The Equilibrium Effects of Automatic Enrollment in Health Insurance*

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Abstract

This paper shows that automatic enrollment rules shape insurer competition and long-run equilibrium outcomes in health insurance markets. We evaluate several enrollment rules following the termination of Colombia's largest insurer, using an equilibrium model in which insurers compete on provider networks and consumers exhibit inertia and adverse selection. Reassigning consumers randomly to incumbent insurers in equal proportions raises consumer surplus and broadens both hospital and non-hospital networks without increasing spending, because it induces healthy consumers to switch actively in the year after reassignment. Failing to endogenize insurers' supply decisions reverses the conclusions about which rules improve welfare.

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

JEL codes: I10, I11, I13, I18.

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1 Introduction

A common policy tool in health insurance markets is automatic enrollment, whereby individuals are assigned to a health plan when they first become eligible for coverage or when their incumbent plan closes, but are allowed to switch typically after a year (Dorn et al., 2018).[1] This policy tool has recently received attention in the academic literature for its potential to impact consumer welfare and market outcomes (e.g., McIntyre et al., 2021; Macambira et al., 2022; Wallace, 2023; Shepard and Wagner, 2023). However, most of the empirical evidence studies automatic enrollment as a static phenomenon without considering its long-run consequences or how insurers' supply decisions might respond.

In this paper, we show that automatic enrollment rules shape competition in health insurance markets and their long-run outcomes, and that failing to endogenize insurers' supply decisions would lead to fundamentally different conclusions about how these rules impact welfare. To see why, note that if consumers were reassigned permanently, an enrollment rule would simply determine each insurer's stock of enrollees and its welfare effects would reduce to a matching problem. But automatic enrollment is temporary: consumer switching after the reassignment period shapes how insurers respond to the rule, so welfare depends not only on the quality of the initial match but on the competition the rule sets in motion.

The mechanisms behind the long-run impacts of automatic enrollment are the well-studied phenomena of inertia and adverse selection (Handel, 2013; Ericson, 2014; Polyakova, 2016). When inertia disproportionately affects sick consumers, enrollment rules that induce healthy consumers to switch after reassignment intensifies insurer competition for these profitable switchers, and equilibrium plan characteristics become shaped by the preferences of the healthy. This raises consumer welfare when those preferences favor plan characteristics that benefit all consumers, such as broad healthcare provider networks.[2]

[1] Automatic enrollment is used in Medicaid managed care (in states like CA and NY) when individuals who become eligible for Medicaid fail to engage in active plan choice (Macambira et al., 2022), Medicare Advantage after an incumbent plan closes Abaluck et al. (2021), and in the US health insurance exchanges to renew insurance coverage through a particular health plan (Anderson et al., 2021).

[2] Conversely, rules that induce sick consumers to switch tend to reduce welfare. In that case, since insurers cannot attract healthy types, they resort to "harvesting" their stock of enrollees, for example by narrowing their networks.

Our empirical setting is the Colombian healthcare system, where a health insurer with strong geographical presence, called SaludCoop, was abruptly terminated by the government in December 2015. At the time of its termination, SaludCoop operated in 43% of municipalities nationwide and covered nearly 50% of enrollees in some of these markets. The termination was sudden, politically motivated, and unrelated to SaludCoop's overall performance. The government assigned SaludCoop enrollees to a smaller insurer, called Cafesalud, during the first three months of 2016, after which enrollees could switch.

This setting provides a unique opportunity to study automatic enrollment rules, but it also presents some challenges. The sheer magnitude of SaludCoop's termination allows us to estimate effects for the majority of the country and to identify parameters that we would otherwise not have been able to identify (e.g., separating state dependence from preference heterogeneity in consumer inertia). However, we do not have empirical variation in which insurers individuals are assigned to or in enrollment rules (as in other settings, e.g., Wallace, 2023), since all SaludCoop enrollees were assigned to a single incumbent insurer. Our methodological contribution therefore lies in being able to trace the effects of counterfactual enrollment rules using a structural model of insurer competition.

Our data encompass 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.[3] In this system, insurers compete primarily on their networks of providers and negotiated prices to deliver a single health insurance plan. Other aspects of the plan (premiums, cost-sharing, and benefits) are tightly regulated and uniform across insurers, and insurers receive risk-adjusted per capita transfers from the government.

We characterize insurers by two dimensions of network breadth: hospitals and non-hospital providers (clinics, physician practices, pharmacies, and diagnostic providers). Since the impact of enrollment rules depends on how inertia and adverse selection vary across consumers, we begin by documenting this variation. First, we show that insurer switching rates respond far more to changes in network breadth among SaludCoop en-

[3]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.

rollees than among the general population, demonstrating the existence of inertia driven mainly by preference heterogeneity (because SaludCoop enrollees were not matched to Cafesalud based on their preferences for network breadth). Second, we show that sicker consumers sort into insurers with broader hospital networks but not into those with broader non-hospital networks, consistent with adverse selection on hospital networks specifically. The presence of inertia and adverse selection suggests that automatic enrollment can affect insurer competition by shaping which consumers actively choose their plan after reassignment.

We provide causal evidence of the impact of the observed enrollment rule on consumer switching and insurer competition using an event study design. We find that switching rates rose by 43% in markets with SaludCoop presence versus those without, with larger effects among healthy enrollees. Treated markets consequently experienced a significant decline in insurer concentration, and such decline was more pronounced in markets where SaludCoop enrollees were healthiest at baseline, consistent with enrollment rules driving competition by inducing healthy consumers to switch.

To explore counterfactual enrollment rules, we specify an equilibrium model of insurer competition on hospital and non-hospital networks. In the model, insurers simultaneously choose their network breadths to maximize the present discounted value of their profits. The profit function incorporates a random utility model of demand in which consumers choose their insurer based on hospital and non-hospital network breadth, out-of-pocket costs, and inertia, with all parameters allowed to vary by diagnosis. On the supply side, insurers' marginal and fixed costs are non-linear functions of both network types. Insurer profits evolve according to exogenous transition probabilities across diagnoses and endogenous transition probabilities across insurers. Our equilibrium concept is a static Nash equilibrium.

Demand estimation faces two identification challenges. First, network breadth and healthcare costs, which determine out-of-pocket costs, are jointly determined by insurers in anticipation of consumer demand, generating simultaneity bias. Second, the inertia indicator conflates state dependence with preference heterogeneity, making it difficult to identify the welfare-relevant component of inertia. We address the first challenge using an

instrumental variable approach and the second by exploiting the exogenous reassignment of SaludCoop enrollees to Cafesalud, whose network decisions were independent of any pre-existing consumer preferences for that insurer.

Demand estimates show that consumers with chronic conditions are willing to pay between two and four times more for a given increase in the breadth of hospital networks than for the same increase in the breadth of non-hospital networks, while healthy consumers show the opposite pattern. Inertia is substantial as consumers are nearly twice as likely to choose their previous insurer, and this parameter reflects primarily preference heterogeneity rather than state dependence. Notably, consumers with chronic conditions are willing to forgo broader hospital and non-hospital networks in exchange for remaining with their incumbent insurer, more so than consumers without chronic diseases.

On the supply side, identification of marginal cost parameters relies on within-consumer type variation in healthcare costs across insurers, while identification of fixed cost parameters uses within-insurer variation in marginal variable profits across markets. We estimate the supply side on pre-termination data to later test the model's out-of-sample fit. We find that insurers have heterogeneous marginal and fixed costs. Marginal costs increase with hospital network breadth but decrease with the interaction between the two network types, reflecting economies of scope in network management. Fixed costs increase with both network types, but the effect is considerably larger for non-hospital networks. Hence, the administrative burden of expanding non-hospital coverage – which requires contracting with a larger number of individual providers – drives fixed cost heterogeneity across insurers. Before using the model for counterfactual simulations, we show that it performs well out-of-sample and, in particular, that it accurately predicts the observed distribution of hospital and non-hospital network breadth in 2016 under the observed enrollment rule that assigned SaludCoop enrollees to Cafesalud.

The counterfactual automatic enrollment rules we examine next include random enrollment, enrollment in the insurer with the broadest hospital network, and consumer own-choice without a specified insurer default, among others. To predict each rule's equilibrium effects, we first ask which consumers are most likely to switch in the first year following reassignment. In this partial equilibrium exercise, rules with random assign-

ment induce more switching among higher-profit consumers than rules with deterministic assignment, suggesting the former would expand network breadth in equilibrium relative to the latter.

Indeed, simulating the full equilibrium, we find that random enrollment (in equal proportions to all insurers) outperforms all other rules across several dimensions: hospital and non-hospital network breadth both increase by 14%, per capita healthcare spending remains unchanged, and short-run consumer surplus increases by 9% relative to the observed scenario. The low match quality between the consumer and their assigned insurer in the random enrollment rule incentivizes consumers to switch (particularly the healthy, as the sick have a higher value of inertia), which intensifies insurer competition, and hence increases network breadth.

By contrast, the own choice rule results in narrower hospital and non-hospital networks. Because patients choose their insurer, they choose one with a high match value, making it less likely for them to switch even if other insurers broaden their networks. This gives incentives for insurers to "harvest their enrollees" and shrink their networks to reduce costs. These results are in line with Marone and Sabety (2022), who show that allowing for free consumer choice in insurance markets is not always beneficial for welfare, and this conclusion is specially stark in our setting when supply-side decisions are taken into account.

Insurers' endogenous response to the enrollment rules is key to our results. When we do not allow insurers to respond endogenously to the rules by changing their network breadths, 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 which are ubiquitous across health systems. In the context of insurer terminations, prior research (including our own) has examined its 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 networks – and shows that assigning consumers to insurers that include their existing providers can improve consumer satisfaction, albeit holding insurers' supply decisions fixed. We complement this work by endogenizing insurers' network breadth choices and showing that this has important implications for welfare.

More broadly our paper relates to the literature on optimal assignment mechanisms which has studied patient waitlists for general practitioners (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 characterize how inertia and adverse selection matter for the long-run equilibrium (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

Our setting is Colombia's contributory healthcare system, part of the universal healthcare system of the country, for which enrollment is compulsory for individuals who pay payroll taxes (and their dependents). The contributory system covers approximately half of the country's population.[4] Enrollees have access to a single health plan defined and funded by the government, which is operated by private and public insurers. Insurers negotiate with providers to determine network inclusions and health service prices, but other plan

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

elements are regulated and uniform across insurers, including premiums, cost-sharing rates and benefits.[5] Hence, provider networks are the main dimension in which insurers compete for enrollees. Consumer premiums are zero; instead, 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).[6]

Automatic Enrollment Rules. To maintain their license with the Ministry of Health, insurers must satisfy several requirements: holding risk-based capital above government-defined thresholds, avoiding losses for more than two consecutive years, and maintaining high enrollee satisfaction as measured by Ministry surveys. Failure to meet these conditions may result in forced termination (Decree 780 of 2016).

In December 2015, the government terminated SaludCoop due to its engagement in illegal activities and financial malpractice.[7] SaludCoop had diverted nearly $250 billion to investments outside the healthcare system and submitted false health claims to the government for reimbursement. At the time of its termination, SaludCoop covered nearly 20% of enrollees nationwide (around 4 million individuals), who were transferred to an incumbent insurer called Cafesalud during the first three months of 2016. After this 90-day grace period, enrollees were free to switch. Prior to the termination, Cafesalud covered less than 5% of enrollees nationwide.

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. To strengthen the capacity to absorb the massive transfer of enrollees, the government also gave Cafesalud additional financial resources of around $70 million.[8]

Following SaludCoop's termination, the Ministry of Health issued Decree 780 of 2016, which for the first time established formal rules for reassigning enrollees when a health

[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.

[6]Appendix Figure 1 compares these risk-adjusted transfer against observed healthcare costs, showing that younger, relatively healthier enrollees can be substantially more profitable than older, sicker ones.

[7]See El Colombiano.

[8]See El Tiempo.

plan is terminated. Under Article 2.1.11.3, enrollees without chronic conditions are split evenly: half are randomly assigned in equal proportions to insurers operating in their municipality of residence, while the other half are assigned in proportion to each insurer's local market share. Enrollees with chronic conditions, by contrast, are reassigned entirely based on local market share. In both cases, reassigned enrollees must remain with their new insurer for 90 days before they are permitted to switch plans.[9]

Although Decree 780 did not apply to the SaludCoop cohort, it codified the kind of automatic enrollment rules that are likely to govern future plan terminations in Colombia and elsewhere. This raises a fundamental question of whether such rules are optimal. If automatic enrollment allocates displaced consumers to insurers with networks poorly matched to their healthcare needs – particularly for the sickest patients who rely most heavily on hospital access – the welfare costs of plan terminations could be substantially larger than the direct disruption of switching insurers. Understanding how insurers respond to these rules, and how consumers sort across networks in their aftermath, is therefore essential for designing automatic enrollment mechanisms that preserve access to care.

3 Data

We use administrative data from the contributory healthcare system encompassing individual-level enrollment, linked with health claims and earnings from 2013 to 2017 for the subset of individuals aged 19 or older.[10] 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

[9] We focus on SaludCoop's termination in our analysis because it was sudden, politically motivated, and unrelated to its overall performance. While other insurers were terminated between 2013 and 2017, these operated in the subsidized scheme and had flailing profits.

[10] The enrollment data is known as *Base de Datos Única De Afiliados* (BDUA) and the claims data is the *Base de Suficiencia* from the Ministry of Health.

the International Classification of Diseases, 10th Revision, ICD-10), 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 diagnoses, we assign the one that accounts for the largest share of their healthcare cost.

We complement enrollment and claims information with data from insurers' public income statements submitted to the National Health Superintendency. These files report insurers' total administrative costs, which we use in some of our descriptive analysis as measures of fixed costs.

We focus on the 13 largest insurers in the contributory system, which account for 99% of enrollees in 2015. Excluding SaludCoop and Cafesalud, we observe all 11 remaining insurers for at least three years, 8 for four or more years, and 7 for the full five years. Insurers are missing from the health claims data for the years in which they fail to pass the Ministry of Health's data quality filters. Although we do not observe Cafesalud in 2017, we are able to follow 78% of SaludCoop's enrollees over the full sample period because they had switched out of Cafesalud by then.

For insurers in our sample, we also 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 lists the hospitals, clinics, and physician practices included in each insurer's network, but do not specify the 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 (Resolution 1441 of 2016), insurers may add or drop providers throughout the year. In our final network data, one quarter of insurer-provider pairs are inferred from health claims.

Given that networks are insurers' main dimension of competition, we characterize each

insurer along two dimensions of network breadth: hospitals and non-hospital providers (clinics, pharmacies, physician practices, and diagnostic providers). Hospital network breadth is defined as the fraction of hospitals in a market covered by the insurer. Non-hospital network breadth is defined analogously. We identify hospitals as facilities with an intensive care unit, and define markets as municipalities – similar to counties in the US – consistent with the municipality-specific enrollment rules the Colombian government has considered. Our main analysis focuses on the 13 largest municipalities defined by the National Administrative Department of Statistics (DANE), where we observe meaningful variation in both hospital and non-hospital networks and which represent nearly 41% of the country's population.[11]

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.

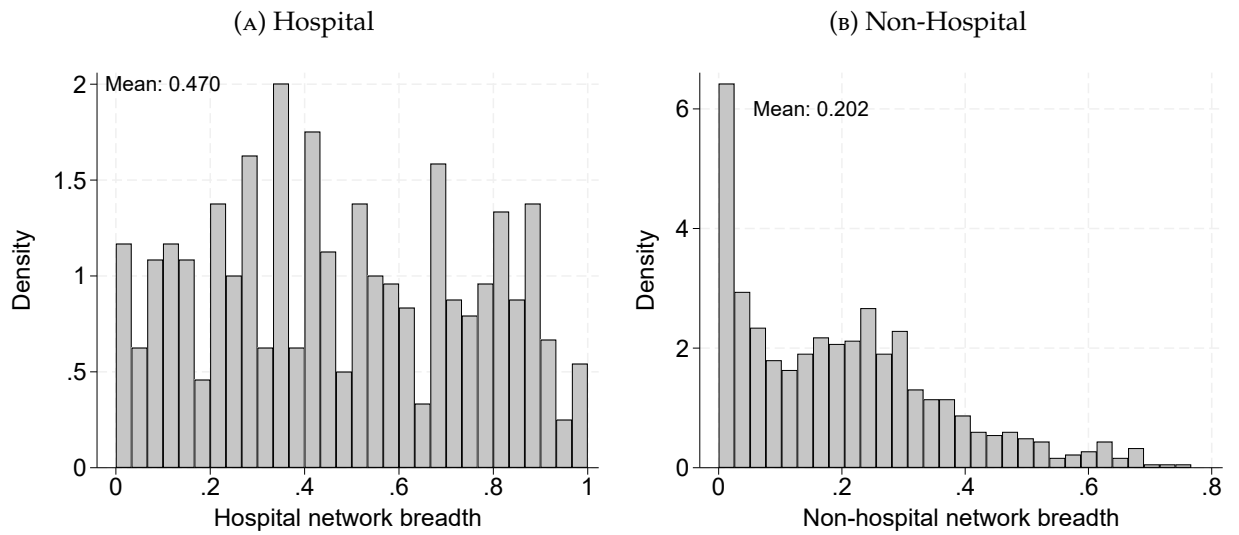
Table 1 presents pooled summary statistics for the full sample in column (1), the continuously enrolled subsample in column (2), and the continuously enrolled in the 13 largest municipalities in column (3). An observation represents a person-year. The latter is our preferred sample for model estimation for two reasons. First, annualized

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

healthcare costs for the continuously enrolled are free from measurement error arising from enrollment spells shorter than a year. Second, spillover effects across markets are substantial, as consumers may travel to larger municipalities for certain types of care; focusing on residents of the 13 largest municipalities minimizes this bias.[12]

Across the three samples, a little under 60% of consumers are classified as healthy. The most prevalent conditions are cardiovascular disease, followed by cancer and diabetes. Average annual earnings are higher in column (3) because both wages and the cost of living are higher in large municipalities. On average, individuals in the full sample have annual healthcare costs of 786 thousand pesos (US$257 of 2016), of which around 145 thousand pesos (US$47) are out-of-pocket. The lower standard deviation of total healthcare cost in column (3) relative to column (1) reflects the exclusion of small-market outliers.

FIGURE 1: Distribution of Municipal Network Breadth



Note: Figure shows the distribution of hospital network breadth in Panel A and non-hospital network breadth in Panel B. An observation in these histograms is an insurer-market-year conditional on the 13 largest municipalities and for insurers that operate in the contributory system. In Panel A, we condition to markets that have at least one hospital. Hospitals are identified as institutions with an intensive care unit.

Figure 1 shows the distribution of hospital and non-hospital network breadth in the 13 largest municipalities. Both measures vary substantially across insurers, markets, and

[12] 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.

years. Average hospital network breadth equals 0.47, while average non-hospital network breadth equals 0.20. Non-hospital networks are narrower on average because there are more clinics and physician practices than hospitals in any given market.

4 Reduced-Form Patterns

4.1 Network breadth preferences and costs

Insurers' network responses to automatic enrollment rules depend on which consumers each rule induces to switch after reassignment. This section documents the two forces governing these switching decisions – inertia and adverse selection – and shows that the costs of expanding each network type mediate the magnitude of insurers' responses.

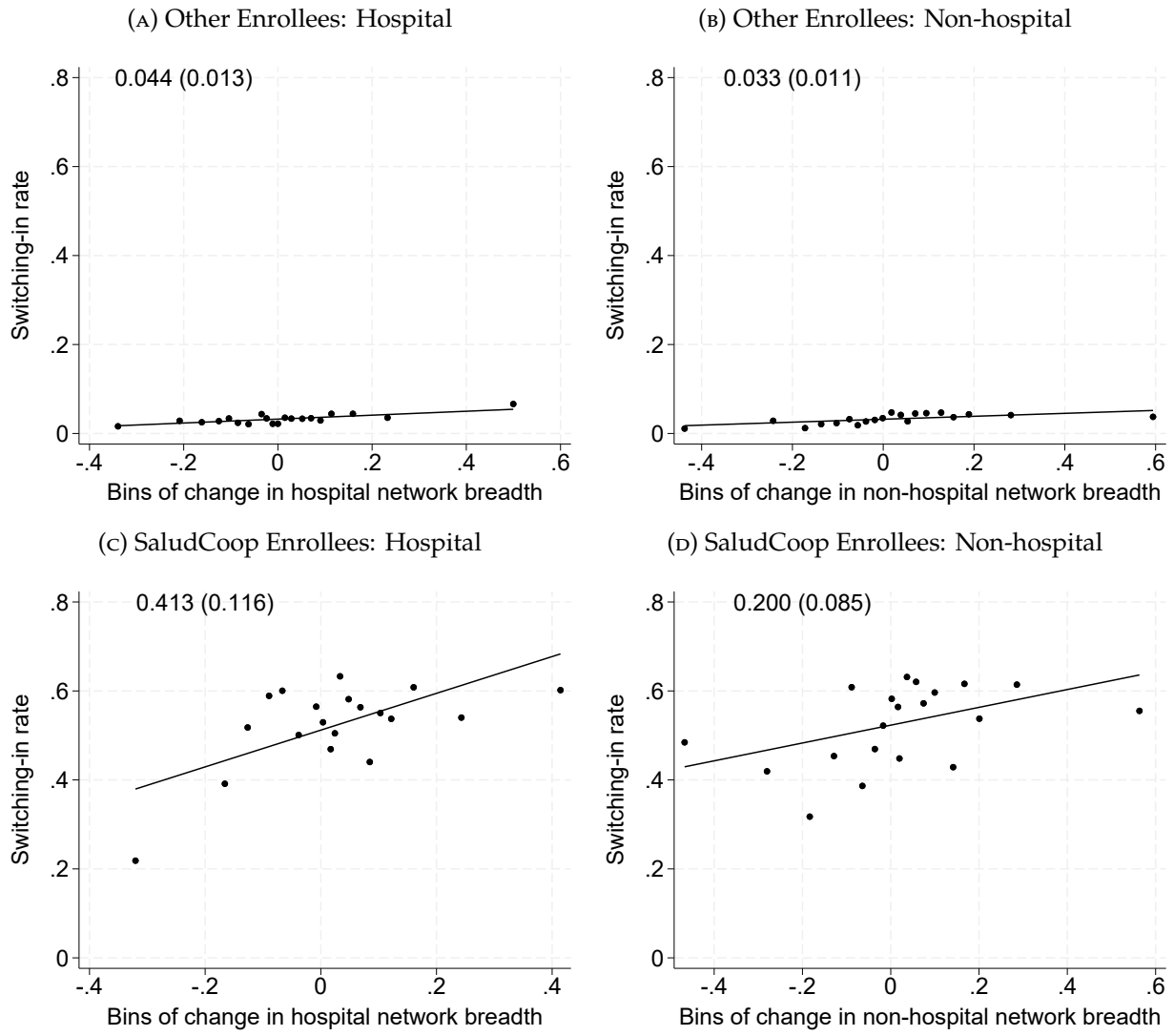
Using our preferred sample, Figure 2 examines the sensitivity of enrollment decisions to each type of network, separately for non-displaced enrollees (those enrolled to other incumbent insurers) (Panels A and B) and for enrollees displaced from SaludCoop (Panels B and C). Each panel presents a scatterplot of the average switch-in rate by bins of the change in network breadth over time. The slope coefficient and standard error are reported in the upper left corner of each panel.

The patterns are striking. Among non-displaced enrollees, consumers are more likely to switch into insurers that expand their hospital and non-hospital networks, with slope coefficients of 0.044 and 0.033, respectively. Both correlations are precisely estimated but small in magnitude, consistent with high switching costs that dampen sensitivity to network breadth among the general population.

Among SaludCoop enrollees, the patterns are qualitatively similar but substantially larger. The correlation with hospital network breadth is nearly ten times larger than among non-displaced enrollees, and the correlation with non-hospital network breadth is about six times larger. Two features of Panels C and D stand out relative to Panels A and B. First, there is a much higher switching rate among SaludCoop enrollees than non-displaced enrollees, reflecting the absence of switching costs. Because SaludCoop enrollees were forced into Cafesalud for only three months before re-choosing, their subsequent decisions

capture network preferences more cleanly than in Panels A and B, where state dependence may dampen sensitivity to network breadth.

FIGURE 2: Correlation Between Switching Rate and Change in Network Breadth



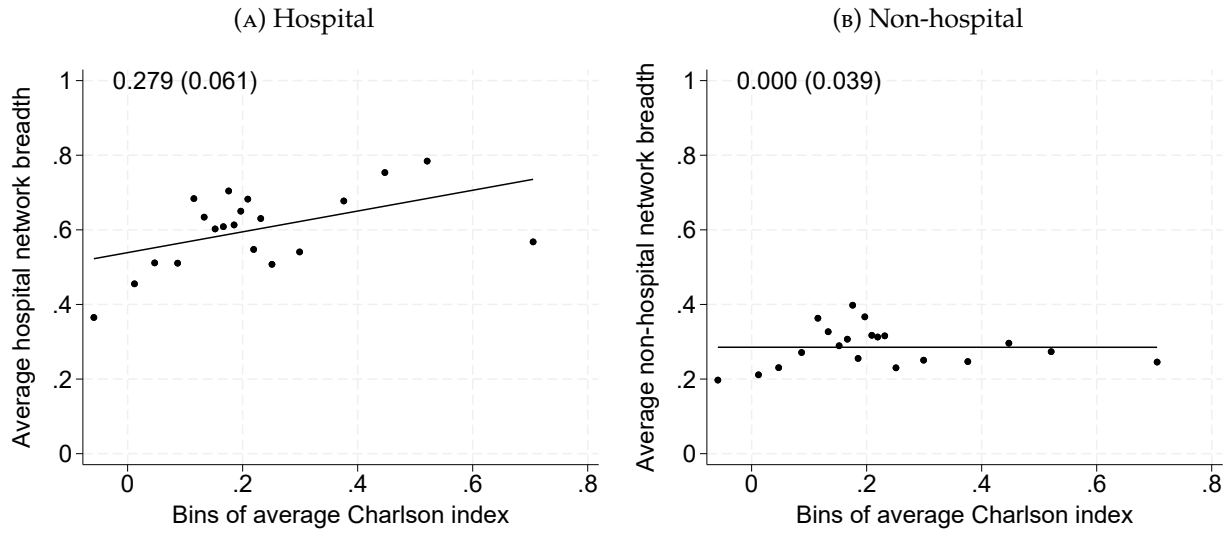
Note: Figure presents a scatter plot of the average switch-in rate by 20 equally sized bins of the change in hospital network breadth (left column) and non-hospital network breadth (right column) over time. Panels A and B condition on consumers enrolled with incumbent insurers. Panels C and D condition on consumers enrolled with SaludCoop in 2015. To construct this figure, we aggregate our preferred sample to the insurer-market-year level, calculating average switch-in rates and average changes in hospital and provider network breadth. Then, we produce the binned scatterplots after residualizing each variable with market-by-year fixed effects. Solid lines represent linear fits and the numbers in the upper corner of each panel report the slope coefficient and standard error from this regression.

Second, SaludCoop enrollees respond more strongly to hospital network expansion than to non-hospital network expansion compared to the general population. This is consistent with the hypothesis that SaludCoop enrollees were in worse health than the

typical consumer and therefore placed greater weight on access to hospital care.

Figure 3 confirms this interpretation. Consumers with a higher Charlson Index – a measure of disease burden – tend to sort into insurers with broader hospital networks, but the correlation between the Charlson Index and non-hospital network breadth is essentially zero. Hence, adverse selection operates exclusively through the hospital network dimension.

FIGURE 3: Correlation Between Charlson Index and Network Breadth

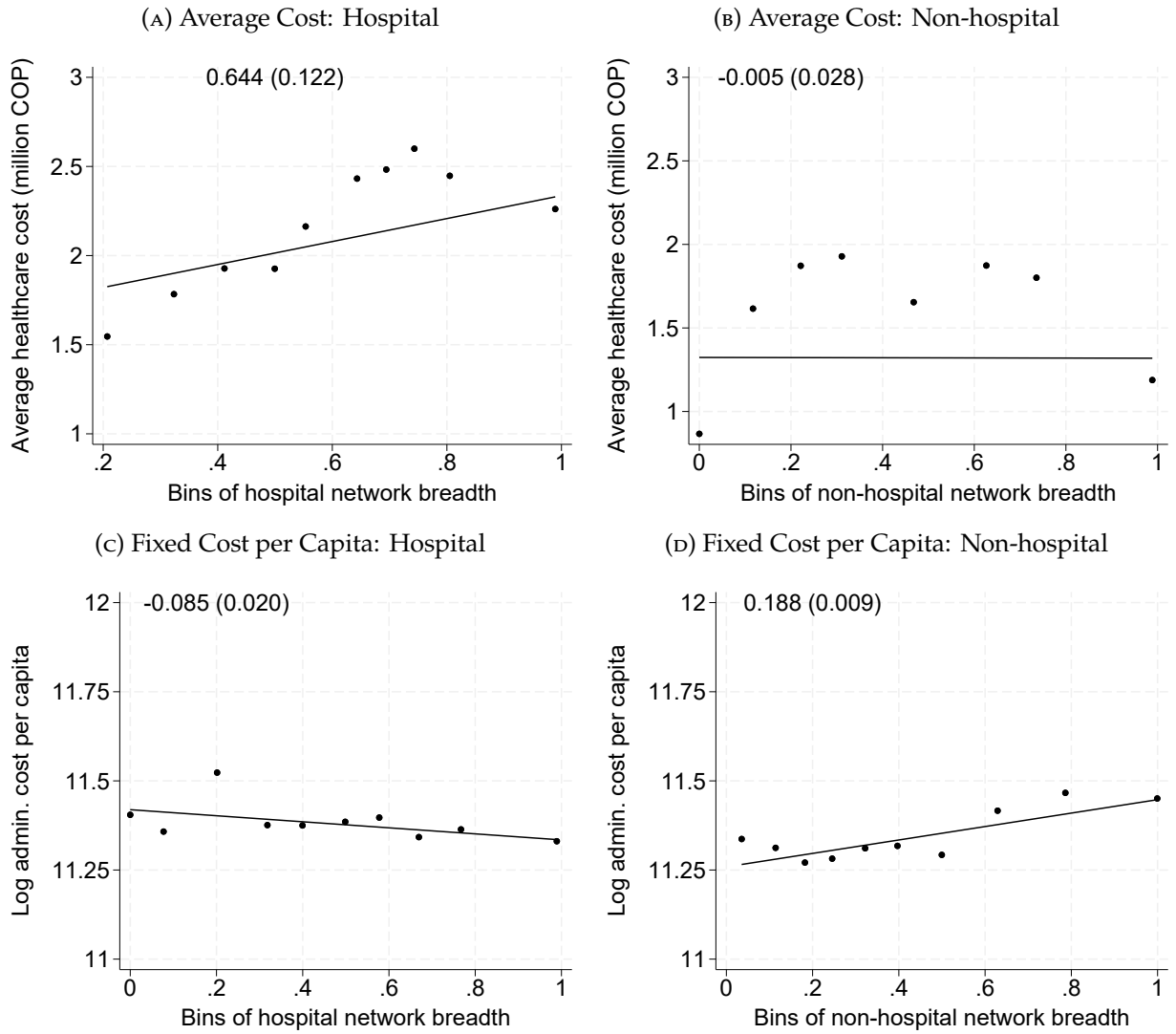


Note: Figure presents a scatter plot of the average hospital network breadth in Panel A and average non-hospital network breadth in Panel B by 20 equally sized bins of the average Charlson index. To construct this figure, we aggregate our preferred sample to the insurer-market-year level, calculating the average Charlson index and the average hospital and provider network breadth. Then, we produce the binned scatterplots after residualizing each variable with market-by-year fixed effects. Solid lines represent linear fits, and the numbers in the upper corner of each panel report the slope coefficient and standard error from this regression.

The sorting of sicker consumers into broader hospital networks has direct implications for insurers' costs. Figure 4, Panels A and B show that average healthcare costs are strongly increasing in hospital network breadth but essentially flat with respect to non-hospital network breadth. The fixed cost patterns in Panels C and D tell a complementary story. We proxy these costs with public data on total administrative costs reported by insurers to the National Health Superintendency. Fixed costs per capita are slightly decreasing in hospital network breadth but increasing in non-hospital network breadth. This pattern reflects a fundamental difference in the cost structure of establishing hospital and non-hospital networks. Hospitals are few and large, so adding one to the network represents a substantial expansion in coverage that spreads fixed costs over a larger enrollee base,

generating economies of scale. Non-hospital providers, by contrast, are numerous and small, so expanding non-hospital coverage requires negotiating and maintaining contracts with a large number of individual facilities and physician practices, raising fixed costs at the margin.

FIGURE 4: Correlation Between Average Cost, Fixed Cost Per Capita, and Network Breadth



Note: Panels A and B present a scatter plot of the average healthcare cost by 20 equally sized bins of hospital network breadth and non-hospital network breadth, respectively. Panels C and D present a scatter plot of the log administrative cost per capita by 20 equally spaced bins of hospital network breadth and non-hospital network breadth, respectively. To construct Panels A and B, we aggregate our preferred sample to the consumer type-insurer-market-year level, calculating average healthcare costs and hospital and non-hospital network breadths. To construct Panels C and D, we use insurer-year-level income statements reporting administrative costs and divide this by their total number of enrollees. Solid lines represent linear fits and the numbers in the upper corner of each panel report the slope coefficient and standard error from this regression.

4.2 Impact of Automatic Reassignment to Cafesalud

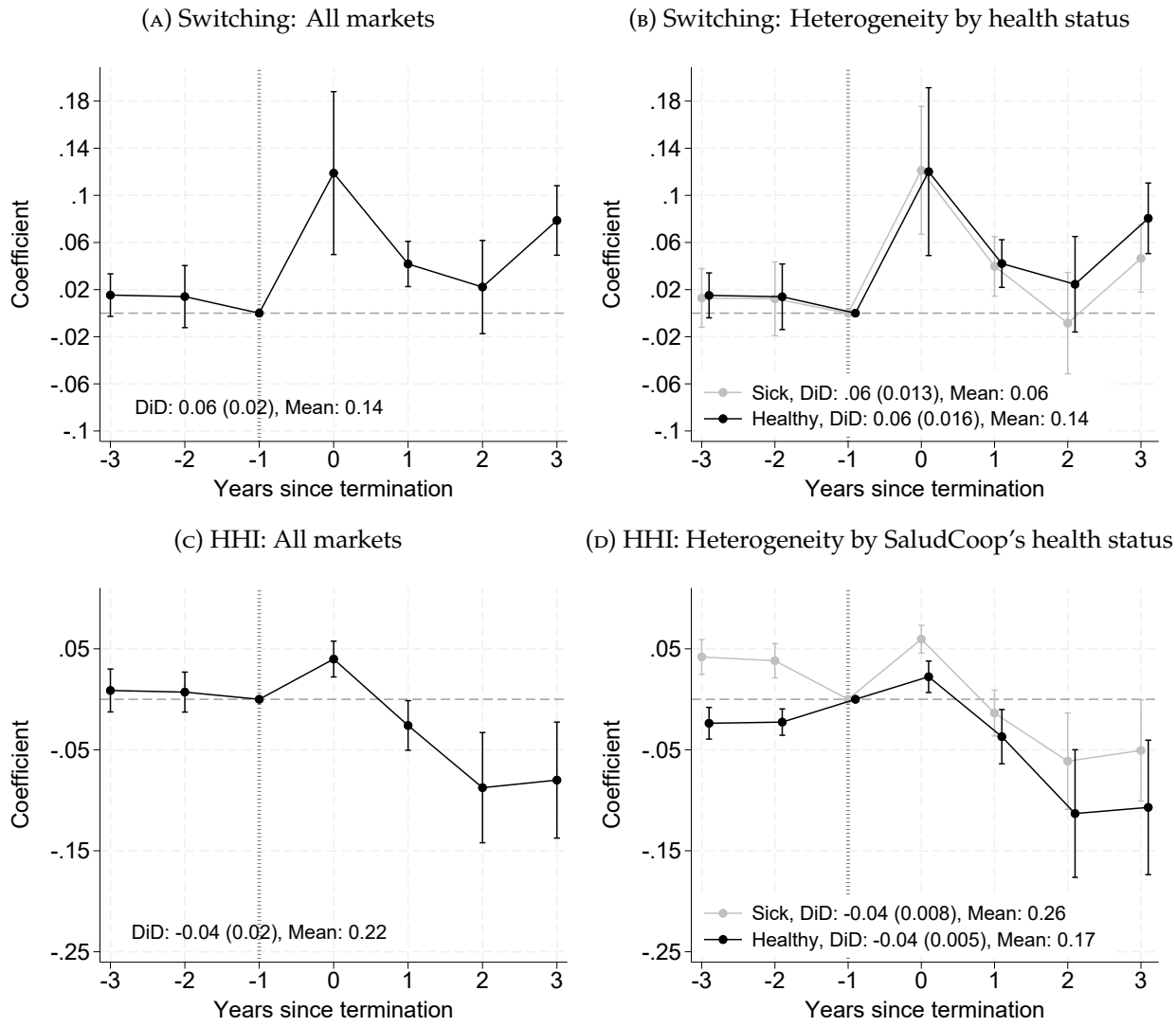
We now turn to estimating the causal effect of automatic enrollment on market outcomes, exploiting the reassignment to Cafesalud in the following event study:

$$y_{it} = \beta_{\tau_{m(i)}} + \alpha_i + \delta_{m(i)} + \gamma_t + \varepsilon_{it}$$

where i indexes an individual, t a year, and m a municipality. Treated municipalities are those where SaludCoop operated in 2015; all others serve as controls. y_{it} is an outcome for individual i in year t, $\tau_{m(i)}$ is the number of years since treatment in i's municipality of residence m (normalized to -1 for control municipalities), and α_i, $\delta_{m(i)}$, γ_t are individual, municipality, and year fixed effects, respectively. For outcomes that vary only at the market level, we estimate the event study on municipality-year observations. Standard errors are clustered at the municipality level throughout.

Figure 5, Panel A shows that switching rates rose 43% relative to baseline in treated markets after reassignment. Panel B shows this increase was larger among healthy consumers than sick ones (defined by a zero versus positive Charlson index in 2014), providing direct evidence that inertia binds less for the healthy. Panels C and D turn to insurer competition proxied by market concentration. Insurer HHI fell 22% relative to the pre-termination mean, and the decline was concentrated where SaludCoop enrollees were relatively healthy at baseline. Together, the four panels trace the mechanism: healthy consumers, facing lower inertia, switched out of Cafesalud at higher rates, and insurers competed for their enrollment, reducing concentration. Sick consumers largely remained with their assigned insurer, leaving concentration among high-cost enrollees less affected. This heterogeneity foreshadows a central result of the structural model: the welfare consequences of automatic enrollment rules depend on which consumers are induced to switch after reassignment.

FIGURE 5: Impact of Termination on Market Outcomes



Note: Figure presents coefficients and 95% confidence intervals of an event study regression where the treatment group are municipalities where SaludCoop operated in 2015. In Panels A and B an observation is an individual-year and the outcomes is an indicator for whether the individual switched insurer. In Panels C and D n observation in these regressions in a market-year and observations are weighted by the number of enrollees. The dependent variable is the insurer HHI, constructed conditional on insurers that participate in the contributory system and have minimum market share in a municipality greater than 0.002%. Panels A and C report results using all individuals and markets. Panel B reports results using individuals with Charlson index equal to zero (in black) and with Charlson index greater than zero (in gray). Panel D reports results using markets with above (in gray) vs below (in black) median fraction of SaludCoop enrollees with Charlson Index greater than zero. The bottom corner of each figure reports the coefficient and standard error of a 2×2 difference-in-difference regression, as well as the mean of the dependent variable among treated markets.

5 Model

We develop an equilibrium model of insurer competition to trace the effects of counterfactual enrollment rules. In the model, insurers simultaneously choose their hospital and

non-hospital network breadths in each market to maximize the present discounted value of profits, taking rivals' choices as given. Consumers then choose an insurer to enroll with.

5.1 Insurer Demand

The indirect utility of consumer i of type $\theta(i)$ from choosing insurer j in market m and year t is:

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

where H_{jmt}^k denotes network breadth for $k \in \{\text{hospital}, \text{non-hospital}\}$; $c_{\theta jmt}(\mathbf{H}_{jmt})$ denotes out-of-pocket costs, which depend on the vector of network breadths $\mathbf{H}_{jmt}$; $y_{ijm,t-1}$ is an indicator for whether the consumer chose the same insurer in the previous year; $y_{ijm,t-1}^{SC}$ is its interaction with an indicator for SaludCoop enrollees in 2017; and $\xi_{\theta j}$ is an insurer-by-consumer-type fixed effect capturing idiosyncratic preferences of consumer types for insurers, defined as $\xi_{\theta j} = \xi_{\text{sex},j} + \xi_{\text{age group},j} + \xi_{\text{diagnosis},j}$. We define consumer type θ as 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 chronic diseases, or no diseases).

To estimate this demand function, we use consumers' out-of-pocket costs as directly obtained from the data.[13] But 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 as seen in Appendix Figure 2), we allow the out-of-pocket cost to depend on both network types:

$$c_{\theta jmt} \equiv r_\theta C_{\theta jmt}(\mathbf{H}_{jmt})$$

[13]For consumers who earn 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 earn 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.

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

As documented in Section 4, consumers exhibit substantial inertia in insurer choice. We capture this inertia in the model with an indicator for whether the consumer chose the same insurer in the previous year. This indicator conflates two distinct sources of inertia: state dependence, whereby consumers develop an attachment to their current insurer beyond their underlying preferences, and unobserved preference heterogeneity, whereby consumers simply prefer the same insurer period after period because of its characteristics. SaludCoop's termination allows us to separately identify these two components. Because SaludCoop enrollees were exogenously assigned to Cafesalud, the incumbent indicator for these enrollees captures only preference heterogeneity, not genuine attachment to their assigned plan.

The distinction between state dependence and preference heterogeneity matters for the design of automatic enrollment rules and for measuring welfare. If inertia were entirely driven by preference heterogeneity, reassigning consumers to a new insurer would have no lasting effect on their plan choices – they would simply re-sort according to their preferences once allowed to switch and this directly determines their long-run welfare. State dependence, by contrast, implies that the default insurer shapes future choices beyond the initial assignment period, making the choice of default consequential for long-run market outcomes but not necessarily for welfare. Accurately decomposing these two sources of inertia is therefore important for predicting how different enrollment rules will affect equilibrium network breadth and consumer welfare.

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.

5.2 Nash Equilibrium

If consumer utility depended only on network breadth and reassignment were permanent, the optimal enrollment rule would be trivial: assign consumers to the insurer with the broadest networks. Two features of our setting complicate this prediction. First, consumers may face a trade-off between network breadth and out-of-pocket costs, so broader coverage does not unambiguously raise welfare. Second, insurers respond endogenously to the composition of their assigned enrollees. For example, if all patients are assigned to the insurer with the broadest networks and these patients are relatively sick, the insurer may respond by subsequently narrowing its networks, both to minimize costs among its stock of enrollees and to deter further enrollment of high-cost patients from terminated insurers. The welfare consequences of any enrollment rule therefore depend on how insurers adjust their network decisions. Capturing this endogenous supply response requires a model of insurer competition, and developing such a model is our main contribution relative to existing work that holds the supply side fixed (e.g., Wallace, 2023; Brot-Goldberg et al., 2023).

Insurers maximize the present discounted value of their profits, choosing the vector of network breadths (hospital and non-hospital) conditional on rivals' choices. The insurer profit function is:

$$\Pi_{jm}(\mathbf{H}_m) = \sum_{\theta} \underbrace{\pi_{ijm}(\mathbf{H}_m, \theta, y)}_{\text{per-enrollee profit}} N_{\theta ym} + \underbrace{\sum_{t=1}^{T} \zeta^t \sum_{\theta, y} (1-\rho_\theta)\mathcal{P}(\theta', j|\theta, y)\pi_{ijm}(\mathbf{H}_m, \theta', y)N_{\theta ym}}_{FP_{\theta jmt}} - \underbrace{\sum_k F^k_{jm}}_{\text{fixed cost}}$$

where per-enrollee profit is:

$$\pi_{ijm}(\mathbf{H}_m, \theta, y) = (R_{\theta m} - (1-r_\theta)C_{\theta jm}(\mathbf{H}_{jm}))s_{ijm}(\mathbf{H}_m, y)$$

The insurer's marginal cost is

$$C_{\theta jmt} = \exp\left(\sum_k \tau_1^k H^k_{jmt} + \tau_3 H^{\text{hosp}}_{jmt} H^{\text{prov}}_{jmt} + \gamma_\theta + \eta_m + \delta_j + \epsilon_{\theta jmt}\right) \tag{2}$$

And the fixed cost for network type k is:

$$F_{jm}^{k} = \exp\left(\omega H_{jm}^{k} + \nu_{jm}^{k}\right)$$

In this profit function, $\mathbf{H}_m = \{\mathbf{H}_{jm}\}_{j=1}^{J_m}$ is the vector of network breadths 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),[14] 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),[15] 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:

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

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 statistically unrelated to hospital and non-hospital network breadth at the 5% level.

The fixed cost for network type k is denoted by F_{jm}^{k}, where ν_{jm}^{k} is the model's structural error. We allow this error to differ across network types because, as seen in Figure 4 Panels C and D, economies of scale are heterogeneous across hospital and non-hospital networks.

[14] We hold market size fixed to abstract from dynamic incentives that may arise when insurers anticipate population growth. For example, insurers may invest in network breadth today to attract future enrollees in expanding markets. Incorporating such dynamics is left for future work.

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

In the marginal cost function, γ_θ, η_m, and δ_j are consumer type, market, and insurer fixed effects, respectively,[16] and $\epsilon_{\theta jmt}$ 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.[17]

In this model, insurers make a one-time choice of network breadth that affects both current and future profits as patient age, transition into diagnoses, and switch insurers.[18] The first-order condition (FOC) of the insurer's profit maximization problem is:

$$FOC^k_{jm}(\mathbf{H}_m) \equiv MP^k_{jm}(\mathbf{H}_m) - \omega e^{\omega H^k_{jm} + \nu^k_{jm}} = 0$$

where $MP^k_{jm}(\mathbf{H}_m)$ denotes the marginal variable profit associated with network type k. Taking logs yields:

$$\log(MP^k_{jm}(\mathbf{H}_m)) = \log(\omega) + \omega H^k_{jm} + \nu^k_{jm} \tag{3}$$

which is the regression we take to the data (and where $\log(\omega)$ is absorbed by the regression's intercept).

6 Identification and Estimation

In this section we discuss parameter identification in each component of the model and present our estimation results.

[16] Our functional form for the marginal cost is informed by the descriptive evidence in Figure 4, Panels A and B, that shows that healthcare costs increase and decreasing rates in hospital and non-hospital network breadth.

[17] 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.

[18] For simplicity, we do not model the dynamic decision of choosing 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 hospital and non-hospital network breadth.

6.1 Insurer Demand

Identification. Two sources of endogeneity may bias our demand estimates. First, unobserved health status may be correlated with both plan choice and out-of-pocket costs: individuals with worse unobserved health may select into insurers with broader networks and incur higher out-of-pocket costs conditional on enrollment, which may attenuate both the estimated disutility of out-of-pocket costs and the preference for network breadth. Second, insurers may design their hospital and non-hospital networks in response to the unobserved demand composition of the local market, creating a correlation between network breadth and the individuals' logit shocks. For instance, if insurers expand hospital coverage in higher-income or healthier neighborhoods, then the estimated preference for network breadth may be biased.

We address the endogeneity of out-of-pocket costs and network breadth through a control function approach, using Hausman-style instruments constructed from the insurer's behavior in other markets. Specifically, we instrument each variable with the insurer's average out-of-pocket costs, hospital and non-hospital network breadth, respectively, across all municipalities excluding the focal market. The identifying assumption is that local demand shocks are uncorrelated across markets conditional on controls. To maximize the number of markets available for constructing the instruments and to strengthen the exclusion restriction, we use data from all municipalities in the country rather than restricting to the 13 largest. We additionally instrument hospital network breadth with the number of competing insurers in the focal market, which shifts network design through the degree of insurer competition.

Results. We estimate the demand model on a 10% random sample of continuously enrolled individuals residing in the 13 largest municipalities for dimensionality reasons. Table 2, column (1) reports naïve estimates without correcting for endogeneity, and column (2) presents our main specification with control functions. Appendix Table 2 presents first-stage estimates, where we see that our instruments are strongly correlated with the endogenous variables.

TABLE 2: Insurer Demand Model

		(1) No CF		(2) Main	
		coef	se	coef	se
Hospital network breadth		2.359	(0.045)	9.926	(0.291)
Non-hospital network breadth		4.019	(0.053)	4.499	(0.190)
OOP spending		-9.397	(0.091)	-5.279	(0.220)
Incumbent		2.235	(0.007)	2.235	(0.014)
Incumbent SC		0.536	(0.016)	0.191	(0.032)
Hospital network breadth	× Male	0.014	(0.028)	0.015	(0.047)
	× Age	-0.015	(0.001)	-0.016	(0.002)
	× Cancer	0.505	(0.057)	0.391	(0.110)
	× Diabetes	1.304	(0.107)	1.032	(0.189)
	× Cardiovascular	1.254	(0.045)	1.122	(0.079)
	× Pulmonary	0.936	(0.149)	0.594	(0.265)
	× Renal	1.165	(0.185)	1.075	(0.379)
	× Other disease	1.168	(0.069)	0.979	(0.114)
Non-hospital network breadth	× Male	-0.249	(0.033)	-0.144	(0.070)
	× Age	-0.009	(0.001)	-0.006	(0.002)
	× Cancer	-1.689	(0.067)	-1.586	(0.159)
	× Diabetes	-1.309	(0.120)	-1.365	(0.242)
	× Cardiovascular	-1.271	(0.052)	-1.351	(0.098)
	× Pulmonary	-0.925	(0.178)	-0.895	(0.399)
	× Renal	-1.710	(0.218)	-2.277	(0.461)
	× Other disease	-1.617	(0.082)	-1.447	(0.140)
OOP spending	× Male	-0.788	(0.034)	-0.780	(0.072)
	× Age	0.002	(0.001)	-0.012	(0.002)
	× Cancer	10.250	(0.090)	4.306	(0.205)
	× Diabetes	10.957	(0.108)	4.894	(0.230)
	× Cardiovascular	10.680	(0.085)	5.738	(0.209)
	× Pulmonary	9.978	(0.106)	4.206	(0.267)
	× Renal	9.552	(0.091)	3.700	(0.226)
	× Other disease	10.427	(0.089)	5.665	(0.222)
Incumbent	× Male	0.012	(0.004)	0.021	(0.007)
	× Age	0.022	(0.000)	0.022	(0.000)
	× Cancer	-0.042	(0.008)	-0.020	(0.015)
	× Diabetes	-0.057	(0.016)	-0.061	(0.032)
	× Cardiovascular	-0.146	(0.007)	-0.130	(0.015)
	× Pulmonary	-0.381	(0.022)	-0.373	(0.052)
	× Renal	-0.085	(0.030)	-0.075	(0.062)
	× Other disease	0.151	(0.010)	0.169	(0.019)
CF OOP spending				3.707	(0.062)
CF OOP spending^2				-1.156	(0.198)
CF Hospital network				-7.443	(0.283)
CF Hospital network^2				0.984	(0.113)
CF Provider network				-0.706	(0.154)
CF Provider network^2				-3.853	(0.174)
N		16403317		16304161	
Pseudo-R^2		0.520		0.522	

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 largest municipalities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales, Pereira, Cúcuta, Pasto, Ibagué, Montería, Cartagena, and Villavicencio. Column (1) presents the model without instruments. Column (2) presents the model with instruments for OOP spending, and hospital and non-hospital network breadth implemented through a control function. Specifications include insurer, insurer-by-age group, insurer-by-diagnosis, and insurer-by-sex fixed effects. Robust standard errors in parenthesis for column (1) and bootstrap standard errors in parenthesis in column (2) based on 50 resamples of choice occasions.

Consistent with the endogeneity concerns discussed above, the naïve estimates are attenuated toward zero for hospital and non-hospital network breadth. Control function coefficients at the bottom of the table are also statistically significant, confirming that network breadth and out-of-pocket costs are endogenous.

Focusing on column (2), we find that consumers on average have strong preferences for broader hospital and non-hospital networks and experience significant disutility from higher out-of-pocket costs. The implied average elasticity of insurer demand with respect to the out-pocket cost is -0.41. Individuals with chronic diseases have much stronger preferences for hospital network breadth than their healthier counterparts, and positive but weaker preferences for non-hospital network breadth.

Patients are nearly twice more likely to choose the insurer they were enrolled with in the previous year. This inertia reflects primarily preference heterogeneity rather than state dependence, since the interaction coefficient between the inertia indicator and being a previous SaludCoop enrollee is positive and significant.[19] Monetizing the overall inertia estimate (using $-\frac{\hat{\lambda}_\theta}{\hat{\alpha}_\theta}$) yields a median switching cost of 0.52 million pesos (slightly under one monthly minimum wage in 2016 or \$171).

Table 3 summarizes our estimates of consumers' willingness-to-pay (wtp) for a 10 percentage point increase in hospital and non-hospital network breadth (computed as $-\frac{10}{\alpha_\theta}\frac{\partial s_{ijm}}{\partial H^k_{jm}}$ and taking into account the dependence of out-of-pocket costs to network breadth) and for remaining with their incumbent insurer (computed as $-\frac{\hat{\lambda}_\theta}{\hat{\alpha}_\theta}$). Consumers with chronic conditions are willing to pay between two and eight times more than healthy consumers to remain with their incumbent insurer. They also place a higher value on broader hospital networks but not on broader non-hospital networks relative to healthy consumers, as seen in columns (2) and (3), respectively.

Columns (4) and (5) report the ratio of wtp for remaining with the incumbent insurer to wtp for hospital and non-hospital networks, respectively. Among individuals with chronic conditions, the value of remaining with the incumbent insurer is large relative to the value of a significant improvement in hospital and non-hospital network breadth,

[19] The reason why SaludCoop enrollees would be less likely to switch in 2017 is because their 2016 choice reflects their preferences for network breadth.

suggesting that inertia is the dominant force governing their insurer choices. Among individuals without chronic conditions, the relative value of inertia is smaller, indicating that this group is more willing to switch insurers in exchange for broader networks, and especially for broader non-hospital network access. Appendix Table 3 confirms that the demand model fits the data well in-sample.

TABLE 3: Switching Cost and Willingness-to-Pay for Networks

	WTP remain w/ same insurer (1)	WTP hospital network (2)	WTP non-hosp network (3)	WTP ratio hospital network (4)	WTP ratio non-hosp network (5)
Cancer	2.108	0.653	0.196	3.229	10.762
Cardiovascular	3.722	1.561	0.465	2.385	8.001
Diabetes	2.003	0.698	0.212	2.870	9.429
Pulmonary	1.822	0.516	0.169	3.532	10.778
Renal	1.161	0.306	0.088	3.787	13.150
Other disease	4.446	1.543	0.436	2.881	10.204
No disease	0.522	0.273	0.130	1.913	4.004

Note: Table shows the median willingness to pay to remain with the same insurer in column (1), the median willingness-to-pay for a 10 percentage point increase in hospital network breadth in column (2), the median willingness-to-pay for a 10 percentage point increase in non-hospital network breadth in column (3), and the average ratio between columns (1) and (2) and between columns (1) and (3), in columns (4) and (5) respectively. All measures of willingness to pay are in millions of pesos per capita.

6.2 Insurer Marginal Costs

Identification. Given the richness and size of our data, we can calculate insurers' marginal costs as the average healthcare cost across all individuals who are of type θ. We then estimate the marginal cost function using a poisson pseudo-likelihood regression on the sample of all continuously enrolled individuals residing in *any* municipality (Wooldridge, 2023).[20]

The main identification challenge is unobserved patient selection into insurers based on network breadth. For example, unobservably sicker consumers within a given consumer type may choose insurers with broader hospital and non-hospital networks, which would bias our estimates of τ_1^k upward. However, our consumer type definition is sufficiently rich to largely address this concern. By combining sex, age group, and diagnosis, we

[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.

define 168 distinct consumer types whose average costs we use as the dependent variable. Within each type, the remaining variation in health status that could drive selection is limited. To verify the direction of the bias, we estimate two versions of the marginal cost function: one that excludes consumer type fixed effects and one that includes them. If unobserved selection is the primary source of bias, the coefficient on network breadth should be larger in the specification without consumer type fixed effects.

Results. Table 4 presents the results. Column (1) excludes consumer type fixed effects and column (2) includes them. Both specifications include an indicator for whether the market has no hospitals, since hospital network breadth is mechanically zero in those markets. Comparing the two columns reveals the direction of the bias from unobserved selection. The coefficients on hospital network breadth and the interaction between network types are stable across columns. By contrast, the coefficient on non-hospital network breadth flips sign and shrinks towards zero, consistent with the upward bias from unobserved selection.

Focusing on column (2), insurers' marginal costs are increasing in hospital network breadth but decreasing in non-hospital network breadth. Insurers also enjoy economies of scope as evidenced by the negative and precisely estimated coefficient on the interaction between the two network types. On average, a one percentage point increase in hospital network breadth raises insurers' cost per enrollee by 4,400 pesos ($1.4 of 2016), based on the average marginal effect reported at the bottom of the table. Appendix Figure 3 presents the in-sample fit of the marginal cost model and Appendix Figure 4 provides further evidence of adverse selection, showing that the marginal cost of expanding hospital network breadth is positively correlated with consumers' willingness to pay for it, while the correlation is considerably weaker for non-hospital network breadth.

6.3 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,

TABLE 4: Insurer Marginal Cost Model

	Average cost per consumer type	
Variable	(1)	(2)
Hospital network breadth	0.108	0.132
	(0.023)	(0.022)
Non-hospital network breadth	0.102	-0.031
	(0.018)	(0.017)
Hospital network × Non-hospital network	-0.152	-0.190
	(0.038)	(0.036)
No hospitals in market	-0.066	-0.019
	(0.040)	(0.038)
Constant	0.562	0.970
	(0.028)	(0.026)
Hospital avg. marginal effect	0.038	0.044
Non-hospital avg. marginal effect	0.102	-0.137
Consumer type FE	No	Yes
Market FE	Yes	Yes
Insurer FE	Yes	Yes
N	967116	967116
Pseudo-R^2	0.047	0.254

Note: Table presents non-linear least squares regression of average costs per consumer type. An observation is a consumer type-insurer-municipality-year. Column (1) includes market and insurer fixed effects. Column (2) additionally includes consumer type fixed effects. Estimation uses data from 2013 to 2017 from all municipalities in the country. The bottom of the table reports the average marginal effect of a 1 percentage point increase in hospital and non-hospital network breadth. Robust standard errors in parenthesis.

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 full sample of individuals in the 13 largest municipalities (independent of their enrollment spell lengths). Their summary statistics are presented in Appendix Tables 4 and 5.

6.4 Insurer Fixed 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' fixed costs. However, since we have multiple years of data, our model is over-identified for these parameters. In other words, equation (3) represents a system of $J \times M \times K$ equations in the same number of unknowns, but we have $J \times M \times K \times T$ data points.

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.[21] 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 from Tables 2 and 4. 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.[22]

After simulating insurers' marginal and total variable profits, we estimate the fixed cost parameters using the FOCs.[23] In all markets, marginal variable profits are positive (see in Appendix Table 6), suggesting fixed costs play a role in our characterization of insurers' decisions to offer network breadth.

TABLE 5: Insurer Fixed Cost Model

Variable	Log marginal variable profits	
	Hospital	Non-hospital
	(1)	(2)
Network breadth	1.634	4.991
	(0.732)	(1.303)
Constant	11.934	10.196
	(0.597)	(0.731)
Insurer FE	No	Yes
Market FE	Yes	Yes
N	85	85
R^2	0.519	0.759

Note: Table presents OLS regression of log marginal variable profits on hospital network breadth and non-hospital network breadth in columns (1) and (2), respectively. An observation in these regressions is an insurer-market. The specification in column (1) includes market fixed effects and the specification in column (2) additionally includes insurer fixed effects. Robust standard errors in parenthesis.

Results. Table 5 presents the results separately for hospital and non-hospital networks. For both network types, the coefficient on network breadth is positive and statistically significant, indicating that fixed costs increase with network breadth and deter insurers

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

[22] Dropout probabilities depend mostly on the likelihood of becoming unemployed rather on insurers' network breadth and in Appendix Table 1 we showed that transition probabilities across diagnoses are statistically unrelated to network breadth at the 5% level.

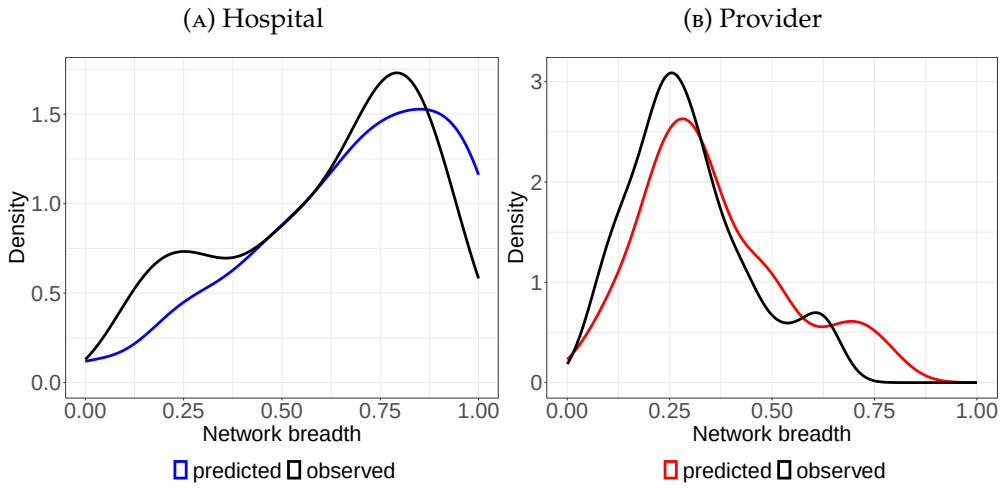
[23] We do not use the data on insurers' total administrative costs for this estimation because the information is aggregated to the national level and only varies over years.

from expanding their networks indefinitely. The effect is considerably larger for non-hospital than for hospital networks, consistent with the descriptive evidence in Figure 4 showing that fixed costs per capita rise more steeply with non-hospital network breadth. This finding reflects the higher administrative burden of contracting with individual providers to form a broad non-hospital network.

6.5 Out-of-sample Fit

To evaluate the model's out of sample fit, we simulate insurers' network breadth choices in 2016 under the government-mandated enrollment rule that reassigned SaludCoop enrollees to Cafesalud. For these enrollees, we assume that $y_{ijm,t-1} = 1$ when assigned to Cafesalud.[24] Figure 6 compares the observed distribution of hospital and non-hospital network breadth (in black) with the model's predictions (in blue and red). The model closely replicates insurer's actual choices with slight over-predictions for both types of networks.

FIGURE 6: Out-of-sample Prediction of Network Breadth



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

[24]This assumption is reasonable given that, during the 90-day grace period, the government required Cafesalud to maintain the same provider network as SaludCoop.

6.6 Robustness Checks

We conduct several robustness checks on our estimation. Appendix Tables 7 and 8 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 the demand model. In the marginal cost model, the coefficients are more sensitive though the qualitative pattern underlying our counterfactuals is preserved (marginal costs rise with hospital breadth, fall with non-hospital breadth, and exhibit economies of scope between the two). Thus, we view the first-year definition as a conservative bound in the counterfactuals.

6.7 Adverse Selection and Inertia

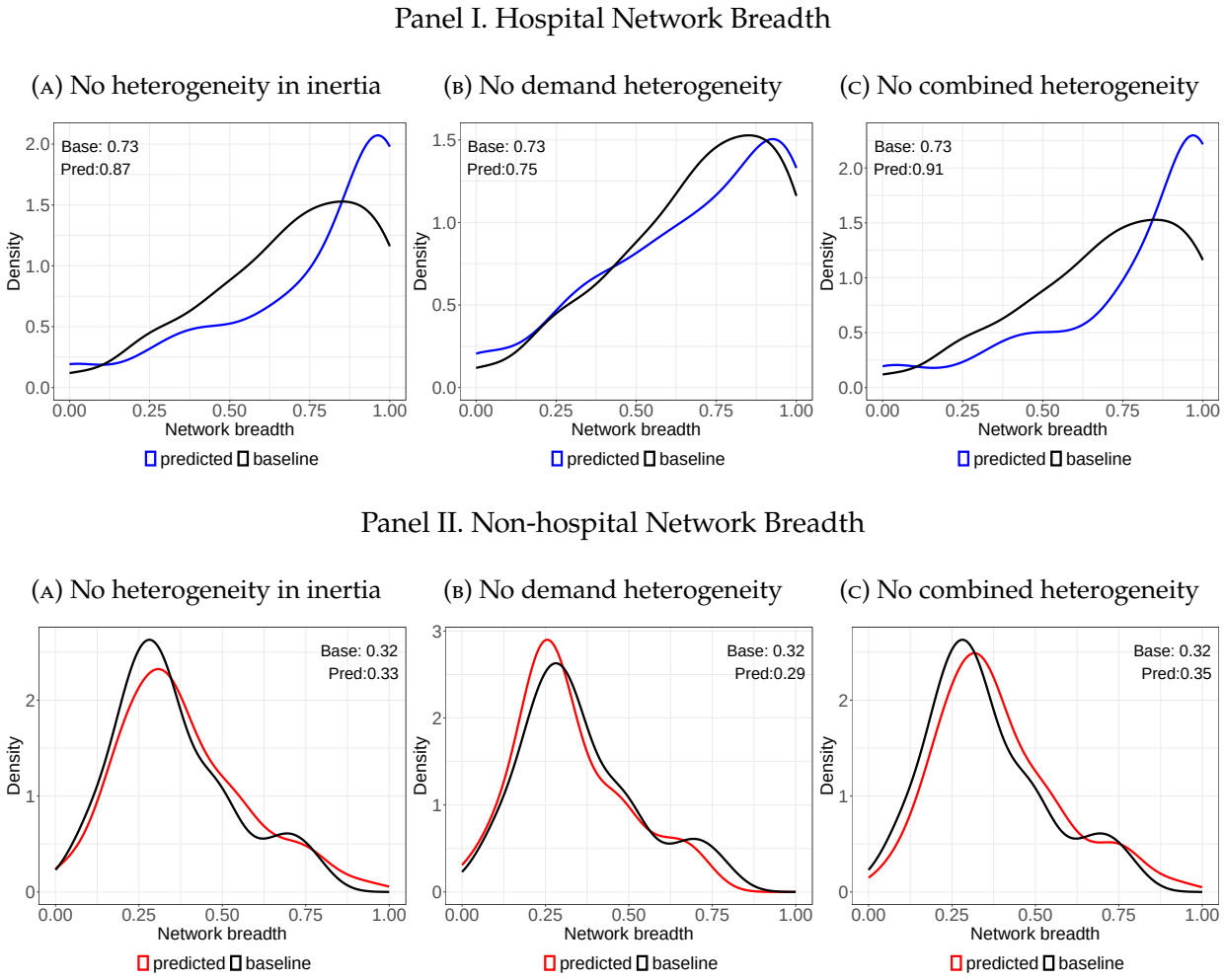
Before examining counterfactual enrollment rules, we use our model estimates to assess how each mechanism – inertia and adverse selection – independently impacts equilibrium network breadth. In Figure 7 we present three sets of results. Panel A shows the counterfactual distribution of network breadth after we eliminate heterogeneity in the value of inertia, setting $\lambda_\theta = \lambda$ in equation (1).[25] In this case, consumers with chronic conditions would become less likely to switch relative to the scenario with full heterogeneity (presented in black and labelled "baseline"), since their baseline λ_θ are smaller. We find that the distributions of network breadth shift to the right. Average hospital network breadth increases by 19% and average non-hospital network breadth by 3%, suggesting that insurers respond to relatively greater switching of healthy consumers by expanding their networks.

Panel B presents the counterfactual distribution of network breadth after we reduce adverse selection by eliminating heterogeneity in network preferences across consumers, setting $\beta^k_\theta = \beta^k$ in equation (1). Homogenizing preferences raises the average willingness to pay for hospital networks – which sick consumers value more – while lowering it

[25] 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.

for non-hospital networks – which healthy consumers value more. This has opposing implications for insurers' network decisions: hospital network expansion becomes more attractive since it no longer disproportionately attracts high-cost sick consumers, while non-hospital network expansion becomes less attractive since the average demand for it falls. In line with this intuition, we find that hospital network breadth increases by 3% relative to the baseline scenario while non-hospital network breadth falls by 9%.

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



Note: Figure presents the counterfactual (in blue and red) and full-heterogeneity baseline (in black) distribution of hospital network breadth (Panel I) and non-hospital network breadth (Panel II). 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.

Together, these results indicate that alleviating adverse selection and inertia have op-

posing effects on equilibrium network breadth, with inertia generally dominating in our setting. In Panel C, where we eliminate both the heterogeneity in inertia and in network preferences, we find that network breadth for both types increase 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.

7 Counterfactual Automatic Enrollment Rules

7.1 Setup

We compare alternative enrollment rules after SaludCoop's termination along the dimensions of 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:[26]

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

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 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.

[26]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.

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

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 network breadths in 2015, we compute the FOCs for each insurer and market. From these FOCs, we solve for network breadth as $H_{jm}^k = (\log(MP_{jm}^k) - \hat{v}_{jm}^k)/\tilde{\omega}^k$, which we then use as starting point in the next iteration. We iterate until the maximum residual network breadth by absolute value is less than 10^{-4}. In counterfactuals, the solution to this set of equations is likely unique given the rich preference and cost heterogeneity across insurers, but a direct proof of uniqueness is challenging.

7.2 Predictions

To predict how each enrollment rule will affect equilibrium network breadth, we characterize whether healthy or sick consumers will be likely to switch in each scenario.

Specifically, we compute, among SaludCoop enrollees in the first year following reassignment, the covariance between a measure of switching propensity and a measure of per capita profit that captures heterogeneity by health status but abstracts from network breadth. A positive covariance would indicate that the rule induces greater switching among higher-profit individuals. Hence, insurers will expand their networks to attract them. Conversely, a negative covariance would imply that lower-profit individuals are more likely to switch, and insurers will reduce network breadth to avoid attracting them.

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

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

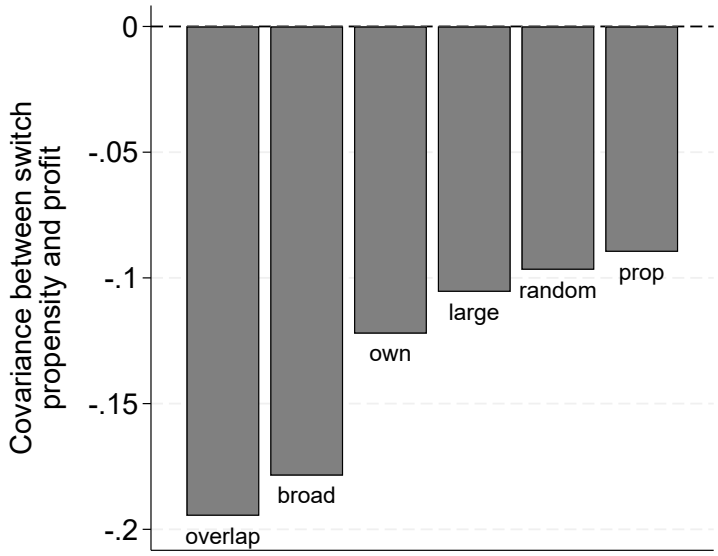
Intuitively, if the match value with SaludCoop is higher than the match value with the assigned insurer, the individual will be more likely to switch; and this effect is amplified if the consumer has relative low value of inertia.

We calculate the per capita profit abstracting from provider networks, as:

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

Figure 8 shows a clear ranking of the enrollment rules in terms of the covariance between p_i and π_i. All rules generate a negative covariance, indicating that consumers who are more likely to switch tend to be less profitable. However, the two rules with a random assignment component – where mismatches between consumers and their assigned insurer are most likely – produce the least negative covariances, meaning they disproportionately induce switching among relatively more profitable consumers. Thus, assignment rules with random components are more likely to increase network breadth in equilibrium, while rules based on network overlap, broadest network, or own choice would tend to reduce network breadth.

FIGURE 8: Covariance Switching Metric



Note: Figure shows the covariance between the switching propensity and the marginal cost in absence of 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 $H_{jm} = 0$.

7.3 Results

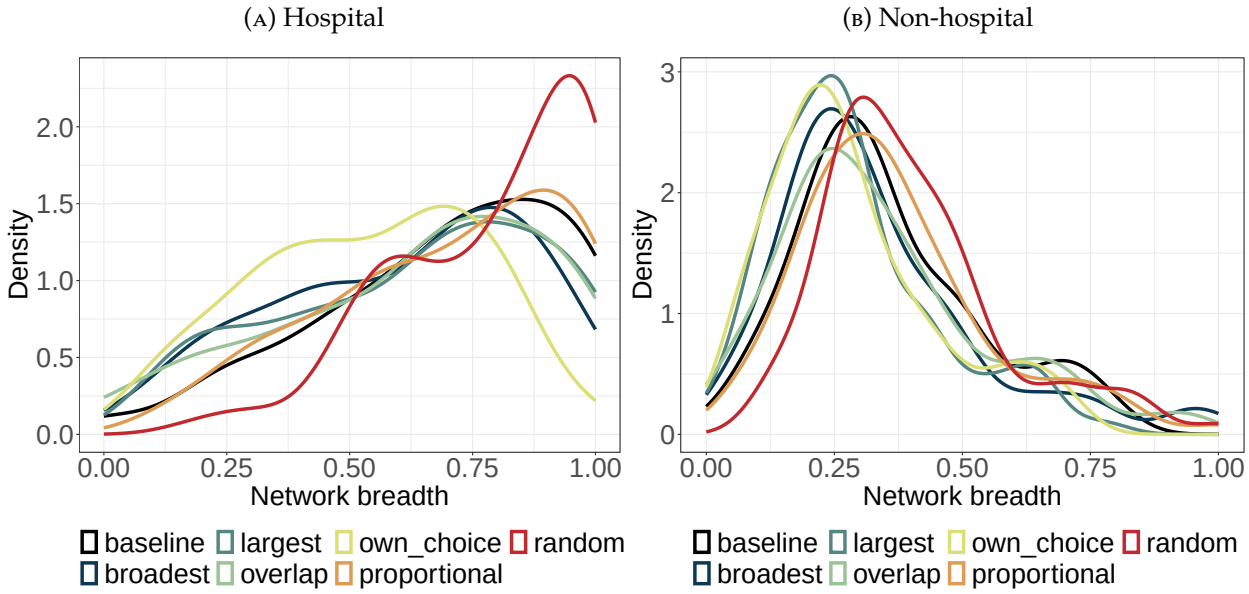
Figure 9 presents the counterfactual distribution of hospital network breadth in Panel A and non-hospital network breadth in Panel B under each enrollment rule. In line with our predictions in the previous subsection, rules with random assignment components increase both types of network breadth relative to the baseline scenario, while other rules generate distributions that are largely indistinguishable from the baseline scenario or worse, particularly the own-choice rule.

Under random enrollment, both types of network breadth increase by 14% relative to baseline. Weighting by demand, the increases equal 5% and 10% for hospital and non-hospital networks respectively, suggesting that the gains are concentrated among insurers with smaller market shares as seen in Appendix Figure 6. Proportional enrollment generates the second largest unweighted increases, with hospital and non-hospital network breadth rising by 1% and 6% respectively.

By contrast, allowing consumers to choose their health plan freely without a default

insurer minimizes the pool of profitable consumers willing to switch, weakening competition and reducing hospital and non-hospital network breadth by 23% and 20% respectively relative to the baseline scenario. The own-choice rule thus generates the worst equilibrium outcomes across both network dimensions, highlighting that free consumer choice is not always welfare-enhancing in the presence of inertia when supply-side responses are taken into account.

FIGURE 9: Counterfactual Network Breadth



Note: Figure presents the distribution of hospital and non-hospital network breadth under each enrollment rule. We depict the model's prediction of the observed assignment rule in black, labelled "baseline."

Table 6 summarizes other outcomes of interest. Column (1) reports consumer surplus without allowing insurers to respond endogenously to the rules, while column (2) reports consumer surplus allowing for endogenous network breadth supply responses. Columns (3) through (7) report average marginal costs, adverse selection on hospital and non-hospital networks, and hospital and non-hospital network breadth respectively, all allowing for endogenous supply responses.

The ranking of enrollment rules based on consumer surplus in column (1) differs markedly from the ranking in column (2). Random enrollment appears to be among the worst rules holding the supply side fixed, but generates the highest consumer surplus – an increase of 9% relative to the observed scenario – when insurers are allowed to

respond endogenously. This highlights one of our model's main contribution: failing to account for supply-side responses leads to fundamentally different conclusions about which enrollment rules improve consumer welfare.

Table 6: Outcomes Under Counterfactual Enrollment Rules

Scenario	Cons. surplus No supply (1)	Consumer surplus (2)	Marginal cost (3)	Selection on hospitals (4)	Selection on non-hospital (5)	Hospital network (6)	Non-hospital network (7)
baseline	—	5.241	0.441	0.447	0.416	0.831	0.341
random	5.176	5.699	0.451	0.439	0.408	0.874	0.376
proportional	5.209	5.305	0.525	0.443	0.392	0.808	0.350
largest	5.203	4.992	0.496	0.494	0.477	0.767	0.296
broadest	5.230	4.924	0.515	0.449	0.374	0.757	0.333
overlap	5.265	5.231	0.503	0.448	0.383	0.757	0.344
own choice	4.891	3.889	0.465	0.444	0.397	0.656	0.293

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. Columns (4) present the correlation between willingness-to-pay for hospital networks and marginal costs. Column (5) presents the same measure as (4) but for non-hospital networks. Columns (6) and (7) present the demand-weighted hospital and non-hospital 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.

Random enrollment not only outperforms other rules in terms of consumer surplus but also reduces adverse selection on hospital networks relative to the baseline scenario, as seen in column (4), and generates the lowest increase in healthcare spending per capita. The proportional rule performs second best in terms of consumer surplus, increasing it by 1% relative to the baseline scenario, while also reducing adverse selection on non-hospital networks. Instead, the largest and broadest rules, which assign consumers to the insurer with the largest market share or broadest hospital network, reduce consumer surplus relative to the baseline scenario despite appearing more targeted, because under these rules match values are relatively high for the majority of consumers, giving weaker incentives for insurers to compete on network breadth.

The own-choice rule generates the largest reduction in consumer surplus, falling 26% relative to the baseline scenario, as well as the narrowest hospital and non-hospital networks. These results reflect two reinforcing mechanisms: first, utility is mechanically lower because without a default insurer consumers do not experience the welfare gains from inertia during the first year of enrollment (the inertia indicator equals zero in the first year); second and more importantly, the absence of a default insurer disproportionately

encourages switching among sick consumers who value hospital networks most, giving insurers incentives to narrow their networks.

7.4 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 3 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 hospital network breadth more than healthy ones, in relative terms, sick consumers value a 10 percentage point increase in hospital network breadth less than what they value remaining with their incumbent insurer (see columns 1 and 2 of Table 3). This suggests that by expanding their networks insurers will attract more healthy consumers than sick ones.

Figure 10, Panel A confirms these predictions: switching rates out of the assigned insurer are higher under random enrollment than under all other rules, particularly among healthy consumers.[27] Importantly, healthy consumers switch at higher rates than sick consumers under every rule, but the gap is largest under random enrollment.

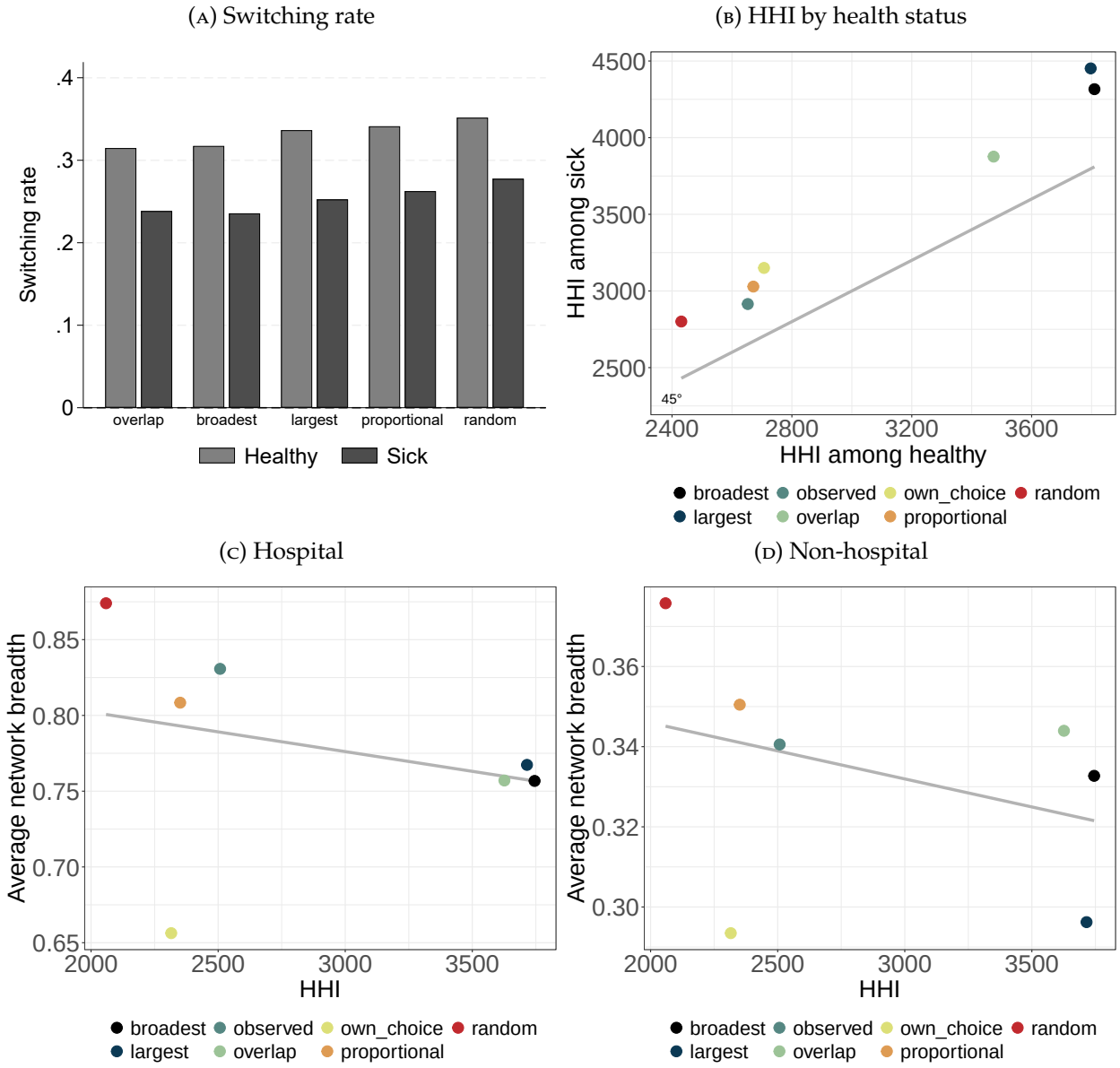
In terms of adverse selection, random enrollment spreads the health risk more evenly across insurers because sick consumers are more likely to stick with their assigned health plan. Therefore, we can expect insurer market concentration among sick patients to be lower than under other enrollment rules.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

Panels C and D connect these concentration patterns to network breadth outcomes. Automatic enrollment rules that generate lower HHI are associated with broader hospital and non-hospital networks, while rules that increase market concentration are associated

[27] We omit the own-choice and observed rules since switching rates are mechanically equal to one in both cases. In the own-choice rule we consider the "assigned" insurer to be SaludCoop, hence naturally everyone switches out. In the observed rule, among the continuously enrolled, all SaludCoop enrollees end up leaving Cafesalud.

with narrower networks.

FIGURE 10: The Role of Consumer Inertia and Selection in Insurer Competition



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 conditional on individuals without diseases ("healthy") against average HHI conditional on individuals with chronic diseases ("sick"). The gray line is the 45 degree line. Panel C presents a scatter plot of average HHI across markets against average hospital network breadth across insurers and markets for each enrollment rule and Panel D against average non-hospital network breadth. The dashed gray line corresponds to a linear fit.

Who switches has important implications for equilibrium outcomes. Under the own-choice rule, all SaludCoop consumers shop for a new insurer in the first year after the termination since there is no incumbent relationship to generate inertia, and network

breadth disproportionately attracts sick consumers who value hospital access most, hence insurers reduce network breadth. Indeed, in prior work (Buitrago et al., 2025), we showed that when sick consumers are the marginal switchers, insurers drop high-cost providers specializing in chronic care (such as public hospitals and cancer centers), possibly to minimize costs and deter further enrollment of unprofitable patients. This explains why the own-choice rule generates the narrowest networks in equilibrium despite giving consumers the most freedom to choose.

7.5 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 network breadth and consumer surplus implies that the dynamic consequences of inertia can be reversed with short-run policies. Random enrollment essentially nudges consumers into 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, holding health plan offerings fixed.

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, in a setting with automatic enrollment rules which encourage some consumers to actively choose their plan after the initial assignment, we predict that equilibrium outcomes will reflect the preferences and profitability of those consumers. This prediction generalizes to other settings, including ones where insurers also compete on premiums.

8 Conclusions

This paper shows automatic enrollment in health insurance impacts insurer competition and long-run equilibrium outcomes by determining which consumers are more likely

to switch after reassignment. To test this we use data from Colombia's contributory healthcare system where insurers compete mainly on their network of covered hospitals and non-hospital 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 smaller incumbent insurer.

To compare counterfactual enrollment rules after the termination, we propose and estimate an equilibrium model of insurer competition on hospital and non-hospital network breadth. We find that enrolling patients randomly to incumbent insurers in equal proportions is effective at increasing consumer welfare and both types of 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 leads to different conclusions about the rules that improve consumer welfare.

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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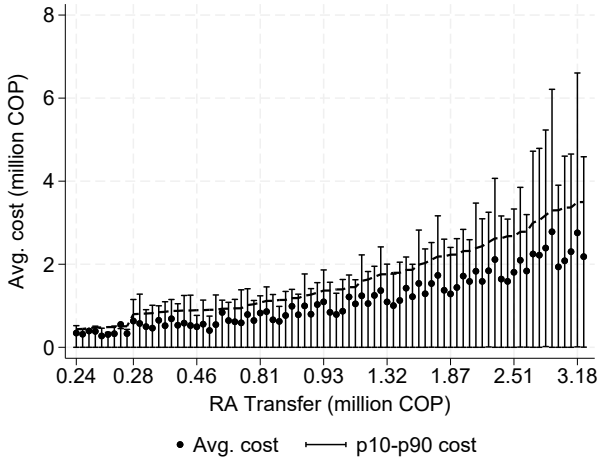
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Supplemental Appendix

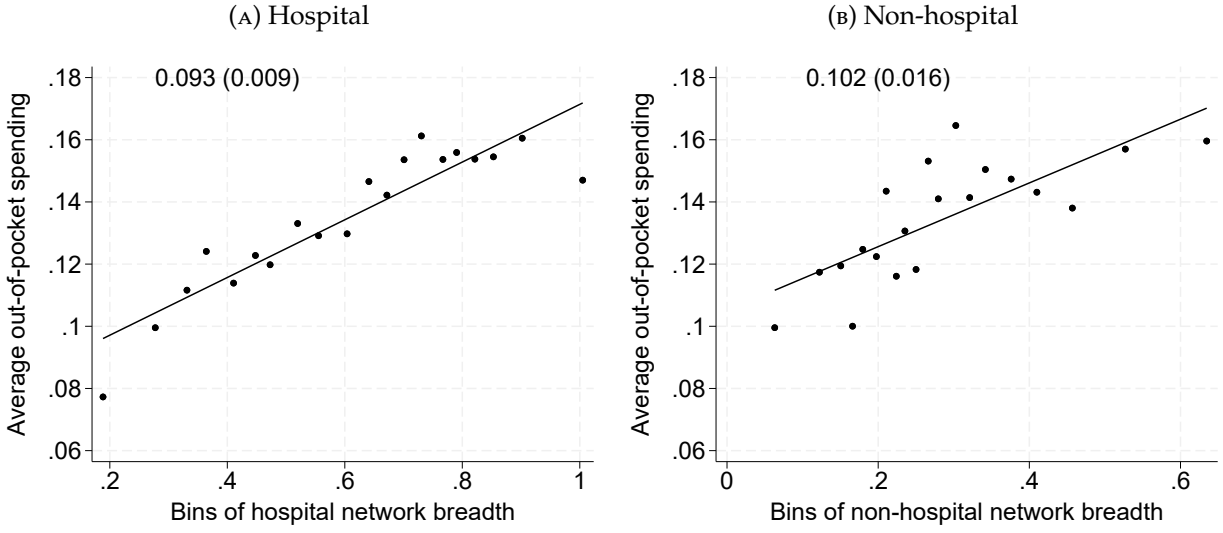
Appendix A Additional Descriptives and Results

Appendix Figure 1: Risk-Adjustment Fit Among Continuously Enrolled



Note: Figure presents the mean (black circles), and the 10th and 90th percentiles (error bars) of healthcare cost per risk-adjusted transfer among the continuously enrolled. The dashed line is the 45 degree line.

Appendix Figure 2: Correlation Between Out-of-Pocket Costs and Network Breadth



Note: Figure presents a scatter plot of the average hospital and non-hospital network breadth by 20 equally sized bins of the average Charlson index. To construct this figure, we aggregate our preferred sample to the insurer-market-year level, calculating average Charlson index and hospital and non-hospital network breadth. Then, we calculate 20 equally sized bins of the Charlson index. Finally, we compute the average of each type of network breadth per bin. Solid lines represent linear fits.

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

	Any diagnosis
Hospital network breadth	0.148
	(0.076)
Non-hospital network breadth	-0.138
	(0.090)
Constant	0.147
	(0.041)
Insurer FE	Yes
Municipality FE	Yes
Year FE	Yes
Observations	1371744
R^2	0.0274

Note: Table presents OLS regression of an indicator for having any chronic disease on hospital and non-hospital network breadth. Specification includes insurer, municipality, and year fixed effects. Estimation uses the random sample for model estimation conditional on observed choices and consumers who did not have a chronic disease in $t-1$. Standard errors in parenthesis are clustered at the insurer-market level.

Appendix Table 2: First-Stage Regressions of Demand

	OOP spending	Hospital network	Non-hospital network
	(1)	(2)	(3)
OOP spending in other markets	1.286	0.313	0.088
	(0.018)	(0.108)	(0.076)
Hospital network breadth in other markets	0.505	-0.402	0.741
	(0.087)	(0.512)	(0.363)
Number of competitors in other markets	0.001	-0.003	0.003
	(0.000)	(0.003)	(0.002)
Non-hospital network breadth in other markets	0.003	0.086	0.396
	(0.027)	(0.158)	(0.112)
Constant	-0.061	0.581	-0.097
	(0.026)	(0.155)	(0.110)
Insurer FE	Yes	Yes	Yes
Insurer-age group FE	Yes	—	—
Insurer-male FE	Yes	—	—
Insurer-diagnosis FE	Yes	—	—
Observations	73941	464	464
R^2	0.270	0.645	0.523

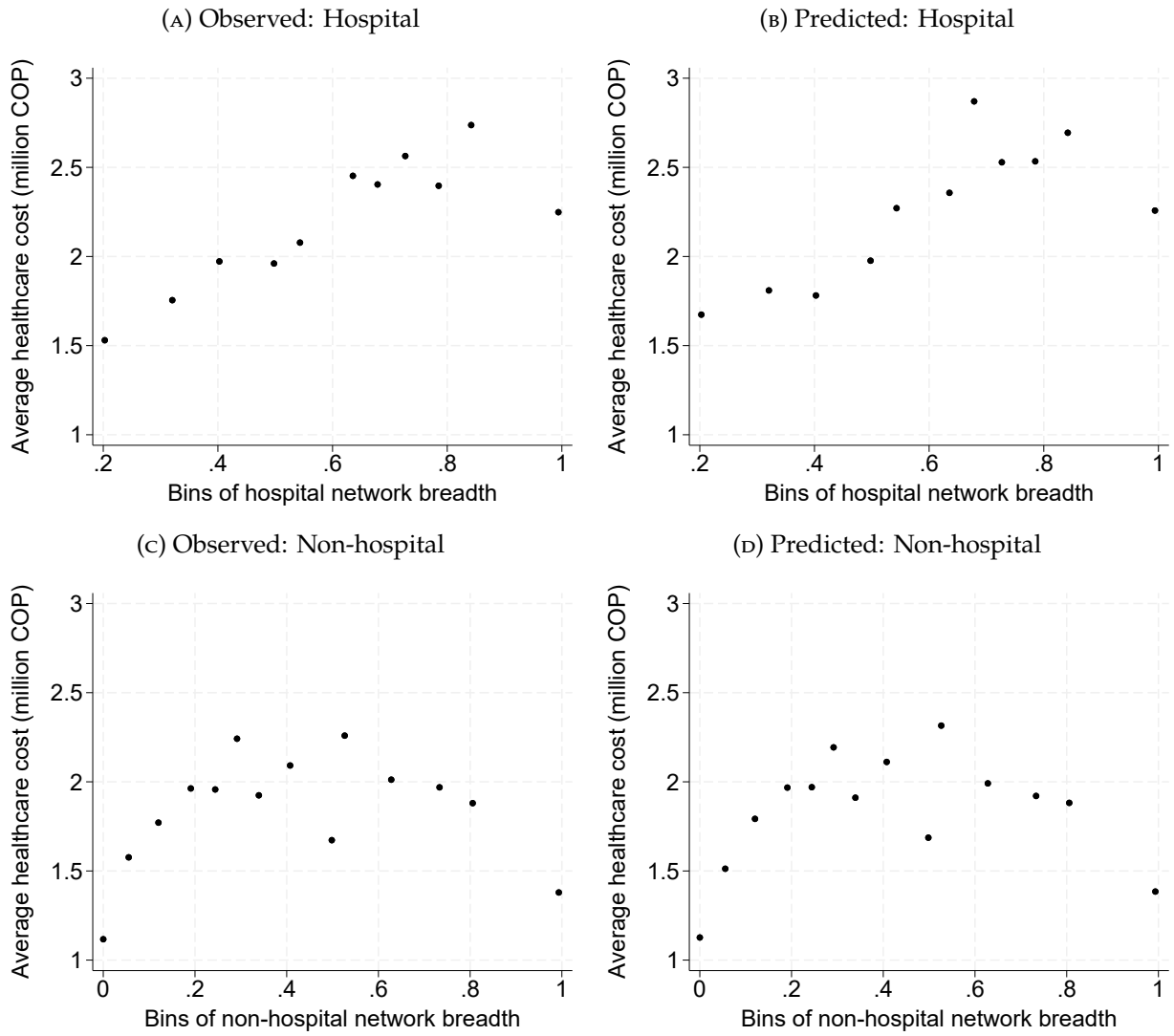
Note: Table presents the control function for out-of-pocket spending in column (1), for hospital network breadth in column (2), and for non-hospital network breadth in column (3). To estimate each regression, we collapse the insurer choice data to the level at which each variable varies: consumer type-insurer-municipality-year for out-of-pocket spending and insurer-municipality-year for network breadth. Hausman instruments (out-of-pocket spending, hospital and non-hospital network breadth in other markets) are computed using data for all the country without restricting to the 13 largest municipalities. Robust standard errors in parenthesis.

Appendix Table 3: Insurer Market Shares

	Observed	Predicted
Insurer A	1.786	1.499
Insurer B	10.979	7.995
Insurer C	7.903	6.528
Insurer D	9.495	8.057
Insurer E	8.694	7.580
Insurer G	11.875	12.632
Insurer H	1.706	1.221
Insurer I	7.921	6.737
Insurer J	10.273	9.425
Insurer K	8.803	16.846
Insurer L	3.520	4.195
Insurer M	3.653	3.143
Insurer N	13.393	14.142

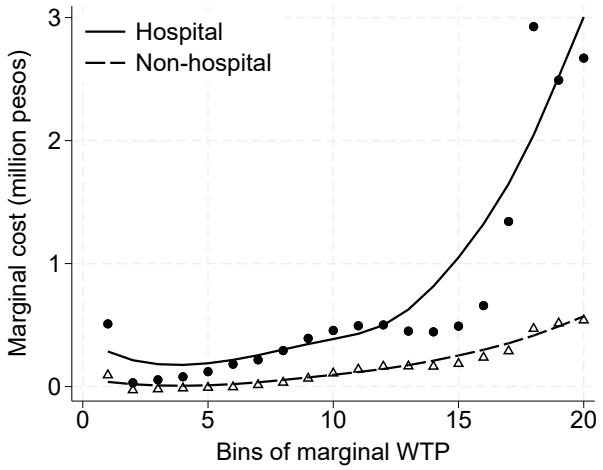
Note: Table presents observed and model predicted insurer market shares in the 13 largest municipalities using estimates from the insurer demand model. Consumers' discrete choice is simulated by drawing type-I extreme value shocks. We set the control function coefficients to zero to make these predictions.

Appendix Figure 3: Marginal Cost Model In-Sample Fit



Note: Figure presents a scatter plot of observed and predicted average cost per enrollee by 20 equally sized bins of hospital network breadth in panels A and B, and non-hospital network breadth in panels C and D.

Appendix Figure 4: Model Evidence of Adverse Selection



Note: Figure shows the insurer's short-run marginal cost in thousand of pesos $\partial C_{\theta jmt}(\mathbf{H}_{jmt})s_{ijmt}(\mathbf{H}_{mt})/\partial H^k_{jmt}$ averaged within 2-equally sized bins of consumer marginal willingness-to-pay for an additional percent in hospital and non-hospital network breadth calculated as $-\alpha_\theta^{-1}(\partial s_{ijmt}/\partial H^k_{jmt})$.

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

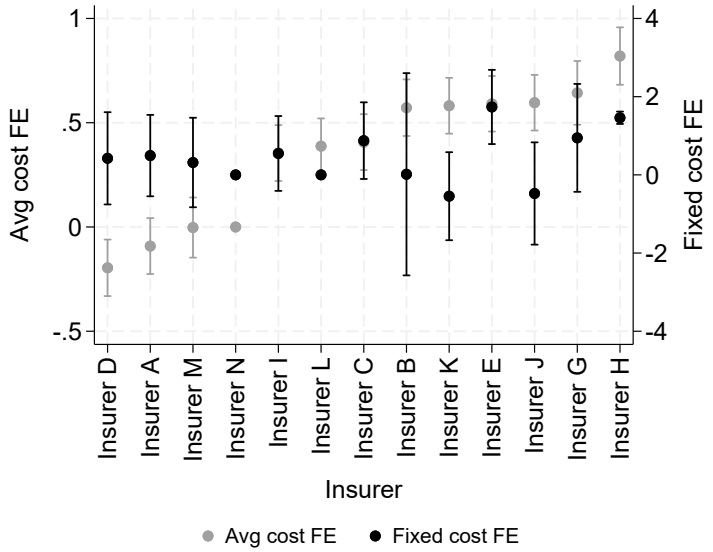
Note: Table presents mean and standard deviation in parenthesis of non-parametric estimates of the annual probability of dropping out of the contributory system. Uses data from 2013 to 2017.

Appendix Table 6: Insurer Marginal Variable Profits

Insurer	Mean	SD
Insurer A	602136	303362.6
Insurer B	360406.5	559940.7
Insurer C	246154.9	606832.6
Insurer D	292699.5	846406.8
Insurer E	2850187	833666
Insurer G	292619	320204.6
Insurer H	605339.6	218637.1
Insurer J	285505	385485.8
Insurer K	293950.2	648103.4
Insurer L	228262	372500.3
Insurer M	412356.4	530558.1
Insurer N	400681.7	509911.1

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

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 fixed cost model in black (right vertical axis).

Appendix B Robustness Checks

Appendix Table 7: Insurer Demand Model with First-Year Diagnoses

		(1) Main		(2) First diagnosis	
Variable		coef	se	coef	se
Hospital network breadth		9.926	(0.128)	9.526	(0.127)
Non-hospital network breadth		4.499	(0.087)	4.404	(0.086)
OOP spending		-5.279	(0.113)	-1.538	(0.110)
Incumbent		2.235	(0.007)	2.208	(0.007)
Incumbent SC		0.191	(0.017)	0.163	(0.017)
Hospital network breadth	× Male	0.015	(0.028)	-0.079	(0.029)
	× Age	-0.016	(0.001)	-0.007	(0.001)
	× Cancer	0.391	(0.057)	-0.311	(0.054)
	× Diabetes	1.032	(0.105)	0.236	(0.102)
	× Cardiovascular	1.122	(0.046)	0.048	(0.045)
	× Pulmonary	0.594	(0.156)	-0.527	(0.153)
	× Renal	1.075	(0.189)	0.000	(0.172)
	× Other disease	0.979	(0.069)	-0.097	(0.065)
Non-hospital network breadth	× Male	-0.144	(0.034)	-0.022	(0.035)
	× Age	-0.006	(0.001)	-0.010	(0.001)
	× Cancer	-1.586	(0.069)	-0.543	(0.066)
	× Diabetes	-1.365	(0.121)	-0.780	(0.120)
	× Cardiovascular	-1.351	(0.053)	-0.249	(0.054)
	× Pulmonary	-0.895	(0.192)	-0.114	(0.193)
	× Renal	-2.277	(0.222)	-1.587	(0.209)
	× Other disease	-1.447	(0.084)	-0.275	(0.080)
OOP spending	× Male	-0.780	(0.040)	-0.207	(0.034)
	× Age	-0.012	(0.001)	-0.015	(0.001)
	× Cancer	4.306	(0.112)	-1.868	(0.109)
	× Diabetes	4.894	(0.129)	-1.420	(0.125)
	× Cardiovascular	5.738	(0.107)	-1.462	(0.104)
	× Pulmonary	4.206	(0.131)	-1.245	(0.125)
	× Renal	3.700	(0.119)	-1.296	(0.117)
	× Other disease	5.665	(0.118)	-1.345	(0.110)
Incumbent	× Male	0.021	(0.004)	0.012	(0.004)
	× Age	0.022	(0.000)	0.023	(0.000)
	× Cancer	-0.020	(0.008)	-0.007	(0.008)
	× Diabetes	-0.061	(0.016)	-0.178	(0.015)
	× Cardiovascular	-0.130	(0.007)	-0.158	(0.007)
	× Pulmonary	-0.373	(0.022)	-0.311	(0.021)
	× Renal	-0.075	(0.030)	-0.229	(0.028)
	× Other disease	0.169	(0.010)	-0.004	(0.010)
CF OOP spending		3.707	(0.033)	3.911	(0.031)
CF OOP spending^2		-1.156	(0.103)	-0.232	(0.064)
CF Hospital network		-7.443	(0.120)	-7.173	(0.118)
CF Hospital network^2		0.984	(0.065)	1.003	(0.065)
CF Provider network		-0.706	(0.068)	-0.755	(0.067)
CF Provider network^2		-3.853	(0.105)	-4.084	(0.105)
N		16304161		16304161	
Pseudo-R2		0.520		0.520	

Note: Table presents maximum likelihood estimates of the insurer demand model using a conditional logit. Column (1) presents our main model. Column (2) present a model where 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-by-age group, insurer-by-sex, and insurer-by-diagnosis fixed effects. Robust standard errors in parenthesis.

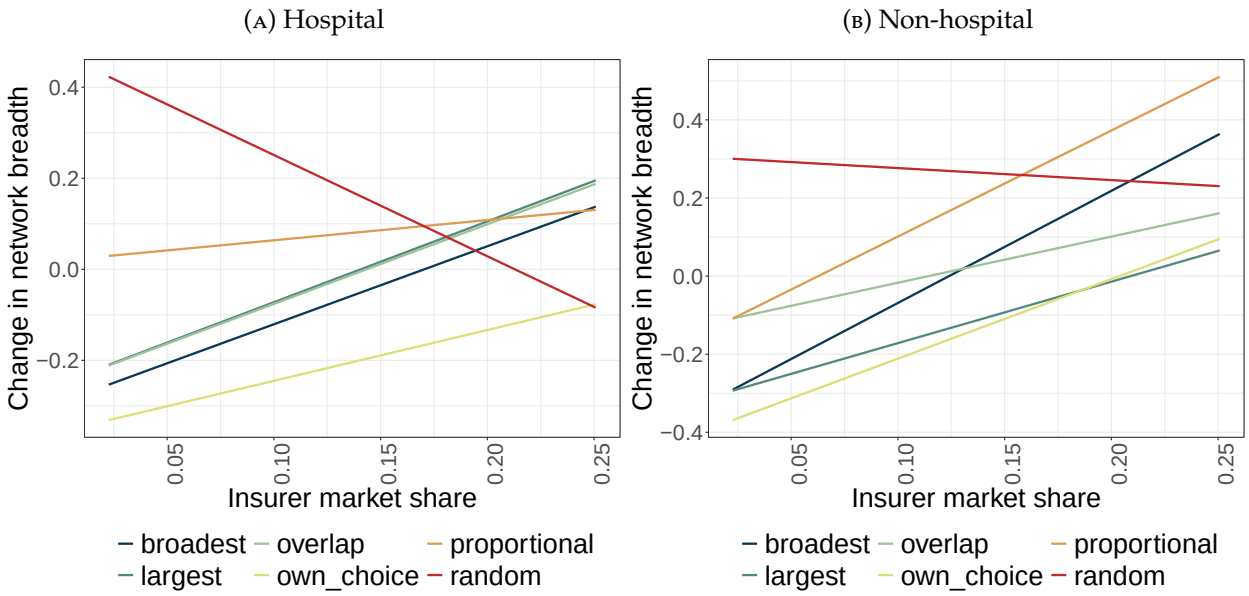
Appendix Table 8: Insurer Marginal Cost Model with First-Year Diagnosis

	(1) Main		(2) First diagnosis	
Variable	coef	se	coef	se
Hospital network breadth	0.132	(0.022)	0.037	(0.021)
Non-hospital network breadth	-0.031	(0.017)	-0.093	(0.016)
Hospital network × Non-hospital network	-0.190	(0.036)	-0.132	(0.035)
No hospitals in market	-0.019	(0.038)	-0.008	(0.045)
Constant	0.970	(0.026)	1.123	(0.029)
Insurer FE	Yes		Yes	
Consumer type FE	Yes		Yes	
Market FE	Yes		Yes	
N	967116		1006577	
Pseudo-R^2	0.254		0.278	

Note: Table presents non-linear least squares regression of average costs per consumer type. Column (1) presents the main model. Column (2) presents model in which individuals are marked as having a diagnosis if they received one in their first enrollment year. An observation is a combination of consumer type, insurer, municipality, and year. Specifications include insurer, consumer type, and municipality fixed effects. Estimation uses data from 2013 to 2017 from all municipalities in the country. Robust standard errors in parenthesis.

Appendix C Additional Counterfactual Results

Appendix Figure 6: Counterfactual Network Breadth per Insurer



Note: Figure shows a linear fit between the change in network breadth and the insurer's market share in each counterfactual enrollment rule. Panel A focuses on hospital networks and Panel B in non-hospital networks.