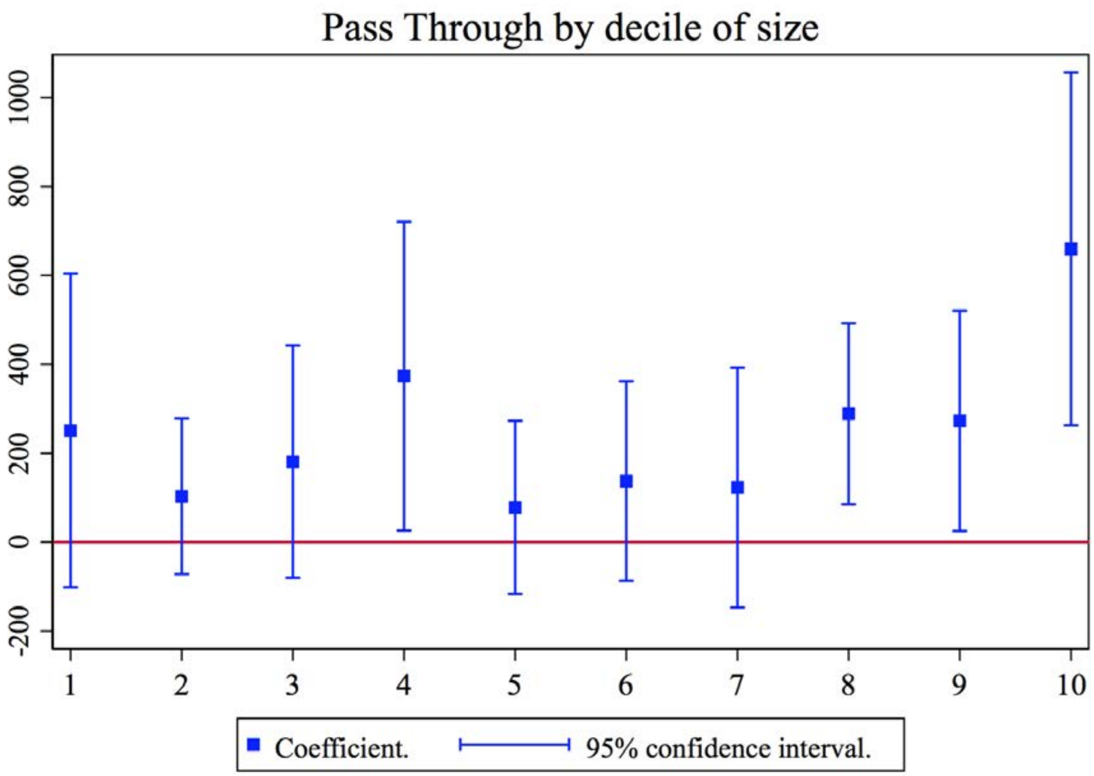


Figure A2: Effect of risk on premium by state



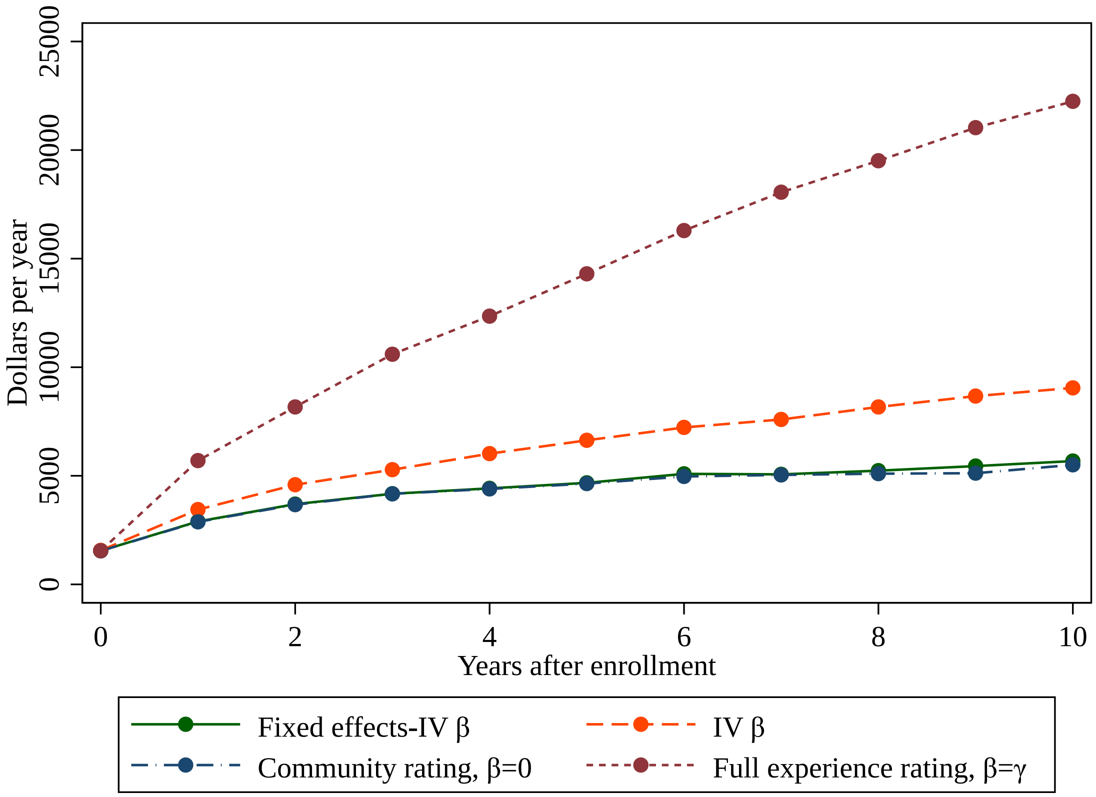
Note: Coefficients from our preferred specifications allowing different effects by state.

Figure A3: Effect of risk on premium by employer size



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

Figure A4: Simulated mean certainty equivalent loss from risk, small employers only



Note: Figure based on authors' calculations as described in paper. Smaller employers are those with 13 or fewer covered lives in all sample years.

Table A1: Pass-through from expected risk to claims using splines

	Dependent Variable: Paid amount ($)			
Regressor:	(1)	(2)	(3)	(4)
Spline employee ACG score, $r_{ijt} \in [0, 1)$	2,746***	2,836***		
	(94)	(96)		
Spline employee ACG score, $r_{ijt} \in [1, 2.5)$	3,174***	3,190***		
	(151)	(151)		
Spline employee ACG score, $r_{ijt} \in [2.5, 5)$	4,284***	4,282***		
	(361)	(361)		
Spline employee ACG score, $r_{ijt} \in [5, \infty)$	4,692***	4,689***		
	(398)	(398)		
Spline employee ACG score, $r_{ijt} \in [0, .32)$			2,503***	2,633***
			(559)	(563)
Spline employee ACG score, $r_{ijt} \in [.32, .57)$			3,756***	3,814***
			(411)	(411)
Spline employee ACG score, $r_{ijt} \in [.57, 1.13)$			1,189***	1,289***
			(421)	(420)
Spline employee 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 variables indicate the total claims amount paid by USIC for that enrollee. The sample is covered individuals with an ACG score in 2014 only. Standard errors are clustered at the employer level. *** indicates significance at the 1% level.

Table A2: Pass through from risk to premiums using splines

Dependent variable: annual employer mean premium, p_{jt}				
	(1)	(2)	(3)	(4)
Health risk for enrolled, R_{jt} (.,.69)	188	2,364***	196	147
	(237)	(240)	(333)	(231)
Health risk for enrolled, R_{jt} [.69,.94)	856***	1,520***	782**	889***
	(247)	(322)	(382)	(301)
Health risk for enrolled, R_{jt} [.94,1.28)	23	5,326***	−115	390*
	(243)	(317)	(362)	(222)
Health risk for enrolled, R_{jt} [1.28,.)	190	1,089***	215	−35
	(131)	(110)	(143)	(112)
Sample	All	All	Smaller	Larger
Sample			employers	employers
Instrument	R^p_{jt}	R^p_{jt}	R^p_{jt}	R^p_{jt}
Employer FE	Yes	No	Yes	Yes
Market FE	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Observations	31,044	31,044	16,187	14,857

Note: each observation is one employer during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. R_{jt} is calculated based on individuals that stay in the employer with an ACG score from last year. Smaller employers are those with 13 or fewer covered lives in all sample years; larger employers are all others. Standard errors are clustered at the employer level. *** indicates significance at the 1% level and ** indicates significance at the 5% level.

Table A3: Pass through from expected risk to premiums, with chronic conditions

Dependent Variable: Annual employer mean premium, p_{jt}					
Panel A: Effect controling for chronic conditions					
Regressor:	(1)	(2)	(3)	(4)	(5)
Health risk for enrolled, R_{jt}	213**	169*	211**	212**	193**
	(93)	(94)	(97)	(94)	(96)
Lag % cancer at employer		1,423***			
		(344)			
Lag % transplant at employer			257		
			(1,816)		
Lag % AMI at employer				555	
				(626)	
Lag % diabetes at employer					1,007***
					(316)
Instrument	R^p_{jt}	R^p_{jt}	R^p_{jt}	R^p_{jt}	R^p_{jt}
Year FE	Yes	Yes	Yes	Yes	Yes
Employer FE	Yes	Yes	Yes	Yes	Yes
Observations	31,044	31,044	31,044	31,044	31,044
Panel B: Effect controling for chronic conditions					
Health risk for enrolled, R_{jt}	213**	202**	211**	222**	215**
	(93)	(95)	(95)	(95)	(94)
Lag % hypertension at employer		399***			
		(149)			
Lag % heart failure at employer			276		
			(543)		
Lag % kidney disease at employer				−1,071	
				(674)	
Lag % asthma at employer					−391**
					(199)
Instrument	R^p_{jt}	R^p_{jt}	R^p_{jt}	R^p_{jt}	R^p_{jt}
Year FE	Yes	Yes	Yes	Yes	Yes
Employer FE	Yes	Yes	Yes	Yes	Yes
Observations	31,044	31,044	31,044	31,044	31,044

Note: each observation is one employer during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. R_{jt} is calculated based on covered individuals with an ACG score. Chronic disease regressors indicate the mean percent of enrollees with a claim for the disease in the previous year. Standard errors are clustered at the employer level. *** indicates significance at the 1% level.

Table A4: Effects 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}	-5	-0.03	2
	(21)	(0.22)	(12)
Instrument	R^p_{jt}	R^p_{jt}	R^p_{jt}
Year FE	Yes	Yes	Yes
Employer-plan FE	Yes	Yes	Yes
Observations	35,210	35,210	35,210

Note: each observation is one employer/plan during one year. Each dependent variable is a measure of plan benefits. Mean risk score is calculated based on covered individuals with an ACG score. Standard errors are clustered at the employer level. ** indicates significance at the 5% level and * indicates significance at the 10% level.

Table A5: Pass through from risk to premiums with heterogeneity by different periods

Dependent variable: annual employer mean premium, p_{jt}				
	(1)	(2)	(3)	(4)
Health risk for enrolled, R_{jt}	243	1,839***	27	1,654***
	(177)	(90)	(56)	(109)
Sample Years	2013-14	2013-14	2014-15	2014-15
Instrument	R^p_{jt}	R^p_{jt}	R^p_{jt}	R^p_{jt}
Employer FE	Yes	No	Yes	No
Market FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	22,203	22,203	21,083	21,083

Note: each observation is one employer during one year. The dependent variable is the premium charged the employer by USIC divided by the number of covered lives. R_{jt} is calculated based on individuals that stay in the employer with an ACG score from last year. Standard errors are clustered at the employer level. *** indicates significance at the 1% level and ** indicates significance at the 5% level.