Why Do Insurers Selectively Enter Counties within a Rating Area on the ACA Marketplaces?*

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Abstract

Each state has a set number of geographic "rating areas," typically made up of counties, that all insurers participating in the state's ACA Marketplace must uniformly use as the geographic unit for varying premiums. This paper shows that it is quite common for insurers to not sell any plans in certain counties, while serving other counties in the same rating area. We provide empirical evidence that risk screening and provider network setup costs are the main mechanisms driving these selective entry patterns. We find no evidence that insurers limit their service area to avoid competition.

Keywords: Affordable Care Act; Health Insurance Marketplace; Rating Area

JEL Classification Codes: I11, I13, L1

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1 Introduction

The Patient Protection and Affordable Care Act (ACA) established state-by-state health insurance Marketplaces which came into full operation in October 2013. On the ACA Marketplaces, insurers sell health insurance plans that are subject to numerous regulations. Importantly, insurers must accept all applicants regardless of their preexisting conditions. Premiums can be adjusted only for an individual's age, tobacco use, family enrollment and geographic location. To limit insurers' ability to vary premiums by geographic region, each state is divided into a set number of geographic "rating areas," which are typically made up of a collection of counties. The ACA requires that an insurer price its ACA health insurance plan *uniformly* in all counties within the same rating area, conditional on consumers' age, smoking status and family enrollment. However, the ACA does *not* require that a plan be sold in all counties within the rating area.

This paper investigates whether insurers sell plans that cover only a strict subset of counties within a rating area – a phenomenon which we refer to as *"partial rating area offering,"* – and if so, what the underlying mechanisms are. If insurers issue ACA Marketplace plans that are sold in some but not all counties of a rating area, then the geographic risk adjustments are effectively based on counties, not rating areas. Empirical investigation of partial rating area offering is thus helpful in understanding whether the geographic rating regulation delivers its intended goal of overseeing insurers' ability to vary premiums.

Understanding *why* insurers limit their service area within a rating area is necessary in designing policies that could effectively increase insurer participation on the ACA Marketplaces.[1] This is highly policy relevant as the degree of insurer competition is lower on the ACA Marketplaces compared to other individual health insurance markets.[2] For example, if insurers use partial rating area offering to divide up a rating area with their competitors and avoid head-on competition, then a direct regulation on insurers' service area could be called for. On the other hand, if partial rating area offering is driven by insurers avoiding high-cost counties where it is almost impossible not to incur a loss, then mandating all plans

[1] An insurer's service area is a set of counties where the insurer offers at least one plan.

[2] In 2016, an individual had 3.5 insurers to choose from on the ACA Marketplaces. According to the Kaiser Family Foundation, the average person on Medicare in 2017 had 6 Medicare Advantage insurers to choose from.

be offered in all counties of a rating area might instead trigger insurer exits.

We start by assessing the prevalence of partial rating area offering on the ACA Marketplaces. The main data for this paper come from the 2016 Marketplace Public Use Files (PUF) collected by the Centers for Medicare and Medicaid Services (CMS). The data cover over 30 states that receive support from the federal government for their Marketplace operations. Based on various statistics we develop, we show that partial rating area offering is quite common on the Marketplaces. For example, about 30% of insurers exclude at least one county from their service area while selling plans to other counties in the same rating area. We find that about 40% of potential Marketplace enrollees have restricted insurance choices due to partial rating area offering.

We present three possible explanations for the prevalence of partial area offering and generate their testable predictions. The first potential explanation is *risk screening*. As counties within a rating area could differ in their risk distributions, insurers might limit their service area to risk select counties. For example, insurers could avoid entering counties that have a higher share of unhealthy consumers.

The second potential explanation is that insurers might selectively enter counties in a rating area to avoid competition, which we refer to as the *market segmentation* hypothesis. Considering that the average number of active insurers in a county is only 3.5 in our sample, the desire to segment a market and avoid competition might potentially explain insurers' selective entry patterns.

The third potential explanation is that insurers might not enter counties where they face significant entry costs associated with building provider networks, which we refer to as the *entry cost* hypothesis. All plans sold on the ACA Marketplaces have to ensure a sufficient choice of providers. Costs associated with meeting network adequacy standards and establishing a competitive network could be significant for insurers. This will be especially true if an insurer does not have legacy provider networks.

We empirically examine the testable implications of our hypotheses in multiple steps. First, we look for descriptive evidence. We find that descriptive patterns of our data are in line with the risk screening and entry cost hypotheses, while they provide little empirical support for the market segmentation hypothesis. For example, we find that counties with the worst health measures have the lowest insurer participation rate within a rating area. Insurers are less likely to enter counties where they do not have existing provider networks and therefore face higher entry costs. Insurers who compete in multiple markets should be in a better position to sustain market segmentation arrangements as they can be deterred from unilateral deviations. However, the selective entry patterns are not more prevalent in rating areas involving insurers who are also co-present in more markets elsewhere, providing descriptive evidence against the market segmentation hypothesis.

Next, we develop a novel nonparametric correlation test to investigate the relative importance of the risk screening and market segmentation hypotheses. The risk screening hypothesis predicts that in equilibrium, insurers' county-level entry decisions should be positively correlated. That is, if one insurer believes that a particular county in a rating area has higher-risk consumers and decides against offering a plan in the county, so should other insurers. The market segmentation hypothesis, in contrast, predicts that there should be a negative correlation. This is because under market segmentation, insurers should avoid entering counties where their competitors are present.

To put these predictions to a test, we develop a correlation measure that quantifies the average alignment of insurers' county-level entry decisions in a rating area. We test a null hypothesis of independent and random entry against alternative hypotheses of positively or negatively correlated entry. We strongly reject the null in favor of positively correlated entry. The correlation test therefore prefers the risk screening hypothesis over the market segmentation hypothesis.

Finally, we do regression analyses to examine different testable implications in a unified framework. Consistent with the descriptive analysis and the correlation test, the regression results show that risk screening and entry costs are insurers' primary concerns when they decide which counties to enter on the ACA Marketplaces, while market segmentation is not.

Our findings have the following policy implications. First, providing insurers with subsidies that are tied to their service area could increase insurer participation in higher-risk counties that are underserved by insurers due to risk screening. Second, a direct regulation on insurers' service area is unlikely to be effective in increasing insurer participation. This is because anti-competitive considerations do not seem to drive the selective entry patterns on the ACA Marketplaces. If active insurers were forced to enter all counties including those with higher risks or no legacy networks, they might exit the Marketplaces altogether. Third, our empirical conclusion that fixed costs associated with building provider networks are an important barrier to entry implies that insurers might use narrow networks to lower entry costs in a region where it faces significant network setup costs. Indeed, we find empirical evidence that insurers offer plans with narrower networks in counties where they do not have existing provider networks.

Our paper contributes to the growing literature on insurer participation and pricing on the ACA Marketplaces. Abraham et al. (2017) find that smaller counties have less insurer entry on the federal ACA Marketplaces. Similar to Dafny et al. (2015), they find that there is a negative relationship between insurer participation and premiums. Dickstein et al. (2015) find that rating areas composed of more heterogeneous counties have fewer insurers and higher premiums on the ACA Marketplaces. To the best of our knowledge, our paper is the first to systematically quantify the prevalence of selective entry patterns within geographic rating areas on the ACA Marketplaces.

Our paper also contributes to the literature on risk selection in insurance markets. Decarolis and Guglielmo (2017) and Carey (2017) study, in the context of Medicare, how insurers design plan benefits for risk selection. Shepard (2016) studies the inclusion of high-cost "star" hospitals in plans' network as a screening tool in the pre-ACA Massachusetts Marketplace. Geruso et al. (2019) find that insurers use prescription drug formularies to risk screen consumers in the ACA Marketplaces. Our analysis contributes to this literature by showing that insurers use the scope of their service area to avoid enrolling high-risk consumers when they are required to charge the same price to all consumers.

Our findings on the relationship between network setup costs and insurer entry shed light on the debate over narrow networks on the ACA Marketplaces. Dafny et al. (2017) and Polsky et al. (2016) examine the prevalence of narrow provider networks and their potentials for lowering premiums on the Marketplaces. We show that narrow networks may be used by insurers to expand their service area without incurring substantial entry costs.

In a broader scope, our paper is related to the literature on the design of the ACA markets. There are several papers in this literature that use data from the pre-ACA Massachusetts Marketplace which had regulation settings similar to the ACA, such as age-based pricing (Ericson and Starc, 2015), individual mandate (Hackmann et al., 2015) and subsidies (Finkelstein et al., 2017; Jaffe and Shepard, 2017).[3] Tebaldi (2017), Polyakova and Ryan (2019) and Aizawa (2019), among others, have also contributed to the empirical literature on the design of subsidies on the ACA Marketplaces.[4]

The novel correlation test we develop to disentangle the relative importance of risk selection and market segmentation is related to recent tests of affiliation in the auction literature (Roosen and Hennessy, 2004; de Castro and Paarsch, 2010; Jun et al., 2010; Aradillas-Lopez, 2016). The notion of affiliation is stronger than positive correlation, and it was first introduced into economics by Milgrom and Weber (1982) in auction settings.[5] For example, the test developed by Aradillas-Lopez (2016) is based on the result that in competitive auctions where bidders' values are affiliated, bidders' participation decisions will also be affiliated. If the test rejects the null hypothesis of affiliation, it could suggest that bidders are not acting competitively, such as acting in collusion. Similarly, our correlation test is also capable of detecting anti-competitive market segmentation in a nonparametric way. In contrast to Aradillas-Lopez (2016), our test does not require a firm's participation decisions to be *i.i.d.* across markets, an important relaxation in our settings as an insurer's county entry decisions within a rating area are unlikely to be independent.

The remainder of the paper is structured as follows. In Section 2, we provide the institutional background of the ACA Marketplaces and present our data. In Section 3, we demonstrate the prevalence of partial rating area offering. In Section 4, we present possible explanations for the partial rating area offering phenomenon and generate testable predications. In Section 5, we provide empirical evidence for the testable predictions. Finally, in Section 6, we conclude.

[3]Studies that use estimates based on non-individual health insurance markets and use simulations to study ACA-like settings include Handel et al. (2015), Aizawa and Fang (2020), and Azevedo and Gottlieb (2017).

[4] Tebaldi (2017) examines subsidy designs in the context of the California ACA Marketplace. Polyakova and Ryan (2019) study the welfare implications of targeted benefits provided by private firms with market power in the context of the ACA Marketplaces. Aizawa (2019) emphasizes the interaction between the ACA and the labor market sorting in the health insurance system design.

[5]For a formal definition of affiliation, see Milgrom and Weber (1982).

2 Background and Data

2.1 Background

The ACA was signed into law in 2010 and represents the most significant health care reform of the US health care system since the enactment of Medicare and Medicaid in 1965. The persistent and high uninsured rate (18% in 2009) was the major motivation for the ACA. One of the most important pillars of the ACA is the establishment of state-based health insurance Marketplaces. In the Marketplaces, insurers sell health insurance plans to individuals without access to employer-sponsored health insurance (ESHI), such as the unemployed or self-employed individuals. Plans offered on the Marketplaces are classified into four metal tiers based on their actuarial value: Bronze plans have an actuarial value of 60%, Silver 70%, Gold 80% and Platinum 90%.[6]

The ACA provides premium and cost-sharing subsidies to low-income individuals who purchase insurance on the Marketplaces. Premium subsidies are available to individuals with incomes below 400% of the federal poverty line (FPL), and cost-sharing subsidies are available to individuals with incomes below 250% of FPL who purchase Silver plans. Plans within the Silver category are the most popular as cost-sharing subsidies are available only for these plans. Marketplace insurers have to offer at least one Silver plan in any county they wish to operate.

On the ACA Marketplaces, insurers must accept all applicants regardless of their pre-existing conditions. Premiums can be adjusted only for an individual's age, tobacco use, family composition and geographic location. Each state has a set number of geographic rating areas that all insurers participating in the state's Marketplace must uniformly use in their price setting. On the ACA Marketplaces, insurers can determine the *service area* of a plan, which is the set of counties where the plan is sold within a rating area. In most cases, the smallest unit of a plan's service area is a county because the federal government almost never approves plans that are not sold to all residents of a county. While the ACA requires that an insurer price its plan uniformly in all counties within a rating area, it does

[6] There is also a Catastrophic category which consists of plans that have low monthly premiums and high deductibles. However, there are strict restrictions on who can buy Catastrophic plans: only people under the age of 30 or people with a hardship exemption are eligible.

not require that the insurer sell its plan in all counties within the rating area.

The default rating areas for each state was the Metropolitan Statistical Areas (MSAs) plus the remainder of the state that is not included in a MSA. We refer to this division method as the "MSAs+1" rule. States were given a chance to seek approval from the Department of Health and Human Services (HHS) for a number of rating areas that is greater than the number of MSAs plus one, provided that the division method was based on counties, three-digit zip codes, or MSAs/non–MSAs. If a state requested rating areas in excess of MSAs+1, they had to demonstrate how the new division method would (1) reflect significant differences in health care costs by rating area, (2) lead to stability in rates over time, (3) apply uniformly to all insurers in a market, and (4) not be unfairly discriminatory.[7]

If a state already had an existing rule to divide the state into rating areas, the state frequently kept the division rule to minimize shocks to insurers (Giovannelli et al., 2014). States without such legacy struggled to develop rating areas that reflected significant differences in health care costs but that would not result in insurers charging higher premiums to regions with greater health risks, as that would violate the community rating provision of the ACA which prohibits price discriminations based on health (Giovannelli et al., 2014). Table A.1 in Appendix A provides information about each state's method for dividing the state into rating areas. The geographic scope of implemented rating areas varies greatly by state. Seven states (Alabama, New Mexico, North Dakota, Oklahoma, Texas, Virginia, and Wyoming) have the federal default MSAs+1. Six states (Delaware, Hawaii, New Hampshire, New Jersey, Rhode Island, and Vermont) and District of Columbia have a single rating area, meaning that there is no premium adjustment for geographic location within the state. On the other extreme, states like Florida and South Carolina have single-county rating areas.

2.2 Data and sample construction

Data. Our main data come from the 2016 Marketplace Public Use Files (PUF) provided by the Centers for Medicare and Medicaid Services (CMS). The data cover all individual health insurance plans sold in 38 states which rely on the federal government (HHS) to run their Marketplaces in 2016. These states are considered to have a "federally-facilitated"

[7]Source: Centers for Medicare and Medicaid Services.

Marketplace, as opposed to a state-based Marketplace in which a state is responsible for performing all Marketplace functions for the individual market.[8] The last column in Table A.1 in Appendix A shows which states have federally-facilitated Marketplaces. Among other things, the Marketplace PUF provides information about each plan's service area which is a set of counties where the plan is sold. We use this information to examine whether insurers selectively offer plans within a rating area.

Insurers' decisions about which counties to enter within a rating area may be affected by county characteristics. To explore this channel, we use two county-level datasets: the Area Health Resources Files (AHRF) provided by the HHS and County Health Rankings (CHR) by the Robert Wood Johnson Foundation. Both datasets provide information about various health and socioeconomic characteristics at the county level.

Entry costs may also be important in studying insurers' entry decisions. All Marketplace plans must meet network adequacy standards, which means that Marketplace plans should have ability to deliver care by providing reasonable access to enough in-network physicians. Therefore, costs associated with building provider networks may account for a substantial fraction of insurers' entry costs. Note that these costs can be significantly lower if an insurer has sold other lines of health insurance products in a market it wishes to enter as the insurer can use existing provider networks.

To proxy Marketplace insurers' entry costs associated with building provider networks, we use information about the insurers' Medicare Advantage (MA) service area obtained from the CMS. Medicare is a federal program that primarily provides health insurance for Americans aged 65 and older. MA plans are a type of Medicare plans offered by private insurers who receive capitated payments from the federal government and provide Medicare-covered services to enrollees. Most MA enrollees have *managed* MA plans which are required to establish provider networks that cover areas no smaller than a county. Therefore, whether a Marketplace insurer had sold managed MA plans in a county prior to the opening of the Marketplaces is informative about insurers' county-level entry costs on the Marketplaces.

[8] The degree to which states with federally-facilitated Marketplaces rely on the HHS varies: 27 states have Marketplaces that are entirely operated by the HHS, 7 states perform in-person consumer assistance while delegating all other functions to the HHS, and 4 states are responsible for performing their own Marketplace functions, except that they rely on the federal IT platform. In this paper, we refer to the 38 states that rely on the HHS for any support as having federally-facilitated Marketplaces.

Sample:	(1) Single-county RAs included	(2) Single-county RAs excluded
Insurers	235	214
Plans	3,779	3,212
States	36	34
RAs	405	259
Counties	2,481	2,335

Table 1: 2016 Marketplace PUF sample size
Notes: The sample consists of individual health insurance plans offered in federally-facilitated marketplaces in 2016. In both columns, Alaska and Nebraska are excluded as they use zip codes to define rating areas. Catastrophic plans are also excluded as there are strict restrictions on who can buy these plans. Column (1) includes rating areas (RAs) which comprise just one county. Column (2) excludes single-county rating areas, which eliminates Florida and South Carolina as rating areas in these two states always consist of one county. Our partial rating area offering analysis is on the sample in Column (2).

The sample period of the MA data is from August 2012 to July 2013, which covers 12 months prior to the first-ever deadline for insurers to submit Marketplace plan information to the government.

Sample construction. In the 2016 Marketplace PUF, there are 4,125 individual health plans offered in 38 federally-facilitated Marketplaces. We impose the following set of restrictions to construct our sample. First, we exclude two states (Alaska and Nebraska) which use zip codes, rather than counties, to define rating areas. This is because our unit of analysis is at the county level, which is typically the smallest unit of a plan's service area permitted on the Marketplaces. Imposing this restriction leaves us with 4,059 plans offered by 235 insurers in 36 states and 405 rating areas. Second, we exclude 280 plans that are in the Catastrophic category.[9] Finally, we exclude rating areas that consist of a single county. The is because in single-county rating areas, there can be no partial rating area offering by definition. Out of 405 rating areas, 146 consist of a single county. Excluding single-county rating areas eliminates all plans from Florida and South Carolina as rating areas in these two states always consist of a single county. Table 1 presents the sample size before and after excluding single-county rating areas. The size of our final 2016 Marketplace PUF sample is in Column (2) of Table 1: it consists of 3,212 plans offered by 214 insurers in 34 states and 259 rating areas.

[9]This is because, as explained earlier, there are strict restrictions on who can buy Catastrophic plans.

Sample:	(1) Counties in single-county RAs	(2) Counties in multi-county RAs
Statistics:	Mean	Mean
Active insurers in a county	3.45	3.51
Active insurers in a rating area	3.45	4.99
Active plans in a county	45.23	33.06
Active plans in a rating area	45.23	47.58
Non-elderly population below 400% FPL	167,063	40,434
Share who are obese	0.31	0.31
Smoker share	0.20	0.22
Share without leisurely physical activity	0.27	0.28
Physically unhealthy days/month	4.09	3.84
Share without access to physical activity	0.31	0.40
Limited access to good food (0-1)	0.34	0.30
Observations (counties)	146	2,335

Table 2: Counties in single-county RAs vs. multi-county RAs
Notes: The table reports mean characteristics of counties in single-county rating areas (RAs) and counties in multi-county RAs.

Single-county vs. multi-county rating areas. As partial rating area offering can happen only in rating areas with at least two counties, our sample consists multi-county rating areas. Before we proceed further, we examine whether counties in multi-county rating areas are disadvantaged by having fewer insurers or plans to choose from compared to counties in single-county rating areas where no partial rating area offering can occur.

Table 2 shows that for an average county located in multi-county rating areas, there are 3.51 active insurers, which is close to the average number of active insurers for counties located in single-county rating areas (3.45).[10] However, the table reveals that if there were no partial entry, i.e., all insurers in a multi-county rating area entered all counties in the rating area, then the average number of active insurers could be as high as 4.99 for counties located in multi-county rating areas.

Table 2 reveals that consumers living in multi-county rating areas do have fewer plans to choose from than consumers living in single-county rating areas. In counties that belong to single-county rating areas, the average number of available plans is 45.23. In counties that belong to multi-county rating areas, the average number of available plans is only 33.06. If there were no partial entry, i.e., all plans in a multi-county rating area were offered in

[10]We say an insurer is *active* in a county if it sells at least one plan in the county. We say an insurer is *active* in a rating area if it is active in at least one of the counties that belong the rating area.

all counties in the rating area, counties in multi-county rating areas could have as many as 47.58 plans to choose from. This suggests that understanding mechanisms underlying partial rating area offering in multi-county rating areas can be helpful in enriching the insurance choice set of consumers living in multi-county rating areas.

3 Prevalence of Partial Rating Area Offering

In this section, we document how prevalently insurers sell plans in a strict subset of counties within a rating area. We first develop various statistics based on the service area of an insurer. We then define analogous statistics based the service area of a plan.

3.1 Prevalence of partial rating area offering based on insurers' service area

We index health insurance plans by $p = 1, ..., P$; rating areas by $r = 1, ..., R$; counties by $c = 1, ..., C$; and insurers by $i = 1, ..., I$. For each plan p, $\mathbb{I}_P(p) \in \{1, ..., I\}$ denotes the insurer who offers plan p. $\mathcal{C}(r)$ denotes the set of counties in rating area r. Using the Marketplace PUF sample, we can construct the following indicator of whether a plan is sold in a county:

$$O^P(p, c) = \begin{cases} 1 & \text{if plan } p \text{ is sold in county } c, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Using these notations, we can construct several auxiliary objects reported in Table 3, which will be helpful for notational clarity throughout the rest of the paper. We say an insurer is *active in a county* if it sells at least one plan in the county.[11] We say an insurer is *active in a rating area* if it is active in at least one of the counties located in the rating area.

We develop three statistics to evaluate how prevalently insurers selectively enter counties within a rating area. First, we develop an *insurer-rating area-level* measure to assess how comprehensively an insurer serves a rating area. For every insurer i and for every rating area

[11] As mentioned in Section 2, insurers active in any given county offer at least one Silver plan in the county.

Notations	Descriptions
Set of plans	
$\mathcal{P}_I(i) = \{p : \mathbb{I}_P(p) = i\}$	Set of plans offered by insurer i.
$\mathcal{P}_C(c) = \left\{p : O^P(p, c) = 1\right\}$	Set of plans offered in county c.
$\mathcal{P}_R(r) = \cup_{c \in \mathcal{C}(r)} \mathcal{P}_C(c)$	Set of plans offered in rating area r.
Set of insurers	
$\mathcal{I}_C(c) = \{i : i = \mathbb{I}_P(p) \text{ for } p \in \mathcal{P}_C(c)\}$	Set of active insurers in county c.
$\mathcal{I}_R(r) = \cup_{c \in \mathcal{C}(r)} \mathcal{I}_C(c) = \{i : i = \mathbb{I}_P(p) \text{ for } p \in \mathcal{P}_R(r)\}$	Set of active insurers in rating area r.
Set of counties	
$\mathcal{C}_I(i) = \{c : \mathcal{P}_I(i) \cap \mathcal{P}_C(c) \neq \emptyset\}$	Set of counties in which insurer i is active.
$\mathcal{C}_P(p) = \left\{c : O^P(p, c) = 1\right\}$	Set of counties in which plan p is offered.
Set of rating areas	
$\mathcal{R}_I(i) = \{r : \mathcal{C}(r) \cap \mathcal{C}_I(i) \neq \emptyset\}$	Set of rating areas in which insurer i is active.
$\mathcal{R}_P(p) = \{r : \mathcal{C}(r) \cap \mathcal{C}_P(p) \neq \emptyset\}$	Set of rating areas in which plan p is offered.

Table 3: Notations and definitions

Notes: The table defines and describes various sets for notational clarity. $\mathbb{I}_P(p) \in \{1, ..., I\}$ denotes the insurer who sells plan p, $\mathcal{C}(r)$ denotes the set of counties in rating area r, and $O^P(p, c)$ is the indicator for whether plan p is sold in county c.

r where the insurer is active, we compute the share of counties where the insurer offers at least one plan:

$$B_1^I(i, r) = \frac{|\mathcal{C}_I(i) \cap \mathcal{C}(r)|}{|\mathcal{C}(r)|}. \tag{2}$$

The denominator is the number of counties in rating area r, and the numerator is the number of counties in rating area r in which insurer i offers at least one plan (see Table 3 for the definition of the set $\mathcal{C}_I(i)$).

Second, we develop a *county-level* measure to evaluate how completely a county is serviced by insurers active in its rating area. For every county c, we compute the fraction of active insurers in its rating area that sell at least one plan in the county:

$$B_2^I(c) = \frac{|\mathcal{I}_C(c)|}{|\mathcal{I}_R(r) : c \in \mathcal{C}(r)|}. \tag{3}$$

The denominator is the number of active insurers in rating area r to which county c belongs, and the numerator is the number of active insurers in county c.[12]

Third, we develop a *rating area-level* measure to quantify how comprehensively counties in a rating area are serviced by insurers active in the rating area. To do this, we compute the average of the first measure, $B_1^I(i, r)$, or the second measure, $B_2^I(c)$, both of which yield

[12] The definitions for sets $\mathcal{I}_C(c)$ and $\mathcal{I}_R(r)$ are provided in Table 3.

Measure	Unit	Obs.	Share of obs. < 1	Mean	Std
$B_1^I(i,r)$	Insurer-RA	1,236	0.29	0.85	0.28
$B_2^I(c)$	County	2,335	0.41	0.83	0.26
$B_3^I(r)$	RA	259	0.52	0.89	0.14

Table 4: Partial rating area offering based on insurers' service area
Notes: The table reports how prevalently partial rating area offering takes place based on insurers' service area.

the same result:

$$\begin{aligned} B_3^I(r) &= \frac{1}{|\mathcal{I}_R(r)|} \sum_{i \in \mathcal{I}_R(r)} B_1^I(i,r) \\ &= \frac{1}{|\mathcal{C}(r)|} \sum_{c \in \mathcal{C}(r)} B_2^I(c). \end{aligned} \tag{4}$$

Table 4 reports the summary statistics of the three measures of partial rating area offering. We find that in 29% of 1,236 instances where an insurer is active in a rating area, the insurer enters some but not all of the counties in a rating area, resulting in $B_1^I(i,r) < 1$. On average, an insurer offers plans in 85% of counties in a rating area where it is active. Indeed, we find that out of 214 insurers in our sample, 116 insurers (about 54%) engage in partial rating area offering by not selling any plans in at least one county that belongs to a rating area where they are active. From the second measure $B_2^I(c)$, we find that 41% of 2,335 counties in our sample are excluded by at least one active insurer in their rating areas. On average, a county is serviced by 83% of insurers active in its rating area. Finally, using the third measure $B_3^I(r)$, we find that 52% of 259 multi-county rating areas have at least one active insurer who does not operate in all of their counties.

3.2 Prevalence of partial rating area offering based on plans' service area

To provide a more complete picture of the partial rating area offering phenomenon on the ACA Marketplaces, we now define three analogous statistics based on the service area of a plan. First, for every rating area r and every plan p offered in the rating area, i.e.,

Measure	Unit	Obs.	Share of obs. < 1	Mean	Std
$B_1^P(p,r)$	Plan-RA	12,258	0.33	0.81	0.30
$B_2^P(c)$	County	2,335	0.57	0.79	0.25
$B_3^P(r)$	RA	259	0.63	0.87	0.15

Table 5: Partial rating area offering based on plans' service area
Notes: The table reports how prevalently partial rating area offering takes place based on plans' service area.

$p \in \mathcal{P}_R(r)$, we define

$$B_1^P(p,r) = \frac{|\mathcal{C}_P(p) \cap \mathcal{C}(r)|}{|\mathcal{C}(r)|}. \tag{5}$$

The denominator is the number of counties in rating area r, and the numerator is the number of counties in rating area r where plan p is offered.

Second, we develop a county-level measure to evaluate how completely a county is served by plans that are offered in the county's rating area:

$$B_2^P(c) = \frac{|\mathcal{P}_C(c)|}{|\mathcal{P}_R(r) : c \in \mathcal{C}(r)|}. \tag{6}$$

The denominator is the number of plans that are offered in the rating area to which county c belongs, and the numerator is the number of plans offered in county c.

Lastly, we develop a rating area-level measure to quantify how completely counties in a rating area are serviced by plans active in the rating area. This measure can be computed either by taking the average of $B_1^P(p,r)$ or by taking the average of $B_2^P(c)$:

$$\begin{aligned} B_3^P(r) &= \frac{1}{|\mathcal{P}_R(r)|}\sum_{p\in\mathcal{P}_R(r)} B_1^P(p,r) \\ &= \frac{1}{|\mathcal{C}(r)|}\sum_{c\in\mathcal{C}(r)} B_2^P(c). \end{aligned} \tag{7}$$

Table 5 reports the summary statistics of the three measures of partial rating area offering based on plans' service area. The results are quantitatively similar to Table 4 which quantifies partial rating area offering based on insurers' service area. For example, out of 2,335 counties located in multi-county rating areas, 57% are excluded by at least one plan offered in their respective rating area. About 63% of 259 multi-county rating areas in our sample have at least one Marketplace plan that is not sold to all of their counties.

Sample restrictions:	(1) Aged 65- and below 400% FPL	(2) Aged 65-, below 400% FPL and uninsured in 2013
Individuals affected by partial entry	36,337,053	8,333,593
Share affected by partial entry	0.38	0.40

Table 6: Consumers affected by partial rating area offering on the ACA Marketplaces
Notes: In both columns, the sample is initially restricted to individuals living in multi-county rating areas in 34 states with federally-facilitated Marketplaces. Column (1) restricts the sample to non-elderly individuals with incomes below 400% of FPL. Column (2) further restricts the sample to individuals who were uninsured in 2013. Note that enrollment in the ACA Marketplaces started on October 1, 2013.

To sum, partial rating area offering happens on the ACA Marketplaces, and it is not uncommon to observe insurers that serve only a subset of counties within a rating area. The prevalence of partial rating area offering implies that even though the ACA specifies rating areas as the geographic unit for allowing premium variations, some insurers are effectively varying premiums by county, which is a finer geographic scope than a rating area.

3.3 Magnitude

Table 6 presents the number and share of individuals who faced restricted choices on the Marketplaces in 2016 due to partial rating area offering. We consider non-elderly individuals with incomes below 400% of FPL as potential enrollees on the Marketplaces. This is because as explained earlier in Section 2, premium subsidies are available to this group of lower-income individuals. Column (1) shows that among these potential enrollees who lived in multi-county rating areas, 38% lived in counties that were excluded from the service area of at least one active insurer in their rating area, i.e., $B_2^I(c) < 1$. Column (2) further restricts the sample to individuals who were uninsured in 2013: 40% of these individuals faced restricted insurer choices due to partial rating area offering.[13] Together with the prevalence of partial rating area offering documented in Tables 4 and 5, evidence presented in this section shows that the magnitude of selective entry within a rating area is substantial on the ACA Marketplaces.

[13] Enrollment in the ACA Marketplaces started on October 1, 2013.

4 Testable Hypotheses

This section presents several possible explanations for the partial rating area offering phenomenon documented in Section 3.

4.1 Possible explanations

Risk selection. As counties within a rating area could differ in their health risk distributions, insurers might limit their service area within a rating area to risk select counties. If risk selection is a key driver of the partial rating area offering phenomenon, we have the following testable predictions. First, to the extent that all insurers face the same county characteristics such as the market size and risk distribution, we expect insurers' county entry decisions to be *positively correlated*. That is, if one insurer believes that a particular county in a rating area has higher-risk consumers and decides against offering a plan in the county, so should other insurers.

Second, partial rating area offering should be more prevalent in states with the MSAs+1 division rule. Some states attempt to group counties with similar social economic and health characteristics into rating areas, while some states follow the simple MSAs+1 rule. For the states that follow the MSAs+1 rule, it is likely that counties in the same rating area differ more in their risk distributions. Thus, if risk selection is a key driver, partial rating area offering will be more prevalent in the states with the MSAs+1 division rule.

Third, partial rating area offering should be more prevalent at the plan level than at the insurer level. If counties within a rating area have heterogeneous risk distributions, then offering a single plan may not maximize an insurer's profit. This is because the ACA mandates that premiums be the same for all counties within a rating area. Instead, insurers could target counties of different risk distributions with different plans and charge separate premiums. In this case, partial rating area offering will be more prevalent at the plan level than at the insurer level.

Lastly, if risk screening is a key driver of partial rating area offering, insurers should be less likely to enter higher-risk counties within a rating area. As argued in Hendren (2013), insurers have an incentive to reject observably high-risk individuals (rather than charging them a high price) because they are likely to have greater amounts of private information which would aggravate adverse selection. Therefore, if risk selection is the primary reason why insurers selectively enter counties on the Marketplaces, we should observe less entry in counties with more adverse health characteristics.

Market segmentation. Insurers might selectively enter counties within a rating area to avoid competition. Considering that the average number of active insurers in a county is only 3.5, the desire to avoid competition might potentially explain insurers' partial entry in a rating area.[14] If market segmentation is a key driver of partial rating area offering, we have the following testable predictions. First, we expect insurers' county entry decisions to be *negatively correlated*. This is because insurers will avoid entering a county where their competitors are present under market segmentation.

Second, market segmentation to avoid competition requires that insurers be deterred from unilateral deviations. To the extent that market segmentation arrangements are easier to uphold if the insurers are engaged in multi-market contacts, we expect the selective entry patterns documented in Section 3 to be more prevalent in rating areas involving insurers who are also co-present in more markets elsewhere.

Entry costs. Insurers might not enter a county within a rating area if they have to incur a significant cost to meet network adequacy requirements or to have a competitive provider network. The ACA requires that all qualified health plans sold on the Marketplaces ensure "a sufficient choice of providers" and include "essential community providers that serve predominantly low income, medically underserved individuals." In order to test the potential role of entry costs in explaining the partial rating area offering phenomenon, we note the following implications. First, if an insurer already has a presence in a county in other lines of health insurance products, e.g., Medicare Advantage plans, the insurer will have a lower cost of building (or expanding) the provider network necessary for ACA plans. Thus, an insurer should be more likely to sell ACA plans in a county where it has legacy provider networks.

[14] The degree of insurer competition is higher in other health insurance markets: for example, according to the Kaiser Family Foundation, the average person on Medicare in 2017 had 6 Medicare Advantage insurers to choose from.

Second, partial rating area offering should be more prevalent among plan types that only cover in-network providers. While the ACA network adequacy requirement applies to all Marketplace plans, states have considerable discretion in actual implementation of the requirement. In particular, according to a state survey conducted by the National Association of Insurance Commissioners (NAIC), in most if not all states, network adequacy oversight is more comprehensive for Health Maintenance Organization (HMO) and Exclusive Provider Organization (EPO) plans than for Point of Service (POS) and Preferred Provider Organization (PPO) plans (NAIC, 2014). This is because HMOs and EPOs put more restrictions on consumers' provider choice and do not reimburse health care services delivered by providers outside their network. In contrast, POS and PPO plans cover out-of-network providers for an additional cost.[15] Therefore, if fixed costs associated with meeting the network adequacy requirement are the primary driver of partial rating area offering, we expect plans that are selectively offered to have a higher chance of being a HMO/EPO plan than a PPO/POS plan.

Third, if network adequacy is important in explaining the selective entry patterns detected in Section 3, then the prevalence of partial rating area offering should be similar when it is measured at the insurer level or at the plan level. Suppose the reason why an insurer does not sell an ACA plan in a particular county is because it is too costly for the insurer to build an adequate provider network in the county. Then, we should not expect the insurer to offer different plans in that county. The reason is simple: if the insurer does not have an adequate provider network in a county for one plan, it does not have an adequate provider network for other plans either. Therefore, if entry costs are insurers' primary concern in their service area determination, the prevalence of partial rating area offering should be similar when it is measured at the insurer level or at the plan level.

4.2 Testable implications

Below, we summarize the implications of the three hypotheses.

[15] The main difference between EPOs and HMOs is that HMOs require primary care physicians while EPOs do not. The main difference PPOs and POSs is that while POSs usually require primary care physicians and their referrals to see a specialist, PPOs do not have such requirements. In our 2016 Marketplace PUF sample, HMOs have the largest share (52%), followed by PPOs (31%), POSs (10%), and EPOs (8%).

Hypothesis A. The *risk selection* hypothesis has the following predictions:

1. Insurers' county entry decisions within a rating area should be positively correlated.
2. Partial rating area offering should be more prevalent in rating areas located in states that use the MSAs+1 rule to determine rating areas.
3. Partial rating area offering should be more prevalent when measured at the plan level than at the insurer level.
4. Insurers should be less likely to enter higher-risk counties within a rating area.

Hypothesis B. The *market segmentation* hypothesis has the following predictions:

1. Insurers' county entry decisions within a rating area should be negatively correlated.
2. Partial rating area offering should be more prevalent in rating areas involving insurers who are also co-present in more markets elsewhere.

Hypothesis C. The *entry cost* hypothesis has the following predictions:

1. Insurers should be more likely to sell ACA plans in a county where they have legacy provider networks.
2. Partial rating area offering should be more prevalent among HMO and EPO plans.
3. Partial rating area offering should be equally prevalent when measured at the plan level and at the insurer level.

5 Empirical Results

We empirically examine the testable implications of Hypotheses A, B, and C in the following steps. In Section 5.1, we provide descriptive evidence on each of the hypotheses' predictions, except for those on insurers' entry correlation. In Section 5.2, we develop a novel correlation

RA division method:	Default MSAs+1	Otherwise
Insurer coverage measures		
Mean of $B_1^I(i,r)$	0.76	0.86
Mean of $B_2^I(c)$	0.64	0.89
Mean of $B_3^I(r)$	0.88	0.89
Plan coverage measures		
Mean of $B_1^P(p,r)$	0.76	0.82
Mean of $B_2^P(c)$	0.61	0.86
Mean of $B_3^P(r)$	0.87	0.87
Observations		
States	7	27
Rating areas	45	214
Counties	618	1,717

Table 7: Partial rating area offering by states' rating area division rule
Notes: The table compares the magnitude of partial rating area offering between states that use the federal default method to define rating areas (which is MSAs plus the remainder of the state) and the remaining states with a non-default division method. In our 2016 Marketplace PUF sample, a total of 7 states use the default MSAs+1 division method (Alabama, New Mexico, North Dakota, Oklahoma, Texas, Virginia, and Wyoming).

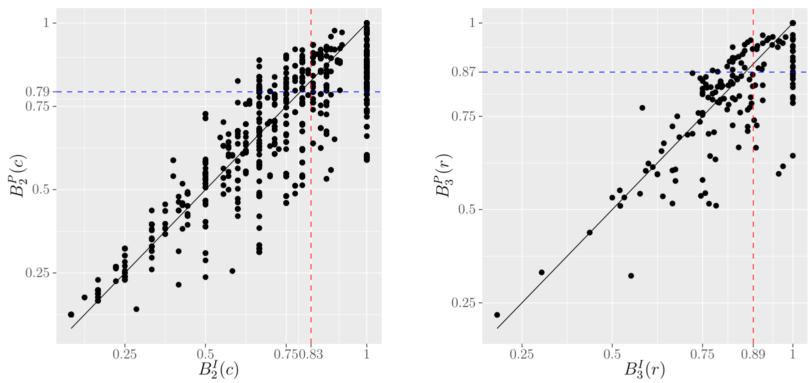
test to determine whether the correlation between insurers' county entry decisions is positive as predicted by Hypothesis A or negative as predicted by Hypothesis B. In Section 5.3, we conduct regression analyses to examine the different testable implications in a unified framework.

5.1 Descriptive analysis

This section examines whether descriptive patterns of our data are in line with each of the hypotheses' testable implications.

Hypothesis A. We first examine whether partial rating area offering is more concentrated in rating areas located in states that use the MSAs+1 rule to divide rating areas. Table 7 reveals that partial rating offering is indeed more prevalent in states with the MSAs+1 division rule, consistent with Hypothesis A. For example, counties located in states with the MSAs+1 division rule are serviced by only 64% of insurers active in their rating areas. For counties located in states with a non-default division rule, the insurer participation rate is much higher at 89%.

Next, we examine if partial rating area offering is more pronounced when measured at the



Panel A Panel B

Figure 1: Plan-level vs. insurer-level partial rating area offering

Notes: Panel A plots for each county, the insurer coverage measure $B_2^I(c)$ on the horizontal axis and the plan coverage measure $B_2^P(c)$ on the vertical axis. Panel B plots for each rating area, the insurer coverage measure $B_3^I(r)$ on the horizontal axis and the plan coverage measure $B_3^P(c)$ on the vertical axis. Dashed lines represent the mean of each variable.

plan level than at the insurer level, as predicted by Hypothesis A. The left panel in Figure 1 compares the insurer coverage (x-axis) and plan coverage (y-axis) at the county level. The right panel compares the insurer coverage (x-axis) and plan coverage (y-axis) at the rating area level. Both panels show that there are slightly more observations below the 45-degree line. This implies that selective entry is more pronounced at the plan level, but only by a small margin.

Finally, we examine if insurers avoid entering relatively high risk counties in a rating area. We demean county health measures by their respective rating area average to examine how risky a county is relative to other counties in the same rating area. Figure 2 reports the results. The insurer participation rate in a county, $B_2^I(c)$, drops substantially at the top quantile which represents the highest risk counties. Such patterns provide suggestive evidence for risk screening, consistent with Hypothesis A.[16]

Hypothesis B. We examine if partial rating area offering is more concentrated in rating areas involving insurers who are also co-present in more markets elsewhere. To do this, for a given rating area, we compute the average number of *other* rating areas where insurers

[16] We have reproduced Figure 2 using the plan coverage measure $B_2^P(c)$ as the y-axis variable. The results look very similar to Figure 2.

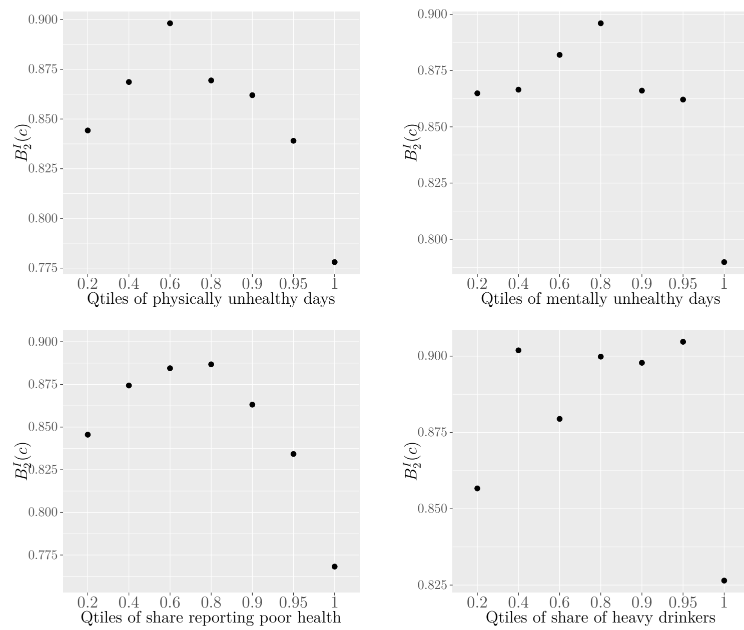


Figure 2: County health risks and insurer participation rate

Notes: Let x_c represent a county health measure that is either (1) the mean number of physically unhealthy days per month, (2) the mean number of mentally unhealthy days per month, (3) the share of the county population reporting poor health, or (4) the share of the county population that are heavy drinkers. For each rating area r, we compute the mean value of x_c using counties that belong to the rating area, denoted by $\overline{x}_r$. We compute the *demeaned* county health measure as $x_c - \overline{x}_r$ (assuming county c belong to rating area r). The x-axis represents quantiles (Qtiles) of $x_c - \overline{x}_r$. The y-axis represents the mean of $B_2^I(c)$ for each quantile.

active in the rating area are again co-present pairwise, denoted by $OtherMktContact(r)$.[17] Table 8 presents various partial entry measures by grouped values of $OtherMktContact(r)$. There is no negative relationship between $OtherMktContact(r)$ and either insurer or plan coverage measures. That is, rating areas involving insurers who are co-present in more markets elsewhere do not have more pronounced partial entry. This result provides descriptive evidence *against* Hypothesis B.

Hypothesis C. To examine if data patterns are in line with Hypothesis C, we first examine if a Marketplace insurer is more likely to enter a county where it can use the legacy of its

[17] Specifically, for each active insurer i and its competitor j in rating area r, we compute the number of other rating areas where they compete and denote it by $OtherMktContact(i, j, r)$. We average it over all competitor j's to compute $OtherMktContact(i, r)$, which represents the average number of other markets where insurer i is co-present with its competitors from rating area r. Finally, we average $OtherMktContact(i, r)$ over all i's and obtain $OtherMktContact(r)$.

$OtherMktContact(r)$:	[0,3.6)	[3.6, 6)	[6,10)	10+
Insurer coverage measures				
Mean of $B_1^I(i,r)$	0.76	0.88	0.89	0.84
Mean of $B_2^I(c)$	0.67	0.90	0.92	0.85
Mean of $B_3^I(r)$	0.85	0.90	0.92	0.86
Plan coverage measures				
Mean of $B_1^P(p,r)$	0.69	0.85	0.86	0.86
Mean of $B_2^P(c)$	0.62	0.84	0.89	0.88
Mean of $B_3^P(r)$	0.79	0.87	0.89	0.89
Number of rating areas	60	58	68	61

Table 8: Partial entry by multi-market contact

Notes: For each active insurer i and its competitor j in a given rating area r, we compute the number of other rating areas where they are co-present. Call this variable $OtherMktContact(i,j,r)$. We average it over all competitor j's to compute $OtherMktContact(i,r)$, which represents the average number of other markets where insurer i is co-present with its competitors from rating area r. We average $OtherMktContact(i,r)$ over all active insurer i's in the rating area and obtain $OtherMktContact(r)$. The table shows how the magnitude of partial rating area offering varies by $OtherMktContact(r)$. The table excludes rating areas with just one active insurer as $OtherMktContact(r)$ cannot be computed.

	(1) Share of MA counties within a RA where insurer sells ACA plans	(2) Share of non-MA counties within a RA where insurer sells ACA plans
Mean	0.91	0.79
1st quartile	1.00	0.60
3rd quartile	1.00	1.00
Insurer-RA pairs	566	790

Table 9: ACA Marketplace entry probability in MA vs. non-MA counties

Notes: For each insurer, we classify a county as the insurer's MA county if the insurer had sold managed MA plans in the county before the ACA, and as a non-MA county otherwise. Then, in each of the rating areas where the insurer is active, we compute the share of the insurer's MA counties and the share of the insurer's non-MA counties where the insurer sells ACA Marketplace plans. Columns (1) and (2) report summary statistics of the former and the latter shares, respectively.

existing provider networks. For each insurer, we classify a county as the insurer's MA county if the insurer had sold managed MA plans in the county before the ACA, and as a non-MA county otherwise. Then, in each of the rating areas where the insurer is active, i.e., $r \in \mathcal{R}_I(i)$, we compute the share of the insurer's MA counties and the share of the insurer's non-MA counties where the insurer sells ACA Marketplace plans. Table 9 summarizes the results. On average, a Marketplace insurer enters 91% of counties in a rating area where it sold managed MA plans before the ACA. In contrast, the insurer enters only about 79% of counties where it did not have any MA plans. This pattern suggests that insurers may be avoiding counties in a rating area where they face relatively large fixed costs of building a provider network.

	Partial RA plans		Complete RA plans	
Plan type	Plans	Share	Plans	Share
EPO	164	0.09	87	0.06
HMO	1,126	0.62	531	0.38
POS	210	0.11	116	0.08
PPO	328	0.18	650	0.47
Total	1,828		1,384	

Table 10: Distribution of plan types by whether plans are partially offered
Notes: The table reports the distribution of plan types conditional on whether a plan is partially offered in any of its serviced rating areas.

Next, we analyze if partial entry is more severe among HMO/EPO plans, as predicted by Hypothesis C. We classify a Marketplace plan as a "Partial RA Plan" if it is partially sold in any of rating areas where it is offered, i.e., $B_1^P(p,r) < 1$ for any $r \in \mathcal{R}_P(p)$. Otherwise, we classify the plan as a "Complete RA Plan". Among 3,212 plans, 1,828 plans (representing 57%) are categorized as a Partial RA Plan. Table 10 shows the distribution of plan types among Partial RA Plans and Complete RA plans, respectively. Consistent with Hypothesis C, HMO plans are much more dominant among Partial RA plans, while PPO plans are a lot more common among Complete RA Plans.

Finally, we examine if the partial rating area offering phenomenon is equally prevalent both at the plan level and at the insurer level, as predicted by Hypothesis C. As discussed above, Figure 1 shows that there seems to be slightly more pronounced selective entry at the plan level than at the insurer level. However, as the difference is small, it does not provide strong descriptive evidence to refute Hypothesis C.

5.2 Correlation test

This section develops a novel statistical test to examine whether the correlation between insurers' county entry decisions in a rating area favors the risk selection hypothesis (Hypothesis A) or the market segmentation hypothesis (Hypothesis B). Hypothesis A predicts that insurers' county entry decisions will be positively correlated, while Hypothesis B predicts that they will be negatively correlated.

5.2.1 Correlation construction

Using the notations introduced in Section 3, we construct a nonparametric measure of correlation. For each insurer i active in rating area r, $i \in \mathcal{I}_R(r)$, and for each county that belongs to the rating area, $c \in \mathcal{C}(r)$, define an indicator $O^I(i,c)$ as follows:

$$O^I(i,c) = \begin{cases} 1 \text{ if } i \in \mathcal{I}_C(c), \\ 0 \text{ if } i \notin \mathcal{I}_C(c) \end{cases} \tag{8}$$

where $\mathcal{I}_C(c)$ is the set of insurers active in county c.

Define $\tilde{\mathcal{I}}_R(r) \subset \mathcal{I}_R(r) \times \mathcal{I}_R(r)$ as the set of all 2-combinations of $\mathcal{I}_R(r)$. For example, if $\mathcal{I}_R(r) = \{i_1, i_2, i_3\}$, then the set $\tilde{\mathcal{I}}_R(r)$ consists of three pairs of insurers, $\tilde{\mathcal{I}}_R(r) = \{(i_1,i_2),(i_1,i_3),(i_2,i_3)\}$. The number of elements in $\tilde{\mathcal{I}}_R(r)$ equals $\begin{pmatrix} |\mathcal{I}_R(r)| \\ 2 \end{pmatrix}$. Similarly, define $\tilde{\mathcal{C}}(r) \subset \mathcal{C}(r) \times \mathcal{C}(r)$ as the set of all 2-combinations of $\mathcal{C}(r)$. The number of all possible 2-combinations is $\left|\tilde{\mathcal{C}}(r)\right| = \begin{pmatrix} |\mathcal{C}(r)| \\ 2 \end{pmatrix}$.

For each pair of insurers active in the rating area $(i,i') \in \tilde{\mathcal{I}}_R(r)$ and for each pair of counties that belong to the rating area $(c,c') \in \tilde{\mathcal{C}}(r)$, we define $o(i,i';c,c')$ as the following:

$$o(i,i';c,c') = \begin{cases} 1 & \text{if } O^I(i,c) = O^I(i',c) \text{ and } O^I(i,c') = O^I(i',c'), \\ -1 & \text{if } O^I(i,c) \neq O^I(i',c) \text{ and } O^I(i,c') \neq O^I(i',c'), \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

In words, $o(i,i';c,c')$ takes value 1 if insurers i and i' are completely aligned regarding their entry decisions in counties c and c'; -1 if they are completely opposed; and 0 for any other cases.

For a given rating area r, we define $CORR(r)$ as the *average* value of $o(i,i';c,c')$ over all possible insurer pairs $(i,i') \in \tilde{\mathcal{I}}_R(r)$ and county pairs $(c,c') \in \tilde{\mathcal{C}}(r)$:

$$CORR(r) = \frac{1}{\begin{pmatrix} |\mathcal{I}_R(r)| \\ 2 \end{pmatrix} \cdot \begin{pmatrix} |\mathcal{C}(r)| \\ 2 \end{pmatrix}} \sum_{(i,i') \in \tilde{\mathcal{I}}_R(r)} \sum_{(c,c') \in \tilde{\mathcal{C}}(r)} o(i,i';c,c'). \tag{10}$$

# RAs with some partial entry ($B_3^I(r) < 1$)	135
: # RAs where $CORR(r) > 0$	121
: # RAs where $CORR(r) = 0$	2
: # RAs where $CORR(r) < 0$	12
: Mean $CORR(r)$ using nonequal weights*	0.37
: Mean $CORR(r)$ using equal weights	0.34
: Median $CORR(r)$	0.34
: Standard deviation $CORR(r)$	0.27
# RAs with no partial entry ($B_3^I(r) = 1$)	112
Observations	247

Table 11: Empirical correlations between insurers' county entry decisions
Notes: The table reports empirical correlations based on the 2016 Marketplace PUF sample. The sample is restricted to rating areas with at least two counties and two participating insurers. For rating areas with no partial entry, the correlation measure is one by construction. *: For each rating area with some partial entry, we compute its weight as the denominator in Equation (10) divided by the sum of this value for all rating areas with some partial entry. These weights are used to compute the mean using nonequal weights.

In words, $CORR(r)$ measures the average alignment of insurers' entry decisions across counties in a given rating area. We say insurers' county entry decisions are positively correlated in rating area r if $CORR(r) > 0$ and negatively correlated if $CORR(r) < 0$. Appendix B provides illustrative examples of $CORR(r)$.

5.2.2 Empirical correlations

We compute the correlation measure $CORR(r)$ for each rating area in our 2016 Marketplace PUF sample. To compute the correlation measure $CORR(r)$, we restrict to rating areas with at least two insurers. This restriction reduces the number of rating areas in the sample from 259 to 247.[18]

Table 11 reports the empirical correlations. In 2016, there was partial entry in 135 rating areas which represents 55% of all rating areas in our sample. Among the rating areas with partial entry, 90% had a strictly positive correlation, and only about 9% had a strictly negative correlation. Table 11 therefore suggests that the risk screening motive stated by Hypothesis A may be a more relevant driver of partial rating area offering than the market segmentation motive stated by Hypothesis B.

[18] In the 12 rating areas that are dropped due to having a single insurer, there was no partial entry, i.e., $B_3^I(r) = 1$.

5.2.3 Test construction

We now develop a statistical test to determine if insurers' county entry decisions are positively correlated. We construct a null hypothesis of independent and random insurer entry and use our correlation measure to determine if the null can be rejected in favor of positively correlated or negatively correlated insurer entry.

Consider a rating area where each insurer decides the set of counties to enter with the constraint that it has to enter at least one county.[19] Let $a_i \in \{0,1\}^{|\mathcal{C}(r)|}$ denote insurer i's choice, where the kth element in vector a_i denotes insurer i's entry status in county k. For example, if there are three counties, and insurer i chooses $a_i = (1,0,0)$, it implies that insurer i only enters county 1. Let $\mathcal{A}(r)$ denote the set of possible choices, i.e., $a_i \in \mathcal{A}(r)$. The set $\mathcal{A}(r)$ excludes a zero vector because insurers have to be active in at least one county. The number of possible choices is given by

$$|\mathcal{A}(r)| \quad = \quad 2^{|\mathcal{C}(r)|} - 1. \tag{11}$$

For example, consider a rating area with two counties. The choice set $\mathcal{A}(r)$ is given as $\mathcal{A}(r) = \{(1,0),(0,1),(1,1)\}$, and the number of choices in the set is $|\mathcal{A}(r)| = 2^2 - 1 = 3$.

Null hypothesis. *In a given rating area r, county entry decisions are independent across insurers. Each insurer randomly chooses a set of counties to enter with an equal probability, i.e., each insurer chooses an action in the set $\mathcal{A}(r)$ with probability $\frac{1}{|\mathcal{A}(r)|}$.*

To better illustrate the null, consider a rating area with two counties. Under the null, we have $Pr(a_i, a_j) = Pr(a_i) \cdot Pr(a_j)$ for insurers $i \neq j$, as insurers make independent county entry decisions. The null therefore precludes the competition effect. Also, we have $Pr(d_i = (1,0)) = Pr(d_i = (0,1)) = Pr(d_i = (1,1)) = \frac{1}{3}$ for any insurer i, as the null assumes random entry by insurers. It therefore precludes the risk screening mechanism.

We can derive the analytical forms of $E[CORR(r)]$ and $\text{Var}[CORR(r)]$, which we detail in Appendix C. We find that under the null, $E[CORR(r)]$ depends only on the number of counties in the rating area. As the number of counties approaches to infinity, $E[CORR(r)]$

[19] We impose this constraint as we study correlations among insurers that are active in at least one of the counties in the rating area.

converges to zero under the null. $\text{Var}[CORR(r)]$ depends only on the number of counties and the number of insurers in the rating area.

We assume all rating area observations are independent, implying that correlation measures $\{CORR(r)\}_{r=1}^{r=R}$ are also independent, where R is the number of rating areas with at least two insurers and two counties. Define $\overline{CORR} = \sum_{r=1}^{R=1} CORR(r)$, which is the sum of all correlation measures. Then mean and variance of $\overline{CORR}$ under the null are given as the following:

$$E[\overline{CORR}] = \sum_{r=1}^{R} E[CORR(r)], \quad \text{and} \tag{12}$$

$$\text{Var}[\overline{CORR}] = \sum_{r=1}^{R} \text{Var}[CORR(r)]. \tag{13}$$

By the Lindeberg-Lyapunov Central Limit Theorem, we have

$$t_R = \frac{\overline{CORR} - E[\overline{CORR}]}{\sqrt{\text{Var}[\overline{CORR}]}} \xrightarrow{d} N(0,1) \tag{14}$$

as $R \longrightarrow \infty$. Therefore, we reject the null of independence and randomization in favor of a positive correlation if the test statistic t_R is sufficiently large, and we reject the null in favor of a negative correlation if t_R is sufficiently small.[20]

5.2.4 Test results

Table 12 reports the correlation test result. We perform the test on two different samples: one sample consists of all rating areas with at least two insurers and two counties, and the other sample is further restricted to rating areas with partial entry. We obtain a large test statistic (higher than 25) in both samples. We therefore reject the null in favor of a positive correlation. This result implies that the desire to avoid high-cost counties has a greater impact on insurers' county-level entry decisions than the desire to avoid competition. Thus, the result favors the risk selection hypothesis (Hypothesis A) over the market segmentation hypothesis (Hypothesis B). This result is in line with the descriptive evidence in Section 5.1

[20] In Appendix D, we compare our correlation test with recent nonparametric tests of affiliation in the auction literature.

Sample:	(1) All RAs	(2) RAs with partial entry
$\overline{CORR}$	158.42	46.42
$E[\overline{CORR}]$	4.04	1.49
$\text{Var}[\overline{CORR}]$	15.47	3.20
t_R	39.25	25.11
p-value	<1e-7	<1e-7
Sample size (R)	247	135

Table 12: Correlation test results

Notes: The table reports the correlation test results based on the 2016 Marketplace PUF sample. Column (1) uses all rating areas with at least two insurers and two counties. Column (2) further restricts the sample to rating areas where there is partial entry by at least one insurer, i.e., $B_3^I(r) < 1$.

which supports Hypothesis A rather than Hypothesis B.

5.3 Regression analysis

Econometric model. As a final empirical exercise to test the competing explanations for partial rating area offering, we conduct regression analyses. We first use within-rating area variations. This analysis examines if insurers' decisions to selectively enter a county *within* a rating area are in line with each of the hypotheses' implications.

$$\begin{aligned} O^I(i,c) &= \underbrace{\alpha_1}_{\text{A:–}} AdverseRisk_c + \underbrace{\alpha_2}_{\text{B:–}} \sum_{i' \neq i} O^I(i',c) + \underbrace{\alpha_3}_{\text{C:+}} O_{MA}(i,c) + \tau_i + \eta_r + \varepsilon_{i,c} \quad (15) \\ O^P(p,c) &= \underbrace{\alpha_1}_{\text{A:–}} AdverseRisk_c + \underbrace{\alpha_2}_{\text{B:–}} \sum_{i' \neq i} O^I(i',c) + \underbrace{\alpha_3}_{\text{C:+}} O_{MA}(i,c) + \underbrace{\alpha_4}_{\text{C:–}} HMO/EPO_p \\ &\quad + \alpha_5 MetalLevel_p + \tau_i + \eta_r + \varepsilon_{p,c} \quad (16) \end{aligned}$$

The dependent variable in Equation (15) is insurer i's entry status in county c, where c belongs to a rating area where the insurer is active. $AdverseRisk_c$ is a vector of county characteristics that are informative about the county's risk distribution. It includes various health characteristics as well as the number of potential Marketplace consumers. Hypothesis A predicts that coefficients on adverse health measures will be negative as insurers will avoid entering high risk counties when risk screening is their primary concern. As having a large number of potential consumers increases the possibility of risk pooling, Hypothesis A also predicts that the coefficient on the number of potential consumers will be positive.

The term $\sum_{i' \neq i} O^I(i', c)$ is the number of competing insurers active in county c. If the vector $AdverseRisk_c$ adequately accounts for heterogeneous county health risks, then insurers' risk screening motive should be controlled. So if market segmentation is present as stated in Hypothesis B, then the coefficient on $\sum_{i' \neq i} O(i', c)$ will be negative, implying a negative correlation among insurers' county entry decisions.

$O_{MA}(i, c)$ is an indicator for whether insurer i offered managed MA plans in county c before the opening of the ACA Marketplaces. When $O_{MA}(i, c) = 1$, it implies that the insurer has already incurred a substantial share of fixed costs associated with building its provider network. Therefore, Hypothesis C predicts that the coefficient on $O_{MA}(i, c)$ will be positive. We include insurer fixed effects τ_i to control for unobserved heterogeneity across insurers. We include rating area fixed effects η_r as we are primarily interested in why insurers selectively enter some counties but not others *within* a rating area.

Equation (16) is similar to Equation (15), except that we analyze at the plan-county level rather than at the insurer-county level. The dependent variable $O^P(p, c)$ is whether plan p is offered in county c which belongs to a rating area where the plan is active. Compared to Equation (15), we include an additional control HMO/EPO_p which is an indicator for whether the plan is either an HMO or EPO plan. As explained earlier, Hypothesis C predicts that the coefficient on HMO/EPO_p will be negative. $MetalLevel_p$ is the metal class of a plan which is either Bronze, Silver, Gold, or Platinum. In both Equations (15) and (16), standard errors are clustered at the county level.

We also estimate the following regressions to test the hypotheses' implications that are identified from across-rating area variations:

$$\begin{aligned} B_1^I(i, r) &= \underbrace{\alpha_1}_{\text{A:}-} MSAs1_s + \underbrace{\alpha_2}_{\text{B:}-} OtherMktContact_r + \underbrace{\alpha_3}_{\text{C:}+} B_{MA}^I(i, r) + \tau_i + \varepsilon_{i,r} && (17) \\ B_1^P(p, r) &= \underbrace{\alpha_1}_{\text{A:}-} MSAs1_s + \underbrace{\alpha_2}_{\text{B:}-} OtherMktContact_r + \underbrace{\alpha_3}_{\text{C:}+} B_{MA}^I(i, r) + \underbrace{\alpha_4}_{\text{C:}-} HMO/EPO_p \\ &\quad + \alpha_5 MetalLevel_p + \tau_i + \varepsilon_{p,r} && (18) \end{aligned}$$

In Equation (17), the dependent variable is an insurer's marketing breadth in a rating area where it is active, and in Equation (18), it is a plan's marketing breadth in a rating area where it is offered.[21] The key control to test Hypothesis A is now $MSAs1_s$ in both equations. The variable $MSAs1_s$ is an indicator for whether the state to which the rating area belongs used the federal default method to define rating areas (MSAs plus the remainder of the state) or adopted a new division rule. As described in Section 4, Hypothesis A predicts that the coefficient on $MSAs1_s$ will be negative.

As explained in Section 5.1, $OtherMktContact_r$ is the average number of other rating areas where active insurers in rating area r are co-present pairwise. Market segmentation is easier to be sustained in rating areas involving insurers who are co-present in more markets elsewhere. Therefore, Hypothesis B predicts that the coefficient on $OtherMktContact_r$ will be negative.

To test Hypothesis C, we now have $B^I_{MA}(i,r)$ which represents the share of counties in rating area r where insurer i offered managed MA plans before the opening of the ACA Marketplaces. Hypothesis C predicts that the coefficient on $B^I_{MA}(i,r)$ will be positive. As Equations (17) and (18) utilize across-rating area variations, we no longer have rating area fixed effects. We still include insurer fixed effects which net out differences between insurers. In both Equations (17) and (18), standard errors are clustered at the rating area level.

Sample construction. As explained in Section 2, we complement the 2016 Marketplace PUF sample with MA service area data and county-level data from the AHRF and CHR. Some counties in the AHRF and CHR have incomplete information about county health variables contained in $AdverseRisk_c$, including the share of smokers, self-reported physically unhealthy days per month, and the share without access to physical activity. To estimate Equations (15) and (16), we exclude counties with missing values for any of the variables in $AdverseRisk_c$. This reduces the number of unique counties in the sample from 2,335 to 1,895.[22] Table E.1 in Appendix E reports the mean and standard deviation values of the controls in Equations (15) and (16). As Equations (17) and (18) do not include county characteristics as controls, the number of unique counties in the sample used to estimate these equations remains at 2,335, as reported in Column (2) in Table 1. Table E.2 in Appendix E reports the mean and standard deviation values of the controls in Equations (17) and (18).

[21]The exact definitions of $B^I_1(i,r)$ and $B^P_1(p,r)$ were introduced in Section 3.

[22]The number of states remains the same at 34.

Dependent variable:	(1) $O^I(i,c)$		(2) $O^P(p,c)$	
$AdverseRisk_c$				
Share who are obese	-0.108	(0.125)	0.085	(0.119)
Smoker share	-0.064	(0.088)	-0.102	(0.081)
Share without leisurely physical activity	-0.379	(0.124)	-0.303	(0.110)
Physically unhealthy days/month	-0.006	(0.004)	-0.002	(0.004)
Share without access to physical activity	-0.044	(0.022)	-0.051	(0.022)
Limited access to good food (0-1)	-0.059	(0.037)	-0.110	(0.039)
Non-elderly pop. below 400% FPL (10k)	0.002	(0.001)	0.002	(0.001)
$\sum_{i' \neq i} O^I(i',c)$	-0.009	(0.009)	-0.008	(0.008)
$O_{MA}(i,c)$	0.289	(0.022)	0.299	(0.022)
HMO/EPO_p			-0.156	(0.016)
$MetalLevel_p$				
Bronze			-omitted-	
Silver			0.001	(0.000)
Gold			0.000	(0.001)
Platinum			-0.001	(0.002)
Mean of dependent variable	0.80		0.76	
Observations	8,670		85,602	

Table 13: Regression results with RA fixed effects

Notes: Column (1) reports the key coefficient estimates of Equation (15). Column (2) reports the key coefficient estimates of Equation (16). Both regressions are estimated by a linear probability model and include insurer and rating area fixed effects. Standard errors are clustered by county in both regressions and are reported in parentheses.

Results. Table 13 reports the key coefficient estimates of Equations (15) and (16). Table 14 reports the key coefficient estimates of Equations (17) and (18). Below, we discuss whether the results provide empirical support for each of Hypotheses A, B, and C. Note that we have done several robustness checks, and the results are very similar.[23]

Hypothesis A. The regression results provide strong evidence that risk screening is an important driver for partial rating area offering. In Table 13, most of the estimated coefficients on adverse county health measures are negative and statistically significant. Also, the number of potential enrollees is positively correlated with insurers' entry decisions. In Table 14, as predicted by Hypothesis A, the estimated coefficients on $MSAs1$ are negative

[23] We have estimated Equations (15)-(18) using only rating areas where there is selective entry by insurers, i.e., $B_3^I(r) < 1$. We have also estimated Equations (16) and (18) using Silver plans only, which are the most popular plans as cost-sharing reduction subsidies for lower-income consumers are available only for Silver plans. In all cases. we have verified that the results are very similar to Tables 13 and 14.

Dependent variable:	(1) $B^I(i,r)$		(2) $B^P(p,r)$	
$MSAs1_s$	-0.367	(0.213)	-0.387	(0.232)
$OtherMktContact_r$	0.007	(0.004)	0.010	(0.004)
$B^I_{MA}(i,r)$	0.338	(0.050)	0.335	(0.044)
HMO/EPO_p			-0.120	(0.030)
$MetalLevel_p$				
Bronze			-omitted-	
Silver			0.002	(0.001)
Gold			-0.002	(0.002)
Platinum			-0.002	(0.004)
Mean of dependent variable	0.85		0.81	
Observations	1,236		12,258	

Table 14: Regression results without RA fixed effects

Notes: Column (1) reports the key coefficient estimates of Equation (17). Column (2) reports the key coefficient estimates of Equation (18). Both regressions are estimated by an OLS model and include insurer fixed effects. Standard errors are clustered by rating area in both regressions and are reported in parentheses.

and statistically significant. For example, Column (1) in Table 14 reports that the share of counties serviced by an insurer within a rating area, $B^I(i,r)$, is lower by 36.7 percentage points in rating areas located in states with the MSAs+1 division rule. These regression results are consistent with descriptive evidence presented in Section 5.1 and the correlation test reported in Table 12, which all find strong empirical support for Hypothesis A.

Hypothesis B. Consistent with the correlation test result which finds no evidence for market segmentation, the regression results also provide little empirical support for market segmentation. Table 13 shows that the estimated coefficients on the number competing insurers are negative but their standard errors are large. In Table 14, the estimated coefficients on $OtherMktContact_r$ are positive, providing evidence against Hypothesis B.

Hypothesis C. In line with descriptive evidence shown in Section 5.1, the regression results also provide strong evidence that entry costs associated with building provider networks are important in understanding selective entry patterns of insurers. Table 13 shows that the estimated coefficients on $O_{MA}(i,c)$ are large and statistically significant. For example, Column (1) of Table 13 reports that having sold managed MA plans in a county before the ACA is associated with a 28.9 percentage point increase in the probability of selling ACA plans in the county. Similarly, Table 14 shows that the estimated coefficients on $B^I_{MA}(i,r)$ are positive and statistically significant. Furthermore, the estimated coefficients on HMO/EPO_p are negative and statistically significant in both Tables 13 and 14. For example, Column (2) of Table 13 reports that being a HMO/EPO plan rather than a PPO/POS plan is associated with a 15.6 percentage point decrease in the plan's offer probability in a county. We therefore find strong evidence that one of the main reasons why insurers limit their service area within a rating area is to avoid incurring substantial costs associated with establishing provider networks.

5.4 Discussion

We have shown that there is strong empirical evidence for Hypotheses A and C, but little empirical support for Hypothesis B. Our results imply that risk screening and entry costs are insurers' primary concerns when they decide which counties to enter on the ACA Marketplaces, while market segmentation is not. We conclude this section by discussing policy implications of our empirical results.

First, our finding that risk screening is one of the key mechanisms driving the selective entry patterns implies that providing insurers with subsidies that are tied to their service area could increase insurer participation on the ACA Marketplaces. The ACA has a risk adjustment program which is intended to reduce risk screening by insurers. It transfers funds from plans with lower-risk enrollees to plans with higher-risk enrollees, thereby limiting insurers' incentive to avoid enrolling individuals in worse health. However, the empirical results in this section show that insurers still avoid enrolling higher-risk consumers by limiting their service area within a rating area. While narrowing the geographic unit based on which insurers can vary premiums down to counties might reduce risk selection by insurers, it will undermine the community rating provision of the ACA which prohibits insurers from charing higher premiums to individuals in worse health. A better approach will be to provide insurers with subsidies that are tied to their service area. This remedy could potentially increase insurer participation in higher-risk counties that have traditionally had a difficult time attracting insurers.

Second, the fact that we find little empirical support for market segmentation implies that a direct regulation on insurers' service area may not be effective in increasing insurer participation on the ACA Marketplaces. Our empirical results show that anti-competitive considerations are not what drive the selective entry patterns on the Marketplaces. Therefore, mandating that all plans be offered in all counties within a rating area, including counties with higher risks or no legacy networks, might instead trigger insurers to exit the Marketplaces.

Lastly, our empirical conclusion that fixed costs associated with building provider networks are an important barrier to entry implies that insurers might use narrow networks to lower entry costs in a region where it does not have existing networks. Previous studies find that a large of fraction of ACA plans have restricted provider networks (for example, see Polsky et al. (2016) and Dafny et al. (2017)). Using data from Massachusetts' pioneer exchange, Shepard (2016) finds evidence that insurers use narrow networks to risk screen consumers, even with sophisticated risk adjustment. Our finding suggests that insurers on the ACA marketplaces might use narrow networks as an effective tool to reduce entry costs associated with building provider networks.

To find descriptive evidence for this claim, we link the 2016 Marketplace PUF sample with provider network data downloaded directly from URLs submitted by insurers on the federally facilitated Marketplaces.[24] The goal is to examine if insurers offer plans with narrower networks in counties where they do not have legacy networks. Using the provider network data, we compute an ACA plan's network breadth in a county where it is *offered* by dividing the number of physicians in the county who are in the plan's network by the number of all physicians in the county. We denote this network breadth measure by $Network(p, c)$.

To examine if insurers offer plans with narrower networks in counties where they do not have existing MA networks, we estimate the following regression:

$$Network(p, c) = \alpha_1 O_{MA}(i, c) + \alpha_2 HMO/EPO_p + \alpha_3 MetalLevel_p + \tau_i + \sigma_c + \varepsilon_{p,c}. \quad (19)$$

[24] Insurers participating in federally-facilitated Marketplaces are required to submit URLs where they upload plan network information such as covered providers' NPIs, names, addresses, specialties and gender. We manually downloaded provider information from each of the working URLs as of October 2015. There are several accuracy problems detected in the downloaded provider data such as missing NPIs and highly inaccurate address information. To deal with these issues, we use SK&A data which provide information about 556,882 physicians identified by their NPIs. From the downloaded provider data, we only keep physicians with NPIs who can be found in the SK&A data. We use address information listed in the SK&A data for accuracy.

Dependent variable:	$Network(p, c)$	
$O_{MA}(i, c)$	0.046	(0.014)
HMO/EPO_p	-0.054	(0.010)
$MetalLevel_p$		
Bronze	-omitted-	
Silver	0.001	(0.000)
Gold	-0.001	(0.000)
Platinum	-0.014	(0.002)
Mean of dependent variable	0.58	
Observations	69,497	

Table 15: Relationship between network size and entry costs
Notes: The table reports the key coefficient estimates of Equation (19). The regression is estimated by an OLS model and includes insurer and county fixed effects. Standard errors are clustered by county and are reported in parentheses.

The dependent variable is a plan's network breadth in a county where it is offered. As described in Section 5.3, $O_{MA}(i, c)$ is an indicator of whether insurer i offered managed MA plans in county c before the ACA. We include county fixed effects (σ_c) to net out differences in counties. We include insurer fixed effects (τ_i) to control for insurer heterogeneity. Table 15 reports the results. Consistent with our conjecture, not having existing MA networks in a county is associated with a 4.6 percentage point decrease in the share of physicians covered by a Marketplace plan in the county. The results provide empirical evidence that insurers seem to use narrow networks to reduce entry costs on the Marketplaces.

6 Conclusion

In this paper, we investigate whether and why insurers sell plans that cover only a strict subset of counties within a rating area. Using federal Marketplace data, we show that about 40% of potential ACA Marketplace enrollees have restricted insurance choices due to partial rating area offering. We provide empirical evidence that risk screening and entry costs are insurers' primary concerns when they decide which counties to enter within a rating area, while market segmentation is not. Our findings shed light on the design of policies that could increase insurer participation on the ACA Marketplaces.

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A Appendix: Division of Rating Areas by State

State	Division	RAs	Multi-county RAs	Counties	FFM
Alabama	MSAs+1	13	8	67	1
Alaska	3-Digit Zip Codes	3		29	1
Arizona	Counties	7	5	15	1
Arkansas	Counties	7	7	75	1
California	Counties/3-Digit Zip Codes	19		58	0
Colorado	Counties	9	4	64	0
Connecticut	Counties	8	0	8	0
Delaware	Counties	1	1	3	1
District of Columbia	Counties	1	0	1	0
Florida	Counties	67	0	67	1
Georgia	Counties	16	16	159	1
Hawaii	Counties	1	1	5	1
Idaho	3-Digit Zip Codes	7		44	0
Illinois	Counties	13	12	102	1
Indiana	Counties	17	16	92	1
Iowa	Counties	7	7	99	1
Kansas	Counties	7	7	105	1
Kentucky	Counties	8	8	120	0
Louisiana	Counties	8	8	64	1
Maine	Counties	4	4	16	1
Maryland	Counties	4	4	24	0
Massachusetts	3-Digit Zip Codes	7		14	0
Michigan	Counties	16	15	83	1
Minnesota	Counties	9	9	87	0
Mississippi	Counties	6	6	82	1
Missouri	Counties	10	10	115	1
Montana	Counties	4	4	56	1
Nebraska	3-Digit Zip Codes	4		93	1
Nevada	Counties	4	3	17	1
New Hampshire	Counties	1	1	10	1
New Jersey	Counties	1	1	21	1
New Mexico	MSAs+1	5	2	33	1
New York	Counties	8	8	62	0
North Carolina	Counties	16	16	100	1
North Dakota	MSAs+1	4	2	53	1
Ohio	Counties	17	17	88	1
Oklahoma	MSAs+1	5	4	77	1
Oregon	Counties	7	7	36	1
Pennsylvania	Counties	9	9	67	1
Rhode Island	Counties	1	1	5	0

South Carolina	Counties	46	0	46	1
South Dakota	Counties	4	4	66	1
Tennessee	Counties	8	8	95	1
Texas	MSAs+1	26	16	254	1
Utah	Counties	6	5	29	1
Vermont	Counties	1	1	14	0
Virginia	MSAs+1	12	12	134	1
Washington	Counties	5	4	39	0
West Virginia	Counties	11	10	55	1
Wisconsin	Counties	16	14	72	1
Wyoming	MSAs+1	3	1	23	1
Total		499	298	3,143	38

Table A.1: Division of rating areas by state

Notes: The column "Division" reports the way each state is divided into rating areas: "MSAs+1" means the state is divided into MSAs plus the remainder of the state not included in a MSA, "Counties" means rating areas are composed of a single or multiple counties, and "3-Digit Zip Codes" means rating areas are composed of a single or multiple 3-digit zip codes. The column "RAs" reports the number of rating areas in each state. The column "Multi-county RAs" reports, for each state that uses counties to define rating areas, the number of rating areas that have two or more counties. The column "Counties" reports the number of counties in each state. The column "FFM" reports whether each state has a federally-facilitated marketplace.

B Appendix: Illustrative Examples of the Correlation Measure

Example 1. Consider rating area r with two counties, c_1 and c_2. There are two insurance companies, insurer 1 and insurer 2, and a total of 5 plans, $\{a, b, d, e, f\}$, that are offered in the rating area. Suppose insurer 1 offers plan a in county c_1 and plan b in county c_2; insurer 2 offers plan d in both counties, plan e in county c_1, and plan f in county c_2. The object $o(1, 2; c_1, c_2)$ as defined in Equation (9) is 1. The correlation measure $CORR(r)$ is computed as

$$\begin{aligned} CORR(r) &= \frac{1}{\begin{pmatrix} 2 \\ 2 \end{pmatrix} \cdot \begin{pmatrix} 2 \\ 2 \end{pmatrix}} o(1, 2; c_1, c_2) \\ &= 1. \end{aligned}$$

As both insurers are active in all counties of the rating area, we could say that they are perfectly aligned in their county entry decisions, resulting in a correlation measure of one.

Example 2. As in the previous example, consider rating area r with two counties, c_1 and c_2, and two insurance companies, insurer 1 and insurer 2. There is again a total of 5 plans, $\{a, b, d, e, f\}$, that are offered in the rating area. Now suppose that insurer 1 offers plans a and b in county c_1, and insurer 2 offers plans d, e, and f in county c_2. The object $o(1, 2; c_1, c_2)$ as defined in Equation (9) is -1. The correlation measure $CORR(r)$ is then computed as

$$\begin{aligned} CORR(r) &= \frac{1}{\binom{2}{2} \cdot \binom{2}{2}} o(1, 2; c_1, c_2) \\ &= -1. \end{aligned}$$

As the two insurers perfectly segment the rating area, the correlation measure results in -1.

Example 3. Rating area r again has two counties, c_1 and c_2, but now there are three insurance companies, insurer 1,2, and 3. There is a total of 7 plans, $\{a, b, d, e, f, g, h\}$, that are offered in the rating area. Insurer 1 offers plans a, b and d in county c_1; insurer 2 offers plan e in both counties and plan f in county c_2; and insurer 3 offers plans g and h in county c_2. The objects $o(\cdot, \cdot; \cdot, \cdot)$ as defined in Equation (9) are: $o(1, 2; c_1, c_2) = 0, o(1, 3; c_1, c_2) = -1, o(2, 3; c_1, c_2) = 0$. Thus the correlation measure $CORR(r)$ is computed as

$$\begin{aligned} CORR(r) &= \frac{1}{\binom{3}{2} \cdot \binom{2}{2}} \{o(1, 2; c_1, c_2) + o(1, 3; c_1, c_2) + o(2, 3; c_1, c_2)\} \\ &= \frac{1}{3}\{0 + (-1) + 0\} \\ &= -\frac{1}{3}. \end{aligned}$$

While no pair of insurers are perfectly aligned in their county entry decisions, insurer 1 and insurer 3 are perfectly misaligned in their county entry decisions. As a result, the overall correlation measure for the rating area is negative at $-\frac{1}{3}$.

C Appendix: $E[CORR(r)]$ and Var$[CORR(r)]$ under the Null

We derive the analytical forms of $E[CORR(r)]$ and Var$[CORR(r)]$ under the null hypothesis stated in Section 5.2. For notational simplicity, define function $C(n,k)$ as the combination function:

$$C(n,k) = \begin{cases} \frac{n!}{(n-k)!k!} & \text{if } n \geq k, \\ 0 & \text{otherwise.} \end{cases} \tag{C.1}$$

Analytical Form of $E[CORR(r)]$**.** For any given pair of insurers (i,i') and a pair of counties (c,c'), the probability that $o(i,i';c,c') = 1$ is

$$Pr[(O(i,c)\!=\!O(i',c) \text{ and } O(i,c')\!=\!O(i',c')] = 3\left(\frac{2^{|\mathcal{C}(r)|-2}}{|\mathcal{A}(r)|}\right)^2 + \left(\frac{2^{|\mathcal{C}(r)|-2}-1}{|\mathcal{A}(r)|}\right)^2. \tag{C.2}$$

The probability that $o(i,i';c,c') = -1$ is

$$Pr[O(i,c)\!\neq\!O(i',c) \text{ and } O(i,c')\!\neq\!O(i',c')] = 2\left(\frac{2^{|\mathcal{C}(r)|-2}}{|\mathcal{A}(r)|}\right)^2 + 2\left(\frac{2^{|\mathcal{C}(r)|-2}}{|\mathcal{A}(r)|}\cdot\frac{2^{|\mathcal{C}(r)|-2}-1}{|\mathcal{A}(r)|}\right). \tag{C.3}$$

The expected value of $o(i,i';c,c')$ is

$$\begin{aligned} E[o(i,i';c,c')] &= Pr[(O(i,c)\!=\!O(i',c) \text{ and } O(i,c')\!=\!O(i',c')] \\ &\quad -Pr[(O(i,c)\!\neq\!O(i',c) \text{ and } O(i,c')\!\neq\!O(i',c')] \\ &= \frac{1}{|\mathcal{A}(r)|^2} \\ &= \frac{1}{(2^{|\mathcal{C}(r)|}-1)^2} \end{aligned} \tag{C.4}$$

which only depends on the number of counties in the rating area. The expected value of $CORR(r)$ under the null is

$$\begin{aligned} E[CORR(r)] &= \frac{1}{C(|\mathcal{I}|,2)\cdot C(|\mathcal{C}|,2)} \sum_{(i,i')\in\tilde{\mathcal{I}}_R(r)} \sum_{(c,c')\in\tilde{\mathcal{C}}(r)} E[o(i,i';c,c')] \\ &= \frac{1}{(2^{|\mathcal{C}(r)|}-1)^2}. \end{aligned} \tag{C.5}$$

As the number of counties in a rating area approaches to infinity, the mean correlation converges to zero under the null.

Analytical Form of Var$[CORR(r)]$**.** Express $\mathrm{Var}[CORR(r)]$ as

$$\mathrm{Var}[CORR(r)] = E[CORR(r)^2] - (E[CORR(r)])^2. \tag{C.6}$$

We already computed $E[CORR(r)]$ under the null, so it suffices to derive the expression for $E[CORR(r)^2]$ which can be written as

$$E[CORR(r)^2] = \frac{1}{(C(|\mathcal{I}|,2)\cdot C(|\mathcal{C}|,2))^2} E\left[\left(\sum_{(i,i')\in\mathcal{I}_R(r),(c,c')\in\mathcal{C}(r)} o(i,i';c,c')\right)^2\right]. \tag{C.7}$$

We can express the expectation term on the right hand side of the equation as the following:

$$\begin{aligned} E\left[\left(\sum_{(i,i')\in\mathcal{I}_R(r),(c,c')\in\mathcal{C}(r)} o(i,i';c,c')\right)^2\right] &= \sum_{(i,i')\in\mathcal{I}_R(r),(c,c')\in\mathcal{C}(r)} E\left[o(i,i';c,c')^2\right] \\ &+ \sum_{\substack{(i,i'),(\tilde{i},\tilde{i}')\in\mathcal{I}_R(r),(c,c'),(\tilde{c},\tilde{c}')\in\mathcal{C}(r)\\(i,i',c,c')\neq(\tilde{i},\tilde{i}',\tilde{c},\tilde{c}')}} E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\right]. \end{aligned} \tag{C.8}$$

The analytical form of $E\left[o(i,i';c,c')^2\right]$ under the null is

$$\begin{aligned} E\left[o(i,i';c,c')^2\right] &= Pr[o(i,i';c,c')=1] + Pr[o(i,i';c,c')=-1] \\ &= \left(3\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + \left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^2\right) + \left(2\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + 2\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right) \\ &= \frac{2^{2|\mathcal{C}|-1}-2^{|\mathcal{C}|}+1}{(2^{|\mathcal{C}|}-1)^2}. \end{aligned} \tag{C.9}$$

So we have

$$\sum_{(i,i')\in\mathcal{I}_R(r),(c,c')\in\mathcal{C}(r)} E\left[o(i,i';c,c')^2\right] = C(\mathcal{I},2)\cdot C(\mathcal{I},2)\cdot\left(\frac{2^{2|\mathcal{C}|-1}-2^{|\mathcal{C}|}+1}{(2^{|\mathcal{C}|}-1)^2}\right). \tag{C.10}$$

$E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\right]$ where $(i,i',c,c')\neq(\tilde{i},\tilde{i}',\tilde{c},\tilde{c}')$ can be written as

$$\begin{aligned} E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\right] &= Pr[o(i,i';c,c')=1 \text{ and } o(i,\tilde{i}';c,c')=1] \\ &+Pr[o(i,i';c,c')=-1 \text{ and } o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')=-1] \\ &-Pr[o(i,i';c,c')=1 \text{ and } o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')=-1] \\ &-Pr[o(i,i';c,c')=-1 \text{ and } o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')=1]. \end{aligned} \tag{C.11}$$

The exact expression of $E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\right]$ under the null depends on the presence of common insurers between the two pairs of insurers (i,i') and $(\tilde{i},\tilde{i}')$, and the presence of common counties between the two pairs of counties (c,c') and $(\tilde{c},\tilde{c}')$. We compute the analytical form of $E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\right]$ under each of the following six cases.

Case 1: There is no common insurer between (i,i') and $(\tilde{i},\tilde{i}')$. As the null assumes insurers' county entry decisions are independent, we get the following analytical form[25]:

$$\begin{aligned} E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 1}\right] &= E\left[o(i,i';c,c')\right]\cdot E\left[o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\right] \\ &= \frac{1}{|\mathcal{A}|^4} \\ &= \frac{1}{(2^{|\mathcal{C}|}-1)^4}. \end{aligned}$$

Case 2: There is one common insurer between (i,i') and $(\tilde{i},\tilde{i}')$, and the two pairs of counties

[25] Note that $(c,c')=(\tilde{c},\tilde{c}')$ is allowed.

are identical, i.e., $(c, c') = (\tilde{c}, \tilde{c}')$.

$$\begin{aligned}
E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 2}\right] &= 3\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^3 + 1\cdot\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^3 \\
&\quad +2\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^3 + \frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^2 + \left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|} \\
&\quad -2\left(2\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^3 + \frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^2 + \left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right) \\
&= 3\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^3 + 1\cdot\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^3 \\
&\quad -\left(2\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^3 + \frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^2 + \left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right).
\end{aligned}$$

Case 3: There is one common insurer between (i, i') and $(\tilde{i}, \tilde{i}')$, and there is one common county between (c, c') and $(\tilde{c}, \tilde{c}')$.

$$\begin{aligned}
& E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 3}\right] \\
= \; & \frac{2^{|\mathcal{C}|-3}-1}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^2 + 5\frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + 2\frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|} \\
& +\frac{2^{|\mathcal{C}|-3}-1}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + 4\frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + 2\frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|} + \frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^2 \\
& -2\left(\frac{2^{|\mathcal{C}|-3}-1}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|} + 4\frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + 3\frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right).
\end{aligned}$$

Case 4: There is one common insurer between (i, i') and $(\tilde{i}, \tilde{i}')$, and there is no common county between (c, c') and $(\tilde{c}, \tilde{c}')$.

$$\begin{aligned}
& E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 4}\right] \\
= \; & 9\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + 6\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|} + \frac{2^{|\mathcal{C}|-4}-1}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^2 \\
& +8\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + 6\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|} + \frac{2^{|\mathcal{C}|-4}-1}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + \frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^2 \\
& -2\left(9\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\right)^2 + 5\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|} + \frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\left(\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right)^2 + \frac{2^{|\mathcal{C}|-4}-1}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-2}-1}{|\mathcal{A}|}\right).
\end{aligned}$$

Case 5: The two pairs of insurers are identical, i.e., $(i, i') = (\tilde{i}, \tilde{i}')$, and there is one common

	Number of $\{(i,i';c,c'),(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\}$ Combinations
Case 1	$C(\lvert\mathcal{I}\rvert,2)\cdot C(\lvert\mathcal{I}\rvert-2,2)\cdot C(\lvert\mathcal{C}\rvert,2)^2$
Case 2	$2C(\lvert\mathcal{I}\rvert,2)\cdot C(\lvert\mathcal{I}\rvert-2,1)\cdot C(\lvert\mathcal{C}\rvert,2)$
Case 3	$4C(\lvert\mathcal{I}\rvert,2)\cdot C(\lvert\mathcal{I}\rvert-2,1)\cdot C(\lvert\mathcal{C}\rvert,2)\cdot C(\lvert\mathcal{C}\rvert-2,1)$
Case 4	$2C(\lvert\mathcal{I}\rvert,2)\cdot C(\lvert\mathcal{I}\rvert-2,1)\cdot C(\lvert\mathcal{C}\rvert,2)\cdot C(\lvert\mathcal{C}\rvert-2,2)$
Case 5	$2C(\lvert\mathcal{I}\rvert,2)\cdot C(\lvert\mathcal{C}\rvert,2)\cdot C(\lvert\mathcal{C}\rvert-2,1)$
Case 6	$C(\lvert\mathcal{I}\rvert,2)\cdot C(\lvert\mathcal{C}\rvert,2)\cdot C(\lvert\mathcal{C}\rvert-2,2)$
Total	$2C(C(\lvert\mathcal{I}\rvert,2)\cdot C(\lvert\mathcal{C}\rvert,2),2)$

Table C.1: Number of $\{(i,i';c,c'),(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\}$ Combinations for Each of the Six Cases
Notes: The table reports the number of $\{(i,i';c,c'),(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\}$ combinations for each of the six cases when we sum over the left-hand side of Equation (C.12). For $n<k$, $C(n,k)=0$ as defined in Equation (C.1).

county between (c,c') and $(\tilde{c},\tilde{c}')$.

$$E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 5}\right] = \left(\frac{2^{|\mathcal{C}|-3}-1}{|\mathcal{A}|}\right)^2 + 7\left(\frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|}\right)^2 + 2\frac{2^{|\mathcal{C}|-3}-1}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|} + 6\left(\frac{2^{|\mathcal{C}|-3}}{|\mathcal{A}|}\right)^2.$$

<u>Case 6</u>: The two pairs of insurers are identical, i.e., $(i,i')=(\tilde{i},\tilde{i}')$, and there is no common county between (c,c') and $(\tilde{c},\tilde{c}')$.

$$\begin{aligned}E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 6}\right] &= \left(\frac{2^{|\mathcal{C}|-4}-1}{|\mathcal{A}|}\right)^2 + 15\left(\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\right)^2 + 2\frac{2^{|\mathcal{C}|-4}-1}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|} + 14\left(\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\right)^2 \\ &\quad -2\left(2\frac{2^{|\mathcal{C}|-4}-1}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|} + 14\left(\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\right)^2\right) \\ &= \left(\frac{2^{|\mathcal{C}|-4}-1}{|\mathcal{A}|}\right)^2 + 15\left(\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\right)^2 - \left(2\frac{2^{|\mathcal{C}|-4}-1}{|\mathcal{A}|}\cdot\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|} + 14\left(\frac{2^{|\mathcal{C}|-4}}{|\mathcal{A}|}\right)^2\right).\end{aligned}$$

Using the number of $\{(i,i';c,c'),(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\}$ combinations for each of the six cases (reported in Table C.1), we obtain the following expression:

$$\sum_{\substack{(i,i'),(\tilde{i},\tilde{i}')\in\mathcal{I}_R(r),(c,c'),(\tilde{c},\tilde{c}')\in\mathcal{C}(r)\\(i,i',c,c')\neq(\tilde{i},\tilde{i}',\tilde{c},\tilde{c}')}} E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')\right] \tag{C.12}$$

$$\begin{aligned}
= \quad & C(|\mathcal{I}|,2)\cdot C(|\mathcal{I}|-2,2)\cdot C(|\mathcal{C}|,2)^2\cdot E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 1}\right]\\
& +2C(|\mathcal{I}|,2)\cdot C(|\mathcal{I}|-2,1)\cdot C(|\mathcal{C}|,2)\cdot E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 2}\right]\\
& +4C(|\mathcal{I}|,2)\cdot C(|\mathcal{I}|-2,1)\cdot C(|\mathcal{C}|,2)\cdot C(|\mathcal{C}|-2,1)\cdot E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 3}\right]\\
& +2C(|\mathcal{I}|,2)\cdot C(|\mathcal{I}|-2,1)\cdot C(|\mathcal{C}|,2)\cdot C(|\mathcal{C}|-2,2)\cdot E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 4}\right]\\
& +2C(|\mathcal{I}|,2)\cdot C(|\mathcal{C}|,2)\cdot C(|\mathcal{C}|-2,1)\cdot E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 5}\right]\\
& +C(|\mathcal{I}|,2)\cdot C(|\mathcal{C}|,2)\cdot C(|\mathcal{C}|-2,2)\cdot E\left[o(i,i';c,c')\cdot o(\tilde{i},\tilde{i}';\tilde{c},\tilde{c}')|\text{Case 6}\right].
\end{aligned}$$

Using Equations (C.10) and (C.12), we obtain the analytical form for $E[CORR(r)^2]$. As the analytical form for $E[CORR(r)]$ has already been computed, we obtain the analytical form for $\text{Var}[CORR(r)]$.

D Appendix: Connections with Affiliation Tests

Here we discuss and contrast our correlation test with some recent nonparametric tests of affiliation in the auction literature. The notion of affiliation is stronger than positive correlation, and it was first introduced into economics by Milgrom and Weber (1982) in auction settings.[26] Affiliation of bidders' signals has testable implications for observable decision variables, such as bids and participation decisions. Since then, various tests have been developed to test affiliation in the context of auctions (Roosen and Hennessy, 2004; de Castro and Paarsch, 2010; Jun et al., 2010; Aradillas-Lopez, 2016). In particular, Aradillas-Lopez (2016) developed a non-parametric test for affiliation of bidders' participation decisions based on the aggregate number of bidders.[27] The test is based on the result that in competitive auctions where bidders' values are affiliated, bidders' participation decisions will also be affiliated. This implies that, under the null hypothesis of affiliation, the aggregate number of bidders

[26]For a formal definition of affiliation, see Milgrom and Weber (1982).
[27]Refer to Section 2.5.1 in Aradillas-Lopez (2016) for details.

in auctions must satisfy some inequality. If the test rejects the null hypothesis of affiliation, it could suggest that bidders are not acting competitively, such as acting in collusion.

One of the main hypotheses that we test in this paper is whether partial rating area offering can be explained by insurers' incentive to segment a rating area and avoid competition. As market segmentation could also be sustained as a result of collusion among insurers, it could be tempting to apply Aradillas-Lopez (2016)'s test of affiliation to our setting. A county will correspond to an auction, and insurers' county entry decisions would correspond to bidders' participation decisions in auctions. Aradillas-Lopez (2016)'s test of affiliation is based on the number of bidders in auctions. Applied to our setting, we would use the number of entering insurers in a county as the analog of the number of bidders in an auction. Using multiple observations of counties, we would compute Aradillas-Lopez (2016)'s test statistic, and decide whether to reject the null of affiliation among insurers' entry decisions in a county. Finding evidence for the null of affiliation would be supportive of the importance of common market level shocks, while finding evidence against the null would be supportive of the market segmentation hypothesis.

However, one key assumption needed to properly implement Aradillas-Lopez (2016)'s test is that bidders' participation decisions are *i.i.d.* across auctions. Applied to our setting, this assumption would imply that insurers' county entry decisions are *i.i.d.* across all counties. However, insurers' county entry decisions within a rating area are unlikely to be independent. It is reasonable to assume that insurers in a given rating area decide simultaneously which counties to enter with the constraint that premiums of the same plan have to be identical for all counties within the rating area. In this case, insurers' entry decisions in counties that belong to the same rating area would not be independent, and Aradillas-Lopez (2016)'s test would not be applicable. That is why we develop our correlation test which is also nonparametric but is better suited to test the relative importance of common market characteristics and competitive pressure in the context of insurer competition under the geographic rating regulation.

E Appendix: Additional Tables

	(1) Insurer-county-level regression sample		(2) Plan-county-level regression sample	
Controls	Mean	Std	Mean	Std
$AdverseRisk_c$				
Share who are obese	0.31	0.04	0.31	0.04
Smoker share	0.22	0.06	0.22	0.06
Share without leisurely physical activity	0.27	0.05	0.27	0.05
Physically unhealthy days/month	3.85	1.08	3.84	1.10
Share without access to physical activity	0.35	0.20	0.35	0.20
Limited access to good food (0-1)	0.28	0.12	0.28	0.11
Non-elderly pop. below 400% FPL (10k)	6.11	14.80	5.87	14.03
$\sum_{i' \neq i} O^I(i', c)$	3.62	2.16	3.56	2.18
$O_{MA}(i, c)$	0.39	0.49	0.41	0.49
HMO/EPO_p			0.53	0.50
$MetalLevel_p$				
Bronze			0.33	0.47
Silver			0.42	0.49
Gold			0.23	0.42
Platinum			0.02	0.15
Observations	8,670		85,602	

Table E.1: Summary statistics of the controls in Equations (15) and (16)

Notes: The table reports the mean and standard deviation values of the controls in Equations (15) and (16) in the main text.

	(1) Insurer-RA-level regression sample		(2) Plan-RA-level regression sample	
Controls	Mean	Std	Mean	Std
$MSAs1_s$	0.14	0.35	0.12	0.33
$OtherMktContact_r$	6.66	3.56	6.52	3.60
$B^I_{MA}(i, r)$	0.40	0.47	0.44	0.48
HMO/EPO_p			0.56	0.50
$MetalLevel_p$				
Bronze			0.33	0.47
Silver			0.42	0.49
Gold			0.23	0.42
Platinum			0.02	0.15
Observations	1,236		12,258	

Table E.2: Summary statistics of the controls in Equations (17) and (18)

Notes: The table reports the mean and standard deviation values of the controls in Equations (17) and (18) in the main text.