Enrollee Reassignment Rules After Health Plan Terminations*

Giancarlo Buitrago
Universidad Nacional de Colombia and HUN

Paul Rodríguez-Lesmes
Universidad del Rosario

Natalia Serna
Stanford University

Marcos Vera-Hernández
University College London, IFS, and CEPR

December 14, 2024

Abstract

Health plan terminations are common in managed care systems around the world. This paper examines how to reassign consumers to incumbent insurers after such terminations. We propose an equilibrium model of competition in which insurers can respond to the reassignment rules using their provider networks. The setting is Colombia where the largest health insurer was terminated by the government in December 2015 and where insurers compete mainly on provider network breadth. We find that random reassignment outperforms other reassignment rules in terms of consumer welfare, health care spending, and provider network breadth because it reduces market power. However, this policy is ineffective at reducing adverse selection due to slight increases in switching rates.

Keywords: Health insurer terminations, Health care provider networks, Market power, Adverse selection.

JEL codes: I10, I11, I13, I18.

*Buitrago: gbuitragog@unal.edu.co, Rodríguez-Lesmes: paul.rodriguez@urosario.edu.co, Serna: nserna@stanford.edu, Vera-Hernández: m.vera@ucl.ac.uk. We are deeply grateful to the Colombian Ministry of Health for providing the data for this research. The findings of this paper do not represent the views of any institution involved. All errors are our own.

1 Introduction

Health insurer and healthcare provider terminations or closures are common in health systems around the world. In Switzerland, for example, the number of mandatory health insurance companies decreased from 100 to 56 between 2000 and 2018. And in the U.S., nearly 9 thousand Medicare Advantage plans encompassing 350 thousand individuals (Abaluck et al., 2021) and 27 Medicaid managed care plans covering around 400 thousand beneficiaries (Politzer, 2021) were terminated between 2006 and 2014. Studies document that patients forgo care and make fewer claims after these terminations (Politzer, 2021; Barnett et al., 2017; Lavarreda et al., 2008). Such care interruptions in turn increase mortality (Buitrago et al., 2024). Despite prior causal estimates of how insurer and provider terminations affect health care utilization and health outcomes, there is still little understanding of how policymakers should handle such terminations to guarantee continuity of care for patients or reduce health care spending.

We contribute to this understanding by demonstrating that reassignment rules after insurer terminations trade off adverse selection and market power. That is, we show that reassignment rules that reduce market power in equilibrium can exacerbate adverse selection and vice versa. This trade off implies that the prediction of how reassignment rules impact welfare and health care spending is ambiguous.

To quantify these impacts, we use data from the Colombian contributory health care system between 2013 and 2017.[1] This system is specially relevant to study the trade off between market power and adverse selection after insurer terminations for two reasons. The first reason is that insurers compete mainly on their provider networks (and negotiated provider prices) to deliver one national health insurance

[1]The contributory system covers the half of the population who pay payroll taxes (and their families). The other half is covered by the subsidized system, which is fully funded by the government.

plan.[2] We show that in this setting consumers are more likely to choose insurers with broader provider networks, particularly the sick, which is consistent with adverse selection. We also show that despite the strong regulation of health plan characteristics, provider network breadth varies substantially across insurers perhaps because of their heterogeneous costs.

The second reason is that the largest health insurer which covered 20% of enrollees, called SaludCoop, was terminated by the government in December 2015. SaludCoop's termination was politically motivated and was due to its engagement in illegal activities. SaludCoop was vertically integrated with 38 hospitals, which were also forced to shutdown after December 2015. The government reassigned SaludCoop's enrollees to an incumbent insurer called Cafesalud during the first 3 months of 2016, after which they were allowed to switch. In these three months, Cafesalud had to guarantee access to care through SaludCoop's network of providers. Prior to the termination, Cafesalud covered only 5% of the market. We show that SaludCoop's enrollees switched out of Cafesalud at disproportionate rates and that in markets where Cafesalud's network was forced to increase by a greater magnitude during the 90-day grace period, SaludCoop's enrollees had relatively better outcomes than in markets where the network did not increase by a large magnitude. These descriptive patterns suggest that reassignment rules matter for outcomes.

To characterize the Colombian system, we propose an equilibrium model of insurer competition that endogenizes provider network breadth (the fraction of providers in a market that are covered by the insurer). The model captures the fundamental feature that allowing patients to endogenously switch after the terminations would exacerbate adverse selection but could potentially lead to greater consumer welfare

[2] A provider can be either a hospital, a clinic, or a physician practice. We exclude stand-alone physicians.

since individuals make choices of insurer that better match their health status and idiosyncratic preferences. Our model builds on the intuition developed in Wallace (2023) by introducing the novel feature that insurers respond to the reassignment policies using their provider networks.

In the model, insurers compete by simultaneously choosing their provider network breadth in every market to maximize the present discounted value of their profits, following Serna (2024). In the profit function, insurer demand is a random utility model where consumers choose their insurer based on provider network breadth and out-of-pocket costs. Consumers experience insurer inertia captured by an indicator for their past choices. We model insurers' average cost per consumer and fixed cost of network formation as non-linear functions of provider network breadth. Insurer profits then evolve according to exogenous transition probabilities across diagnoses and endogenous transition probabilities across insurers.

SaludCoop's termination allows us to identify the parameters of our model. The termination induced discontinuous changes in incumbent insurers' provider networks as well as changes in consumers' choice sets, which we use to identify the preference for network breadth in the demand function and the parameters of insurers' average cost per consumer. Moreover, the discontinuous change in switching rates from SaludCoop's enrollees identifies the value of insurer inertia in the demand model. Finally, we estimate the parameters of insurers' fixed costs using pre-termination data, so that we can test our model's out-of-sample fit.

Our estimates show that all consumers have preferences for broad provider networks but that this preference is stronger for patients with chronic diseases than for patients without diagnoses. Consumers are nearly 4 times more likely to choose an insurer if they were enrolled with it in the previous year. This translates into a median switching cost of 1.1 million pesos (roughly 1.6 monthly minimum wages in 2016), which is higher for patients with chronic diseases than patients without diagnoses. We also find that insurers are heterogeneous in their average cost per consumer and their fixed costs of establishing a provider network. The model provides evidence of adverse selection in provider network breadth in line with the descriptive evidence, since patients with relatively higher willingness-to-pay for provider network breadth are more expensive to the insurer. Our equilibrium model makes accurate out-of-sample predictions of insurers' choices of provider network breadth in every market when we impose the observed reassignment rule in which SaludCoop's enrollees are reassigned to Cafesalud.

We then move to simulating the impact of alternative policies for reassigning SaludCoop's enrollees to incumbent insurers. We consider the following policies: random reassignment, reassignment to the incumbent insurer with the highest network overlap with SaludCoop ("overlap"), reassignment to incumbent insurers in proportion to their market shares ("proportional"), reassignment to the largest incumbent insurer ("largest"), and reassignment to the incumbent insurer with the broadest provider network ("broadest"). Because consumers are highly inertial, these reassignment rules will impact the long-run distribution of market shares and health status across insurers and therefore the degree of market power. Moreover, to the extent that consumers are reassigned to insurers that do not match their idiosyncratic preferences, under certain reassignment policies consumers will switch disproportionately after the termination increasing adverse selection.

In line with this intuition, we find that random reassignment outperforms all other reassignment rules in terms of provider network breadth (increasing 24%), health care spending per capita (decreasing 3%), and consumer welfare per capita (increasing 4%), because under this policy the health risk is more evenly distributed across insurers, reducing their profit margins by about 20% on average relative to the observed rule. Instead, reassignment to the largest insurer generates the lowest average provider network breadth and one of the highest average profit margins. Random reassignment also leads to a slightly greater degree of adverse selection relative to other reassignment rules because healthy individuals switch at slightly higher rates after the termination.[3]

This paper makes several contributions to the literature. Our first contribution is in showing the trade off between market power and adverse selection when thinking of how to reassign patients to incumbent insurers after a health plan termination. Most prior literature studying insurer and provider terminations has focused on documenting its impacts on healthcare utilization and spending (Bischof and Kaiser, 2021; Politzer, 2021; Bonilla et al., 2024). However, the question of how to reassign patients to incumbent insurers after these terminations has received less attention. One exception is Wallace (2023), who in the context of Medicaid managed care in New York in which insurers also compete mainly on provider networks, shows that policies other than random reassignment can increase consumer satisfaction albeit holding insurers' supply-side decisions fixed.

Our second contribution is in modelling insurers' choices of provider network breadth while allowing for consumer inertia in insurer choice in a tractable way, and showing that this model performs well out-of-sample. The model builds on extensive prior work that shows the impact of insurer competition on negotiated prices holding provider networks fixed (Ho and Lee, 2017; Gowrisankaran et al., 2015; Ho, 2009); that endogenizes provider networks within a bargaining framework (Ghili, 2022; Liebman, 2022; Ho and Lee, 2019); and that documents adverse selection (Shepard, 2022; Kreider et al., 2022), willingness-to-pay (Ericson and Starc, 2015), and heterogeneous

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

costs (Dafny et al., 2015, 2017; Polsky et al., 2016) in network design.

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

2 Setting, Data, and Descriptives

Our setting is Colombia's contributory healthcare system, which covers the half of the population in the country who pays payroll taxes (and their families). Enrollees in this system have access to a national health insurance plan that is provided by private and public insurers. Insurers negotiate with providers to determine network inclusions and health service prices, but other elements of the health plan are regulated.[4]

We use administrative data from the contributory healthcare system encompassing individual-level enrollment, linked with health claims and average annual income from 2013 to 2017 for the subset of individuals aged 19 or older. The enrollment data is a snapshot of enrollment for every June in this period. If we observe an individual being enrolled with insurer A in June of year t and then again in June of year $t+1$, we assume that this individual did not switch their insurer during the months in between; we label these individuals as the "continuously enrolled." The health claims data report date, service, diagnosis code (International Classification of Diseases Code 10), provider, insurer, and negotiated price of the service.[5] Using the

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

[5] The claims data exist only for insurers in the contributory system that pass the Ministry of

diagnosis codes that accompany each claim we classify individuals as having one of the following health conditions: Cancer, Cardiovascular disease, Diabetes, Pulmonary disease, Renal disease, other disease, or no diseases. When one individual has multiple diseases, we assign the diagnosis that accounts for the largest share of the individual's healthcare cost.

We also have data on insurers' network of covered providers between 2013 and 2017. The provider network data report the hospitals, clinics, and physician practices included in the insurer's network. As robustness, we complement these data with networks inferred from health claims, considering a provider as in-network whenever it delivers more than 100 claims for an insurer.[6]

We characterize each insurer in every municipality by its provider network breadth. Provider network breadth is defined as the fraction of providers in a municipality that an insurer covers. We define a market as a municipality, since the reassignment rules that we will consider in counterfactuals will be municipality-specific.[7] There are 1,123 municipalities and 33 states in the country.

In the rest of this section we will provide descriptive evidence to support 3 main facts that will inform our model specification: first, provider network breadth is higher in less concentrated insurance markets; second, provider network breadth varies substantially across insurers despite the strong regulation of other characteristics of the health plan mainly because of heterogeneity in their average and fixed costs; and third, consumers have preferences for network breadth and experience substantial

Health's data quality filters. Excluding SaludCoop and Cafesalud, out of the 11 remaining insurers, we observe 7 for all 5 years, 8 for 4 or more years, and 11 for 3 or more years. In our final sample we focus on these 11 insurers.

[6] In inferring networks from claims we do not consider claims made at the emergency department, as individuals can go out-of-network for emergency care. 1/4 of observations in the final network data correspond to these filled-in values.

[7] This is unlike Serna (2024) who defines states as markets to avoid spillovers in networks across markets. Spillovers will also matter in our setting, which is why later on we focus on the subsample of 13 main capital cities.

inertia in insurer choice.

2.1 Summary Statistics

Table 1: Summary Statistics of Main Samples

Variable	Full sample (1)	Continuously enrolled (2)	Random sample for model (3)
Male	0.50 (0.50)	0.46 (0.50)	0.51 (0.50)
Age	43.3 (16.7)	47.1 (16.2)	47.2 (16.0)
Income†	0.80 (1.30)	0.91 (1.50)	1.36 (1.87)
Cancer	0.08 (0.28)	0.09 (0.29)	0.07 (0.26)
Cardiovascular	0.18 (0.38)	0.20 (0.40)	0.15 (0.35)
Diabetes	0.03 (0.17)	0.04 (0.18)	0.02 (0.16)
Pulmonary	0.01 (0.11)	0.01 (0.12)	0.01 (0.10)
Renal	0.01 (0.09)	0.01 (0.10)	0.01 (0.09)
Other diseases	0.08 (0.26)	0.08 (0.27)	0.06 (0.23)
No diseases (healthy)	0.57 (0.50)	0.52 (0.50)	0.54 (0.50)
Healthcare cost	0.81 (4.46)	0.88 (4.59)	0.85 (0.90)
Out-of-pocket spending	0.13 (0.50)	0.14 (0.52)	0.15 (0.09)
Individual-Years	75,918,492	49,784,135	2,469,402

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

Table 1 presents pooled summary statistics in the full sample in column (1), the subsample who are continuously enrolled in column (2), and a random sample of 500,000 continuously enrolled individuals who reside in the 13 main municipalities in the country in column (3).[8] This latter sample is our preferred sample for model estimation because annualized healthcare costs for the continuously enrolled will not suffer from measurement error arising from enrollment spell lengths of less than a

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

year; and because we can expect spillovers in provider networks across markets to be small when focusing on the 13 main municipalities. An observation in Table 1 is an individual-year.

In the three samples, a little under 60% of the observations correspond to consumers who are healthy. The most prevalent health conditions are cardiovascular diseases followed by cancer. The average annual income is higher in our sample for model estimation than in the other samples because we focus on the 13 main municipalities, which have higher wages than the rest of the country. On average, individuals in the full sample have an annual healthcare cost of 810 thousand pesos ($269), corresponding to 130 thousand pesos ($42) in out-of-pocket spending.

2.2 Provider Network Breadth

Table 2: Summary Statistics of Provider Network Breadth

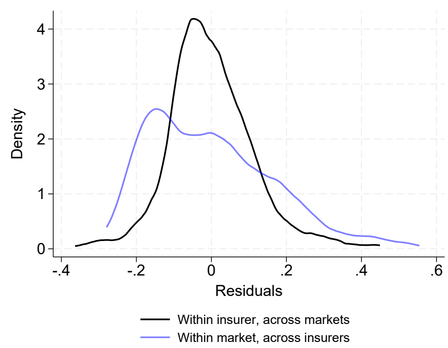
Insurer	Main cities
EPS001	0.129 (0.098)
EPS002	0.356 (0.156)
EPS003	0.178 (0.080)
EPS005	0.237 (0.074)
EPS008	0.098 (0.084)
EPS010	0.224 (0.156)
EPS012	0.088 (0.142)
EPS013	0.221 (0.091)
EPS016	0.518 (0.149)
EPS017	0.180 (0.130)
EPS018	0.115 (0.141)
EPS023	0.164 (0.104)
EPS037	0.320 (0.063)

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

Table 2 presents the mean and standard deviation in parenthesis of our measure of provider network breadth for each insurer in the 13 main municipalities. Provider network breadth varies substantially across insurers despite all other elements of the national health insurance plan being strictly regulated. To further examine this variation, Figure 1 shows the distribution of residuals of a linear regression of provider network breadth on insurer-by-year fixed effects in black and on market-by-year fixed effects in blue. The Figure shows that most of the residual variation in provider network breadth is across insurers rather than across markets.

FIGURE 1: Residual Variation in Provider Network Breadth

(A) Main cities



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

To provide evidence of what drives this heterogeneity in provider network breadth across insurers, Figure 2 presents the empirical relation between log average cost per consumer type and percentiles of provider network breadth in the 13 main municipalities. We define a consumer type 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, no diseases). In Panel A, which averages across all insurers, we see that log average costs are concave with respect to provider network breadth.[9] This cost structure is heterogeneous across insurers as seen in Panel B, which depicts the empirical relation for three insurers as

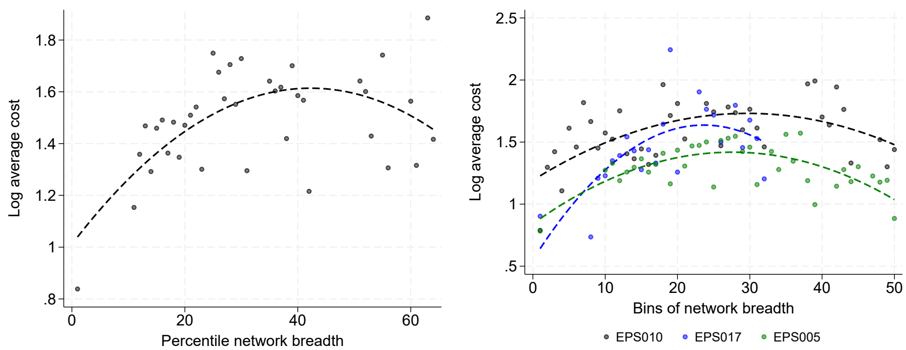
[9]This concavity likely reflects the fact that insurers enjoy economies of scope when covering multiple services within a provider as shown in Serna (2024). However, we do not have data on service-level provider listings for this sample period to test this hypothesis.

an example.

Figure 3 also shows that insurers are heterogeneous in their fixed costs. We use insurers' public income statements from 2013 to 2017 to obtain their total administrative costs. The figure shows that the log of total administrative cost ranges from 15 to 19 across insurers and that it is positively correlated with insurers' average provider network breadth.

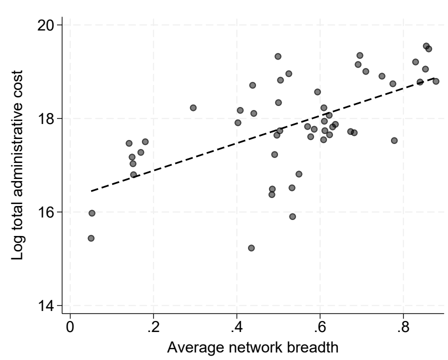
FIGURE 2: Empirical Relation Between Average Cost and Network Breadth

(A) Pooled (B) Per insurer



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

FIGURE 3: Correlation Between Administrative Cost and Network Breadth



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

2.3 Switching Decisions

The variation provider network breadth across insurers also suggests that consumers may take into account the breadth of the network when making enrollment decisions. Moreover, the fact that provider network breadth does not vary meaningfully between 2013 and 2015 indicates that perhaps those enrollment choices are characterized by inertia.

To describe consumers' choices, Table 3 presents the fraction of enrollees that switch their insurer every year. Column (1) uses the full sample, where individuals can switch to insurers in the subsidized system; while columns (2) and (3) use the sample of continuously enrolled and the sample for estimation, respectively, where consumers can only switch to other insurers conditional on staying within the contributory system. Because of the different choice sets, the switching rate in the full sample is much larger than in the other samples. In 2015, 13.7% of enrollees switched their insurer in the full sample, while only 2.8% and 2.2% switched in columns (2) and (3), respectively. Across the three samples, there is a substantial increase in the switching rate in 2016 caused by SaludCoop's termination.

2.4 SaludCoop's Termination

In December 2015, the government terminated the *largest* health insurer in the country, called SaludCoop (EPS013), and the 38 hospitals that were vertically integrated with it. The government terminated SaludCoop due to its engagement in illegal activities. SaludCoop diverted nearly $250 billion to investments outside the healthcare system and submitted false health claims to the government for reimbursement. SaludCoop covered nearly 20% of enrollees in the country (around 4 million individuals), who were transferred to an incumbent insurer called Cafesalud (EPS003) during the first three months of 2016. After this 3-month period, enrollees were allowed to switch. Prior to the termination, Cafesalud covered less than 5% of enrollees.

Table 3: Switching Rate

Year	Full sample (1)	Continuously enrolled (2)	Random sample for model (3)
2014	0.198	0.050	0.034
2015	0.137	0.028	0.022
2016	0.296	0.202	0.137
2017	0.152	0.067	0.054

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

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

2.5 Observed Reassignment Rule

The fact that sick consumers are less likely to switch than healthy ones and that in general consumers are highly inertial, indicates that reassignment rules after insurer terminations have the potential to permanently affect the distribution of health risk across insurers and therefore their market power. There is a substantial amount of

Table 4: Correlates of Switching Behavior

	Switch-in
Network breadth	0.116
	(0.02)
Sick	-0.453
	(0.01)
Network breadth×Sick	0.601
	(0.05)
Observations	98,082

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

work documenting that default choices matter for outcomes in the context of health insurance (e.g., Handel and Kolstad, 2015; Bhargava et al., 2017; McIntyre et al., 2021). In this subsection we show that the government's reassignment policy also had differential impacts on SaludCoop's enrollees depending on Cafesalud's characteristics in a given market. We use an event study framework in the sample of continuously enrolled who live in the 13 main municipalities, to compare outcomes among SaludCoop's enrollees (treated group, T_i) against the rest of enrollees (control group), before and after the termination. The regression of interest is:

$$y_{it} = \sum_{k=-3,k\neq-1}^{k=3} \beta_k \mathbf{1}\{t - t^* = k\} \times T_i + \eta_i + \gamma_t + \varepsilon_{it}$$

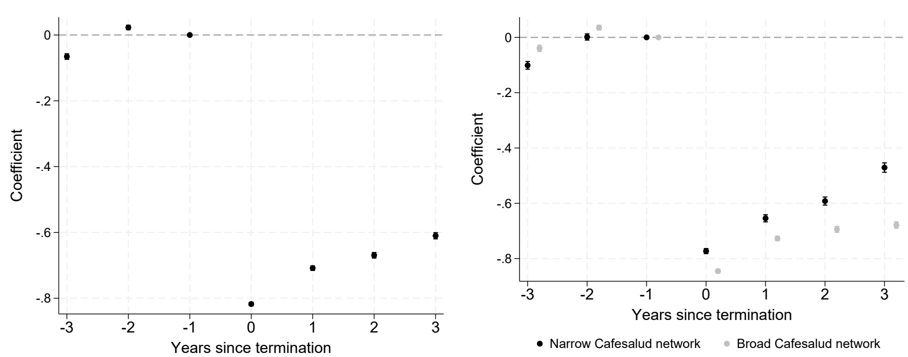
where y_{it} is an outcome for consumer i in year t, t^* is the termination year which we take to be 2016 corresponding to our enrollment data, η_i are consumer fixed effects, and γ_t are year fixed effects.Standard errors are clustered at the individual level.

Figure 4, Panel A shows that SaludCoop's enrollees had substantially lower health care spending after the termination relative to the rest of enrollees. Their health care spending falls by around 600K pesos in 2019 ($183), which is an 80% decrease relative to baseline. In Panel B we explore the heterogeneity of these effects by how broad Cafesalud's network was relative to SaludCoop's in 2015. Because Cafesalud was forced to cover SaludCoop's network during the 90-day grace period, Cafesalud will experience a large increase in provider network breadth in markets where it had a relatively narrow network in the pre-period.

First of all, we note that in none of the 13 main municipalities Cafesalud had a broader network than SaludCoop. In markets where the difference between Cafesalud's and SaludCoop's network was below average depicted in black, we find that health care spending fell by a smaller magnitude than in markets where the difference was above average. This finding suggests that the reassignment rule had an impact on health care spending through its impact on provider network breadth.

Figure 4: Impact of SaludCoop's Termination on Outcomes

(a) Total health care spending (b) By Cafesalud's pre-period network



Note: Figure shows coefficients and 95% confidence intervals of an event study specification comparing SaludCoop's enrollees against the rest of enrollees, before and after the termination. Estimation uses the sample of continuously enrolled individuals in the contributory system who reside in the 13 main municipalities. In both panels the outcome is the individual's total health care spending. In Panel B, estimates in black condition on markets where the difference between Cafesalud's and SaludCoop's provider network breadth in 2015 was below-average,while estimate in gray condition o

In Appendix Figure 2 we also report that market concentration measured by the Herfindahl-Hirschman Index (HHI) fell in the 13 main municipalities where SaludCoop operated relative to municipalities where it did not operate. In previous work, we also showed that SaludCoop's termination induced a substantial reduction in provider network breadth among incumbent insurers. We reproduce the results from that previous work on our sample of 13 main municipalities in Appendix Figure 3. The discontinuous changes in provider networks, switching rates, and consumer choice sets caused by the termination will be essential to identify the parameters of our model in the next section.

3 Model

We are interested in comparing different enrollee reassignment rules after health plan terminations in terms of equilibrium provider network breadth, degree of adverse selection, consumer surplus, and health care spending. To do so, we develop a model of insurer competition that allows us to measure these equilibrium outcomes. In the model insurers first choose their provider network breadth in every market to maximize the present discounted valued of profits conditional on rival choices, and then consumers choose an insurer to enroll with conditional on provider network breadth and out-of-pocket costs.

3.1 Insurer Demand

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

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

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

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

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

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

Consumers also experience inertia in insurer choice as seen in Table 3, which is captured in the model by the indicator for past choices. We do not distinguish whether inertia comes from the consumer's preference for their past insurer or whether it comes from state dependence. This distinction is not necessary in our case as both sources of inertia will have the same impact on the counterfactual reassignment rules that we consider.

Assuming that the preference shock ε_{ijmt} is distributed type-I extreme value, 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.

3.2 Nash Equilibrium

If our demand model depended only on provider network breadth, the answer of how best to reassign patients after insurer terminations in order to maximize consumer welfare would be trivial: we should reassign them to the insurers with the broadest provider networks. The demand trade off between coverage and out-of-pocket costs and the possibility that insurers to respond to the policy by changing their coverage decisions would instead result in ambiguous effects on welfare. For example, if all patients are reassigned to the insurer with the broadest provider network and these patients are relatively sick, then the insurer would respond by narrowing its network to minimize costs among their current enrollees and to discourage enrollment from other sick patients. This ambiguity on patient welfare can only be captured in counterfactuals with a model of how insurers choose their provider network breadth.

Insurers maximize the present discounted value of their profits choosing the vector of provider network breadths in every market conditional on rival choices. The insurer profit function is:

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

where per-enrollee profit is:

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

and average cost per enrollee is:

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

In this profit function, $H_m = \{H_{jm}\}_{j=1}^{J_m}$ is the vector of provider network breadth across all insurers in market m, $N_{\theta my}$ is the market size of type-θ consumers in market m that chose incumbent y, ζ^t is a discount factor (set to 0.95), $\rho_{\theta'}$ is the probability that a consumer type θ drops out of the contributory system (into the subsidized system), and $\mathcal{P}(\theta', j|\theta, y)$ is the transition probability from type θ at insurer y in period t to type θ' at insurer j in period $t+1$. We assume that transition probabilities are separable in consumer types and insurers such that $\mathcal{P}(\theta', j|\theta, y) = P(\theta'|\theta)P(j|y, \theta)$.[10] In the fixed cost structure, ω is the curvature of the fixed cost of network formation and ν_{jm} is the unobserved cost component, that we model as the sum of an insurer-specific component and a random component $\nu_{jm} = \nu_j + \psi_{jm}$. This functional form is chosen following the descriptive evidence from Figure 3.

In the average cost function, γ_θ, η_m, and δ_j are consumer type, municipality, and insurer fixed effects, respectively. Here too, our functional form is informed by the evidence in Figure 2. Moreover, $\varepsilon_{\theta jmt}$ is white noise. Finally, $R_{\theta m}$ is the total risk-adjusted transfer from the government plus average copayments. This total transfer encompasses three payments: one that compensates for the enrollee's sex, age, and municipality of residence; one that compensates for a few diseases (known as the High-Cost Account); and one that compensates for enrollee disabilities.[11]

[10] This separability implies that a consumer's current health status affects which insurer they decide to enroll with tomorrow, but consumers do not anticipate their future health status when making this decision. This also implies that the probability of changing health status does not depend on the insurer.

[11] Diseases compensated in the High-Cost Account include: cervical cancer, breast cancer, stomach cancer, colon cancer, prostate cancer, lymphoid leukemia, myeloid leukemia, hodgkin lymphoma, non-hodgkin lymphoma, epilepsy, rheumatoid arthritis, and HIV-AIDS. See Resolution 000248 of

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

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

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

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

The Role of Market Concentration. Equation (2) reveals the role of market concentration (and perhaps market power) on insurers' choices of provider network breadth. Take one market and year, and suppose for simplicity that insurers have the same average cost and fixed cost structures $AC_{\theta j} = AC_\theta$ and $FC_j = FC$. Averaging the FOCs across insurers weighting by their market share $s_{j\theta}$ yields:

$$\begin{aligned} &\sum_\theta (R_\theta - (1-r_\theta)AC_\theta)\Big(\sum_j \frac{\partial s_{j\theta}}{\partial H_j} s_{j\theta}\Big) - \sum_\theta (1-r_\theta)\frac{\partial AC_\theta}{\partial H_{jk}} \overbrace{\Big(\sum_j s_{j\theta}^2\Big)}^{HHI_\theta} \\ &+ \sum_{t=1}^{T} \zeta^t \sum_{j\theta} s_{j\theta} FP - \sum_{j\theta} s_{j\theta} \frac{\partial FC_j}{\partial H_j} = 0 \end{aligned} \tag{3}$$

Equation (3) shows that the impact of adverse selection on provider network breadth is

2014 from the Ministry of Health. For an explanation of how disability transfers are calculated and other considerations of insurer revenues see https://www.minsalud.gov.co/Normatividad_Nuevo/Resoluci%C3%B3n%206411%20de%202016.pdf.

attenuated in less concentrated markets. In the second term, HHI has a multiplicative effect on the increase in insurers' average cost following an increase in provider network breath. Thus, concentrated markets with adverse selection may be characterized by narrower provider networks than markets with the same degree of adverse selection but with lower levels of concentration.

4 Estimation and Identification

4.1 Insurer Demand

We estimate our insurer demand model on the sample for model estimation which encompasses 500,000 randomly chosen continuously enrolled individuals who reside in one of the 13 main municipalities. The coefficient on provider network breadth β_i is identified from the exogenous changes in provider networks within insurer and across markets and years caused by SaludCoop's termination (see Appendix Figure 3). We identify the coefficient associated with the out-of-pocket cost, α_i, from exogenous variation in income across patients within an insurer, which generate variation in the coinsurance rates as well aas from the exogenous changes in consumers' choice sets after the termination. Finally, given that enrollees in the contributory system are highly inertial as seen in Table 3, the parameter λ_i is only identified from SaludCoop's enrollees who switch out of Cafesalud on or after 2016.

Table 5 presents the results of our demand model. We find that consumers on average have a preference for broad provider networks and that this preference is stronger among the group of individuals with chronic diseases relative to those without diseases. Consumers derive disutility from higher out-of-pocket payments, but those with chronic diseases are substantially less responsive to prices than individuals without diagnoses. Our estimates also show evidence of significant inertia in insurer choice, as patients are nearly 4 times more likely to choose the insurer they were enrolled with in the previous year. This translates into an estimate of the median switching cost (computed as $\hat{\lambda}_i/\hat{\alpha}_i$) of 1.1 million pesos (roughly 2.6 times the monthly minimum wage in 2016). We also find that individuals with chronic conditions have higher switching costs than individuals without diagnoses. For example, the switching cost for consumers with cancer equals 2.9 million pesos on average and for consumers without diagnoses it equals 1.0 million pesos. Appendix Table 1 shows the in-sample fit of our demand model.

4.2 Insurer Average Costs per Enrollee

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

The endogeneity stemming from unobserved patient selection into insurers based on provider network breadth (unobservably sicker consumers choosing broader networks) would make it so that estimates for τ_1 are biased upwards. Thus, we use SaludCoop's termination as an instrument for provider network breadth in a control function approach. Our instrument is the interaction between an indicator for municipalities where SaludCoop operated, an indicator for the post-termination period, and provider network breadth in 2015, $T_m \cdot P_t \cdot H_{jm,2015}$. This instrument isolates the exogenous changes in provider network breadth that occurred right after the termination.

In the first stage, we regress provider network breadth on the instrument, and

Table 5: Insurer Demand Model

		Network breadth	OOP spending	Incumbent
Main coefficient		3.97 (0.04)	-4.13 (0.08)	3.90 (0.01)
Interactions				
Demographics	Male	-0.04 (0.03)	0.45 (0.05)	0.04 (0.004)
	Age 19-24	1.29 (0.06)	0.85 (0.12)	-1.12 (0.01)
	Age 25-29	1.17 (0.05)	0.80 (0.09)	-0.53 (0.01)
	Age 30-34	1.02 (0.05)	0.10 (0.09)	-0.39 (0.01)
	Age 35-39	0.85 (0.05)	0.27 (0.12)	-0.25 (0.01)
	Age 40-44	0.92 (0.05)	0.25 (0.09)	-0.26 (0.01)
	Age 45-49	0.83 (0.05)	-0.43 (0.10)	-0.24 (0.01)
	Age 50-54	0.76 (0.05)	-0.09 (0.09)	-0.19 (0.01)
	Age 55-59	0.63 (0.06)	0.12 (0.07)	-0.17 (0.01)
	Age 60-64	0.53 (0.06)	-0.38 (0.09)	-0.14 (0.01)
	Age 65 or more	(ref)	(ref)	(ref)
Diagnoses	Cancer	-0.91 (0.05)	2.61 (0.11)	-0.13 (0.01)
	Diabetes	-0.12 (0.08)	3.61 (0.09)	-0.07 (0.01)
	Cardio	0.14 (0.04)	1.91 (0.10)	-0.16 (0.01)
	Pulmonary	0.67 (0.13)	3.38 (0.11)	-0.21 (0.02)
	Renal	-0.25 (0.15)	3.48 (0.09)	-0.11 (0.03)
	Other	-0.05 (0.06)	3.15 (0.1)	0.14 (0.01)
	Healthy	(ref)	(ref)	(ref)
Individuals			500,000	
Observations			24,093,373	
Pseudo-R^2			0.62	

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

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

Second-stage results are presented in Table 6 and first-stage results are in Appendix Table 2. Our findings show that insurers' average cost per enrollee is increas-

Table 6: Insurer Average Cost Model

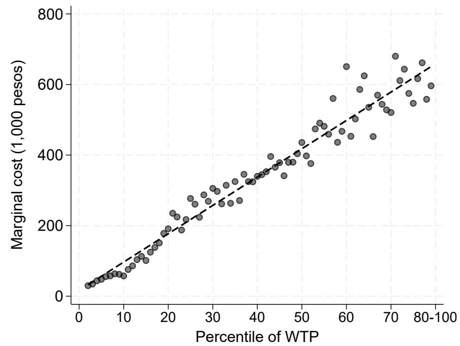
Variable	coef	se
Network breadth	0.37	(0.02)
Network breadth^2	-0.44	(0.01)
Insurer FE		
EPS001	0.21	(0.005)
EPS002	0.10	(0.002)
EPS003	-0.15	(0.003)
EPS005	-0.07	(0.003)
EPS008	0.15	(0.003)
EPS009	-4.06	(1.611)
EPS010	0.10	(0.002)
EPS012	0.19	(0.005)
EPS013	-0.07	(0.003)
EPS016	0.23	(0.002)
EPS017	0.17	(0.003)
EPS018	0.29	(0.003)
EPS023	-0.05	(0.004)
EPS037	(ref)	(ref)
F-statistic	36.41	
Observations	1,012,037	
R-squared	0.99	

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

ing in provider network breadth at a decreasing rate. The average marginal effect of network breadth on insurers' average cost per enrollee equals $20,976$ pesos (\$10.5 of 2014). Average costs per enrollee are also heterogeneous across insurers. Conditional on the consumer type, we find for example that the average cost is higher for EPS010 and EPS016 than for the reference insurer. Appendix Figure 4 provides the in-sample average cost model fit.

With our demand and average cost estimates, in Figure 5 we report the relation between the cost of increasing provider network breadth by 1% and patient willingness-to-pay for an additional percentage point in provider network breadth. Consistent with adverse selection, we find that patients who have the highest willingness-to-pay for provider network breadth are also the most expensive to the insurer on the margin.

Figure 5: Model Evidence of Adverse Selection



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

4.3 Dropout and Transition Probabilities

We estimate dropout and transition probabilities across diagnoses non-parametrically from the data and outside of the model. To compute these probabilities we use the use the full sample of individuals in the 13 main municipalities regardless of their enrollment spell lengths. Summary statistics of resulting probabilities are presented in Appendix Tables 3 and 4.

4.4 Insurer Fixed Costs

To operationalize our model of insurer competition we take the world as of the beginning of 2015 before SaludCoop is terminated. We use the 2015 cross-section of individuals to forward-simulate marginal and total variable profits for $T = 100$ periods. In every period and for every combination of sex, age, diagnosis, insurer, incumbent insurer, and municipality, we compute demand and average costs (and their derivatives) using our estimates in Tables 5 and 6. Conditional on a consumer type θ, transitions across periods are governed by dropout probabilities and transition probabilities across diagnoses and insurers.

After simulating insurers' marginal and total variable profits, we estimate the fixed cost parameters using the FOCs. Marginal variable profits in the left-hand side of equation (2) are positive across all insurers and markets as seen in Appendix Table 5. A non-zero marginal variable profit is both inconsistent with profit maximization and suggestive that fixed costs play a role in our characterization of insurers' decision to offer provider network breadth. Table 7 presents estimates of the fixed cost parameters. Fixed costs are convex with respect to provider network breadth and heterogeneous across insurers. The structural error accounts for 59% of the variation in marginal variable profits.

4.5 Out-of-sample fit

Our choice of using data from 2015 to estimate the fixed cost parameters stems from the fact that our model is over-identified, that is, our supply model predicts a static choice of provider network breadth but our data spans several years. Using data before SaludCoop's termination allows us to test the out-of-sample fit of the supply model.

We use our estimates to predict the choices of provider network breadth in 2016 imposing the government's rule of reassigning SaludCoop's enrollees to Cafesalud. For this prediction we assume that $y_{ijm,t-1} = 1$ for these enrollees when enrolled with Cafesalud.[12] Figure 6 shows the observed distribution of provider network breadth in

[12]This assumption is supported by the fact that the government forced Cafesalud to cover the same network of providers as SaludCoop only during the first 3 months of 2016, but Cafesalud was

Table 7: Insurer Fixed Cost Model

	Log Marginal Variable Profits	
Variable	coef	se
Network breadth	7.46	(2.72)
<u>Insurer FE</u>		
EPS001	0.66	(0.46)
EPS002	-0.33	(0.61)
EPS003	-0.17	(0.72)
EPS005	-2.15	(0.66)
EPS008	2.99	(0.42)
EPS009	—	—
EPS010	-0.19	(0.66)
EPS012	0.71	(0.53)
EPS013	0.51	(0.55)
EPS016	-2.40	(1.03)
EPS017	-2.55	(1.07)
EPS018	-0.66	(0.93)
EPS023	0.86	(1.08)
EPS037	(ref)	(ref)
Observations	98	
R-squared	0.41	

Note: Table presents OLS regression of the log of marginal variable profits on network breadth and insurer fixed effects. Estimation uses data from the 13 main municipalities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales, Pereira, Cúcuta, Pasto, Ibagué, Montería, Cartagena, and Villavicencio. Robust standard errors in parenthesis.

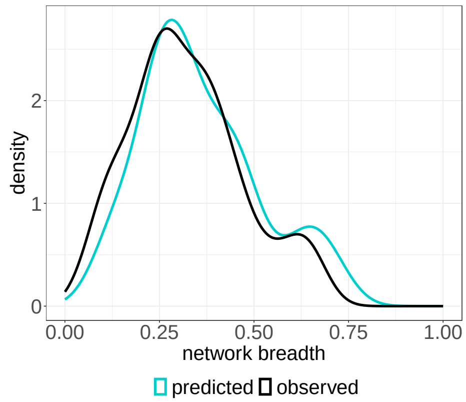
black and our model's prediction in blue. We find that our model accurately predicts insurers' choices of provider network breadth.

5 Reassignment Rules

In this section, we compare alternative enrollee reassignment rules after SaludCoop's termination along the dimensions of provider network breadth, short-run average consumer surplus per capita, short-run average health care spending per capita, and degree of adverse selection and market power. Short-run average consumer

allowed to change its network after the 90-day grace period. Hence, with our annual model of insurer choice, this means that enrollees did not necessarily view Cafesalud as equivalent to SaludCoop.

Figure 6: Out-of-sample Prediction of Provider Network Breadth



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

surplus per capita is defined as the inclusive value from the logit demand system, $CS = \left(\sum_{ijm} s_{ijm}\right)^{-1}\left(\sum_{ijm} s^{cf}_{ijm} \log(\sum_{j\in\mathcal{J}_{mt}} \exp(d^{cf}_{ijmt}))\right)$, where variables with superscripts cf denote their value in the counterfactual. Short-run health care spending per capita is given by $AC = \left(\sum_{ijm} s_{ijm}\right)^{-1}\left(\sum_{\theta(i)jm} AC_{\theta jm} s_{ijm}\right)$. We summarize market power with the insurers' average short-run profit margin defined as $\left(\sum_{ijm} s_{ijm}\right)^{-1}\left(\sum_{ijm}(R_{\theta m} s_{ijm} - \frac{\partial AC_{\theta jmt}(H_{jmt}) s_{ijmt}(H_{mt})}{\partial H_{jmt}} - (\tilde{\omega} H_{jm} + \nu_j + \psi_{jm})/T)\right)$. Finally, in the style of Einav and Finkelstein (2011), we measure the degree of adverse selection by the correlation between consumers' willingness-to-pay for provider network breadth and insurers' marginal cost associated with an increase in provider network breadth (as in Figure 5).

We consider the following reassignment rules in each market:

1. *Random*: SaludCoop's enrollees are randomly reassigned to incumbent insurers.

2. *Overlap*: SaludCoop's enrollees are reassigned to the incumbent insurer with the greatest network overlap with SaludCoop.

3. *Proportional*: SaludCoop's enrollees are reassigned to incumbent insurers in

proportion to their 2015 market shares. For example, suppose EPS010 covers 30 enrollees, EPS016 covers 20 enrollees, and EPS013 (SaludCoop) covers 50 enrollees in a market. Then, after SaludCoop's termination, EPS010 receives 30 SaludCoop's enrollees ($= 50 \times \frac{30}{20+30}$) and EPS016 receives 20 ($= 50 \times \frac{20}{30+50}$). We choose these "new" SaludCoop's enrollees randomly.

4. *Broadest*: SaludCoop's enrollees are reassigned to the incumbent insurer with the broadest provider network.

5. *Largest*: SaludCoop's enrollees are reassigned to the incumbent insurer with the largest market share in 2015 (excluding SaludCoop).

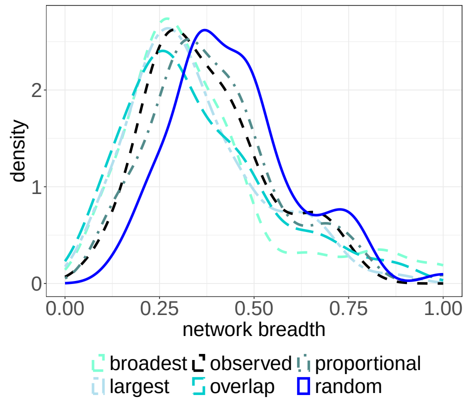
In each reassignment rule, using as starting value the vector of provider network breadth in 2015, we compute the FOCs for each insurer and market. From these FOCs, we solve for provider network breadth as $H_{jm} = (\log(MP_{jm}) - \hat{\nu}_j - \psi_{jm})/\tilde{\omega}$, which we then use as starting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

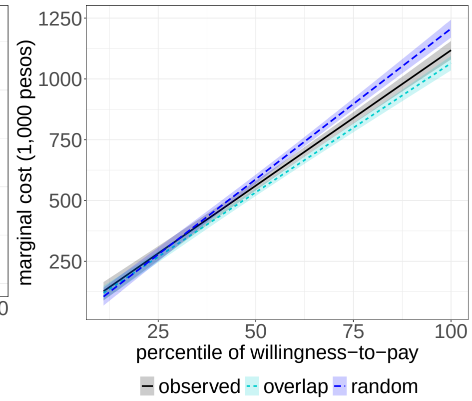
Figure 7, Panel A presents the counterfactual distribution of provider network breadth under each reassignment rule. We find that under random reassignment, average network breadth increases 24% relative to the observed scenario and this increase is similar across most incumbent insurers (see Appendix Figure 5). Proportional reassignment generates the second largest increase in provider network breadth equal to 10%, but all other reassignment rules are indistinguishable from the distribution in the observed rule. Figure 7, Panel B shows that under random reassignment, the degree of adverse selection worsens slightly relative to the observed scenario, while other reassignment rules such as overlap reassignment diminish somewhat the correlation between insurers' marginal costs and consumer's willingness-to-pay for the network.

Figure 7: Counterfactual Provider Network Breadth and Adverse Selection

(A) Provider network breadth

(B) Adverse selection





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

Table 8 summarizes other outcomes of interest for each reassignment rule. We find that random reassignment not only outperforms other rules in terms of provider network breadth, but it also generates the greatest increase in consumer surplus per capita (4%) and the greatest decrease in health care spending per capita (3%) relative to the observed scenario.

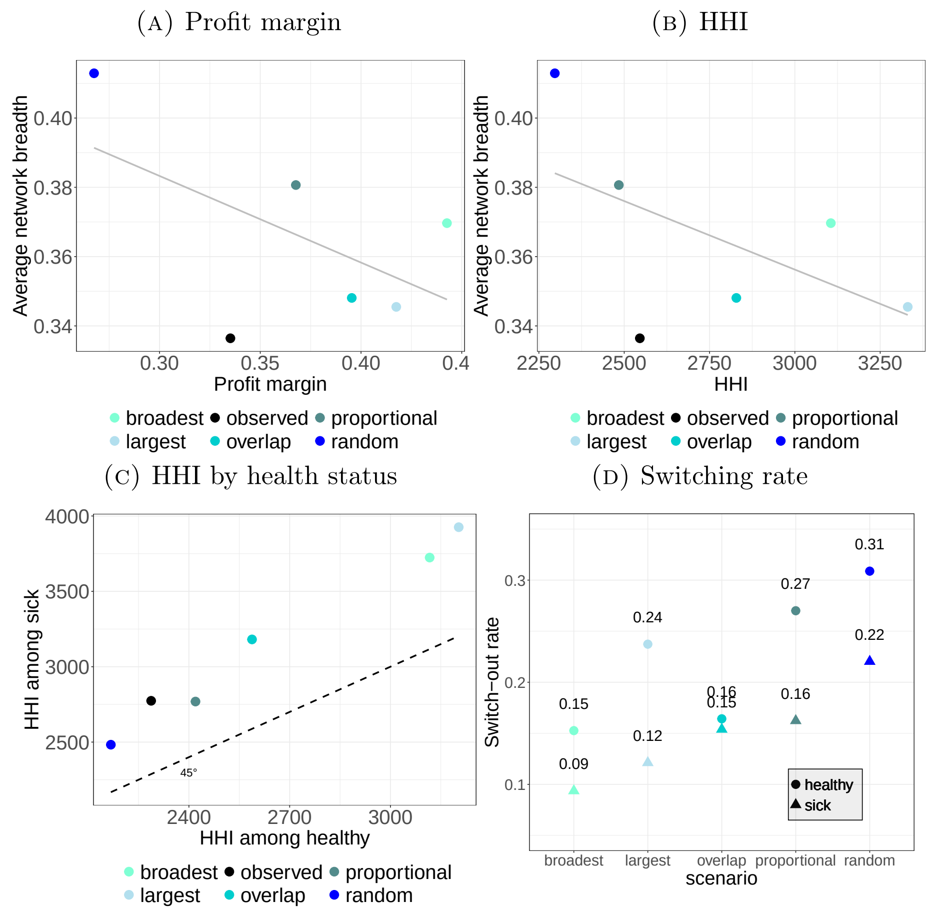
Table 8: Outcomes Under Counterfactual Reassignment Rules

	Network breadth	Consumer surplus[†]	Adverse selection	Average spending[†]
Observed	0.359	2.62	9.9	0.71
Overlap	0.350	2.66	9.9	0.75
Random	0.445	2.72	11.3	0.69
Proportional	0.394	2.67	10.8	0.74
Largest	0.345	2.67	10.2	0.76
Broadest	0.359	2.69	11.4	0.77

Note: Table presents the market share-weighted average of provider network breadth, consumer surplus per capita, and health care spending per capita under each reassignment rule. The degree of adverse selection is the coefficient on the percentile of consumers' willingness-to-pay for network breadth of a linear regression of insurers' marginal cost. (†) measured in millions of COP. The average exchange rate in 2016 was 3,050 COP/USD.

Why does random reassignment outperform other rules across most of the outcomes we consider? Our model provides several explanations for this. Leveraging strong consumer inertia, one explanation is that random reassignment reduces the degree of market power by evenly distributing SaludCoop's enrollees' health risk among incumbent insurers.

FIGURE 8: The Role of Market Power and Switching



Note: Panel A presents a scatter plot of market share-weighted average profit margin across insurers and markets against average network breadth for each reassignment rule. Panel B presents a scatter plot of average HHI across markets against average network breadth across insurers and markets for each reassignment rule. The gray line in panels A and B corresponds to a linear fit. Panel C presents a scatter plot of average HHI conditional on individuals without diseases ("healthy") against average HHI conditional on individuals with chronic diseases ("sick"). The dashed black is the 45 degree line. Panel D presents the switching rate among the healthy and the sick for each reassignment rule conditional on SaludCoop's enrollees.

Figure 8, Panel A shows indeed that the average profit margin falls 20% under random reassignment relative to the observed scenario, but in all other reassignment rules profit margins increase by as much as 32% as in the "broadest" rule. Panel B also shows that the average HHI across markets in equilibrium is the lowest under random reassignment compared to other rules. Consistent with evenly spreading the distribution of health risk across incumbent insurers, Panel C shows that only random reassignment reduces market concentration among both individuals with chronic diseases ("sick") and individuals without diagnoses ("healthy") relative to the observed rule.

Another explanation for why random reassignment outperforms other rules in terms of provider network breadth is that both healthy and sick consumers prefer to have broad provider networks and even though the preference is stronger among the sick, healthy consumers have substantially lower switching costs than sick ones. If under the random rule the reassigned insurer is a poor match for healthy consumers' idiosyncratic preferences, then increased switching from these individuals would partly incentivize insurers to broaden their networks (trading off potential increases in out-of-pocket costs). Figure 8, Panel D presents the switching rate among SaludCoop's enrollees in the first year after the reassignment period, conditional on whether they are healthy or sick.[13] In line with our intuition, we find that switching rates among the healthy are relatively high under random reassignment compared to other rules.

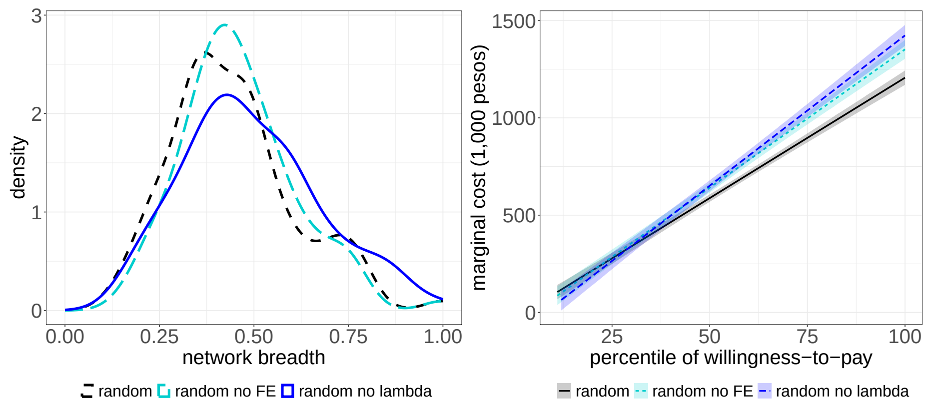
To further investigate the role of consumer switching in incentivizing insurers to offer broad networks, in Figure 9 we conduct two additional counterfactual analyses conditional on random reassignment in which we eliminate the switching cost by setting $\lambda_i = 0$ ("random no lambda") and in which we set the idiosyncratic preference for particular insurers to zero $\xi_{\theta j} = 0$ ("random no FE"). High switching costs and high fixed effects make demand less responsive to provider network breadth, giving

[13] We exclude the observed reassignment rule in which SaludCoop's enrollees are transferred to Cafesalud because comparisons against this rule have low external validity.

insurers market power and incentivizing them to offer relatively narrow networks.

FIGURE 9: Counterfactual Outcomes under Random Reassignment

(A) Network breadth (B) Adverse selection



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

Panel A shows that setting each of these components of insurer demand to zero result in even broader networks relative to baseline random reassignment. Average provider network breadth under random reassignment without switching costs is 10% higher and without fixed effects is 3% higher than baseline. Increased switching relative to baseline random reassignment also generates a stronger correlation between insurers' marginal cost and consumers' willingness-to-pay for provider network breadth as seen in Panel B.

Our results suggest that the effectiveness of different reassignment rules after insurer terminations in improving consumer welfare and reducing health care costs will depend on how the rules impact market power and adverse selection. These impacts in turn depend on how the preference for network breadth and the switching cost vary with consumers' health status. We expect this trade off to be relevant not only in managed care systems where insurers compete mainly on their provider networks but also in settings where they compete on other plan characteristics such as premiums.

6 Conclusions

This paper explores how to reassign enrollees to incumbent insurers after their insurer is terminated. We compare different reassignment rules in terms of consumer welfare, health care spending, and provider network breadth. Our setting is Colombia's contributory healthcare system where insurers compete mainly on their network of covered providers and where the largest health insurer, which covered 20% of enrollees, was terminated by the government in December 2015. The government reassigned these enrollees to a single incumbent insurer which covered only 5% of the market.

To compare counterfactual reassignment rules, we propose and estimate an equilibrium model of insurer competition on provider network breadth. We find that random reassignment to incumbent insurers is effective at increasing consumer welfare and provider network breadth and at reducing health care spending, but it results in a slightly higher degree of adverse selection compared to the observed scenario and compared to other rules such as reassignment based on network overlap. We show that the two main reasons for why random reassignment outperforms other rules is that it substantially reduces insurer market power and incentivizes healthy individuals –who also have a preference for broad networks– to switch. We also demonstrate that the impact of adverse selection on provider network breadth is attenuated in less concentrated markets.

The findings of this paper indicate that policymakers should consider the trade off between market power and adverse selection when deciding how to reassign individuals to incumbent insurers after a plan termination. This has been a relatively unexplored area of research despite plan terminations being very common across health systems. For example, in the U.S., the states of Arizona, Minnesota, Missouri, Texas, and Washington have seen closures of Medicaid managed care plans who lose the auction to participate in the program. In Medicare Advantage, several health plans have also been terminated due to changes in national reimbursement policies (Pelech, 2018). Our findings are broadly applicable to these systems where insurers also compete on provider networks and where premiums are strongly regulated.

References

Abaluck, J., M. Caceres, P. Hull, and A. Starc (2021): "Mortality Effects and Choice Across Private Health Insurance Plans," *The Quarterly Journal of Economics*, 136, 1557–1610.

Barnett, M. L., Z. Song, S. Rose, A. Bitton, M. E. Chernew, and B. E. Landon (2017): "Insurance Transitions and Changes in Physician and Emergency Department Utilization: An Observational Study," *Journal of General Internal Medicine*, 32, 1146–1155.

Bhargava, S., G. Loewenstein, and J. Sydnor (2017): "Choose to Lose: Health Plan Choices from a Menu with Dominated Option," *The Quarterly Journal of Economics*, 132, 1319–1372.

Bischof, T. and B. Kaiser (2021): "Who Cares When You Close Down? The Effects of Primary Care Practice Closures on Patients," *Health economics*, 30, 2004–2025.

Bonilla, L., M. Cardona, N. Papageorge, C. Posso, and M. Zahn (2024):

"Healthcare Plans and Patient Outcomes: Evidence from Bankruptcy-Induced Random Assignment in Colombia," *Working Paper*.

Buitrago, G., P. Rodriguez-Lesmes, N. Serna, and M. Vera-Hernandez (2024): "The Role of Hospital Networks in Individual Mortality," *Working paper*.

Dafny, L., I. Hendel, and N. Wilson (2015): "Narrow Networks on the Health Insurance Exchanges: What Do They Look Like and How Do They Affect Pricing? A Case Study of Texas," *American Economic Review*, 105, 110–114.

Dafny, L. S., I. Hendel, V. Marone, and C. Ody (2017): "Narrow Networks on the Health Insurance Marketplaces: Prevalence, Pricing, and the Cost of Network Breadth," *Health Affairs*, 36, 1606–1614.

Einav, L. and A. Finkelstein (2011): "Selection in Insurance Markets: Theory and Empirics in Pictures," *Journal of Economic Perspectives*, 25, 115â38.

Ericson, K. M. and A. Starc (2015): "Measuring Consumer Valuation of Limited Provider Networks," *American Economic Review*, 105, 115–119.

Ghili, S. (2022): "Network Formation and Bargaining in Vertical Markets: The Case of Narrow Networks in Health Insurance," *Marketing Science*, 41, 433–662.

Gowrisankaran, G., A. Nevo, and R. Town (2015): "Mergers When Prices Are Negotiated: Evidence from the Hospital Industry," *American Economic Review*, 105, 172–203.

Handel, B. and J. Kolstad (2015): "Getting the Most from Marketplaces: Smart Policies on Health Insurance Choices," .

Ho, K. (2009): "Insurer-provider networks in the medical care market," *American Economic Review*, 99, 393–430.

Ho, K. and R. S. Lee (2017): "Insurer Competition in Health Care Markets," *Econometrica*, 85, 379–417.

——— (2019): "Equilibrium Provider Networks: Bargaining and Exclusion in Health Care Markets," *American Economic Review*, 109, 473–522.

Kreider, A., T. Layton, M. Shepard, and J. Wallace (2022): "Adverse Selection and Network Design Under Regulated Plan Prices: Evidence from Medicaid," .

Lavarreda, S. A., M. Gatchell, N. Ponce, E. R. Brown, and Y. J. Chia (2008): "Switching Health Insurance and its Effects on Access to Physician Services," *Medical care*, 46, 1055–1063.

Liebman, E. (2022): "Bargaining in Markets with Exclusion: An Analysis of Health Insurance Networks," .

McIntyre, A., M. Shepard, and M. Wagner (2021): "Can Automatic Retention Improve Health Insurance Market Outcomes?" *AEA Papers and Proceedings*, 111, 560â66.

Pelech, D. (2018): "Paying More for Less? Insurer Competition and Health Plan Generosity in the Medicare Advantage Program," *Journal of Health Economics*, 61, 77–92.

Politzer, E. (2021): "A Change of Plans: The Impact of Involuntary Switching in Health Insurance," *Working Paper*.

Polsky, D., Z. Cidav, and A. Swanson (2016): "Marketplace Plans With Narrow Physician Networks Feature Lower Monthly Premiums Than Plans With Larger Networks," *Health Affairs*, 35, 1842–1848.

Rambachan, A. and J. Roth (2023): "A More Credible Approach to Parallel Trends," *Review of Economic Studies*, 90, 2555–2591.

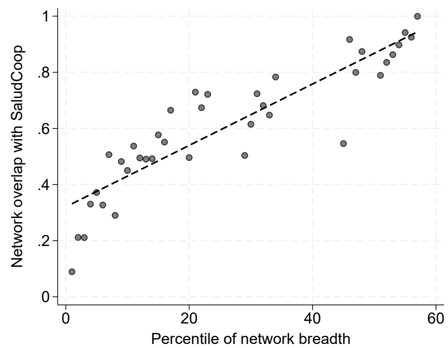
Serna, N. (2024): "Non-Price Competition, Risk Selection, and Heterogeneous Costs in Provider Networks," *Working Paper*.

Shepard, M. (2022): "Hospital Network Competition and Adverse Selection: Evidence from the Massachusetts Health Insurance Exchange," *American Economic Review*, 112, 578–615.

Wallace, J. (2023): "What Does a Provider Network Do? Evidence from Random Assignment in Medicaid Managed Care," *American Economic Journal: Economic Policy*, 15, 473–509.

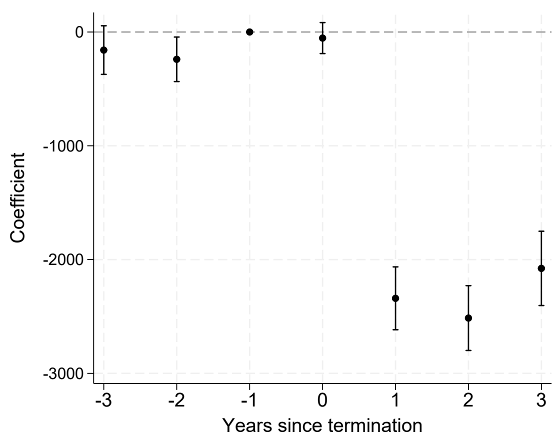
Appendix A Additional Descriptives and Results

Appendix Figure 1: Correlation Between Network Breadth and Network Overlap



Note: Figure shows network overlap between each incumbent insurer and SaludCoop averaged within percentiles of the incumbent insurer's network breadth in 2015. Network overlap is calculated as the fraction of providers in SaludCoop's network (denominator) that are also in the incumbent insurer's network (numerator). The dashed line corresponds to a linear fit.

Appendix Figure 2: Impact of SaludCoop's Termination on Market Concentration

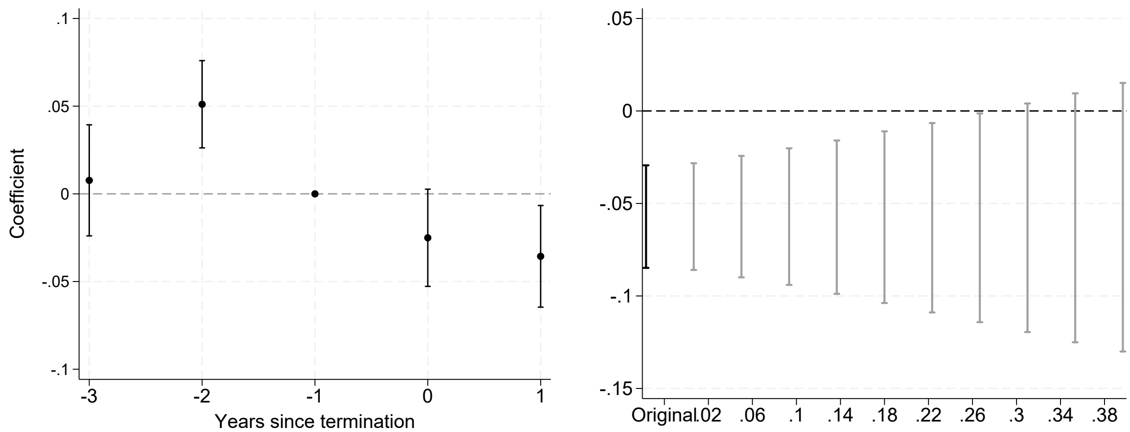


Note: Figure presents coefficients and 95% confidence intervals of a dynamic difference-in-difference design using as outcome the Herfindahl-Hirschmann Index. An observation is a municipality-year. Treatment is defined as municipalities where SaludCoop operated in 2015 (conditional on the 13 main municipalities) and the control group are municipalities where it did not operate. Relative time indicators are constructed relative to the termination year, which we take to be 2016.

Appendix Figure 3: Impact of SaludCoop's Termination on Provider Network Breadth

(a) Event study specification

(b) Robustness to parallel trends



Note: Panel A presents coefficients and 95% confidence intervals of a dynamic difference-in-difference design using as outcome provider network breadth among incumbent insurers. An observation is an insurer-municipality-year. Treatment is defined as municipalities where SaludCoop operated in 2015 (conditional on the 13 main municipalities) and the control group are municipalities where it did not operate. Relative time indicators are constructed relative to the termination year, which we take to be 2016. Panel B presents robustness to parallel pre-trends for the $t+1$ estimator using Rambachan and Roth (2023)'s estimator. The original $t+1$ estimator is presented in black and robustness to different degrees of deviation of parallel trends are presented in light gray.

Appendix Table 1: Insurer National Market Shares

	Observed	Predicted
EPS001	2.08	2.07
EPS002	9.86	9.86
EPS003	7.51	7.50
EPS005	9.81	9.84
EPS008	9.10	9.11
EPS010	12.06	12.04
EPS012	1.84	1.85
EPS013	7.22	7.20
EPS016	9.95	9.95
EPS017	8.60	8.60
EPS018	3.50	3.49
EPS023	3.93	3.95
EPS037	14.54	14.56

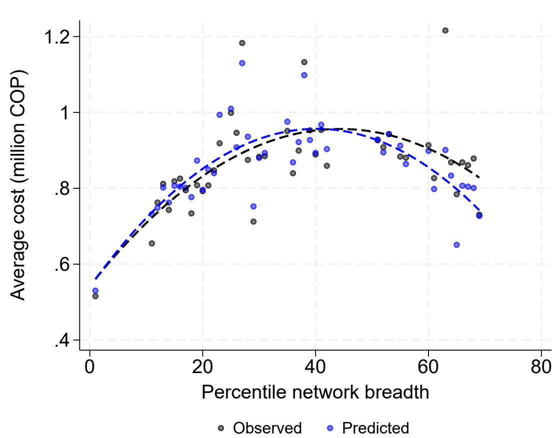
Note: Table presents observed and model predicted insurer national market shares using estimates from the insurer demand model. Consumers' discrete choice is simulated by drawing type-I extreme value shocks.

Appendix Table 2: First-Stage Regression for Insurer Average Costs

	coef	se
$T_m \cdot P_t \cdot H_{jm,2015}$	0.21	(0.03)
Insurer FE		
EPS001	-0.04	(0.02)
EPS002	0.08	(0.02)
EPS003	-0.10	(0.02)
EPS005	-0.03	(0.02)
EPS008	0.07	(0.01)
EPS009	-0.44	(0.05)
EPS010	0.06	(0.04)
EPS012	0.10	(0.05)
EPS013	-0.10	(0.02)
EPS016	0.20	(0.02)
EPS017	0.19	(0.01)
EPS018	0.07	(0.05)
EPS023	-0.10	(0.03)
EPS037	(ref)	(ref)
F-statistic	36.41	
Observations	1,007,628	
R-squared	0.71	

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

Appendix Figure 4: Average Cost Model In-Sample Fit



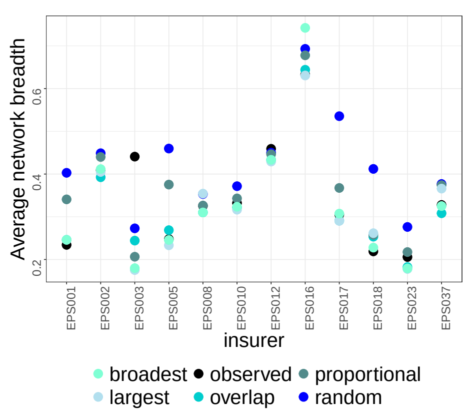
Note: Figure shows a scatter plot of observed and predicted average cost per enrollee in millions of COP by percentile network breadth in black and blue, respectively.

Appendix Table 3: Annual Transition Probabilities Across Diagnoses

	Cancer	Cardio	Diabetes	Pulmonary	Renal	Other	Healthy
Cancer	0.502	0.146	0.016	0.027	0.017	0.049	0.243
	(0.172)	(0.152)	(0.016)	(0.082)	(0.072)	(0.042)	(0.178)
Cardio	0.041	0.668	0.025	0.021	0.021	0.054	0.170
	(0.097)	(0.237)	(0.067)	(0.036)	(0.047)	(0.130)	(0.203)
Diabetes	0.035	0.165	0.603	0.018	0.021	0.032	0.125
	(0.077)	(0.103)	(0.168)	(0.030)	(0.030)	(0.043)	(0.148)
Pulmonary	0.047	0.164	0.016	0.494	0.011	0.063	0.204
	(0.044)	(0.094)	(0.010)	(0.164)	(0.021)	(0.033)	(0.166)
Renal	0.050	0.247	0.034	0.017	0.435	0.048	0.169
	(0.105)	(0.184)	(0.043)	(0.028)	(0.132)	(0.034)	(0.157)
Other	0.050	0.158	0.015	0.029	0.018	0.488	0.244
	(0.056)	(0.128)	(0.013)	(0.039)	(0.078)	(0.176)	(0.186)
Healthy	0.039	0.084	0.011	0.011	0.003	0.037	0.815
	(0.093)	(0.123)	(0.062)	(0.017)	(0.004)	(0.093)	(0.182)

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 Figure 5: Counterfactual Provider Network Breadth per Insurer



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

Appendix Table 4: Summary Statistics of Annual Dropout Probabilities

	mean	sd
Female	0.078	(0.038)
Male	0.090	(0.041)
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	(0.014)
Age 40-44	0.083	(0.014)
Age 45-49	0.076	(0.014)
Age 50-54	0.070	(0.015)
Age 55-59	0.062	(0.016)
Age 60-64	0.053	(0.016)
Age 65-69	0.048	(0.015)
Age 70-74	0.052	(0.018)
Age 75 or more	0.073	(0.029)
Cancer	0.088	(0.032)
Cardio	0.076	(0.038)
Diabetes	0.073	(0.037)
Pulmonary	0.088	(0.035)
Renal	0.077	(0.028)
Other	0.074	(0.037)
Healthy	0.114	(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 5: Insurer Marginal Variable Profits

	mean	sd
EPS001	50,468	71,865
EPS002	171,652	276,967
EPS003	404,220	632,558
EPS005	41,520	131,189
EPS008	1,450,330	—
EPS010	175,721	282,882
EPS012	352,226	—
EPS016	160,489	218,048
EPS017	230,904	605,397
EPS018	101,342	193,882
EPS023	132,883	184,248
EPS037	259,325	443,109

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