How to Promote Health Insurer Competition: Evidence from Automatic Enrollment Rules*

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Abstract

Policies that encourage competition in health insurance markets may have limited impacts on consumer welfare when adverse selection and consumer inertia are pervasive. In this paper, we show that automatic enrollment rules can effectively promote competition in the presence of these market failures. We evaluate the impact of automatic enrollment rules after the termination of the largest insurer in Colombia. Using a model of insurer competition, we find that re-enrolling patients randomly to incumbent insurers worsens adverse selection but leads to higher consumer surplus and broader provider networks, without increasing spending, because it encourages active plan choice among healthy consumers.

Keywords: Health insurer competition, Market power, Adverse selection, Inertia.

JEL codes: I10, I11, I13, I18.

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1 Introduction

A central challenge in health insurance markets is managing competition in the presence of consumer inertia and adverse selection. Designing interventions that effectively promote insurer competition and enhance consumer welfare in these markets is notoriously difficult (Song et al., 2012; Cutler and Reber, 1998). On the one hand, regulations that address adverse selection often have limited impacts on competition and welfare because consumers fail to actively engage in plan choice (Ho et al., 2017). On the other hand, policies that reduce inertia can have ambiguous impacts on market outcomes because of adverse selection (Saltzman et al., 2021; Polyakova, 2016; Ericson, 2014; Handel, 2013). Due to these inherent trade-offs, the question of how regulators can effectively manage competition remains open. This question is particularly timely given rising market power in several sectors of health care (e.g., Trish and Herring, 2015; Dunn and Shapiro, 2014; Cutler and Morton, 2013).

In this paper, we show that regulators can actively shape competition in health insurance markets through the design of automatic enrollment rules when both inertia and adverse selection are pervasive. Our analysis centers on the Colombian health care system, where the largest health insurer, called SaludCoop, was abruptly terminated by the government in December 2015. Following this termination, the government faced the challenge of assigning SaludCoop's consumers to the remaining incumbent insurers. The enrollment rule had the potential to either enhance or diminish insurer competition, providing an opportunity to examine its effects on key market outcomes such as consumer surplus, healthcare spending, and health plan design.

We show that automatic enrollment rules impact competition and welfare through adverse selection and inertia. Specifically, rules that reduce inertia in equilibrium can exacerbate adverse selection, but enhance competition and welfare because insurers can offer a more generous health plan to effectively attract profitable consumers. Conversely, rules aimed at mitigating adverse selection can increase inertia and market power since insurers cannot effectively attract healthy types and resort to "harvesting" their stock of enrollees.

At the time of its termination, SaludCoop covered 20% of enrollees in the country. The termination was sudden and politically motivated, stemming from issues related to corruption and financial malpractice. The government chose to assign SaludCoop enrollees to a smaller insurer, called Cafesalud, during the first three months of 2016. During this initial 90-day period, Cafesalud was required to guarantee access to care through SaludCoop's network of providers. After this grace period, enrollees were allowed to switch out of Cafesalud and into another insurer of their choice.

To study counterfactual enrollment rules, we have individual-level enrollment and health claims data from the Colombian contributory health system between 2013 and 2017, representing more than 25 million individuals yearly who pay payroll taxes.[1] In this system, insurers compete primarily on their provider networks and negotiated provider prices to deliver a single public health insurance plan. Other aspects of the plan are tightly regulated including premiums, cost-sharing, and benefits. Insurers receive annual per capita payments from the government that are risk-adjusted for sex, age, and location.

We start by providing evidence of substantial adverse selection and inertia in the contributory system. First, we show that consumers tend to prefer insurers with broader provider networks, particularly those with worse health status, consistent with adverse selection. Second, we document persistently low switching rates across insurers, which contribute to the concentration of high-risk enrollees within a subset of insurers, potentially granting the remaining ones substantial market power. In this environment, automatic enrollment rules can impact competition and market outcomes by changing the initial distribution of health risk while leveraging consumer inertia.

Indeed, we show that the observed enrollment rule—in which former SaludCoop enrollees are assigned to Cafesalud—had substantial impacts on market concentration and healthcare spending. Using a difference-in-differences design comparing markets where SaludCoop operated against those where it did not operate, we estimate substantial reductions in insurer HHI and annual healthcare spending per capita among SaludCoop enrollees, of about US$183. Effects on healthcare spending are heterogeneous based on

[1]The contributory system encompasses the portion of the population that pays payroll taxes (and their families), while the other half is covered by a subsidized system fully funded by the government.

the breadth of Cafesalud's network, suggesting the impacts of automatic enrollment rules depend on the characteristics of the assigned insurer (Geruso et al., 2023; Abaluck et al., 2021).

To characterize the mechanisms through which enrollment rules impact competition and explore counterfactual rules, we propose an equilibrium model of insurer competition on provider network breadth—defined as the fraction of providers in a market that are covered by the insurer. The model captures the crucial feature that allowing patients to endogenously switch could exacerbate adverse selection but could also improve consumer welfare, as individuals choose insurers that more closely align with their health status and idiosyncratic preferences.

In the model, following Serna (2024), insurers compete by simultaneously choosing their provider network breadth across various markets to maximize the present discounted value of their profits. The profit function incorporates a random utility model, where consumers choose their insurer based on provider network breadth, expected out-of-pocket costs, and inertia. Consumer inertia is represented by an indicator reflecting their past choices. We model insurers' marginal and administrative costs as non-linear functions of provider network breadth, drawing on empirical relationships observed in the data. Insurer profits evolve according to both exogenous transition probabilities across diagnoses and endogenous transition probabilities across insurers.

Our demand estimates show that all consumers prefer broader provider networks but this preference is stronger among patients with chronic diseases. Consumers are nearly 4 times more likely to choose an insurer if they were enrolled with it in the previous year, which translates into a median switching cost of 1.2 million pesos (roughly 2.5 times the monthly minimum wage in 2016). On the supply-side, we find that insurers have heterogeneous marginal and administrative costs, contributing to the observed asymmetry in network breadth choices.

Consistent with the descriptive evidence, the model generates adverse selection in provider network breadth: patients with a higher willingness to pay for broader networks tend to be more costly for insurers. Finally, we show that our equilibrium model produces accurate out-of-sample predictions of insurers' network breadth decisions when applied to the observed enrollment rule that assigns SaludCoop enrollees to Cafesalud.

Using the model estimates, we proceed to simulate the impact of alternative policies for enrolling SaludCoop patients to incumbent insurers. We consider the following policies: random enrollment (individuals are evenly and randomly assigned to incumbent insurers), overlap enrollment (individuals are assigned to the insurer with the greatest network overlap with SaludCoop in their municipality of residence), proportional enrollment (individuals are randomly assigned to incumbent insurers in proportion to their pre-termination market shares), largest enrollment (individuals are assigned to the largest incumbent insurer in their municipality of residence), broadest enrollment (individuals are assigned to the incumbent insurer with the broadest network in their municipality of residence), and own choice (individuals are free to choose their insurer after the termination).

Our findings show that automatic enrollment rules that encourage healthy individuals to engage in active plan choice while inducing inertia among the sick can outperform other rules even in the presence of adverse selection. This dynamic incentivizes insurers to compete more aggressively for profitable, low-risk switchers by expanding their networks, thereby offsetting the negative effects of selection. A key condition for this result is that competition on premiums is limited or absent, and that healthy individuals also value broad network access.

For example, random enrollment, which satisfies these conditions, outperforms all other assignment rules across several dimensions: provider network breadth increases by 13%, per capita healthcare spending remains largely unchanged, and consumer surplus increases by 3%. In this case, the inertia of sicker consumers leads to a more balanced distribution of health risk across insurers over time, reducing their average profit margins by approximately 16% relative to the observed enrollment rule. However, this comes at the cost of intensifying adverse selection due to increased switching among healthy consumers.[2]

By contrast, the own-choice rule results in one of the lowest levels of average provider

[2]Following Einav and Finkelstein (2011), we measure the degree of adverse selection as the correlation between insurers' marginal costs and consumer's willingness-to-pay for network breadth.

network breadth and among the highest average profit margins. In this scenario, switching is concentrated among chronically ill patients who are typically unprofitable, incentivizing insurers to reduce costs by narrowing their networks, dropping high-cost providers.

Taken together, these results—though derived from the Colombian health system—-highlight a broader regulatory challenge: balancing the opposing forces of adverse selection and consumer inertia when designing insurance market policies. Within this context, we show that automatic enrollment rules can be an effective tool for fostering competition. They may promote broader provider coverage and enhance consumer welfare, all without necessarily increasing healthcare spending.

Contributions and literature. This paper makes a key contribution to the literature by developing a model of automatic enrollment rules following insurer terminations. While prior research has examined the effects of insurer exits on healthcare utilization, spending, and health outcomes under a fixed assignment rule (e.g., Bonilla et al., 2024; Bischof and Kaiser, 2021; Politzer, 2021), relatively little attention has been given to how alternative enrollment policies shape overall market outcomes. A notable exception is Wallace (2023), who studies Medicaid managed care in New York—a setting in which insurers also compete primarily through their provider networks—and shows that assigning consumers to insurers that include their existing providers can improve consumer satisfaction. However, that analysis holds insurers' supply-side decisions fixed.

In contrast, our model endogenizes insurers' network breadth choices to evaluate the equilibrium effects of centralized automatic enrollment policies. In doing so, we build on recent work on optimal assignment mechanisms in other contexts, such as GP waitlists (Huitfeldt et al., 2024) and pension plans (Carroll et al., 2009). We also contribute to the broader literature on default options across markets (e.g., Beshears et al., 2024; Shepard and Wagner, 2023; Madrian and Shea, 2001), by introducing supply-side competition into the analysis. Within health care specifically, existing research has primarily focused on how inertia shapes consumer plan choices (e.g., Drake et al., 2022; Polyakova, 2016; Ericson, 2014; Handel, 2013), or on how enrollment rules affect demand-side outcomes (e.g., Brot-Goldberg et al., 2023; Macambira et al., 2022). Complementing this work, we evaluate impacts of default assignment rules influence on the supply side of the health insurance market.

The remainder of this paper is organized as follows: section 2 describes the empirical setting and the data, section 3 presents the reduced-form results for the causal impact of the observed enrollment rule on market outcomes, section 4 introduces the model, section 5 discusses identification and provides model estimates, section 6 simulates counterfactual reassignment policies, and section 7 concludes.

2 Setting, Data, and Descriptives

Our setting is Colombia's contributory healthcare system, which covers the half of the population in the country who pays payroll taxes (and their families).[3] Enrollees in this system have access to one plan that is provided by private and public insurers. Insurers negotiate with providers to determine network inclusions and health service prices, but other elements of the plan are regulated, such as premiums, cost-sharing, and benefits.[4] Instead, insurers receive annual per-capita risk-adjusted transfers from the government that poorly fit realized healthcare costs (Riascos et al., 2014).[5]

We use administrative data from the contributory healthcare system encompassing individual-level enrollment, linked with health claims and average annual income from 2013 to 2017 for the subset of individuals aged 19 or older. The enrollment data is a snapshot of enrollment for every June. Hence, if we observe an individual enrolled with insurer A in June of year t and then again in June of year $t+1$, we assume this individual did not switch their insurer during the months in between; we label these consumers as

[3]The remaining half of the population is covered by the subsidized system which is fully funded by the government.

[4]Insurance premiums are zero. Cost-sharing rules are indexed to the enrollee's monthly income level but are standardized across insurers and providers. However, a consumer's total out-of-pocket cost may vary across insurers because the coinsurance rates multiply the health service prices that insurers negotiate with providers.

[5]The risk adjustment formula uses health claims data from year $t-2$ to determine payments for year t. The risk adjustment factors are sex, age, and municipality of residence. The formula does not include information about diagnoses. Insurers are also partly compensated for their enrollees' health at the end of every year through a mechanism known as the High-Cost Account (HCA). The HCA compensates for cervical cancer, breast cancer, stomach cancer, colon cancer, prostate cancer, lymphoid leukemia, myeloid leukemia, hodgkin lymphoma, non-hodgkin lymphoma, epilepsy, rheumatoid arthritis, and HIV-AIDS (Resolution 0248 of 2014 from the Ministry of Health). These ex-post payments represents only 0.4% of ex-ante payments (Serna, 2024).

the *continuously enrolled*.

The health claims data report date of service, service code, diagnosis code (following the International Classification of Diseases Code 10), provider identifier, insurer identifier, and negotiated price of the service.[6] Using the diagnosis codes that accompany each claim and following Riascos et al. (2014)'s categorization, we classify individuals as having one of the following health conditions: Cancer, Cardiovascular disease, Diabetes, Pulmonary disease, Renal disease, other disease, or no diseases. When an individual has multiple diseases, we assign the diagnosis that accounts for the largest share of the individual's healthcare cost.

We also have data on insurers' network of covered providers between 2013 and 2017. The provider network data report the hospitals, clinics, and physician practices included in each insurer's network. We do not observe the specific services the provider is in network for. We complement these data with networks inferred from health claims, considering a provider as in-network whenever it delivers more than 100 claims for an insurer.[7] 1/4 of observations in the final network data comes from claims.

Given that the main dimension of competition is provider networks, we characterize each insurer by its provider network breadth, defined as the fraction of providers covered by the insurer in each market. We set markets as municipalities since the automatic enrollment rules we consider in counterfactuals are municipality-specific. There are 1,123 municipalities and 33 states in the country.

Table 1 presents pooled summary statistics of enrollees in the raw data in column (1), in the subsample who are continuously enrolled in column (2), and in a random sample of 500,000 continuously enrolled individuals who reside in the 13 main municipalities in the country in column (3).[8] The latter is our preferred sample for model estimation for two reasons. First, annualized healthcare costs for the continuously enrolled will not suffer

[6]The claims data exist only for insurers in the contributory system that pass the Ministry of Health's data quality filters. Excluding SaludCoop and Cafesalud, out of the 11 remaining insurers, we observe 7 for all 5 years, 8 for 4 or more years, and 11 for 3 or more years. In our final sample we focus on these 11 insurers.

[7]When inferring networks from claims we do not consider claims made at the emergency department, as individuals can go out-of-network for emergency care.

[8]These municipalities are Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales, Pereira, Cúcuta, Pasto, Ibagué, Montería, Cartagena, and Villavicencio.

Table 1: Summary Statistics of Main Samples

Variable	(1) Raw		(2) Continuous		(3) Random	
	mean	sd	mean	sd	mean	sd
Male	0.476	(0.499)	0.471	(0.499)	0.516	(0.500)
Age	43.26	(16.73)	44.01	(16.93)	44.02	(16.43)
Income	0.804	(1.296)	0.816	(1.336)	1.223	(1.670)
Cancer	0.083	(0.276)	0.084	(0.278)	0.071	(0.258)
Cardiovascular disease	0.179	(0.383)	0.186	(0.389)	0.127	(0.333)
Diabetes	0.030	(0.170)	0.031	(0.174)	0.021	(0.144)
Pulmonary disease	0.013	(0.113)	0.014	(0.116)	0.010	(0.099)
Renal disease	0.009	(0.097)	0.010	(0.099)	0.008	(0.087)
Other disease	0.076	(0.265)	0.077	(0.267)	0.052	(0.222)
Healthy (No diagnoses)	0.565	(0.496)	0.552	(0.497)	0.573	(0.495)
Total healthcare cost	0.786	(4.379)	0.822	(4.516)	0.795	(1.193)
OOP spending	0.145	(0.420)	0.150	(0.434)	0.157	(0.126)
Individuals x Years	75,918,492		68,328,039		1,697,193	

Note: Table presents the mean and standard deviation in parenthesis of each variable. Column (1) uses the full sample of individuals aged 19 or older who were enrolled with an insurer in the contributory *or* the subsidized systems between 2013 and 2017. Column (2) uses the subsample of individuals who were always enrolled with an insurer in the contributory system through the sample period. Column (3) uses a random sample of 500,000 individuals who were always enrolled with an insurer in the contributory system and reside in the 13 main municipalities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales, Pereira, Cúcuta, Pasto, Ibagué, Montería, Cartagena, and Villavicencio. (†) measured in millions of COP of 2014.

from measurement error arising from enrollment spell lengths of less than a year. Second, spillover effects across markets are substantial because consumers typically travel to the main municipalities to receive care. These spillover effects can bias our estimates of consumer preferences for provider networks. Hence, by focusing on individuals who reside in the 13 main municipalities we are able to overcome this limitation.[9] An observation in this table is a person-year.

In the three samples, a little under 60% of consumers are healthy. The most prevalent health conditions are cardiovascular diseases followed by cancer and diabetes. The average annual income is higher in our sample for model estimation because cost of living is higher in the 13 main municipalities relative to the rest of the country. On average, individuals in the raw data have an annual healthcare cost of 786 thousand pesos (US$257 of 2016), corresponding to around 145 thousand pesos (US$47 of 2016) of out-of-pocket spending.

[9]An alternative way to deal with these spillover effects is to define markets as states as in Serna (2024). However, given that our data on networks does not distinguish the services for which a provider is in-network, we do not have enough variation in network breadth to estimate such a model. Moreover, municipality-specific enrollment rules are more reasonable than state-level rules because consumers can enroll only with insurers that operate in their municipality of residence and insurer entry decisions may vary across municipalities within a state.

The remainder of this section presents descriptive evidence supporting three key facts that will inform our model specification. First, despite stringent regulation of other aspects of the plan, provider network breadth varies significantly across insurers, largely due to differences in their marginal and administrative costs. Second, consumer preferences for provider network breadth align with patterns of adverse selection, and consumers exhibit substantial insurer inertia. Third, markets are highly concentrated among patients with chronic health conditions, suggesting that these patients have stronger match values with specific insurers and that some insurers may yield market power.

2.1 Provider Network Breadth

Table 2 presents the mean and standard deviation (in parenthesis) of provider network breadth for each insurer across the 13 main municipalities. Despite strict regulation of all other aspects of the health plan, provider network breadth varies significantly among insurers, ranging from an average of 0.09 to an average of 0.52. To further examine this variation, Figure 1 presents the distribution of residuals of a linear regression of provider network breadth on insurer-by-year fixed effects (in black) and on market-by-year fixed effects (in gray). The figure reveals that most of the residual variation stems from differences across insurers rather than across markets.

Table 2: Summary Statistics of Provider Network Breadth

Insurer	Main cities	
	mean	sd
Insurer A	0.129	(0.098)
Insurer B	0.355	(0.156)
Insurer C	0.178	(0.080)
Insurer D	0.237	(0.074)
Insurer E	0.098	(0.084)
Insurer G	0.223	(0.156)
Insurer H	0.088	(0.142)
Insurer I	0.222	(0.091)
Insurer J	0.518	(0.149)
Insurer K	0.179	(0.130)
Insurer L	0.115	(0.141)
Insurer M	0.164	(0.104)
Insurer N	0.319	(0.063)

Note: Table presents the mean and standard deviation in parenthesis of the fraction of providers in a municipality that are covered by each insurer from 2013 to 2017. Summary statistics use data from the 13 main municipalities.

Which factors contribute to this variation in provider network breadth? Figure 2 illustrates the empirical relationship between the log of average cost per consumer type and percentiles of provider network breadth across the 13 main municipalities. A consumer type is defined by a combination of sex, age group (19-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75+), and diagnosis (cancer, cardiovascular, diabetes, pulmonary, renal, other, or no diseases). Panel A, which aggregates the data across insurers, shows that log average costs exhibit a concave relationship with respect to provider network breadth.[10] This cost structure varies substantially across insurers, as illustrated in Panel B, which presents the empirical relationship for three selected insurers.

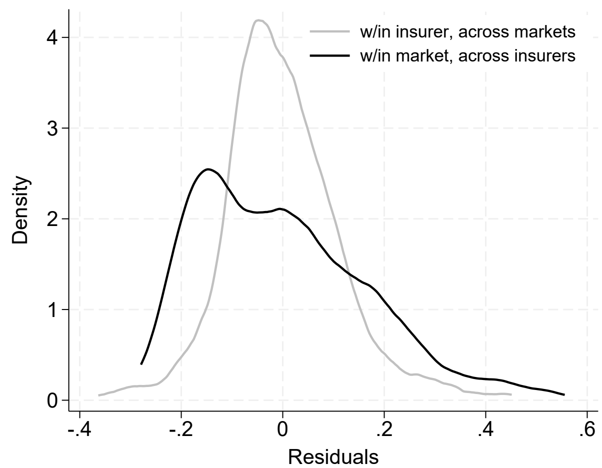


Figure 1: Residual Variation in Provider Network Breadth

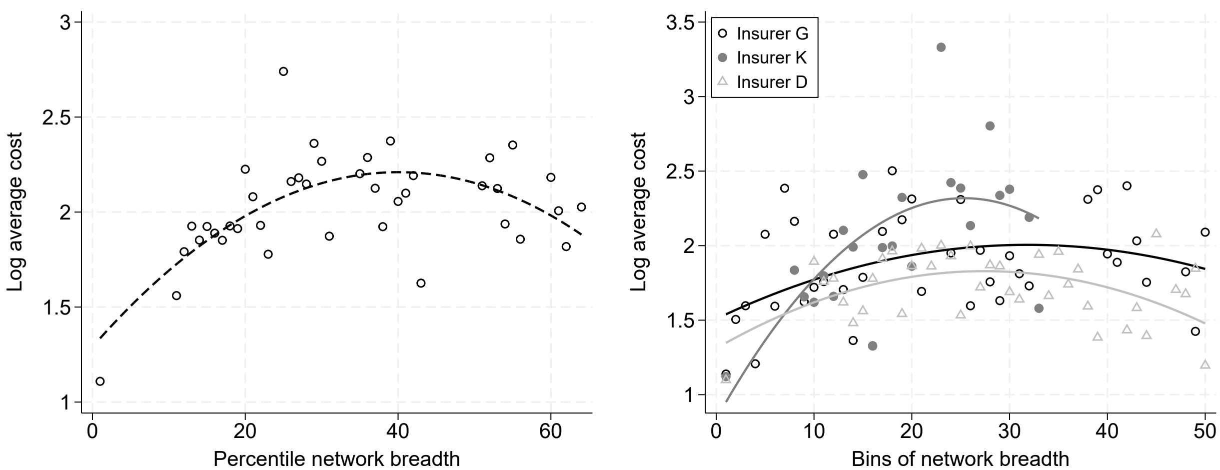
Note: Figure presents the distribution of residuals of a linear regression of network breadth on insurer-by-year fixed effects in black, and on municipality-by-year fixed effects in blue. Regressions use the sample pf 13 main municipalities.

Figure 3 shows that insurers are also heterogeneous in their administrative costs. We use insurers' public income statements from 2013 to 2017 to obtain their total administrative costs, which measure expenses related to billing and auditing activities. These administrative costs are one of the highest components of health care spending in managed care health systems (Council on Health Care Spending and Value, 2022) and depend on managing providers within the network (Cutler, 2020; Chernew and Mintz, 2021).

Panel A shows that the log of administrative costs ranges from 15 to 19 across insurers and is positively correlated with provider network breadth. Panel B then shows that the

[10]This concavity likely reflects patterns of economies of scope when covering multiple services within a provider as shown in Serna (2024).

strength of this correlation varies across insurers. Differences between insurers in their cost structure may help explain why some insurers choose broader networks than others.



(A) Pooled (B) Per insurer

FIGURE 2: Empirical Relation Between Average Cost and Network Breadth

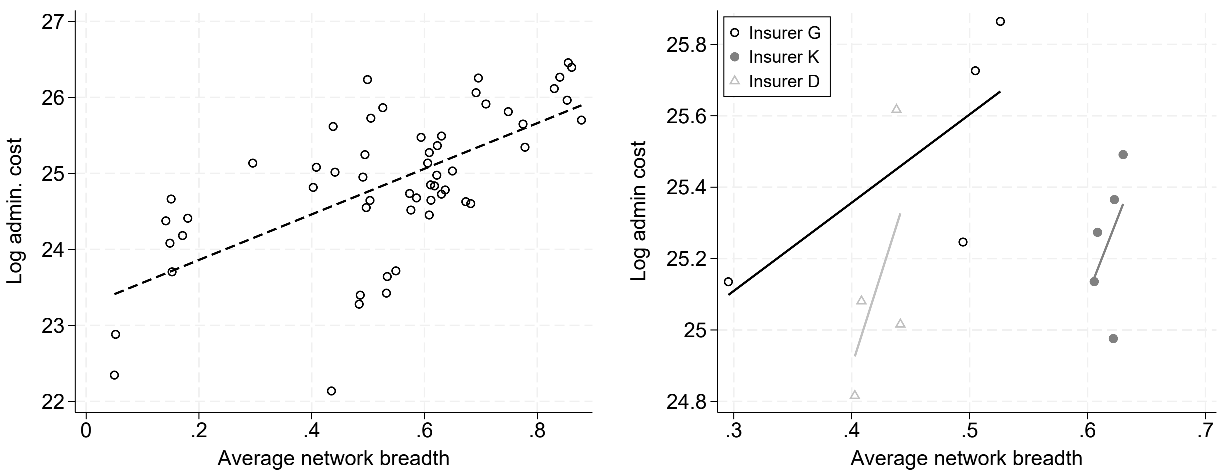
Note: To construct this figure we aggregate the individual-level data on the continuously enrolled by calculating the average annual healthcare cost by consumer type, insurer, municipality, and year. Consumer types are a combination of sex, age group (19-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75+), and diagnosis (cancer, cardiovascular, diabetes, pulmonary, renal, other, no diseases). Panel A of the figure presents a scatter plot of the average cost by percentile of network breadth. Panel B presents the same scatter plot conditional on four insurers for exposition. Dashed lines in each panel correspond to a quadratic fit.

2.2 Switching Decisions

The variation in provider network breadth across insurers suggests that consumers may consider network size when making enrollment decisions. Furthermore, the small changes in provider network breadth between 2013 and 2015 indicate that these enrollment choices may be influenced by inertia.

To describe consumers' choices, Table 3 presents the fraction of enrollees that switch their insurer every year. Column (1) uses the raw data, where individuals can switch to insurers in the subsidized system (the portion of the Colombian health system that cover low-income individuals); while columns (2) and (3) use the sample of continuously enrolled and the sample for model estimation, respectively, where consumers can only switch to other insurers conditional on staying within the contributory system.

Because of the different choice sets, the switching rate in the raw data is much larger than in the other samples. In 2015, 3.5% of enrollees switched their insurer in the raw data, while only 2.7% and 1.7% switched in the samples considered in columns (2) and (3), respectively. Across all samples, the switching rate saw a significant increase in 2016 due to SaludCoop's termination, which serves as our primary source of identification. We detail this event in the following subsection.



(A) Pooled (B) Per insurer

FIGURE 3: Correlation Between Administrative Cost and Network Breadth

Note: Scatter plot of the log of total administrative costs obtained from insurers' public income statements and average provider network breadth across markets. A dot is a combination of insurer and year. The dashed line is a linear fit.

TABLE 3: Switching Rate

Year	Full sample	Continuously enrolled	Random sample for model
	(1)	(2)	(3)
2014	0.044	0.044	0.016
2015	0.035	0.027	0.017
2016	0.206	0.193	0.112
2017	0.083	0.064	0.051

Note: Table presents the fraction of enrollees in year t that switch out of their insurer by $t+1$. Column (1) uses the full sample of individuals aged 19 or older who were enrolled with an insurer in the contributory *or* the subsidized systems between 2013 and 2017. Column (2) uses the subsample of individuals who were always enrolled with an insurer in the contributory system through the sample period. Column (3) uses a random sample of 500,000 individuals who were always enrolled with an insurer in the contributory system and reside in the 13 main cities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales, Pereira, Cúcuta, Pasto, Ibagué, Montería, Cartagena, and Villavicencio.

2.3 SaludCoop's Termination

In December 2015, the government terminated the *largest* health insurer in the country, called SaludCoop, and the 38 hospitals that were vertically integrated with it. The government terminated SaludCoop due to its engagement in illegal activities and financial malpractice. SaludCoop diverted nearly $250 billion to investments outside the healthcare system and submitted false health claims to the government for reimbursement. SaludCoop covered nearly 20% of enrollees in the country (around 4 million individuals), who were transferred to an incumbent insurer called Cafesalud during the first three months of 2016. After this 3-month period, enrollees were allowed to switch. Prior to the termination, Cafesalud covered less than 5% of enrollees.

Table 4: Correlates of Switching Behavior

	Switch-in
Network breadth	0.159
	(0.026)
Chronic disease	-0.462
	(0.019)
Network breadth x chronic disease	0.613
	(0.066)
Constant	0.593
	(0.005)
Observations	57,862

Note: Table shows a linear regression of an indicator for whether consumer i switched into insurer j in year t on insurer j's network breadth and its interaction with an indicator for whether the consumer has a chronic disease. Estimation uses the subsample of individuals who were enrolled with SaludCoop in 2015 from our sample for model estimation and is restricted to the post-termination years, 2016 and 2017. Specification includes individual fixed effects. Standard errors in parenthesis are clustered at the individual level.

We explore SaludCoop enrollees' switching decisions in Table 4. Using our random sample for model estimation, we regress an indicator for whether the enrollee switched into an insurer on or after 2016 on the insurer's provider network breadth and an interaction with whether the enrollee has a chronic disease. We find that SaludCoop enrollees tended to switch towards insurers with broad networks after the 90-day grace period, which suggests that consumers have preferences for network breadth. Consumers with chronic diseases are less likely to switch than healthy ones and have a stronger preference for broad provider networks, also suggesting that insurer choices are characterized by adverse selection.

Conditional on the disease, consumers also seem to have idiosyncratic preferences for certain insurers. Figure 4 reports the distribution of market shares on the number of enrollees with a particular chronic disease. We rank-order insurers within each diagnosis, hence the identity of the insurer that is ranked first among patients with cancer might be different from the one ranked first among patients with diabetes for example. We see that some insurers have significantly higher demand from individuals with specific health conditions, indicating that match values vary across different diagnoses and that the health risk may be substantially concentrated in this market.

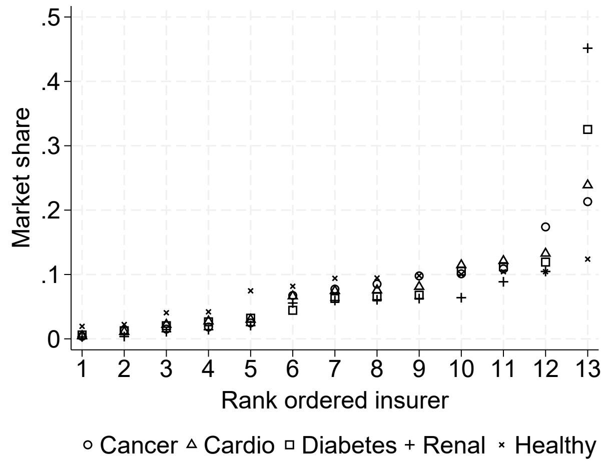


FIGURE 4: Insurer Match Values per Disease

Note: Using the sample for model estimation, this figure reports the distribution of insurer market shares on the number of enrollees with cancer, cardiovascular disease, diabetes, renal disease, and no diseases ("healthy"). Within each disease, insurers are organized in increasing ordered based on their market share. Thus, two different insurers can have the same rank.

3 Reduced-Form Impact of Automatic Enrollment on Market Outcomes

The tendency of sicker consumers to switch insurers less frequently than healthier ones—coupled with general consumer inertia—suggests that the automatic enrollment rule following SaludCoop's termination could have persistent effects on the distribution of health risk across insurers and, in turn, their market power. Consistent with this idea, extensive research has shown that default choices play a significant role in shaping outcomes in health insurance markets (e.g., Handel and Kolstad, 2015; Bhargava et al., 2017; McIntyre et al., 2021). In this section, we quantify the impact of the government's enrollment policy on outcomes for SaludCoop's former enrollees.

We use an event study framework on the sample of continuously enrolled individuals, comparing outcome trends between SaludCoop enrollees (treatment group) against enrollees living in municipalities where SaludCoop did not operate (control group), before and after the termination. The regression of interest is:

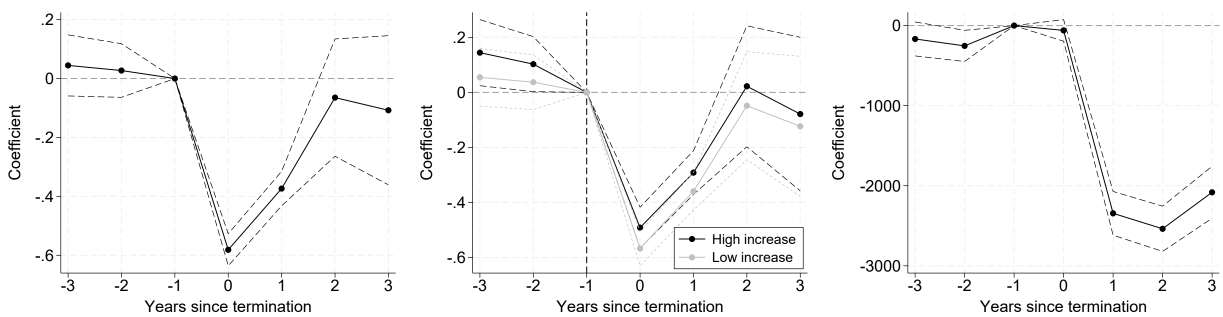
$$y_{it} = \beta_{\tau_{it}} + \eta_{j(i)} + \gamma_t + \varepsilon_{it}$$

where y_{it} is an outcome for consumer i in year t, τ_{it} is the number of years since individual i in the treatment group was impacted by the termination (normalizing those in the control group to -1), $\eta_{j(i)}$ are insurer fixed effects, and γ_t are year fixed effects. Standard errors are clustered at the insurer level, since treatment is defined by the first insurer the individual is enrolled with. We condition our estimation to individuals we observe at least one year before and one year after the termination.

In this regression, $\beta_{\tau_{it}}$ represents the causal effect of the termination on SaludCoop enrollees. This effect is identified if outcome trends among the treated group would have evolved parallel to the control group had the termination not occurred. We provide an indirect test of this assumption by looking at the statistical significance of pre-termination coefficients.

Figure 5 presents the results. Panel A shows that SaludCoop enrollees had parallel healthcare spending trends relative to the rest of enrollees but their spending fell substantially right after the termination. The reduction in spending among SaludCoop enrollees was around 600 thousand pesos in 2016 (US$183) when they were first assigned to Cafesalud, which corresponds to an 72% decline relative to baseline. The impact on healthcare spending diminishes over time and reverts to pre-termination levels by the end of the sample period.

Panel B explores the heterogeneity of these spending effects by how broad was Cafesalud's network relative to SaludCoop's in 2014. Because Cafesalud was forced to cover SaludCoop's network during the 90-day grace period, Cafesalud will experience a large increase in provider network breadth in markets where it had a relatively narrow network in the pre-period. We estimate that in markets where Cafesalud's network was forced to increase by a greater magnitude to match SaludCoop's, depicted in black, healthcare spending fell by a smaller magnitude compared to counterpart markets depicted in gray. This finding suggests that enrollment rules may impact healthcare spending through insurers' provider network breadth decisions.



(A) Total health care spending (B) Cafesalud's pre-period network (C) Insurer HHI

FIGURE 5: Impact of SaludCoop's Termination on Outcomes

Note: Figure shows coefficients and 95% confidence intervals of an event study specification comparing SaludCoop enrollees against enrollees in markets where SaludCoop did not operate, before and after the termination. Estimation uses the sample of continuously enrolled individuals in the contributory system. In Panels A and B the outcome is total health care spending in millions of COP. In Panel B, estimates in black condition on markets where the difference between Cafesalud's and SaludCoop's provider network breadth in 2014 was below the 25th percentile (−0.01), while estimates in gray condition on markets where this difference was above the 75th percentile (0.001). In Panel C the outcome is insurer HHI. An observation in this regression is a market-year. Treatment is defined as the 13 main municipalities where SaludCoop operated in 2015.

In Panel C we quantify the impact of the termination on insurer market concentration. We construct a measure of insurer HHI based on market shares on the number of enrollees. In this regression, an observation is a municipality-year and treatment is defined as the 13 main municipalities where SaludCoop operated (control markets are those where SaludCoop did not operate). We find that after the grace period in 2016, market concentration fell dramatically, perhaps suggesting insurer competition was intensified by consumer switching during this period.

In previous work, we also showed that SaludCoop's termination induced substantial reductions in provider network breadth among incumbent insurers (Buitrago et al., 2025). We reproduce the results from that previous work on the sample of 13 main municipalities in Appendix Figure 1, Panel B. The discontinuous changes in provider networks, switching rates, and consumer choice sets caused by the termination will be essential to identify the parameters of our model in the next section.

4 Model

We are interested in comparing different automatic enrollment rules after SaludCoop's termination in terms of equilibrium provider network breadth, degree of adverse selection, consumer surplus, and healthcare spending. To do so, we develop a model of insurer competition that allows us to measure these equilibrium outcomes. In the model, insurers first choose their provider network breadth in every market to maximize the present discounted valued of their profits conditional on rivals' choices. Then, consumers choose an insurer to enroll with conditional on provider network breadth, out-of-pocket costs, and their past insurer.

We make the simplifying assumption that insurers compete on provider network breadth broadly, without distinguishing network breadth across types of providers. This assumption is adequate for the Colombian health system where most providers are small clinics and physician practices that are generally homogeneous in terms in of quality, and where there are only around 20 top-tier academic medical centers across the country. By characterizing insurer choices with a single index involving the coverage of hospitals, clinics, and physician practices we are also better able to describe the choices of healthy consumers who tend to visit these smaller providers.

4.1 Insurer Demand

We model the indirect utility of consumer i who is of type θ from choosing insurer j in market m in year t as a function of network breadth H_{jmt}, out-of-pocket costs $c_{\theta jmt}(H_{jmt})$, and past choices $y_{ijm,t-1}$:

$$u_{ijmt} = \underbrace{\beta_i H_{jmt} + \alpha_i c_{\theta jmt}(H_{jmt}) + \lambda_i y_{ijm,t-1} + \xi_{\theta j}}_{d_{ijmt}} + \varepsilon_{ijmt}$$

where $\xi_{\theta j} = \xi_{\text{sex},j} + \xi_{\text{age group},j} + \xi_{\text{diagnosis},j}$ is an insurer-by-consumer type fixed effect. We define a consumer type as a combination of sex, age group, and diagnosis as before. These fixed effects capture the match value between consumers of type θ and insurer j, which will matter for counterfactual enrollment rules as they will determine the extent to which consumers are willing to switch towards insurers that are a better match for them.

We back-out consumers' out-of-pocket costs from the data using their total health care cost and the cost-sharing rules that apply to them given their income level. The out-of-pocket cost implicitly accounts for the insurer's negotiated prices with providers in its network since it is the sum of negotiated prices across providers weighted by the coinsurance rate. To appropriately capture the cost-coverage trade-off that consumers face in counterfactuals, we allow the out-of-pocket cost to depend on provider network breadth as follows:

$$c_{\theta jmt} \equiv r_\theta AC_{\theta jmt}(H_{jmt})$$

where r_θ is the coinsurance rate and $AC_{\theta jmt}(H_{jmt})$ is the insurer's marginal cost, described in the next subsection.

Consumers experience inertia in insurer choice as seen in Table 3. We capture this inertia in the model with an indicator for past choices. We do not distinguish whether inertia comes from limited information, consumer's preference for their past insurer, or state dependence. This distinction is not necessary in our case as these sources of inertia will have the same equilibrium impact on outcomes within the counterfactual enrollment rules that we consider. However, identifying them could provide avenues for additional counterfactuals and is left for future research.

Assuming the preference shock ε_{ijmt} is distributed type-I extreme value, the consumer's choice probability is given by:

$$s_{ijmt} = \frac{\exp(d_{ijmt})}{\sum_{k \in \mathcal{J}_{mt}} \exp(d_{ikmt})}$$

where $\mathcal{J}_{mt}$ is the set of insurers that operate in market m in year t. Note that there is no outside option as enrollment is mandatory in Colombia.

4.2 Nash Equilibrium

If the consumer's utility were a function only of provider network breadth, the answer of how to enroll patients after the termination to maximize consumer surplus would be trivial: we should enroll them with the insurer that has the broadest network. The demand trade-off between coverage and out-of-pocket costs and the possibility that insurers respond to the enrollment policy by changing their coverage decisions would make this prediction ambiguous. For example, if all patients are assigned to the insurer with the broadest provider network and these patients are relatively sick, then the insurer would respond by narrowing its network to minimize costs among its stock of enrollees and to discourage enrollment from other sick patients. This ambiguity on patient welfare can only be captured in counterfactuals with a model of how insurers respond to the policy.

Insurers maximize the present discounted value of their profits choosing the vector of provider network breadth conditional on rivals' choices. The insurer profit function is:

$$\Pi_{jm}(H_m) = \sum_{\theta} \pi_{ijm}(H_m, \theta, y) N_{\theta m y} + \sum_{t=1}^{T} \zeta^t \sum_{\theta', y'} \underbrace{(1-\rho_\theta)\mathcal{P}(\theta', j|\theta, y)\pi_{ijm}(H_m, \theta', y) N_{\theta' m y}}_{FP_{\theta jmt}}$$
$$- \underbrace{(\omega H_{jm} + \nu_{jm}) H_{jm}}_{ADC_{jm}}$$

where per-enrollee profit is:

$$\pi_{ijm}(H_m, \theta, y) = (R_{\theta m} - (1 - r_\theta) AC_{\theta jm}(H_{jm})) s_{ijm}(H_m, y)$$

and insurers' marginal cost is:

$$AC_{\theta jmt} = e^{\tau_1 H_{jmt} + \tau_2 H_{jmt}^2 + \gamma_\theta + \eta_m + \delta_j + \epsilon_{\theta jmt}} \tag{1}$$

In this profit function, $H_m = \{H_{jm}\}_{j=1}^{J_m}$ is the vector of provider network breadth across all insurers in market m, $N_{\theta m y}$ is the market size of type-θ consumers in market m that chose incumbent insurer y, ζ^t is a discount factor (set to 0.95), ρ_θ is the probability that a consumer type θ drops out of the contributory system (into the subsidized system), and $\mathcal{P}(\theta', j|\theta, y)$ is the transition probability from type θ at insurer y in period t to type θ' at insurer j in period $t+1$.

We assume transition probabilities are separable in consumer types and insurers as follows: $\mathcal{P}(\theta', j|\theta, y) = P(\theta'|\theta)P(j|\theta, y)$. This separability implies that a consumer's current health status affects which insurer they decide to enroll with tomorrow but that the probability of transitioning across health statuses is independent of the insurer. A formal derivation of this simplification is presented below:

$$
\begin{aligned}
\mathcal{P}(\theta', j|\theta, y) &= P(\theta'|j, \theta, y)P(j|\theta, y) && \text{Chain rule} \\
\mathcal{P}(\theta', j|\theta, y) &= P(\theta'|\theta)P(j|\theta, y) && \text{Conditional independence of } \theta' \text{ and } j \text{ given } \theta \\
\mathcal{P}(\theta', j|\theta, y) &= P(\theta'|\theta)s_{ijm}(H_m, y) && \text{Replacing the choice probability among type } \theta
\end{aligned}
$$

Appendix Table 1 provides evidence of the second step in this derivation by showing that conditional on not having a diagnosis in year t, the probability of being diagnosed with a chronic disease in year $t+1$ is unrelated to provider network breadth.

Insurers' administrative cost structure is denoted by ADC_{jt}, where ω captures the curvature of the function and ν_{jm} is the model's structural error. We assume this error is the sum of an insurer-specific cost component and an unobserved cost component: $\nu_{jm} = \nu_j + \psi_{jm}$. In the marginal cost function, γ_θ, η_m, and δ_j are consumer type, municipality, and insurer fixed effects, respectively.[11] Moreover, $\epsilon_{\theta jmt}$ is white noise. Finally, $R_{\theta m}$ is the risk-adjusted transfer from the government plus average copayments. This transfer encompasses three types of payments: a compensation for the enrollee's demographic characteristics (sex, age, and municipality of residence), a compensation for a coarse list of diseases (known as the High-Cost Account), and disability compensations.[12]

In this model insurers make a one-time choice of provider network breadth that affects both current and future profits as patient age, transition into diagnoses, and switch insurers. For simplicity we do not model the dynamic decision of choosing provider network breadth every period. Our specification of insurer profits is thus a compromise between

[11]Our functional form for the marginal cost is informed by the descriptive evidence in Figure 2.

[12]For an explanation of how disability transfers are calculated and other considerations of insurer revenues see Resolución 06411 de 2016.

having a tractable model to conduct counterfactuals and a realistic model of how profits would evolve for a given choice of provider network breath.

Given demand, marginal costs, and transition and dropout probabilities, the first-order condition (FOC) of the insurer's profit maximization problem is:

$$MP_{jm}(H_m, \theta, y) = \tilde{\omega} H_{jm} + \nu_j + \psi_{jm} \tag{2}$$

where $MP_{jm}(H_m, \theta, y)$ denotes the marginal variable profit and $\tilde{\omega} = 2\omega$.

5 Estimation and Identification

5.1 Insurer Demand

Identification. The preference for provider network breadth is identified from exogenous changes in provider networks within insurer and across markets caused by SaludCoop's termination (see Appendix Figure 1). To identify the parameters on out-of-pocket costs we rely on two sources of variation: first, on the exogenous changes in income across patients within an insurer, which generates variation in the coinsurance rates. And, second, on the exogenous changes in consumers' choice sets after the termination. Finally, given that enrollees in the contributory system are highly inertial as seen in Table 3, the parameter on past choices capturing inertia is only identified from SaludCoop enrollees who switch out of Cafesalud on or after 2016.

We estimate our insurer demand model on the sample for model estimation involving 500,000 randomly chosen continuously enrolled individuals who reside in one of the 13 main municipalities. Table 5 presents the results. We find that consumers on average have a preference for broad provider networks and that this preference is stronger among the group of individuals with chronic diseases relative to those without diseases.

Consumers derive disutility from higher out-of-pocket payments, but those with chronic diseases are substantially less responsive to prices than individuals without diagnoses. We estimate an average out-of-pocket price elasticity of insurer demand of −0.23,

Table 5: Insurer Demand Model

	Network breadth		OOP spending		Incumbent	
Variable	coef	se	coef	se	coef	se
Mean coefficient	3.982	(0.050)	-2.681	(0.118)	3.591	(0.007)
Interactions						
Male	-0.198	(0.027)	0.220	(0.046)	0.006	(0.004)
Age 19-24	1.175	(0.058)	-0.538	(0.125)	-1.441	(0.009)
Age 25-29	1.208	(0.057)	-0.203	(0.114)	-0.689	(0.009)
Age 30-34	1.046	(0.058)	-0.436	(0.105)	-0.467	(0.009)
Age 35-39	0.959	(0.060)	-0.442	(0.111)	-0.333	(0.009)
Age 40-44	0.892	(0.062)	-0.249	(0.105)	-0.321	(0.009)
Age 45-49	0.861	(0.063)	-0.298	(0.099)	-0.272	(0.009)
Age 50-54	0.862	(0.065)	-0.138	(0.092)	-0.214	(0.010)
Age 55-59	0.681	(0.069)	0.136	(0.074)	-0.182	(0.010)
Age 60-64	0.523	(0.073)	-0.050	(0.081)	-0.133	(0.011)
Cancer	-1.030	(0.054)	1.899	(0.121)	-0.022	(0.008)
Cardiovascular	-0.045	(0.043)	1.574	(0.119)	-0.082	(0.007)
Diabetes	-0.079	(0.097)	2.639	(0.138)	-0.017	(0.016)
Other disease	-0.490	(0.066)	2.225	(0.143)	0.156	(0.010)
Pulmonary	0.263	(0.143)	2.634	(0.124)	-0.224	(0.022)
Renal	-0.827	(0.162)	2.409	(0.118)	-0.077	(0.028)
Individuals			500,000			
Observations			16,410,468			
Pseudo-R^2			0.52			

Note: Table presents maximum likelihood estimates of the insurer demand model using a conditional logit. Estimation uses a random sample of 500,000 individuals enrolled throughout the sample period from 2013 to 2017 in the 13 main capital cities or municipalities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales, Pereira, Cúcuta, Pasto, Ibagué, Montería, Cartagena, and Villavicencio. Specification includes insurer fixed effects. Robust standard errors in parenthesis.

which is higher in absolute value for consumers without diagnoses and generally within the ballpark of other estimates in the literature (e.g., Abaluck and Gruber, 2011).

Our findings also show evidence of significant inertia in insurer choice, as patients are nearly 4 times more likely to choose the insurer they were enrolled with in the previous year. This translates into an estimate of the median value of inertia (computed as $\hat{\lambda}_i/\hat{\alpha}_i$) equal to 1.2 million pesos (roughly 2.5 times the monthly minimum wage in 2016). Finally, we find that individuals with chronic conditions have a higher value of inertia than individuals without diagnoses because they are insensitive to out-of-pocket costs. For example, the value of inertia for consumers with cancer equals 3.5 million pesos on average and for consumers without diagnoses it equals 1.1 million pesos. Appendix Table 2 shows the in-sample fit of our demand model.

5.2 Insurer Marginal Costs

Identification. Given the richness and size of our data, we can calculate insurers' marginal cost as the average across all individuals who are of type θ. We then estimate the marginal cost function using non-linear least squares on the sample of all continuously enrolled individuals residing in any municipality.

One challenge with estimating equation (1) is endogeneity stemming from unobserved patient selection into insurers based on provider network breadth (unobservably sicker consumers choosing broader networks), which would bias our estimates of τ_1 upwards. To address this, we use SaludCoop's termination as an instrument for provider network breadth in a control function approach. Our instrument, in the style of shift-share, is the interaction between an exogenous indicator for municipalities where SaludCoop operated times an indicator for the post-termination period ("shift") and provider network breadth in 2015 ("share"), $T_m \cdot P_t \cdot H_{jm,2015}$. This instrument isolates changes in provider network breadth that occurred right after the termination in markets where SaludCoop operated. Appendix Figure 1 provides evidence of parallel trends in network coverage among treated and control markets as required for the shift-share approach.

In the first stage, we regress provider network breadth on the instrument, and insurer, age group, sex, diagnosis, municipality, and year fixed effects. We include the residuals of this regression and their squares as predictors in the second stage given by equation (1). The second stage has the same set of fixed effects as the first stage; however, due to convergence issues, we only include indicators for the main 13 municipalities rather than the full set of municipality dummies.

Second-stage results are presented in Table 6 and first-stage results are in Appendix Table 3. Our findings show that insurers' marginal cost is increasing in provider network breadth at a decreasing rate. The average marginal effect of network breadth on insurers' marginal cost equals $8,583$ pesos (US$2.8 of 2016). Marginal costs are also heterogeneous across insurers. Conditional on the consumer type, we find for example that the marginal cost is higher for insurers G and H than for the reference insurer. Appendix Figure 2 presents the in-sample fit of the marginal cost model and Appendix Figure 3 the estimated consumer type fixed effects.

Table 6: Insurer Marginal Cost Model

Variable	coef	se
Network breadth	0.403	(0.022)
Network breadth^2	-0.380	(0.018)
Insurer FE Insurer A	0.323	(0.006)
Insurer B	0.040	(0.003)
Insurer C	-0.164	(0.004)
Insurer D	-0.069	(0.004)
Insurer E	0.101	(0.004)
Insurer F	-2.556	(0.829)
Insurer G	0.077	(0.003)
Insurer H	0.229	(0.007)
Insurer I	-0.018	(0.004)
Insurer J	0.245	(0.003)
Insurer K	0.141	(0.004)
Insurer L	0.395	(0.004)
Insurer M	-0.043	(0.006)
Insurer N	(ref)	(ref)
F-statistic	45.49	
Observations	1,135,511	
R^2	0.99	

Note: Table presents non-linear least squares regression of average costs per consumer type on network breadth and network breadth squared. An observation is a combination of consumer type, insurer, municipality, and year. Specification controls for the residuals and the squared residuals of a control function that regresses network breadth on our instrument. The instrument is the interaction between the treatment indicator for municipalities where SaludCoop operated, the post-termination period indicator, and network breadth in 2015. Specification includes dummies for insurer, year, sex, age group, diagnosis, and 13 main municipalities. We do not report municipality nor consumer type fixed effects for ease of exposition. Estimation uses data from 2013 to 2017 from all municipalities in the country and uses analytic weights given by the number of enrollees per observation. Table reports standard errors in parenthesis and first-stage F-statistic.

With our demand and marginal cost estimates, in Figure 6 we report the relation between the cost of increasing provider network breadth by 1% and patient willingness-to-pay for an additional percentage point in provider network breadth. Consistent with adverse selection, we find that patients who have the highest willingness-to-pay for provider network breadth are also the most expensive to the insurer.

5.3 Dropout and Transition Probabilities

We estimate dropout and transition probabilities across diagnoses non-parametrically from the data and outside of the model. To compute these probabilities we use the use the full sample of individuals in the 13 main municipalities (independent of their enrollment spell lengths). Summary statistics of resulting probabilities are presented in Appendix Tables 4 and 5.

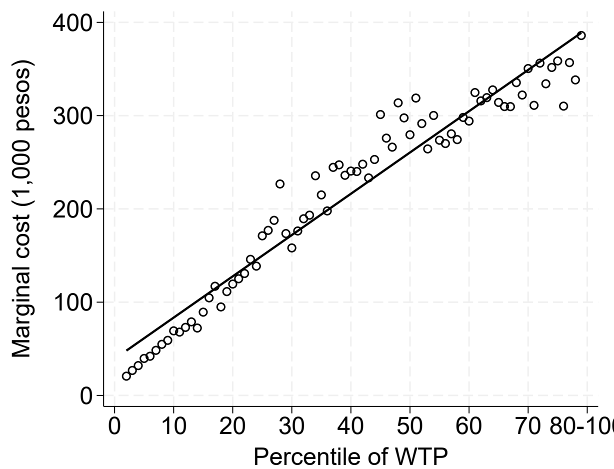


FIGURE 6: Model Evidence of Adverse Selection

Note: Figure shows the insurer's short-run marginal cost in thousand of pesos $\partial AC_{\theta jmt}(H_{jmt})s_{ijmt}(H_{mt})/\partial H_{jmt}$ averaged within each percentile of consumer willingness-to-pay for an additional percent in network breadth calculated as $-\alpha_i^{-1}(\partial s_{ijmt}/\partial H_{jmt})$.

5.4 Insurer Administrative Costs

Our model of insurer competition is static and generates predictions of each insurer's provider network breadth. Because the model is static, we only require data from a single year to estimate the remaining parameters related to insurers' administrative costs. However, since we have access to multiple years of data, the model is over-identified for these parameters.

We choose to operationalize our model of insurer competition using data from 2015 before SaludCoop is terminated, to later test the model's out-of-sample fit. We use the 2015 cross-section of individuals to forward-simulate marginal and total variable profits for $T = 100$ periods. In every period and for every combination of sex, age, diagnosis, insurer, incumbent insurer, and municipality, we compute demand and marginal costs (and their derivatives) using our estimates in Tables 5 and 6. Then, conditional on a consumer type θ, transitions across periods are governed by dropout probabilities, exogenous transition probabilities across diagnoses, and endogenous transition probabilities across insurers.

After simulating insurers' marginal and total variable profits, we estimate the administrative cost parameters using the FOCs. Marginal variable profits in the left-hand side of equation (2) are positive across all insurers and markets as seen in Appendix Table 6. A non-zero marginal variable profit is both inconsistent with profit maximization and suggestive that administrative costs play a role in our characterization of insurers' decision to offer provider network breadth.

Identification. A key difficulty with using insurers' FOC to estimate the parameters of the administrative cost is the endogeneity of provider network breadth. This variable is potentially correlated with the unobserved (to us) administrative cost component, leading to biased estimates of a naïve OLS regression. Hence, to identify the parameters of this cost function we require an instrument that affects insurers' marginal variable profits in a given market only through its impact on network breadth in that market.

We follow the literature on industrial organization to construct a Hausman-style instrument for supply (it is typically used for demand estimation). Our logic is as follows: as seen in Figure 1, insurers' network breadth decisions are highly correlated within insurer and across markets, suggesting insurers likely adopt country-wide coverage policies, which is specially true for the 13 main municipalities. This suggests we can use the average network breadth across all other markets where the insurer operates as an instrument for local network breadth, since coverage decisions in other markets are uncorrelated with local cost shocks. We implement this instrument using 2SLS.

Table 7 presents second-stage estimates and Appendix Table 7 presents first-stage results. Our instrument is strong as seen by the first-stage F-statistic. In the second stage, we find that network breadth has a positive effect on total administrative costs and that insurers are heterogeneous in their cost structure. Our estimated insurer fixed effects in the administrative cost function are largely unrelated to the marginal cost fixed effects as seen in Appendix Figure 4. This indicates that insurers mainly enjoy economies of scale in network breadth and that administrative costs are a determinant of coverage choices. The structural error accounts for 64% of the variation in marginal variable profits.

Table 7: Insurer Administrative Cost Model

	Log Marginal Variable Profits	
Variable	coef	se
Network breadth	6.206	(2.436)
<u>Insurer FE</u>		
Insurer A	0.880	(0.451)
Insurer B	-0.151	(0.585)
Insurer C	-0.312	(0.680)
Insurer D	-1.460	(0.655)
Insurer E	3.056	(0.414)
Insurer G	-0.013	(0.642)
Insurer H	0.813	(0.502)
Insurer I	0.661	(0.535)
Insurer J	-2.049	(0.949)
Insurer K	-1.708	(0.917)
Insurer L	-0.421	(0.768)
Insurer M	0.862	(1.022)
Insurer N	0.000	(.)
Constant	9.486	(0.888)
F-statistic	36.18	
Observations	98	
R^2	0.331	

Note: Table presents 2SLS regression of the log of marginal variable profits on network breadth and insurer fixed effects. The instrument for network breadth is the average network breadth across all other markets where the insurer operates. Estimation uses data from the 13 main municipalities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales, Pereira, Cúcuta, Pasto, Ibagué, Montería, Cartagena, and Villavicencio. Robust standard errors in parenthesis.

5.5 Out-of-sample Fit

To evaluate the model's predictive performance, we simulate insurers' provider network breadth choices in 2016 under the government-mandated enrollment rule that reassigned SaludCoop enrollees to Cafesalud. For this prediction, we assume that $y_{ijm,t-1} = 1$ for SaludCoop enrollees assigned to Cafesalud. This assumption is reasonable given that, during the 90-day grace period, the government required Cafesalud to maintain the same provider network as SaludCoop. As a result, enrollees may have perceived Cafesalud as a close substitute. Figure 7 compares the observed distribution of provider network breadth (in black) with the model's predictions (in blue), showing that the model closely replicates insurers' actual choices.

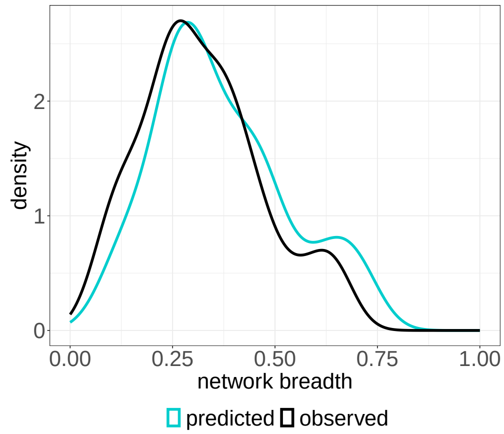


Figure 7: Out-of-sample Prediction of Provider Network Breadth

Note: Figure presents the distribution of observed provider network breadth for 2016 in black and the distribution of predicted provider network breadth for 2016 imposing the observed reassignment rule in which SaludCoop enrollees are transferred to Cafesalud in blue. An observation is an insurer-market.

6 Counterfactual Automatic Enrollment Rules

6.1 Setup

In this section, we compare alternative enrollment rules after SaludCoop's termination along the dimensions of provider network breadth, short-run average consumer surplus per capita, short-run average health care spending per capita, and degree of adverse selection and market power. Short-run average consumer surplus per capita is defined as the inclusive value from the logit demand system,

$$CS = \Big(\sum_{ijm} s_{ijm}\Big)^{-1}\Big(\sum_{ijm} s_{ijm}^{cf} \log(\sum_{j\in\mathcal{J}_{mt}} \exp(d_{ijmt}^{cf}))\Big)$$

where variables with superscripts cf denote their value in the counterfactual. Short-run healthcare spending per capita is given by

$$AC = \Big(\sum_{ijm} s_{ijm}\Big)^{-1}\Big(\sum_{\theta(i)jm} AC_{\theta jm} s_{ijm}\Big)$$

We summarize market power with the insurers' average short-run profit margin defined as

$$\Big(\sum_{ijm} s_{ijm}\Big)^{-1}\Big(\sum_{ijm}(R_{\theta m}s_{ijm} - \frac{\partial AC_{\theta jmt}(H_{jmt})s_{ijmt}(H_{mt})}{\partial H_{jmt}} - (\tilde{\omega}H_{jm} + \nu_j + \psi_{jm})/T)\Big)$$

Finally, in the style of Einav and Finkelstein (2011), we measure the degree of adverse selection by the correlation between the consumer's willingness-to-pay for provider network breadth and insurers' marginal cost of increasing network breadth (as in Figure 6).

We evaluate the following enrollment rules in each market:

1. *Random*: SaludCoop enrollees are randomly assigned in equal proportion to incumbent insurers in their municipality of residence.

2. *Overlap*: SaludCoop enrollees are assigned to the incumbent insurer with the greatest network overlap with SaludCoop in their municipality of residence.

3. *Proportional*: SaludCoop enrollees are assigned to incumbent insurers in proportion to their 2015 market shares in their municipality of residence. For example, suppose Insurer A covers 30 enrollees, Insurer B covers 20 enrollees, and SaludCoop covers 50 enrollees in a market. Then, after SaludCoop's termination, Insurer A receives 30 SaludCoop enrollees (= $50 \times \frac{30}{20+30}$) and Insurer B receives 20 (= $50 \times \frac{20}{30+50}$). We choose these "new" SaludCoop enrollees randomly.

4. *Broadest*: SaludCoop enrollees are assigned to the incumbent insurer with the broadest provider network in their municipality of residence.

5. *Largest*: SaludCoop enrollees are assigned to the incumbent insurer with the highest market share in 2015 in their municipality of residence (excluding SaludCoop).

6. *Own choice*: Enrollees are free to choose their insurer after excluding SaludCoop from the choice set.

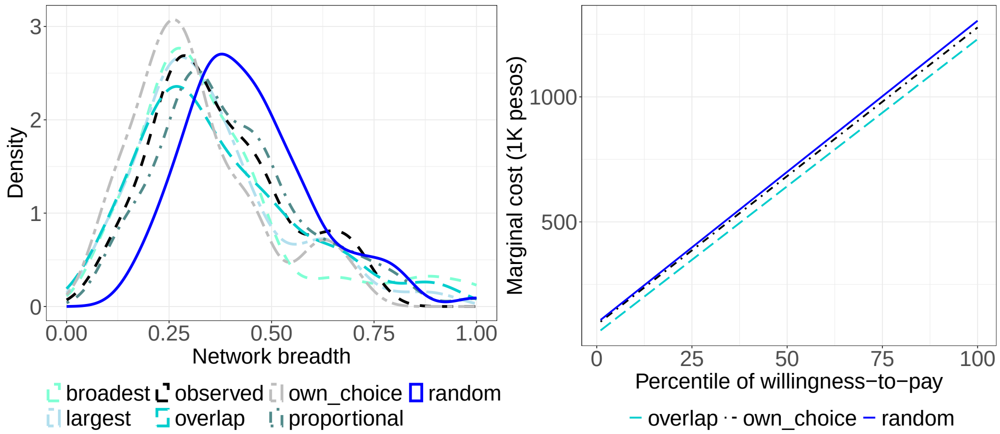
Enrollment rules that seek to maintain individuals' access to former providers, such as overlap enrollment and broadest enrollment, can be interpreted as mitigating additional impacts of adverse selection by leveraging inertia, since presumably consumers made their initial choices of insurer considering the providers they are most likely to visit given their unobserved health status. Instead, rules that incentivize consumers to switch due to their preferences for network breadth, such as random enrollment and proportional enrollment, can be interpreted as reducing the impact of inertia while exacerbating adverse selection.

In each automatic enrollment rule, using as starting value the vector of provider network breadth in 2015, we compute the FOCs for each insurer and market. From these FOCs, we solve for provider network breadth as $H_{jm} = (\log(MP_{jm}) - \hat{\nu}_j - \psi_{jm})/\tilde{\omega}$, which we then use as starting point in the next iteration. We iterate until the maximum residual provider network breadth by absolute value is less than 10^{-5}.

6.2 Results

Figure 8, Panel A presents the counterfactual distribution of provider network breadth under each enrollment rule. We find that under random enrollment the unweighted increase in average network breadth relative to the observed scenario equals 13% and the increase weighted by demand is 6%. As seen in Appendix Figure 5, these coverage increases are heterogeneous across insurers. Proportional enrollment generates the second largest increase in provider network breadth weighted by demand, which is equal to 4%, but most other rules are indistinguishable from the distribution in the observed equilibrium. In particular, we find that letting consumers choose their insurer freely without setting their default after the termination reduces demand-weighted average network breadth by 8%. Later in this section we delve into the mechanisms explaining these results.

Panel B shows that, under random enrollment, adverse selection worsens slightly compared to the own-choice scenario and that the correlation is particularly strong towards the higher end of the distribution of willingness-to-pay where most individuals with chronic diseases are represented. In contrast, other rules—such as overlap enrollment—somewhat weaken the correlation between insurers' marginal costs and consumers' willingness to pay for their networks.



(A) Provider network breadth (B) Adverse selection

Figure 8: Counterfactual Provider Network Breadth and Degree of Adverse Selection

Note: Panel A presents the distribution of provider network breadth under each enrollment rule. We depict the model's prediction of the observed assignment rule in black. Panel B presents the linear prediction of a regression of insurers' marginal cost of increasing provider network breadth by 1 percentage point on percentiles of the consumers' willingness-to-pay for provider network breadth. We present the linear predictions for the own-choice rule in black, random assignment in dark blue, and overlap assignment in light blue.

Table 8: Outcomes Under Counterfactual Enrollment Rules

Scenario	Consumer surplus*	Marginal cost*	Adverse selection	Network breadth
Proportional	3.156	0.519	0.521	0.401
Broadest	3.129	0.547	0.528	0.365
Largest	3.127	0.543	0.524	0.352
Observed	3.131	0.490	0.507	0.395
Overlap	3.135	0.530	0.520	0.371
Own choice	2.999	0.518	0.509	0.313
Random	3.215	0.490	0.528	0.446

Note: Table presents the average provider network breadth and the demand-weighted average consumer surplus per capita, health care spending per capita (labelled marginal cost), and degree of adverse selection under each enrollment rule. The degree of adverse selection is the correlation between the percentile of consumers' willingness-to-pay for network breadth and the insurers' marginal cost. (*) measured in millions of COP. The average exchange rate in 2016 was 3,050 COP/USD.

Table 8 summarizes other outcomes of interest for each enrollment rule. We find that random enrollment not only outperforms other rules in terms of provider network breadth, but it also generates the greatest increase in consumer surplus per capita (3%) and virtually no changes in healthcare spending per capita relative to the observed scenario. Conversely, the own-choice rule reduces consumer surplus by 4% because in our setting we consider inertia to be potentially welfare-enhancing.

In the own-choice rule, former SaludCoop enrollees derive no value from inertia ($y_{ijm,t-1}$ equals zero in the first year after the termination), while in other enrollment rules default insurers matter for welfare. Our assumption that inertia factors into consumer surplus builds upon the literature that has examined the impacts of defaults on welfare-relevant outcomes such as healthcare utilization (e.g., Brot-Goldberg et al., 2023; Macambira et al., 2022) and financial savings decisions (e.g., Blumenstock et al., 2018).

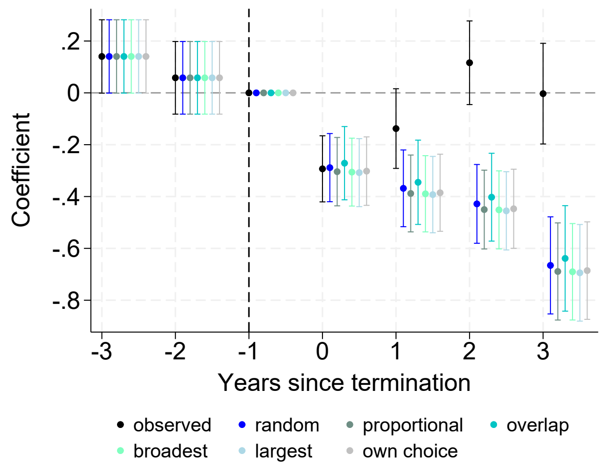


FIGURE 9: Event Study Simulation under Different Enrollment Rules

Note: Figure presents event study coefficients and 95% confidence intervals comparing municipalities where SaludCoop operated (treatment group) against municipalities where SaludCoop did not operate (control group) before and after the termination. The data is at the municipality-year level and the outcome is health care spending per capita (denoted average cost in the structural model). Outcomes for control municipalities are the same across specifications. Outcomes for the treated group are conditional on the 13 main municipalities and vary across counterfactual enrollment rules. Standard errors are clustered at the municipality level.

In Figure 9 we use our model estimates to predict healthcare spending per capita (i.e., marginal costs) in the first 4 years after the termination and produce analogous event study results as in Figure 5. Because our model is estimated with data from the 13 main municipalities in which SaludCoop operated, it applies only to treated markets. Thus, we assume healthcare spending in the control group—comprised of markets where SaludCoop did not operate—is the same as in Figure 5, but vary outcomes in the treatment group depending on the counterfactual automatic enrollment rule. We report in black a version of the event study results from Figure 5 in which the treatment group is comprised of individuals previously enrolled with SaludCoop and residing in the 13 main municipalities.

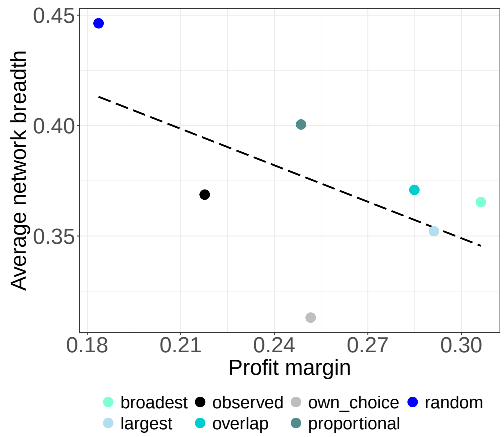
By construction, all the pre-termination period coefficients and standard errors are the same across specifications. The year of the termination, we find that healthcare spending per capita decreases by a similar amount across all scenarios. However, two to three years after the termination, our counterfactual enrollment rules predict substantially different outcomes than what was observed. For example, we predict that healthcare spending per capita among SaludCoop enrollees would have continued to decrease by about 400 thousand pesos relative to baseline (US$131 of 2016), while in the observed scenario spending levels revert to their pre-termination levels. Overall, we do not find significant differences in predicted spending trends between the counterfactual rules, but note that point estimates are slightly smaller in magnitude under random and overlap assignment compared to other rules.

6.3 Mechanisms

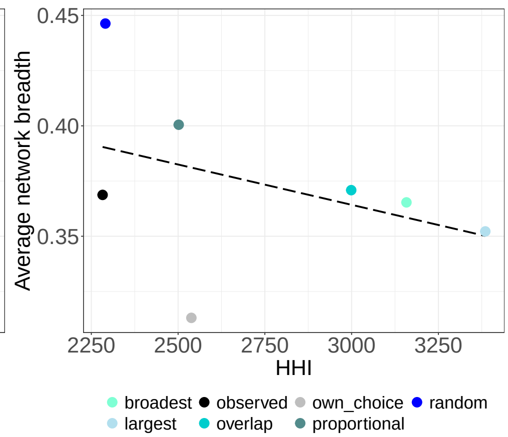
Why does automatic random enrollment outperform other assignment rules across most of the outcomes we examine? Our model offers two explanations. First, as shown in Table 5, sicker consumers have a significantly higher value of inertia than their healthier counterparts. Hence, by randomly allocating patients among incumbent insurers, the policy more evenly distributes SaludCoop enrollees' health risk across the market. One implication of this is that on average insurers' profit margins should be lower under this policy.

Indeed, Figure 10, Panel A shows that the average profit margin falls 16% under random enrollment relative to the observed scenario. In contrast, all other rules increase profit margins—by as much as 40% under the rule that assigns consumers to the insurer with the broadest network in their area of residence. Panel B further shows that random enrollment generates the lowest average HHI across markets in equilibrium. And consistent with evenly spreading the distribution of health risk across incumbent insurers, Panel C shows that only random enrollment reduces market concentration among both individuals with chronic diseases ("sick") and individuals without diagnoses ("healthy") relative to the observed rule.

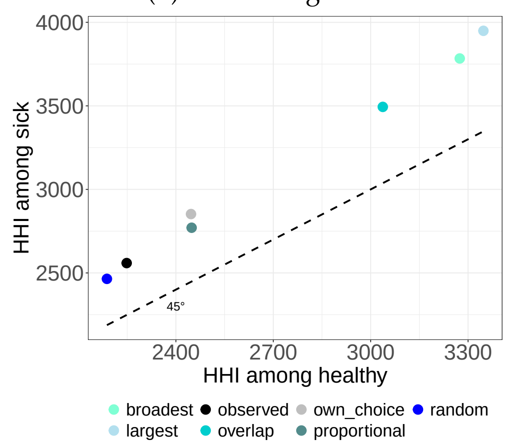
The second explanation for why random enrollment outperforms other rules in terms of provider network breadth is that healthy consumers—who are profitable—both value broad networks and have lower inertia. Thus, if the assigned insurer is a poor match for healthy consumers' idiosyncratic preferences given $\xi_{\theta j}$, they will switch at disproportionate rates relative to the observed equilibrium, encouraging insurers to compete more aggressively using their networks.



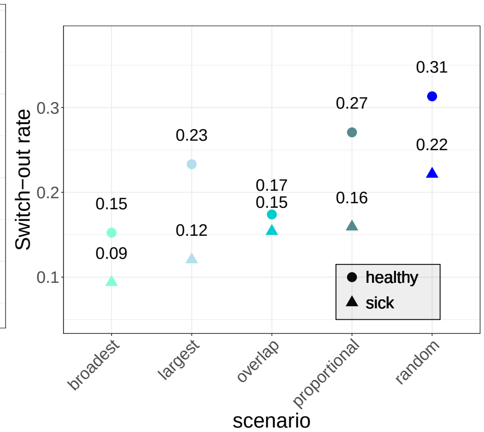
(A) Profit margin



(B) HHI



(C) HHI by health status



(D) Switching rate

FIGURE 10: The Role of Consumer Inertia in Market Power

Note: Panel A presents a scatter plot of market share-weighted average profit margin across insurers and markets against average network breadth for each enrollment rule. Panel B presents a scatter plot of average HHI across markets against average network breadth across insurers and markets for each enrollment rule. The dashed black line in panels A and B corresponds to a linear fit. Panel C presents a scatter plot of average HHI conditional on individuals without diseases ("healthy") against average HHI conditional on individuals with chronic diseases ("sick"). The dashed black line is the 45 degree line. Panel D presents the switching rate among the healthy and the sick for each enrollment rule among SaludCoop enrollees. We exclude the observed and own-choice rules because switching rates in those scenarios equal 100%.

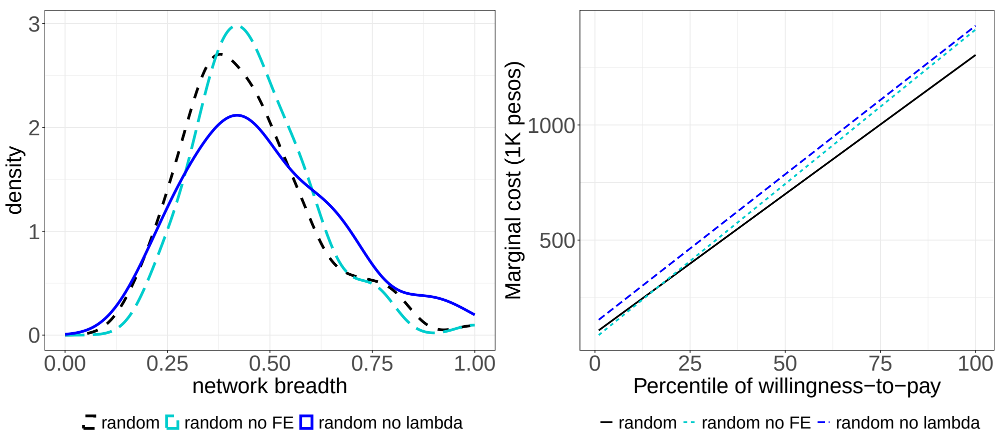
We provide evidence for this mechanism in Figure 10, Panel D, which shows switching rates among SaludCoop enrollees during the first year after assignment, conditional on chronic disease status (sick vs. healthy). We omit the own-choice and observed rules from the figure, as switching rates are mechanically 100% in both cases. Consistent with our intuition, switching rates among healthy consumers are notably higher under random enrollment than under other assignment rules.

Who switches has important implications for equilibrium outcomes. Allowing consumers to freely choose their insurer raises overall switching relative to the other rules, but disproportionately among sick individuals as seen in Appendix Figure 6. Conversely, under random enrollment, switching is concentrated among the healthy. In prior work, we showed that when sick consumers switch plans, insurers have stronger incentives to drop high-cost providers—such as public hospitals and cancer centers—that specialize in treating chronic conditions (Buitrago et al., 2025). This dynamic helps explain why equilibrium network breadth declines under the own-choice rule.

To further investigate the role of inertia in incentivizing or discouraging insurers to offer broad networks, in Figure 11 we conduct two additional counterfactual analyses conditional on random enrollment. First, we eliminate the value of inertia by setting $\lambda_i = 0$ ("random no lambda"). Second, we set the idiosyncratic preference for particular insurers to zero $\xi_{\theta j} = 0$ ("random no FE"). The idea is that strong inertia and idiosyncratic preferences make demand less responsive to provider network breadth, granting insurers market power and incentivizing them to offer relatively narrow networks.

Panel A presents the distribution of provider network breadth in each counterfactual. We see that setting each component of insurer demand to zero leads to even broader networks relative to baseline random enrollment. Average provider network breadth without inertia is 5% higher and without idiosyncratic preferences is 2% higher than baseline. Increased switching relative to baseline random assignment also generates a stronger correlation between insurers' marginal cost and consumers' willingness-to-pay for provider network breadth as seen in Panel B. This correlation is much higher after eliminating the value of inertia than after removing idiosyncratic preferences, suggesting adverse selection differentially worsens in the former case.

In summary, our results suggest that the effectiveness of different automatic enrollment rules in improving consumer welfare and reducing health care costs will depend on how the rules impact inertia and adverse selection and on who ends up switching.



(A) Network breadth

(B) Adverse selection

Figure 11: Counterfactual Outcomes under Random Enrollment

Note: Panel A presents the distribution of provider network breadth across insurers and markets under random enrollment. The baseline random rule is presented in black, the random rule setting the demand fixed effects to zero is in light blue, and the random rule setting the switching cost to zero is in dark blue. Panel B presents the prediction of a linear regression of insurers' marginal cost on percentiles of consumers' willingness-to-pay for provider network breadth under random reassignment at baseline in black, without demand fixed effects in light blue, and without inertia in dark blue.

6.4 Discussion

Equilibrium outcomes under the counterfactual enrollment policies we consider arise from imposing a default insurer only during the first year after SaludCoop's termination, but consumers are allowed to switch after this initial period. The fact that a one-year policy has lasting effects on the distribution of provider network breadth and consumer surplus implies that the dynamic consequences of inertia can potentially be reversed with short-run policies. Random enrollment essentially nudges consumers to engage in active choice resulting in improved outcomes once supply-side decisions are taken into account. This result builds on the seminal work of Handel (2013) who shows that nudges can exacerbate adverse selection and reduce welfare.

Although we cannot identify the specific sources of inertia (switching costs, inattention, information frictions, etc.), our model captures the equilibrium implications of these choice frictions in a reduced-form way, particularly for insurer market power. In this context, counterfactual results suggest that, independent of which sources lead to these frictions, regulators can effectively improve market outcomes and reduce market power in the Colombian health system using automatic enrollment rules. While the specific estimates derive from Colombian insurance data, our results underscore the trade-off between adverse selection and inertia and the role of defaults when designing insurance regulations.

A reminder of these inherent trade-offs is timely given the increased popularity of random enrollment policies in health insurance markets like Medicaid managed care (Geruso et al., 2023; Wallace, 2023; Macambira et al., 2022) and of own-choice policies in Medicare Advantage when a plan closes (California Health Advocates, 2025).

7 Conclusions

This paper shows that regulators can promote health insurer competition by designing automatic enrollment rules that encourage healthy consumers to switch, even when adverse selection is pervasive. Our setting is Colombia's contributory healthcare system where insurers compete mainly on their network of covered providers and where the largest health insurer, which covered 20% of enrollees, was terminated by the government in December 2015. Initially, the government assigned these enrollees to a single incumbent insurer which covered only 5% of the market.

To compare counterfactual enrollment rules, we propose and estimate an equilibrium model of insurer competition on provider network breadth. We find that enrolling patients randomly to incumbent insurers in even proportions is effective at increasing consumer welfare and provider network breadth, but worsens adverse selection relative to other rules such as enrollment based on network overlap between the incumbent insurer and the terminated one. We show that the main reason why random enrollment outperforms other rules is that it substantially reduces inertia among healthy consumers who value broad networks. This encourages insurers to compete more aggressively for these profitable patients, rather than resorting to harvesting their stock of enrollees.

Our findings highlight the trade-off between inertia and adverse selection when designing regulations that promote insurer competition and therefore have implications outside of Colombia for health systems where plan terminations are common.

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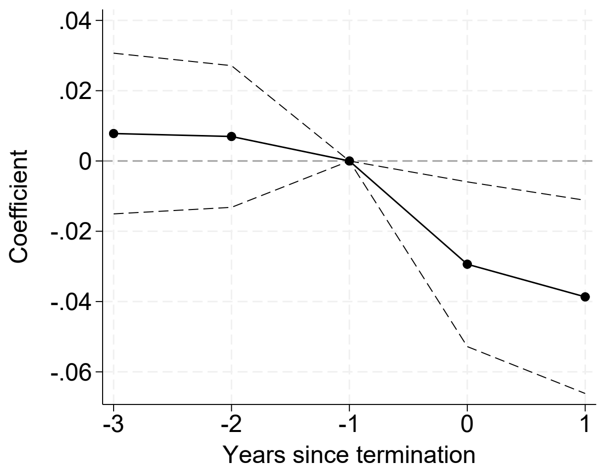
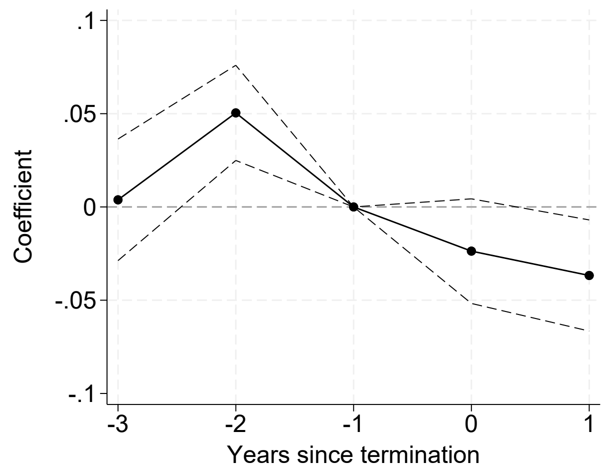
Appendix A Additional Descriptives and Results



(A) All markets



(B) Main markets

Appendix Figure 1: Impact of SaludCoop's Termination on Provider Network Breadth

Note: Figure presents coefficients and 95% confidence intervals of a dynamic difference-in-difference design using as outcome provider network breadth among incumbent insurers. An observation is an insurer-municipality-year. Treatment is defined as municipalities where SaludCoop operated in 2015 and the control group are municipalities where it did not operate. Relative time indicators are constructed relative to the termination year, which we take to be 2016. Panel A uses information from all markets. Panel B conditions the treatment group to the 13 main municipalities.

Appendix Table 1: Conditional Independence of Transition Probabilities and Network Breadth

Variable	Any diagnosis
Network breadth	0.00608
	(0.00512)
Consumer type FE	Yes
Observations	1370766
R^2	0.0642

Note: Table presents OLS regression of an indicator for having any chronic disease on network breadth. Specification includes consumer type (male, age group, income group) fixed effects. Estimation uses the random sample for model estimation and conditions on consumers who did not have a chronic disease in $t-1$. Standard errors in parenthesis are clustered at the consumer type level.

Appendix Table 2: Insurer National Market Shares

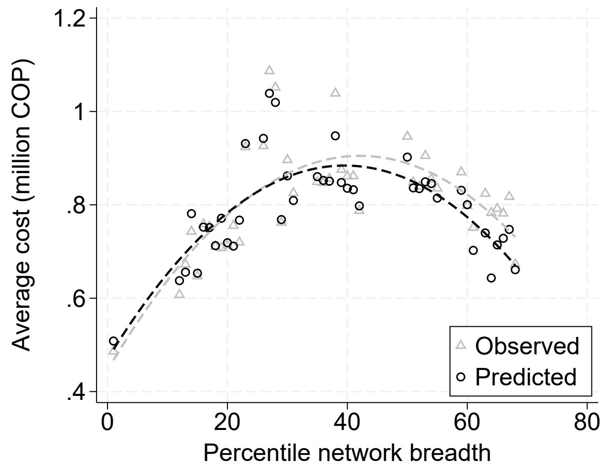
	Observed	Predicted
Insurer A	1.7209	1.71548
Insurer B	10.92981	10.93889
Insurer C	7.915541	7.917073
Insurer D	9.397281	9.406119
Insurer E	8.817205	8.794344
Insurer G	11.8911	11.91544
Insurer H	1.736043	1.740344
Insurer I	7.994966	7.986835
Insurer J	10.18435	10.19725
Insurer K	8.860984	8.865344
Insurer L	3.549743	3.525291
Insurer M	3.666584	3.644311
Insurer N	13.33549	13.35328

Note: Table presents observed and model predicted insurer national market shares using estimates from the insurer demand model. Consumers' discrete choice is simulated by drawing type-I extreme value shocks.

Appendix Table 3: First-Stage Regression for Insurer Marginal Costs

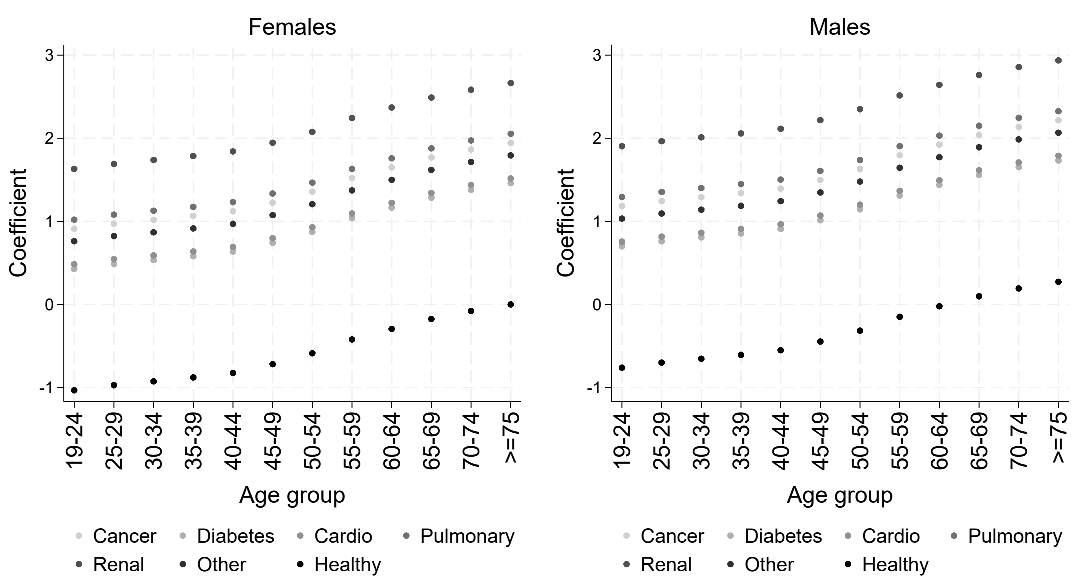
Variable	coef	se
$T_m \cdot P_t \cdot H_{jm,2015}$	0.224	(0.033)
Insurer FE Insurer A	-0.043	(0.024)
Insurer B	0.074	(0.022)
Insurer C	-0.112	(0.017)
Insurer D	-0.030	(0.018)
Insurer E	0.064	(0.013)
Insurer F	-0.447	(0.049)
Insurer G	0.052	(0.038)
Insurer H	0.092	(0.052)
Insurer I	-0.105	(0.018)
Insurer J	0.193	(0.022)
Insurer K	0.180	(0.012)
Insurer L	0.067	(0.050)
Insurer M	-0.108	(0.027)
Constant	0.330	(0.014)
F-statistic	45.49	
Consumer type FE	Yes	
Market FE	Yes	
Observations	1,135,511	
R^2	0.714	

Note: Table presents OLS regression of municipal network breadth on the instrument, and insurer, municipality, year, age group, sex, and diagnosis dummies. The instrument is the interaction between the treatment indicator for municipalities where SaludCoop operated, the post-termination period indicator, and network breadth in 2015. An observation is a combination of consumer type, insurer, municipality, and year. Estimation uses data from 2013 to 2017 from all municipalities in the country winsorizes average costs, and uses analytic weights given by the number of enrollees per observation. Standard errors in parenthesis are clustered at the municipality level. Table reports the F-statistic associated with the instrument.



Appendix Figure 2: Marginal Cost Model In-Sample Fit

Note: Figure shows a scatter plot of observed and predicted average cost per enrollee in millions of COP by percentile network breadth in black and blue, respectively.



Appendix Figure 3: Consumer Type Fixed Effects in Marginal Cost Model

Note: Figure shows coefficients and 95% confidence intervals of the consumer type fixed effects in the marginal cost model. The left panel depicts fixed effects for females and the right panel for males.

Appendix Table 4: Annual Transition Probabilities Across Diagnoses

		Cancer	Cardio	Diabetes	Pulmonary	Renal	Other	Healthy
Cancer	mean	0.508	0.147	0.015	0.027	0.017	0.049	0.236
	sd	0.172	0.152	0.016	0.082	0.072	0.042	0.179
Diabetes	mean	0.041	0.670	0.025	0.021	0.021	0.056	0.165
	sd	0.096	0.237	0.067	0.036	0.047	0.133	0.198
Cardio	mean	0.035	0.165	0.613	0.018	0.022	0.032	0.115
	sd	0.076	0.104	0.166	0.031	0.030	0.043	0.133
Pulmonary	mean	0.048	0.162	0.016	0.494	0.011	0.069	0.200
	sd	0.044	0.090	0.010	0.169	0.021	0.076	0.168
Renal	mean	0.049	0.242	0.034	0.017	0.468	0.049	0.142
	sd	0.104	0.184	0.042	0.028	0.137	0.035	0.152
Other	mean	0.050	0.163	0.015	0.028	0.017	0.492	0.235
	sd	0.056	0.141	0.014	0.038	0.078	0.179	0.180
Healthy	mean	0.039	0.085	0.010	0.011	0.003	0.032	0.820
	sd	0.094	0.123	0.062	0.017	0.004	0.071	0.175

Note: Table presents mean and standard deviation in parenthesis of non-parametric estimates of annual transition probabilities across diagnoses. Uses data from 2013 to 2017.

Appendix Table 5: Summary Statistics of Annual Dropout Probabilities

	mean	sd
Female	0.079	0.037
Male	0.091	0.040
Age 19-24	0.172	0.036
Age 25-29	0.130	0.020
Age 30-34	0.102	0.015
Age 35-39	0.090	0.015
Age 40-44	0.083	0.014
Age 45-49	0.076	0.014
Age 50-54	0.070	0.015
Age 55-59	0.063	0.016
Age 60-64	0.054	0.017
Age 65-69	0.049	0.016
Age 70-74	0.054	0.019
Age 75 or more	0.075	0.030
Cancer	0.090	0.032
Diabetes	0.076	0.038
Cardiovascular	0.073	0.036
Pulmonary	0.089	0.034
Renal	0.078	0.026
Other disease	0.074	0.037
Healthy	0.113	0.054

Note: Table presents mean and standard deviation in parenthesis of non-parametric estimates of the annual probability of dropping out of the contributory system. Uses data from 2013 to 2017.

Appendix Table 6: Insurer Marginal Variable Profits

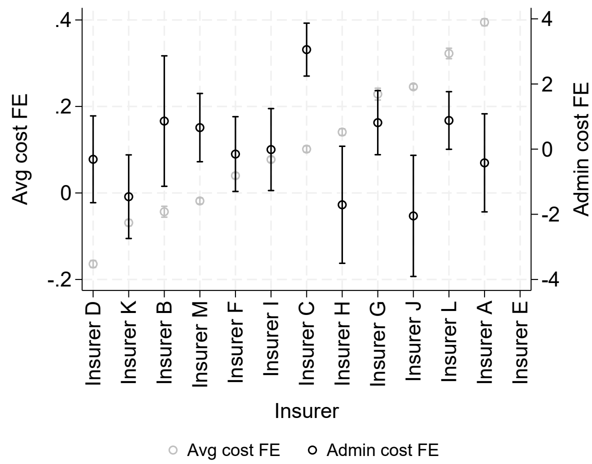
Insurer	mean	sd
Insurer A	148813.4	—
Insurer B	262427.9	412761.6
Insurer C	103488.6	242689.3
Insurer D	104453.6	314412.9
Insurer E	2140533	—
Insurer G	332389.2	561580.9
Insurer H	452825.4	—
Insurer I	180135.1	250473
Insurer J	199596.2	262640
Insurer K	462973.6	1118031
Insurer L	160122.7	287081.3
Insurer M	209145.2	288066.2
Insurer N	247480.4	411626.3

Note: Table presents mean and standard deviation of marginal variable profits per insurer measured in millions of pesos.

Appendix Table 7: First-Stage Regression for Insurer Marginal Costs

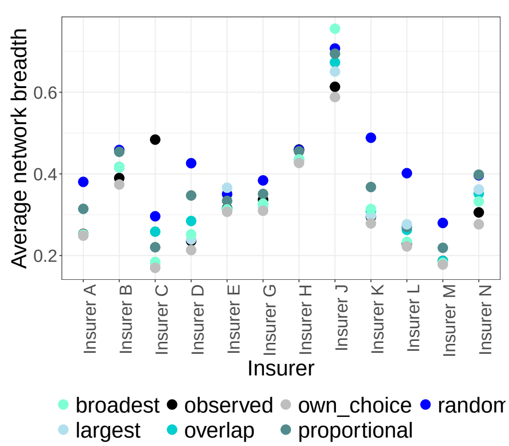
Variable	coef	se
Instrument	-5.415	(0.900)
<u>Insurer FE</u>		
Insurer A	-1.790	(0.286)
Insurer B	0.515	(0.074)
Insurer C	-0.919	(0.129)
Insurer D	-0.531	(0.076)
Insurer E	-1.711	(0.286)
Insurer G	0.047	(0.015)
Insurer H	-1.600	(0.286)
Insurer I	-0.482	(0.070)
Insurer J	1.924	(0.269)
Insurer K	-0.132	(0.021)
Insurer L	-0.625	(0.088)
Insurer M	-0.837	(0.121)
Insurer N	(ref)	(ref)
Constant	2.039	(0.286)
F-statistic	36.18	
Observations	98	
R^2	0.913	

Note: Table presents OLS regression of network breadth on the instrument and insurer fixed effects. The instrument is the iaverage network breadth across all other markets where the insurer operates excluding the focal market. Robust standard errors in parenthesis. Table reports the F-statistic associated with the instrument.



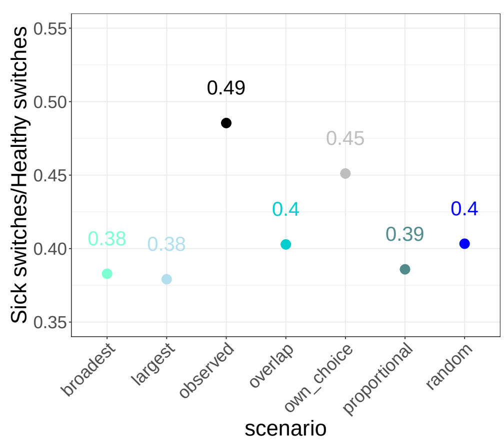
Appendix Figure 4: Insurer Fixed Effects in Marginal and Administrative Costs

Note: Figure shows the estimates insurer fixed effects from the marginal cost model in gray (left vertical axis) and from the administrative cost model in black (right vertical axis).



Appendix Figure 5: Counterfactual Provider Network Breadth per Insurer

Note: Figure shows average provider network breadth across markets separately for each insurer and each counterfactual reassignment rule after SaludCoop's termination.



Appendix Figure 6: Ratio of Sick to Healthy Switches under Counterfactual Enrollment Rules

Note: Figure shows the ratio of the number of sick individuals who switch to the number of healthy individuals who switch under each enrollment rule. Sick individuals are those with any chronic disease diagnosis.