Non-Price Competition and Risk Selection Through Hospital Networks

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Abstract

Health insurers can engage in risk selection through the design of their hospital networks. I measure the impact of risk selection incentives on hospital network breadth using a model of insurer competition in networks applied to data from Colombia's health care system. Every aspect of the Colombian national insurance plan is regulated by the government except for hospital networks, which insurers can choose separately for different services. I find that insurers risk-select by providing narrow networks in services that unprofitable patients require. Improving the risk adjustment formula increases average network breadth by 4.6%-28.0% and consumer welfare by 2.9%-8.0%, depending on how many risk factors are included. Simulations of the model with deregulated premiums show that price and non-price competition are substitutes for risk selection as a zero-premium policy can generate narrow networks. The results provide new evidence on hospital networks as a dimension of non-price competition and cream-skimming in health care markets.

Keywords: Hospital networks; Risk selection; Health Insurance; Risk adjustment.

JEL codes: I11, I13, I18, L13.

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1 Introduction

Risk selection is a first-order concern in the design of health insurance markets. Insurers may attempt to disproportionately enroll healthy (profitable) patients rather than sick (unprofitable) patients by carefully crafting various aspects of the insurance contract, such as cost-sharing rules, premiums, and hospital networks. This type of selection has been shown to reduce access to insurance (Shepard, 2022) and health care (Ellis and McGuire, 2007), and in principle it can lead a market to unravel altogether (Kong et al., 2022).

Most prior studies have focused on how risk selection affects premiums, holding other aspects of the insurance plan fixed (e.g, Cabral et al., 2018; Ho and Lee, 2017; Dafny et al., 2015). Less attention has been paid to whether insurers strategically choose the non-price characteristics of their plans to cream-skim the market. In this paper I study how insurers engage in risk selection through the design of their hospital networks. I measure the impact of risk selection incentives on the breadth of hospital networks, and simulate the effects of counterfactual policies like risk adjustment that aim to reduce insurers' incentives to risk-select.

My empirical setting is Colombia, where private insurers provide a national health insurance plan in a system similar to the Medicare Advantage program in the United States. However, a key difference is that almost all aspects of the insurance contract are closely regulated: premiums, coinsurance rates, copays, and maximum out-of-pocket amounts are all set by the government. The only element of the public health insurance plan that is unregulated is hospital networks, which insurers can choose separately for different services. The strict regulation and near universal coverage of the national insurance plan makes the Colombian system an ideal setting to study risk selection through network breadth.

Health insurers in Colombia have discretion over which services to cover at which hospitals, so they can use their service-specific hospital networks as a mechanism to select risks and minimize costs. By offering a narrow network in services that costly patients demand the most, insurers can effectively discourage enrollment from these patients. This kind of non-price, service-level risk selection has been studied from a theoretical perspective by Cao and McGuire (2003) and Frank et al. (2000), and documented by Park et al. (2017), who find that insurers in Medicare Advantage engage in risk selection by placing services that sick individuals need in higher cost-sharing tiers.[1]

[1]Related patterns have been shown for drug coverage. Geruso et al. (2019) find that in the context of the ACA Exchanges, drugs commonly used by predictably unprofitable individuals appear on higher tiers of an insurer's drug formulary. Lavetti and Simon (2018) report similar results in the context of Medicare Part D.

I start by documenting basic evidence that insurers use their service-level hospital networks to risk-select. First, I show that the coarseness of the government's risk adjustment formula generates incentives to risk-select, because it leaves significant variation in expected patient profitability depending on the types of services the patient is likely to need. I then provide evidence that hospital networks tend to be narrower for less profitable services. Finally, I show that patients tend to select insurers that have broad networks in services the patient is likely to need. For example, patients with renal disease are more likely to choose insurers with broad networks of dialysis providers.

I then develop and estimate a model of insurer competition in service-level hospital network breadth and consumer demand for insurance. The model allows me to quantify how hospital network breadth, health care costs, and consumer welfare respond to changes in the regulatory environment or to policies aimed at reducing insurers' incentives to risk select. This question has become increasingly relevant with the prevalence of network adequacy rules (Mattocks et al., 2021; Haeder et al., 2015). An important simplification I make is to measure network breadth with a single index: the fraction of all hospitals in a market that can provide the service that are covered by the insurer. The cost of this approach is that it implicitly assumes hospitals' identities are not important–what matters is how many hospitals are in the network, not which hospitals–but the advantage is that this simplification allows me to tractably model insurers' equilibrium choices of service-specific network breadths.

For consumer demand, I model new enrollees' myopic and static discrete choices of insurance carrier. The enrollees' indirect utility is a function of insurers' network breadth per service and out-of-pocket costs. Out-of-pocket costs depend on network breadth to reflect the cost-coverage trade-off that consumers face when making enrollment decisions. Consumers may have strong preferences for broader networks, but enrolling with a broad network carrier is associated with higher out-of-pocket costs. On the supply side, I model insurers' average cost per enrollee as a nonlinear function of service-level network breadth and enrollee characteristics. The average cost function depends on the types of consumers that insurers enroll, allowing for potential economies of scope across services. The function represents an approximation to an equilibrium where insurers and hospitals bargain over service prices and then consumers make claims for those services.

Insurers maximize profits by choosing their vector of network breadths conditional on rivals' choices. To approximate a steady-state equilibrium, I assume insurers make a one-time choice of service-specific network breadth, recognizing that this choice will affect both current and future profits. Consumers are assumed to have infinite inertia: once they choose an insurer, they stay with that insurer. However, future profits from a given patient evolve as that patient ages and transitions between health states, with transition probabilities computed from the claims data. Preference heterogeneity for network breadth and cost heterogeneity across insurers are sufficient for an asymmetric equilibrium in network breadth per service to exist. Without sufficient heterogeneity in preferences and costs and with myopic consumers, my model would predict that all insurers choose narrow networks in all services.

I estimate the model on a novel administrative dataset that encompasses all enrollees to the contributory health care system in Colombia during 2010 and 2011, which represents nearly half of the population in the country (25 million individuals) and their medical claims (650 million). As is usual in the literature on hospital networks (Gowrisankaran et al., 2015; Capps et al., 2003), I use the claims-level data to recover each insurer's network of hospitals in each of the service categories provided by the national insurance plan.

Demand estimates show that, conditional on sex and age, individuals with chronic conditions have higher willingness-to-pay for network breadth than healthy individuals, which is consistent with strong adverse selection. I find that insurers' average cost function exhibits economies of scope and that the network formation cost is heterogeneous across insurers, services, and markets. The estimates imply that if an insurer unilaterally increases network breadth for a service, roughly half of the resulting cost increase is due to adverse selection (attracting sicker patients). I also find that insurers' marginal costs are positively correlated with consumer willingness-to-pay for network breadth, a classic adverse selection result.

I use my model to quantify how hospital networks respond to changes in the regulatory environment and how these network breadth changes affect health care costs and consumer welfare. In a first set of counterfactual simulations, I examine how equilibrium choices of network breadth depend on the government's risk adjustment mechanism. If there were no risk adjustment at all, insurers would reduce average network breadth by 6.7% and consumer welfare would fall by only 13,753 pesos ($7.2) per capita per year for those with chronic conditions. These small welfare effects are due to out-of-pocket cost savings partially compensating reductions in coverage. By contrast, if risk adjustment were made more granular, insurers would increase average network breadth by 4.6%-28.0%, depending on how many risk factors are included in the formula. In the case of "perfect" risk adjustment, consumer welfare increases by 49,161 pesos ($25.9) per capita per year specially for those with chronic diseases.

Finally, I conduct a set of simulations to understand how deregulation of premiums would affect insurers' equilibrium choices of network breadth, given that in the current regulation premiums are zero. I assume insurers compete over premiums and network breadth per service and can discriminate premiums across sex, age group, and income level in every market. Insurers receive premiums in addition to the risk adjusted transfers from the government and consumers pay premiums in addition to tax contributions to the system. I find that premiums are U-shaped with respect to the enrollee's age, higher for males than for females, and higher for low-income individuals, reflecting the correlation between these demographic characteristics and health status. Deregulating premiums incentivizes insurers to increase their network breadth per service by around 28%. Thus, the model illustrates that price and non-price competition are substitutes from the point of view of risk selection. The zero-premium policy adopted by the Colombian government generates narrow networks in equilibrium.

My paper contributes to the literature on risk selection in health insurance by identifying hospital networks as a selection mechanism and by quantifying the effect of risk adjustment and premium setting on service-specific hospital network breadth. Existing literature has focused on the impact of premiums on enrollment (Einav et al., 2019; Finkelstein et al., 2019; Tebaldi, 2017; Decarolis, 2015), of risk adjustment on selection effort (Brown et al., 2014; McWilliams et al., 2012; Nicholson et al., 2004), and of risk adjustment on premiums (Cabral et al., 2018; McGuire et al., 2013; Pauly and Herring, 2007). Other papers deal with alternative selection mechanisms such as insurer advertising (Aizawa and Kim, 2018) and drug formulary design (Geruso et al., 2019).

The most closely related paper is Shepard (2022), who shows that sick individuals' strong preferences for a star hospital incentivizes insurers to drop this hospital from their networks in the context of the Massachusetts Exchange. My paper builds on his intuition by showing that selection incentives exist on the multidimensional choice of service-specific network breadth, but differs by proposing an equilibrium model of insurer competition in network breadth that allows me to conduct counterfactual simulations and predict market structure in health systems where insurers compete mainly on the non-price characteristics of their insurance plans.

2 Institutional Background and Data

The Colombian health care system, established in 1993, is divided into a "contributory" and a "subsidized" regime. The first covers formal employees and independent workers who are able to pay their monthly tax contribution to the system (nearly 51% of the population). The second covers individuals who are poor enough to qualify and are unable to contribute (the remaining 49%). The national health care system has almost universal coverage, which means that risk selection does not happen on the individual's decision of whether to enroll or not but on the decision of which insurer to enroll with.

Private insurers in Colombia's contributory system provide the national insurance plan to enrollees who contribute a fraction of their monthly income.[2] The national plan covers a comprehensive list of more than 7,000 services or procedures and 673 medications as of 2010. The government sets premiums for the national plan to zero and sets cost-sharing rules as functions of the enrollee's income level, but they are standardized across insurers and providers.[3] Hospital networks are the only dimension in which insurers differ. Insurers can form these networks separately for each of the services offered in the national health insurance plan. For example, insurers can choose to offer a broad network for orthopedic care, but a narrow network for cardiology. Although the government does stipulate a set of network adequacy rules to guarantee appropriate access to health services, these rules are very coarse and relate only to the provision of primary care, urgent care, and oncology.[4]

At the end of every year, insurers report to the government all health claims made through the national insurance plan that they reimbursed hospitals in their network for. The data for this paper are the enrollment files of all enrollees to the contributory system during 2010 and 2011 (25 million), and their claims reports to the government (650 million). I focus on the sample of individuals with continuous enrollment spells or no gaps in enrollment (9 million) and their associated claims (270 million). This distinguishes consumers whose choices are not conflated by variation in income across time, job loss, or informality, which are the main reasons for variation in enrollment spells.[5] Of the continuously enrolled, 2/3 are *current enrollees* or individuals who are enrolled throughout 2010 and 2011. The remaining 1/3 are *new enrollees* or individuals who enroll for the first time in 2011. Because there is near universal coverage, new enrollees to the contributory system can be

[2] Contributions equal 12% of the monthly income for independent workers and 8% for formally employed individuals with an additional 4% paid by the employer.

[3] Cost-sharing in the national insurance plan follows a three-tiered system. As of 2010, for individuals earning less than 2 times the minimum monthly wage (MMW) the coinsurance rate equals 11.5%, the copay equals 2,100 pesos, and the maximum expenditure amount in a year equals 57.5% times the MMW. This corresponds to an actuarial value of 92%. For those with incomes between 2 and 5 times the MMW, the coinsurance rate is 17.3%, the copay is 8,000 pesos, and the maximum expenditure is 230% times the MMW. The associated actuarial value is 84%. Finally, for people with incomes above 5 times the MMW, the coinsurance rate equals 23%, the copay 20,900 pesos, and the maximum expenditure amount is 460% times the MMW, all corresponding to an actuarial value of 78%. The average exchange rate during 2011 was $1,847 COP/USD.

[4] For more information visit https://www.minsalud.gov.co/sites/rid/Lists/BibliotecaDigital/RIDE/VS/PSA/Redes-Integrales-prestadores-servicios-salud.pdf

[5] Because the continuously enrolled represent only 36% of all enrollees to the contributory system, I conduct robustness checks on my descriptive analysis using all enrollees.

individuals who move from the subsidized system after they find a job, or those who for some reason were uninsured for 12 continuous months and then enroll in the health care system.[6] In the sample of current enrollees, only 0.06% switch their insurance carrier from 2010 to 2011, which indicates the extent of consumer inertia in this market. Even among patients whose diagnoses change from one year to the other, the switching rate is only 0.1%.

The enrollment files have basic demographic characteristics like sex, age, municipality of residence, and enrollment spell length in the year. Although I do not observe individual income per month, using aggregate income data from enrollees to the contributory system I assign each individual the average income for his or her municipality, sex, and age. The health claims data report date of provision, service description, service price, provider, insurer, and ICD-10 diagnosis code for each claim.

Every claim is associated to a 6-digit service code from the national insurance plan, which I assign to one of 58 service categories ("service" for short) describing surgical and non-surgical procedures in parts of the body.[7] Examples of these service categories are procedures in cardiac vessels, procedures in stomach, procedures in intestines, imaging, consultations, and hospital admissions. Each category, in turn, covers more detailed medical procedures. For instance, procedures in cardiac vessels includes angioplasty, pericardiotomy, heart transplant, and aneurysm excision. Procedures in intestines includes colonoscopy, duodenectomy, and colectomy. Hospital admissions includes ICU admission, NICU admission, and general acute care admission by type of hospital room. The complete list of services is provided in appendix 2.

Health claims reports to the government come from the 23 private insurers that participated in Colombia's contributory health care system during my sample period. I focus on the 14 largest insurers that account for over 97% of enrollees. Insurers compete for enrollees separately in every market, which I define as a Colombian state (similar in size to an MSA in the US); there are 32 markets in my data. The Colombian insurance market is highly concentrated: the top 3 companies cover over 50% of individuals (see appendix table 3). All insurers have presence in the central region of the country, but peripheral markets, characterized by difficult geographical access, have fewer

[6] Even if new enrollees in 2011 had enrollment before the start of my sample period in 2010, decree 806 of 1998 and decree 1703 of 2002 established that after three continuous months of non-payment of tax contributions, a person would be disenrolled and lose any information so far reported to the system. Enrollment after non-payment is therefore a "fresh-start" in the contributory system. Moreover, in 2011 only around 500 thousand enrollees switched from an insurer in the subsidized system that also had presence in the contributory system.

[7] The first two digits of the service codes (known as CUPS for its Spanish acronym) indicate the anatomical area where the procedure is performed, the third digit is the type of procedure, and the fourth and fifth digits define more specifically the methods used for the procedure. See Resolution 4678 of 2015 from the Ministry of Health.

insurers. The smallest market has a duopoly of carriers (see panel A of appendix figure 1).

Health claims can be provided either by in-network stand-alone doctors, clinics, or hospitals. In 2011, Colombia's health care system had around 11,200 hospitals and small clinics, that comprised only 1/6 of all providers in the country. I focus on the sample of hospitals and clinics ("hospitals" for short) that provide inpatient, surgical, urgent care, and diagnostic services, which are in the upper tail of the distribution of health care costs, where variance is high and risk selection incentives are more salient. My hospital sample selection criteria matters because I recover the insurers' service-level hospital network from observed claims. This can be problematic, particularly for small providers, because it may be the case that there are zero claims from a provider who is actually in-network. To avoid this type of measurement error, my sample focuses on relatively large hospitals for which there are sufficient claims in each service category to infer them as being part of an insurer's network. Appendix figure 2 shows the distribution of number of claims per hospital, insurer, and service.

I obtain the list of 1,663 hospitals in 2011 and 1,453 in 2010 that satisfy my sample definition from the Ministry of Health's Registry of Health Care Providers.[8] I match hospitals in my claims data to the registry and end up with a 97% match rate in 2010 and an 87% match rate in 2011. The matched sample of hospitals, which represents 3% of all providers in the country, accounts for 32% of total health care costs and 27% of total claims in the contributory system. It also accounts for 40% of total costs and claims per insurer on average. Panel B of appendix figure 1 shows the total number of hospitals per market. The largest market has 196 hospitals and the smallest market has 7 of them.

3 Descriptive Evidence

Private insurers in the contributory system are reimbursed by the government at the beginning of every year (ex-ante) with capitated risk-adjusted transfers, and at the end of every year (ex-post) with the High-Cost Account. The ex-ante risk adjustment formula controls for sex, age group, and municipality of residence. The formula does not include information about a patient's previous diagnoses. For year t, the base un-adjusted capitated transfer is calculated using the claims data from all insurers from year $t-2$. This transfer is roughly equal to the present value of the average annual health care cost per enrollee. Then, for each risk pool defined by a combination of sex,

[8] The registry can be accessed through the following website: https://prestadores.minsalud.gov.co/habilitacion/

age group, and municipality, the government calculates a risk adjustment factor that multiplies the base transfer. Appendix table 1 shows the national base transfer and its value for some specific municipalities. Appendix table 2 shows the risk group multipliers for 2011.

Because of the coarsely defined risk pools, the current ex-ante risk adjustment formula poorly fits realized health care costs. Riascos et al. (2014, 2017) find that the R^2 of the government's formula is only 0.017. Using the demographic information contained in the enrollment files, I can recover the ex-ante risk-adjusted transfer that each insurer received for each of its enrollees. Ex-ante reimbursements range from 162.2 thousand pesos (males aged 15-18) to 2.2 million pesos (for females aged 75 or older), with an average of 650.8 thousand pesos; while realized costs range from 0 to 300 million pesos.

The High-Cost Account compensates insurers that enroll an above-average share of people with any of the following chronic diseases: 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. The per-patient reimbursement equals the average cost of treatment for each disease. These reimbursements come from insurers that enroll a below-average share of individuals with those diseases.[9] My data contain total High-Cost Account transfers that each insurer received per year. Total ex-post transfers represent only 0.4% of total ex-ante transfers per insurer during the sample period, suggesting these ex-post transfers do not provide much risk adjustment. Despite compensating insurers for a few diagnoses, selection incentives are still present after ex-post risk adjustment as shown in Riascos (2013) and Riascos and Camelo (2017), because these adjustments are miscalculated.

Selection incentives exist because annual health care costs exhibit an enormous variation across patients conditional on government risk-adjusted transfers. Figure 1 shows that the mean and the variance (as reflected in the difference between 90th and 10th percentiles) of health care costs increase with the government's reimbursement or the individual's risk score. The rising trend in total costs by risk score suggests that insurers have incentives to engage in selection against old individuals. The rising trend in variance suggests that there is scope to select consumers in the upper tail of the distribution who are more likely to be overcompensated by the risk adjustment formula (Brown et al., 2014).

The coarse nature of the risk adjustment formula and the high variance in health care costs generate large variation in profits per enrollee that incentivizes risk selection. Table 1 presents the

[9] See Resolution 000248 of 2014 from the Ministry of Health.

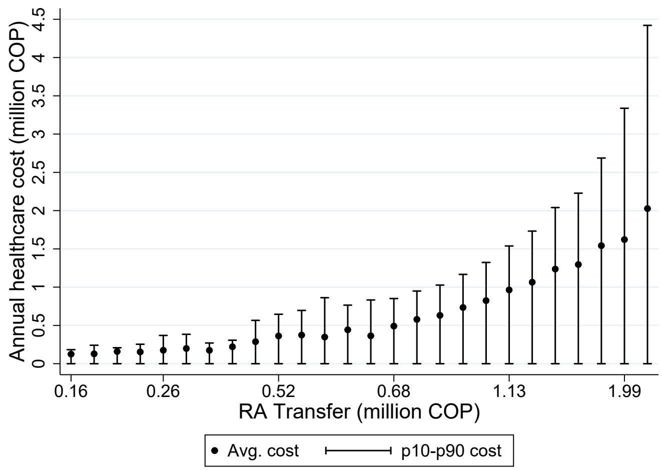


Figure 1: Health care cost by risk-adjusted transfer

Note: This figure presents the mean, 10th, and 90th percentiles of annual health care cost by level of the ex-ante risk-adjusted transfer from the government. The ex-ante transfer is the individual's risk score.

mean, 1st and 99th percentiles of profits per capita in the sample of current enrollees and new enrollees during 2011. The profit is calculated as the government's ex-ante and ex-post transfers, plus revenues from copayments and coinsurance rates, minus total realized health care costs. If the risk adjustment formulas were able to completely eliminate risk selection incentives, the variance in the distribution of profits per enrollee should be similar across insurers, but this is not the case. The table also shows that new enrollees' average profit is significantly higher than that of current enrollees, and their distribution of profits per capita less skewed to the left. Thus selection efforts should be stronger among new enrollees.

3.1 Measuring network breadth

Insurers in Colombia have discretion over how many hospitals to cover for each service, but it is mandatory that they cover at least one hospital for every service in the national insurance plan. This means that network breadth is defined over the number of hospitals *conditional on the service*, but not over services. Although insurers' coverage choices are in part determined by differences in hospital specialty and available capacity, these choices also depend on the type of consumers that insurance companies want to risk select upon. As an example of these service-level networks, appendix table 4 shows which insurers covered the services of cardiology, dialysis, and hospital admissions at three particular hospitals in the country. The table shows for example that at Fundación Valle del Lili, EPS010 covers cardiology, but not admissions. EPS002 covers dialysis, but not cardiology nor

Table 1: Distribution of profit per enrollee

	Current			New		
Insurer	Mean	P1	P99	Mean	P1	P99
EPS001	0.15	-7.76	2.06	0.49	-0.73	2.11
EPS002	0.09	-5.61	1.82	0.35	-1.12	1.99
EPS003	0.07	-5.94	1.88	0.42	-0.82	2.11
EPS005	0.14	-8.37	1.99	0.39	-1.62	2.11
EPS008	0.08	-6.54	1.88	0.30	-2.40	2.02
EPS009	-0.36	-15.25	1.87	0.26	-3.32	1.99
EPS010	0.10	-5.68	1.87	0.39	-1.03	2.11
EPS012	0.08	-6.35	1.80	0.36	-1.00	1.90
EPS013	0.08	-5.30	1.86	0.34	-1.00	1.99
EPS016	0.08	-6.25	1.90	0.38	-1.27	1.99
EPS017	0.04	-6.23	1.83	0.31	-1.60	1.99
EPS018	0.04	-6.22	1.83	0.28	-1.63	1.68
EPS023	0.10	-4.51	1.68	0.33	-0.82	1.68
EPS037	0.13	-17.16	2.15	0.66	-1.34	3.12
Total	0.08	-7.77	1.99	0.41	-1.28	2.11

Note: Table presents mean, 1st and 99th percentiles of profit per enrollee for each insurer in the sample of current enrollees and new enrollees. Profit per enrollee is calculated as the risk-adjusted transfers (ex-ante and ex-post), plus revenues from copays and coinsurance rates, minus total health care cost. Profits are measured in millions of 2011 Colombian pesos.

admissions. While EPS005 covers admissions, but not dialysis nor cardiology.

If insurers use their service-level hospital networks to select risks, then differences in risk selection efforts should appear as differences in network breadth. I define network breadth as the fraction of all hospitals in a market offering a particular service that are covered by the insurer. Table 2 shows that there is significant heterogeneity in network breadth per service across insurers and markets. EPS013 and EPS016 have relatively broad networks in almost all markets, covering an average of 49.7% and 55.0% of hospitals per service during 2011, respectively; while smaller insurers, like EPS008 and EPS023, tend to cover between 12.6% and 10.0% of hospitals per service in the average market. For the majority of insurance companies, network breadth exhibits small declines from 2010 to 2011 due to hospital entry.

Network breadth defined as a continuous measure in the unit interval is my primary object of interest in the rest of this paper. Enrollee satisfaction surveys conducted by the Colombian Ministry of Health show that narrow networks are one of the main reasons for dissatisfaction with an insurance company. Patients enrolled with insurers that have low network breadth typically have to travel longer distances to seek care, so network breadth can be interpreted as a measure of proximity to hospitals (see appendix figure 3).

By collapsing networks to an index per service, I am effectively assuming that, conditional on the

Table 2: Distribution of network breadth per service

	2010		2011	
Insurer	Mean	SD	Mean	SD
EPS013	52.7	32.6	49.7	31.5
EPS016	46.5	27.1	55.0	26.2
EPS037	37.0	29.7	34.2	27.9
EPS002	29.6	23.7	30.3	23.6
EPS017	16.5	21.9	16.3	20.0
EPS010	10.0	14.4	9.4	13.2
EPS005	27.2	24.9	27.7	23.7
EPS018	14.2	21.6	12.2	18.6
EPS003	22.4	20.5	20.4	19.4
EPS008	10.8	14.8	12.6	16.3
EPS023	11.5	17.5	10.0	15.7
EPS009	11.8	20.2	9.5	14.6
EPS001	13.1	12.5	12.1	11.6
EPS012	17.1	19.1	13.8	14.9

Note: Mean and standard deviation of network breadth per service for each insurer across markets during 2010 and 2011.

service, hospital quality is constant. This simplification is useful to explain the existence of narrow networks in equilibrium, but it could be losing important information if it matters *which* hospitals are included in the network, and not just how many. One reason why this information might be important is if some hospitals are star hospitals. Or, more generally, if some hospitals have higher quality than others. However, I show using various tests that this is not an issue. First, star hospitals are not as common in Colombia as they are in other countries like the United States. Second, I find that hospital quality and network breadth are positively correlated (see appendix table 5), thus high-quality hospitals are more likely to be included in a broad network as they are in a narrow network. The information about hospital quality can then be subsumed in the information about network breadth. Finally, sections 5 and 6 provide additional evidence that variation in hospital quality is not problematic for my insurer demand and cost models by conducting several robustness checks.

3.2 Network breadth as a means of risk selection

The descriptive statistics show that there is substantial variation in service-level network breadth and profits per enrollee across insurers and markets that are suggestive of differences in selection efforts. In this subsection I link profits per enrollee with service utilization to characterize selection incentives at the service level by replicating figures in Geruso et al. (2019) with my data.

In figure 2 I show whether the current risk adjustment systems are effective at neutralizing

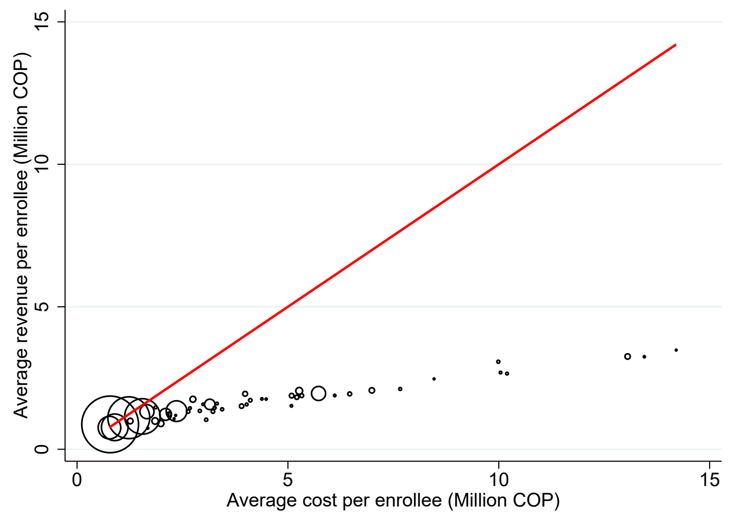


Figure 2: Service-level selection incentives after risk adjustment

Note: Scatter plot of average revenue and average cost per enrollee. Each dot is a service weighted by the number of individuals who make claims for the service. Revenues are calculated as government ex-ante and ex-post transfers, plus revenues from copays and coinsurance rates. The red line is a 45 degree line. One enrollee can be represented in several dots if she makes claims for different services. Enrollees who make zero claims are not represented in this figure.

service-level risk selection. The figure plots the average cost per enrollee against the average revenue per enrollee conditional on patients who make claims for each service. Every dot in the figure represents a service weighted by the number of patients who make claims for it. Patients who make claims for several services will be represented in several dots, while patients who make zero claims (and are the most profitable) are not represented in this figure. The red line is the 45 degree line, which splits the space into services that are overcompensated by the risk-adjusted transfers (above the line) and those that are undercompensated (below the line). The main takeaway is that patients who make any claim are likely to be unprofitable; but this is especially true for patients who have claims in certain services such as procedures in heart valves, cardiac vessels, and pancreas, which are located toward the right of this figure. In the case of procedures in heart valves, average costs are almost 5 times larger than average revenues per enrollee.[10]

The striking differences between revenues and costs per service arise from the simple fact that government payments do not compensate for enrollee characteristics that predict service usage. But insurers can set up their hospital networks separately per service. The existence of services that are outliers in terms of profits per enrollee suggests a scope for insurers to engage in service-level risk selection through their choice of hospital networks.

[10] These findings hold when using information from all individuals enrolled to the contributory system without constraining enrollment to be continuous.

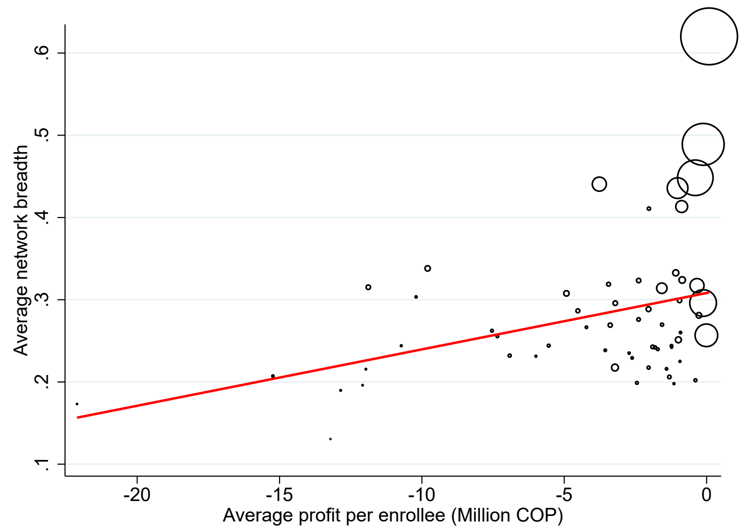


Figure 3: Correlation between network breadth and service profitability

Note: Scatter plot of average revenue and average cost per enrollee. Each dot is a service weighted by the number of individuals who make claims for the service. Profits are calculated as government ex-ante and ex-post transfers, plus revenues from copays and coinsurance rates, minus total health care costs. The red line corresponds to a linear fit. One enrollee can be represented in several dots if she makes claims for different services. Enrollees who make zero claims are not represented in this figure.

One way to test whether the data are consistent with selection at the service level is to show whether network breadth covaries with the profitability of a service, a version of the positive correlation test in Chiappori and Salanie (2000). Figure 3 plots the average profit per enrollee against average network breadth per service across insurers and markets. Average profits are calculated conditional on patients who make claims for the service. The red line corresponds to a linear fit and shows that relatively profitable services, such as consultations and procedures in teeth and tongue, tend to have broader networks than relatively unprofitable services, such as procedures in heart valves and cardiac vessels. This positive correlation is consistent with service-level network breadth being a mechanism for risk selection.

3.3 Selection vs. Moral Hazard

Variation in service profitability stems primarily from variation in service-level health care costs that is not accounted for by the risk adjustment mechanisms. Health care cost variation, in turn, can be due either to selection or moral hazard, which the previous descriptive evidence conflates. In this section I assess how much of the variation in costs can be explained by adverse selection and cream-skimming alone.

To separate selection from moral hazard, I start by estimating a regression on the sample of current enrollees who received a diagnosis in 2010. The dependent variable is the number of claims or an indicator for making a claim during 2011 in a service that is associated with treatment of their health condition diagnosed in 2010. The regression specification is given by:

$$y_{ijm}^{k,2011} = \beta_0 + \beta_1 H_{jm}^{k,2011} + \mathbf{d}_i^{2010}\beta_2 + \gamma_m + \varepsilon_{ijm},$$

where $H_{jm}^{k,2011}$ is insurer j's network breadth for service k during 2011, $\mathbf{d}_i^{2010}$ is a vector of demographics and diagnoses received during 2010, and γ_m is a market fixed effect. This specification captures the extent of selection into moral hazard as in Einav et al. (2013) in the sense that a positive correlation between service-specific network breadth and number of claims or probability of a claim for that service in $t+1$ would be suggestive of patients enrolling in carriers with more generous coverage for services that they anticipate needing given their health conditions in t.

Results presented in table 3 are suggestive of this source of selection. Column (1) shows that the probability of childbirth in 2011 among women who were in childbearing age during 2010 is increasing in network breadth for delivery services. The probability of dialysis claims, antirheumatic drug claims, and chemotherapy claims are also positively correlated with network breadth for dialysis, procedures in bones and joints, and chemotherapy, respectively. Column (2) uses the full sample of individuals enrolled in 2011 as a robustness check.

While the positive correlation between network breadth and number of claims conditional on 2010 health status could be explained by moral hazard rather than by selection, the correlation with the likelihood of making claims is unlikely the result of moral hazard. For example, given that all patients with renal disease make at least one dialysis claim, the positive correlation between network breadth and likelihood of a dialysis claim is not due to moral hazard. The positive correlation may also be unlikely the result of adverse selection as it requires individuals knowing if and when they will develop a disease.

However, focusing on the admittedly small sample of switchers, appendix table 6 shows that consumers whose health status changes over time tend to switch towards the insurer that has the broadest network for services they need given their newly diagnosed conditions relative to their incumbent insurer, which is consistent with selection into moral hazard. Results are similar for patients who switched but received a diagnosis in 2010 as seen in appendix table 7.

To isolate the effect of risk selection or cream-skimming, I explore whether insurers' network breadth choices are correlated with their enrollees' baseline costs and risk scores. I estimate a regression in the spirit of Brown et al. (2014) to compare baseline costs of switchers into insurers

Table 3: Service-specific network breadth and types of claims

	(1) Current	(2) Full
(1) Any childbirth claim		
H_{jm} Delivery	0.02***	0.01***
	(0.001)	(0.001)
N	1,085,206	3,078,555
(2) Any dialysis claim		
H_{jm} Dialysis	0.03***	0.03***
	(0.004)	(0.003)
(3) log(dialysis claims+1)		
H_{jm} Dialysis	0.09***	0.07***
	(0.009)	(0.007)
N	83,768	120,330
(3) Any antirheumatic drug claim		
H_{jm} Bones and Joints	0.002	0.002**
	(0.001)	(0.001)
(4) log(antirheumatic drugs+1)		
H_{jm} Bones and Joints	0.003*	0.003**
	(0.002)	(0.001)
N	102,612	156,385
(5) Any chemotherapy claim		
H_{jm} Therapy	0.003*	-0.002
	(0.002)	(0.001)
(6) log(chemotherapy claims+1)		
H_{jm} Therapy	-0.002	-0.003
	(0.003)	(0.002)
N	439,176	785,727

Note: OLS regressions of the probability of childbirth, any dialysis claim, any antirheumatic drug claim, and any chemotherapy claim during 2011, on service-level network breadth, conditional on the sample of individuals who received a diagnosis during 2010. Column (1) uses the sample of current enrollees and column (2) uses the full sample without constraining enrollment to be continuous. All models include market fixed effects and control for sex and age group. Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1.

that reduce their network breadth over time to baseline costs of stayers in insurers that expand their network breadth. By focusing on baseline costs rather than current costs as outcome, this analysis also separates risk selection from moral hazard.

Given that the fraction of switchers in my data is very small, these exercises will only be suggestive of the effectiveness of risk selection. The regression specification is as follows:

$$y_{ikm}^{2010} = \beta_0 + \beta_1(H_{jkm}^{2010} - H_{jkm}^{2011}) + \beta_2 S_{im} + \beta_3 S_{im} \times (H_{jkm}^{2010} - H_{jkm}^{2011}) + \mathbf{d}_i\beta_4 + \lambda_k + \delta_j + \eta_m + \varepsilon_{ikm}$$

Here y_{ikm}^{2010} is either the logarithm of total health care cost of individual i in service k and market m during 2010 or an indicator for having non-zero claims. S_{im} is an indicator for whether the consumer switched carriers from one year to the other. The subscript j denotes the insurer chosen in 2011, so H^{2010}_{jkm} is the 2010 network breadth of insurer j' and H^{2011}_{jkm} is the 2011 network breadth of insurer j. $\mathbf{d}_i$ is a vector of demographics and diagnoses, λ_k is a service fixed effect, δ_j is an insurer fixed effect, and η_m is a market fixed effect. The coefficient of interest is β_3.

Table 4: Selection on baseline costs and risk

	$\log(\text{total cost}^{2010}_{ijkm}+1)$ (1)	$\text{any claim}^{2010}_{ijkm}$ (2)	$\log(\text{risk transfer}^{2011}_{new})$ (3)
$H^{2010}_{j'km} - H^{2011}_{j'km}$	0.004*	-0.0001	-0.17***
	0.002	0.0002	0.008
Switch	-0.09***	-0.007***	—
	0.02	0.001	
Switch × $(H^{2010}_{j'km} - H^{2011}_{j'km})$	-0.23***	-0.02***	—
	0.08	0.007	
Demog+Diag	Y	Y	—
Market	Y	Y	Y
Service	Y	Y	—
Insurer	Y	Y	Y
N	14,457,009	14,457,009	2,653,415
R^2	0.50	0.51	0.06

Note: Columns (1) and (2) use a random sample of 250,000 current enrollees. Column (1) presents results of an OLS regression of the logarithm of 2010 total service-specific costs on a switching indicator and the difference in network breadth between 2010 and 2011 for the 2011 choice of insurer. Column (2) shows results of an OLS regression for an indicator of non-zero service-specific claims on the same variables as before. Both columns include demographics and diagnoses indicators, as well as insurer, service, and market fixed effects. Column (3) presents results of an OLS regression of the logarithm of new enrollees' risk-adjusted transfer on the difference in network breadth between 2010 and 2011, and market and insurer fixed effects. Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1.

The choice of service-specific network breadth is an effective risk selection mechanism on enrollee's baseline costs. Column (1) of table 4 shows that individuals who switch into carriers that reduce their network coverage over time tend to be less costly in that service than individuals who do not switch. Results in column (2) for the probability of making a claim in each service are consistent with this finding.[11]

To overcome the issue of low statistical power in the previous results, I regress new enrollees' risk score on the changes in network breadth (aggregating across services) for the insurer they enroll with. The risk score is given by the ex-ante risk-adjusted transfer from the government, which is known to insurance companies before networks are formed. Results in column (3) of table 4 show that insurers that reduce their overall hospital network breadth tend to enroll new enrollees with

[11] Results in column (1) of table 4 are robust to alternative modelling specifications such as using a two-part model for baseline costs, with a first stage logit for the probability of having non-zero cost, and a second stage log-linear regression conditional on having non-zero cost. Results also hold when defining changes in network breadth between the insurer chosen in 2010 (j') and the one chosen in 2011 (j).

lower ex-ante risk scores compared to insurers that expand their network breadth over time. This finding indicates that even in the absence of switching or under strong consumer inertia, network breadth can serve as a tool to select individuals who are ex-ante less risky.[12]

3.4 Trade-offs to Broad vs. Narrow Networks

Given that broad networks attract less profitable patients, and insurers cannot charge premiums to cover the higher costs resulting from a broad network, why don't all insurers choose to have narrow networks? Aside from possible heterogeneity in the costs of network formation, it is important to note that broad networks attract more of every kind of patient. Appendix 6 shows that, relative to narrow network carriers, insurers that offer broad networks have higher demand from patients with chronic diseases who are usually unprofitable, but also higher demand from healthy individuals who are profitable. In general, results in the appendix suggest that consumers have strong preferences for broader networks and that this preference is heterogeneous across individuals.

4 Model

In this section I put together the descriptive findings to model insurer competition in hospital networks. In the model, insurers first simultaneously set their vector of service-specific network breadths in every market. Then, given service-level network breadths, consumers make enrollment decisions.

The model of insurer demand will focus on the sample of new enrollees in 2011 for which selection efforts are stronger. New enrollees do not experience inertia when making their *first* enrollment decision. These individuals select insurers based on their initial observable demographics and diagnoses, on the insurers' network breadth per service, and on their implied out-of-pocket costs. The demand model captures the cost-coverage trade-off that consumers face when making enrollment choices by allowing out-of-pocket costs to depend on network breadth. To the extent that healthy consumers care more about out-of-pocket costs than network breadth relative to sick consumers, insurers will be able to screen healthy individuals by choosing narrow networks at the service level. I also assume that, after making their first insurer choice, enrollees do not switch. This last assumption is based on the near-zero fraction of enrollees in the data that switch their insurance carrier from one year to the other.

[12] Findings are qualitatively similar if I use the level of network breadth rather than changes in network breadth over time. High coverage carriers tend to enroll individuals with higher risk scores.

On the supply side, I assume insurers are forward looking and compete for the set of new enrollees every period by choosing their vector of network breadth per service. In making coverage choices, insurers internalize the dynamic incentives introduced by consumers facing infinite switching costs. With infinite switching costs, the dynamic programming problem of network formation every period can be approached as a static problem in steady state where insurers choose network breadth per service once. Insurers maximize the sum of current and future discounted profits by simultaneously choosing their vector of network breadths, so the solution concept is a steady state Nash equilibrium.

I allow insurers to be heterogeneous in their average cost per enrollee and network formation cost, which in addition to preference heterogeneity can help rationalize the asymmetric equilibrium in network breadth observed in the data. Because asymmetries in network breadth could be generated by this cost heterogeneity alone rather than by adverse selection in demand, the supply model is needed to assess the relative importance of these two factors.

4.1 Insurer Demand

Assume a new enrollee i living in market m is of type θ and with probability $q_{\theta km}$ she will need each of the $k = \{1, ..., K\}$ services. An individual's type is given by the combination of sex, age category (<1, 1-4, 5-14, 15-18, 19-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, $\geq$75), and diagnosis $d \in D =$ {cancer only, cardiovascular disease only, diabetes only, renal disease only, other disease only, two or more comorbidities, and no diseases}. Diagnoses in the list are groupings of ICD-10 codes following Riascos et al. (2014), which are both exhaustive and mutually exclusive. These diagnoses were chosen for being the most expensive in Colombia and thus the most likely to be undercompensated by the current risk adjustment formula. For example, the most expensive patients with renal disease had annual health care cost of over 55 million pesos in 2011, more than 100 times the monthly minimum wage.

I assume the individual knows her diagnoses before making her first enrollment choice. This could be either because of medical family history or because, prior to enrolling in the contributory system, she went to the doctor and received a diagnosis. Enrollees know their health condition because selection occurs on observable, un-reimbursed (or poorly reimbursed) consumer characteristics such as those associated with health status. The consumer observes each insurer's network breadth in service k and market m, H_{jkm}; weights each service by the probability of claiming it $q_{\theta km}$, conditional on the diagnosis; and then makes a one-time myopic choice of carrier. Denote by u_{ijm}

the indirect utility of a new enrollee i in market m for insurer j, which takes the following form:

$$u_{ijm} = \beta_i \sum_k q_{\theta km} H_{jkm} - \alpha_i c_{\theta jm}(H_{jm}) + \phi_j + \varepsilon_{ijm} \tag{1}$$

where

$$\beta_i = (x_i\ y_i)'\beta$$
$$\alpha_i = x_i'\alpha$$

The vector x_i includes consumer demographics such as sex, age (continuous), indicators for the diagnoses in D, type of municipality indicators, and an intercept.[13] The vector y_i includes income level indicators. $c_{\theta jm}$ is the average out-of-pocket cost of consumer type θ at insurer j, which depends on the insurer's vector of network breadth H_{jm}, either because negotiated prices are higher or because patients tend to consume more health services the broader is the network. The coefficient ϕ_j is an insurer fixed effect that captures unobserved insurer quality and ε_{ijm} is an *iid* unobserved shock to preferences assumed to be distributed T1EV. In terms of parameters, β_i^D represents the preference for network breadth, and α_i represents the marginal disutility of a one million pesos increase in out-of-pocket costs.

Average out-of-pocket costs are the sum of coinsurance payments, copays, and tax contributions to the health system as seen below:

$$c_{\theta jm} = \text{Coins}_{\theta jm} + \text{Copay}_{\theta jm} + (1/3) \times \text{Tax}_y$$

The tax contribution equals 12% of the enrollee's monthly income, 1/3 of which is paid by the enrollee and 2/3 by her employer. Tax contributions vary only across income categories y, while coinsurance payments and copays depend not only on income but also on the insurer's negotiated service prices with hospitals and on the individual's health care utilization. Prices and utilization are correlated with the insurer's choice of service-level network breadth because of insurer-hospital price bargaining and because of patient moral hazard. Appendix figure 5 shows that out-of-pocket costs in fact vary substantially across insurers and across consumer types. To capture this correlation, I assume that out-of-pocket payments are a linear function of the insurers' average cost per enrollee

[13] In the government's risk adjustment formula, municipalities are grouped into urban, normal, and peripheral. Urban municipalities belong to metropolitan areas, normal municipalities are those adjacent to metropolitan areas, and peripheral municipalities are those characterized by difficult geographical access.

$AC_{\theta jm}$, which in turn depends on network breadth as follows:

$$c_{\theta jm} = \mu_y AC_{\theta jm}(H_{jm}) + \epsilon_{\theta jm} \tag{2}$$

where $\epsilon_{\theta jm}$ is a standard normal error term. I estimate equation (2) separately by income group to recover μ_y; results are presented in appendix table 9. If out-of-pocket costs were composed of only coinsurance payments, then μ_y would be equal to the coinsurance rate. But because these out-of-pocket costs involve payments (tax contributions) that individuals make directly to the health care system and that insurers *do not cover*, μ_y will be different from the coinsurance rate. A more detailed description of insurers' average cost per enrollee is provided in the next subsection.

The first term on the right side of equation (1) can be interpreted as a reduced-form approximation to the consumer's expected utility for the network obtained from a 2-step model, in which first the individual chooses an insurer and then chooses an in-network hospital, as in Ho and Lee (2017). In the case of Ho and Lee (2017), the insurer offers the same network of hospitals to consumers of different medical conditions. In my case, variation in network breadth across services and variation in the likelihood of making claims for those services, together imply that the network can also be disease-specific.

The probability of making a claim, $q_{\theta km}$, is calculated from the claims data in a preliminary step as the average prediction per consumer type, service, and market, from a logistic regression estimated at the patient level given by:

$$\text{logit}(\text{Any claim}_{ikm}) = \psi_k + \psi_\theta + \psi_m + \psi_{ikm} \tag{3}$$

The dependent variable is an indicator for whether consumer i living in market m made a claim in service category k. On the right side, ψ_k, ψ_θ, and ψ_m are service, consumer type, and market fixed effects, respectively. ψ_{ikm} is a mean zero shock to the claim probability that is independent of network breadth conditional on consumer observable characteristics.

Even though new consumers are myopic when choosing their insurance carriers, I assume that their expectations over the type of services they will need conditional on their initial health condition are correct on average, and that these expectations do not depend on the insurer they enroll with. I estimate equation (3) on data from both current and new enrollees in 2010 and 2011. Appendix figure 4 presents the distribution of $q_{\theta km}$ separately for healthy and sick individuals, and for a few service categories.

I allow preferences for network breadth to vary across demographic characteristics and diagnoses to capture the extent of service-specific adverse selection documented in the descriptive section. However, I do not explicitly model unobserved heterogeneity with inclusion of random coefficients. Instead I include preference shocks ε_{ijm} that are independent across choice alternatives. This means that the only way in which risk selection can arise in my model is through the observable characteristics.

The second term on the right of equation (1) captures differences in prices and utilization across insurers, giving rise to consumer sorting based on out-of-pocket payments. This sorting is needed to rationalize the existence of narrow network carriers in the *observed* equilibrium since myopic, healthy new enrollees disproportionately choose narrow network carriers with lower implied out-of-pocket costs. I allow out-of-pocket costs to depend on network breadth to reflect the cost-coverage trade-off that consumers face when making enrollment decisions. Out-of-pocket costs are aggregated across services because a service-level calculation would require imputing costs for consumer-insurer combinations for which I do not observe claims being provided for a service, so measurement errors and mechanical bias would be much more likely.

Integrating out the preference shock, the probability that consumer i in market m enrolls with insurer j is:

$$s_{ijm}(H_m) = \frac{\exp\left(\beta_i \sum_k q_{\theta km} H_{jkm} - \alpha_i c_{\theta jm}(H_{jm}) + \phi_j\right)}{\sum_{j' \in \mathcal{J}_m} \exp\left(\beta_i \sum_k q_{\theta km} H_{j'km} - \alpha_i c_{\theta j'm}(H_{j'm}) + \phi_{j'}\right)}$$

Identification. Network breadth and average out-of-pocket costs in the consumer's utility function may be endogenous if they are correlated with unobserved insurer quality or unobserved consumer characteristics. Coverage decisions also entail strategic interactions between insurers that may introduce correlation with unobserved characteristics. My identification strategy for network breadth follows Nevo (2000) and Shepard (2022) in the use of fixed effects that absorb the endogenous variation in this variable. Identification of out-of-pocket costs relies on Petrin and Train (2010)'s control function approach.

For network breadth, my demand specification aggregates H_{jkm} across services, eliminating the endogenous variation in that dimension. The demand function also includes insurer fixed effects that control for unobserved insurer-level characteristics that may be correlated with network breadth. These fixed effects do not capture unobserved quality that varies *within* insurers nor *within* markets. However appendix tables 13-15 illustrate that this type of variation is not concerning for identification purposes. The tables provide robustness checks of my demand model that include additional insurer-level quality measures that vary across markets and consumer types. A more detailed discussion of these exercises is provided in section 5.1. β_i in my main specification is therefore identified from variation in market demographics, which generates exogenous variation in $q_{\theta km}$. For example, for exogenous reasons some markets will have a higher prevalence of respiratory diseases, which makes insurers offer broader hospital coverage for procedures in lungs in these markets than they would in markets with lower prevalence of the disease.

Identification of the marginal disutility for out-of-pocket costs relies on exogeneity of coinsurance rates, copayments, and required tax contributions to the system. This helps correct part of the bias introduced by negotiated service prices, which affect coinsurance payments. Nonetheless, it is possible that consumers choose their insurer based on unobserved quality that is correlated with negotiated prices and unaccounted for by coinsurance rates and copayments.

An example of unobserved quality that could potentially bias my estimates is the insurer's coverage of star hospitals. If consumers disproportionately enroll with carriers that cover star hospitals and these carriers in turn negotiate higher prices with those hospitals, then my model would interpret consumers as having low sensitivity to out-of-pocket costs, biasing α_i towards zero. To address this issue, my preferred demand specification is one that uses an instrument for out-of-pocket costs in a control function approach (Petrin and Train, 2010). The instrument is the reference price per service created by the government in 2005 –explained in more detail in the next subsection. Reference prices are supply shifters; they affect insurer-hospital negotiations but are unobserved by consumers. Moreover, reference prices only affect demand through their effect on out-of-pocket costs.[14] I also conduct additional robustness checks in section 5 to verify that star hospital coverage is not a meaningful source of bias.

[14] In the first step I estimate the following linear regression:

$$c_{\theta(i)jm} = \gamma_0 + \gamma_1(1 - r_i) \sum_k q_{\theta km} A_k + \lambda_\theta + \delta_j + \eta_m + \varphi_{\theta(i)jm}$$

where r_i is the coinsurance rate of individual i and A_k is the government's reference price for service k. From this regression I obtain the residual $\hat{\varphi}_{\theta(i)jm}$ and standardize it at the market level, by subtracting the mean and dividing by the standard deviation. Then, I estimate equation (1) including the standardized residual, $\hat{\varphi}^z_{\theta(i)jm}$, and its interactions with enrollee sex, age, diagnosis indicators, income level indicators, and an intercept:

$$u_{ijm} = \beta_i \sum_k q_{\theta km} H_{jkm} - \alpha_i c_{\theta jm}(H_{jm}) + x_i' \hat{\varphi}^z_{\theta jm} + \phi_j + \varepsilon_{ijm}$$

The maintained assumption is that $\hat{\varphi}^z_{\theta jm}$ is correlated with ε_{ijm} but that, conditional on $\hat{\varphi}^z_{\theta jm}$, ε_{ijm} is independent of $c_{\theta jm}$. First stage results are presented in appendix table 10.

4.2 Insurer Average Costs per Enrollee

Following Shepard (2022), I assume the realized annual health care cost of consumer i of type θ under the observed service-specific networks, $C^{obs}_{ijm}(H_{jm})$, equals the average cost of a type-θ consumer plus a random shock: $C^{obs}_{ijm}(H_{jkm}) = AC_{\theta jm}(H_{jkm}) + \omega_{ijm}$. If sex, age, and diagnoses are observable or predictable by the insurer before the cost shock is realized, then ω_{ijm} is orthogonal to $AC_{\theta jm}(H_{jkm})$ conditional on θ and I can recover this cost directly from the data by taking the average of observed costs across individuals of type θ: $AC_{\theta jm}(H_{jkm}) = \frac{1}{N_{\theta jm}} \sum_{\theta(i)=\theta} C_{ijm}(H_{jkm})$. By the law of large numbers, this average will equal the insurer's average costs per consumer type. I then model the logarithm of average cost per consumer type as a function of network breadth, as follows:

$$\log(AC_{\theta jm}(H_{jm})) = \tau_0\Big(\sum_k q_{\theta km}A_k\Big) + \tau_1\Big(\sum_k q_{\theta km}H_{jkm}\Big) + \frac{1}{2K_m}\tau_2 \sum_k \sum_{l\neq k} q_{\theta km}q_{\theta lm}H_{jkm}H_{jlm} + \lambda_\theta + \delta_j + \eta_m \tag{4}$$

where K_m is the number of service categories available in market m, that is, services that existing hospitals in the market can provide. A_k is the reference price for service k (explained in more detail below), λ_θ is a consumer type fixed effect, δ_j is an insurer fixed effect, and η_m is a market fixed effect. In appendix 9 I show that this average cost function per enrollee has a direct relation to a model where consumers choose a hospital to receive service k.

The coefficient τ_1 represents the elasticity of average costs with respect to insurer j's network breadth. τ_2 captures the average degree of complementarity between pairs of services. If $\tau_2 < 0$, then insurers have economies of scope across services, so greater coverage for service $l \neq k$ makes it more attractive to the insurer to provide higher coverage for service k. I include this measure of scope economies to rationalize the fact that insurers with broad networks in one service, tend to offer broad networks in other services as well (see appendix figure 6). For instance, EPS013, EPS016, and EPS037 tend to have generous coverage across all services and markets, while EPS008, EPS009, and EPS012 tend to have narrower networks across all services. Scope economies can come from insurers receiving price discounts at hospitals with which they have bargained previously.

The first two terms in the right-hand side of equation (4) are multiplied by $q_{\theta km}$ to capture the fact that increasing network breadth for one service does not increase the average cost of all consumer types by the same magnitude. The effect on average costs will depend on how likely it is that the consumer makes a claim in that service category, which is known by insurance companies before making coverage decisions. For example, increasing network breadth for c-sections is likely going to increase the average cost of women in childbearing ages but not the average cost of men.

Identification. The parameters of equation (4) are identified from variation in average costs within consumer types across insurers that are identical except for their network breadth per service. My source of identification does not rely on different consumers implying different costs for similar insurers as in Tebaldi (2017) but, *conditional* on the composition of enrollee pools, for different coverage levels per service to imply different costs to the insurer. The average cost specification aggregates network breadth across services and includes a rich set of fixed effects that absorb the endogenous variation of network breadth across and within insurers due to selection.

If selection happens mostly on observables, then consumer type fixed effects in equation (4) help correct the endogenous variation in network breadth across enrollees. If selection happens mostly on unobservables, then it should be the case that there is unobserved cost variation within consumer types. One way to check this is to test whether estimates are robust to a more granular definition of consumer type. I conduct robustness checks of this style in appendix table 17 using patient-level data.[15]

Service reference prices. In 2005, the Colombian government published a list of reference prices for all the services included in the national health insurance plan. The list was created by a group of government officials and medical experts with the purpose of reimbursing hospitals in the event of terrorist attacks, natural disasters, and car accidents.[16] Although they were not meant to guide price negotiations between insurers and hospitals, there is evidence that insurers use these reference prices as starting points in their negotiations with hospitals (Ruiz et al., 2008). I use the reference prices as a measure of average claim cost for service k in the insurers' average cost function and as an instrument for demand. Figure 4 shows the average total claim cost for each service in the horizontal axis calculated directly from the claims data in black and the price instrument in red. The correlation between these two measures equals 0.77.[17]

4.3 Competition in Network Coverage

Insurers compete separately in every market, choosing their service-specific network breadth after taking expectations of demand and costs. Let $\pi_{ijm}(H_m, \theta)$ be insurer j's annual per-enrollee profit

[15] My average cost model aggregates total healthcare cost to the consumer type level to avoid econometric issues that arise from the overwhelming amount of zeros in health care costs at the patient-level.

[16] Decree 2423 of 1996

[17] Let p_k^R be the reference price for service k and f the average inflation rate from 2005 to 2011, then $A_k = p_k^R \times (1+f)^6$.

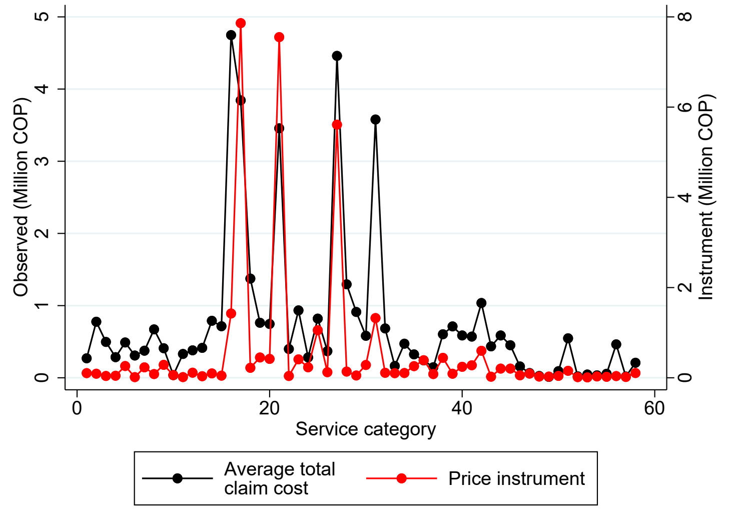


Figure 4: Average claims cost and reference prices

Note: For every service in the horizontal axis, this figure shows the average cost of a claim calculated from the data in black and the average reference price in red.

in market m, which depends on j's network breadth and its rivals', all collected in the vector H_m, as well as on the enrollee's type θ. The annual per-enrollee profit is given by:

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

where $R_{\theta m}$ is the per-capita revenue including ex-ante and ex-post risk-adjusted transfers from the government and average copayments, $AC_{\theta jm}$ is the average cost of a type-θ consumer net of patients' coinsurance payments with r_i denoting the coinsurance rate, and s_{ijm} is consumer i's choice probability for insurer j in market m.

I focus on a steady state Nash equilibrium in which insurers choose networks to maximize the sum of annual profits and future discounted profits minus the cost of network formation:

$$\Pi_{jm}(H_m) = \sum_{\theta} \Big(\underbrace{\pi_{ijm}(H_m, \theta)N_{\theta m}}_{\text{annual profit}} + \underbrace{\sum_{s=t+1}^{T} \zeta^s \sum_{\theta'} (1 - \rho_{\theta' m})\mathcal{P}(\theta'|\theta)\pi_{ijm}(H_m, \theta')N_{\theta' m}\Big)}_{\text{future profit}}$$
$$\underbrace{- \sum_{k} \Big(\omega H_{jkm} + \xi_{jkm}\Big) H_{jkm}}_{\text{network formation cost}}$$

Insurers take into account the future profits associated with each enrollee since, after making their first enrollment choice, individuals experience infinite switching costs. $N_{\theta m}$ is the market size of consumers type θ, which is fixed over time, so there are no dynamics introduced by changes in population. In the expression for future profits, $\rho_{\theta m}$ represents the probability that type θ drops out of the contributory system. This probability is (assumed) exogenous to the choice of network breadth as it is mostly governed by the event of falling into unemployment. $\mathcal{P}(\theta'|\theta)$ is the transition probability from type θ in period t to type θ' in period $t+1$. Future profits at year t are discounted by a factor of ζ^t, and I set ζ equal to 0.95.[18]

In addition to its indirect effect on insurer profits through expected costs and demand, I assume network breadth involves a direct cost to the insurer, which can be interpreted as an administrative cost associated with inclusion of an additional hospital to the network, where:

$$\xi_{jkm} = \xi_j + \xi_k + \xi_m + \Delta\xi_{jkm}$$

This network formation cost is nonlinear in network breadth, ω capturing whether the cost function is convex. The network formation cost is also heterogeneous across insurers, services, and markets, with ξ_j, ξ_k, and ξ_m representing the insurer-, service-, and market-specific cost components, respectively. I assume $\Delta\xi_{jkm}$ is a network formation cost shock that is *iid* across insurers, services, and markets, as well as over time. This cost shock is observed by insurers but unobserved to the econometrician, and it is mean independent of insurers' network formation cost shifters. By making unobserved costs have a multiplicative effect on network breadth, I am implicitly assuming that cost shocks can affect network breadth across all services and markets. For example, the insurer may have an outstanding managerial or bargaining team that makes it less costly to offer broad networks across all services.

With adverse selection, the trade-off associated with providing a broad network for a given service is that it increases both demand and costs. By doing so, not only does the insurer attract more consumers overall because of strong preferences for broad networks, but disproportionately attracts those with a high likelihood of claiming the service. The positive relation between network breadth and demand creates vertical differentiation in this model. Rivals' choices of network breadth also affect insurer j's profits. Willingness-to-pay for insurer j are a function of own and rival network breadth. Moreover, rival network breadth impacts insurer j's total average cost through its effect on the composition of insurer j's enrollee types given that there is no outside option. Variation

[18] In the formulation of insurer profits, I use θ to denote sex-age-diagnosis combinations as opposed to sex-age group-diagnosis, for simplicity in notation, but to be consistent between transition probabilities and periods over which future profits are calculated (years).

in willingness-to-pay across consumer types and rivals generates horizontal differentiation in this model.

Profit maximization involves a set of $J \times K$ first-order conditions (FOC) in each market, which assuming an interior solution in network breadth, is given by:

$$\sum_i \left(\frac{\partial \pi_{ijm}}{\partial H_{jkm}} N_{\theta m} + \sum_{s=t+1}^{T} \zeta^s \sum_{\theta'} (1-\rho_{\theta' m}) \mathcal{P}(\theta'|\theta) \frac{\partial \pi'_{ijm}}{\partial H_{jkm}} N_{\theta' m} \right) = 2\omega H_{jkm} + \xi_{jkm} \tag{5}$$

The left-hand side of equation (5) represents the marginal variable profit MVP_{jkm} and the right-hand side is the marginal cost of network formation. The derivative of the short-run per enrollee profit, which enters MVP_{jkm}, is in turn:

$$\begin{aligned} \frac{\partial \pi_{ijm}}{\partial H_{jkm}} = & \underbrace{\overbrace{R_{\theta m} \frac{\partial s_{ijm}}{\partial H_{jkm}}}^{\text{Selection}} + \overbrace{R_{\theta m} \frac{\partial s_{ijm}}{\partial AC_{\theta jm}} \frac{\partial AC_{\theta jm}}{\partial H_{jkm}}}^{\text{Endogenous OOP}}}_{\text{Marginal revenue}} \\ & \underbrace{- (1-r_i) \Big(\overbrace{AC_{\theta jm} \frac{\partial s_{ijm}}{\partial H_{jkm}} + s_{ijm} \frac{\partial AC_{\theta jm}}{\partial H_{jkm}}}^{\text{Selection}} + \overbrace{AC_{\theta jm} \frac{\partial s_{ijm}}{\partial AC_{\theta jm}} \frac{\partial AC_{\theta jm}}{\partial H_{jkm}}}^{\text{Endogenous OOP}} \Big)}_{\text{Marginal cost}} \end{aligned} \tag{6}$$

Equation (6) shows the effect of adverse selection and out-of-pocket cost endogeneity on insurers' network breadth choices. If the insurer increases its network breadth for a particular service, revenues will increase due to selection because individuals prefer broader networks overall, so insurer demand increases. Selection also increases insurers' costs because broader networks for a particular service attract consumers who are more expensive in that service, and because changes in network breadth increase the cost of the average consumer. The endogeneity in out-of-pocket costs has opposite effects on marginal revenues and marginal costs. An increase in network breadth, which may incentivize individuals to consume more health care, increases consumers' out-of-pocket costs and thus puts a downward pressure on insurer demand. An increase in network breadth also reduces insurers' cost because individuals whose out-of-pocket costs increase and whose enrollment may be discouraged, are also the most expensive in that service category.

Model discussion. My model of insurer competition extends and complements the work in Shepard (2022), who models the binary decision of an insurer to include or exclude a star hospital from its network in the context of the Massachusetts Health Exchange. In my case, I allow for insurer heterogeneity in network breadth across different services and model the dynamic incentives that insurers face when setting up their networks, which are introduced by infinite consumer inertia.

This model is robust to different assumptions about consumers. Notice that if consumers were forward looking rather than myopic and could anticipate their future diagnoses, the equilibrium would be one where all insurers choose broad networks. However, the equilibrium implications of myopia are similar to a model where consumers are forward looking but (wrongly) believe that switching costs are zero, so they can re-optimize every period. Equilibrium implications of myopia are also similar to a model where consumers heavily discount the future and therefore choose their insurer based on current preferences and characteristics. This means that even without myopia, the model would generate adverse selection on network breadth and co-existence of broad and narrow network carriers in equilibrium. On a similar note, network formation costs allow the model to better fit the data, but are not required to rationalize the asymmetric equilibrium in network breadth. As long as the effects of adverse selection are strong relative to insurers' cost heterogeneity, the model can explain the observed data patterns.

Identification. Rewriting the FOC

$$MVP_{jkm}(H_{jkm}) = 2\omega H_{jkm} + \xi_j + \xi_k + \xi_m + \Delta\xi_{jkm}, \quad \forall\ H_{jkm} \in (0,1) \tag{7}$$

makes explicit the endogeneity between H_{jkm} and the network formation cost shocks, $\Delta\xi_{jkm}$. Insurance companies observe $\Delta\xi_{jkm}$ before or at the same time as they are deciding on their network breadth per service. For instance, if an insurer hires a highly trained manager to bargain with hospitals or if an insurance company is vertically integrated with its network, then $E[\Delta\xi_{jkm}|H_{jkm}] < 0,\ \forall\ H_{jkm} \in (0,1)$ and OLS estimation of (7) would result in ω that is biased towards zero.[19] Identification of network formation cost parameters thus relies on instrumental variables Z_{jkm} that are correlated with network breadth but not with the cost shock, and that are correlated with marginal variable profits only through network breadth, such that $E[\Delta\xi_{jkm}Z_{jkm}] = 0,\ \ \forall\ H_{jkm} \in (0,1)$.

The instrument set is populated as follows. First, I include the set of insurer, market, and service fixed effects in equation (7). Second, because I use data from 2011 in estimating the model and $\Delta\xi_{jkm}$ is assumed *iid* over time, I use the service-specific network breadth in 2010. Third, I include the average probability that a female, a person aged 19-44, and an individual without

[19]Vertical integration is restricted by the Colombian government to up to 30% of an insurance company's assets. So, endogeneity stemming from integration is unlikely.

diseases make a claim for service k in market m. These probabilities are calculated as the average prediction of equation (3) across consumers that share the demographic traits above. Finally, I include the interaction between 2010 network breadth and the average service claim probability of a person aged 19-44.

The moment conditions at an interior solution, given by $E[\Delta\xi_{jkm}Z_{jkm}] = 0$, can only rationalize the observed equilibrium in markets where no insurer chooses a corner solution in any of the services. In other words, the model is rejected by the data in markets where insurers choose service-level network breadth equal to zero or one. Thus, to estimate the parameters of the network formation cost as described by the FOC, I restrict my sample to the four largest markets in the country (Antioquia 05, Atlántico 08, Bogotá 11, and Valle de Cauca 76) that cover 60% of the population in the contributory regime, and to the top 10 insurers in these markets that cover 87% of enrollees (EPS001, EPS002, EPS003, EPS005, EPS010, EPS013, EPS016, EPS017, EPS018, EPS037). In this final sample, all insurers choose an interior solution in H_{jkm}, $\forall\ k, m$. In dropping the smallest insurers I am assuming that only competition among the largest carriers determines their network breadth choices, and that small insurers move only after the top companies make their choices.[20]

5 Estimation

5.1 Insurer Demand

The insurer demand model is a conditional logit, which I estimate by maximum likelihood. To reduce the computational burden, I estimate equation (1) on a random sample of 500,000 new enrollees. First stage control function results for out-of-pocket costs are presented in appendix table 10. Results in table 5 show that insurer demand is decreasing in out-of-pocket costs and increasing in network breadth, suggestive of selection into health insurance. A one million pesos increase in out-of-pocket costs reduces demand for carriers by 7.52 percentage points on average, corresponding to an average elasticity of -0.51.[21] A one percentage point increase in network breadth across all services increases the choice probability by 5.64 percentage points on average.[22]

[20]More generally, without dropping observations at the corners, the parameters of the network formation cost are partially identified. Note that the FOC at $H_{jkm} = 0$ is $MVP_{jkm} - \xi_j - \xi_k - \xi_m - \Delta\xi_{jkm} < 0$, and at $H_{jkm} = 1$, is $MVP_{jkm} - \tilde{\omega} - \xi_j - \xi_k - \xi_m - \Delta\xi_{jkm} > 0$. Estimation can be pursued using these moment inequalities following Pakes et al. (2015). But, to rationalize the corner at zero, the network formation cost should additionally include a fixed cost term. While this approach would utilize the entirety of markets for estimation, it is computationally costlier. Moreover, set identification of ω and the extensive set of fixed effects is not necessarily guaranteed.

[21]The elasticity with respect to out-of-pocket costs is $\frac{\partial s_{ijm}}{\partial c_{\theta jm}} \frac{c_{\theta jm}}{s_{ijm}}$, which is averaged across consumers and insurers.

[22]This marginal effect of network breadth is calculated as $\beta^D \sum_k q_{\theta lkm}$ and averaged across consumers and insurers.

Interactions between consumer and insurer characteristics matter for enrollment decisions. Males are less sensitive to out-of-pocket expenses than females but have a stronger taste for network breadth. Older patients are both less likely to enroll in broad network carriers and more sensitive to out-of-pocket costs compared to younger patients. One explanation for this is that old individuals have had more contact with the health care system and are more likely to concentrate their care in a few providers. Given that old consumers tend to have higher out-of-pocket costs, the findings also imply that the average demand elasticity for patients aged 65 or older (-0.84) is almost twice that of patients aged 19-44 (-0.46).

Individuals with chronic conditions do not necessarily have stronger preferences for network breadth than their healthy peers but they are significantly less responsive to out-of-pocket costs. Interactions between network breadth and indicators for each chronic disease are all negative and significant compared to individuals without diagnoses. Instead, interactions between average out-of-pocket spending and diagnosis indicators are all positive and significant. Despite these patterns in preferences, the implied average elasticity for individuals without diseases (-0.50) is smaller than for patients with renal disease (-1.49) because their out-of-pocket costs are relatively low. Appendix 8.3 presents some measures of the in-sample model fit.

With my estimates of the preference for network breadth and out-of-pocket costs, I calculate patient willingness-to-pay for an additional percentage point of network breadth for each service as $\frac{1}{|\alpha_i|}\frac{\partial s_{ijm}}{\partial H_{jkm}}$, measured in thousands of pesos. Differences in willingness-to-pay across consumer types will be suggestive of adverse selection in insurer demand. Consumers with relatively high willingness-to-pay for a particular service will tend to sort into carriers with high network breadth for that service.

Table 6 presents the average willingness-to-pay across services, insurers, and markets, conditional on consumer observable characteristics. Patients with chronic conditions have a higher willingness-to-pay for network breadth than individuals without diagnoses, consistent with strong adverse selection. For instance, patients with cancer are willing to pay 22.0 thousand pesos in a year (a one time payment of 4% of monthly income) for an additional hospital in the average service, which corresponds to a one percentage point increase in network breadth; while healthy individuals are willing to pay only 2.1 thousand pesos.[23] Willingness-to-pay is higher for males than for females, the first of which have a relatively high prevalence of long-term diseases. Average willingness-to-pay

[23]The measure of willingness-to-pay can also be interpreted in terms of travel times to the nearest hospital. For example, the estimates imply that patients with cancer are willing to pay 22.0 thousand pesos in a year for a reduction of approximately 10 minutes per visit in travel time to the nearest hospital.

Table 5: Insurer demand

Insurer choice		Coefficient	Std. Error
Network		1.93***	0.03
OOP spending	(million COP)	-7.52***	0.55
Interactions			
Network	Demographics		
	Male	0.29***	0.01
	Age	-0.01***	0.00
	Diagnoses		
	Cancer	-0.34***	0.02
	Cardiovascular	-0.33***	0.01
	Diabetes	-0.43***	0.04
	Renal	-0.59***	0.08
	Other	-0.53***	0.02
	>=2 diseases	-0.61***	0.02
	Healthy	(ref)	(ref)
	Location		
	Normal	-0.03***	0.01
	Special	0.64***	0.04
	Urban	(ref)	(ref)
	Income		
	Low	0.61***	0.03
	Medium	0.41***	0.03
	High	(ref)	(ref)
OOP spending	Demographics		
	Male	1.35***	0.23
	Age	-0.03***	0.01
	Diagnoses		
	Cancer	3.18***	0.49
	Cardiovascular	2.72***	0.47
	Diabetes	1.66*	0.91
	Renal	2.97***	0.60
	Other	2.48***	0.48
	>=2 diseases	2.46***	0.45
	Healthy	(ref)	(ref)
	Location		
	Normal	5.31***	0.43
	Special	-2.37	2.05
	Urban	(ref)	(ref)
N		5,800,610	
N enrollees		500,000	
Pseudo-R^2		0.17	

Note: This table reports results of a conditional logit for the insurer choice model estimated on a random sample of 500,000 new enrollees using a control function approach. The first stage is a regression of out-of-pocket costs on reference prices per service. Standardized residuals of the first-stage regression and its interactions with consumer demographics are included as controls. Includes insurer fixed effects. Robust standard errors reported. ***p<0.01, **p<0.05, *p<0.1.

Table 6: Average willingness-to-pay per consumer type

Characteristic	Willingness-to-pay
Diagnosis	
Cancer	22.0
Cardiovascular	7.0
Diabetes	4.8
Renal	5.3
Other	14.8
>=2 diseases	6.7
Healthy	2.1
Sex	
Female	2.4
Male	3.0
Age group	
<1	1.0
1-4	3.5
5-14	3.0
15-18	2.6
19-44	2.9
45-49	1.8
50-54	1.7
55-59	3.8
60-64	2.5
65-69	2.8
70-74	1.9
>=75	1.6

Note: This table presents the average (across services, insurers, and markets) willingness-to-pay for an additional percentage point of network breadth conditional on consumer characteristics. Willingness-to-pay is calculated as $\frac{1}{|\alpha_i|}\frac{\partial s_{ijm}}{\partial H_{jkm}}$ and is measured in thousand COP.

is also non-monotonic with respect to age.

Robustness checks. Although insurer fixed effects in the demand function control for insurer-level unobserved quality that may be correlated with network breadth or out-of-pocket costs, this unobserved quality could vary within insurers or across consumer types in ways that are not captured by the fixed effects. In the appendix I conduct several robustness checks to show that this type of unobserved quality does not pose a threat to identification. In the first exercise reported in appendix table 13, I estimate a demand function that includes an indicator of star hospital coverage per insurer, market, and service. In the second exercise in appendix table 14, I estimate demand in the subsample of markets without star hospitals. In the third exercise reported in appendix table 15, I use enrollee satisfaction survey data from the Ministry of Health to obtain two measures of insurer quality that vary across markets: average waiting times for a doctor appointment and average insurer quality from a likert scale. The results of these exercises show that my estimates are robust to the inclusion of insurer and hospital quality measures, although the coefficient on out-of-pocket costs decreases in magnitude in the second exercise. Results are also robust to the use of different provider samples for constructing my measure of network breadth, as seen in appendix table 16.

5.2 Insurer Average Costs Per Enrollee

I estimate equation (4) for the logarithm of insurers' average cost per consumer type-θ and market in the sample of new and current enrollees, conditional on observed choices in 2010 and 2011. Table 7 shows the results, and appendix figure 8 presents the estimated consumer type fixed effects with their corresponding 95% confidence intervals. Average costs are increasing in network breadth and decreasing in the interaction between network breadth for different pairs of services. This suggests that insurer coverage decisions are characterized by economies of scope. A 1% increase in network breadth for service k decreases the average cost of providing service $l \neq k$ by 0.51% per enrollee.[24] The magnitude of scope economies varies across services as seen in appendix figure 7, and across consumer types as seen in appendix table 19. However, scope economies are smaller in magnitude than the direct effect of network breadth on average costs. My estimates show that a 1% increase in network breadth raises average costs by 1.93% per enrollee.[25]

Panel (a) of figure 5 shows that in the sample of new enrollees, the predicted average cost per consumer is U-shaped with respect to the enrollee's age, higher for healthy females than for healthy males after the age of 19, and higher for patients with chronic illnesses than for healthy enrollees, overall. In panel (b), these differences in average costs generate significant variation in expected profits per consumer type. Expected profits are calculated as the average risk-adjusted transfers (ex-ante and ex-post) minus the predicted average cost. Since the ex-ante risk adjustment formula controls for only sex, age category, and municipality of residence, most of the variation in profits across consumer types comes from differences in diagnoses and network breadth.[26] The fact that there are types of consumers for which the average profit is negative, such as females aged 19 or older with cancer, males aged 60 or older with renal disease, or males aged 19-44 with diabetes, means that insurers have incentives to risk-select and choose their service-specific hospital networks

[24] Calculated as the average of $100 \times \frac{1}{2K_m}\hat{\beta}_2^S \sum_{l \neq k} q_{\theta km} q_{\theta lm} H_{jlm}$

[25] Calculated as the average of $100 \times \hat{\beta}_1^S q_{\theta km}$

[26] Profit variation per enrollee can also be partly explained by differences in sex, age, and location if the risk adjustment formula imperfectly compensates insurers in these dimensions.

Table 7: Insurer average costs per enrollee

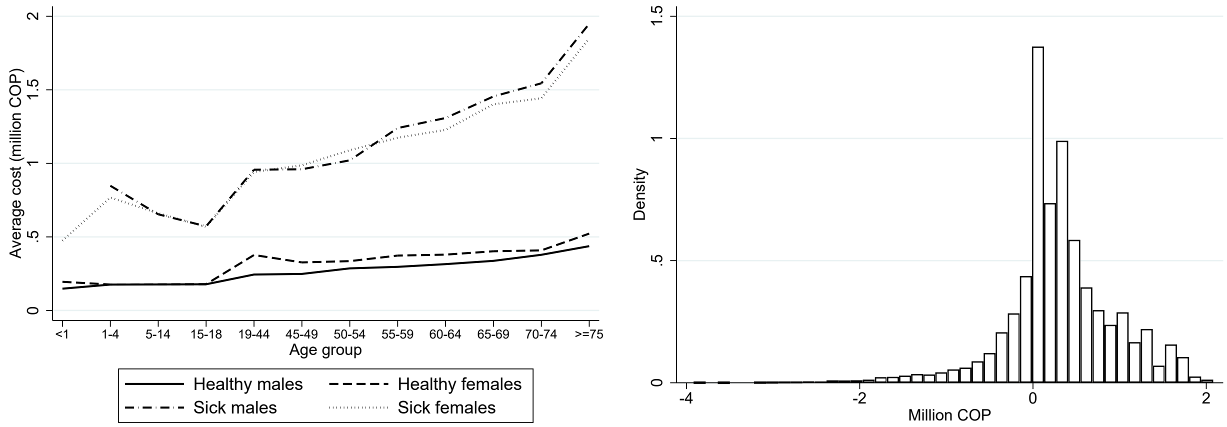
Variable	Coefficient	Std. Error
Network	0.30***	0.04
Scope economies	-5.27***	0.84
Avg. ref. price	-0.71***	0.19
Insurer		
EPS001	-0.05	0.04
EPS002	-0.48***	0.03
EPS003	-0.19***	0.02
EPS005	0.03	0.02
EPS008	0.15**	0.07
EPS009	0.11	0.07
EPS010	-0.19***	0.03
EPS012	-0.24***	0.04
EPS013	-0.07***	0.02
EPS016	-0.21***	0.02
EPS017	-0.27***	0.04
EPS018	-0.16***	0.04
EPS023	-0.26***	0.03
EPS037	(ref)	(ref)
N	27,747	
R^2	0.42	

Note: OLS regression of logarithm of average costs per insurer, market, and consumer type on network breadth, economies of scope, and service reference price. Includes insurer, market, and consumer type fixed effects. Robust standard errors reported.

to avoid these enrollees.

My average cost model is robust to more granular definitions of consumer type as seen in appendix table 17. So there is no relevant source of unobserved cost heterogeneity. Results are also robust to estimating on the sample of markets without star hospitals in appendix table 18. Thus ignoring hospital quality does not introduce bias in my estimates.

Model-based evidence of adverse selection. With my demand and average costs estimates I can test for the presence of adverse selection implied by the model by looking at the correlation between the insurers' marginal cost with respect to network breadth and the patients' willingness-to-pay for network breadth along the lines of Einav et al. (2010). Marginal costs for service k are given by $\frac{\partial(AC(H_{jkm})s_{ijm}(H_{jkm}))}{\partial H_{jkm}}$, and willingness-to-pay for network breadth over service k is $\frac{1}{|\alpha_i|}\frac{\partial s_{ijm}(H_{jkm})}{\partial H_{jkm}}$. Averaging across services, I find that these two variables are strongly positively correlated, suggesting that the endogenously selected patients with the highest willingness-to-pay for network breadth are also the most expensive to the insurer, a classic adverse selection result.



(a) Predicted average cost

(b) Predicted profit per consumer type

Figure 5: Predicted average cost and surplus per consumer type

Note: Panel (a) of this figure shows the predicted average cost conditional on age group, separately for healthy and sick, males and females. Panel (b) shows the distribution of risk-adjusted transfer minus predicted average cost per consumer type.

5.3 Competition in Network Breadth

The third piece of the insurers' profit function left to estimate is the network formation cost. To recover the network formation cost I use the first order condition from the insurers' profit maximization problem. Demand and average cost estimates allow me to compute the left-hand side of equation (5) denoting marginal variable profits (MVP). Appendix 11 presents some summary statistics of this variable as well as of dropout probabilities and transition probabilities, which are calculated off-line non-parametrically from the data. The fact that MVPs are positive for all insurer-service-market triplets suggests a role for network formation costs in explaining the profit maximizing choices of network breadth.

Table 8 presents the results of a 2-step GMM estimation for log MVP in equation (7) on the subsample of four largest markets and 10 largest insurers in those markets, where the observed equilibrium is an interior solution. The specification includes insurer, market, and service fixed effects, but only the first two are reported for exposition. I find that network formation costs are strictly convex in network breadth. The elasticity of marginal variable profits with respect to network breadth for service k equals 3.4. The first-stage F-statistic for the endogenous variable is greater than the 1% critical value; thus lagged network breadth and average market demographics are strong predictors of the observed equilibrium (see appendix table 23). As a measure of out-of-sample fit, appendix figure 9 compares the model's predicted ratio of total costs to total revenues per insurer to the ratio obtained from insurers' public income statements. Appendix table 24 also

Table 8: Model of insurer network formation costs

$\log(MVP_{jmk})$	Coefficient	Std. Error
Network	3.41***	0.07
Insurer FEs		
EPS001	-0.79***	0.04
EPS002	-0.14***	0.04
EPS003	-0.50***	0.04
EPS005	-1.37***	0.04
EPS010	0.38***	0.04
EPS013	-0.37***	0.04
EPS016	-0.34***	0.04
EPS017	-0.80***	0.04
EPS018	-0.53***	0.04
EPS037	(ref)	(ref)
Market FEs		
Market 05	(ref)	(ref)
Market 08	5.34***	0.08
Market 11	4.95***	0.08
Market 76	6.18***	0.08
First stage F-stat	774.5	
N	2,262	
R^2	0.97	

Note: This table presents a 2-step GMM estimation of equation (7) on the subsample of markets 05, 08, 11, 76, and the subsample of the 10 largest insurers in these markets. Excluded instruments are described in section 4.3. Robust standard errors and first-stage F-statistic for the endogenous variable, network breadth, are reported. ***p<0.01, **p<0.05, *p<0.1.

shows that network formation costs are robust to estimating in the subsample of markets without star hospitals.

Magnitude of adverse selection. Changes in network breadth generate profit variation that can be decomposed into its portions explained by variations in demand, average costs, and network formation costs. The variation in profits that is explained by changes in demand evidence the magnitude of adverse selection. To quantify this magnitude, I decompose profit changes that result from a partial equilibrium exercise where an insurer unilaterally increases network breadth for service k by 10%, while holding its rivals fixed. If my model is able to rationalize the choices of network breadth observed in the data, the decomposition exercise should show that there are no profitable one-shot deviations.[27]

Table 9 presents the average percentage change in short-run demand ($\%\Delta s_{ijm}$), total revenues ($\%\Delta R_{\theta m} s_{ijm}$), total average costs ($\%\Delta AC_{\theta jm} s_{ijm}$), average cost per enrollee ($\%\Delta AC_{\theta jm}$), and

[27] In this exercise I do not impose the FOC, so predictions of network formation costs are in absence of the cost shock, $(\hat{\omega} H_{jkm} + \hat{\xi}_j + \hat{\xi}_k + \hat{\xi}_m) H_{jkm}$.

Table 9: Decomposition of short-run profit changes after network breadth increase

Service	$\%\Delta s_{ijm}$	$\%\Delta R_{\theta m} s_{ijm}$	$\%\Delta AC_{\theta jm} s_{ijm}$	$\%\Delta AC_{\theta jm}$	$\%\Delta F_{jm}$
Cardiac vessels	0.01	0.01	0.01	0.00	0.01
Stomach	0.01	0.01	0.01	0.00	0.02
Intestines	0.23	0.23	0.25	0.02	0.24
Imaging	3.35	3.35	3.68	0.32	3.07
Consultations	11.13	11.13	12.61	1.31	7.47
Laboratory	4.92	4.92	5.44	0.49	4.43
Nuclear medicine	0.08	0.08	0.08	0.01	0.09
Hospital admissions	0.58	0.58	0.63	0.05	0.57

Note: This table shows the average percentage change in demand ($\%\Delta s_{ijm}$), total revenues ($\%\Delta R_{\theta m} s_{ijm}$), average costs per enrollee ($\%\Delta AC_{\theta jm}$), total average costs ($\%\Delta AC_{\theta jm} s_{ijm}$), and network formation costs ($\%\Delta F_{jm}$), following an insurer unilaterally increasing network breadth for the service in the row by 10%, while holding its rivals' choices fixed and assuming $\Delta\xi_{jkm} = 0$.

network formation costs ($\%\Delta F_{jm}$) across insurers and markets, following a 10% increase in network breadth for the service in the row. First of all, I find that for every service total costs increase by a greater magnitude than total revenues, so there are no profitable deviations. Second, because changes in network breadth are weighted by the probability of making claims for each service, a 10% increase in coverage of consultations generates the largest variations in demand and costs compared to other services. Finally, findings indicate that the change in demand explains on average 48% of the change in insurer total costs, while cost heterogeneity explains the remaining 52%.

6 The Effect of Risk Adjustment on Network Breadth

In this section, I use my model estimates to conduct two counterfactual exercises that reveal how risk adjustment affects network breadth and consumer welfare. In view of the growing prevalence of network adequacy rules in countries like the United States, as well as concerns about narrow networks in Colombia itself, analyzing how hospital networks respond to changes in the regulatory environment is important. While incentivizing insurers to broaden their networks might seem desirable to improve access to care, broader networks are also associated with higher health care costs. The goal of my counterfactual analysis is to quantify the extent to which hospital networks respond to risk adjustment and the resulting pass-through to health care costs.

In the first counterfactual exercise, I eliminate the observed risk adjustment mechanisms and impose a uniform transfer across all consumer types that is equal to the national average cost per capita. In the second exercise, I improve the government's risk adjustment formula by reimbursing diagnoses ex-ante. In both scenarios, I hold short-run government spending, dropout probabilities, and transition probabilities fixed. Keeping government spending fixed allows changes in networks to be determined only by changes in how resources are redistributed across insurers but not by the level of the transfer itself. Dropout probabilities are mostly determined by the event of becoming unemployed rather than by the individual choosing not to enroll with a particular insurer due to changes in the network. Because risk adjustment does not impact consumers' tax contribution to the health care system, it is also reasonable to assume that dropout probabilities are fixed under alternative risk adjustment formulae.

I assume that the probability of transitioning to new diagnoses depends on the natural disease and age progression rather than on network breadth. But health care consumption and service prices are allowed to vary in the counterfactual simulations, with changes captured in a reduced-form way by the insurers' average cost function per enrollee. I also assume that choice sets and utility and cost parameters are fixed, so that the set of insurers that participate in every market does not change. For computational tractability, I conduct my counterfactual analyses in a single market: Bogotá, which is the capital city of Colombia and the largest market in the country. This market represents 28.7% of all continuously enrolled individuals in the contributory regime and has presence of all 14 insurers.

One concern in the counterfactual analyses is that the model may admit multiple equilibria in insurers' choices of network breadths.. For instance, my measure of scope economies can make it such that every firm choosing complete networks or no coverage at all are both feasible equilibria. In the case of the insurers' average cost function, the magnitude of scope economies is small enough relative to the direct effect of network breadth on average costs per enrollee so as to not pose concerns about uniqueness. The rich preference and cost heterogeneity also prevent multiple equilibria from arising.

Whether there are multiple equilibria in this market depends on the shape of the insurers' profit functions and, thus, on the shape of the best response functions. While a direct proof of uniqueness in the model is challenging given insurers' strategic interactions and the 58 dimensions of network breadth, in appendix 13 I provide intuition for the sign of the second partial derivative of the insurers' profit function with respect to network breadth, all else equal. In computing the counterfactual analyses, I also use several different starting values for the vector of service-level network breadth and confirm that they all converge to the same equilibrium.

6.1 No Risk Adjustment

I start by describing the effect of eliminating the risk adjustment systems. In this counterfactual scenario, the per capita transfer to each insurer equals the national base transfer from appendix table 1 times an adjustment factor λ calibrated to match observed short-run government spending:

$$R^{cf}_{\theta m} = \lambda \times UPC_{National}, \quad \forall(\theta, m)$$

The counterfactual transfer eliminates variation across sex and age groups. Failure to compensate for individuals' health risk should exacerbate risk selection, incentivizing insurers to drop coverage in services that unprofitable patients require. Appendix figure 11 shows the distribution of the difference between the counterfactual transfer without risk adjustment and the observed transfer per consumer type. For example, for males aged 19-44 with cancer, insurers receive 25 thousand pesos less than in the observed risk adjustment system where the transfer equals 625 thousand pesos. For healthy males in the same age bracket, insurers receive 236 thousand pesos more than the observed transfer of 347 thousand pesos.

Panel A of table 10 presents the percentage change in counterfactual relative to the observed scenario, of average network breadth, insurer total average costs, short-run average costs per enrollee, and short-run consumer welfare for healthy and sick individuals.[28] Under no risk adjustment, average network breadth falls by 6.7%. This reduction in coverage explains the 0.9% decrease in average costs per enrollee and the resulting 0.7% decrease in insurers' total average costs. The fact that total average costs fall with the reduction in coverage indicates that the direct effect of network breadth on costs is larger than its effect on scope economies.

While the reduction in average network breadth is relatively large, its effect on consumer welfare is muted by reductions in out-of-pocket costs. The average elasticity with respect to out-of-pocket costs goes from -0.51 in the observed scenario to -0.69 in counterfactual. Eliminating risk adjustment results in a 2.1% decrease in short-run consumer welfare for individuals without diseases and in a 3.3% decrease in welfare for those with chronic conditions. The welfare effect on patients with diseases is greater in magnitude because access to and quality of care worsen, in particular for services that these patients a more likely to claim. A back-of-the-envelope calculation indicates

[28] Insurer total average costs in the market are calculated as:
$\sum_{ij}\left(AC_{\theta j}s_{ij} + \sum_{s=t+1}^{T}\beta^s\sum_{\theta'}(1-\rho_{\theta'})\mathcal{P}(\theta'|\theta)AC_{\theta' j}s'_{ij}\right)$,
Short-run average cost per enrollee is $(1/N)\sum_{ij}AC_{\theta j}$,
and short-run consumer welfare is $\sum_i |\alpha_i|^{-1}\log(\sum_j \exp(\beta_i^D \sum_k q_{\theta k}H_{jk} - \alpha_i c_{\theta j} + \delta_j))$

Table 10: Counterfactual changes in networks, costs, and welfare under no risk adjustment

Variable	%Δ in CF
Panel A. Overall	
Avg. network breadth	-6.7
Total avg. cost	-0.7
Avg. cost per enrollee	-0.9
Consumer welfare (healthy)	-2.1
Consumer welfare (sick)	-3.3
Panel B. Avg. network breadth per service	
Skull, spine, nerves, glands	-7.5
Eyes, ears, nose, mouth	-17.1
Pharynx, lungs	-28.9
Heart and cardiac vessels	3.4
Lymph nodes, bone marrow	16.0
Esophagus, stomach and intestines	6.0
Liver, biliary tract	-6.0
Abdominal wall	-25.7
Urinary system	-16.9
Reproductive system	-14.9
Bones and facial joints	-19.5
Joints, bones, muscles, tendons	-9.3
Skin	-2.6
Imaging, lab, consultation	-6.2
Hospital admission	-10.1

Note: Panel A of this table presents the percentage change in counterfactual under no risk adjustment relative to predictions at observed risk adjustment, of average network breadth across insurers, insurer total average costs, short-run average cost per enrollee, and short-run consumer welfare for the healthy and sick. Panel B presents the percentage change in counterfactual of average network breadth by service category, where I collapse the 58 original categories into 15 broader groups. The counterfactual is calculated with data from Bogotá only and the 10 largest insurers.

that the overall reduction in welfare is equivalent to 13,753 pesos ($7.2) per capita per year.

Panel B of table 10 shows that the reduction in average network breadth happens across all services. For exposition purposes, I collapse the 58 service categories into 15 broader groups. When they are not compensated for their enrollees' health risk, insurers reduce coverage of relatively expensive services like hospital admissions by 10.1% and procedures in skull and spine by 7.5%. For less expensive services, the reduction in average network breadth is smaller but still sizable. For instance, average coverage of imaging, lab, and consultations falls by 6.2%.

Consistent with adverse selection, insurers for which average network breadth falls by a greater magnitude see larger declines in total short-run demand from the healthy than the sick as seen in appendix figure 13. Panel A of appendix figure 16 also shows that insurers that reduce their network breadth by a greater magnitude have greater long-run profits compared to those that drop network coverage by a small amount.

Counterfactual results represent a lower bound (in absolute value) of the effect of eliminating risk adjustment when there are no star hospitals as seen in appendix table 26. In this appendix table I compare results obtained from using my main estimates to predict counterfactual outcomes in markets without star hospitals, against results obtained from a model that is both estimated and evaluated in markets without star hospitals. The comparison between these two scenarios provides a measure of the magnitude and direction of the potential bias introduced by ignoring star hospital coverage. Results in the appendix suggest that my main estimates may be biased towards not finding significant effects of the counterfactual policies.

6.2 Improved Risk Adjustment

I now move to the opposite exercise where I improve the current risk adjustment formula either by compensating for a list of diagnoses ex-ante or by making capitated transfers exactly match insurers' average cost per enrollee ("perfect" risk adjustment). If allowing for variation in per-capita transfers across diagnoses helps better predict health care costs, then risk selection incentives should decrease, resulting in broader networks. Results in this counterfactual will be suggestive of how strong demand-side selection incentives are relative to cost incentives in generating narrow networks in equilibrium, since improved risk adjustment effectively eliminates demand-side incentives.

For the first approach, I assume the counterfactual risk-adjusted transfer is given by the annualized average cost per consumer type θ. More formally, this is:

$$R_{\theta m}^{cf} = \lambda \times a_m \times 360 \times \frac{\sum_{\theta(i)=\theta} T_i}{\sum_{\theta(i)=\theta} b_i}$$

where T_i is the total health care cost of individual i of type θ, b_i is the number of days enrolled to the contributory system during the year, a_m is the market multiplier from appendix table 1, and λ is an adjustment factor calibrated to match observed short-run government spending. I use two sets of exhaustive and mutually exclusive diseases to compensate for ex-ante. The first is the list of 7 diseases used in the model of section 4. The second is a more granular list of 30 health conditions presented in appendix table 25.[29] These conditions are obtained by grouping the ICD-10 codes accompanying an individual's claims following Riascos et al. (2014).[30] In both cases, when the prediction of the annualized health care cost equals zero for a consumer type, I replace it for

[29]The more granular list of 30 diseases still imperfectly compensates insurers for an individuals' health care cost compared, for example, to CMS' Hierarchical Conditions Categories risk adjustment formula in the Medicare program in the US, which controls for 79 conditions.

[30]See https://www.alvaroriascos.com/researchDocuments/healthEconomics/CLD_xCIE10.tab

the value in the observed risk adjustment system which conditions on sex, age group, and location.

For the second approach, the capitated transfer is:

$$R^{cf}_{\theta jm} = \lambda \times \widehat{AC}^{obs}_{\theta jm}$$

where λ is an adjustment factor as before and $\widehat{AC}^{obs}_{\theta jm}$ is the individual's predicted average cost conditional on observed networks. This transfer differs from the previous method in that it compensates insurers for both diagnoses and network breadth. By making the risk adjusted transfer match the insurers' average cost per enrollee, the profit function per enrollee collapses to the coinsurance rate times the average cost per enrollee times demand.

Using different sets of health care cost predictors allows me to compare changes in network breadth, costs, and welfare across different degrees of risk adjustment. Appendix figure 12 presents the distribution of the difference between counterfactual payments and observed risk adjusted transfers per consumer type. With compensations that control for the list of 7 diseases, insurers receive 1.8 million pesos more for males aged 19-44 with cancer, but receive only 0.4 million pesos more for females aged 19-44 with the same health condition.

Table 11 shows the percentage change in network breadth, insurer costs, and consumer welfare under the improved risk adjustment formula with 7 disease categories in column (1), with the list of 30 disease categories in column (2), and with "perfect" risk adjustment in column (3). Effects on each of these variables are greater the more granular the risk adjustment formula is. Average network breadth increases 4.6% relative to the observed scenario in column (1), 10.9% in column (2), and 28.0% in column (3). Network breadth increases across all services as seen in panel B of the table, but disproportionately for services that mostly sick patients tend to claim. This is consistent with weakened selection incentives and with demand-side adverse selection being a main factor in determining narrow networks and an asymmetric equilibrium in network breadth. Counterfactual results in column (1) are qualitatively similar to those obtained from a model that is estimated and evaluated in markets without star hospitals as seen in appendix table 26; thus, ignoring star hospital coverage does not introduce significant bias in my predictions.

Insurers that expand their network breadth by a greater amount in counterfactual also see large increases in demand from sick individuals (see appendix figure 14). However, greater demand does not translate into higher profits (see panel (b) of appendix figure 16). Column (2) of table 11 shows that insurers' total short-run average costs increase 3.6% in counterfactual, while total

Table 11: Counterfactual changes in networks, costs, and welfare under improved risk adjustment

Variable	%Δ in CF (1) 7 diseases	(2) 30 diseases	(3) "Perfect"
Panel A. Overall			
Avg. network breadth	4.6	10.9	28.0
Total avg. cost	1.0	3.6	2.9
Avg. cost per enrollee	1.1	3.7	3.0
Consumer welfare (healthy)	2.8	9.9	7.7
Consumer welfare (sick)	3.4	10.7	11.1
Panel B. Avg. network breadth per service			
Skull, spine, nerves, glands	-2.0	-7.3	14.9
Eyes, ears, nose, mouth	8.0	13.3	7.1
Pharynx, lungs	11.4	18.5	62.4
Heart and cardiac vessels	6.4	15.6	52.3
Lymph nodes, bone marrow	6.5	19.4	59.0
Esophagus, stomach and intestines	4.0	13.5	31.2
Liver, biliary tract	1.8	7.3	-0.6
Abdominal wall	19.0	37.9	106.7
Urinary system	13.2	26.9	76.2
Reproductive system	5.9	11.5	25.6
Bones and facial joints	4.6	7.6	19.3
Joints, bones, muscles, tendons	6.2	13.4	21.3
Skin	5.0	12.1	18.9
Imaging, lab, consultation	2.9	10.0	21.3
Hospital admission	0.5	1.0	37.5

Note: Panel A of this table presents the percentage change in counterfactual under improved risk adjustment relative to predictions at observed risk adjustment, of average network breadth, insurer total average costs, short-run average cost per enrollee, and short-run consumer welfare for the healthy and sick. Panel B presents the percentage change in counterfactual of average network breadth by service category, where I collapse the 58 original categories into 15 broader groups. Column (1) shows results from an improved formula that compensates insurers ex-ante for sex, age, location, and a list of 7 diseases. Column (2) uses a list of 30 diseases in addition to sex, age group, and location. Column (3) corresponds to perfect risk adjustment, where the capitated transfer equals the individual's average cost. The counterfactual exercises are calculated with data from Bogotá only and the 10 largest insurers.

revenues increase by an average of 2.7% across insurers; variation that can only stem from changes in demand. Consumer out-of-pocket costs also increase in counterfactual due to changes in the average cost per enrollee. In the case of "perfect" risk adjustment, these changes imply an average elasticity of -0.66, which represents a 29% increase (in absolute value) from baseline.

With the improved risk adjustment formula that uses the list of 30 disease categories, I find that consumer welfare for patients with any chronic condition increases 10.7% relative to the observed scenario. For consumers without diseases, welfare increases by a smaller magnitude equal to 9.9%. The overall effect on consumer welfare is 62,442 pesos ($32.9) per capita per year. Welfare effects from improved risk adjustment are greater for patients with chronic diseases because their willingness-to-pay for network breadth is higher than that of healthy individuals. Note that even though greater network breadth increases consumers' out-of-pocket costs, the resulting marginal disutility is averaged-out with insurer competition. The direct effect of network breadth on welfare thus dominates the effect on out-of-pocket costs.

If allowing diagnoses to enter the ex-ante risk adjustment formula results in greater network coverage and welfare for patients most at need of care, at no extra cost for the government, why hasn't this formula been implemented in Colombia? First, there are information frictions that prevent a diagnosis-specific risk adjustment to have positive hospital network effects. Recall that risk-adjusted transfers for year t are calculated using claims data from year $t-2$, which might not be informative about the prevalence of diseases in t. Second, allowing for variation across diagnoses could incentivize insurers to engage in upcoding practices, which are difficult to observe and therefore penalize. Despite these challenges, the Colombian government is currently undergoing a modification of the risk adjustment system that consists of reimbursing insurers for bundles of services that, according to medical experts, patients with certain health conditions, such as diabetes, need during the course of treatment. While this new reimbursement will not keep government spending fixed, it will involve compensating insurers for currently unprofitable services. If and after these changes are fully implemented, my model predicts that hospital networks should expand.

7 The effect of Premiums on Network Breadth

One outstanding question is whether regulating premiums –and hence forcing insurers to compete on other dimensions of the health insurance plan– effectively generates competition in risk selection. This is an interesting economic question since little is known about the interaction between price and non-price competition in health insurance markets, and since selection incentives can exist because of price regulation. In this section I study how hospital network breadth responds to premiums by simulating market outcomes under premium deregulation.

I assume insurers compete Nash-Bertrand on premiums and are allowed to discriminate premiums based on the enrollee's income level, sex, and age group in each market. In the observed scenario the monthly contribution to the health care system equals 12% of the enrollee's monthly income, 1/3 of which is paid by the enrollee and 2/3 by her employer. Under counterfactual premiums, I assume the same split of the cost of enrollment between consumers and their employers.[31] Insurers receive premiums in addition to the government's risk-adjusted transfers and consumers pay these premiums in addition to the tax contributions to the system.

[31] Self-employed individuals pay the full amount of their contribution to the health care system. In counterfactual, I am implicitly assuming no one is self-employed.

More formally, the counterfactual out-of-pocket costs are:

$$\text{Coins}_{\theta jm} + \text{Copay}_{\theta jm} + \text{Tax} + (1/3) \times \tilde{P}_{\theta jm}$$

where $\tilde{P}_{\theta jm}$ is insurer j's total premium in market m for consumer type θ. I also assume that dropout probabilities are fixed in counterfactual conditional on network breadth. To the extent that premiums are not significantly greater than observed contributions to the system, conditional on network coverage, an individual is not necessarily more likely to drop out of the system.

Let $P_{\theta jm} = (1/3) \times \tilde{P}_{\theta jm}$, individual i's choice probability for insurer j in market m is:

$$s_{ijm}(H_m) = \frac{\exp\left(\beta_i \sum_k q_{\theta km} H_{jkm} - \alpha_i P_{\theta jm} - \alpha_i c_{\theta jm} + \phi_j\right)}{\sum_{j' \in \mathcal{J}_m} \exp\left(\beta_i \sum_k q_{\theta km} H_{j'km} - \alpha_i P_{\theta j'm} - \alpha_i c_{\theta j'm} + \phi_{j'}\right)} \tag{8}$$

While equation (8) implicitly assumes that the sensitivity of demand to premiums is the same as to coinsurance payments and copays, I conduct analyses allowing the average component of α_i across patients to be greater for premiums than for out-of-pocket costs. This is following Abaluck and Gruber (2011) who find that consumers are more responsive to premiums than to other measures of cost-sharing in the context of prescription drug coverage in Medicare Part D.[32]

Under counterfactual premiums, the short-run per enrollee profit is given by:

$$\pi_{ijm}(H_m, P_m) = (R_{\theta m} + \tilde{P}_{\theta jm} - (1 - r_i) AC_{\theta jm}(H_{jm})) s_{ijm}(H_m, P_m)$$

where $P_m = \{\{P_{\theta jm}\}_{\theta(i)=\theta}\}_{j=1}^{\#\mathcal{J}_m}$. Insurers simultaneously choose premiums and network breadth per service taking into account the future profits associated to each new consumer that enrolls with it. The solution concept is a steady state Nash equilibrium. Insurers choose steady state premiums and networks to maximize:

$$\Pi_{jm}(H_m, P_m) = \sum_\theta \left(\pi_{ijm}(H_m, P_m, \theta) N_{\theta m} + \sum_{s=t+1}^{T} \beta^s \sum_{\theta'} (1 - \rho_{\theta' m}) \mathcal{P}(\theta'|\theta) \pi_{ijm}(H_m, P_m, \theta') N_{\theta' m}\right) - \sum_k \left(\omega_0 H_{jkm} + \xi_{jkm}\right) H_{jkm}$$

[32] I calibrate the fixed component of α_i associated to premiums in a way that generates similar average premium elasticities as in Abaluck and Gruber (2011), equal to -1.17, and as in Shepard (2022), equal to -1.48.

The FOC with respect to premiums is:

$$\frac{\partial \Pi_{jm}}{\partial P_{\theta jm}} = \sum_i \left(\frac{\partial \pi_{ijm}}{\partial P_{\theta jm}} N_{\theta m} + \sum_{s=t+1}^{T} \beta^t \sum_{\theta'} (1-\rho_{\theta' m}) \mathcal{P}(\theta'|\theta) \frac{\partial \pi'_{ijm}}{\partial P_{\theta jm}} N_{\theta' m} \right) = 0$$

where

$$\frac{\partial \pi_{ijm}}{\partial P_{\theta jm}} = \Omega\Big(R_{\theta m} + \tilde{P}_{\theta jm} - (1-r_i)AC_{\theta jm}\Big) + s_{ijm}(H_m, P_m)$$

and

$$\Omega(j,j') = \begin{cases} -s_{ijm}(1-s_{ijm})\alpha_i & \text{if} \quad j = j' \\ s_{ijm}s_{ij'm}\alpha_i & \text{if} \quad j \neq j' \end{cases}$$

The annual premium can be solved for from the FOC above, which determines a fixed point iteration in the vector of premiums.

The FOC with respect to the service-level network breadth is given by the equation below, from which H_{jkm} can also be solved for in a fixed point:

$$\frac{\partial \Pi_{jm}}{\partial H_{jkm}} = \sum_i \left(\frac{\partial \pi_{ijm}}{\partial H_{jkm}} N_{\theta m} + \sum_{s=t+1}^{T} \beta^t \sum_{\theta'} (1-\rho_{\theta' m}) \mathcal{P}(\theta'|\theta) \frac{\partial \pi'_{ijm}}{\partial H_{jkm}} N_{\theta' m} \right) - \Big(2\omega_0 H_{jkm} + \xi_{jkm}\Big) = 0$$

I estimate this counterfactual exercise in data from Bogotá for simplicity. Computation proceeds as a nested fixed point. For every guess of the equilibrium vector of network breadth, I solve for the fixed point in premiums in an inner loop. Then, in the outer loop, I solve for the fixed point in network breadth.

Figure 6 presents the distribution of observed monthly contributions to the health care system and monthly premium pass-through to consumers, when the coefficient on premiums equals the coefficient on out-of-pocket costs in demand. I find that premiums are smaller than observed tax contributions to the system but exhibit greater dispersion across consumer types. This pattern is independent of how the average component of α_i is calibrated. The average monthly contribution equals 50.8 thousand pesos with a standard deviation of 17.7 thousand pesos, while the average consumer monthly premium equals 38.1 thousand pesos with a standard deviation of 37.2 thousand pesos.

Table 12 presents the average annual premium paid by consumers conditional on demographic characteristics, measured in thousands of pesos. The average component of α_i for premiums is set to

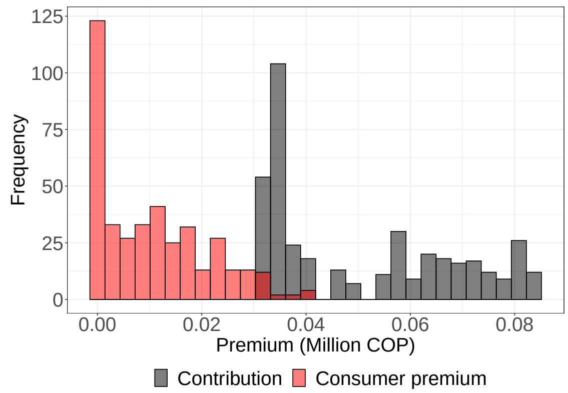


Figure 6: Distribution of counterfactual monthly premium

Note: This figure shows the distribution of observed monthly tax contribution to the health care system in black and counterfactual monthly premium paid by consumers in red when the coefficient on premiums equals the coefficient on out-of-pocket costs in insurer demand.

1 and 1.5 times the average component for out-of-pocket costs in columns (1) and (2), respectively. Counterfactual premiums are correlated with the enrollee's underlying health. Focusing on column (2), average annual premiums are 74 thousand pesos higher for males than for females, reflecting men's higher likelihood of developing chronic diseases. Premiums are also U-shaped in age following the pattern of average health care costs, and weakly decreasing in income because high-income individuals tend to be healthier than low-income individuals.

Findings show a positive correlation between total premiums and insurer market share in the number of enrollees. For example, EPS037, which has a market share of 15% in the counterfactual, charges an average annual premium that is 58 thousand pesos higher than that of EPS002, which has a market share of 7%. Premiums are the smallest component of total out-of-pocket costs for the average consumer even when insurers substantially expand their networks. This suggests that there is a small pass-through of hospital coverage to premiums because of insurer competition, a finding opposite to Cabral et al. (2018).

Panel A of table 13 presents the percentage change in counterfactual relative to the observed scenario of average network breadth, insurer total average costs, short-run average cost per enrollee, insurer total revenue, and short-run consumer welfare for healthy and sick individuals. The panel also shows the implied average elasticity with respect to annual premiums received by the insurer.[33] Consumer welfare in counterfactual is monetized using the estimate of consumer sensitivity to out-of-pocket costs rather than the estimate for premiums to allow for a fair comparison with the

[33]The individual elasticity with respect to annual premiums is calculated as $\frac{\partial s_{ijm}}{\partial P_{\theta jm}} \frac{P_{\theta jm}}{s_{ijm}}$ and then averaged across individuals.

observed scenario. The fixed component of demand sensitivity to premiums is set to 1 and 1.5 times the fixed component of out-of-pocket costs in columns (1) and (2), respectively.

Table 12: Average annual premium

Variable		Avg. premium	
		1.0α	1.5α
Sex	Female	89	84
	Male	165	158
Age group	<1	—	—
	1-4	—	—
	5-14	145	139
	15-18	151	147
	19-44	107	104
	45-49	86	80
	50-54	73	67
	55-59	184	175
	60-64	139	132
	65-69	124	117
	70-74	135	128
	>=75	125	119
Income group	< 2 x MMW	203	196
	[2,5] x MMW	51	46
	> 5 x MMW	—	—
Insurer	EPS001	145	137
	EPS002	52	51
	EPS003	82	88
	EPS005	170	163
	EPS010	168	150
	EPS013	109	111
	EPS016	97	98
	EPS017	111	105
	EPS018	174	159
	EPS037	161	146

Note: Table presents average annual premiums paid by consumers (1/3 of total premiums) conditional on demographic characteristics and insurer, measured in thousands of pesos. Columns (1) and (2) set the average component of α_i for premiums equal to 1 and 1.5 times the average component for out-of-pocket costs, respectively.

Deregulating premiums incentivizes insurers to broaden their networks. Average network breadth increases 31.6% in column (1) and 27.7% in column (2). Price and non-price competition in this market are thus substitutes from the point of view of risk selection. If allowed to charge and discriminate premiums, insurers would cream-skim the market using premiums rather than service-level networks. The effect of premium competition on average network breadth decreases with the implied demand elasticity to premiums, which goes from -0.9 in column (1) to -1.2 in column (2). The increase in coverage happens across all services as seen in panel B of the table. While relatively

Table 13: Changes in networks, costs, and welfare under premium deregulation

Variable	%Change in CF	
	(1) 1.0α	(2) 1.5α
Panel A. Overall		
Avg. network breadth	31.6	27.7
Total avg. cost	4.2	1.5
Avg. cost per enrollee	5.5	3.4
Total revenue	21.5	18.4
Consumer welfare (healthy)	5.3	-3.5
Consumer welfare (sick)	4.2	-9.2
Elasticity	-0.9	-1.2
Panel B. Avg. network breadth per service		
Skull, spine, nerves, glands	21.7	16.5
Eyes, ears, nose, mouth	59.8	72.1
Pharynx, lungs	96.7	107.7
Heart and cardiac vessels	39.1	36.1
Lymph nodes, bone marrow	20.3	10.3
Esophagus, stomach and intestines	20.0	10.6
Liver, biliary tract	18.7	10.5
Abdominal wall	71.1	67.1
Urinary system	51.3	48.4
Reproductive system	36.6	35.7
Bones and facial joints	40.7	40.2
Joints, bones, muscles, tendons	32.0	31.1
Skin	27.6	26.6
Imaging, lab, consultation	20.4	11.1
Hospital admission	21.9	14.6

Note: Panel A of this table presents the percentage change in counterfactual under premium deregulation relative to predictions at observed risk adjustment, of average network breadth, insurer total average costs, short-run average cost per enrollee, insurer total revenue, and short-run consumer welfare for the healthy and sick. Panel B presents the percentage change in counterfactual of average network breadth by service category, where I collapse the 58 original categories into 15 broader groups. The counterfactual is calculated with data from Bogotá only and the 10 largest insurers. The average component of α_i for premiums is set to 1 and 1.5 times the average component for out-of-pocket costs in columns (1) and (2), respectively.

expensive services such as hospital admissions or procedures in skull and spine see smaller increases in average network breadth compared to relatively cheap services such imaging, lab, consultations, or procedures in skin, the effect is still substantial.

Total insurer average costs increase 1.5% in column (2), a finding that is explained by the direct effect of networks on average costs being larger than the effect of selection or changes in demand. With all insurers choosing broad networks, service-level network breadth exhibits less heterogeneity across carriers. As a result there is no significant variation in demand from sick and healthy individuals as seen in appendix figure 15. These small selection effects also explain why changes in network breadth are orthogonal to changes in insurer profits in panel (c) of appendix figure 16.

Premium deregulation generates a significant transfer of surplus from consumers to insurers. Focusing on column (2), panel A of table 13 shows that insurer total revenues increase 18.4% in counterfactual. Revenues increase completely at the expense of consumers with and without chronic diseases, for whom welfare falls 9.2% and 3.5%, respectively. In the case of healthy individuals, who have a low willingness-to-pay for network breadth and a high sensitivity to out-of-pocket costs, welfare losses due to higher out-of-pocket payments overcompensate welfare gains from having broader networks in every service. The increase in out-of-pocket costs comes from increases in coinsurance payments, which are affected by network breadth, but not necessarily from premiums. For healthy consumers and consumers with chronic diseases, welfare effects depend on how the sensitivity of demand to premiums is calibrated.

The fall in consumer welfare in a scenario where individuals are more sensitive to premiums than to coinsurance payments is problematic. If healthy individuals could drop out of the health care system, a premium deregulation policy could unravel the market. By making the healthy disproportionately choose uninsurance, broad network carriers would face significant uninsurable costs from the remaining enrollees with chronic diseases. Market equilibria under premium deregulation could be restored not only by making enrollment mandatory, but also by having the government pay a fraction of premiums. These types of premium subsidy policies have been widely studied in the context of the Health Insurance Exchanges in the United States.

8 Conclusions

Risk selection is a main concern in public health insurance systems with regulated competition, where governments make risk adjusted payments to private insurers. In this paper I show that health insurers can engage in risk selection using their hospital networks. Existing literature has focused on the interaction between risk selection and insurer competition on premiums, but less explored is the interaction of risk selection with non-price competition. I model insurer competition in service-level hospital networks in the context of the Colombian health care system, where the government sets premiums to zero and compensates private insurers with per-capita risk adjusted payments that control only for sex, age, and location.

Selection incentives in Colombia exist because the risk adjustment formula is coarse, because health care costs vary substantially after risk adjustment, and because risk adjusted payments do not compensate insurers for relatively expensive services nor diagnoses that predictably use those services. However, insurers in this market have discretion over which services to cover at which hospitals, making hospital networks service-specific. Therefore, conditional on risk adjustment, insurers engage in risk selection by offering a narrow network in unprofitable services, that is, services that unprofitable patients –usually with chronic conditions– tend to demand the most.

Given the increasing popularity of network adequacy rules in countries like the United States and the policy debate surrounding access to care in Colombia, a key question is how to incentivize insurers to expand their networks while reducing selection incentives and containing health care costs. I use my model of insurer competition to answer this question by measuring the effect of typical policies used to combat risk selection, such as risk adjustment and premium setting, on service-level network breadth while holding government spending fixed.

I find that eliminating risk adjustment makes insurer competition a race to the bottom in terms of network breadth. Average network breadth falls 6.7%, and the reduction is largest in services that sick individuals require the most. As a result consumer welfare falls by $7.2 per capita per year relative to the observed scenario. Improving the risk adjustment formula by compensating insurers for sex, age, location, and a list diagnoses results in service-level networks that are broader on average, particularly for services that individuals with chronic diseases are more likely to claim. With an improved risk adjustment formula, average network breadth increases between 4.6% and 28%, and consumer welfare increases between $9.3 and $32.9 per capita per year depending on how many risk factors are included in the formula. Despite the positive welfare gains at no additional cost to the government, implementing an improved risk adjustment system is difficult because of information frictions between hospitals, insurers, and the regulator.

Allowing insurers to compete Nash-Bertrand in premiums results in substantially broader hospital networks for every insurer and service. Thus price and non-price competition are substitutes from the point of view of risk selection. The increase in service-level network breadth comes at the expense of higher out-of-pocket costs, which significantly reduces welfare for consumers with and without diseases.

In quantifying the extent to which networks respond to risk adjustment and premiums, the findings of this paper speak to the trade-off between having better access to care and containing health care costs. Findings can help policymakers in the design of public health systems with private provision of health insurance. But policy implications extend beyond these types markets to ones where private insurers compete on the non-price characteristics of their health insurance plans.

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