The Effects of Price Regulation in Markets with Strategic Entry: Evidence from Health Insurance Markets

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Abstract

Regulators often enact price restrictions with the goal of improving access to products at affordable prices. However, the design of these regulations may interact with firm strategic entry and exit decisions in ways that mitigate the effects of pricing regulation or eliminate access to certain products entirely. In the US individual health insurance market, the Affordable Care Act established community rating areas made up of groups of counties in which insurers must offer plans at uniform prices, but insurers do not have to enter all counties in a rating area. The exact design of each market has been left to individual states. Allowing partial entry creates trade-offs in rating area design: larger areas may support more competition, but heterogeneous areas may promote partial entry as firms choose to not enter high cost areas. To evaluate these trade-offs, I develop a model of insurer entry and pricing decisions and investigate how insurers respond to rating area design. I find that banning partial entry increases overall entry, average prices, and consumer welfare. I quantify the trade-offs of increasing rating area size and find returns to size concentrated when marginal costs are similar across counties in a rating area. Regulators must balance promoting competition with pooling high and low cost consumers in rating area design.

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1 Introduction

When designing markets where there are large incentives for firms to price discriminate, regulators often seek to both promote competition and limit price variation across consumers to promote access. They may restrict the range of prices that firms can charge different consumers, with the goal of reducing price dispersion or lowering prices. However, firms can respond to these regulations by adjusting their product offerings, which could come at the expense of consumer access to the market. For instance, in response to a price cap, firms may exit the market rather than adjust prices downward. The regulator then faces a difficult challenge of how to achieve their pricing and accessibility goals, given that it is often difficult to directly regulate entry decisions. These challenges are present in many markets, including consumer lending (Cuesta and Sepulveda (2021)) and pharmaceuticals (Dubois and Lasio (2018), Maini and Pammolli (2022)).

These concerns are particularly important in the market for health insurance. Health insurance exchanges typically feature modified "community rating" pricing regulations to prevent insurers from price discriminating on pre-existing health conditions. Community rating, expanded to the entire US individual insurance market by the Patient Protection and Affordable Care Act (ACA), requires insurers to charge the same price to all consumers, regardless of health status, within a rating area. Rating areas are determined by states and are typically groups of counties. However, insurers can partially enter rating areas and offer insurance only to a subset of counties.

Under this regulatory structure, there are ambiguous effects of rating area size on entry and equilibrium prices. As rating area size increases, the bigger market size supports more competition as fixed costs can be spread over more consumers. However, larger rating areas may be more heterogeneous in the cost of providing health insurance, creating an incentive for insurers to only enter areas with lower cost consumers and lessening competition in high cost areas. While more competition typically lowers prices, the pricing regulation creates pricing spillovers as increased competition in one county of a rating area drives down prices in other counties. Additionally, in heterogeneous rating areas, there will be cross-subsidization of high cost geographies by lower cost geographies for insurance plans offered throughout the rating area.

In this paper, I investigate how insurers respond to community rating area design. I examine policies that ban partial entry and increase the size of rating areas. Such policies have received substantial attention recently to address concerns about insurer participation in rural markets; Mueller et al. (2018), NACRHHS (2018), and Frank (2019) propose to expand rating areas and remove the ability of insurers to make partial rating area offerings. I model entry and pricing decisions and evaluate how firm behavior along these dimensions changes in response to counterfactual rating area policies. I find that banning partial entry while holding current design fixed increases both insurer participation and prices. Prices increase because the marginal entrants charge higher prices, including in counties they entered in the status quo, since costs are higher in the previously selectively non-entered counties. Selectively non-entered counties are counties that an insurer does not enter while participating elsewhere in the rating area. I also find benefits to increasing rating area size, as long as the rating area is homogeneous in terms of costs. Larger heterogeneous rating areas are partially entered. Therefore, regulators must balance managing the level of competition and the level of price variation.

To motivate the development of this model, I first document patterns in the US individual exchange market from 2015-2018. I exploit the fact that rating areas are limited by state borders to demonstrate that counties with constrained rating areas, identified as counties where the nearest metropolitan area is across a state line, are in smaller rating areas. As a result, they have fewer insurers, are less likely to have been selectively non-entered, and have higher prices. The equilibrium price effects could be due to direct competition effects, to spillover effects of competition elsewhere in the rating area, or to the direct effect of pricing regulations.

While these findings suggest there is some effect of how these markets are designed, I cannot distinguish between various mechanisms using a descriptive approach. I develop a structural model of insurer entry and pricing behavior and estimate counterfactuals that quantify trade-offs in rating area design. Using data from Oregon from 2016-2019, I estimate a model of consumer demand for health insurance products on Oregon's health insurance exchange, leveraging variation in enrollment patterns across different age and income groups and in the subsidies provided to consumers by the federal government. I recover estimates of marginal costs using a Nash-in-pricing assumption on firm behavior combined with administrative data on the average medical claims of enrollees. Finally, I estimate fixed cost parameters using moment inequalities, leveraging variation in firms' observed entry decisions.

I find significant variation across counties in the price elasticity of demand for health insurance. These differences largely arise from differences in the demographic make-up of counties in terms of age and income. There is also considerable heterogeneity in the estimated marginal costs of providing insurance to consumers across counties, even within rating areas. Counties with higher marginal costs relative to the rest of their rating area are more likely to be selectively non-entered. I estimate fixed costs of entering rating areas that include both network formation costs and regulatory costs of entry. All three of these factors can drive partial entry decisions: firms may want to sell to inelastic low cost consumers and avoid locations in which it is costly to form networks. The regulatory costs of entry will create economies of scale in entering multiple counties within a rating area.

When designing these markets, regulators must decide whether to allow partial entry and how big rating areas should be. Using the model estimates, I examine how entry and pricing would change under counterfactual policies. I first examine a policy that disallows partial entry. The policy will increase entry if profits in entered counties are sufficiently high to offset losses that would be incurred in non-entered counties. These losses could either come from high fixed costs in non-entered counties or from price adjustments made when entering everywhere in a rating area. I find that entry on net increases when partial entry is prohibited, with the gains in entry occurring in places that are selectively non-entered in the status quo. On average, new entrants charge higher prices than status quo entrants. Even though prices increase, consumer welfare increases 19.5% as a result of additional choices of health insurance plans offered by new entrants.

I then consider the effects of changing rating area size when partial entry is not allowed. I first consider county-level rating areas. When each county is its own rating area, a substantial number of counties go unserved by any insurer. Price variability across geographies increases over 300%, with the highest price increases occurring in low income, less dense areas. These areas have the highest marginal costs, so prices better reflect the underlying costs in each county. I also consider state-wide rating areas. Here, only one insurer enters and price variation is eliminated. While there is an increasing relationship between the number of rating areas and price variation, designs with an intermediate number of rating areas support more competition.

Allowing partial entry introduces further trade-offs with rating area size. Due to computational challenges created by multiplicity of equilibria, I do not fully re-draw rating areas and allow partial entry, but instead quantify the trade-offs a regulator faces in adding an additional county to a rating area. I do so by comparing outcomes when grouping two counties together to outcomes when rating areas are set at the county level. Grouping counties together will affect both prices and entry. Firms that enter both counties regardless of whether they are grouped together must equalize their prices across the two counties because of the pricing regulation. This change will benefit consumers in high cost counties and hurt unsubsidized consumers in low cost counties. Since some components of fixed costs are shared between counties, grouping counties together can create markets that support more competition. However, if the discrepancy between optimal prices in the two counties is high, firms may enter only one of the counties in the rating area. Overall, I find that entry increases, with the largest gains in entry occurring in counties that were grouped with a county with similar marginal costs. Prices increase in counties whose costs are substantially below those of the other county in their rating area. Gains in consumer surplus occur in counties grouped with similar counties, as there is additional entry without substantial price changes.

This paper expands our understanding of the interplay between pricing regulations and entry decisions, which can inform regulators considering price and entry regulations in new settings. First, the health insurance setting includes variation across consumer groups in both the elasticity of demand and marginal costs as well as high fixed costs of entry, expanding the number of settings to which the insights can be applied. In the market for pharmaceuticals, there is geographic variation in demand elasticities and high fixed costs of entering new markets, but marginal costs are negligible (Maini and Pammolli (2022); Dubois and Lasio (2018)). Marginal cost variation is important in the health insurance setting; regulators want to both prevent high mark ups and spread risk across consumers. Consumer lending features variation in marginal costs but no additional fixed costs of serving new consumer groups (Cuesta and Sepulveda (2021)). Additionally, health insurance is a setting where equity may be a first-order concern[1] for regulators who have the ability to regulate both entry and pricing.[2]

This paper also expands our understanding of the effects of rating areas on market structure. Dickstein et al. (2015) find descriptively that counties in larger rating areas have more competition from insurers on their exchanges and lower premiums, with the important caveat that this relationship is reversed when a rural county is grouped with urban counties in a heterogeneous rating area.[3] I quantify the trade-offs of larger market sizes in terms of competition and price variation and explore how a ban on partial entry affects these relationships. Fang and Ko (2018) explicitly study the causes of partial rating area offerings and find that they are largely driven by disadvantageous market conditions in areas that are sicker and lack urban populations. I build on this work by examining how different rating area designs

[1]Regulators may care about variable prices because of traditional price discrimination concerns where they want to equalize mark ups across consumer types. They may also care about equalizing prices even if serving different consumers has different marginal costs. These concerns are common in settings with risk pooling like insurance or consumer lending, but may be present in other settings as well.

[2]California does not allow partial rating area offerings.

[3]Dickstein et al. (2015) do not explicitly model insurer entry decisions or explore how the ability of insurers to partially enter changes the way that market size affects the outcomes of competition.

and entry requirements affect consumer welfare. This paper also builds on work studying the individual health insurance exchanges (Saltzman (2019); Tebaldi (2022); Polyakova and Ryan (2019)) and is closely related to work studying age pricing restrictions on the exchanges (Ericson and Starc (2015); Orsini and Tebaldi (2017))[4], but adds the complication of an entry problem.

Finally, this paper fits into the broader literatures on insurer competition (Ho and Lee (2017); Dafny (2010); Dafny et al. (2012); Dafny et al. (2015)) and firm entry decisions (Bresnahan and Reiss (1991); Mazzeo (2002); Dranove et al. (2003)). In the entry literature, it builds on work that uses moment inequalities to model how firms make entry or product positioning decisions (Ciliberto and Tamer (2009); Eizenberg (2014); Dickstein and Morales (2018); Wollmann (2018); Cattaneo (2018)) and applies these methods to study the behavior of health insurers.

The rest of this paper is organized as follows. In Section 2, I describe the institutional details surrounding the ACA and community rating and map them to a simple model of pricing behavior. In Section 3, I highlight patterns on the federal exchanges related to rating areas, describe an empirical strategy for identifying the effects of rating area design, and present results showing that geography matters for competition among insurers. In Section 4, I develop a model of insurer entry in a two-stage game. I discuss the estimation of this model in the setting of Oregon's state-run health insurance exchange in Section 5. I present results in Section 6. In Section 7, I present results from counterfactual simulations. Finally, I conclude in Section 8.

2 Optimal Pricing Under Community Rating

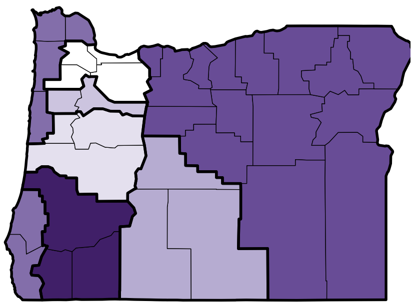
In this section, I discuss the institutional details of the community rating system imposed on the ACA Exchanges and how they affect optimal pricing and entry decisions.

2.1 Context

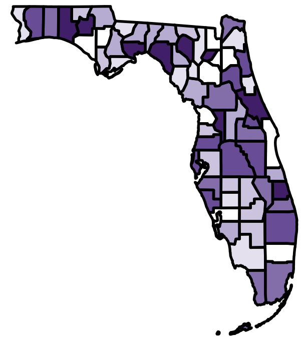
The ACA was passed in 2010 and established health insurance exchanges on which individuals could purchase health insurance with the goal of increasing access to health insurance. States were given considerable latitude in how to implement these exchanges. Several states

[4]Geographic community rating across consumers with different costs is similar to restrictions on age rating, which pool the risks of younger consumers and older consumers. However, in the case of geographic restrictions, insurers have the option to selectively not sell to a group of higher cost consumers.

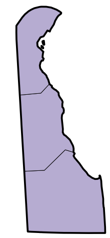
Figure 1: Variation in Rating Area Design



(a) Oregon's Rating Areas



(b) Florida's Rating Areas



(c) Delaware's Rating Areas

Notes: This figure shows various ways that states have defined their rating areas. Oregon has 7 rating areas, shown in subfigure (a). There are 36 counties in the state of Oregon. Florida, shown in subfigure (b), has both 67 counties and 67 rating areas. Delaware has combined its three counties into a single rating area, shown in subfigure (c).

set up their own exchanges, but most used the platform set up by the federal government, healthcare.gov. The ACA implemented regulations on pricing and provided federal subsidies to consumers. Under the ACA, the federal government sets baseline regulations, with many states adding additional regulations.

Rating of Health Care Plans

The ACA introduced guaranteed issue to the US individual health insurance market. Guaranteed issue prevents insurers from denying coverage based on pre-existing conditions. To prevent insurers from functionally denying coverage by charging high prices to those with pre-existing conditions (experience rating), the ACA also implemented community rating to prevent insurers from charging different prices based on underlying health status. Under community rating, the price of a plan is constant across a community rating area within age rating bins. Insurers may vary the price of a plan by the age of the consumer, with restrictions on how much more older consumers may be charged. Some states additionally allow price variation based on smoking status. Appendix Figure B4 shows the age multipliers that insurers are allowed to charge to different consumers.

States decide the rating areas in their state, and these rating areas determine the community rating pools. The default guidance is to establish one rating area for each Metropolitan

Statistical Area (MSA) with all rural counties grouped into a single rating area.[5] There is considerable variation in how the states draw these rating areas. Some states have a single rating area (typically states with small, relatively homogeneous populations), while others have many. Three states (Connecticut, Florida, and South Carolina) define each county as its own rating area, which in Florida's case means 67 rating areas. Most states chose to use counties as their unit of geography for designating rating areas, though some use MSAs or zip codes. Figure 1 highlights the variation in rating area design, by showing a state that grouped counties together (Oregon) in panel (a), a state that established rating areas at the county level (Florida) in panel (b), and a state that established a single rating area at the state level (Delaware) in panel (c).

Once these rating areas are established, insurers must charge uniform prices up to age and tobacco-rating regulations. However, they have the choice to make a partial entry where they only offer a plan to a subset of counties. Entry decisions are typically made at the county level.[6] Figure 2 highlights the counties where we observe this partial entry phenomenon. Partial entry occurs frequently across a wide variety of states; in 2017, 31.8% of counties on healthcare.gov experienced partial entry.

In the years since the implementation of the ACA, there have been concerns over the number of insurers operating on the individual exchanges in rural areas. Several counties struggled to recruit any insurers in some years, and many counties are only served by a single insurer. Despite this geographic heterogeneity, it is difficult to measure the effects of lack of competition directly, given that counties with few insurers likely differ from counties with many insurers in unobservable ways.

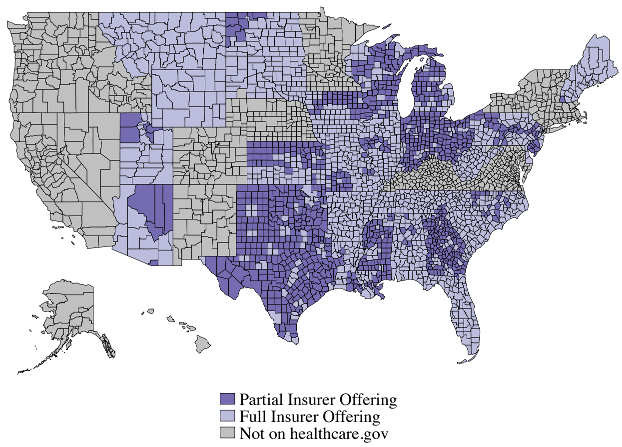
Metal Levels and Subsidies

Plans sold on the federally facilitated exchanges are categorized into different "metal levels": bronze plans cover roughly 60% of medical costs, silver plans cover 70%, gold plans cover 80%, and platinum plans cover 90%. In some areas, catastrophic health care plans are also available, but only to consumers under the age of 30 or who have a hardship exemption.

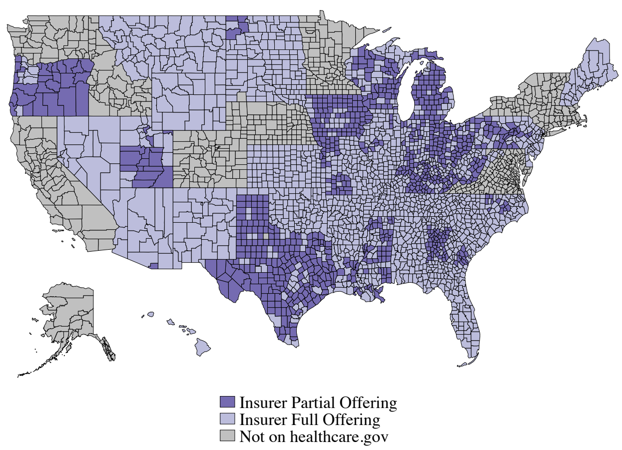
[5] Alabama, New Mexico, North Dakota, Oklahoma, Virginia, and Wyoming define rating areas as MSAs + 1. Texas previously defined rating areas in this way, but reorganized rating areas in 2021 so rural areas would be grouped with close urban areas to encourage more competition. Before this reform, 177 rural counties in Texas were grouped into a single rating area, with considerable heterogeneity in costs and frequent partial entry.

[6] In a limited number of circumstances, a regulator may allow an insurer to partially enter into a subset of zip codes within a county with sufficient justification. Such partial entries are rare, so I consider entry decisions to be made at the county level when rating areas are established as groups of counties.

Figure 2: Prevalence of Partial Insurer Entry on the Individual Insurance Exchanges



(a) 2015 Data



(b) 2017 Data

Notes: This figure shows the prevalence of partial insurer entry on individual health insurance exchanges and how it changes over time. Subfigure (a) shows in dark purple all the counties in the United States where there is an insurer that offers plans elsewhere in the rating area, but does not sell them to that county. Counties shown in light purple have all insurers who sell in their rating area enter. Counties in grey either are in states that do not participate in healthcare.gov or define their rating areas at the zip code level. Subfigure (b) shows the analogous measure in 2017. In 2017, there was higher participation on healthcare.gov. There were also changes from 2015 in where insurance was partially offered.

Recall that my empirical exercise will focus on Oregon. Oregon's exchange is state-run and federally facilitated; enrollment is managed through healthcare.gov but the state exercises additional control over the marketplace. In Oregon, no insurers offer platinum plans. Insurers in Oregon must offer a plan on the bronze, silver, and gold level with standardized financial features. Insurers may offer additional plans, but in a very limited capacity. These limits on plan offering make Oregon a good market to study questions around entry, as they limit additional dimensions in firm decision making.

In all states, given the high costs of purchasing insurance, the federal government provides subsidies to assist low income consumers. There are two kinds of subsidies available, both tied to silver plans. Advanced Premium Tax Credits (APTC) provide premium assistance to consumers under 400% of the Federal Poverty Line (FPL).[7] These subsidies are benchmarked to the second cheapest available silver plan in a consumer's county.[8] There is a cap on how much consumers spend on premiums that varies based on household size and income levels; the subsidy provided is the difference between that amount and the price of the benchmark plan for the consumer's household. This subsidy can be used for any plan, but there is no rebate to the consumer if they purchase a plan that costs less than the amount of the subsidy. Because of these subsidies, the price that an individual consumer pays for the same health care plan will depend not only on their age (age rating) and where they live (community rating) but also on their household income.

There are additional subsidies for cost sharing that are available to consumers with household incomes of 100-250% of the FPL.[9] These cost subsidies are available only for silver plans and vary based on household income within this range. For the lowest income consumers, these Cost Sharing Reductions (CSRs) will improve the actuarial coverage of a silver plan to that of a platinum plan. In many cases, these plans for low income consumers will financially dominate plans from higher metal levels.

2.2 A Simple Example

I now present a simplified model of insurer entry and pricing to highlight how variation in marginal costs, the elasticity of demand, or fixed costs can complicate insurer entry decisions under a policy of community rating. I begin by considering the entry and pricing decisions of an oligopolistic insurer under different community rating area designs without fixed costs.

Consider two counties, county H and county L, that a state regulator is considering

[7] During the coronavirus pandemic, eligibility for subsidies was extended to consumers with higher incomes, but my sample period ends in 2019.

[8] If only one silver plan is available, it automatically becomes the benchmark plan.

[9] The intention of the ACA was that consumers who have household incomes of below 100% FPL would be covered by Medicaid. This is not always the case in states that did not expand Medicaid, creating gaps in access to affordable health insurance coverage. In the state of Oregon, Medicaid was expanded, so individuals with household incomes of less than 100% FPL are eligible for Medicaid.

grouping together as one rating area. The costs in county H, c_H, are higher than the costs in county L, c_L. Profits for the insurer are given by the following expression:

$$\Pi = N_H s_H \cdot (p_H - c_H) + N_L s_L \cdot (p_L - c_L) \tag{1}$$

where N_x is the size of the market in county $x \in \{L, H\}$ and s_x is the share of the market that the insurer captures in county $x \in \{L, H\}$.

Absent the two counties being grouped together, an oligopolistic insurer would charge prices that are a function of the costs in each county and the elasticity of demand in each county. From the firm's first order conditions, these are given by:

$$p_H^* = c_H - \frac{s_H}{\frac{\partial s_H}{\partial p_H}}$$
$$p_L^* = c_L - \frac{s_L}{\frac{\partial s_L}{\partial p_L}}$$

If the insurer enters both counties, an oligopolistic insurer would charge the following price:

$$p_H = p_L = p^* = \frac{-N_H s_H + -N_L s_L + N_H c_H \frac{\partial s_H}{\partial p} + N_L c_L \frac{\partial s_L}{\partial p}}{N_H \frac{\partial s_H}{\partial p} + N_L \frac{\partial s_L}{\partial p}} \tag{2}$$

This expression includes the costs in each county, the elasticity of demand in each county, and the size of each county. These expressions are very similar to those used in the literature studying the effects of age rating restrictions (e.g. Ericson and Starc (2015), Orsini and Tebaldi (2017)).

Two features of this pricing equation are worth noting. First, there will be transfers from high cost counties to low cost counties. Second, these dynamics will be exacerbated by selection into insurance which may be present even with an individual mandate; absent subsidies, consumers in low cost areas may select out of the insurance market, driving up costs as the remaining customers become higher cost on average.

Under community rating regulations, partial entry is permitted. This feature differentiates the problem from age rating. In this setting, an insurer now can also choose to only enter into one county within a rating area, in which case they would charge the price they would if there was no rating area grouping. Insurers will choose to make a partial entry when there is constrained pricing and the profits from only entering one county are higher than the profits from entering both. That is, the following conditions must hold for the insurer to enter both counties:

$$N_H s_H \cdot (p^* - c_H) + N_L s_L \cdot (p^* - c_L) \geq N_H s_H (p^*_H - c_H)$$
$$N_H s_H \cdot (p^* - c_H) + N_L s_L \cdot (p^* - c_L) \geq N_L s_L (p^*_L - c_L)$$

To illustrate an extreme scenario where this might occur, consider the case where $p^*_L < c_H$. In this case, keeping prices fixed and adding an additional county to the set of counties in which insurance is offered will cause the insurer to lose money. If the costs of losing market share in county L when prices are raised to the new optimal price for both counties are sufficiently high, the insurer will prefer to only remain in county L.

Up until now, I have considered the case where there are no fixed costs of entry; rating areas only shift entry decisions through the effects on pricing. With fixed costs of entry, rating area size affects both the potential heterogeneity of the rating area, but also the size of variable profits relative to fixed costs. Entry into a single county within a rating area will only occur when the variable profits of entering that county exceed the fixed costs of entry. When counties are grouped in a single rating area, if the fixed costs of entering both counties are less than the sum of entering each separately, we should see (weakly) more entry absent pricing regulation. Thus, with price regulation, there are two opposing forces in increasing rating area size: aggregating counties allows fixed costs to be spread over a larger market, but it may be profitable to only offer insurance in a subset of counties due to the pricing rules.

3 Descriptive Evidence

In this section, I provide evidence of a relationship between rating area design and market outcomes in a national setting. I first show that geography matters for entry and pricing decisions. In particular, I demonstrate that rural counties adjacent to metropolitan areas show different entry and pricing patterns than counties that are either not adjacent to metropolitan areas or are in metropolitan areas. I also show that rating area pricing rules may be binding. That is, when firms can charge different prices, they tend to do so.

Neither analyses addresses the fact that rating area design is non-random. To address this concern, I use state borders as a constraint on rating areas. I find that when rating areas are constrained by state borders, rating areas are smaller, equilibrium entry decisions are different, and prices are higher.

3.1 Data

I study the national market for individual health insurance by examining counties in states in which insurance is sold through healthcare.gov and rating areas are defined at the county level.[10] I use the Qualified Health Plan (QHP) Landscape Individual Market data, the Centers for Medicare and Medicaid Services (CMS) Marketplace Open Enrollment Period Public Use Files, the American Community Survey (ACS), the Area Health Resources Files (AHRF), and the County Health Rankings. These data cover 2015-2018.

The QHP Landscape Individual Market data has information for each plan sold in each county, including information on premiums and cost sharing. CMS Marketplace Open Enrollment Period Public Use Files have enrollment data on the number of people who enroll in health insurance and at what metal level for each county. Demographic information at the county level comes from the ACS. The AHRF contain further information about the availability of health care providers. I supplement this with the County Health Rankings which include information on the health characteristics of each county.

3.2 Patterns

Previous research examining rating areas highlights the importance of rating areas for rural counties (e.g. Dickstein et al. (2015)). I build on this existing work by looking at the distinction between rural and metropolitan areas in the prevalence of partial entry. In particular, I compare counties that are rural and not adjacent to a metropolitan area to counties that are rural and adjacent to a metropolitan area. Counties that are not adjacent to a metropolitan area will be less likely to be combined in a rating area with metropolitan counties. I use the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture to classify counties.

Table 1 compares market outcomes between metropolitan counties, counties that are not metropolitan but are adjacent to a metropolitan area, and non-metropolitan counties that are not adjacent to a metropolitan area. Of the three groups, rural counties adjacent to metropolitan areas are most likely to experience partial entry. These counties also have a higher level of overall insurer competition relative to non-adjacent rural counties, but a lower level of competition compared to metropolitan areas. The price of the benchmark plan is highest in non-adjacent rural counties. These results suggest trade-offs from rating area design: being near metropolitan areas is associated with more missing insurers, but also

[10] Alaska and Nebraska establish rating areas at the three-digit zip code level. Virginia uses both counties and cities.

Table 1: Metropolitan Adjacency and Partial Entry

	Metro	Metro Adj.	Not Metro Adj.
Partial Entry	0.30	0.37	0.27
Number of Insurers	3.32	2.74	2.10
Benchmark	3,064.90	3,232.29	4,273.86
Number of Counties in RA	8.48	15.31	18.59
Population in RA (10,000s)	106.27	55.12	58.23

Notes: This table provides summary statistics on the national sample split by whether counties are rural and non metropolitan adjacent, rural and metropolitan adjacent, or metropolitan. It includes data from 2015-2018 from 35 states that use healthcare.gov for their exchange enrollment.

a higher level of insurance competition overall. However, these results are not causal and so should be interpreted with caution; counties that are adjacent to metropolitan areas are likely to differ from non-adjacent counties in ways related to insurance markets as well.

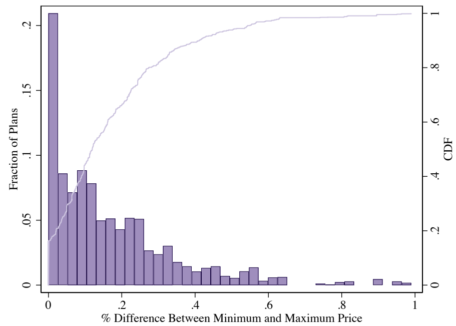
The previous analysis suggested geography matters for entry decisions. I now provide evidence of a potential relationship between rating area design and the level of price variation in the price of health insurance. It is unclear what the socially optimal level of price variation should be, given the presence of federal subsidies in this market. States considered carefully the amount of price variation when setting up their exchanges. However, if insurers charge the same prices regardless of rating areas, changing rating area design is unlikely to affect the level of price variation.

For each plan that is offered in multiple rating areas in a single year, I calculate the difference between the maximum and minimum base prices that are charged. I plot this distribution in Figure 3. Over 80% of plans offered in multiple areas have minimum and maximum prices that differ by more than 2%. Some plans have maximum prices that are almost double the cheapest price at which they are offered.

3.3 Cross-State Identification Strategy

A challenge in evaluating how rating areas affect insurer competition is that rating areas were not draw randomly. In particular, counties in rating areas of different designs may have different characteristics that influenced their inclusion in their rating area, insurer's entry decisions, and prices. To address this concern, I use geographic variation in the location of

Figure 3: Distribution of Price Differences for Plans Across Rating Areas



Notes: This figure shows the distribution of the percent difference in prices between the cheapest price at which a plan is offered in a state and the most expensive price at which it is offered for plans that are offered in more than one rating area. These plans are plans offered on healthcare.gov between 2015 and 2018 in states that use counties to define rating areas.

large urban areas relative to state lines.

State lines create a restriction on how rating areas can be drawn. If a regulator would like to group a county with a metropolitan area, but that area is across the state border, it will mechanically be assigned to a different area. This rating area is likely to be smaller and more homogeneous than the rating area that would have been drawn in the absence of the state line. Thus, I compare counties that are within the same state and are equidistant from the nearest metropolitan area, but where one metropolitan area is in a different state and the other is in the same state.

I estimate the following regression:

$$Y_{ist} = \alpha_s + \tau_t + \beta_1 \cdot \text{Rural}_i + \beta_2 \cdot \text{Distance}_i + \beta_3 \cdot \text{CrossState}_i + \gamma \cdot X_{it} + \epsilon_{ist} \tag{3}$$

where Y_{ist} is the outcome of interest, α_s are state fixed effects, τ_t are time fixed effects, Rural_i is an indicator for whether the county is rural, CrossState_i is an indicator for whether the county is across a state line from the nearest metropolitan area, and X_{it} is a vector of time-varying, county-level controls.

The outcomes Y_{ist} that I consider are the population of the rating area (in units of 10,000), whether an insurer who offers insurance elsewhere in the rating area declines to entry the county, the total number of insurers competing in the county, and the price of insurance.

Table 2 shows the estimated coefficients from equation 3. Column 1 looks at the effects

Table 2: State Borders, Rating Area Design, and Market Outcomes

	(1) RA Size	(2) Missing Insurer?	(3) # Insurers	(4) Log(Price)
Rural	24.28***	0.0866***	-0.180***	0.0191***
	(4.905)	(0.0184)	(0.0370)	(0.00596)
Miles to Metro / 100	-19.00***	-0.0392***	-0.163***	0.0474***
	(3.014)	(0.0149)	(0.0298)	(0.00489)
Cross State=1	-12.22***	-0.0505***	-0.254***	0.0386***
	(3.223)	(0.0166)	(0.0372)	(0.00649)
N	8211	8211	8211	8211
Outcome Mean	97.52	0.361	2.546	8.166
R2	0.719	0.372	0.607	0.756

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the results of a regression of market outcomes on state and time fixed effects, indicators for whether the county is a rural county, a vector of time-varying controls, and an indicator of whether the county is across a state line from the nearest metropolitan area. Rating area size is measured by the size of the population in the rating area divided by 10,000. Missing insurer denotes a dummy variable for whether at least one insurer who offers in the rating area does not offer insurance to that particular county. Price refers to the price of the benchmark plan, the second cheapest silver plan.

on rating area size as measured by the total population in the rating area. As expected, counties that are further away from metropolitan areas and counties whose rating areas are constrained by state borders are located in smaller rating areas.

Columns 2 and 3 address two different measures of entry behavior. Column 2 measures whether the county was selectively non-entered. That is, they are less likely to have an insurer who sells elsewhere in their rating area and does not sell to them. Rural counties are more likely to be selectively non-entered, consistent with previous evidence in this paper. Counties further from metropolitan areas are less likely to be selectively non-entered, though this relationship is not statistically significant. Counties whose rating areas are constrained by state lines are less likely to be selectively non-entered. Column 3 looks at the total number of insurers. Rural counties have fewer insurers, counties that are further away from metropolitan areas have fewer insurers, and counties whose rating area is constrained by a state line have fewer insurers. These patterns are consistent with previous descriptive evidence.

Column 4 examines the effects on log prices. Prices are higher in rural counties and counties that are further away from metropolitan areas, as we would expect from Table 1. They are also 4% higher in counties whose rating area is constrained by a state line, providing evidence that rating areas affect the prices that consumers pay.

It is possible that even absent rating areas, market conditions would be different in counties that are across state lines from their nearest metropolitan areas compared to those that are not. To evaluate whether this may be the case, I assess how balanced the two groups of counties are on observable characteristics, residualized for state fixed effects, an indicator for being rural, and the distance from the nearest metropolitan area. This balance table is available in Appendix Table A1. I find that the groups are largely balanced on observable characteristics, though there is weak evidence that the median income in cross-state counties is slightly lower than in non-cross-state counties. While this could lead to lower demand for health insurance and affect entry, there are no differences in the fraction of the population in the income bins relevant for exchange subsidies, which is perhaps the more relevant income metric.

I additionally check whether there are differences in market outcomes in the three states that establish rating areas at the county level. If there were large differences between counties that are and are not across state lines from the nearest metropolitan area, and those differences affect outcomes through a channel unrelated to rating area size and composition, these differences would exist in these states. In Appendix Table A4, I find no differences in rating area size or competition. There are small differences in price levels in the opposite direction of my main findings, suggesting that if there are differences in underlying conditions unrelated to rating area size, they are attenuating the results.

In Appendix Figure A1, I show that the results are robust to adding MSA fixed effects, dropping county controls, and dropping the restriction that only states that did not establish rating areas at the county level are included. I estimate additional specifications that use whether the county is part of an HRR that crosses state lines or an HSA that crosses state lines as the shifter for rating areas rather than whether the nearest metropolitan county is across a state line. Because HSAs are smaller and less frequently cross state lines, in this specification, the estimates are often much smaller, but not directionally different.

From this analysis, I conclude that rating areas affect both entry and pricing, but I cannot disentangle why these pricing effects occur. There are three mechanisms through which price changes could happen: (1) the direct effects of changing the composition of the rating area, which affects optimal pricing; (2) the effects of changing the number of insurers in the county itself (direct effects of competition); and (3) the effects of changing the number of insurers elsewhere in the county, given that insurers have to set uniform prices throughout the rating area (spillover effects of competition). To disentangle these equilibrium effects, I develop a model of insurer entry and pricing competition.

4 Model

I now develop a model of how insurance providers make entry and pricing decisions under a community rating system. I do so in a two-stage game in which firms maximize expected profits. In the first stage, insurers learn their realization of shocks to their fixed costs and then simultaneously make decisions about which markets to enter. In the second stage, taking entry decisions as given, firms learn their realizations of shocks to marginal costs and demand and then simultaneously set prices.

I solve the model backwards. In the second stage, I model how consumers make decisions about health insurance enrollment and recover marginal cost parameters from inverting the firm's first order conditions. In the first stage of the game, I take a revealed preference approach to entry decisions and use moment inequalities to recover parameters of fixed costs.

I model this entry decision as a static problem; entry into the individual market in one period does not affect the costs of entering into the market in future periods. This is reasonable in this setting since the exchange market is a relatively small part of most insurers' total enrollment (on average, 18% of their total enrollment). Lower entry costs in the future are likely to be related to network set up costs, which will be shared across exchange and non-exchange markets.

4.1 Stage 2: Demand

I model consumers as solving a discrete choice problem over insurance plans. Consumer i makes a decision about which plan j to buy from the choice set available to them in county m in year t, where the outside option is remaining uninsured. I model the consumer's indirect utility function, following the general set up of Polyakova and Ryan (2019):

$$U_{ijmt} = -\alpha_{d(i)} p_{ijmt} + \psi_{a(i)} + \gamma \cdot \mathbb{I}[y(i) \leq 250\% FPL] \times \mathbb{I}[AV_j = 70] + \delta_{jmt} + \epsilon_{ijmt} \quad (4)$$

I normalize the utility of the outside option, remaining uninsured, to zero. Consumers receive disutility from their demographic-specific prices, p_{ijmt}, which is the price that a consumer i pays for plan j in market m and time t taking into account the premium subsidies that are available and their age. The price sensitivity, $\alpha_{d(i)}$, varies based on the consumer's age and income.

Consumers receive an age-specific utility, $\psi_{a(i)}$, from being insured. This term captures all the utility differences between having any insurance plan and remaining insured, including the value of having insurance, the disutility of having to learn about the exchanges and pick a plan, and the financial penalty that applied prior to 2019 from the individual mandate. It varies by age to capture differences across consumers in how much they value insurance.

Consumers who are eligible for CSR subsidies (those with incomes less than 250% FPL) receive additional utility when they enroll in silver plans that are subsidized further. Their additional preference for these plans is captured by γ.

There is a mean level of market-specific utility provided by a plan δ_{jmt}. Separately, I further decompose δ using metal level, insurer, time, and place fixed effects (and interactions of these elements), as follows:

$$\delta_{jmt} = \alpha_{c(m)n(j)} + \tau_{c(m)t} + \alpha_m + \alpha_{c(m)v(j)} + \xi_{jmt} \tag{5}$$

where $c(m)$ indexes the rural classification of the county m, $\alpha_{c(m)n(j)}$ is a classification-specific insurer fixed effect, $\tau_{c(n)t}$ is a classification-specific year fixed effect, α_m is a county fixed effect, and $\alpha_{c(n)v}$ is a classification-specific metal level fixed effect. ξ_{jmt} is a disturbance term that will capture market-specific unobserved plan heterogeneity.

$\alpha_{n(j)}$ captures brand effects and different values from vertically integrated and non-vertically integrated health insurance plans. α_m captures differences across counties in the value of insurance, beyond the differences created by variation in the age-distribution across counties. τ_t captures differences across time in the value of having insurance, which is allowed to vary by rural status. This term will capture the elimination of the individual mandate penalty in 2019. $\alpha_{v(j)}$ captures the differences in the utility of various metal level plans. I allow the brand, actuarial value, and time fixed effects to vary with the county's classification as a metropolitan, metropolitan-adjacent, or rural county. Allowing these fixed effects to vary by county characteristics is particularly important for insurer fixed effects, as some firms may only have strong networks in urban areas. I do not include any additional financial features of plans, because the primary financial features of the plans are standardized in this setting.

Finally, consumers receive some unobserved demand shock ϵ_{ijmt}, which I assume to be distributed Extreme Value Type I. This specification leads to the standard logit choice probabilities for each consumer.

4.2 Stage 2: Firm Pricing Problem

In the second stage, insurers set prices simultaneously in a Nash-Bertrand pricing game. In the first stage of the game, firms choose a bundle b of counties to enter. Given this choice and the observed draws of demand shocks, ξ, and marginal cost shocks, ω, an insurer n chooses prices to maximize variable profits, given by:

$$\pi_{nbrt} = \sum_{m \in b} N_{mt} \sum_{d} w_{dmt} \sum_{v} s_{ndmvt}(p_{nvt}; \theta, p_{-nt}) \cdot (A_d p_{nvt} - C_d c_{nvmt})$$

where N_{mt} is the size of the market in county m in time t, w_{dmt} is the share of the market in county m in demographic group d, s_{ndmvt} is the market share for insurer n in demographic group d in market m of metal level v, p_{nvt} is the price that the insurer n sets for the metal level plan in the rating area, p_{-nt} are the prices all other insurers set in the market, θ is the parameters of consumer demand, A_d is the age multiplier (statutorily given), C_d is the demographic specific cost shifter, and c_{nvmt} is the county-level base cost to the insurer. I allow the cost of insuring consumers of various ages to vary linearly. Each consumer bin has a specific C_d that multiplies the base cost of insuring a consumer in a given market at a given metal level.

Firms take first order conditions and set them equal to zero. Prices will be equal to the marginal cost plus a mark-up that depends on the elasticity of demand.

4.3 Stage 1: Entry

In the first stage, insurers simultaneously make entry decisions about which bundle of counties to enter within each rating area. They do not yet know shocks to demand, ξ_{jmt}, or to marginal costs, ω_{jmt}, but they do know the distribution from which these are drawn. They form expectations of second period variable profits, $VP_{nrt}(b; b_{-n}, \theta, \xi, \omega)$ over these distributions where b is the bundle of counties that they choose to enter and b_{-n} are the bundles chosen by their competitors.

I assume that firms make entry decisions to maximize expected profits $\mathcal{E}[\Pi_{nbrt}(b_{-n}, \theta, \xi, \omega) \mid$

$\mathcal{J}_{nt}]$, where

$$\begin{aligned}\Pi_{nbrt}(b_{-n}, \theta, \xi, \omega) &= \sum_{m \in b} D_{nmt}(p_{nbt}; b_{-n}, \theta, \xi) \cdot (p_{nbt} - c_{nmt}(\omega)) - F_{nbrt} \\ &= VP_{nrt}(b; b_{-n}, \theta, \xi, \omega) - F_{nbrt}\end{aligned}$$

and $\mathcal{J}_{nt}$ denotes the information set of the firm at the time of their entry decision. More formally, I assume that:

Assumption 1. *Firms maximize expected profits. That is, for all insurers n in rating area r in time t, $\mathcal{E}[\Pi_{nbrt} - \Pi_{nb'rt} \mid \mathcal{J}_{nt}] \geq 0$, where b is the observed chosen bundle and b' is any alternative bundle.*

Assumption 1 states that firms maximize expected profits given their information $\mathcal{J}_{nt}$ at the time of their entry decision. It allows firms to make expectational errors with respect to fixed costs.[11] For instance, firms could underestimate the difficulty of negotiating insurance contracts with a particular hospital. I denote these expectational errors ν_1.

Firms simultaneously make entry decisions to form a Nash equilibrium where there are no profitable unilateral deviations.

5 Estimation

I estimate this model in the setting of the state-run exchange in Oregon. Oregon is a good setting to study for two reasons. First, the availability of data on enrollment both on and off the exchange and on claims from their APAC database is helpful in estimating the parameters of the model. Second, Oregon's requirement to offer three standardized plans with limitations on additional plans helps to justify the focus on the entry decision, rather than a plan menu design problem, in this model.

Table 3: Summary Statistics: Counties in Oregon

	Mean	Min	Max
a. Market Characteristics			
Market Size	11,293.13	140.00	89,374.00
# Insurers	3.33	1.00	7.00
% Enrolled	32.48	11.99	58.66
% of Enrollees in Silver	58.19	33.76	80.49
Benchmark Price	4,055.16	2,556.00	5,258.40
% Partial Non Entry	73.61	0.00	100.00
# Insurers Partial Non-Entry	1.08	0.00	3.00
% Post-HS	60.03	40.51	81.54
b. Demand Demographics			
% Market $<$ 18	11.91	1.59	26.11
% Market 18–34	29.41	7.14	58.57
% Market 35–54	34.61	15.24	44.61
% Market $\leq$ 250 FPL	59.97	48.35	70.32
% Market 250–400 FPL	25.07	18.35	34.04
c. Marginal Cost Characteristics			
Average Claims	3,789.44	1,411.07	12,760.36
Population	112,746.23	1,344.00	807,555.00
Household Income	48,923.79	33,387.00	80,845.00
% Female	49.94	45.40	52.18
% White	89.10	69.49	96.15
% Black	0.79	0.00	5.47
% Hispanic	11.77	1.90	35.88
% HS	28.78	13.89	38.47
Number of Doctors	419.56	0.00	5,821.00
Number of Hospitals	1.80	0.00	9.00
d. Fixed Cost Characteristics			
# ECPs	6.65	1.00	39.00
% Off Exchange Entry $t-1$	73.53	44.44	100.00
Number of Counties	36		

Notes: This table presents summary statistics on the market characteristics and inputs to the structural model estimated in this paper for counties in Oregon. Market demographics comes from the ACS and SAHIE. Average claims comes from the Oregon All Payer All Claims database. Health care characteristics come from the AHRF.

5.1 Data

Table 3 reports summary statistics for counties in Oregon from 2016-2019.[12] There are 36 counties grouped into 7 rating areas in the state. On average, there are 3.3 insurers selling insurance in each county, with lower levels of competition in later years. In 2016, 9 insurers participated in the Oregon exchange; by 2019, this dropped to 5. In 74% of county-year observations, there is a partial entry. Because this partial entry is concentrated in lower population counties, this corresponds to about a third of consumers experiencing a partial entry.

Data on plan market shares comes from the Oregon insurance regulator.[13] These data contain information on insurer-metal level at the zip code level, which I aggregate to the county level. I define the market size as being all consumers who purchase exchange insurance plus all consumers who remain uninsured. Data on the uninsured comes from the Census' Small Area Health Insurance Estimates (SAHIE). The insurance regulator also provides information on off-exchange enrollment, which can be used to create a measure of whether an insurer was active in a geographic area outside of the exchange.

As in the national sample, information on pricing comes from the QHP Public Use files from CMS. From the CMS Public Use Enrollment files, I construct a measure of the fraction of consumers with incomes $\leq$ 250% FPL who enroll in silver plans. I also use the CMS enrollment files in conjunction with the American Community Survey (ACS) and SAHIE to measure the fraction of the market in various age and income bins and the fraction in each group who are uninsured. Refer to Appendix B for a further description of how I construct these shares. To estimate marginal costs, I use county demographics and health information, as well as claims for all insurers at the county-metal level that come from the Oregon All Payer All Claims database. These data are censored for county-metal levels that have fewer than 10 individuals enrolled. Finally, I use data from CMS on the number of Essential Community Providers (ECPs). Insurers are required to contract with a certain percentage of these providers to operate on the exchange, which will affect the fixed costs of operating a plan.

[11] These could also be interpreted as errors in firm's expectations of variable profits. This would be mathematically equivalent, but complicate the notation.

[12] I start the analysis in 2016 because Oregon fully managed their exchange in 2014 and 2015 and shifted enrollment to healthcare.gov in 2016, potentially changing enrollment patterns. Excluding the first two years of operation also means that the market is more stable in the years I am studying. I end the analysis in 2019 to avoid complications arising from the coronavirus pandemic.

[13] Data downloaded from http://www4.cbs.state.or.us/ex/imd/reports/rpt/index.cfm?ProgID=UM8903.

5.2 Demand

I estimate demand using a generalized method of moments (GMM) estimator. I use the standard Berry (1994) inversion and exactly match plan market shares. I construct moments based on two instruments for price, shares enrolled in the outside option for various demographic groups, and the share of consumers eligible for cost-sharing reductions (CSR) who enroll in a silver plan. These micro moments help identify different price sensitivities across different groups, different valuations for insurance, and heterogeneous preferences for silver plans. I do not allow for further unobserved heterogeneity in the sensitivity to price as it would be difficult to identify how this heterogeneity varies across geographic space, which is crucial in this setting.

Combined, these give me 20 moments based on the enrollment patterns of various demographic groups (4 from the outside option enrollment based on age, 3 from outside option enrollment based on income, 12 from outside option enrollment based on age-income, 1 from silver enrollment of low income consumers). I additionally instrument for price using the county-level price of the benchmark plan and the share of the market in the oldest income bin. These shift prices due to the regulations around price setting: the price of the benchmark plan will shift the level of subsidies available for consumers, and the share of the market in the oldest income bin will change the optimal pricing of the plan for reasons unrelated to unobserved plan quality.

I aggregate consumer demographics to 12 bins made up of 4 age bins (0-17, 18-34, 35-54, 55-64) and 3 income bins ($\leq$ 250% FPL, 250-400% FPL, $>$ 400% FPL). For each age bin, I assign the median age rating curve multiplier. For consumers in the $\leq$ 250% FPL, I assign IRS expected contributions associated with an individual with an income of 200% FPL, reflecting the fact that consumers with lower incomes are eligible for Medicaid in Oregon. For consumers with incomes in the range 250-400%, I assign the IRS expected contributions for individuals with incomes of 300% of the FPL.[14]

These demographic groupings were chosen to reflect reported demographics in the CMS Public Use Enrollment files. I use these files in conjunction with the Small Area Health Insurance Estimates to construct both the shares of the market in each demographic group and the share of each demographic group enrolled in the outside option. I additionally construct outside option market shares for each age-income demographic group for a subset of counties that are sufficiently large, using the 1 year ACS microdata from the IPUMS USA

[14]The expected percentage of income contributed to health insurance premiums is flat between 300 and 400% of the FPL.

Database (Ruggles et al. (2021)). More details on how I construct outside option market shares are provided in Appendix B.

Estimation follows Berry et al. (2004). This estimation is implemented using a MPEC following Dube et al. (2012) as follows:

$$\min_{\theta,\xi} g(\delta)' W g(\delta)$$
$$\text{s.t. } \hat{s}_{jm}(AV, p, \delta; \theta) = s_{jm} \ \forall\ j, m$$

where $\theta = (\alpha_{d(i)}, \psi_{a(i)}, \gamma)$ and $g(\delta)$ contain my instrumental variable moments and my demographic micro-moments.

5.2.1 Identification

Berry et al. (1995) established that, conditional on individual-specific components of utility, there is a unique δ that maps to plan enrollments. I treat insurer characteristics and non-price plan characteristics as independent from ξ, unobserved plan quality. I justify this because non-price financial plan characteristics are set by the regulator and ξ is realized after entry costs are paid, which will affect network (and thus plan) quality. To address price endogeneity, I use variation in actual prices paid created by regulatory features of the ACA, following the existing literature on the exchanges (Saltzman (2019), Tebaldi (2022), and Polyakova and Ryan (2019)).

Because of the income-based nature of subsidies and age-rating, there is within-market variation in prices across consumers with different demographic characteristics. I observe the share of consumers who buy any plan by age and income bins so I can measure variation within market in enrollment patterns across ages and incomes. Then, the variation in enrollment patterns within market across demographic groups identifies the disutility of price, $\alpha_{d(i)}$. Similarly, $\psi_{a(i)}$ is identified by variation across ages in enrollment in the outside option. This variation will be exogenous as long as consumers do not sort across counties in response to market regulations.

I also leverage the cross-market variation in prices that arises from regulations. The price that consumers pay for a plan will depend on the price of the benchmark plan, which may vary within rating areas because of different insurers operating in different counties. As a reminder, prices are established at the rating area level. Thus, consumers in different markets may face different prices for the same plan unrelated to unobserved plan characteristics. I also leverage that prices are constrained for different age groups. Given that older consumers are less price elastic, markets where the pool of consumers is older will have higher prices for plans with identical characteristics. I include the price of the benchmark plan and the share of the market in the oldest income group as instruments for additional variation that further aids in the identification of the disutility of price.

Finally, I identify the marginal willingness to pay for silver plans for those who receive cost-sharing reductions, γ, using variation in the share of consumers who enroll in silver plans who are eligible for cost-sharing reductions across markets with different prices, and relative to enrollment patterns of consumers who are not eligible for cost-sharing reductions.

5.3 Marginal Costs

Because prices are set at the bundle-level, inverting the firm's first order conditions yields an expression for marginal costs at the bundle-level that are a function of prices, shares, and the derivative of shares with respect to prices. Thus, with demand estimates in hand, I can recover bundle-level estimates of marginal costs. However, I model marginal costs as varying across counties within a rating area. It is not possible to simply back out county-level marginal costs from prices and implied mark ups. Instead, I use the fact that for a risk-neutral insurer, costs at the bundle-level will be the weighted average of costs at the county-level.

This fact allows me to use a three-step process to estimate county-level marginal costs. In the first step, I take first order conditions where marginal costs are evaluated at the bundle-level rather than the county-level.[15] I assume that the age curve captures the differences across age bins in the cost of insuring consumers such that $C_d = A_d$.

In the second step, I project the bundle-level marginal cost estimates on bundle-level observable characteristics as follows:

$$c_{nbvt} = \alpha_n + \alpha_v + \tau_t + \beta_1 \text{Claims}_{bt} + \beta_2 V_{bt} + \beta_3 V_{bt} \cdot \mathcal{I}[VI_n] + \omega_{nbv} \tag{6}$$

where c_{nbvt} is the marginal cost for insurer n in bundle b for metal level v in year t, α_i are insurer fixed effects, α_v are metal level fixed effects, τ_t are year fixed effects, Claims_{bt} are

[15] Due to low enrollment in some bronze and silver plans, the implied elasticities for these plans are very close to zero, which implies implausibly high mark ups on these plans. To address this, I use the first order condition only for silver plans, which do not suffer from the same low elasticity problem, and impose a ratio of costs between bronze, silver, and gold plans that is equal to the the difference in actuarial values between these plans. Imposing this ratio is reasonable given the presence of risk adjustment in this market, which attempts to ensure that the differences in costs between plans is not related to selection into different metal levels.

average claims for the bundle for exchange plans in county n, V_{bt} are the weighted average of health characteristics of the bundle, and $\mathcal{I}[VI_n]$ is an indicator for the firm being vertically integrated. V_{bt} includes the County Health Rankings z-scores for health outcomes and health factors; the number of doctors; the number of hospitals; the share of the population that are White, Black, Hispanic, have high school educations, have more than a high school education; the population, and median household income. More details are available in Appendix C. I weight these regressions by plan enrollment.

Finally, once I have estimates of the parameters in Equation 6, I construct county-specific marginal costs by applying these estimates to county characteristics. In particular, I calculate c_{nmvt} as:

$$\hat{c}_{nmvt} = \hat{\alpha}_n + \hat{\alpha}_v + \hat{\tau}_t + \hat{\beta}_1 \text{Claims}_{mt} + \hat{\beta}_2 V_{mt} + \hat{\beta}_3 V_{mt} \cdot \mathcal{I}[VI_n]$$

5.4 Fixed Costs

Firms simultaneously decide which counties to enter, forming a Nash equilibrium in entry decisions. In this Nash equilibrium, taking rivals' actions as fixed, there are no profitable deviations that firms can make in terms of their entry decisions. In particular, there is (1) no county that firms could enter that they do not currently enter that would make them higher profits in the rating area overall than their current entry decisions, and (2) no county that they currently enter where they would make higher profits by not entering. For computational reasons, I consider only these one county deviations.

Under the assumption of no profitable unilateral deviations, I form revealed preference inequalities from firms' observed entry decisions that provide upper and lower bounds on fixed costs. For notational simplicity, I proceed using θ to denote all the non-fixed cost parameters in the model.

For counties that are entered:

$$F_{nmt} \leq E[VP_{nt}(b_{nt}; b_{-nt}, \theta) - VP_{nt}(b_{nt} - 1^m; b_{-nt}, \theta)] = \overline{F_{nmt}}(\theta)$$

Analogously for products that aren't entered:

$$F_{nmt} \geq E[VP_{nt}(b_{nt} + 1^m; b_{-nt}, \theta) - VP_d(b_{nt}; b_{-nt}, , \theta)] = \underline{F_{nmt}}(\theta)$$

These inequalities can be used to find bounds on fixed costs. I assume the following functional form for fixed costs:

$$F_{nbrt} = F_{nrt} + \sum_{m \in b} F_{nmt}$$

where F_{nrt} are the regulatory and marketing costs of offering a plan in rating area r and F_{nmt} are the costs of setting up a network for county m. I assume that $F_{nrt} = F_R$ for all rating areas and insurers.[16]

I further decompose the components of the fixed costs of entering into a county m as follows:

$$F_{nmt} = \alpha + \beta \cdot \mathcal{I}[\text{Presence}]_{nm,t-1} + \gamma \text{ECP}_m + \nu_1 + \nu_2$$

where $\mathcal{I}[\text{Presence}]_{nm,t-1}$ is an indicator for whether the firm had a presence in the market off-exchange, and ECP_m is the normalized number of essential community providers in the county. To offer insurance on the exchanges, firms must contract with a certain percentage of these providers.

ν_1 is a mean zero expectational error term that is unknown to firms at the time they make their entry decisions. Including this term allows the model to rationalize instances where it would otherwise predict that a firm should enter into a given county, but they do not enter.

Following the notation introduced in Pakes et al. (2015), ν_2 is an error term that is known to firms at the time they enter, but is not known to the econometrician. ν_2 allows for fixed costs to vary across markets and firms in ways that are not otherwise captured by this parameterization. However, the presence of this term introduces a selection problem. Firms that receive high draws of ν_2 will be less likely to enter. Therefore, conditional on observing whether firms enter, ν_2 will not be mean zero.

5.4.1 Identification

The primary challenge in identifying fixed costs comes from the presence of the structural error term, ν_2. To address this problem, I make two additional assumptions following Eizenberg (2014).

[16] This assumption requires that the costs of actuaries and interacting with the regulator are the same regardless of the size of the rating area, the characteristics of the insurer, or time. Relaxing this assumption would pose challenges as far as being able to identify reasonably sized bounds in a moment inequalities approach.

Assumption 2. *There is bounded support for fixed costs.*

$$\sup_{n,m}\{F_{nmt}\} = F_t^U < \infty, \inf_{n,m}\{F_{mnt}\} = F_t^L > -\infty$$

Assumption 2 implies that there is some finite level of profitability that would induce all firms to enter into each county. Fixed costs being bounded below is not a strong assumption given that we typically would expected fixed costs to be positive.

Assumption 3. *The support of the bounds on fixed costs is in the support of the expected change in variable profit that results from the entry or non-entry of a single county in a given year t. That is,*

$$[F_t^l, F_t^U] \subset \textit{supp(expected change in variable profit due to entry} \\ \textit{or non-entry of a single firm in a county in year } t)$$

Assumption 3 requires that any firm would (weakly) enter a given county if entering that county was as profitable as entry into a single county for the most profitable county-firm combination for a given year. This assumption explicitly ties together variable profits and fixed costs.

Let $[V_t^L, V_t^U]$ denote the support of the expected changes in variable profits. Then,

$$L_{nmt}(\theta) = \begin{cases} V_t^L(\theta) & m \in b_{nt} \\ \underline{F_{nmt}}(\theta) & m \notin b_{nt} \end{cases}$$
$$U_{nmt}(\theta) = \begin{cases} \overline{F_{nmt}}(\theta) & m \in b_{nt} \\ V_t^U(\theta) & m \notin b_{nt} \end{cases}$$

where

$$L_{nmt}(\theta) \leq F_{mnt} \leq U_{nmt}(\theta)$$

I then apply an unconditional expectation to obtain bounds on $\alpha + \beta \cdot \mathcal{I}[\text{Presence}]_{nm,t-1} + \gamma \text{ECP}_m$ that do not depend on whether or not a market was entered. These expectations do not suffer from the selection problem outlined above.

The various parameters will be identified by different decisions made either in places with different characteristics or by different firms. The key variation to identify F_R comes from expected variable profits in rating areas where firms enter no counties or in rating areas where firms only enter into one county. F_R will be identified by the extent to which these profit deviations are different from profit deviations that do not involve entering or exiting a rating area altogether. Similarly, β will be identified by the difference in profit deviations for firms that do have an off market presence and those that do not have an off market presence, and γ by the differences for counties with different numbers of essential community providers.

There are several alternative solutions to this selection problem in the literature. Ciliberto and Tamer (2009) are able to estimate a distribution for the structural error term. While the Ciliberto and Tamer (2009) approach is generally useful in entry settings, it is computationally challenging in this setting since the entry decision is more analogous to a product positioning decision than a binary entry decision. Fan and Yang (2021) develop moment inequalities that allow the estimation of the distribution of sunk costs in settings with product positioning; however, their inequalities require the identification of the best and worst case situations in terms of actions your rivals can take. Identifying these in my setting is a non-trivial problem, since the worst case scenario may not be full entry, but a selective entry decision by your rivals.

Another strand of the literature restricts how the structural error term ν_2 is allowed to vary across observations (Wollmann (2018)). This approach is unattractive in this setting because it limits the ability to identify parameters that are common across firms, markets, or years. In particular, it makes identifying a common fixed cost parameter α challenging.

There are two main drawbacks to my approach. The first is that I assume that fixed costs are related to variable profits, which may not hold for vertically integrated firms in certain markets. The second is that I am unable to estimate a distribution of fixed cost shocks for use in counterfactuals and must make some ad hoc assumptions in order to incorporate fixed cost shocks into counterfactual analysis.

Vertically Integrated Insurers

Vertically integrated insurers will have very different fixed cost structures to other insurers. Rather than just negotiate prices with providers in a given area, expansion into a new geographic area will require building or buying office practices, hospitals, etc. These investments are likely not made on an annual basis, but based on expected profits for years to come. These profits will include both the profits from the exchanges, but also from the bigger commercial market, which is beyond the scope of this project. For this reason, I exclude from my estimation of fixed costs vertically integrated insurers in counties where they have never had a presence, either on or off exchange, during my sample period. In counterfactuals, I restrict vertically integrated firms from entering markets where they have no presence. This restriction is analogous to holding networks of vertically integrated systems fixed, which is common in the literature (for example, Ho and Lee (2019)).

5.4.2 Moments and Inference

I form two primary sets of moment inequalities: those associated with entry deviations and those associated with exit deviations. Denoting the data by W_i, I take expectations of these moments:

$$m_1(W_i, \alpha, \beta, \gamma, F_r) =$$
$$\frac{1}{NMT} \sum_m \sum_t \sum_n L_{nmt} - (\alpha + \beta \mathcal{I}\text{Presence}_{nm,t-1} + \gamma \text{ECP}_m)$$
$$m_2(W_i, \alpha, \beta, \gamma, F_r) =$$
$$\frac{1}{NMT} \sum_m \sum_t \sum_n (\alpha + \beta \mathcal{I}\text{Presence}_{nm,t-1} + \gamma \text{ECP}_m) - U_{nmt}$$

I create further sets of inequalities by interacting with "instruments", which must be uncorrelated with the structural error term (Pakes et al. (2015)). The instruments I include are indicators for the county having a high number of ECPs and indicators for the insurers having a presence in the rating area, being vertically integrated, and being in the market the previous period as well as interactions of these terms. Because of how I handle the selection term, these instruments will satisfy the necessary conditions.

Once I construct these inequalities, I evaluate each inequality over a grid of $\alpha, \gamma, \beta, F_R$ and calculate a test statistic for each value of the parameters. Specifically, I test the null hypothesis:

$$H_{\alpha,\beta} = E[m(W_i, \alpha, \beta, \gamma, F_R)] \leq 0$$

Following Chernozhukov et al. (2019), which discusses inference with a large number of moment inequalities, I use the following test statistic:

$$T_n^{\max}(\theta) = \max[\max_j \frac{\sqrt{n}\overline{m}_{n,j}(\theta)}{\hat{\sigma}_{n,j}}, 0]$$

where $\theta = \alpha, \beta, \gamma, F_R$, n indexes the number of underlying observations in each inequality, and j indexes the different inequalities. I reject the null hypothesis when the test statistic is greater than the critical value to create the confidence set. To compute the critical value, I use the self-normalized method discussed in Chernozhukov et al. (2019) with the following critical value:

$$c^{SN}(\alpha) = \frac{\Phi(1-\alpha/p)}{\sqrt{(1-\Phi^{-1}(1-\alpha/p)^2/n}}$$

where Φ is the distribution of the standard normal distribution, Φ^{-1} is its quantile function, α is the size of the test, and p is the number of moment inequalities.

6 Results

6.1 Demand

Table 4 shows estimates for the parameters of my demand model. I find that low-income consumers are the most price sensitive. This higher price sensitivity holds across all age groups. The drop in price sensitivity is largest moving between <250% FPL and 250-400% FPL. For older consumers, I still see a drop in price sensitivity between consumers with 250-400% FPL and >400% FPL.

Across all income bins, somewhat surprisingly, young adults are the least price sensitive (18-34) and middle-aged (34-54) adults are the most price sensitive, followed by children. These patterns may reflect the fact that while I do not observe households, insurance decisions are made at the household level, rather than the individual level. These middle-aged consumers are most likely to have dependent children who are on the same insurance plan. The oldest consumers are the least price sensitive.

The estimate of the intercept varies with age. I find that the consumers who value having any insurance the most are middle-aged adults, and the consumers who value insurance the least are young adults. Middle-aged adults are more likely to be purchasing insurance for a household, so it is not surprising that they value insurance highly.

I estimate that low income consumers of ages <18, 18-34, 34-54, and 55-64 relative to other consumers value a silver plan an additional $684, $1,347, $443, and $876, respectively. This magnitude is reasonable as the cost sharing subsidies represent a 3-24 percentage point increase, depending on income, in the actuarial value of plans. For some consumers, these subsidies will be the equivalent of moving from a bronze to a silver or a bronze to a gold plan. For comparison, the average base price of a bronze plan is $3,024, a silver plan is $3,820, and a gold plan is \$4,400, so this additional valuation of subsidized plans by consumers is consistent with the increase in coverage that they get by enrolling in silver plans.

In Appendix B, Table B1 shows estimates of the key coefficients of Equation 5. Silver plans are surprisingly valuable, given that low income consumers also receive additional utility from enrolling in a silver plan. Both silver and gold plans are valued more highly by consumers relative to bronze plans. There is considerable heterogeneity in the brand effects of insurers, as well as in how these effects vary by the geographic classification of the market.

I use these estimates to construct own-price elasticities. Figure 4 displays these elasticities across geographic space, exploring both variation in elasticities within a demographic group (subfigure a) as well as the variation that results from different age and income distributions across geographies (subfigure b). There is considerable variation across the state both in the average elasticity within a demographic group and the average overall elasticity. This variation exists within rating areas as well as across rating areas. The average elasticities across all consumers at the county level range from -3.2 to -4.5, which are consistent with other estimates in the literature. Appendix B.2 contains more discussion of the distribution of elasticities across plans and space.

Table 4: Main Demand Estimates

	Mean	Age <18	Age 18-34	Age 34-54	Age 54-65
Coefficient on premium (α), \$1Ks	-				
Income $\leq$ 250%	-	3.575	1.769	6.012	2.806
		(0.131)	(0.832)	(0.527)	(0.197)
Income 250-400%	-	0.613	0.193	1.218	0.351
		(0.010)	(0.426)	(0.044)	(0.005)
Income > 400 %	-	0.702	0.547	0.720	0.116
		(0.010)	(0.422)	(0.029)	(0.002)
Age-specific intercept (ψ)	-	0.660	-1.327	2.085	0.438
		(0.020)	(1.395)	(0.131)	(0.015)
Silver Boost (γ)	2.506	-	-	-	-
	(0.192)				

Notes: This table shows results of the logit choice model. Consumers receive utility following Equation 4. Standard errors shown in parentheses.

6.2 Marginal Costs

Subfigure (c) of Figure 4 shows the base county-level estimates of marginal costs for silver plans. These costs can then be scaled by the age of the consumer to get total marginal costs. Comparing these costs to the map of population density in subfigure (d), there is an inverse relationship between marginal costs and population density. There is considerable variation across geographic space, even within rating areas, in the marginal cost of insuring consumers in different counties. The average marginal cost of a silver plan at the county level varies from around $2,400 to $5,700.

Recall that these marginal cost estimates are the result of a three step procedure. I show the estimates from the intermediate steps in Appendix C. I additionally discuss the sensitivity of the results to inclusion of alternative characteristics in the projection onto bundle-level characteristics; the end-estimates are highly correlated across specifications.

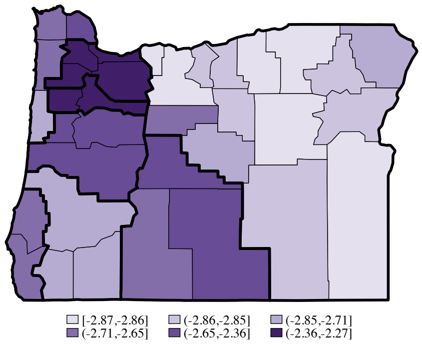
Figure 5 shows the distribution of marginal cost predictions split by whether the county was entered. I find higher marginal costs estimates on average for counties where insurers chose not to enter relative to places where they did enter. In Appendix C, I explore this further in a regression framework and find that counties with higher marginal costs, a more inelastic consumer base, or higher populations are more likely to be entered and are less likely to be partially non-entered when the insurer enters elsewhere in the rating area.

6.3 Fixed Costs

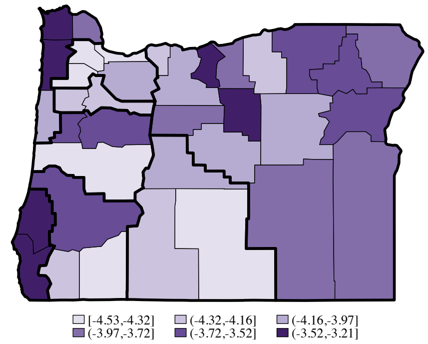
To estimate fixed costs, I first simulate variable profits for both observed entry decisions and one-county deviations from the observed decisions. I do so by drawing demand and marginal cost shocks from the the empirical distributions of shocks, shown in Appendix Figure D1, then finding the pricing equilibrium[17] and calculating firm profits. These distributions of expected profits are shown in Appendix Figure D2.

[17]Because of low enrollment in many gold plans, the implied equilibrium prices for these plans if left unrestricted would be much higher than would be allowed by the regulator. I restrict prices of bronze and gold plans to be a constant multiplier of the price of the silver plans. I use the observed multipliers between bronze, silver, and gold prices from the data. I handle this issue similarly to how I handle it with marginal costs. This imposition can be justified by the institutional details of this setting. While I model pricing decisions as occurring independently in each rating area, in practice, a base price for the plan is set state-wide and insurers set a geographic multiplier. There will be a constant ratio of prices across all the rating areas that the insurer enters. I further impose a limit on the ratio of costs to prices of .65 to handle residual cases where there is very low enrollment in an insurer's plans. This restriction allows my estimated equilibrium prices to be similar to observed prices; while MLR regulations are imposed at the insurer-state level, it is unlikely that the regulator would approve such high mark ups even for a subset of markets.

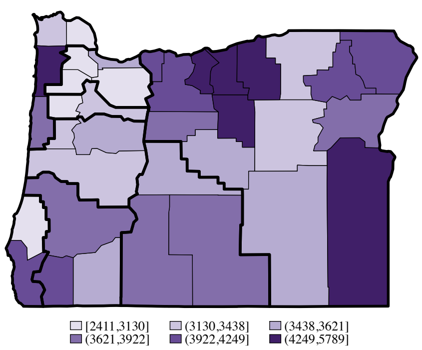
Figure 4: Elasticities and Marginal Costs Across Geographic Space



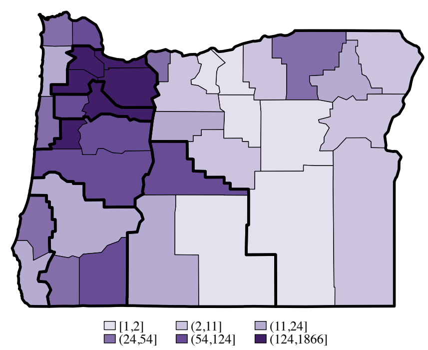
(a) Average Silver Level Elasticities: Consumers 18-34, > 400% FPL



(b) Average Silver Level Elasticities: All Consumers



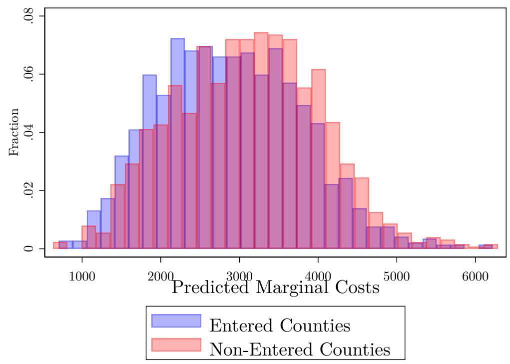
(c) Marginal Cost Estimates



(d) Population Density

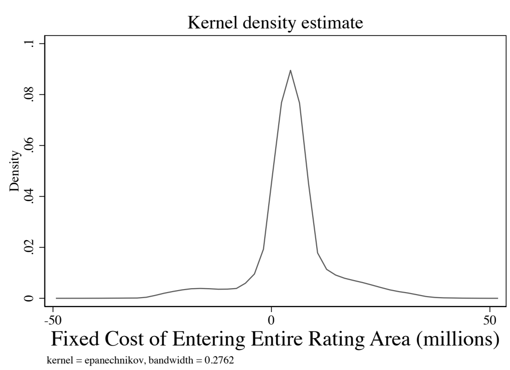
Notes: Subfigure (a) shows the average elasticity for silver plans for consumers 18-34 with incomes > 400% FPL in 2018 at the county level in 2-10. This variation is largely coming from variation across space in the prices and enrollment of offered plans. Plans are equally weighted in calculating the average. Panel (b) shows the average elasticity of silver plans for all consumers in 2019 at the county level. This panel adds to Panel (a) variation that comes from the variation in the age and income distribution across geographic space. These are calculated by weighting plans equally and using the market average of the shares in each demographic group. Panel (c) shows the marginal cost estimates for the silver plan in 2019. Panel (d) shows the population density of each county in Oregon. Population density data comes from the 2014-2019 ACS 5-Year Estimates.

Figure 5: Distribution of Marginal Cost Predictions By Entry Decisions



Notes: This figure shows the distribution of county level marginal costs estimates for counties that were entered and counties that were not-entered. These estimates are calculated using the estimates from the projection of marginal costs recovered from the inversion of first order conditions on rating area characteristics.

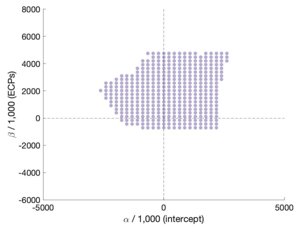
Figure 6: Distribution of Fixed Cost Estimates



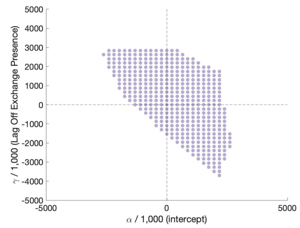
Notes: This figure shows the distribution of rating area fixed cost estimates calculated across rating areas, firms, years, and parameters in the 95% confidence region.

Figure 6 shows the distribution of fixed costs within the 95% confidence region, calculated at the rating area level and assuming that the firm enters every county in a rating area. The vast majority of these estimates are positive (although not all); the estimates primarily fall in the 1 to 12 million dollar range.

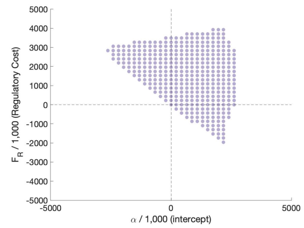
Figure 7: Fixed Cost Parameter Estimates



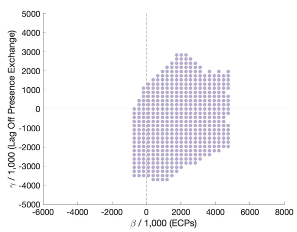
(a) α v. β



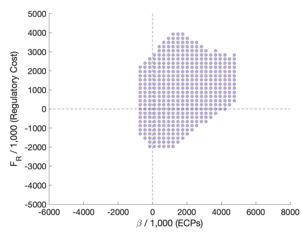
(b) α v. γ



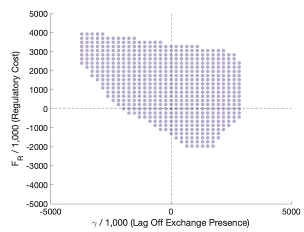
(c) α v. F_R



(d) β v. γ



(e) β v. F_R



(f) γ v F_R

Notes: This figure shows the confidence region projected into two-dimensional space of fixed cost parameters. Purple dots indicate vectors where the null hypothesis was not rejected. To find this set, the test statistic was calculated over the entire grid shown in these figures. This grid was a 45x45x45x45 grid over potential parameter values. Subfigures (a)-(c) show slices of the confidence region for α, the intercept term for entering a county. Subfigures (a), (d), and (e) show slices of the confidence region for β, the coefficient on the number of essential community providers. Subfigures (b), (d), and (f) show slices for γ, the coefficient on the indicator for having a presence off-exchanges in a market in time $t-1$. Subfigures (c), (e), and (f) show slices for F_R, the regulatory cost of entering a rating area.

Figure 7 shows the two dimensional views of the confidence regions for parameter estimates. These represent slices of a four dimensional hyperplane in parameter space and illustrate how values of parameters in the confidence region co-vary. The estimates of β, the coefficient on the number of essential community providers, is almost always positive and relatively small. In most estimates, firms with an off exchange presence in the previous period have lower fixed costs. This parameter is negatively correlated with α, the constant term. I can reject large values of F_R, although the confidence region is wide and contains both positive and negative values.

7 Effects of Alternative Regulations

With estimates of the model of firm decision-making in hand, I validate that the model predicts entry and pricing patterns in a reasonable way, then evaluate the effects of different policy counterfactuals. I first analyze counterfactual policies that ban partial entry. I start by evaluating outcomes holding current rating areas fixed, then vary the size of rating areas. Comparing these counterfactuals illustrates how market size matters for entry and pricing decisions, but by design does not account for partial entry. I then quantify the trade-offs associated with increasing market size when partial entry is allowed by simulating outcomes in two county rating areas and comparing to outcomes in one county rating areas.

7.1 Model Validation

One challenge in establishing the credibility of counterfactuals is that I am unable to simulate entry decisions under status quo policies due to the number of potential equilibria to evaluate. In a three county rating area, firms have 8 possible choices of bundles of counties to enter, with 8^5 potential equilibria to evaluate. This number only grows as rating areas get larger.[18]

Given this computational constraint, I evaluate the fit of the model in two ways. First, I hold entry decisions fixed and simulate prices.[19] I show the results of this exercise in Table 5. Column 1 shows summary statistics in the status quo. Column 2 shows the model estimates. The model matches well on both the percent enrolled in the market and the average price of silver plans, but slightly underestimates the level of price variation, calculated as the standard deviation across counties of the average price of silver plans.

The next exercise is to estimate entry decisions in rating area 3, which only has two counties. Here, partial entry is possible, but the number of possible equilibria is still sufficiently small that I can iterate through all possible equilbria. In 2019, I observe three firms making a full entry (Kaiser, Moda, and Providence), and two firms that do not enter anywhere (Bridgespan and PacificSource). In the model, I find one equilibrium, where Kaiser, Moda, and PacificSource enter, with Moda making a full entry and Kaiser and PacificSource entering partially.

[18] The largest rating area has 15 counties, with $32,768^5$ possible equilibria.

[19] As part of this simulation, I draw vectors of demand and marginal cost shocks and find the Nash pricing equilibrium.

Table 5: Counterfactual Estimates

Outcome	Observed	Model	No Partial Entry	County RAs	Two County RAs
Number of Firms	2.47	.	3.39	2.14	2.42
# Markets Without Entrants	0	.	0	9	5
Avg. Enrollment	30.31%	33.79%	27.32%	21.98%	25.51%
Avg. Silver Price	4740.23	4710.51	4885.84	4939.45	4880.93
Avg. Min Silver Price	4541.04	4346.52	4283.70	4355.34	4368.48
Avg. Max Silver Price	4922.33	5067.64	5593.21	5606.74	5469.53
Std Dev Avg. Silver Price	384.54	207.73	390.40	864.42	750.63
Avg. Subsidy Per Enrollee	.	5411.54	4386.98	4819.55	4896.79
Avg. CS ($)	.	651.30	778.42	596.66	666.24
Avg. Variable Profits (millions)	.	4.50	3.94	3.69	3.64
Total Subsidies (millions)	.	546.82	419.97	414.86	452.73
Total CS (millions)	.	274.44	303.51	270.31	290.92
Total Variable Profits (millions)	.	162.04	141.82	136.44	130.89

Notes: This table presents results of counterfactual simulations compared to the status quo estimate. Column 1 reports the observed values in the data. Column 2 reports the model estimates, holding entry decisions fixed. Columnn 3 reports the estimates from a a counterfactual policy that holds rating areas fixed, but requires insurers to enter either every county in a rating area or not enter the county (no partial entry). Column 4 reports the estimates from a counterfactual that sets rating areas at the county level. It removes the grouping of counties together. Column 5 reports the estimates from a counterfactual that creates rating areas out of two adjacent counties. Firms are allowed to make partial entry decisions. Prices are calculated conditional on entry and are the base prices (before age rating).

7.2 Elimination of Partial Entry

It is ambiguous whether eliminating the ability for firms to make a partial entry decision will increase or decrease net entry in insurance markets.[20] If the counties that firms enter when partial entry is allowed are sufficiently profitable, it would be better for firms to continue to serve the entire rating area. However, if entry into the selectively non-entered county will cause the firm to lose money in the overall rating area, then requiring full entry could cause firms to exit the rating area altogether. The effects on equilibrium prices are also ambiguous: more entry could drive prices down, but marginal firms may set prices higher.

I simulate the market from 2019[21] with current rating areas and the additional restriction that firms may not partially enter. To calculate fixed costs, I take the median value of α, the intercept term. Then, conditional on this value, I take the median values of each additional parameter in the fixed cost parameter confidence region. The resulting vector is contained within the confidence region.[22] I allow for fixed cost shocks, with mean zero and variance equal to 5% of the fixed cost for that firm-county pairing. I identify entry equilibria where no firm may make a unilateral profitable deviation. As previously discussed, I only allow Kaiser to enter markets where they already have an off-exchange market presence.[23] One benefit of the moment inequalities approach is that it allows for the possibility of multiple equilibria. I assume all equilibria are equally likely to occur and average outcomes across equilibria. I discuss the prevalence of multiple equilibria in Appendix E.

Table 5 reports the estimates from this counterfactual in Column 3. The average number of entrants increases relative to the observed number of entrants, suggesting that the profitability in places where firms make a partial entry decision is sufficient to overcome the lack of profitability in places firms selectively non-enter in the status quo. One factor driving this result is that the counties in Oregon that are selectively non-entered are relatively small in terms of market size relative to those that do not experience a partial entry.[24] In places

[20] This counterfactual is of considerable policy interest. It is plausible to think that states might choose to remove the ability to partially enter, as this regulation is in place in California. California acts as an active purchaser on its exchanges and does not allow partial entry, among other additional regulations it places on insurers.

[21] Five firms entered in 2019: Bridgespan, Kaiser, Moda, PacificSource, and Providence.

[22] This procedure results in the following values (in millions): $\alpha = 1.0909, \beta = 1.7544, \gamma = -0.43636, F_R = 1.0909$.

[23] This restriction is analogous to holding Kaiser's network fixed. If Kaiser has a presence only in a subset of counties in a rating area, I do not allow them to enter the rating area. I discuss how relaxing this restriction affects my results in Appendix E.

[24] In Appendix Table E1, I report estimates weighted by county market size, as opposed to the unweighted estimates reported here. Because smaller markets are more likely to have been partially entered in the status quo, this relationship reverses and the average number of entrants decreases when partial entry is banned.

where population is distributed differently, banning partial entry may cause additional exit, so these results can be considered a "better-case" scenario for this policy.

In the appendix, I compare the changes from the status quo policy for selectively non-entered counties and fully entered counties. Appendix Table E2 shows that counties that did not experience a partial entry in the status quo lose entrants while counties that did experience a partial entry gain more entrants than are lost in the fully entered counties.

Despite the increase in the average number of entrants, average prices rise just under 4%, reflecting the fact that marginal entrants who are induced to enter charge higher prices on average. The silver price of newly entered firms is $215 higher than the price of firms who enter in the status quo. Because of the pricing regulations, firms who are induced to newly enter counties within a rating area that charge higher prices must also charge these higher prices in all counties within that rating area they entered in the status quo. This result highlights the presence of competitive spillovers; even if few firms enter one county in the rating area, prices in that county will reflect higher levels of competition elsewhere in the rating area.

Enrollment decreases by 6.5 percentage points, which is perhaps surprising given that the number of firms increases and in many places the prices of existing plans stay the same. This enrollment decrease occurs both in counties that were and were not partially entered in the status quo. In counties that were fully entered in the status quo, this decrease can be attributed to the decrease in the number of firms offering insurance and a rise in the price of the cheapest silver plan. In counties that were partially entered, this decrease in enrollment happens due to how subsidies are calculated. If a new plan is the cheapest or second cheapest plan offered in a county, the benchmark plan will change, decreasing the value of subsidies available to consumers and driving consumers out of the market.

Firm profits fall as firms must enter into counties that are unprofitable in the status quo. Firms that are induced to enter are about $600,000 less profitable than firms that enter in the status quo. Both the total amount of subsidies fall as well as the average subsidy per enrolled consumer. Overall consumer surplus rises 19.5% because of the large increase in the number of choices of plans consumers have, as one more insurer results in three additional plans.[25] However, if the social planner believes that there are benefits to health insurance

[25]Some rise in consumer surplus will be mechanical in a logit demand model with additional draws of the logit error. I additionally estimate the change in the maximum utility for each county weighted across consumer types translated into dollar terms to capture surplus generated by the characteristics of plans rather than the logit error. This term falls roughly 25%, which is not surprising given the fall in enrollment under this policy.

beyond what is captured in consumer surplus, they may be troubled by the fairly substantial drop in enrollment.

Banning partial entry brings community rating regulations closer to age rating regulations where firms are not allowed to select to sell only to a subset of consumer ages. However, fixed costs from geography make analyzing these two sets of restrictions distinct problems. While insurers may wish not to sell to older consumers under age rating restrictions, there are not additional fixed costs when they sell to older consumers. In contrast, firms have to incur large expenses to establish networks in new counties they did not previously serve.

Distributional Consequences

Banning partial entry is likely to have different effects in counties that are low density and low income, and thus more likely to experience a partial entry, and counties that are high density and high income. Beyond aggregate or average effects, a regulator may be interested in the distributional consequences of market reforms. As a benchmark, I compare the effects of a policy that bans partial entry to a policy that establishes rating areas at county levels,[26] which allows pricing to be based solely on the characteristics of each county.

Column 4 of Table 5 reports the estimates from this counterfactual. The most glaring change from the status quo is that the standard deviation of prices across counties increases dramatically by over 300%, consistent with firms using the new flexibility to price discriminate more across markets. Nine counties have no entrants,[27] which causes substantial reductions in the average number of firms that enter, the number of consumers who enroll in insurance, and consumer surplus. Firm profitability also drops dramatically because firms enter fewer markets.

In Figure 8, I examine the correlations between the changes between the status quo model and different counterfactuals and county characteristics. I compare counterfactual estimates of entry, prices, and consumer surplus to those under status quo policies.[28]

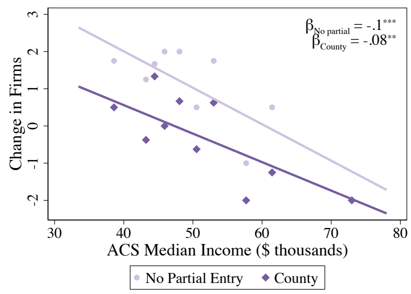
Subfigures (a) and (b) look at changes in entry in counties with varying median incomes and population density, respectively. The patterns are largely similar across both measures. Because low density, low income counties are most likely to be partially entered in the status quo, they benefit in terms of entry from both policies, with larger benefits from the policy

[26] Florida, South Carolina, and Connecticut do so in the status quo.

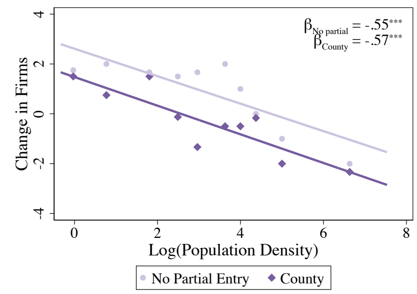
[27] The lack of entrants is driven by large fixed costs of entering rating areas. If this parameter were smaller, fewer counties would go unserved.

[28] As a reminder, entry decisions in the status quo are not modeled here but are taken as given. Entry decisions are modeled under the counterfactual policies.

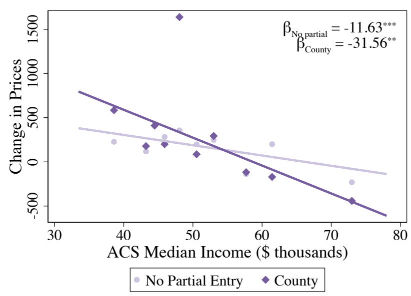
Figure 8: Winners and Losers Under Counterfactual Policies



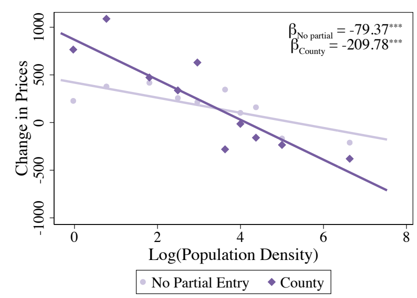
(a) Income and Entry Changes



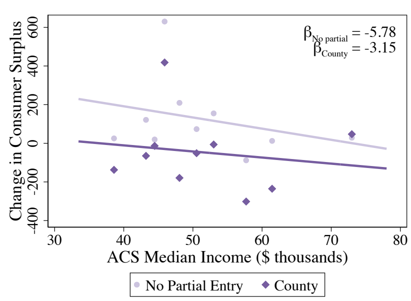
(b) Population Density and Entry Changes



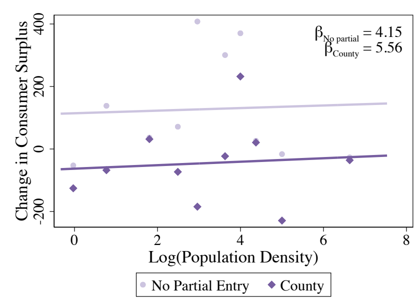
(c) Income and Price Changes



(d) Population Density and Price Changes



(e) Income and Consumer Surplus Changes



(f) Population Density and Consumer Surplus Changes

Notes: This figure explores how characteristics of counties are related to the changes in prices, consumer surplus, and the numbers of entrants. The changes are computed at the county level and are relative to the measures in the status quo. Both consumer surplus and prices are modeled under status quo policies holding entry fixed. The number of firms in the status quo is measured using the observed number of firms.

that bans partial entry.

Subfigures (c) and (d) look at the changes in the average price of silver plans, conditional on entry. While low income, sparsely populated counties gain entrants, they also see increases in the average prices of silver plans in both counterfactuals. Prices increase under a ban on partial entry in counties that are newly entered because the marginal entrant charges more. In the counterfactual that aligns rating areas with counties, prices increase as firms can price according to the marginal cost in each county, and these counties have higher marginal costs. Denser, richer counties see lower average prices for the same reason.

Subfigures (e) and (f) look at changes in consumer surplus. Consumer surplus is slightly higher in low income counties when partial entry is banned, but there is no relationship with population density. The effects of higher prices are offset by additional choices and by subsidies. Given that subsidies are based on the second cheapest plan at the county level, there is some group of consumers for whom price levels post-subsidy do not change; increases in prices largely affect unsubsidized consumers in the market.

Rating Area Size Without Partial Entry

In a world without partial entry, the size of rating areas will affect outcomes for several reasons. First, larger rating areas will decrease price variation. As more counties are grouped into a single rating area, firms must charge a uniform price over more counties. Second, larger rating areas may support more competition because of economies of scope. However, even without partial entry, this relationship will not hold monotonically; as rating areas get larger, price regulations may decrease profitability sufficiently to outweigh the economics of scale. Additionally, given that the fixed costs of entry vary at the county level, requiring firms to enter every county may induce some firms to exit.

To explore these relationships, I trace out how various market outcomes change under five different regulatory regimes in Figure 9.[29] These different regimes vary the size of rating areas. At one extreme, I consider a state-wide rating area. At the other, I consider county rating areas. In between, I consider splitting the state into two rating areas ("split state"),[30] the status quo design, and splitting current rating area into two or three county rating areas ("split current"). I chose these designs such that each design nests smaller designs; that is, counties are never grouped with neighbors they are not grouped with in larger rating area designs.

I consider several market outcomes: the number of entrants, consumer surplus, average prices and price variation, enrollment, and subsidies. In subfigure (a), I find an inverted

[29] Full counterfactual results are available in Appendix Table E3.

[30] This map combines existing rating areas. One rating area contains the eastern counties and the other the western counties.

u-shape relationship with the number of entrants. While small rating areas, those with one, two, or three counties, are not very competitive, the state-wide rating area has only a monopolist insurer. Most firms are unwilling to enter, either because of the lack of profitability due to the state-wide pricing constraint or because of high fixed costs in some locations within the state. In subfigure (c), I show that the insurer that is willing to enter is relatively low-cost compared with their competitors, as shown by the lower average silver price.

In subfigure (d), I show the expected relationship between rating area size and price variation. The bigger the size of rating areas, the less price variation. Both consumer surplus (subfigure (b)) and enrollment (subfigure (e)) are maximized in the "split-state" rating area design. While there is more entry in the current design, consumer surplus and enrollment are maximized in the two rating area design because of lower prices. Subsidies (subfigure (f)) show similar patterns to average prices. A regulator could minimize price variation by having a single rating area, but they must balance that with less entry, highlighting the trade-off between competition and equalizing prices across regions.

7.3 Redesigning Rating Areas

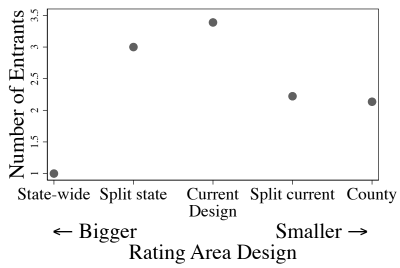
To evaluate how entry and pricing change when rating area size increases and partial entry is permitted, I compare the previous county rating area counterfactual to one where I group counties into two county rating areas.[31] I explore the trade-offs of adding one additional county to a rating area: larger markets mean that firms incur the fixed cost of entering a rating area only once for multiple counties, but prices become more restricted. These pricing restrictions can limit firm profitability and incentivize partial entry.

I try to group counties with their most similar neighbor in terms of marginal costs. Appendix E describes this process. In the resulting rating area map, there remains considerable variation in the difference in marginal costs between grouped counties. Places that are grouped with highly similar neighbors should expect to see more entry because of economies of scale and little incentive to partially enter. However, counties that are grouped with more dissimilar neighbors may be partially non-entered. I also consider the effects on pricing; there are winners and losers when risk is pooled. Low cost places will, on average, experience higher prices and high cost areas will experience lower prices. Price variation across the state will change accordingly.

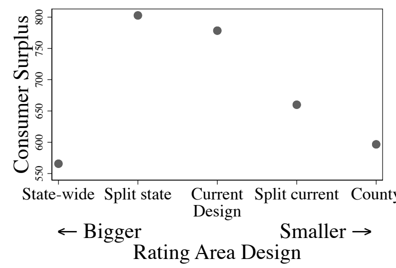
I report the estimates of this counterfactual in Table 5, Column 5. The number of

[31] Recall that there are computational challenges in finding equilibria in rating areas that involve more than two counties.

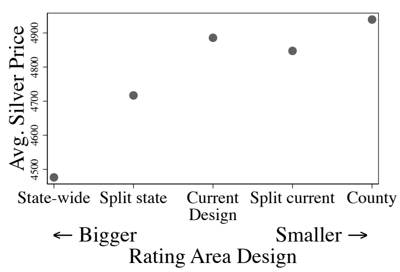
Figure 9: Different Rating Area Designs Under No Partial Entry



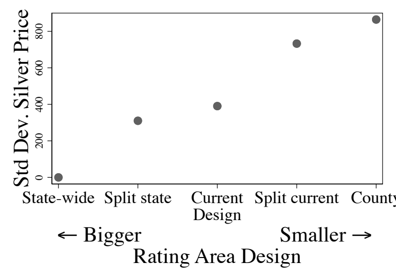
(a) Number of Entrants



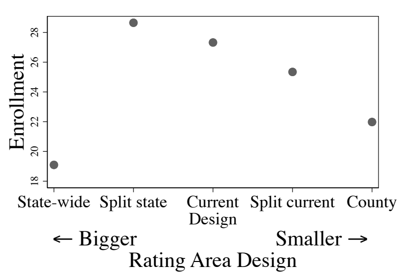
(b) Consumer Surplus



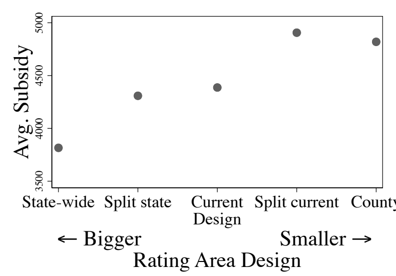
(c) Average Silver Price



(d) Standard Deviation Silver Price



(e) Enrollment

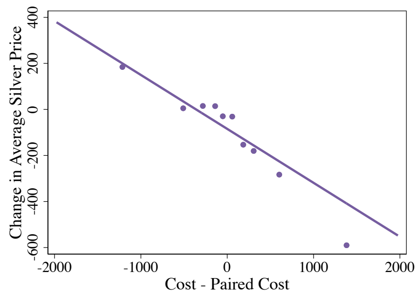


(f) Average Subsidy

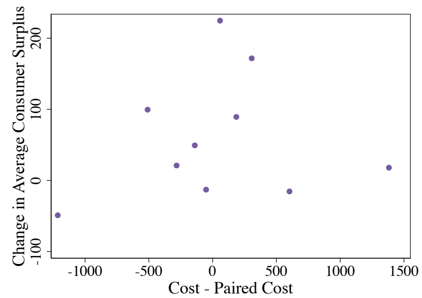
Notes: This figure explores how various outcomes respond to different rating area designs when partial entry is banned. The state-wide policy establishes a single rating area in the state. The split state policy divides the state into two rating areas. The split current divides current rating areas into two or three county rating areas such that there are no counties grouped with counties not in their current rating area.

markets that go unserved drops from 9 to 5, with a sizable increase in enrollment and consumer surplus. Firm variable profits are slightly lower, although firms may still gain due to sharing fixed costs across counties. There is a sizable drop in price variability from the one county counterfactual, but price variability remains much higher than under status quo

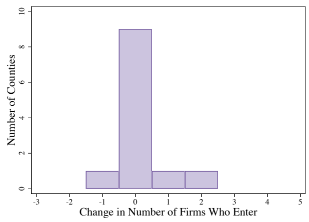
Figure 10: One Versus Two County Counterfactuals



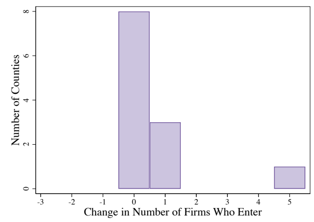
(a) Price Changes and Cost Differences



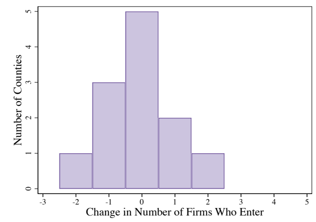
(b) Consumer Surplus Changes and Cost Differences



(c) Counties with Lower Costs



(d) Counties with Same Costs



(e) Counties with Higher Costs

Notes: This figure explores how price, entry, and consumer surplus changes are related to the difference in marginal costs between a county and the county that it is matched with in the two county groupings counterfactual. Subfigure (a) looks at changes in the average silver price in a county between the one county counterfactual and two county counterfactual, relative to the cost difference between a county and its pair. Subfigure (b) performs the same exercise with consumer surplus. Subfigures (c)-(e) show the distribution of change in the number of firms that enter counties that have costs more than $150 less than their pair, counties that have costs within $150 of their pair, and costs that are greater than $150 more than their pair.

policies, where there are 7 rating areas instead of 18.

In Figure 10, I explore how cost heterogeneity factors into the effects of this counterfactual policy. Prices increase significantly in counties that are grouped with other counties with much higher marginal costs, and vice versa. These price effects are blunted by subsidies such that there are not major changes in consumer surplus for counties with large cost differences.

There are large gains in consumer surplus for counties with similar costs. Counties whose pair has costs within $150 of theirs see the largest gains in entrants, while counties that are much more expensive than their pair see exits. Counties that have similar costs tend to be located in the same hospital referral region (HRR); counties whose pair is predominately in the same HRR see an increase of .32 entrants relative to .10 entrants in counties where the new rating area spans two different HRRs.

In Appendix Figure E5, I further explore this relationship by holding one county, Linn County, in the pairing fixed and comparing it with every other adjacent county. Linn County has average marginal costs that range from $264 less than its neighbor to $550 more than its neighbor. I find that grouping Linn County with a neighboring county increases entry when the costs between the two counties are relatively similar; when Linn County is more expensive than its neighbor, less entry occurs than when Linn County is its own rating area.

The effects of rating area size thus depend crucially on the composition of the new rating areas. Homogeneous larger rating areas promote entry, but do not pool high and low cost consumers and so have little effect on price variation. In contrast, heterogeneous areas do smooth prices across counties, but do not have the same benefits in promoting competition. Thus, regulators must balance these goals.

The gains in entry in this counterfactual are largely driven by the presence of relatively large costs of entering into a rating area. If these costs were lower with relatively little benefit of sharing fixed costs across counties, the primary effects of this counterfactual would be the smoothing out of costs across geographic space.

7.4 Discussion

In both exercises that ban and allow partial entry, there are trade-offs between minimizing price variation and encouraging competition. When partial entry is allowed, the benefits of larger market size in terms of entry are concentrated in homogeneous rating areas, which do not change the level of price variation substantially. Without partial entry, I show that the number of entrants drops significantly when the rating area is state-wide, creating a limit on how much price variation can be minimized without jeopardizing competitive markets. Regulators must balance these concerns.

There are several limitations to this analysis. These estimates are from the particular setting of Oregon where both the underlying health care conditions and policy regime may differ from other states. There is considerable heterogeneity in population density that may affect the costs of providing insurance across the state. In states with more homogeneous counties, a regulator may be less concerned both about partial entry and about price variation across the state.[32] Additionally, I model the offering decision of the insurer to be solely about

[32] The results showing banning partial entry increases entry will depend on the relative profitability and market sizes of counties within rating areas. Even within Oregon, this result will not be true for all market

entry, which is justified by Oregon regulations; in many states, insurers have considerable latitude in the plan menus they can offer consumers. That policy environment may allow firms to make multiple partial offerings to different counties within a rating area, regaining some pricing flexibility though those choices.

There are many characteristics of the market that I hold fixed throughout the analysis but that may change in practice. First, I do not allow the marginal costs of providing insurance to change in response to entry decisions. In practice, this may not hold because of changes in consumer composition; the consumers who select into the exchange may have different costs than existing consumers beyond the patterns I will capture by allowing costs to vary by county or age. Alternatively, entry into one market may change the bargaining power of the insurer in a way that affects multiple counties (for instance, with a hospital chain). I do not allow these spillovers because exchange enrollment is a relatively small percent of the total business of an insurer.

I also take as given participation in the individual insurance market. In the longer run, changing the design of insurance markets could affect which firms decide to participate in the individual exchanges, particularly if it makes firms much more or less profitable.

Finally, I do not model how changes in insurance markets affect the market for health care providers. Geddes and Schnell (2022) document that on-demand health care clinics expand in response to private health insurance expansions. An expanded health care provider sector may provide benefits to consumers outside of the market for exchange insurance.

Given the difficulty in predicting how entry will respond to changes to rating area policy, a regulator may be tempted to assume that the entry decisions of firms will remain fixed and estimate changes in prices naively. Previous counterfactuals demonstrate that the regulator should expect entry to change; I evaluate how far off estimates of prices would be if these equilibrium entry changes are not accounted for. Appendix Table E3 shows what predicted outcomes would be if price regulations were at the county or two county rating area level. In both cases, price estimates are below what the model predicts when entry is allowed to adjust. Additionally, the level of price variation is also under-predicted, highlighting that entry plays an important role in determining the level of price variation.

configurations. In Appendix Table E3, I show that banning partial entry for the two county rating areas I consider decreases entry.

8 Conclusion

Firms' ability to selectively enter creates difficulties in designing pricing regulations when the regulator's goals include both consumer access and limited price variability across consumers or groups of consumers. These dynamics are present in the individual health insurance exchange market in the United States where community rating is required to prevent firms from charging too-high prices to individuals with pre-existing conditions. In its current iteration, community rating is done at the regional level, where groups of counties are bundled together into rating areas. Insurers have the option of partially entering rating areas by entering into only a subset of counties, which can undo some of the pricing regulations.

I demonstrate that rating area design affects the market structure of the individual health insurance exchange marketplaces and prices. I build a structural model of insurer entry and pricing to understand the mechanisms behind this result. I model insurers as selecting bundles of counties from the set of possible entry decisions in a rating area. To recover the fixed costs of entry I use a moment inequalities approach, which allows me to recover an identified set.

With the estimates from this model, I estimate market outcomes under counterfactual policies that change the regulatory framework under which insurers make entry decisions. I find that removing the ability to partially enter would increase the number of entrants, improving consumer surplus. Establishing smaller rating areas at the county level decreases price smoothing across geographic areas, and price variability increases substantially. Additionally, these markets may not be big enough to support entry: nine counties see no insurers enter. Larger markets are not always better; when firms must decide whether to serve the whole state at a uniform price or not enter at all, only one firm enters.

Partial entry only complicates these trade-offs. When firms are allowed to partially enter, larger markets support more entry when the rating area is homogeneous. When the market is heterogeneous, prices are equalized across counties, but partial entry can occur. Thus, to support more competition, regulators should aim to group counties that have similar marginal costs or that are in the same HRR. However, these groupings do not necessarily support a goal of decreasing price variation. Geographic-based subsidies can address equity concerns, but are not available for all consumers in the market. Regulators must carefully balance supporting competition and price variation when designing rating areas.

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A Reduced Form Robustness

In this appendix, I present robustness checks for my reduced form evidence from Section 3. I first present a balance table, Table A1 that compares observable characteristics residualized on state fixed effects, an indicator for metropolitan status, and the distance from the nearest metropolitan area. I residualize on these characteristics to ensure that I am making the same comparison that I am in the main specification between two counties in the same state that are equidistant from a metropolitan area, but where one county's rating area is constrained by the state line. Comparing counties without these controls would likely reveal differences that will not affect my specification: various states have different propensities to have counties near metropolitan areas in other states, and the distance from the major metropolitan area will be correlated with the probability that that area is across a state line.

Across most characteristics, I find that there are no large differences between counties where their rating area may be constrained by a state line and those where it is not, as measured by the "cross-state" indicator. I find weak evidence that there may be differences in median income; there is a difference of $769 between the residualized incomes in the two groups of counties. This difference is small relative to median income overall, which has an average of $51,595. I also find very small differences in the percentage of the population with less than a high school education. I find no statistically signficant differences in the population, population density, or racial demographics of the counties. This balance reassures me that the indicator for cross-state is picking up differences in rating area design, rather than other underlying differences between the counties.

Next, I assess the robustness of my estimates to the choice of specification. Figure A1 presents plots of coefficient estimates for my four main outcomes of interest: the size of the rating area, the probability that the county has experienced a partial non-entry, the number of insurers offering insurance, and the price of the benchmark plan. I include estimates of the coefficient on the indicator for whether the nearest metropolitan area is across a state line across specifications. The top coefficient estimate comes from my baseline specification. I then add HRR fixed effects, remove all controls, and remove the restriction on the county being in a state where rating areas are not set at the county line. I use alternative ways of measuring whether the rating area is constrained by a state line: I construct indicators for whether the HRR that the county is in crosses a state line and for whether the HSA that the county is in crosses a state line.

My estimates are largely stable throughout these alternative specifications. I find that the effects are smaller when using the HSA measure. This makes sense because many fewer

Table A1: Balance on Residualized Observable Characteristics

Variable	Not Cross State	Cross State	Difference
Population	1,908.936	-5,957.558	-7,866.494
	(265796.375)	(76,827.727)	(11,527.843)
Population Density	-1.852	5.780	7.632
	(473.851)	(546.994)	(24.224)
Median Income	209.818	-654.816	-864.634*
	(9,261.428)	(8,536.002)	(447.060)
Share Black	-0.001	0.003	0.004
	(0.109)	(0.091)	(0.005)
Share White	0.001	-0.002	-0.003
	(0.121)	(0.145)	(0.006)
Share Hispanic	0.001	-0.004	-0.005
	(0.101)	(0.067)	(0.005)
Share less high school	-0.000	0.001	0.001
	(0.048)	(0.043)	(0.002)
Share more high school	0.000	-0.001	-0.001
	(0.079)	(0.067)	(0.004)
Share under 18	0.000	-0.001	-0.001
	(0.028)	(0.032)	(0.001)
Share $\leq$138% FPL	0.000	-0.000	-0.000
	(0.057)	(0.068)	(0.003)
Share 138-400% FPL	-0.000	0.000	0.000
	(0.032)	(0.030)	(0.002)
Observations	1,704	546	2,255

Notes: This table compares residualized observable characteristics across counties whose nearest major metropolitan area is across a state line and those for which it is not. The observable characteristics are first residualized on state fixed effects, an indicator for whether the county is a non-metropolitan county, and the distance from the nearest metropolitan area.

Table A2: State Borders, Rating Area Design, and Enrollment

	(1) % Enrolled	(2) % Silver	(3) % Bronze	(4) % Gold
Rural	0.0107***	0.00529***	0.00349***	-0.000561
	(0.00253)	(0.00191)	(0.00108)	(0.000517)
Miles to Metro / 100	-0.00364	-0.00509*	0.00162	-0.00234**
	(0.00422)	(0.00287)	(0.00173)	(0.00109)
Cross State=1	-0.00240	-0.00482**	0.00230*	-0.000347
	(0.00260)	(0.00188)	(0.00124)	(0.000503)
N	8208	8208	8208	8208
Outcome Mean	0.279	0.188	0.0651	0.0130
R2	0.705	0.607	0.583	0.409

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the results of a regression of market outcomes on state and time fixed effects, indicators for whether the county is a rural county, a vector of time-varying controls, and an indicator for whether the county is across a state line from the nearest metropolitan area.

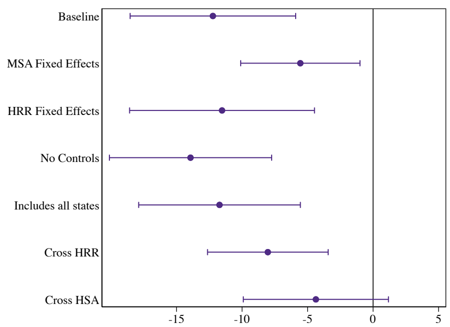
counties are identified as having their rating area constrained by a state-line, since HSAs are much smaller than HRRs. I also find that the effects on insurer partial entry are smaller in the specification without county-specific controls, although they are still negative (but not statistically significant).

I additionally examine alternative measures of market outcomes. Table A2 shows the effects of rating area design on enrollment and Table A3 shows the effect on the average deductible, average price, the average percent paying the individual mandate penalty, and the average premium credit per tax return.

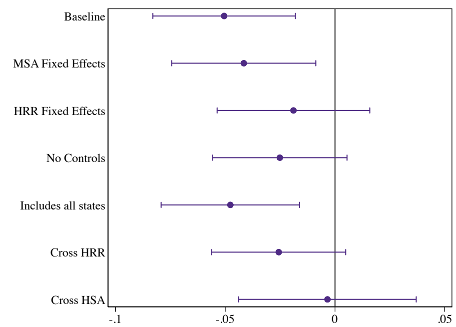
A final robustness check is to perform the same analysis in only Florida, South Carolina, and Connecticut. These states assign rating areas at the county level, so market size should not be affected by whether the nearest metropolitan area is in the same or a different state. Table A4 reports the results from these regressions. There is no relation between being across a state line from the nearest metropolitan area and rating area size or the number of insurers. I find weak evidence of a relationship with prices, but this relationship goes in the opposite direction of the main results in the paper. In these states, there is no partial entry into rating areas, by construction.

Figure A1: Robustness Checks

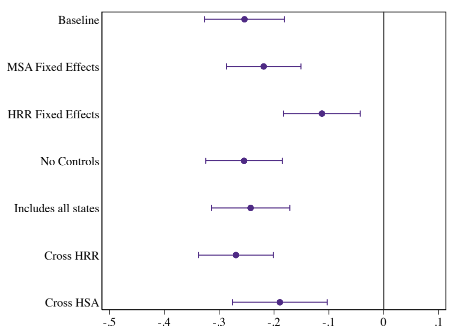
(a) Rating Area Size



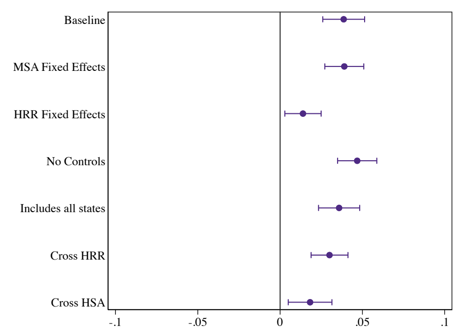
(b) Insurer Partial Offering



(c) Number of Insurers



(d) Log(Benchmark Plan Price)



Notes: These figures show the sensitivity of my baseline estimates of equation 3 to alternative empirical specifications. Each row displays the coefficient estimate from a different empirical specification of the measure of whether rating areas are constrained by state lines. In rows 1-4, this measure is whether the county is in a different state from its nearest metropolitan area. Row 5 instead uses whether any part of the county is in an HRR that crosses a state line. Row 6 uses whether any part of the county is in an HSA that crosses a state line. "HRR Fixed Effects" adds HRR fixed effects to the baseline specification. "No controls" is a specification that removes the county-specific control variables, but keeps state fixed effects, distance from the nearest metropolitan area, and the indicator for non-metropolitan areas. "Includes all states" removes the restriction that excludes counties in states where all rating areas are at the county level.

Table A3: State Borders, Rating Area Design, and Other Outcomes

	(1) Deductible	(2) Avg Price	(3) % Paying Penalty	(4) Credit Per Return
Rural	-52.34	9.224***	0.00125***	0.0136***
	(38.21)	(1.334)	(0.000445)	(0.00321)
Miles to Metro / 100	-95.83***	11.77***	0.00266***	0.00239
	(24.39)	(1.323)	(0.000743)	(0.00491)
Cross State=1	-37.54	12.73***	0.00158***	0.00510
	(30.00)	(1.742)	(0.000454)	(0.00355)
N	8211	9050	3941	3941
Outcome Mean	3410.2	327.3	0.0420	0.174
R2	0.281	0.776	0.675	0.628

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the results of a regression of market outcomes on state and time fixed effects, indicators for whether the county is a rural county, a vector of time-varying controls, and an indicator of whether the county is across a state line from the nearest metropolitan area.

Table A4: County Rating Areas Placebo Check

	(1) RA Size	(2) # Insurers	(3) Log(Price)
Rural	0.0242	-0.0232	0.0641**
	(0.0704)	(0.130)	(0.0314)
Miles to Metro / 100	0.415	-1.553***	0.0743
	(0.263)	(0.456)	(0.108)
Cross State=1	0.0526	-0.122	-0.0617*
	(0.114)	(0.153)	(0.0359)
N	451	451	451
Outcome Mean	22.85	2.477	8.161
R2	1.000	0.776	0.866

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the results of a regression of market outcomes on state and time fixed effects, indicators for whether the county is a rural county, a vector of time-varying controls, and an indicator for whether the county is across a state line from the nearest metropolitan area. Only states that establish their rating area at the county level (Florida, South Carolina, and Connecticut) are included.

B Details of Demand Estimation

B.1 Estimates of Components of δ

B.2 Distribution of Elasticity Estimates

In this section, I discuss the distribution of elasticities and semi-elasticities for each demographic group.

Figure B1 shows the distribution of my elasticity estimates across all demographic groups. Panel (a) shows elasticities for consumers with incomes $\leq$ 250% FPL, Panel (b) shows elasticities for consumers with incomes 250-400% FPL, and Panel (c) shows elasticities for consumers with incomes $>$ 400% FPL. Many elasticities are clustered around zero for low income consumers because these consumers face a zero price for plans after subsidies.

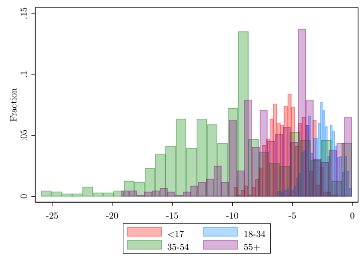
I also compute the semi-elasticities that measure the percent change in enrollment for a \$100 increase in price. I compute these from the perspective of the consumers, so these elasticities do not take into account age rating or the subsidy structure. Figure B2 shows the distribution of semi-elasticity estimates across all demographic groups. Panel (a) shows semi-elasticities for consumers with incomes $\leq$ 250% FPL, Panel (b) shows semi-elasticities for consumers with incomes 250-400% FPL, and Panel (c) shows semi-elasticities for consumers with incomes $>$ 400% FPL. Many of these semi-elasticities, particularly for low-income consumers are quite large. However, for many of these plans, a \$100 increase in the price paid by a consumer represents a very large increase in the price of the plan, due to the structure of the subsidies in this market.

Table B1: Estimates of Components of δ

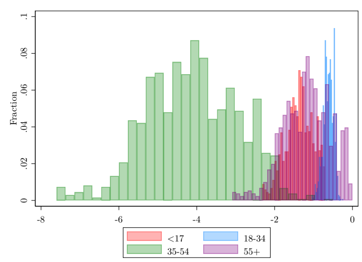
	(1)
Bridgespan	-2.124
Bridgespan × Metro Adj	-0.723
Bridgespan × Not Metro Adj	-0.843
Kaiser	0.888
Kaiser × Metro Adj	-6.160
Lifewise	0.776
Lifewise × Metro Adj	-0.553
Lifewise × Not Metro Adj	-1.209
Moda	1.633
Moda × Metro Adj	-0.966
Moda × Not Metro Adj	-1.294
PacificSource	-1.485
PacificSource × Metro Adj	-0.208
PacificSource × Not Metro Adj	-0.958
Providence	1.790
Trillum	-2.702
Zoom	-1.401
Silver	1.324
Silver × Metro Adj	0.332
Silver × Not Metro Adj	0.497
Gold	0.503
Gold × Metro Adj	0.375
Gold × Not Metro Adj	0.575
N	1355
R^2	0.719

Notes: This table shows coefficient estimates from a linear regression of year, county, insurer, and metal level fixed effects and interactions of these effects with county rural classifications on estimates of δ. The omitted year is 2016, the omitted insurer is Atrio, and the omitted metal level is bronze. This regression also includes county fixed effects which are not reported.

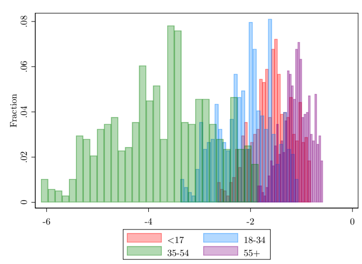
Figure B1: Elasticity Estimates



(a) Consumers with Incomes $\leq 250\%$ FPL



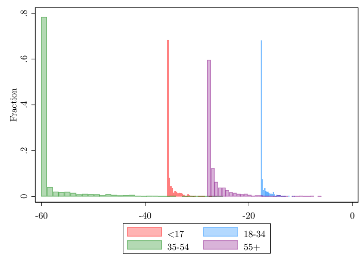
(b) Consumers with Incomes $250 - 400\%$ FPL



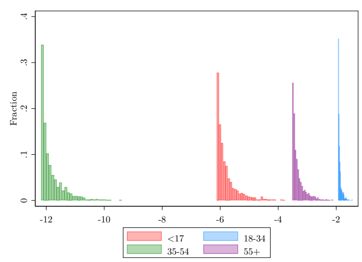
(c) Consumers with Incomes $> 400\%$ FPL

Notes: Panel (a) shows the distribution of elasticities by age for consumers whose incomes are $\leq 250\%$ FPL. Panels (b) and (c) show the same distributions for consumers whose incomes are 250-400% and 400% FPL, respectively. Because many low income consumers have effective prices of zeros after subsidy, causing bunching around zero, I only show elasticities for plans in markets where the price of the plan is positive for that consumer group.

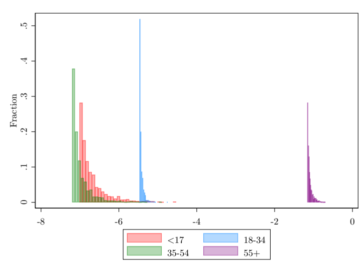
Figure B2: Semi-Elasticity Estimates



(a) Consumers with incomes $\leq 250\%$ FPL



(b) Consumers with Incomes $250 - 400\%$ FPL



(c) Consumers with Incomes $> 400\%$ FPL

Notes: Panel (a) shows the distribution of semi-elasticities by age for consumers whose incomes are $\leq$ 250% FPL. Panels (b) and (c) show the same distributions for consumers whose incomes are 250-400% and 400% FPL, respectively.

B.3 Demographic Outside Option Market Shares

To construct the market size and percentages of each demographic group in the market, I first have to adjust my two sources of enrollment data. The plan level enrollment data comes from the first quarter of the year whereas the CMS enrollment is from the open enrollment period, so the aggregate enrollment from the plan data is lower than the CMS enrollment data. I adjust down the CMS enrollment numbers to match the plan level Q1 enrollment, implicitly assuming that dis-enrollments are evenly distributed across demographic groups.

Using these adjustment demographic enrollments, I construct the percentage of the population in each income bucket using the CMS enrollment by age and the SAHIE estimates of the uninsured population in each income bin.

I perform an analogous exercise for ages using the ACS. If the county is available in the 1 year ACS, I use the 1Y ACS. Otherwise, I use the 5Y ACS that covers 2014-2018. I adjust the uninsured population in the ACS to match the SAHIE, holding the share of the uninsured population in each age bin fixed.

Table B2: Share Enrolled in Outside Option By Demographic Groups

Share Enrolled in Outside Option	
0-17	0.754
18-34	0.778
35-54	0.682
55-65	0.447
$\leq 250\%$ FPL	0.707
$250 - 400\%$ FPL	0.696
$> 400\%$ FPL	0.675
Metro	0.684
Metro-Adj	0.724
Non Metro-Adj	0.629

Notes: Shares constructed from the ACS and SAHIE.

Table B2 shows the share that is enrolled in the outside option by demographic groups. The strongest demographic trend is by age, where older consumers are much more likely to enroll in exchage insurers relative to younger consumers.

I construct the percentages in each age-income demographic group that are in the market by iterating between matching the income percentages and age percentages in the market constructed using the SAHIE, ACS, and CMS enrollment numbers. Table B3 shows these

Table B3: Percentage of Each Demographic Group in the Market

Weights	0-17	18-34	35-54	55-65	Total
$\leq 250\%$ FPL	0.081	0.201	0.191	0.126	0.599
$250 - 400\%$ FPL	0.027	0.066	0.094	0.064	0.250
$> 400\%$ FPL	0.011	0.026	0.061	0.051	0.150
Total	0.119	0.294	0.346	0.241	

Notes: Shares constructed from the ACS and SAHIE.

percentages. The market is majority consumers below 250% of the Federal Poverty Line, who are eligible for both premium subsidies and CSR.

Figure B3 shows the geographic variation in the age and income distribution of consumers in the individual exchange market.

Table B4 shows the average moments that my model tries to match constructed using the microdata downloaded from IPUMS.

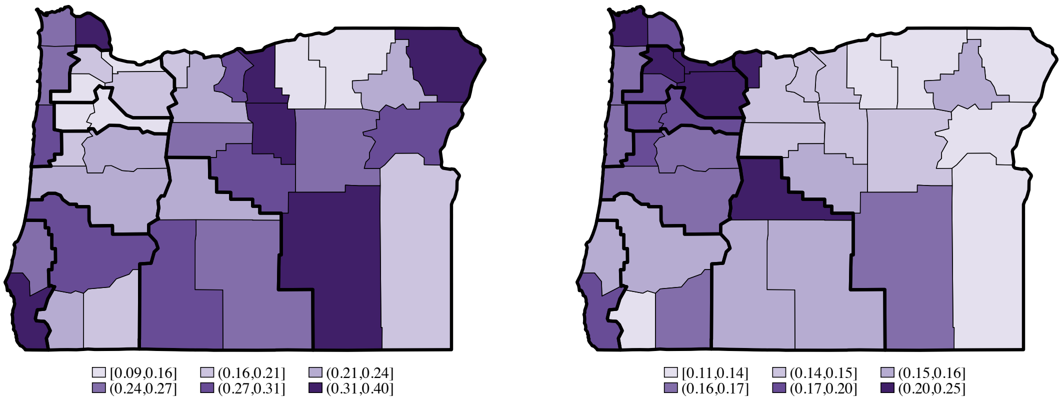
Table B4: IMPUS Moments

Outside Option Shares	0-17	18-34	35-54	55-65	Total
$\leq 250\%$ FPL	0.849	0.725	0.749	0.450	0.706
$250 - 400\%$ FPL	0.418	0.727	0.638	0.413	0.756
$> 400\%$ FPL	0.454	0.892	0.571	0.398	0.636
Total	0.705	0.757	0.686	0.433	

Notes: Shares constructed from the ACS and SAHIE.

I deal with products with zero enrollment (mostly gold products in earlier years) by dropping those products from the market.

Figure B3: Geographic Variation



(a) Share of Market 55+ (b) Share of Market Unsubsidized

Notes: Panel (a) shows the fraction of consumers who I consider to be part of the market for individual health insurance purchased through the exchange who are 55-64 in 2019. Panel (b) shows the fraction of consumers in this market who have incomes too high to receive any kind of subsidy on the exchange. These consumers have incomes above 400% FPL.

B.4 Constructing Prices

I create individualized prices for the 12 demographic groups that I use to estimate demand (three income groups and four age groups).

$$p_{ijm} = \max\{A_i \cdot p_{jm} - s_{im}, 0\}$$

where p_{jm} is the baseline price of the plan and s_{im} is the subsidy based on the benchmark plan in market m for individual i.

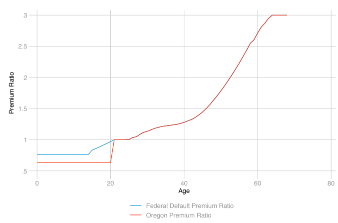
Table B5 shows the values along the age curve that I choose for each age bin. These represent the median age multipliers for each demographic bin along the full demographic age curve, shown in Figure B4. Table B6 shows my calculations for the expected contributions that consumers in each age and income bin must make. These expected contributions go into the calculation of the subsidy for each plan.

Table B5: Values of A_i

Age	0-17	18-34	35-54	55 +
Multiplier	0.635	1.034	1.421	2.714

Notes: Chosen values from the age-curve for each age-bucket used in estimation.

Figure B4: Regulatory Age Pricing Curve



Notes: This figure shows the statutory curve used in age rating of health insurance plans on the individual market in Oregon.

Table B6: Expected Contributions

Income Group	$< 250\%$	$250 - 400\%$	>400% FPL
2016	$6.41\% \cdot \$23,760 = \$1517.25$	$9.66\% \cdot \$35,640 = \$3442.82$	-
2017	$6.43\% \cdot \$24,120 = \$1550.92$	$9.69\% \cdot \$36,180 = \$3505.84$	-
2018	$6.34\% \cdot \$24,280 = \$1539.35$	$9.56\% \cdot \$36,420 = \$3481.75$	-
2019	$6.54\% \cdot \$24,980 = \$1633.69$	$9.86\% \cdot \$37,470 = \$3694.54$	-

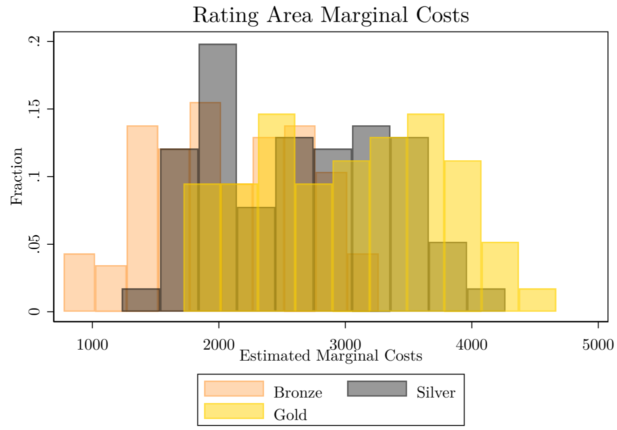
Notes: This table shows the expected percentage of income expected by the IRS and used in the subsidy calculation. It also includes the household income at the percent of the FPL that I chose to use for each income bin, to determine the total expected contribution in dollar terms for each income bin for each year in the sample.

C Details of Marginal Cost Estimation

C.1 Bundle Level Marginal Costs

Figure C1 shows the distribution of bundle-level marginal costs recovered by inverting first order conditions.

Figure C1: Rating Area Distribution of Marginal Costs

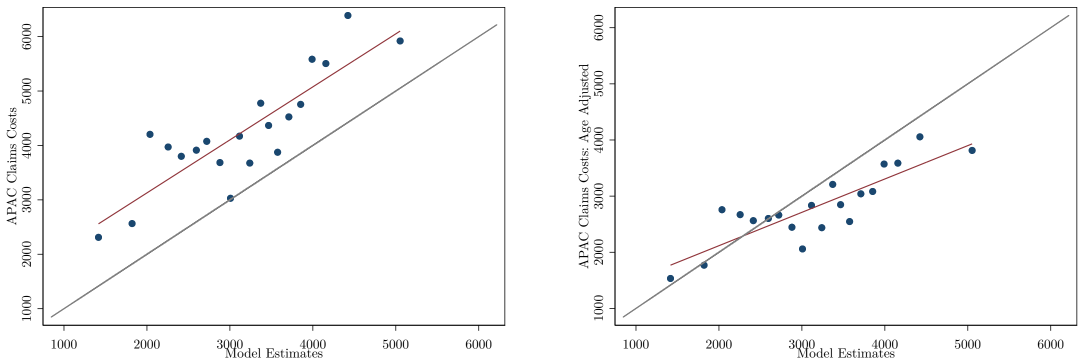


Notes: This figure shows the estimated distribution of marginal costs at the rating area level for Oregon's individual exchange health insurance plans from 2016-2019. Estimates come from inverting the first order condition of the firm for the price of the silver plan, holding the ratio of costs between bronze, silver, and gold plans fixed. This distribution is weighted by plan enrollment.

C.2 All Payer All Claims Data

To refine my marginal cost estimates, I use data from the Oregon All Payer All Claims (APAC) database which allows me to observe claims from all consumers enrolled in the individual exchange plans in the state of Oregon. It excludes data from insurers with fewer than 5,000 covered lives in Oregon. Data is reported to APAC directly from insurers. Unfortunately, plan identifiers are not available for claims, so I calculate claims at the county-metal level-year level. For this reason, I include this data in the projection of marginal costs from first order conditions on to rating area characteristics, rather than using the claims data directly as measures of costs. A second reason to not include claims data directly is risk adjustment, which will be accounted for in premium setting, but not in claims data.

Figure C2: Comparison of Final Marginal Cost Projections to APAC Claims



(a) Not Age Adjusted

(b) Age Adjusted

Notes: Panel A shows a binned scatter plot comparing the claims costs calculated from the APAC claims data at the county-metal level-year level to the estimated marginal cost estimates. The estimated marginal cost estimates are the weighted average of plan estimates weighted based on plan enrollment for each county-metal level-year. Panel B is an analogous exercise that adjusts the APAC claims estimates for the age composition of the market in each county. The 45 degree line is shown in these figures in grey.

I calculate the total dollar amount of claims to the member-month level for both medical and pharmacy claims. I then join these to data on member eligibility at the monthly level. I then compute adjusted annual claims by taking the average monthly claim at the annual level and multiplying by the number of calendar months the member was eligible for that plan. I drop months where members are eligible for more than one health insurance plan. This restriction drops 5.6% of member months. I winsorize the annual claims. I assign claims to the year when the service occurred.

I then take the average of annual claims at the county-year-metal level. I drop counties with low enrollment in the exchange for privacy reasons. For these counties, I assign the average cost for that metal level plan for that year. I additionally construct an alternative measures of these claims costs that are adjusted for the age composition of the market in various counties.

Figure C2 compares the marginal costs estimates from the model to the observed APAC claims.

C.3 Projection of Marginal Cost Characteristics

Table C1 shows the coefficient estimates from projecting rating area marginal costs recovered from first order conditions on rating area characteristics. All columns include issuer, metal level, and year fixed effects. Column 1 only includes APAC claim costs. Column 2 adds the z-scores for health outcomes and health factors from the county health ratings. Column 3 adds information on health care markets from the AHRF. Column 4 adds county demographic information from the ACS. Column 5 adds the interactions with whether the insurer is vertically integrated with the AHRF health care market information.

Table C1: Marginal Costs and Rating Area Characteristics

	(1)	(2)	(3)	(4)	(5)
APAC Costs	0.420***	0.203***	0.212***	0.297***	0.287***
	(0.0456)	(0.0447)	(0.0426)	(0.0448)	(0.0448)
CHR Health Outcomes		383.9***	242.9***	172.3	194.5
		(90.24)	(87.06)	(119.4)	(127.2)
CHR Health Factors		-197.4	-286.4*	-967.5***	-1034.6***
		(158.7)	(151.6)	(352.4)	(346.9)
# Docs			0.127***	1.208***	1.116***
			(0.0321)	(0.185)	(0.214)
# Hospitals			-173.3***	-180.6*	-212.6*
			(25.36)	(103.3)	(108.8)
Share White				-5.978	-5.324
				(21.90)	(20.72)
Share Black				-656.4***	-609.4***
				(146.1)	(155.7)
Share Hispanic				65.32***	64.47***
				(19.01)	(22.31)
HS Education				124.7	126.5
				(91.44)	(93.37)
> HS Education				77.88	75.48
				(54.96)	(58.35)
Population				-0.00212*	-0.00145
				(0.00126)	(0.00138)
HH Income				-0.0498***	-0.0508***
				(0.0170)	(0.0174)
Observations	348	348	348	348	348
R^2	0.861	0.889	0.919	0.950	0.953
Metal Level FEs	X	X	X	X	X
Issuer FEs	X	X	X	X	X
Year FEs	X	X	X	X	X

Standard errors in parentheses

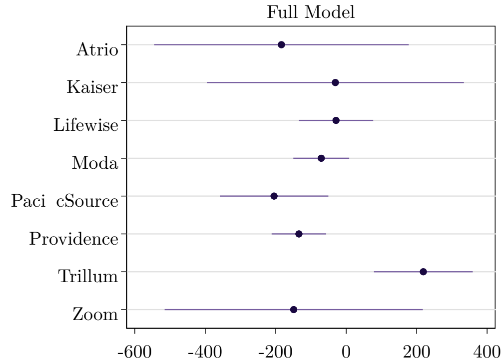
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the estimates from projecting rating area marginal costs recovered by inverting first order conditions on rating area characteristics. Rating area characteristics are enrollment-weighted county characteristics. These regressions are enrollment weighted.

Table C2: Marginal Cost Model Cross Correlations

Variables	Baseline	Add Health Scores	Add AHRF	Add ACS Demos	Add VI Interactions
Baseline	1.000				
Add Health Scores	0.980	1.000			
Add AHRF	0.955	0.972	1.000		
Add ACS Demos	0.927	0.948	0.964	1.000	
Add VI Interactions	0.927	0.948	0.964	0.999	1.000

Figure C3: Issuer Coefficient Estimation



Notes: This figure shows estimates of the issuer fixed effects in Equation 6 of rating area marginal costs onto plan and rating area characteristics. The omitted category is Atrio, a vertically integrated insurer. Kaiser and Zoom are also vertically integrated.

C.4 Marginal Costs, Population Characteristics, and Entry Decisions

As a bridge to thinking about fixed costs and entry decisions, I examine the associations between marginal costs, population characteristics that are related to demand elasticities, and entry decisions. I regress entry decisions on county level marginal costs, county demographic composition, and market size, including rating area fixed effects. Results are presented in Table C3.

In this table, column 1 looks at the relationship between marginal costs, demographic characteristics (age and income bins), and market size on the probability of entry. I find a negative relationship between the marginal costs in a county and entry. I also find a positive relationship with the fraction of the market that is under 18 and the fraction of the market with incomes over 400% of the FPL. Finally, I find a positive relationship with the size of the market.

Column 2 is an analogous exercise looking at the probability that a county is partially non-entered. For this to be true, other counties in the rating area must be entered, so I restrict to counties in rating areas where the insurer entered at least one other county in the rating area.

Table C3: Relationships Between County Characteristics and Entry Decisions

	(1) Entry	(2) Partially Non-Entered
Marginal Cost (MC) ($000s)	-0.0321***	
	(0.00920)	
MC / Avg. Rating Area MC		0.212**
		(0.0919)
Fraction < 18	0.365	-0.156
	(0.239)	(0.236)
Fraction 35-54	-0.141	0.174
	(0.180)	(0.293)
Fraction 55-64	-0.0215	0.0669
	(0.165)	(0.236)
Fraction 250-400% FPL	0.278	0.241
	(0.394)	(0.612)
Fraction >400% FPL	0.662	-1.070*
	(0.514)	(0.614)
Market Size / 10,000	0.0260***	-0.0261***
	(0.00520)	(0.00571)
N	2700	1863
R^2	0.0661	0.0875
Outcome Mean	0.532	0.233
RA FEs	Yes	Yes

Standard errors in parentheses

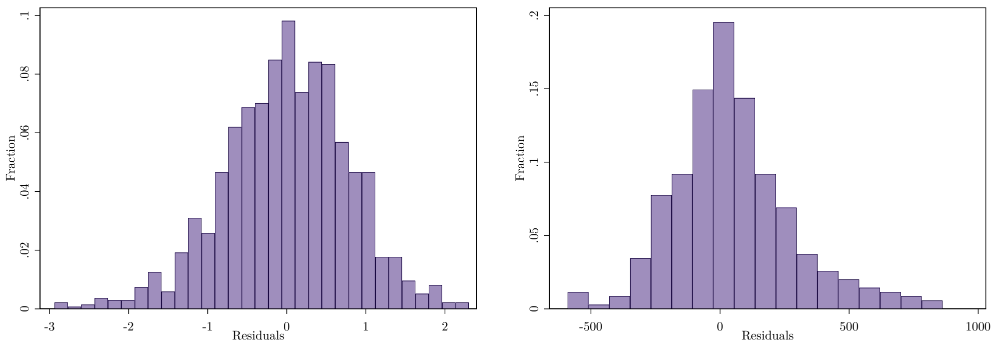
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

D Details of Moment Inequality Estimation

To construct estimates of expected demand and marginal costs (I assume that firms are unaware of demand shocks ξ_{njmt} and marginal cost shocks ϵ_{njmt}), I simulate using draws of these shocks. The empirical distributions are shown in Figure D1. They are both mean zero by construction.

Figure D1: Distribution of Demand and Marginal Cost Shocks

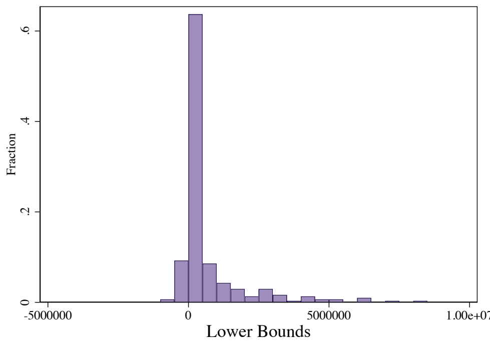


(a) Demand Shocks (b) Marginal Cost Shocks

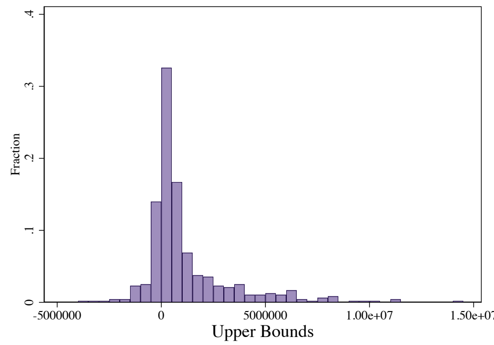
Notes: These figures show the empirical distributions of demand shocks ξ_{njmt} and marginal cost shocks ω_{njmt}. I simulate variable profits by drawing from these distributions.

Figure D2 shows the observed differences in profits, which will be the upper and lower bounds on fixed costs for a given county-insurer-year combination before selection into entry is accounted for. Panel (a) shows the difference between profits for counties that are not entered and the decision to enter that county, which gives lower bounds on what fixed costs for that insurer entering that county would be. Panel (b) is an analogous plot showing the differences between profits for counties that are entered under the observed decision and a deviation not to enter the county. Reassuringly, the observations for these are largely positive, giving us fixed costs that are going to be positive and bounded away from zero.

Figure D2: Observed Bounds



(a) Observed Lower Bounds



(b) Observed Upper Bounds

Notes: These figures show the observed distributions of upper and lower bounds before selection into entry is accounted for. These bounds are computed by taking the difference between simulated expected variable profits for observed entry decisions and then for one-county deviations (either entry or exit of a given county) for 2019.

E Details of Counterfactual Estimation

E.1 Counterfactual Estimate Maps

Figure E1 shows a map of average silver prices for various counterfactual simulations. Figure E2 shows a map of entry decisions for various counterfactual simulations.

E.2 Vertically Integrated Insurers

Vertically integrated insurers may have different incentives when they make entry decisions; entry into a new geographical location for a vertically integrated insurer requires a large capital investment whose returns will be realized over potentially many years. Modeling these decisions is quite different than modeling the decision to set up a network for a non-vertically differentiated insurer. For this reason, in counterfactuals, I restrict vertically integrated insurers (in practice, just Kaiser) from entering into markets where I do not observe any presence, on or off exchange, in previous years.

I evaluate the consequences that this restriction has in the counterfactual where it is the most restrictive, where no partial entry is allowed. Here, allowing Kaiser to enter places that they don't have a presence results in an additional entry in one rating area. However, this rating area is particularly large, so this affects 41.7% of counties.

E.3 Multiple Equilibria

One benefit of my moment inequalities approach is it allows for the possibility of multiple equilibria in entry decisions. By iterating through all possible equilibria, I'm able to identify how often multiple equilibria in entry occur in practice. Holding fixed cost shocks fixed, in the no partial entry counterfactual, I find one rating area with two potential equilibria, both with the same number of firms, but a different combination of firms. In the county counterfactual, I find 6 counties with multiple equilibria. Here, the number of firms is not always unique. Finally, in the two county counterfactual, I find 5 counties with multiple equilibria.

Fixed cost shocks also raise the possibility of multiple equilibria, but in practice, they rarely shift firm entry decisions.

E.4 Two County Groupings

It is non-trivial how to create a rating area map that minimizes the difference between counties in some observable characteristic (in this case, marginal costs) with the restrictions that counties must be grouped into two county pairings with contiguous counties (18 distinct pairings). To find a pairing that approximates this grouping loosely (with no guarantee of the closeness of this map to the "optimal" map), I follow the following algorithm:

Step 1: Rank order counties in the number of adjacent counties.

Step 2: For the county with the fewest possible matches, match that county with its most similar adjacent county.

Step 3: Remove those counties from the list of unmatched counties.

Step 4: Re-rank counties in the number of possible matches.

Step 5: Repeat until all counties are matched.

For marginal costs as the characteristic, I find a pairing for all 36 counties, with considerable variation in how similar counties are to their matched neighbor. These pairings and the absolute value of difference in estimated marginal costs are shown in Figure E4.

E.5 Additional Counterfactual Estimates

Table E1 reports counterfactual estimates where counties are weighted by the size of the population in the market.

Table E2 reports outcomes from the counterfactual policy that bans partial entry broken down by whether or not the county was partially non-entered in the status quo. Table E3 reports results from alternative counterfactual simulations that either do not allow partial entry or hold entry decisions fixed and simulate pricing equilibrium under alternative rating area designs.

Figure E5 shows how outcomes change for Linn County when they are grouped with each adjacent neighbor as opposed to being in a single county rating area.

Table E1: Counterfactual Estimates

Outcome	Observed	Model	No Partial Entry	County RAs	Two County RAs
Number of Firms	3.66	.	2.83	2.04	2.35
# Markets Without Entrants	0	.	0	9	5
Avg. Enrollment	31.10%	30.49%	26.47%	24.51%	27.21%
Avg. Silver Price	4342.12	4542.13	4461.76	4284.43	4291.99
Avg. Min Silver Price	4159.45	3873.03	4002.67	3931.35	3916.99
Avg. Max Silver Price	4502.75	5146.50	5009.53	4647.86	4677.55
Std Dev Avg. Silver Price	361.99	184.71	353.55	426.74	426.26
Avg. Subsidy Per Enrollee	.	4162.26	3696.90	3770.28	3865.03
Avg. CS ($)	.	649.72	718.53	629.50	688.75
Avg. Variable Profits (millions)	.	13.56	12.30	13.53	10.89

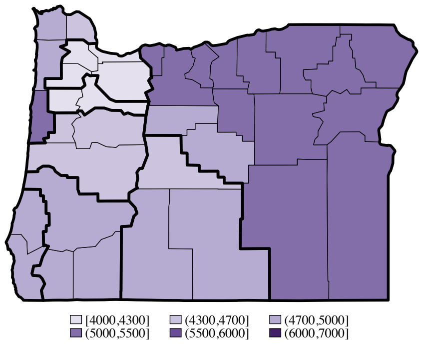
Notes: This table presents results of counterfactual simulations compared to the status quo estimate with statistics calculated using market size weights. Column 1 reports the observed values in the data. Column 2 reports the model estimates, holding entry decisions fixed. Columnn 3 reports the estimates from a a counterfactual policy that holds rating areas fixed, but requires insurers to enter either every county in a rating area or not enter the county (no partial entry). Column 4 reports the estimates from a counterfactual that sets rating areas at the county level. It removes the grouping of counties together. Column 5 reports the estimates from a counterfactual that creates rating areas out of two adjacent counties. Firms are allowed to make partial entry decisions. Prices are calculated conditional on entry and are the base prices (before age rating).

Table E2: No Partial Entry Counterfactual

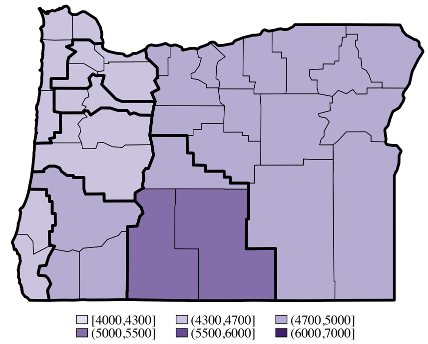
	Not Partially Entered	Partially Entered
Change in Number of Firms	–1.00	1.65
Change in Price	–49.63	261.86
Change in Minimum Price	230.39	–175.59
Change in Enrollment	–0.08	–0.06
Change in Consumer Surplus	–23.97	185.24
Number of Counties	10	26

Notes: This table presents outcomes from the no partial entry counterfactual split by whether or not the county was partially entered in the status quo. Partially entered counties are counties that are missing at least one insurer who sells insurance elsewhere in the rating area.

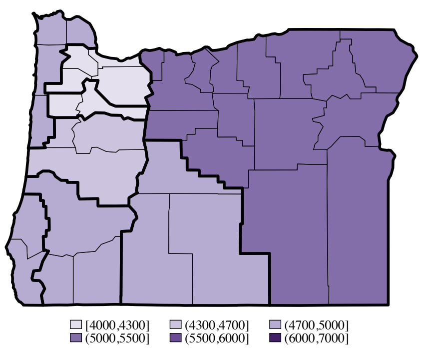
Figure E1: Counterfactual Price Estimates



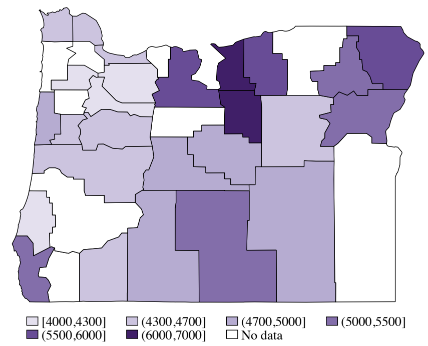
(a) Status Quo Observed Prices



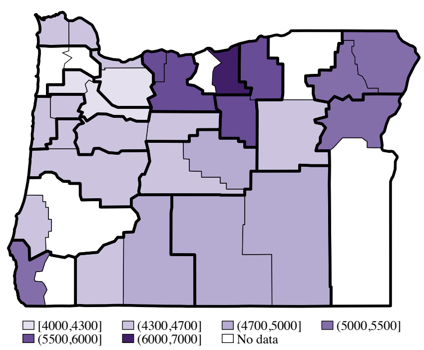
(b) Status Quo Simulated Prices



(c) No Partial Entry Simulated Prices



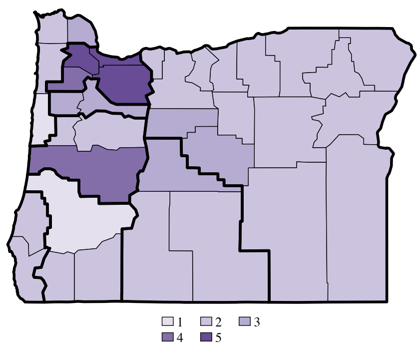
(d) County Rating Area Simulated Prices



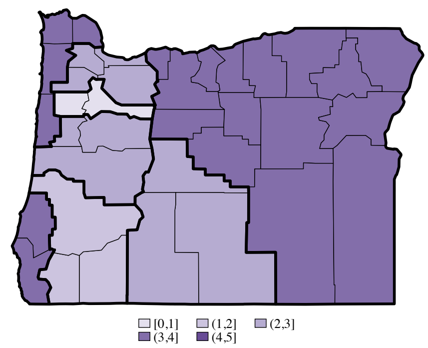
(e) Two County Rating Area Simulated Prices

Notes: This figure compares the average price of silver plans across the status quo, the model's predicted prices holding entry decisions fixed, and the model's predicted prices in counterfactuals where entry decisions are allowed to change. Subfigure (a) shows status quo prices. Subfigure (b) shows the prices predicted by the model. Subfigure (c) shows equilibrium prices in a counterfactual where no partial entry is allowed; firms must make an all-or-nothing decision to enter a rating area. Rating areas are held fixed in this counterfactual as their current design. Subfigure (d) shows equilibrium prices in a counterfactual where rating areas are defined at the county level. There is no partial entry by default in this counterfactual.

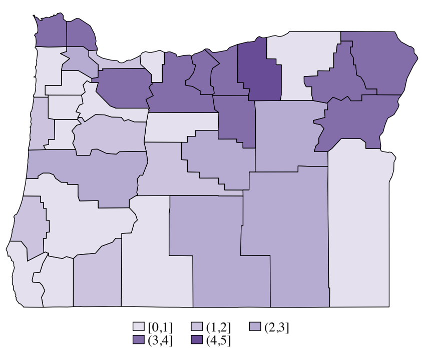
Figure E2: Counterfactual Entry Decisions



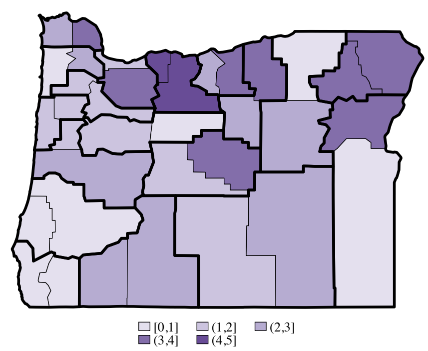
(a) Status Quo Observed Entry Decisions



(b) No Partial Entry Simulated Entry Decisions



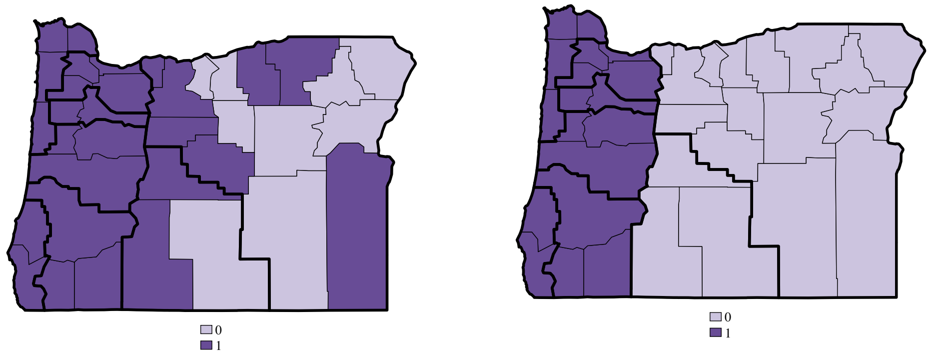
(c) County Rating Area Simulated Entry Decisions



(d) Two County Rating Area Simulated Entry Decisions

Notes: This figure shows the number of entrants observed in the status quo (subfigure (a)) and in different counterfactuals (subfigures (b) and (c)).

Figure E3: Kaiser Entry Restrictions

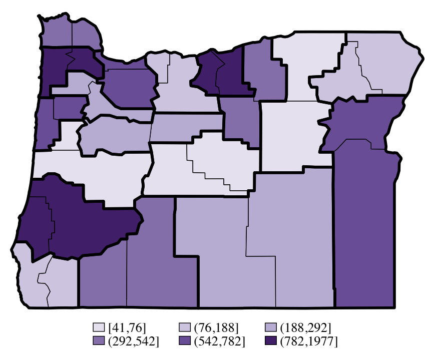


(a) County Allowed Entry Decisions

(b) Rating Area Allowed Entry Decisions

Notes: Subfigure (a) shows the counties where I observe Kaiser having a presence at some point during my sample period. Subfigure (b) highlights the counties that I allow Kaiser to enter in the counterfactual where I do not allow firms to make partial entry decisions. In this counterfactual, Kaiser can only enter into rating areas where they have a presence in every county in the rating area.

Figure E4: Two County Rating Area Groupings



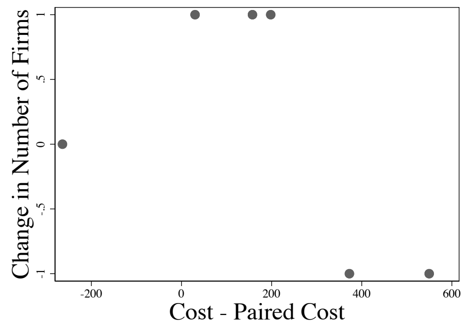
Notes: This figure shows the two county groupings I use in counterfactual estimation. Counties adjacent with the same color are grouped together. Counties in a darker shade of purple are more dissimilar than those in light purple. The difference is measured in dollars of marginal costs.

Table E3: Counterfactual Estimates

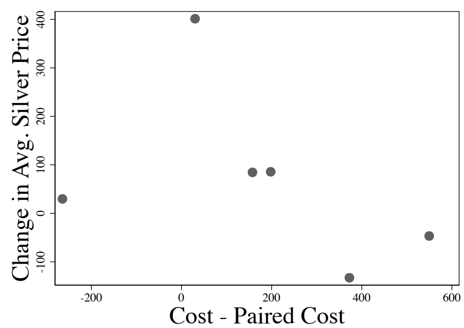
Outcome	State RA: No Partial Entry	Two RAs: No Partial Entry	Two County RAs: No Partial Entry	Split RAs: No Partial Entry	County RAs: No Entry Adjustment	Two County RAs: No Entry Adjustment
Number of Firms	1.00	3.00	1.94	2.22	2.47	2.47
# Markets Without Entrants	0	0	6	4	0	0
Avg. Enrollment	19.10%	28.65%	24.21%	25.34%	34.16%	33.77%
Avg. Silver Price	4476.39	4716.86	4765.08	4847.46	4798.27	4783.79
Avg. Min Silver Price	4476.39	4235.22	4365.80	4411.85	4386.70	4390.97
Avg. Max Silver Price	4476.39	5396.11	5280.33	5406.68	5210.90	5185.90
Std Dev Avg. Silver Price	0.00	310.04	792.57	732.64	572.09	520.30
Avg. Subsidy Per Enrollee	3815.81	4308.75	5007.71	4906.25	5655.25	5581.73
Avg. CS ($)	565.72	802.74	602.06	660.01	644.02	643.79
Avg. Variable Profits (millions)	1.50	3.96	4.04	4.01	4.60	4.51
Total CS (millions)	127.44	324.04	274.88	287.07	279.50	273.73
Total Subsidies (millions)	191.51	425.65	471.19	446.46	558.93	543.60
Total Variable Profits (millions)	54.05	142.63	145.53	144.25	165.63	162.50

Notes: This table presents results of additional counterfactual simulations. Prices are calculated conditional on entry and are the base prices (before age rating). Column 1 presents simulations where rating areas are established at the state level and no partial entry is allowed. Column 2 presents simulations where current rating areas are combined into two rating areas and no partial entry is allowed. Column 3 involves two county rating areas with no partial entry. Column 4 splits current rating areas into two or three county rating areas with no partial entry. Column 5 simulates outcomes with county level rating areas if entry does not adjust. Columnn 6 simulates outcomes with two county ratingn areas if entry does not adjust.

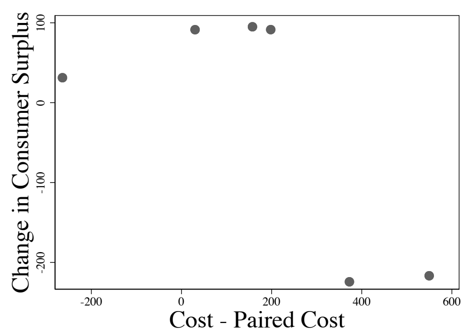
Figure E5: Two County Groupings: Linn County



(a) Number of Entrants



(b) Average Silver Plan Price



(c) Consumer Surplus

Notes: This figure shows how market outcomes change from the one county counterfactual when Linn County is grouped with its six adjacent neighbors. The difference in marginal costs is the difference between Linn County's estimated average marginal cost and its paired county's average marginal cost. Subfigure (a) shows the changes the the number of firms willing to enter. Subfigure (b) shows the change in the average price of silver plans. Subfigure (c) shows the change in consumer surplus.