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 these rules following the termination of the largest insurer in Colombia. Using a model of insurer competition, we find that re-enrolling patients randomly to incumbent insurers leads to higher consumer surplus and broader provider networks, without increasing spending, by encouraging active plan choice among healthy consumers.

Keywords: Health insurer competition, Automatic enrollment, Adverse selection, Inertia.

JEL codes: I10, I11, I13, I18.

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1 Introduction

A central challenge in health insurance markets is managing insurer competition in the presence of consumer inertia (stickiness to plan choice) and adverse selection (Song et al., 2012; Cutler and Reber, 1998). Designing interventions that effectively promote competition and enhance consumer welfare in these markets is notoriously difficult. On the one hand, regulations that address adverse selection often have limited impacts on 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.

In this paper, we show that regulators can shape competition in health insurance markets through the design of automatic enrollment rules. In these rules, consumers who become newly eligible for health insurance (or are forced to switch because their health plan closes) are automatically assigned to incumbent insurers during their first enrollment year but allowed to switch thereafter. We show that when enrollment rules induce healthy individuals to switch from their assigned health plan, insurers compete to attract these profitable switchers, and equilibrium outcomes become shaped by the preferences of these consumers. Competition can result in enhanced consumer welfare if healthy consumers value characteristics of the health plan that sick consumers also value. For example, if healthy individuals value broad healthcare provider networks, then the automatic enrollment rules that encourage their switching will result in broader networks in equilibrium. In contrast, rules that encourage switching among sick patients will tend to decrease consumer welfare because insurers cannot effectively attract healthy types and resort to "harvesting" their stock of enrollees (e.g., by later narrowing their networks).

We conduct our empirical analysis in the Colombian healthcare system, where a health insurer with strong geographical presence, called SaludCoop, was abruptly terminated by the government in December 2015. Following this termination, the government faced the challenge of assigning SaludCoop consumers to the remaining incumbent insurers, providing a unique opportunity to quantify the impacts of automatic enrollment rules on market outcomes.

At the time of its termination, SaludCoop operated in 43% of municipalities nationwide, and in some of these markets, it covered nearly 50% of beneficiaries. 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. After this grace period, enrollees were allowed to switch out of Cafesalud and into another insurer of their choice.

Our data to study counterfactual enrollment rules consist of individual-level enrollment and health claims records from the Colombian contributory health system between 2013 and 2017, representing more than 24 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 health insurance plan. Other aspects of the plan (premiums, cost-sharing, and benefits) are tightly regulated and are the same across insurers.

Focusing on the 13 largest municipalities where we see meaningful variation in provider network breadth across insurers, we start by providing descriptive evidence of substantial adverse selection and inertia in the contributory system.[2] First, we show that consumers tend to prefer insurers with broader healthcare provider networks, particularly those with chronic conditions, consistent with sorting by

[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.

[2]These 13 municipalities are characterized by having strong competition between insurers and providers, represent nearly 41% of the country's population, and are defined by the National Administrative Department of Statistics.

health status. Second, we document persistently low switching rates across insurers, specially among the sick, which contribute to the concentration of high-risk enrollees within a subset of insurers. High inertia suggests that automatic enrollment rules may affect the long-run distribution of health risk across insurers.

To explore counterfactual enrollment rules, we propose an equilibrium model of insurer competition on provider network breadth, which is defined as the fraction of healthcare providers in a market that the insurer covers. In the model, insurers compete by simultaneously choosing their provider network breadth in various markets to maximize the present discounted value of their profits. Our equilibrium concept is therefore a static Nash equilibrium.

The profit function incorporates a random utility model of demand, where consumers choose their insurer based on provider network breadth, expected out-of-pocket costs, and an indicator for whether the consumer chooses the same insurer as the previous year. Consumer preferences for network breadth are heterogeneous across diagnoses to capture differential sorting by health status. The preference for past insurers is also heterogeneous across diagnoses to capture the value of inertia for sick and healthy individuals. SaludCoop's termination allows us to identify the parameters of the demand model because its enrollees were assigned to Cafesalud exogenously (and not because of Cafesalud's provider network breadth) and we observe differential switching out of Cafesalud depending on enrollees' diagnoses.

On the supply-side, we model insurers' marginal and administrative costs as non-linear functions of provider network breadth. Network breadth in these cost functions is endogenous because it is potentially correlated with unobserved patient health. To estimate the cost functions, we use SaludCoop's termination as an instrument for network breadth in a "shift-share" approach, since the termination generates discontinuous and sudden changes in networks among incumbent insurers in the markets where SaludCoop operated. Insurer profits then evolve according to both exogenous transition probabilities across diagnoses and endogenous transition probabilities across insurers.

Our demand estimates show that all consumers are willing to pay for broader healthcare provider networks, and this willingness to pay is much higher among patients with chronic diseases than among those without chronic diseases. We find that consumers are nearly 4 times more likely to choose an insurer if they were enrolled with it in the previous year. This value of inertia is substantially higher for individuals with chronic diseases relative to those without diseases, in line with descriptive evidence.

On the supply-side, we find that insurers have heterogeneous marginal and administrative costs, which help explain why different insurers make different choices of provider network breadth. In particular, we find that while marginal costs increase with network breadth, administrative cost shocks decrease. 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 our model estimates, we first examine how adverse selection and inertia impact equilibrium network breadth. This provides intuition for how counterfactual enrollment rules targeting each mechanism are expected to affect market outcomes. When we eliminate the differential impact of inertia across consumers—making sick individuals more likely to switch plans relative to baseline—we find that networks become 9% narrower relative to the observed equilibrium. This is because sick consumers, who have a stronger preference for broader networks, switch more frequently, encouraging insurers to narrow coverage to avoid attracting them. Instead, when we reduce adverse selection by removing heterogeneity in marginal costs across consumers, we find that average network breadth increases 5%.[3] If insurers' marginal costs are independent of health status, the optimal strategy is to increase network breadth to expand market share. Inertia and adverse selection

[3]Eliminating the heterogeneity in marginal costs across consumers essentially eliminates the correlation between patient willingness-to-pay for network breadth and insurers' costs.

thus have opposite effects on equilibrium network breadth, with inertia generally dominating in our setting.

The counterfactual automatic enrollment rules we examine next, have the potential to impact market outcomes by changing the relative magnitudes of adverse selection and inertia. We evaluate common rules such as random enrollment, enrollment in the insurer with the broadest network, own choice (where consumers choose their own insurer without specifying a default), among others. To predict how each rule is expected to impact equilibrium outcomes, we start by exploring which types of consumers will be more likely to switch in the first year after reassignment. We compute the covariance between a measure of the match value between the consumer and their assigned insurer and the insurer's marginal cost (which is a function of the consumer's health status). A negative covariance indicates the enrollment rule encourages switching among low-cost consumers, and thus that insurers would expand their networks to attract these profitable switchers. We find that rules with some random assignment component generate stronger and more negative covariances relative to more deterministic rules, suggesting they would increase network breadth in equilibrium.

Implementing our full simulation, we find that random enrollment (in equal proportions to all insurers) outperforms all other rules across several dimensions: provider network breadth increases by 13%, per capita healthcare spending remains largely unchanged, and short-run consumer surplus increases by 3%. The low match quality between the consumer and their assigned insurer incentivizes consumers to switch (particularly the healthy as the sick have a higher value of inertia), which intensifies insurer competition.

By contrast, the own choice rule results in the lowest average provider network breadth. Because patients are not automatically assigned to an insurer under this rule, consumers do not experience the potential cost of switching insurer in the first year of the policy, and network breadth becomes a relatively more salient factor in consumers' choices. Individuals with chronic diseases, who have a higher willingness to pay for broad networks, become more likely to switch, and insurers narrow their networks to discourage enrollment of these unprofitable switchers. This shows that allowing for free consumer choice in insurance markets is not always beneficial for welfare when supply-side decisions are taken into account (Marone and Sabety, 2022).

We show that insurers' endogenous response to the assignment rules is key to our results. When we do not allow insurers to respond endogenously to the rules (in terms of network breadth), the ranking of the rules in terms of consumer surplus changes completely, with random enrollment performing worse than other rules and the own-choice rule performing better. The dominance of random enrollment emerges because it incentivizes insurers to respond by increasing network breadth.

Our paper makes a key contribution to the literature by examining how insurers respond to automatic enrollment rules. In the context of insurer terminations, prior research (including our own) has examined effects on healthcare utilization, healthcare spending, and health outcomes under a fixed enrollment rule (e.g., Buitrago et al., 2025; Bonilla et al., 2024; Bischof and Kaiser, 2021; Politzer, 2021). However, relatively little attention has been paid to whether and how alternative enrollment policies shape market outcomes. A notable exception is Wallace (2023), who studies Medicaid managed care in New York—a setting in which insurers also compete primarily on their provider networks—and shows that assigning consumers to insurers that include their existing providers can improve consumer satisfaction, albeit holding insurers' supply-side decisions fixed. We complement this work by endogenizing insurers' network breadth choices and showing that this has important implications for conclusions about welfare.

More broadly our paper relates to the literature on optimal assignment mechanisms which has studied patient waitlists for general practitioners in the UK (Huitfeldt et al., 2024), optimal default choices in pension plans (Carroll et al., 2009) and optimal defaults in healthcare (e.g., Beshears et al., 2024; Brot-Goldberg et al., 2023; Macambira et al., 2022; Shepard and Wagner, 2023; Madrian and Shea, 2001). By introducing supply-side competition into the analysis, we are able to fully characterize the equilibrium impacts of default plans in health insurance and decompose this effect into adverse selection and inertia (Drake et al., 2022; Polyakova, 2016; Ericson, 2014; Handel, 2013).

The remainder of this paper is organized as follows: section 2 describes the empirical setting and the data, section 3 introduces the model, section 4 discusses identification and provides model estimates, section 5 simulates counterfactual reassignment policies, and section 6 concludes.

2 Setting, Data, and Descriptives

Our setting is Colombia's contributory healthcare system, which covers individuals who pay payroll taxes (and their dependents), approximately half of the country's population.[4] 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 and the same across insurers, such as cost-sharing rates, and benefits.[5] Consumer premiums are zero and insurers receive annual per-capita risk-adjusted transfers from the government that poorly fit realized healthcare costs (Espinosa et al., 2023; Riascos et al., 2014).

We use administrative data from the contributory healthcare system encompassing individual-level enrollment, linked with health claims and earnings from

[4]For more details on the structure of Colombia's managed care competition system see Giedion and Uribe (2009).

[5]Cost-sharing rates 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.

2013 to 2017 for the subset of individuals aged 19 or older.[6] 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 consumers with no gaps in coverage between their first and last observed years in the enrollment data as the *continuously enrolled*.

The health claims data report date of service, service code, diagnosis code (following the International Classification of Diseases, ICD), provider identifier, insurer identifier, and negotiated price of the service. 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 diseases, 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.

In our analysis, we focus on the 13 largest insurers in the contributory system that account for 99% of enrollees in 2015. The health claims data contain information from insurers that pass data quality filters imposed by the Ministry of Health. Excluding SaludCoop and Cafesalud, out of the 11 remaining insurers, we observe 7 of them for all five years, 8 for four or more years, and 11 for three or more years. In our final data, we use information from the 13 insurers, considering years in which they are missing as random. We do not observe Cafesalud in 2017 (the last year of our data); however, we are able to follow 78% of SaludCoop's enrollees over the entire sample period because they switched out of Cafesalud by 2017.

For insurers in our sample, we have data on their network of covered providers between 2013 and 2017, obtained through a data request submitted to the National Health Superintendency. The provider network data list the hospitals, clinics, and physician practices included in each insurer's network, but do not specify the

[6] The enrollment data is known as *Base Unica De Afiliados* (BDUA) and the claims data is the *Base de Suficiencia* from the Ministry of Health and Social Protection.

particular services for which each provider is covered. We complement these data with networks inferred from health claims, defining a provider as in-network if it submits more than 100 claims for a given insurer. Providers identified in the claims data may be absent from the official listings due to timing differences in data submission: while the provider listings are submitted at the beginning of the year, insurers may add or drop providers throughout the year. In our final network data, one quarter of the observations are inferred from health claims.

Given that insurers' main dimension of competition is healthcare provider networks, we characterize each insurer by its provider network breadth, defined as the fraction of healthcare providers covered by the insurer in each market. We define markets as municipalities (similar to counties in the US) since the automatic enrollment rules the Colombian government has considered are municipality-specific. In our main analysis, we focus on the 13 largest municipalities defined by the National Administrative Department of Statistics (DANE), where we observe meaningful variation in provider networks and represent nearly 41% of the country's population.[7]

Table 1 presents pooled summary statistics of the full sample (without imposing any sample restrictions) in column (1), the subsample who are continuously enrolled in column (2), and the subsample of continuously enrolled individuals who reside in one of the 13 largest municipalities in column (3). An observation in this table is a person-year. The latter is our preferred sample for model estimation for two reasons. First, annualized healthcare costs for the continuously enrolled will not suffer from measurement error arising from enrollment spell lengths of less than a year. Second, spillover effects across markets are substantial because consumers might travel to a large municipality to receive certain types of care. These spillover effects can bias our estimates of consumer preferences for provider networks. Hence, by focusing on individuals who reside in one of the 13 largest

[7] 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) Full		(2) Continuous		(3) 13 Municipalities	
	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)	44.01	(16.40)
Earnings†	0.804	(1.296)	0.816	(1.336)	1.225	(1.672)
Cancer	0.083	(0.276)	0.084	(0.278)	0.071	(0.257)
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	(0.143)
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	(0.221)
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)	0.792	(1.188)
OOP cost†	0.145	(0.420)	0.150	(0.434)	0.157	(0.126)
Individuals x Years	75,918,492		68,328,039		28,698,816	

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 system between 2013 and 2017. Column (2) uses the subsample of continuously enrolled individuals defined as those without gaps in enrollment between the first and last years we observe them in the enrollment data. Column (3) uses the subsample of continuously enrolled individuals who reside in one of the 13 largest municipalities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales, Pereira, Cúcuta, Pasto, Ibagué, Montería, Cartagena, and Villavicencio. (†) measured in millions of COP of 2014.

municipalities we can minimize this type of bias.[8]

Across the three samples, under 60% of consumers are classified as healthy. The most prevalent health conditions are cardiovascular diseases, followed by cancer and diabetes. Average annual earnings are higher in column (3) because both wages and the cost of living are higher in the 13 largest municipalities relative to the rest of the country. On average, individuals in the full sample 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 cost. The standard deviation of total healthcare cost in column (3) is lower than in column (1) because of the exclusion of small-market outliers.

[8] An alternative way to deal with these spillover effects is to define markets as states as in Serna (2025). 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, the Colombian government has considered municipality-specific enrollment rules.

2.1 Provider Network Breadth

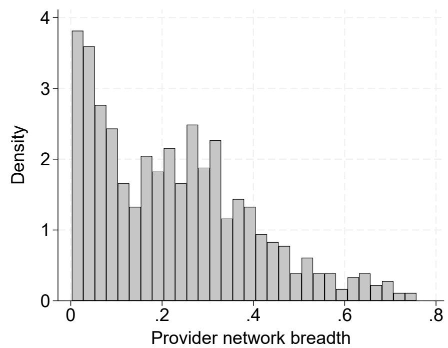


FIGURE 1: Distribution of Municipal Provider Network Breadth

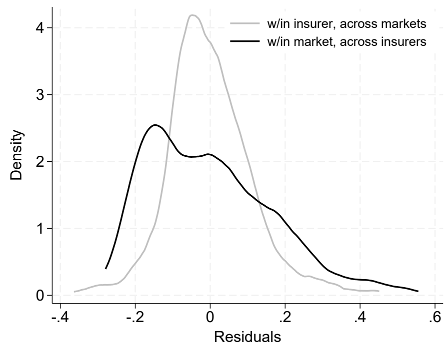
Note: Figure presents the distribution of provider network breadth. An observation in this histogram is an insurer-market-year conditional on the 13 largest municipalities and for insurers that operate in the contributory system.

Figure 1 shows that provider network breadth varies significantly across insurers, markets, and years. There are insurers in our data that have an average network breadth of 0.09 across the markets where they operate, while others have an average of 0.52. These averages are generally smaller compared to other countries like the US because they include all providers and not just hospitals. Dafny et al. (2017) report that provider networks that include institutions smaller than hospitals tend to be much narrower than hospital networks.

To further examine the variation in network breadth, Figure 2 presents the distribution of residuals from a linear regression of provider network breadth on insurer-by-year fixed effects (in gray) and on market-by-year fixed effects (in black). By controlling for time-varying insurer and market characteristics separately, the regressions isolate the extent to which variation in network breadth is attributable to within-market insurer choices rather than structural market factors. The figure shows that most of the residual variation stems from differences across insurers and to a smaller extent across markets.

Which factors contribute to this variation in provider network breadth? Figure 3 illustrates the empirical relationship between the log of average cost per consumer

Figure 2: 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.

type (i.e., insurers' marginal cost) by bins of provider network breadth across the 13 largest 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 diseases, or no diseases). We depict the empirical relationship for three selected insurers, to provide evidence that log average costs exhibit a concave relationship with respect to provider network breadth and that the shape of this cost function varies across insurers.[9]

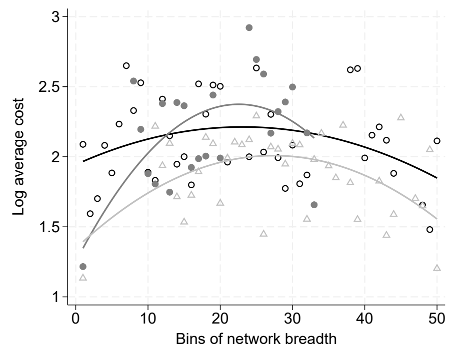
Figure 4 shows that insurers are also heterogeneous in their administrative costs. We use insurers' public income statements from 2013 to 2017 to obtain their total administrative costs, which measure expenses related to billing and auditing activities.[10] In other contexts it has been shown that these administrative costs are one of the highest components of healthcare spending in managed care health

[9]The concavity of the marginal cost function likely reflects patterns of economies of scope when covering multiple services within a provider as shown in Serna (2025).

[10]These data are publicly available at the National Health Superintendency's website. Specifically, we use information from account 51 in these files corresponding to *Gastos de Administración*. These include salaries and wages (account 510503, 510506), fees for statutory audit and external auditing (account 511015), fees for legal and financial consulting (account 511010), lease of medical or scientific goods and equipment (account 512015), and lease of building and office space (account 512010).

systems (Council on Health Care Spending and Value, 2022) and are related to the costs of managing healthcare providers within the network (Cutler, 2020; Chernew and Mintz, 2021).

Figure 3: Empirical Relation Between Average Cost and Network Breadth



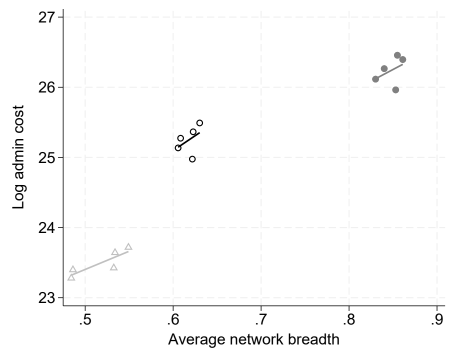
Note: To construct this figure, we aggregate the individual-level data on the continuously enrolled by calculating the average annual healthcare cost for each bin of provider network breadth. Figure presents a scatter plot of this average cost conditional on three selected insurers for exposition. The solid lines correspond to a quadratic fit.

The figure presents the empirical relationship between the log of administrative costs and provider network breadth for three selected insurers for exposition. We see that administrative costs increase with network breadth and the strength of this correlation varies across insurers. Thus, differences between insurers in their cost structure may help explain why some of them choose broader networks than others. However, preference heterogeneity may also factor into these coverage decisions. We turn to describing these preferences next.

2.2 Switching Decisions

The variation in provider network breadth across insurers suggests that consumers may consider network size when making enrollment decisions. To describe consumers' choices, Table 2 presents the fraction of enrollees who switch their insurer every year. Column (1) uses the full sample, which includes individuals who can switch insurers within the contributory system, within the subsidized system, and

Figure 4: Correlation Between Administrative Cost and Network Breadth



Note: Figure presents a 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, presented for three selected insurers for exposition. The solid lines represent linear fits.

across systems (when eligibility to the contributory system is gained or lost).[11] Column (2) uses the subsample of continuously enrolled, and column (3) uses the subsample of continuously enrolled who reside in one of the 13 largest municipalities. Columns (4) and (5) use the continuously enrolled conditional on those without (healthy) and with (sick) diagnoses of chronic conditions, respectively.

Because of transitions across systems, the switching rate in the full sample is higher than in the other samples. In 2015, 3.5% of enrollees switched their insurer in the full sample, compared to 2.7% and 1.7% in columns (2) and (3), respectively. Across all samples, the switching rate increases significantly in 2016 due to SaludCoop's termination, which serves as our primary source of identification. We also see that switching is more common among healthy consumers, suggesting sick ones have higher utility from inertia.

[11]Eligibility to the contributory system is gained (lost) when the individual has earnings equal to least one (less than one) monthly minimum wage. To remain in the contributory system, the individual is also required to make tax contributions every month. Failure to pay taxes for three continuous months can lead to disenrollment.

Table 2: Switching Rate

Year	Full sample (1)	Continuous (2)	13 Municipalities (3)	Healthy continuous (4)	Sick continuous (5)
2014	0.044	0.044	0.016	0.045	0.012
2015	0.035	0.027	0.017	0.032	0.016
2016	0.206	0.193	0.112	0.184	0.204
2017	0.083	0.064	0.051	0.064	0.060

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 system 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. Columns (4) and (5) use the subsample of continuously enrolled individuals without and with chronic conditions, respectively.

2.3 SaludCoop's Termination

To descriptively examine consumers' preferences for provider networks we use SaludCoop's termination in December 2015. The government terminated SaludCoop due to its engagement in illegal activities and financial malpractice.[12] 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 90-day period, enrollees were allowed to switch. Prior to the termination, Cafesalud covered less than 5% of enrollees.

The government selected Cafesalud as the assignment insurer because it had recently been acquired by the same business group as SaludCoop, was in relatively good financial standing, and operated in similar markets as SaludCoop. To strengthen the capacity to absorb the massive transfer of enrollees, the government also gave Cafesalud additional financial resources (around $70 million).[13]

We explore SaludCoop enrollees' switching decisions after the termination in Table 3. We regress an indicator for whether the enrollee switched into an insurer

[12] See El Colombiano.
[13] See El Tiempo.

TABLE 3: 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 a 10% random sample of continuously enrolled individuals residing in one of the 13 largest municipalities. Estimation 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.

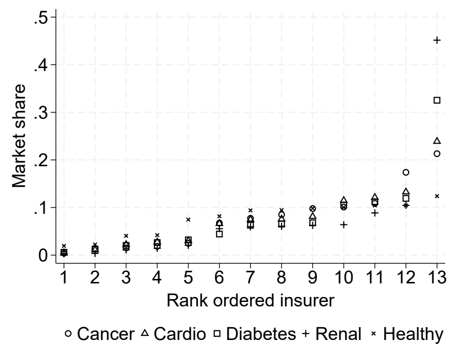
on or after 2016 on the insurer's provider network breadth and an interaction with whether the enrollee has a chronic disease.[14] We find that SaludCoop enrollees tended to switch towards insurers with broad networks after the 90-day grace period, which suggests consumers have preferences for network breadth. Patients with chronic diseases are less likely to switch than healthy ones and have a stronger preference for broad provider networks, consistent with adverse selection.[15]

Conditional on the disease, consumers also seem to have idiosyncratic preferences for certain insurers. Figure 5 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

[14]Although our regression includes individual fixed effects, the chronic disease indicator is identified because the main disease can change over time for a given individual.

[15]Following the termination of SaludCoop, the Colombian Ministry of Health issued Decree 780 of 2016, which for the first time specified how enrollees should be reassigned to incumbent insurers when their health plan is terminated. Article 2.1.11.3 in this Decree indicates that 50% of patients without chronic conditions would be randomly assigned in equal proportions to other insurers operating in their municipality of residence, while the remaining 50% would be assigned in proportion to each insurer's local market share. Patients with chronic conditions, by contrast, would be reassigned entirely based on the insurer's market share within the municipality. Reassigned enrollees are required to remain with their new insurer for a 90-day period, after which they are allowed to switch plans. This decree did not apply to the SaludCoop cohort.

Figure 5: 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.

with diabetes for example. We see that some insurers have a high market share from individuals with specific health conditions, consistent with match values (or the perceived benefits from choosing an insurer) varying across diagnoses. We also see that the health risk may be substantially concentrated in this health system.

Overall, our results in this section provide evidence of three features of Colombia's contributory health system: (i) adverse selection in provider networks, (ii) substantial consumer inertia, and (iii) concentration of high-risk enrollees within a subset of insurers.

3 Model

We are interested in comparing counterfactual 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.

We make the simplifying assumption that insurers compete on provider network breadth, 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 of quality, and where there are only around 20 top-tier academic medical centers across the country. Serna (2025) shows descriptive evidence suggesting quality variation across providers conditional on the health service is indeed small in this health system. Moreover, by characterizing insurer choices with a single index involving the coverage of hospitals, clinics, and physician practices we are better able to describe the choices of consumers who tend to visit these providers (rather than focusing on only hospitals). We also show later on the robustness of our results to controlling for provider size in our measure of network breadth.

3.1 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 an indicator for whether the consumer chooses the same insurer as the previous year $y_{ijm,t-1}$:

$$u_{ijmt} = \underbrace{\beta_\theta H_{jmt} + \alpha_\theta c_{\theta jmt}(H_{jmt}) + \lambda_\theta y_{ijm,t-1} + \xi_{\theta j}}_{d_{ijmt}} + \varepsilon_{ijmt} \tag{1}$$

Here $\xi_{\theta j} = \xi_{\text{sex},j} + \xi_{\text{age group},j} + \xi_{\text{diagnosis},j}$ is an insurer-by-consumer type fixed effect capturing the idiosyncratic match values reported in Figure 5. We define a consumer type as a combination of sex, age group, and diagnosis as before.

To estimate this demand function, we calculate consumers' out-of-pocket costs directly from the data using their total healthcare cost and the cost-sharing rules that apply to them given their earnings.[16] 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. Then in counterfactuals, to appropriately capture the cost-coverage trade-off that consumers face (i.e., broader networks are related to higher out-of-pocket costs), we allow the out-of-pocket cost to depend on provider network breadth as follows:

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

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

Consumers experience inertia in insurer choice as seen in Table 2. We capture this inertia in the model with an indicator for whether the consumer chooses the same insurer as the previous year. We do not distinguish whether inertia comes from limited information or state dependence. However, this distinction is not necessary in our case as these sources of inertia will have the same impact on equilibrium outcomes within the counterfactual enrollment rules we consider.

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.

[16]For consumers who make less than 2 times the monthly minimum wage (MMW), the coinsurance rate is 11.5% of the service price, the copay is 11.7% times the daily minimum wage, and the out-of-pocket maximum is 57.5% times the MMW. For those with incomes between 2 and 5 times the MMW, the coinsurance rate is 17.3%, the copay is 46.1% times the daily minimum wage, and the out-of-pocket maximum is 230% times the MMW. Finally, for those who make 5 or more MMWs, the coinsurance rate is 23%, the copay is 121.5% of the daily minimum wage, and the out-of-pocket maximum is 460% times the MMW.

3.2 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 rules by changing their coverage decisions can 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 could 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 enrollment rules. This is our main contribution relative to existing work (e.g., Wallace, 2023; Brot-Goldberg et al., 2023; Handel, 2013).

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:

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

where per-enrollee profit is:

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

and insurers' marginal cost is:

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

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, $N_{\theta m}$ is the (fixed) market size of type-θ consumers in market m (which already aggregates over the distribution of prior incumbents), ζ^t is a discount factor (set to 0.95 in estimation), ρ_θ is the probability that a consumer type θ drops out of the contributory system (into the subsidized system),[17] 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 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 $t-1$, the probability of being diagnosed with a chronic disease in year t is unrelated to provider network breadth.

Insurers' administrative cost structure is denoted by F_{jt}, where ν_{jm} is the model's structural error. We assume this error is the sum of an insurer-specific cost com-

[17] The dropout probability depends on whether the individual is unemployed and hence it is largely unrelated to the breadth of insurers' provider networks.

ponent 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.[18] 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: 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.[19]

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. Thus, our specification of insurer profits is a compromise between having a tractable model to conduct counterfactuals and a realistic model of how profits would evolve for a given choice of network breadth.

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

$$FOC_{jm} = MP_{jm}(H_m) - \omega e^{\omega H_{jm} + \nu_j + \psi_{jm}}$$

where $MP_{jm}(H_m)$ denotes the marginal variable profit. Setting the FOC to zero and taking logs on each side yields:

$$\log(MP_{jm}(H_m)) = \log(\omega) + \omega H_{jm} + \nu_j + \psi_{jm} \tag{3}$$

which is the regression we take to the data (and where $\log(\omega)$ is absorbed by the regression's intercept). In equilibrium, each insurer chooses the network breadth that sets this FOC to zero conditional on the actions of other insurers. This choice of

[18] Our functional form for the marginal cost is informed by the descriptive evidence in Figure 3.

[19] For an explanation of how disability transfers are calculated and other considerations of insurer revenues see Resolution 06411 of 2016 accessed through https://www.minsalud.gov.co/Normatividad_Nuevo/Resoluci%C3%B3n%206411%20de%202016.pdf.

network breadth is a maximizer of profits since the profit function is quasi-concave. In counterfactuals, the solution to this set of equations is likely unique given the rich preference and cost heterogeneity across insurers, nevertheless a direct proof of uniqueness is challenging.

4 Estimation and Identification

4.1 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). Moreover, to identify the parameters on out-of-pocket costs we rely on two sources of variation: first, on exogenous changes in earnings across patients within an insurer, which generates variation in the coinsurance rates. Second, on exogenous changes in consumers' choice set of insurers after the termination. Finally, given that enrollees in the contributory system are highly inertial as seen in Table 2, the parameter on past choices capturing inertia is mostly identified from SaludCoop enrollees who switch out of Cafesalud on or after 2016.

We estimate our insurer demand model on a 10% random sample of continuously enrolled individuals who reside in one of the 13 largest municipalities for dimensionality reasons. Table 4 presents the results. We find that consumers on average have a preference for broad provider networks and derive disutility from higher out-of-pocket costs.

Although consumers with chronic conditions have weaker stated preferences for network breadth, their substantially lower sensitivity to out-of-pocket costs implies a higher willingness to pay for network breadth compared to individuals without diagnoses (as we will see below). We estimate an average out-of-pocket

Table 4: 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)
Female	(ref)	—	(ref)	—	(ref)	—
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)
Age 65 and above	(ref)	—	(ref)	—	(ref)	—
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)
Healthy	(ref)	—	(ref)	—	(ref)	—
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-by-age group, insurer-by-diagnosis, and insurer-by-sex fixed effects. Robust standard errors in parenthesis.

cost elasticity of demand equal to -0.23, 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 a median value of inertia (computed as $-1 \cdot \hat{\lambda}_\theta / \hat{\alpha}_\theta$) equal to 1.2 million pesos (roughly 2.5 times the monthly minimum wage in 2016 or $393).

Table 5 summarizes our estimates of consumers' willingness-to-pay (wtp) for a 10 percentage point increase in network breadth $-\frac{10}{\alpha_\theta}\frac{\partial s_{ijm}}{\partial H_{jm}}$ and for remaining with their incumbent insurer $-\frac{\hat{\lambda}_\theta}{\hat{\alpha}_\theta}$. Overall, we find that individuals with chronic conditions have a higher wtp for network breadth than individuals without diagnoses because they are insensitive to out-of-pocket costs. Individuals with chronic conditions also have a higher wtp to remain with the same insurer. For example, consumers with cancer are willing to pay 3.5 million pesos on average to remain with their incumbent insurer compared to 1.1 million pesos for consumers without diagnoses. Column (3), which reports the average of ratio between our two wtp measures across individuals, shows that consumers with chronic diseases value their incumbent insurer more than they do a significant increase in network breadth compared to individuals without diagnoses. Appendix Table 2 shows the in-sample fit of our demand model.

Table 5: Average Switching Cost and Willingness-to-Pay for Networks

	WTP remain with same insurer (1)	WTP 10 p.p. increase network breadth (2)	WTP ratio (3)
Cancer	3.484	1.513	12.210
Cardiovascular disease	3.094	1.498	52.719
Diabetes	7.511	2.989	5.649
Pulmonary disease	6.417	2.987	5.502
Renal disease	6.104	2.444	7.984
Other disease	5.713	1.911	8.244
No diagnoses	1.113	0.802	3.652

Note: Table shows the average willingness to pay to remain with the same insurer ($-\lambda_\theta/\alpha_\theta$) incolumn (1), the average willingness-to-pay for a 10 percentage point increase in network breadth ($-\frac{10}{\alpha_\theta}\frac{\partial s_{ijm}}{\partial H_{jm}}$) in column (2), and the average ratio between the measures in columns (1) and (2) across consumers reported in column (3). All measures of willingness to pay are in millions of pesos.

4.2 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.[20]

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)
First stage F-statistic	45.49	
Observations	1,135,511	

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.

One challenge with estimating equation (2) is endogeneity stemming from unobserved patient selection into insurers based on provider network breadth (for example, unobservably sicker consumers choosing insurers with broader networks), which would bias our estimates of τ_1 upwards. To address this endogeneity, we use SaludCoop's termination as an instrument for provider network breadth in a control function approach.

[20] In the estimation of insurer marginal costs we use data from all municipalities rather than the 13 largest municipalities to avoid small cells and potential aggregation bias specially for consumer types characterized by uncommon chronic diseases such as renal disease.

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 (2).[21]

Second-stage results are presented in Table 6 and first-stage results are in Appendix Table 3. Our findings show that insurers' marginal costs are increasing in provider network breadth at a decreasing rate. The average marginal effect of network breadth on insurers' marginal cost equals $8,583$ pesos ($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 presents the estimated consumer type fixed effects.

In Appendix Figure 4 we show that our model delivers patterns of adverse selection since the cost of increasing provider network breadth by 1% is positively correlated with patient wtp for an additional percentage point in provider network breadth.

[21]The second stage has the same set of fixed effects as the first stage; however, due to convergence issues in the non-linear least squares, we only include indicators for each of the 13 largest municipalities rather than the full set of municipality dummies.

4.3 Dropout and Transition Probabilities

We estimate dropout and diagnosis transition probabilities non-parametrically from the data and outside the model. For instance, the dropout probability is calculated as the share of contributory enrollees in year $t-1$ who switch to the subsidized system in year t, while the transition probability is the share of enrollees with disease x in year t who had disease y in $t-1$. To compute these probabilities we use the use the full sample of individuals in the 13 largest municipalities (independent of their enrollment spell lengths). Summary statistics of resulting probabilities are presented in Appendix Tables 4 and 5.

4.4 Insurer Administrative Costs

Our model of insurer competition is static, hence we only require data from a single year to estimate the remaining parameters related to insurers' administrative costs. However, since we have multiple years of data, our model is over-identified for these parameters.

We choose to estimate our model of insurer competition using data from 2015 before SaludCoop is terminated, to later test the supply 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.[22] 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 4 and 6. Then, conditional on a consumer type θ, transitions across periods are governed by exogenous dropout probabilities, exogenous transition probabilities across diagnoses, and endogenous transition probabilities across insurers.[23]

[22]We choose to forward simulate the profit function for 100 periods because the discount factor at $T = 100$ is very close to zero.

[23]Dropout probabilities depend mostly on the likelihood of becoming unemployed rather on insurers' network breadth and in Appendix Table 1 we showed evidence of the exogeneity of transition probabilities across diagnoses.

Table 7: Insurer Administrative Cost Model

Variable	Log Marginal Variable Profits 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	(ref)	(ref)
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.

After simulating insurers' marginal and total variable profits, we estimate the administrative cost parameters using the FOCs. Marginal variable profits in equation (3) 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 (since our demand and marginal cost models have good sample fit) and suggest that administrative costs play a role in our characterization of insurers' decisions to offer provider network breadth.

Identification. A key difficulty with using insurers' FOCs to estimate the parameters of the administrative cost is the endogeneity of provider network breadth. This variable is potentially correlated with the unobserved (to the econometrician) administrative cost shock, which would lead 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.

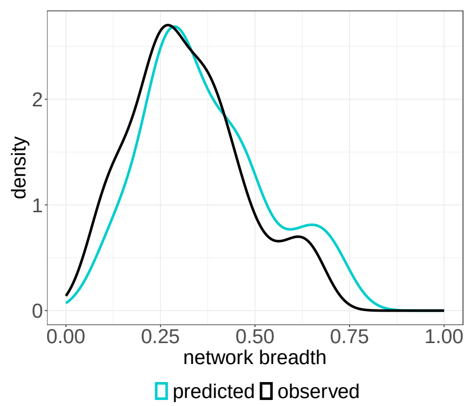
We follow the literature on industrial organization to construct a Hausman-style instrument for supply (it is typically used for demand estimation). Our logic is that, as as seen in Figure 2, insurers' network breadth decisions vary across markets suggesting cost shocks are potentially *uncorrelated* across markets. Additionally, as seen in Figure 5, consumers of certain types have idiosyncratic match values with specific insurers, suggesting demand shocks are *correlated* across markets. This means we can use the average network breadth across all other markets (excluding the focal market) where the insurer operates as an instrument for local network breadth. 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 5. This indicates that insurers mainly enjoy economies of scale in network breadth and that administrative costs are a determinant of broad networks.

4.5 Out-of-sample Fit

To evaluate the model's out of sample fit, 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. Hence, enrollees may have perceived Cafesalud as a close substitute. Figure 6 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 6: 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.

4.6 Robustness Checks

We conduct several robustness checks on our estimation. Appendix Tables 8 and 9 present a version of insurer demand and marginal costs, respectively, where we consider only the diagnoses a person received during the first year they were enrolled. These exercises address potential concerns over mechanical correlation between diagnoses and network breadth. Our estimates of network breadth slope parameters are robust to this definition of diagnoses.

In Appendix Tables 10 and 11 we present demand and marginal cost results, respectively, in which each provider is weighted by its number beds when calculating the measure of network breadth. Weighting by the number beds might help take into account that preferences and costs can differ between large and small providers. We find that the qualitative nature of our main estimates remain consistent in this specification as well.

4.7 Adverse Selection and Inertia

The mechanisms for how counterfactual enrollment rules may impact market outcomes are adverse selection and inertia. In this subsection, we use our model estimates to assess how each mechanism affects equilibrium provider network breadth before implementing our counterfactual enrollment rules.

In Figure 7 we present two sets of results. Panel A presents the counterfactual distribution of provider network breadth after we eliminate heterogeneity in the value of inertia, setting $\lambda_\theta = \lambda$ in equation (1).[24] In this case, consumers with chronic conditions and healthy consumers would have the same likelihood of switching, which is higher than baseline for the former. We find that the distribution of provider network breadth shifts to the left and average network breadth falls by 9%, suggesting insurers respond by narrowing their networks to avoid these unprofitable switchers.

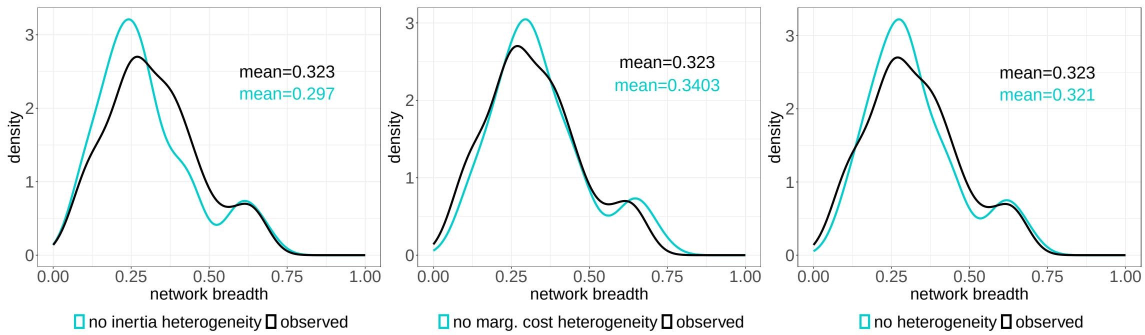
Panel B presents the counterfactual distribution of provider network breadth after we reduce adverse selection by eliminating heterogeneity in marginal costs across consumers, setting $\gamma_\theta = \gamma$ in equation (2). If insurers' marginal costs are uncorrelated with enrollees' health status, their profit-maximizing strategy would be to offer broader networks to expand market share and realize economies of scale. We find that the distribution of network breadth shifts to the right and average network breadth increases by 5% relative to the observed scenario.

These results indicate that alleviating adverse selection and reducing inertia have opposing effects on equilibrium network breadth, with inertia generally dominating in our setting. In Panel C, where we eliminate both the heterogeneity in

[24] In these exercises, we do not re-estimate our model without the interactions but set the interactions to zero holding the rest of parameters fixed to make predictions.

Figure 7: The Impacts of Adverse Selection and Inertia on Provider Network Breadth

(A) No heterogeneity in inertia (B) No marginal cost heterogeneity (C) No combined heterogeneity



Note: Figure presents the counterfactual (in blue) and observed (in black) distribution of provider network breadth. Panel A eliminates heterogeneity in the value of inertia by setting interactions between λ and demographics and diagnoses equal to zero. Panel B eliminates marginal cost heterogeneity across consumers by setting interactions between γ and demographics and diagnoses equal to zero. Panel C eliminates both the heterogeneity in inertia and the marginal cost heterogeneity across consumers.

inertia and marginal costs, we find that network breadth decreases overall. Thus, the counterfactual enrollment rules we examine next will influence market outcomes by shifting the relative magnitude of these two mechanisms. In particular, the results will depend on which consumers are more likely to switch insurers under each rule.

5 Counterfactual Automatic Enrollment Rules

5.1 Setup

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 healthcare spending per capita, and degree of adverse selection. Short-run average consumer surplus per capita is defined as the inclusive value from the logit demand system:[25]

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

Short-run healthcare spending per capita is given by:

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

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 Appendix Figure 4).

We evaluate the following enrollment rules in each market:

1. *Random*: SaludCoop enrollees are randomly assigned in equal proportions 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 randomly 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 (= $50 \times \frac{20}{30+20}$).

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

[25]The calculation of consumer's expected utility that generates this inclusive value would have an integration constant. In our results, we interpret only changes in consumer surplus relative to the observed scenario to average-out this integration constant.

5. *Largest*: SaludCoop enrollees are assigned to the incumbent insurer with the largest 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.

In these enrollment rules, we impose a default insurer only during the first year after SaludCoop's termination but allow consumers to switch after this initial period. In each rule, using as starting value the observed 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}.

5.2 Predictions

To predict how each enrollment rule affects equilibrium network breadth, we characterize whether healthy or sick consumers are more likely to switch. Specifically, we compute, among SaludCoop enrollees in the first year following reassignment, the covariance between the switching propensity and a measure of marginal cost that captures heterogeneity by health status but abstracts from provider networks. A negative covariance indicates that the rule induces greater switching among lower-cost individuals. Hence, insurers will expand their networks to attract them. Conversely, a positive covariance implies that higher-cost individuals are more likely to switch, and insurers will reduce network breadth to avoid attracting them.

We compute a descriptive proxy of switching propensity as the difference between the consumer's match value with SaludCoop and their assigned insurer, divided by the inertia parameter:

$$p_i = \frac{\xi_{\theta(i),\text{SaludCoop}} - \xi_{\theta(i),\text{assigned}}}{\lambda_{\theta(i)}}$$

Intuitively, if the match value with SaludCoop is higher than the match value with the assigned insurer, the individual will be more likely to switch; and this effect is amplified if the consumer has relative low value of inertia.

We calculate the marginal cost, abstracting from provider networks, as:

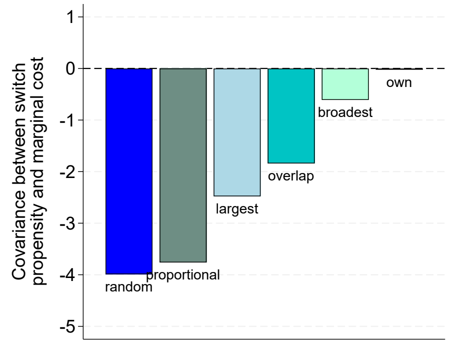
$$C_{\theta(i)m,\text{assigned}} = e^{\gamma_\theta + \eta_m + \delta_j}$$

Figure 8 shows a clear ranking among the different enrollment rules in terms of the covariance between p_i and $C_{\theta(i)m,\text{assigned}}$. Rules that include a random assignment component—where mismatches between consumers and insurers are highly likely—induce substantially higher switching among low-cost consumers than assignment based on network overlap, assignment to the insurer with the broadest network, or the own-choice rule. This pattern suggests that random assignment rules are more likely to increase provider network breadth in equilibrium, as insurers compete more aggressively for profitable switchers by expanding their networks. By contrast, under the other rules, we would expect narrower networks as insurers seek to deter high-cost consumers from enrolling.

5.3 Results

Figure 9, Panel A presents the counterfactual distribution of provider network breadth under each enrollment rule. In line with our predictions, we find that rules with random assignment components increase provider network breadth while other rules generate a distribution of network breadth that is practically indistinguishable from the observed scenario (assignment to Cafesalud), except

Figure 8: Covariance Switching Metric



Note: Figure shows the covariance between the switching propensity and the marginal cost in absence of provider network breadth among SaludCoop enrollees in the first year after the reassignment. Switching propensity is calculated as the difference between the idiosyncratic match value with SaludCoop $\xi_{\theta(i),\text{SaludCoop}}$ and the assigned insurer $\xi_{\theta(i),\text{assigned}}$, divided by the consumer's value of inertia $\lambda_{\theta(i)}$. The marginal cost, abstracting from network breadth, is the prediction from equation (2) assuming $H_{jm} = 0$.

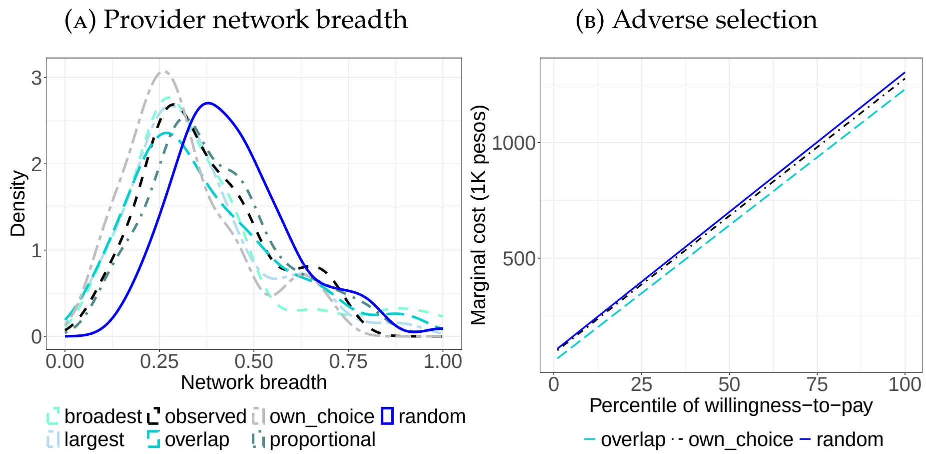
from own-choice which is worse than the observed scenario.

Under random enrollment, the unweighted increase in average network breadth relative to the observed scenario equals 13% and the increase weighted by demand equals 6%. These coverage increases are heterogeneous across insurers and largest for those with high baseline market share as seen in Appendix Figure 6. Proportional enrollment generates the second largest increase in provider network breadth weighted by demand, which is equal to 4%. Letting consumers choose their health plan freely without setting a default insurer after the termination minimizes the pool of low-cost consumers who are willing to switch, decreasing competition, and lowering demand-weighted average network breadth by 8%.

Panel B shows that differences in the degree of adverse selection across a few selected enrollment rules are fairly negligible. This is consistent with Figure 7, which shows that reducing adverse selection has only modest effects on network breadth compared to the much larger impact of reducing inertia among healthy consumers.

Table 8 summarizes other outcomes of interest for each enrollment rule. In column (1) we report consumer surplus without letting insurers respond endoge-

Figure 9: 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.

nously to the rules (hence, keeping network breadth as in the observed scenario). In columns (2) to (4) we report average outcomes allowing for endogenous supply responses. First of all, we find that the ranking of enrollment rules based on consumer surplus in column (1) markedly differs from the ranking in column (2). For example, random enrollment appears to be the worst enrollment rule holding the supply side fixed but it generates the highest increase in welfare (equal to 3%) relative to the observed scenario when insurers are allowed to respond endogenously. This highlights the importance of modeling how insurers design their health plans when evaluating enrollment policies and underscores the main contribution of our paper.

Random enrollment not only outperforms other rules in terms of provider network breadth and consumer surplus but it also generates virtually no changes in healthcare spending per capita relative to the observed scenario. Conversely, when allowing for endogenous supply responses, the own-choice rule reduces consumer surplus by 4% because in our setting we consider inertia to be potentially welfare-enhancing but the incumbent indicator is set to zero in this counterfactual during

Table 8: Outcomes Under Counterfactual Enrollment Rules

Scenario	Cons. surplus no supply* (1)	Cons. surplus* (2)	Marginal cost* (3)	Network breadth (4)
Observed	3.131	3.131	0.490	0.399
Random	3.086	3.215	0.490	0.443
Proportional	3.133	3.156	0.519	0.421
Broadest	3.149	3.129	0.547	0.417
Overlap	3.141	3.135	0.530	0.413
Largest	3.162	3.127	0.543	0.394
Own choice	3.114	2.999	0.518	0.347

Note: Table presents additional counterfactual outcomes for each enrollment rule. Column (1) shows the demand-weighted average consumer surplus per capita without allowing for endogenous supply responses. Column (2) shows the same measure of consumer surplus allowing the supply-side to respond endogenously. Column (3) presents the average marginal cost across insurers, which can be interpreted as the healthcare spending per capita. Column (4) presents the demand-weighted provider network breadth across insurers allowing for endogenous supply responses. (*) measured in millions of COP. The average exchange rate in 2016 was 3,050 COP/USD.

the first year of enrollment. Our assumption that inertia contributes to 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).

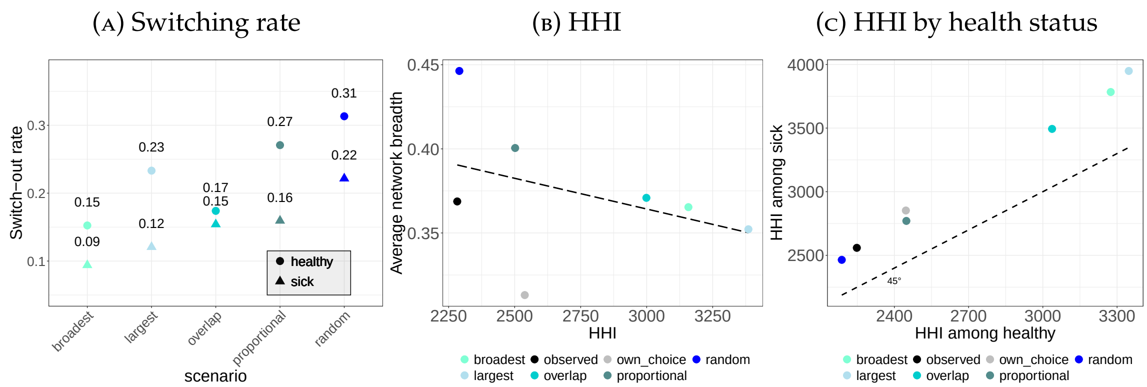
5.4 Analysis of Mechanisms

As shown before, our model offers two explanations for why random enrollment outperforms other rules: inertia and adverse selection. In terms of inertia, the random assignment rule maximizes the set of mismatched consumers, and hence the set of those who are likely to switch. Table 5 showed that the value of inertia for healthy consumers is smaller than for sick consumers. Therefore, incumbent insurers will expand their networks to attract the healthy. Although sick consumers value network breadth more than healthy ones, in relative terms, sick consumers value a 10 percentage point increase in network breadth less than what they value remaining with their incumbent insurer (see column 3 of Table 5). This suggests that by expanding the network insurers will attract more healthy consumers than sick ones.

Figure 10, Panel A confirms that switching rates (out of the assigned insurer) are higher under random enrollment compared to the rest of enrollment rules, particularly among the healthy. In this figure we omit the own-choice and observed rules, as switching rates are mechanically 1 in both cases.[26] Panel B further shows that random enrollment generates the lowest average Herfindahl-Hirschman Index (HHI) across markets in equilibrium.

In terms of adverse selection, random enrollment spreads the health risk more evenly across insurers because sick consumers are more likely to stick with their assigned health plan. Therefore, we can expect insurer market concentration among sick patients to be lower than under other enrollment rules. Indeed, Figure 10, Panel C shows that only random enrollment reduces market concentration among individuals with and without diagnoses relative to the observed rule.

FIGURE 10: The Role of Consumer Inertia in Market Power



Note: Panel A 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%. 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.

Who switches has important implications for equilibrium outcomes. Under the

[26] In the own-choice rule we consider the "assigned" insurer to be SaludCoop, hence naturally everyone switches out. In the observed rule, we see that among the continuously enrolled, all SaludCoop enrollees end up leaving Cafesalud.

own-choice rule all of SaludCoop consumers shop for a new insurer during the first year after the termination (there is no value of inertia in this year) and network breadth disproportionately attracts sick consumers. In prior work, we showed that when sick consumers switch plans, insurers have stronger incentives to drop high-cost providers that specialize in the treatment of chronic health conditions (Buitrago et al., 2025), such as public hospitals and cancer centers. This explains why equilibrium network breadth declines under the own-choice rule.

5.5 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. 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 plan choice resulting in improved outcomes once supply-side decisions are taken into account. This result contrasts with Handel (2013) who shows that nudges can exacerbate adverse selection and reduce welfare.

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 in other contexts. For example, we predict that equilibrium outcomes will reflect the preferences that healthy consumers have for the characteristics of the health plan when the automatic enrollment rules encourage those consumers to engage in active plan choice. This prediction generalizes to other settings, including ones where insurers also compete on premiums.

6 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. To test this we use data from 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 after the termination, we propose and estimate an equilibrium model of insurer competition on provider network breadth. We find that enrolling patients randomly to incumbent insurers in equal proportions is effective at increasing consumer welfare and provider network breadth 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 disproportionately encourages switching among healthy consumers. This incentivizes insurers to compete more aggressively for these profitable patients, rather than resorting to harvesting their stock of enrollees. Importantly, we show that failing to endogenize insurers' network breadth responses to the automatic enrollment rules may lead to different conclusions about the rules that improve consumer surplus.

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.

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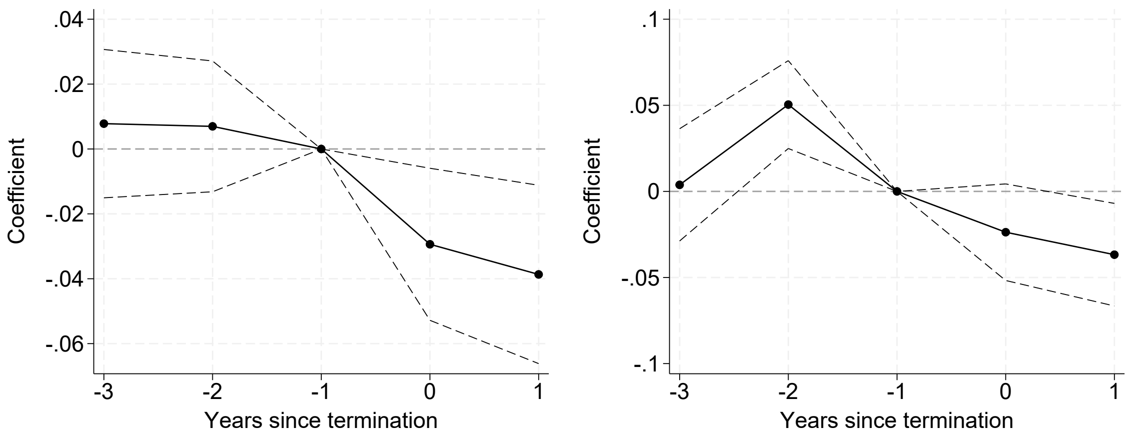
Supplemental Appendix

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 Market Shares

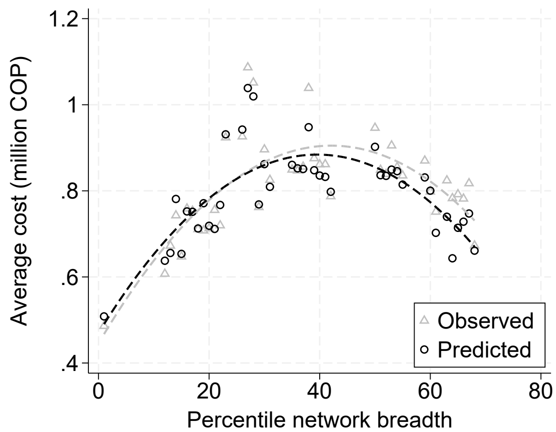
	Observed	Predicted
Insurer A	1.721	1.715
Insurer B	10.930	10.939
Insurer C	7.916	7.917
Insurer D	9.397	9.406
Insurer E	8.817	8.794
Insurer G	11.891	11.915
Insurer H	1.736	1.740
Insurer I	7.995	7.987
Insurer J	10.184	10.197
Insurer K	8.861	8.865
Insurer L	3.550	3.525
Insurer M	3.667	3.644
Insurer N	13.335	13.353

Note: Table presents observed and model predicted insurer market shares in the 13 largest municipalities 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

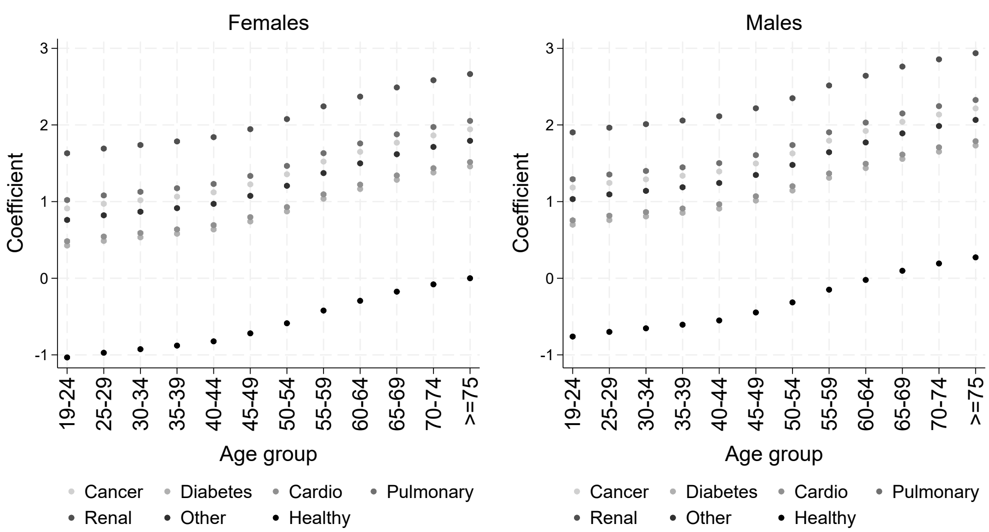
Variable	coef	se
$T_m \cdot P_t \cdot H_{jm,2015}$	0.224	(0.033)
Insurer FE Insurer A	-0.043	(0.024)
Insurer B	0.074	(0.022)
Insurer C	-0.112	(0.017)
Insurer D	-0.030	(0.018)
Insurer E	0.064	(0.013)
Insurer F	-0.447	(0.049)
Insurer G	0.052	(0.038)
Insurer H	0.092	(0.052)
Insurer I	-0.105	(0.018)
Insurer 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

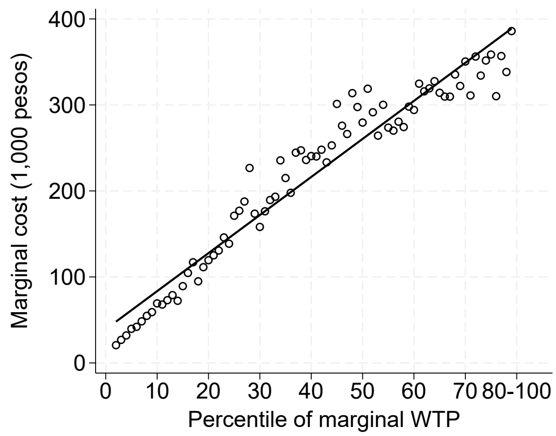
Note: Figure shows a scatter plot of observed and predicted average cost per enrollee in millions of COP by percentile network breadth in black and blue, respectively.



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 Figure 4: Model Evidence of Adverse Selection



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

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

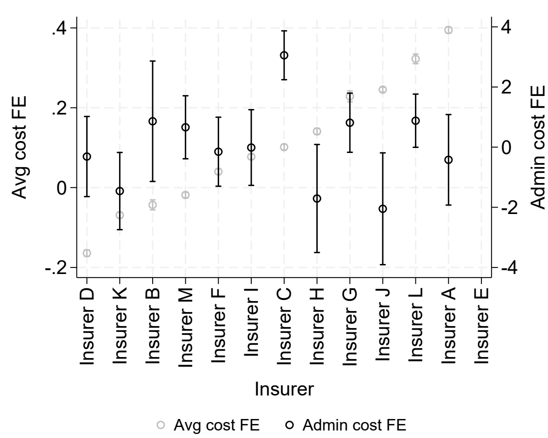
Insurer	mean	sd
Insurer A	148813.4	—
Insurer B	262427.9	412761.6
Insurer C	103488.6	242689.3
Insurer D	104453.6	314412.9
Insurer E	2140533	—
Insurer G	332389.2	561580.9
Insurer H	452825.4	—
Insurer I	180135.1	250473
Insurer J	199596.2	262640
Insurer K	462973.6	1118031
Insurer L	160122.7	287081.3
Insurer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

Variable	coef	se
Instrument	-5.415	(0.900)
Insurer FE		
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 5: 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 B Robustness Checks

Appendix Table 8: Insurer Demand Model with First-Year Diagnoses

	Network breadth		OOP spending		Incumbent	
Variable	coef	se	coef	se	coef	se
Mean	4.106	(0.051)	-2.211	(0.118)	3.621	(0.008)
Interactions						
Male	-0.180	(0.027)	0.307	(0.044)	0.003	(0.004)
Female	(ref)	—	(ref)	—	(ref)	—
Age 19-24	1.014	(0.059)	0.430	(0.095)	-1.463	(0.009)
Age 25-29	1.050	(0.058)	0.534	(0.078)	-0.712	(0.009)
Age 30-34	0.893	(0.059)	0.290	(0.085)	-0.490	(0.009)
Age 35-39	0.822	(0.061)	0.128	(0.109)	-0.357	(0.009)
Age 40-44	0.761	(0.063)	0.297	(0.082)	-0.344	(0.009)
Age 45-49	0.746	(0.063)	0.176	(0.084)	-0.294	(0.009)
Age 50-54	0.749	(0.065)	0.197	(0.083)	-0.229	(0.010)
Age 55-59	0.597	(0.069)	0.339	(0.070)	-0.194	(0.010)
Age 60-64	0.472	(0.073)	0.074	(0.083)	-0.137	(0.011)
Age 65 and above	(ref)	—	(ref)	—	(ref)	—
Cancer	-0.885	(0.052)	0.707	(0.123)	-0.022	(0.008)
Cardiovascular	-0.229	(0.043)	0.473	(0.121)	-0.082	(0.006)
Diabetes	-0.482	(0.096)	1.494	(0.138)	-0.092	(0.015)
Other disease	-0.538	(0.062)	1.272	(0.137)	0.008	(0.009)
Pulmonary	-0.388	(0.143)	1.617	(0.123)	-0.147	(0.020)
Renal	-1.284	(0.161)	1.618	(0.115)	-0.183	(0.027)
Healthy	(ref)	—	(ref)	—	(ref)	—
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. Individuals are marked as having a diagnosis if they received one in the first year of enrollment. 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.

Appendix Table 9: Insurer Marginal Cost Model with First-Year Diagnosis

Variable	coef	se
Network breadth	0.386	(0.024)
Network breadth^2	-0.373	(0.019)
Insurer FE Insurer A	0.408	(0.007)
Insurer B	0.059	(0.004)
Insurer C	0.196	(0.005)
Insurer D	-0.045	(0.004)
Insurer E	0.110	(0.004)
Insurer F	-3.242	(1.307)
Insurer G	0.078	(0.004)
Insurer H	0.243	(0.008)
Insurer I	0.041	(0.004)
Insurer J	0.245	(0.003)
Insurer K	0.140	(0.004)
Insurer L	0.403	(0.004)
Insurer M	0.107	(0.007)
Insurer N	(ref)	(ref)
First stage F-statistic	45.48	
Observations	1,135,511	

Note: Table presents non-linear least squares regression of average costs per consumer type on network breadth and network breadth squared. Individuals are marked as having a diagnosis if they received one in the first year of enrollment. 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.

Appendix Table 10: Insurer Demand Model with Network Breadth Weighted by Beds

	Network breadth		OOP spending		Incumbent	
Variable	coef	se	coef	se	coef	se
Mean	2.775	(0.043)	-1.194	(0.112)	3.625	(0.008)
Interactions						
Male	0.113	(0.024)	0.026	(0.041)	0.003	(0.004)
Female	(ref)	—	(ref)	—	(ref)	—
Age 19-24	0.571	(0.051)	0.061	(0.085)	-1.466	(0.009)
Age 25-29	0.491	(0.050)	-0.009	(0.063)	-0.705	(0.009)
Age 30-34	0.451	(0.050)	-0.535	(0.094)	-0.480	(0.009)
Age 35-39	0.405	(0.052)	-0.713	(0.113)	-0.346	(0.009)
Age 40-44	0.393	(0.054)	-0.443	(0.108)	-0.336	(0.009)
Age 45-49	0.313	(0.055)	-0.382	(0.097)	-0.287	(0.009)
Age 50-54	0.359	(0.057)	-0.196	(0.093)	-0.225	(0.010)
Age 55-59	0.217	(0.060)	0.062	(0.071)	-0.191	(0.010)
Age 60-64	0.258	(0.064)	-0.137	(0.079)	-0.135	(0.011)
Age 65 and above	(ref)	—	(ref)	—	(ref)	—
Cancer	0.102	(0.049)	0.692	(0.115)	-0.026	(0.008)
Cardiovascular	0.641	(0.040)	0.778	(0.112)	-0.091	(0.007)
Diabetes	1.107	(0.094)	1.418	(0.132)	-0.023	(0.016)
Other disease	0.604	(0.059)	1.078	(0.132)	0.142	(0.010)
Pulmonary	0.881	(0.128)	1.291	(0.113)	-0.236	(0.022)
Renal	0.751	(0.152)	1.064	(0.112)	-0.080	(0.028)
Healthy	(ref)	—	(ref)	—	(ref)	—
Individuals	500,000					
Observations	16,410,468					
Pseudo-R^2	0.51					

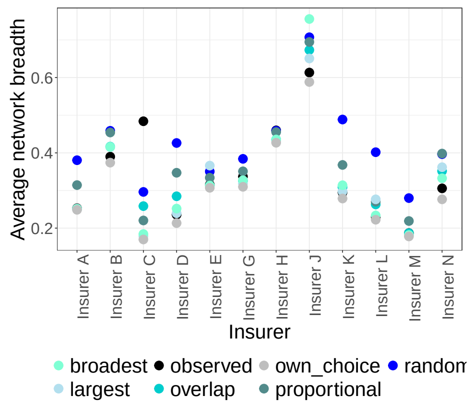
Note: Table presents maximum likelihood estimates of the insurer demand model using a conditional logit. Network breadth is weighted by the provider's number of beds. Estimation uses a random sample of 500,000 individuals enrolled throughout the sample period from 2013 to 2017 in the 13 main capital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

Appendix Table 11: Insurer Marginal Cost Model with Network Breadth Weighted by Beds

Variable	coef	se
Network breadth	0.277	(0.018)
Network breadth^2	-0.269	(0.014)
Insurer FE Insurer A	0.295	(0.007)
Insurer B	0.054	(0.003)
Insurer C	-0.202	(0.005)
Insurer D	-0.100	(0.004)
Insurer E	0.092	(0.004)
Insurer F	-2.600	(0.822)
Insurer G	0.081	(0.003)
Insurer H	0.226	(0.007)
Insurer I	-0.050	(0.004)
Insurer J	0.267	(0.003)
Insurer K	0.174	(0.004)
Insurer L	0.387	(0.004)
Insurer M	-0.083	(0.007)
Insurer N	(ref)	(ref)
First stage F-statistic	36.02	
Observations	1,135,511	

Note: Table presents non-linear least squares regression of average costs per consumer type on network breadth and network breadth squared. Network breadth is weighted by the provider's number of beds. 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 beds-weighted 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.

Appendix C Additional Counterfactual Results



Appendix Figure 6: 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.