Non-Price Competition and Risk Selection Through Hospital Networks

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Abstract

Insurer competition in hospital networks generates incentives for risk selection. I model this type of competition between insurers to understand the effect of risk adjustment and premium setting on hospital network breadth and consumer welfare. I use data from Colombia's universal health care system to estimate the model. 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 narrowing their networks in services that sick, unprofitable patients demand the most. Eliminating risk adjustment reduces average network breadth by 4.2% and consumer welfare by 3.9%. Improving the risk adjustment formula increases average network breadth by 1.6%-9.2% and consumer welfare by 1.3%-5.5%, depending on how many risk factors are included. A zero-premium policy exacerbates underprovision of insurance coverage. Results highlight hospital networks as an important 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 in health insurance is the attempt of insurers to enroll profitable, usually healthy individuals instead of unprofitable patients, usually with chronic diseases. When they have discretion over the insurance plan design, private insurers typically engage in risk selection by offering a menu of contracts that may differ in their cost-sharing rules, premiums, and hospital networks, and then having individuals self-select into the contracts. Risk selection is a main concern in public health insurance systems that rely on regulated competition for insurance provision as it can unravel the market (Kong et al., 2022). This type of selection has been shown to explain the proliferation of narrow network plans (Shepard, 2022) and rationing of care (Ellis and McGuire, 2007). Addressing insurers' incentive to risk-select is, therefore, first-order in government's health policy agendas.

Existing literature has focused on how risk selection arises from insurer competition in prices while holding other elements of the insurance plan fixed (e.g, Ho and Lee, 2017; Dafny et al., 2015). This has motivated policies such as premium subsidies, open enrollment, or informational nudges to contain selection incentives (Polyakova, 2016; Nuscheler and Knaus, 2005). But far less explored is whether insurers strategically choose the non-price characteristics of their plans to cream-skim the market. In this paper I study insurer competition in hospital networks when premiums and cost-sharing are regulated. I show how risk selection arises from this type of competition and measure the effect of typical policies used to combat risk selection, such as risk adjustment and premium setting, on hospital network breadth using the Colombian health care system as a case study.

In Colombia, private insurers (similar to HMOs) provide one national health insurance plan with near universal coverage. The government sets the premium for the national plan to zero and standardizes covered services and prescription medications, coinsurance rates, copays, and maximum out-of-pocket amounts. At the beginning of every year, before health claims are realized, insurers receive ex-ante capitated risk-adjusted payments from the government that control only for the enrollee's sex, age, and location. At the end of every year, after claims are made, insurers also receive ex-post payments that compensate for the onset of a few comorbidities. The risk adjustment systems poorly capture the true variance in health care costs, so that even after transfers are made incentives for selection are still present (Riascos and Camelo, 2017; Riascos, 2013). This health system's arrangement is similar to markets in other countries such as Medicaid Managed Care in the United States. My paper, thus, offers a chance to learn about how the interaction between risk selection and competition in hospital networks play out in different, policy-relevant environments.

The only element of the public health insurance plan that is unregulated is hospital networks, which insurers can choose separately for different services. In Colombia, insurers have discretion over which services to cover at which hospitals, so they can use these 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 avoid 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. More tangentially, 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.

While this paper is not the first to consider the potential of networks to serve as a tool for risk selection, it is the first to quantify the effect of risk adjustment and premium setting on network breadth, health care costs, and consumer welfare. Shepard (2022) in the context of the Massachusetts Health Exchange, shows that sick individuals' strong preferences for expensive providers incentivizes insurers to drop these providers from their networks. I build on his intuition to show that those exclusion incentives are exacerbated under zero premiums and coarse risk adjustment.

To do so, I model insurers' market-level network coverage decisions per service. I assume insurers engage in a simultaneous-move game where they maximize total current profits plus future discounted profits by choosing their vector of service-level network coverage, conditional on their rivals' choices. My solution concept is a steady state Nash equilibrium. This approach resembles the first stage of the game in Liebman (2018), where insurers commit to network size before entering price negotiations with hospitals. I reinterpret network size as the fraction of hospitals in a market offering a particular service that are covered by the insurer. This continuous measure in the unit interval considerably simplifies computation of insurers' equilibrium network breadth choices relative to existing methods in the literature (Prager and Tilipman, 2020; Ghili, 2020; Liebman, 2018; Ho and Lee, 2019), but its limitation is that it ignores hospital identity. If consumers care about hospital identity, collapsing networks to a one-dimensional object per service could be problematic. Nonetheless, I show that, conditional on the service, there is no evidence of differential sorting of consumers into hospitals that is consistent with preferences for hospital identity.

My supply model is similar to that in Shepard (2022), who models insurers' binary decision to include a high-priced hospital in their network. My solution concept can be thought of as mixed strategy equilibrium of the binary decision game, where insurers include a hospital in their network with a probability equal to my network breadth measure. Unlike Shepard (2022), insurers in my context compete in network breadth for several service categories so that their object of choice is multidimensional. Because switching rates are nearly zero in the Colombian market, I also allow insurers to take into account the future profits associated with each enrollee when making their network breadth choices in steady state by assuming that enrollees are locked into their initial insurer choice.

My model consists of three components. First, I model new enrollees' myopic and static discrete choice of insurance carrier. Enrollees' indirect utility is a function of insurers' network breadth per service and average out-of-pocket payments. I allow for sufficient observed heterogeneity in both parameters to capture adverse selection, which means that selection in my model occurs only on observable, un-reimbursed (or poorly reimbursed) consumer characteristics like diagnoses. Second, I model insurers' average cost per enrollee as a flexible function of network breadth and consumer type, that allows insurers to exhibit economies of scope across services. This function represents a reduced-form approximation of an equilibrium where insurers and hospitals bargain over service prices and then consumers make claims for those services. Finally, I model insurers' network formation cost as a service-specific administrative cost associated with inclusion of an additional hospital to the network. The cost shocks associated to network formation are observed by insurance companies but unobserved to the econometrician.

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 across services, since with zero premiums and regulated cost-sharing, insurers have no incentive to invest in complete networks. Despite the incentives to establish a narrow network present in this context, I show that there is a meaningful trade-off in the determination of network breadth: if consumers care about network breadth, a narrow network carrier will attract fewer sick enrollees who are unprofitable, but also fewer healthy enrollees who are profitable conditional on risk adjustment. As long as the number of healthy enrollees in the population sufficiently exceeds the number of sick enrollees, narrow networks carriers will have lower profits in equilibrium compared to broad network carriers.

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 associated health claims (650 million). I focus on individuals with insurance coverage over the entire sample period (9 million) and their claims (250 million). Informality and job loss, which are highly common in Colombia and generate variation in income within individual and across time, mostly explain why the continuously enrolled represent only 36% of all enrollees to the contributory system. Government reimbursement per enrollee is weighted by the number of days a person is enrolled in a year, but this type of variation in enrollment is unpredictable by insurers. 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.

I find that consumers have a strong preference for broader networks and lower out-of-pocket payments, but that the strength of this preference decreases with age and sickness. The estimates imply that, conditional on sex and age, individuals with chronic conditions have a significantly higher willingness-to-pay for network breadth than healthy individuals, which is consistent with strong adverse selection. In terms of supply I find that, conditional on consumer characteristics, insurers' average cost is hump-shaped with respect to network breadth due to economies of scope. While conditional on network breadth, the average cost function is U-shaped with respect to the enrollee's age. I also find that the network formation cost is strictly convex in network breadth. The predicted network formation cost matches the ratio of administrative expenses to accounting profits obtained from insurers' public income statements. A decomposition of profit changes following an insurer unilaterally increasing network breadth for a service shows that adverse selection, or the change in the composition of consumer types in demand, explains on average 46% of the variation in profits; while the direct effect of networks on average costs and network formation costs explains the remaining 54%.

In view of the growing regulation regarding network adequacy in countries like the United States (Mattocks et al., 2021; Haeder et al., 2015), as well as concerns about access to health care in Colombia, I use my model to quantify how hospital networks respond to changes in the regulatory environment and how these network changes affect health care costs. The extent to which insurers respond to regulation in their network breadth choices is reflective of the degree of risk selection in the market.

In the first counterfactual, I eliminate the risk adjustment systems and reimburse insurers with a fixed per capita rate, holding short-run government spending fixed. Eliminating compensations for health risk factors should exacerbate risk selection and incentivize insurers to narrow their networks in services that costly patients require. My findings show that in absence of risk adjustment, insurers drop coverage of relatively expensive services such as hospital admissions by 26.4%, and of relatively cheap services such as consultations and laboratory by 6.2%. In the short-run, eliminating risk adjustment reduces consumer welfare by 3.9% or 73,312 pesos ($38.6) per capita per year due to worsened access to and quality of care.

Then I move to the polar exercise where I improve the government's risk adjustment formula either by reimbursing for a list of diagnoses ex-ante (a dimension currently un-reimbursed) or by making capitated transfers match the individual's average cost ("perfect" risk adjustment). If diagnoses help better predict health care costs, including them in the risk adjustment formula should decrease risk selection incentives and promote broader networks. In keeping with this intuition, I find that average network breadth increases 1.6%-9.2% relative to the observed scenario depending on how many risk factors are included in the formula. The effects on network breadth are larger for services that mostly sick patients tend to claim. Broader network coverage raises consumer welfare for enrollees with chronic diseases by 1.3%-4.8%, which in the case of "perfect" risk adjustment is equivalent to an increase of 98,309 pesos ($51.8) per capita per year.

Finally, to understand how hospital networks respond to price competition, I conduct a counterfactual exercise where insurers compete simultaneously over premiums and network breadth. I assume insurers can discriminate premiums across sex, age group, and income level. Premiums replace risk adjustment, which implies government spending is zero. Findings show that premiums are U-shaped with respect to the enrollee's age, higher for males than for females, and higher for higher income individuals. Deregulating premiums incentivizes insurers to broaden their networks by 46.0% on average across all services. Put differently, a zero-premium policy exacerbates underprovision of insurance coverage. Broader networks increase consumer welfare by 13.3% only for individuals with chronic conditions. But welfare falls 73.7% for those without diseases, who have low willingness-to-pay for network breadth and high demand elasticity with respect to premiums.

The findings of my paper are relevant for Colombia where one the main reasons for dissatisfaction with an insurance company is narrow hospital networks (Ministerio de Salud y Protección Social, 2015). Findings are also relevant for public health insurance systems where private insurers compete on hospital networks such as Medicaid Managed Care (Layton et al., 2018) or the ACA marketplaces in the US. 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 on hospital network breadth. Existing evidence focuses 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 risk selection mechanisms identified in the literature include insurer advertising (Aizawa and Kim, 2018) and insurance plan entry (McNamara et al., 2021).

This paper also contributes to the literature on insurer competition by exploring the effect of adverse selection on insurers' provision of hospital networks that are established at the service level. While Shepard (2022) shows that adverse selection can explain why insurers choose narrow networks in equilibrium, I focus on how risk adjustment and premium setting can alleviate the underprovision of insurance coverage, an issue which the previously cited papers do not directly address. I model insurers' strategic interactions in their hospital network choices in a tractable way. My model can generate predictions about market structure in health insurance systems where insurers compete mainly on the non-price characteristics of their insurance plans.

2 Institutional Background

The Colombian health care system was established in 1993 with Law 100. The system 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 (nearly the remaining 49%). The national health care system has almost universal coverage with variation in the number of uninsured across departments due to difficult geographical access. Universal coverage of the national insurance plan 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 proportion of their monthly income.[1] 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

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

the enrollee's income level, but they are standardized across insurers and providers.[2,3] Enrollment of formal workers and independent workers is compulsory, so dropping out of the system while still receiving a monthly income can lead to monetary sanctions by the National Department of Taxes and Customs.

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. Although the government does stipulate a set of network adequacy rules to guarantee appropriate access to health services, these rules are very coarse.[4] The rules recommend that insurers estimate demand for health services by risk group in each market; analyze hospital supply and installed capacity; and decide which hospitals can meet their demand for primary care, urgent care, oncology, and treatment of certain chronic diseases. After deciding on their network, insurers and hospitals engage in bilateral negotiations over service prices and types of contract (capitation or fee-for-service).

Private insurers 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 health care cost per enrollee. Then, for each risk pool defined by a combination of sex, 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 special 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 this formula is only 1.65% !

The High-Cost Account, on the other hand, compensates insurers for enrollees with any of the following chronic diseases: cervical cancer, breast cancer, stomach cancer, colon cancer, prostate can-

[2] 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%.

[3] The average exchange rate during 2011 was $1,847 COP/USD.

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

cer, lymphoid leukemia, myeloid leukemia, hodgkin lymphoma, non-hodgkin lymphoma, epilepsy, rheumatoid arthritis, and HIV/AIDS. Insurers that enroll an above-average share of people with these conditions receive transfers from those with a below-average share. Given that the list of diseases is not exhaustive, selection incentives are still present after ex-post risk adjustment (Riascos, 2013; Riascos and Camelo, 2017). Regulation of plan characteristics and imperfect risk adjustment, incentivizes private insurers in Colombia's contributory health care system to select risks through the discretionary elements of the national insurance plan, namely the hospital networks per service. The next section describes the dimensions of insurer heterogeneity and the extent of risk selection through hospital networks.

3 Data and Descriptive Evidence

The data for this paper are the cross sections of all enrollees to the contributory system during 2010 and 2011 (25 million), and their claims through the national insurance plan (650 million). I focus on the sample of individuals with continuous enrollment spells or no gaps in enrollment per year (9 million) and their associated claims (270 million).[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. In the sample of current enrollees, I observe only 0.06% switch their insurance carrier from 2010 to 2011, which evidences the extent of consumer inertia in this market. Because there is near universal coverage, new enrollees to the contributory system can be individuals who move from the subsidized system after they find a job, or those who for some reason were uncovered at any particular moment in time and then enroll the health care system.

For every claim, the data reports date of provision, service description, service price, provider, insurer, hospital length-of-stay, ICD-10 diagnosis code, and contract type under which the insurer reimbursed the provider. For every enrollee, the data has basic demographic characteristics like sex, age, municipality of residence, and enrollment spell length in the year. I assign each individual the average income in its municipality, sex, and age group, using aggregate income data from enrollees to the contributory system. With the demographic information, I recover the per capita ex-ante risk-adjusted transfer. I also have data on total High-Cost Account transfers per insurer and year.

[5] Because the continuously enrolled represent only 36% of all enrollees to the contributory system –due to informality, job loss, and variation in income across time for every person– I conduct robustness checks on my descriptive analysis using all enrollees.

Providers that are reimbursed by an insurer in the claims data are considered to be in-network, so I do not observe out-of-network claims. This is not an issue for my analysis given that out-of-network claims are infrequent, they are usually not reimbursed by the insurer, and thus the enrollee has to pay completely out-of-pocket for out-of-network care.

During my sample period there are 23 private insurers in Colombia's contributory health care system. I focus on the 14 largest insurers that account for over 97% of enrollees. Insurers compete separately in every market, which I define as a Colombian state (similar to an MSA in the US) and there are 32 markets in my data. The Colombian insurance market is highly concentrated, with the top 3 companies covering 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 insurers, the smallest of which has a duopoly of carriers (see panel A of appendix figure 1).

Table 1 presents average demographic characteristics of new enrollees and current enrollees by switching status. Switchers in and new enrollees are on average younger and have a lower prevalence of chronic conditions than stayers during 2011. New enrollees are disproportionately male, while switchers and stayers are disproportionately female. Across the three samples, EPS037 has the oldest population of enrollees with an average age of 38 years among stayers, 42 years among switchers, and 43 years among new enrollees. This insurer's population of enrollees is also relatively sicker than it's rivals', with 49% of stayers having a chronic disease.

Table 1: Demographic characteristics of current and new enrollees

	Stayers			Switchers in			New enrollees		
Insurer	Age	Male	Sick	Age	Male	Sick	Age	Male	Sick
EPS013	37.3	44.3	32.6	38.4	39.3	37.6	30.4	58.7	7.2
EPS016	37.6	43.1	33.3	32.9	48.4	28.9	32.1	55.3	6.5
EPS037	52.9	39.6	48.9	42.3	37.2	29.4	42.7	50.6	9.5
EPS002	36.6	44.1	35.8	31.8	45.4	26.7	31.3	59.0	8.8
EPS017	35.2	43.4	30.1	32.7	44.4	23.1	31.9	60.0	9.5
EPS010	37.9	43.3	33.1	29.5	44.0	21.6	33.9	56.3	6.7
EPS018	38.1	44.6	25.9	31.2	40.6	16.4	30.5	56.2	7.4
EPS005	45.4	40.9	19.6	38.8	37.2	21.6	34.9	55.9	5.0
EPS003	38.7	44.0	32.1	37.4	34.6	19.8	33.9	56.2	5.9
EPS008	37.6	42.4	25.3	34.6	41.0	20.8	32.9	57.7	8.8
EPS023	35.0	45.2	27.0	30.3	43.2	18.2	29.3	60.8	6.4
EPS009	38.7	42.5	32.7	33.5	47.2	22.6	32.8	56.7	7.7
EPS012	40.5	43.7	39.3	33.6	39.4	33.3	31.7	58.0	9.7
EPS001	41.7	44.3	27.9	32.1	40.4	11.9	36.6	50.8	4.8

Note: Average age, percentage of males, and percentage of enrollees with chronic diseases by insurer in the sample of stayers, switchers, and new enrollees during 2011.

Current and new enrollees also differ in terms of health care costs. Figure 1 shows the 2011 median total cost and interquartile range by age group. Black lines represent current enrollees and red lines correspond to new enrollees. In both samples, the mean and variance of total health care costs are increasing with age. Current enrollees are more expensive and exhibit greater dispersion in costs relative to new enrollees, who are considerably cheaper conditional on age.

The rising trend in total costs 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). Selection on age is more likely in health care plans that cover the entire population, but less so in markets where insurance is provided to a specific age group like Medicare Advantage in the United States. Conditional on risk adjustment, selection incentives in Medicare Advantage arise mainly from differences in diagnoses rather than differences in age. In Colombia, however, selection on both age and diagnoses is possible with the current risk adjustment systems.

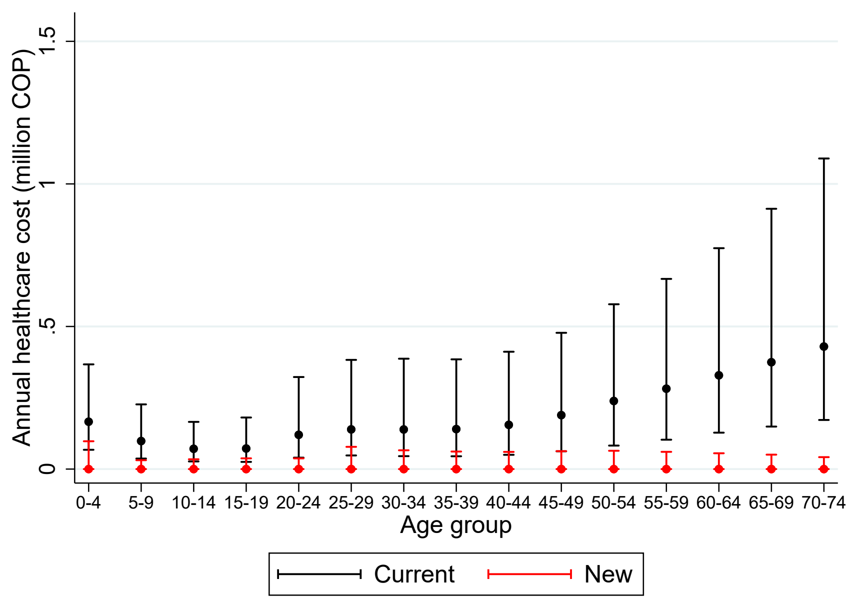


Figure 1: Total health care cost by age group

Note: Figure presents interquartile range and median annual health care cost for current enrollees in black and for new enrollees in red.

The coarse nature of the risk adjustment formula generates heterogeneous profits per enrollee. Table 2 presents the mean, 1st and 99th percentiles of profits per capita in the sample of new enrollees and current enrollees by switching status. The profit is calculated as the government's ex-ante and ex-post transfers, plus revenues from copayments and coinsurance rates, minus total 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. For EPS037, the risk adjustment formulas highly overcompensate health care costs for its cheapest stayers, resulting in the highest 99th percentile across insurers. The formulas also severely undercompensate costs for this insurer's most expensive stayers, resulting in losses of 17 million pesos per enrollee in the 1st percentile of the distribution. The table also shows that new enrollees' average profit is significantly higher than that of switchers in and stayers, and their distribution of profits per capita less skewed to the left. Thus, if insurers engage in risk selection, selection efforts should be stronger among new enrollees.

Table 2: Distribution of profit per enrollee by switching status

	Stayers			Switchers in			Newly enrolled		
Insurer	Mean	P1	P99	Mean	P1	P99	Mean	P1	P99
EPS013	0.08	-5.30	1.86	-0.03	-4.24	1.68	0.34	-1.00	1.99
EPS016	0.08	-6.25	1.90	0.08	-4.80	1.64	0.38	-1.27	1.99
EPS037	0.13	-17.16	2.15	0.49	-1.51	1.99	0.66	-1.34	3.12
EPS002	0.09	-5.62	1.82	0.24	-1.89	1.47	0.35	-1.12	1.99
EPS017	0.04	-6.23	1.83	-0.33	-26.33	1.29	0.31	-1.60	1.99
EPS010	0.10	-5.69	1.87	0.10	-3.82	0.82	0.39	-1.03	2.11
EPS005	0.14	-8.38	1.99	0.12	-7.47	1.67	0.39	-1.62	2.11
EPS018	0.04	-6.23	1.83	0.14	-2.57	1.07	0.28	-1.63	1.68
EPS003	0.07	-5.93	1.88	0.13	-7.64	1.63	0.42	-0.82	2.11
EPS008	0.08	-6.54	1.88	0.02	-5.97	1.59	0.30	-2.40	2.02
EPS023	0.10	-4.51	1.68	0.18	-1.86	1.94	0.33	-0.82	1.68
EPS009	-0.36	-15.25	1.87	0.21	-2.67	2.11	0.26	-3.32	1.99
EPS001	0.15	-7.76	2.06	0.35	-1.14	1.40	0.49	-0.73	2.11
EPS012	0.08	-6.35	1.80	0.30	-1.48	1.72	0.36	-1.00	1.90
Total	0.08	-7.76	1.99	0.13	-3.70	1.63	0.44	-1.14	2.11

Note: Mean, 1st and 99th percentiles of profit per enrollee for each insurer in the sample of current enrollees by switching status and new enrollees. Stayers are individuals whose choice of insurer doesn't change across years. Switchers are individuals whose choice of insurer changes from 2010 to 2011. Surplus is calculated as the risk-adjusted transfers (ex-ante and ex-post), plus revenues from copays and coinsurance rates, minus total health care cost. Surplus is measured in millions of 2011 Colombian pesos.

Given that almost every aspect of the national insurance plan is regulated by the government except for hospital networks that are established at the service level, one way in which insurers can engage in risk selection is by choosing their hospital coverage per service to avoid unprofitable patients. The design of hospital networks is a complicated process that involves bilateral negotiations per service between a handful of insurers and a long list of hospitals. But to understand how this process goes about and observe whether insurers respond to risk selection incentives in their hospital coverage choices, first I need to define what a hospital is and what a service is.

Colombia's provider landscape is characterized by a large number of individual or stand-alone doctors and a relatively small number of hospitals and clinics. In 2011, there were around 11,200 hospitals and small clinics, which comprised nearly 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 sample selection criteria matters because I recover the insurers' service-level hospital network from observed claims. For relatively large hospitals and clinics, as those included in my sample, I can observe at least one claim for each service category that they have contracted with insurers. Instead, for small providers or stand alone doctors, it is likely that there are zero claims for certain services, even if they are part of an insurer's network. Obtaining networks from observed claims can be problematic because I may falsely infer larger networks for larger insurers, which would bias my estimates of consumer preferences for network breadth upwards. I may also falsely infer higher utilization for broader networks, which would bias my estimates of the effect of network breadth on consumer moral hazard. To avoid these issues I drop small providers and focus on a sample of larger hospitals and clinics. I also conduct robustness checks on my network measure later in document, where I focus only on hospitals (dropping clinics) and where I limit the sample to the largest hospitals in the country defined by their number of beds.

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 Special Registry of Health Care Providers.[6] 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 represents 13% of individual health care costs, 10% of individual claims, 32% of total health care costs, and 27% of total claims in the contributory system. 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.

For every claim in my data, I observe the 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

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

[7] The first two digits of the service codes (known as CUPS for its Spanish acronym) indicate the anatomical area where the procedure is developed, 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 by the Ministry of Health.

in cardiac vessels, procedures in stomach, procedures in intestines, imaging, consultations, and hospital admissions. Each category, in turn, covers more detailed medical procedures. For example, 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.

While it is mandatory for insurers to provide coverage of all services in the national insurance plan, they have discretion over the number of hospitals to cover for each service. This means that network breadth is defined over the number of hospitals *conditional on the service*, but not over services. Although hospital coverage per service is in part determined by differences in hospital specialty and available capacity, this coverage also depends on the type of consumers that insurance companies want to risk select upon. As an example of how service-level networks play out and with data from the National Health Superintendency, I obtain the list of covered services per insurer at three of the largest hospitals in the country: Fundación Santa Fe in Bogotá, Fundación Valle del Lili in Cali, and Hospital Pablo Tobón in Medellín. Appendix Tables 4-6 show how service coverage varies across insurers at these hospitals. For instance at Fundación Valle del Lili, EPS010 covers cardiology, nephrology, and oncology, but not general adult admissions, ICU, nor NICU. EPS002 covers dialysis and nuclear medicine, but not cardiology, oncology, nor general adult admissions. EPS005, instead, covers general adult admissions, but not dialysis nor cardiology. At Fundación Santa Fe, EPS005 cover dialysis and radiotherapy but not general medicine. While EPS008 covers oncology but not radiotherapy nor dialysis.

If insurers use their service-level hospital networks to select risks, then differences in risk selection efforts should be reflected in 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 3 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. Smaller insurers, like EPS008 and EPS023, tend to cover between 12.6% and 10.0% of hospitals per service in the average market during 2011. 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

Table 3: 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.

Ministry of Health show that narrow networks is one of the top three reasons for dissatisfaction with an insurance company, together with long waiting times for scheduling doctor appointments, and the amount of paperwork needed from the patient to receive services, procedures, and medications (see appendix figure 2). By collapsing networks to a one-dimensional object for each service, I am effectively ignoring the hospital's identity from the network. This approach would be problematic if consumers care about hospital identity conditional on the service.

One way to check for differential sorting on hospital identity is to compute the standard deviation of claims across hospitals conditional on the service and the insurer. A relatively high standard deviation would be suggestive of patients sorting differentially across providers within a service. While this strategy does not allow me to distinguish the reason for sorting –whether it is the hospital's identity, distance to the hospital, or adverse selection on hospital choice– it does allow me to check for the presence of sorting conditional on the service. Panel (a) of appendix figure 3 shows that for over 65% of insurer-service combinations the standard deviation of claims across hospitals is at most 2, while for 10% of insurer-services the standard deviation is greater than 15 claims.

Panel (b) of appendix figure 3 shows the standard deviation of claims separately for each service in the x-axis. Services are arranged in increasing order with respect to total number of claims. For more than half of the services, the standard deviation of claims is at most 5. These correspond to highly complex services like procedures in brain, skull, cardiac vessels, and stomach. As we move up in number of claims towards less complex services such as primary care, laboratory, and imaging, the standard deviation of claims increases suggesting a role for hospital identity as a determinant of insurer choice. For these less complex services, however, it seems reasonable to assume that consumers care more about distance to the hospital than they do hospital identity. In that case, my measure of network breadth would be reflective of the probability that a hospital is located near the consumer. Because the main capital cities in the country have known star hospitals,[8] another way to deal with hospital identity is to exclude these markets from my estimation. I provide robustness checks of this style later in the document.

3.1 Service-Level Selection and Network Breadth

So far 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. In figure 2 I show whether the current risk adjustment systems are effective at neutralizing 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 category. Revenues per enrollee are calculated as ex-ante and ex-post compensations, plus revenues from copayments. Every dot in the figure represents a service weighted by the number of patients who make claims for it. A patient 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 most commonly utilized services, such as consultations, imaging, and laboratory, are located around the 45 degree line, so risk-adjusted compensations succeed at eliminating selection incentives over individuals that disproportionately use these services. However, there are a number of other services, such as procedures in heart valves, cardiac vessels, and pancreas, for which the risk-adjusted transfer severely undercompensates health care costs. In the case of procedures in heart valves, average costs are almost 5 times larger than average revenues per enrollee; while for procedures in pancreas, average costs can be around 4 times larger than average revenues for patients who make claims for this service. I observe the same pattern between revenues and costs per service using

[8]For example, Fundación Santa Fe in Bogotá, Fundación Valle del Lili in Cali, Hospital Pablo Tobón in Medellín, and Hospital Metropolitano in Barranquilla.

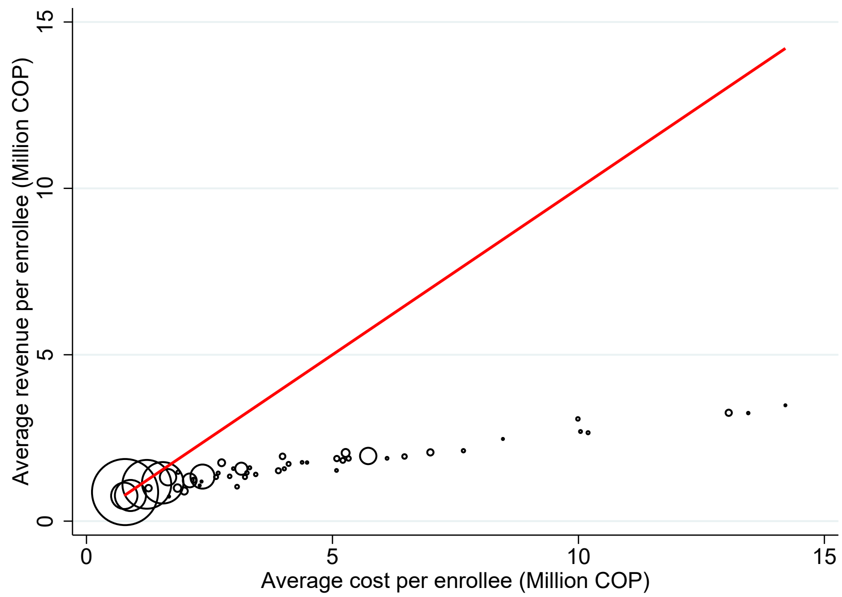


Figure 2: Service-level selection incentives after risk adjustment

Note: Scatter plot of average per enrollee cost and average per enrollee revenue for each service. Each dot is weighted by the number of individuals that make claims for that 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.

data from all individuals enrolled to the contributory system without constraining enrollment to be continuous in panel (a) of appendix figure 4.

The striking differences between revenues and costs arise from the simple fact that government payments do not compensate for specific services or even diagnoses that predictably use those services. Ex-ante compensations control only for sex, age, and location; risk factors that are mostly weakly correlated or orthogonal to the utilization of certain services as seen in figure 3. This figure plots the average cost per service against the fraction of males that make claims for each service in panel (a) and against the average age of patients that make claims for each service in panel (b). Insurers can, nonetheless, set up their hospital networks separately per service. Therefore, 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.

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 by Chiappori and Salanie (2000). Figure 4 plots the average profit per enrollee against average network breadth per service. Profits per enrollee are calculated as government transfers plus revenues from copays and coinsurance rates, minus total health care cost. For every service, I

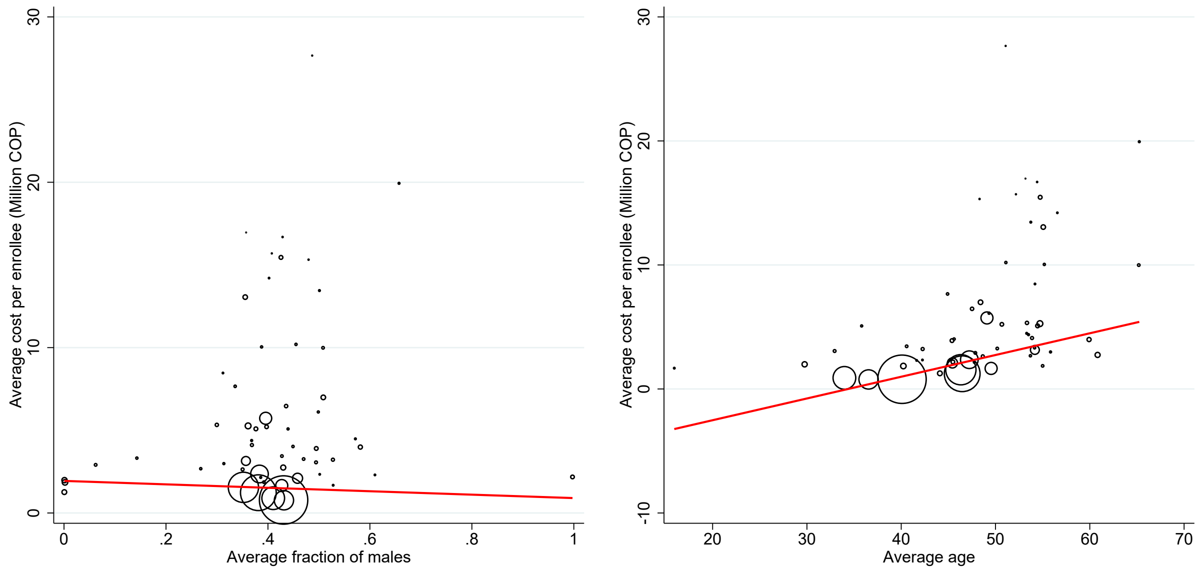


Figure 3: Predictability of cost per service

Note: Scatter plot of average cost per enrollee for patients who make claims for each service against average fraction of males in panel (a) and average age in panel (b). Every dot represents a service weighted by the number of consumers that make claims for that service. The red line represents a linear fit.

calculate the average profit across patients who make claims for that service and plot it against the average network breadth per service calculated across insurers and markets. Every dot represents a service weighted by the number of patients who make claims for it, so individuals who make zero claims and are the most profitable are not represented here. The red line corresponds to a linear fit.

Relatively profitable services, such as consultations and procedures in teeth, tongue, and salivary glands, tend to have broader networks than relatively unprofitable services, such as procedures in heart valves and cardiac vessels. Average network breadth for consultations is 50 percentage points higher than for procedures in heart valves, the first of which is associated to an average profit of 89,000 pesos per enrollee and the second of which has average profit equal to -22 million pesos per enrollee. The positive correlation between network breadth per service and service profitability also holds when using the full sample of individuals enrolled to the contributory system as seen in panel (b) of appendix figure 4, as well as within insurer and market as seen in appendix table 7, where I regress network breadth on average profit per enrollee using different sets of fixed effects.

Figure 4 also shows that there is a positive correlation between network breadth and number of patients who make claims for the service, which is not a story about risk selection but about

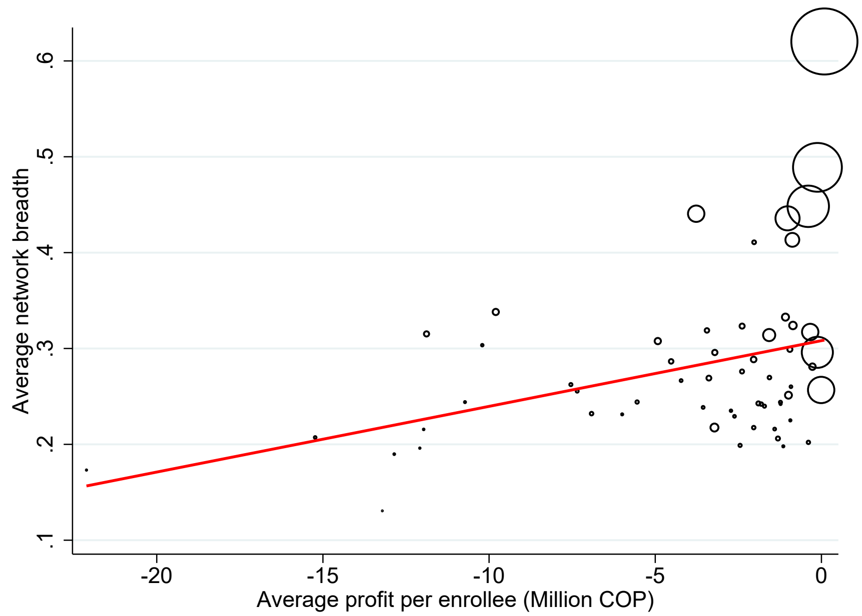


Figure 4: Correlation between network breadth and service profitability

Note: Scatter plot of average per enrollee profit and average network breadth for each service. Each dot is weighted by the number of individuals that make claims for that 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.

capacity. Although we might expect networks to be broader in services that are highly demanded, the level of demand alone does not explain why insurers choose not to cover certain services within a hospital as evidenced in appendix tables 4-6.

3.2 Trade-offs to Broad and Narrow Network Carriers

The evidence above is suggestive of strong selection incentives at the service level, but it is still unclear why network breadth exhibits substantial dispersion across insurers, within service as depicted in figure 5. The figure shows, for every service in the horizontal axis arranged in increasing order with respect to the average profit per enrollee, the median and interquartile range of network breadth. If insurers can not charge higher prices for greater coverage or can not apply different cost-sharing rules to different types of consumers, then in absence of premium competition we would predict that all insurers choose narrow networks across relatively unprofitable services.

In the reduced-form analysis that follows I show evidence of trade-offs to the provision of a narrow and a broad network that are consistent with an asymmetric equilibrium in network breadth per service in absence of price competition. Naturally, these trade-offs arise from differences in costs and demand across insurers that differ in their network breadth per service. But more importantly, trade-

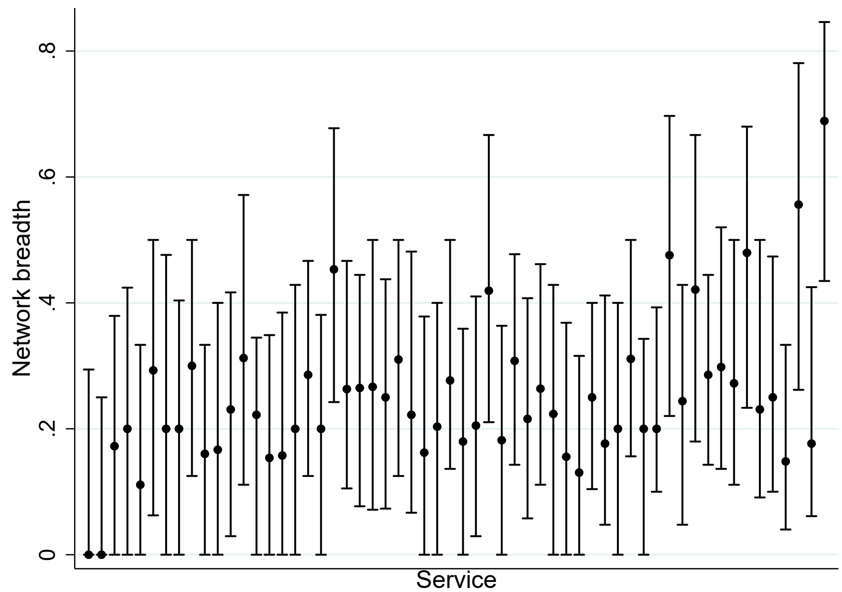


Figure 5: Variation in network breadth within service

Note: Figure presents the median and interquartile range of network breadth in 2011 for each service in the x-axis. Services are arranged in increasing order with respect to the average profit per enrollee conditional on those who make claims for the service.

offs also arise from differences in the composition of consumer types in demand across insurers. The descriptive exercises will only be suggestive of these trade-offs but are not meant to represent causal relationships between demand, costs, and networks. An insurer's network breadth choices depend on its rivals' choices and these strategic interactions are difficult to capture with a linear regression framework. Moreover, these exercises do not allow me to separately identify cream-skimming from adverse selection, or selection from moral hazard. To account for strategic interactions I will need a model of insurer competition in network breadth.

The first part of the trade-off associated with the provision of a broad network is showing that network breadth is correlated with insurer costs. I estimate the following equation using data from 2011:

$$\log(y_{ijmk} + 1) = \beta_0 + \beta_1 H_{jmk} + \mathbf{d}_i \beta_2 + \eta_m + \delta_j + \gamma_k + \varepsilon_{ijk}$$

where y_{ijmk} is individual i's annual health care cost in service m, H_{jmk} is insurer j's network breadth in market k for service m, $\mathbf{d}_i$ is a vector of consumer demographics and diagnoses, and η_m, δ_j, and γ_k are service, insurer, and market fixed effects, respectively.

Results reported in table 4 show that greater network breadth over a particular service is associated with higher annual health care costs in that service, both for the sample of stayers and new enrollees during 2011. Column (3) that uses the full sample of individuals without constraining enrollment to be continuous shows a negative coefficient due to the overwhelming amount of zeros in the dependent variable. Appendix table 8 shows, however, that the correlation between network breadth and costs at the service level is positive when using more appropriate modelling specifications such as a two-part model, 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. The finding that health care cost per service covaries with network breadth is standard and goes in line with the literature on network formation in health insurance that documents insurers with broad networks having lower bargaining leverage with hospitals and agreeing on higher prices (Ho and Lee, 2017).

Table 4: Network breadth, utilization, and costs

	log(total service cost + 1)		
	(1) Stayers	(2) New	(3) Full
H_{jmk}	0.06***	0.02***	-0.01***
	0.003	0.001	0.003
N	14,487,530	14,496,056	14,831,006
R^2	0.44	0.21	0.34

Note: OLS regression of the logarithm of health care cost per service on insurer network breath during 2011. All models include demographic controls, and market and service fixed effects. Models are estimated on a random sample of 250,000 individuals from the sample of stayers with continuous enrollment in column (1), from the sample of new enrollee with continuous enrollment in column (2), and from the full sample without constraining enrollment to be continuous in column (3). Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1.

The second part of the trade-off is showing that insurers that offer a relatively broad network over a particular service also attract people who are more likely to make claims for that service. I estimate the correlation between consumer choice and network breadth during 2011 using the following linear regression at the insurer-market level:

$$s_{jk}^m = \beta_0 + \beta_1 H_{jk}^m + \gamma_k + \varepsilon_{jk}^m$$

Here s_{jk}^m is insurer j's market share in the number of patients with any disease, no diseases, renal disease, cancer, arthritis, pregnancy, or cardiovascular disease. H_{jk}^m is either average network breadth across all services, or network breadth for dialysis, chemotherapy and radiotherapy, procedures in bones and facial joints, delivery, and procedures in heart, respectively.

Panels (3)-(7) of table 5 show a positive correlation between network breadth for a particular service and the insurer's market share in the number of patients with health conditions whose treatment requires that service. For example, an increase of one percentage point in network breadth for procedures in heart is associated to a 0.46 percentage points increase in market share over the number of patients with cardiovascular disease, both in the sample of stayers and new enrollees. Column (3) uses the full sample of individuals without constraining enrollment to be continuous, to check that these correlations are not driven by non-random variation in enrollment spells. The correlation is consistent with positive selection at the service level and with sick consumers having strong preferences for broad networks.

The first two panels of table 5 show that while broad network carriers have higher demand from individuals with any chronic disease, they also have higher demand from healthy consumers relative to narrow network carriers. Network breadth, thus, affects the composition of consumer types in demand. Comparing the estimates across these two specifications suggests that increasing average network breadth across all services has a stronger effect on market share over the number of healthy individuals than over the number of consumers with chronic diseases.

Put together results indicate that, relative to narrow network carriers, insurers that offer broad networks have higher demand from both healthy individuals who are usually profitable, and patients with chronic diseases who are usually unprofitable conditional on risk adjustment. As long as the fraction of healthy individuals in the population is significantly larger than the fraction of patients with diseases, broad network insurers will tend to have higher profits in equilibrium. Broad network carriers also have higher costs relative to narrow network carriers and this cost heterogeneity prevents the equilibrium from being one where all insurers choose complete network coverage.

3.3 Separating Selection from Moral Hazard

The previous regressions using current market shares and costs as dependent variables showed that there is a meaningful trade-off in the determination of network breadth, but they conflate the effects of selection and moral hazard. From previous results it is difficult to assess how much of the increase in costs and demand is coming from (i) individuals consuming more health care because they have access to a broader network (moral hazard), (ii) individuals selecting plans that have better coverage in services they anticipate needing (adverse selection into moral hazard), or (iii) insurers choosing their networks to maximize market share and profits (cream skimming or risk selection).

To separate (ii) from (i) and (iii), I estimate a regression on the sample of current enrollees who

Table 5: Correlation between market share and service-level network breadth

Market share in	(1) Stayers	(2) New	(3) Full
(1) Any disease			
H_{jt} Average	0.56***	0.55***	0.58***
	(0.03)	(0.03)	(0.04)
(2) Healthy			
H_{jt} Average	0.58***	0.57***	0.58***
	(0.04)	(0.03)	(0.04)
(3) Renal disease			
H_{jt} Dialysis	0.37***	0.41***	0.39***
	(0.04)	(0.05)	(0.04)
(4) Cancer			
H_{jt} Therapy	0.44***	0.43***	0.45***
	(0.03)	(0.05)	(0.04)
(5) Arthritis			
H_{jt} Procedures in bones	0.41***	0.37***	0.41***
	(0.04)	(0.03)	(0.04)
(6) Childbirth			
H_{jt} Delivery	0.50***	0.48***	0.50***
	(0.04)	(0.04)	(0.04)
(7) Cardiovascular			
H_{jt} Procedures in heart	0.46***	0.46***	0.45***
	(0.04)	(0.04)	(0.04)
N	424	424	424

Note: OLS regressions of insurer market share in the number of patients with any disease, no diseases, renal disease, cancer, arthritis, childbirth, and cardiovascular disease, on service-level network breadth during 2011. Column (1) uses the sample of stayers from those who are continuously enrolled, column (2) uses new enrollees from those who are continuously enrolled, and column (3) uses the full sample without constraining enrollment to be continuous. All models include market fixed effects. Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1.

received a diagnosis in 2010. The dependent variable is the number of claims made during 2011 in a service that is associated with treatment of their health condition diagnosed in 2010. The regression specification is given by:

$$y_{ijk}^{m,2011} = \beta_0 + \beta_1 H_{jk}^{m,2011} + \mathbf{d}_i^{2010}\beta_2 + \gamma_k + \varepsilon_{ijk},$$

where $y_{ijk}^{m,2011}$ is individual i's number of claims for service m in 2011, $H_{jk}^{m,2011}$ is insurer j's network breadth for service m during 2011, $\mathbf{d}_i^{2010}$ is a vector of demographics and diagnoses received during 2010, and γ_k 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 for that service in $t+1$ would be suggestive of patients enrolling carriers with more generous coverage for services that they anticipate needing given their health conditions in t.

Results presented in table 6 are suggestive of this source of selection. Focusing on column (1), the probability of childbirth in 2011 among women who were in childbearing age during 2010 is increasing in the coverage for delivery services. The number 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. For instance, a percentage point increase in network breadth for dialysis is related to a 0.10% increase in the number of dialysis claims in 2011 among the sample of patients who were diagnosed with renal disease during 2010. Column (2) uses the full sample of individuals enrolled in 2011 as a robustness check.

Table 6: Service-specific network breadth and types of claims

	(1) Stayers	(2) Full
(1) 1{Childbirth}		
H_{jt} Delivery	0.02***	0.01***
	(0.001)	(0.001)
N	1,085,206	3,078,555
(2) ihs(Dialysis claims)		
H_{jt} Dialysis	0.10***	0.09***
	(0.01)	(0.01)
N	83,765	120,329
(3) ihs(Antirheumatic drugs)		
H_{jt} Therapy	0.004*	0.004**
	(0.003)	(0.002)
N	102,602	156,385
(4) ihs(Chemotherapy claims)		
H_{jt} Therapy	0.005	-0.004
	(0.004)	(0.003)
N	439,176	785,727

Note: OLS regressions of the probability of childbirth, and the inverse hyperbolic sine of dialysis claims, antirheumatic drug claims, and chemotherapy claims 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 stayers with continuous enrollment 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.

Next, 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 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, but this and any subsample analysis are potentially underpowered. The fact that people do not switch after their insurer changes its service-level network breadth and potentially becomes suboptimal for the enrollee, does not mean adverse selection in this market is not meaningful. Low switching rates only suggest that either switching costs are too high, individuals have strong loyalty for their insurance carrier, or current enrollees are inattentive. Risk selection is possible on new enrollees and I provide evidence of this later.

Inspired by Brown et al. (2014), the regression specification that compares switchers and stayers is as follows:

$$\begin{aligned} y_{imk}^{2010} =& \beta_0 + \beta_1 (H_{j'mk}^{2010} - H_{j'mk}^{2011}) + \beta_2 Switch_{ik} + \beta_3 Switch_{ik} \times (H_{j'mk}^{2010} - H_{j'mk}^{2011}) \\ & + \mathbf{d}_i \beta_4 + \lambda_m + \delta_{j'} + \eta_k + \varepsilon_{imk} \end{aligned}$$

Here y_{imk}^{2010} is either the logarithm of total health care cost of individual i in service m during 2010 or an indicator for having non-zero claims for service m in 2010. $Switch_{ik}$ 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 $H_{j'mk}^{2010}$ is the 2010 network breadth of insurer j' and $H_{j'mk}^{2011}$ is the 2011 network breadth of insurer j'. $\mathbf{d}_i$ is a vector of demographics and diagnoses, λ_m is a service fixed effect, $\delta_{j'}$ is an insurer fixed effect, and η_k is a market fixed effect. The coefficient of interest is β_3.

The choice of service-specific network breadth is an effective risk selection mechanism on enrollee's baseline costs. Column (1) of table 7 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 don't switch. A percentage point decrease in network breadth is associated to a 23% reduction in baseline costs. Results in column (2) for the probability of making a claim in each service are consistent with this finding. A person who switches into a carrier that reduces its network breadth for a particular service, tends to be 2% less likely to make a claim in that service relative to stayers. This could be either because the individual knows which services she will need and switches into a carrier with good coverage for that service, or because the insurer selectively narrows its service-level network to attract individuals with lower baseline costs in that service.[9]

[9]Results in column (1) of table 7 are robust to alternative modelling specifications. Appendix table 9 shows results of a two-part model of baseline costs, with a first stage logit for the probability of having non-zero cost, and a second

Table 7: Selection on baseline costs and risk

	$\log(\text{total cost}^{2010}_{ijmt}+1)$ (1)	any $\text{claim}^{2010}_{ijmt}$ (2)	$\log(\text{risk transfer}^{2011}_{new})$ (3)
$H^{2010}_{j'mk} - H^{2011}_{j'mk}$	0.004*	-0.0001	-0.17***
	0.002	0.0002	0.008
Switch	-0.09***	-0.007***	—
	0.02	0.001	
Switch × $(H^{2010}_{j'mk} - H^{2011}_{j'mk})$	-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.

To overcome the issue of low statistical power in the previous regression and to show that risk selection is meaningful in this market even in absence of switching, I regress individuals' risk scores on insurers' network breadth choices. The risk score is given by the ex-ante risk-adjusted transfer from the government that varies across sex, age group, and municipality combinations, and that is known to insurance companies before networks are formed. I estimate the following equation on the sample of new enrollees:

$$\log(\text{risk transfer}^{2011}_{ijk}) = \beta_0 + \beta_1(H^{2010}_{j'mk} - H^{2011}_{j'mk}) + \delta_j + \eta_k + \varepsilon_{ijk}$$

where H^{2010}_{jk} and H^{2011}_{jk} are insurer j's total network breadth (across all services) in market k during 2010 and 2011, respectively, δ_j is an insurer fixed effect and η_k is a market fixed effect.

Insurers that reduce their overall hospital network breadth tend to enroll new enrollees with lower ex-ante risk scores compared to insurers that expand their network breadth over time as seen in column (3) of table 7. Appendix table 12 also shows results of a specification that correlates

stage log-linear regression conditional on having non-zero cost.

In the main specification, the change in network breadth is defined over the insurer that was chosen in 2011 (j'). Alternatively, I can define changes in network breadth between the insurer chosen in 2010 (j) and the one chosen in 2011 (j'). Results using this definition are provided in appendix table 10.

Appendix table 11 also provides results of the main specification using only the sample of switchers.

risk-adjusted transfers with the level of network breadth instead of changes in network breadth over time. Results there are consistent with high coverage carriers enrolling individuals with higher risk scores.

This section presented evidence of outstanding risk selection incentives per service and variation in service-level network breadth that responds to those incentives. In the next section, I put together these findings to model insurer competition in hospital networks per service and use the model to measure the impact of typical policies used to combat risk selection. My model of insurer demand will focus on the sample of new enrollees in 2011 for which selection efforts are stronger. New enrollees make active choices of insurer in the sense that they do not experience switching costs nor inertia when making their first enrollment decision. These individuals select carriers based on their initial observable demographic characteristics and diagnoses, as well as on the insurers' network breadth per service and out-of-pocket costs. I assume that new enrollees are myopic about future realizations of their health status and that after making their first insurer choice, these enrollees do not switch. This last assumption is consistent with the near-zero fraction of enrollees in the data that switch their insurance carrier from one year to the other.

Consumer myopia, consumer inertia, and preference heterogeneity help explain the coexistence of broad and narrow network carriers in equilibrium. Broad network carriers attract more of every type of enrollee. But myopic, healthy new enrollees will disproportionately choose narrow network insurers relative to individuals with chronic conditions, as we can expect them to have relatively lower preference for network breadth but relatively higher sensitivity to out-of-pocket costs. Inertia, on the other hand, can prevent the unraveling of insurers that offer broad networks to maximize initial market share but face subsequently higher uninsurable costs (Polyakova, 2016).

From the supply side, I assume insurers are forward looking. Insurers make an initial choice of network breadth per service to compete for the set of new enrollees every period. The insurer knows that people who enroll with it today will be locked-in forever and possibly transition into different diseases. With infinite consumer inertia, the dynamic programming problem of network formation can be approached as a static problem where insurers choose network once but compete every period for new enrollees, who then transition into the insurer's stock of enrollees. The insurers' profit maximization problem, thus, describes a steady state equilibrium in network breadth.

4 Econometric Model

In this section I describe my model of demand for insurance carriers and competition in service-specific network breadth. For carrier demand, I take a discrete choice approach and model new consumers' myopic decisions as a function of network breadth per service and average out-of-pocket payments. For competition in network breadth, I assume insurers are forward looking and maximize the sum of current and future discounted profits by simultaneously choosing their vector of network coverage conditional on their rivals' choices. This choice characterizes a steady state Nash equilibrium. To specify the profit function, I model insurers' average costs per consumer type as a function of network breadth, allowing insurers to enjoy economies of scope across pairs of services.

4.1 Insurer Demand

Start with insurer demand. Assume a new enrollee i of type (θ, l) with income level y living in market k, has diagnosis l. Conditional on diagnosis, with probability $\gamma_{\theta lmk}$ she will need each of the $m = \{1, ..., M\}$ 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 $l \in L$, where L ={cancer only, cardiovascular disease only, diabetes only, renal disease only, other disease only, two or more comorbidities, and no diseases}. Sex and age group combinations are captured by θ. Diagnoses in the list are groupings of ICD-10 codes according to Riascos et al. (2014), which are are both exhaustive and mutually exclusive. These diagnoses were chosen for being the most expensive in Colombia and, thus, the more 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 or $29,000, more than 100 times the monthly minimum wage. The most expensive patients with any type of cancer had annual health care cost of over 20 million pesos in 2011, more than 37 times the monthly minimum wage.

I assume the individual knows her diagnosis before making her first enrollment choice. This could be either because of medical family history or because, while being uncovered, she went to the doctor and received a diagnosis. My estimators on the preference for network breadth and out-of-pocket expenses are robust to a specification of demand where I allow for uncertainty in diagnosis (presented in appendix 6). My preferred demand specification is one where new enrollees know their diagnosis because selection occurs on observable, un-reimbursed (or poorly reimbursed) consumer characteristics such as diagnosis.

The consumer observes the insurer's index of coverage for each service m in market k, H_{jmk}, weights each service by the probability of claiming it $\gamma_{\theta lmk}$, conditional on the diagnosis, and then makes a one-time myopic choice of carrier. Denote by u_{ijk} the indirect utility of a new enrollee i in market k for insurer j, which takes the following form:

$$u_{ijk} = \beta_i^D \sum_m \gamma_{\theta lmk} H_{jmk} - \alpha_i c_{\theta lyjk} + \phi_j + \varepsilon_{ijk} \tag{1}$$

where,

$$\begin{pmatrix} \beta_i^D \\ \alpha_i \end{pmatrix} = \begin{pmatrix} \beta^D \\ \alpha \end{pmatrix} \mathbf{X}_i$$

$\mathbf{X}_i$ is a vector of consumer demographics including sex, age, indicators for the diagnoses in L, and an intercept. $c_{\theta lyj}$ is the average out-of-pocket payment of a type-(θ, l) consumer with income level y at insurer j. ϕ_j is an insurer fixed effect capturing insurer unobserved quality. $\beta_i^D \gamma_{\theta lmk}$ is the marginal utility for an additional percentage point of coverage for service m, α_i is the marginal disutility of average out-of-pocket payments, and ε_{ijk} is an iid unobserved shock to preferences assumed to be distributed T1EV.

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, implies that the network can also be disease-specific. This raises the possibility that insurers engage in risk selection by offering narrow networks at the service level.

The probability of making a claim, $\gamma_{\theta lmk}$, is the average prediction per consumer type, service, and market, of a logistic regression estimated at the patient level given by:

$$1\{Claim_{imk}\} = \psi_m + \psi_\theta + \psi_l + \psi_k + \psi_{imk} \tag{2}$$

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

Even though new consumers make myopic decisions of insurance carrier, I assume that their expectations of 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 (2) on data from both current and new enrollees in 2010 and 2011. Appendix figure 5 presents the distribution of the resulting γ separately for healthy and sick individuals, and for a few service categories including consultations, hospital admissions, imaging, and procedures in cardiac vessels, stomach, and intestines.

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 but with preference shocks ε_{ijk} that are independent across alternatives. This means that the only way in which risk selection can arise in my model is through these observable characteristics. I also note that estimation of a demand model that includes random coefficients on network breadth and out-of-pocket payments yields statistically insignificant unobserved heterogeneity in the former measure (see appendix table 14).

In addition to service-level hospital networks, insurers in Colombia differ in their negotiated service prices with hospitals. Average out-of-pocket payments capture differences in prices and utilization across insurers to generate consumer sorting based on prices. This sorting is needed to rationalize the existence of narrow network carriers in equilibrium since myopic, healthy new enrollees disproportionately choose narrow network carriers with lower implied out-of-pocket costs. Alongside coinsurance payments and copays, average out-of-pocket costs include individuals' tax contributions to the health care system. Consumers contribute a total of 12% of their monthly income; 1/3 of which is paid by the consumer and 2/3 by her employer.

Let $\mathcal{J}_k$ be the set of insurers available in market k and assume individuals have no outside option, since health insurance coverage in Colombia is almost universal. Let $H_{jk} = \{H_{jmk}\}_{m=1}^{M}$ and $H_k = \{H_{jk}\}_{j=1}^{\#\mathcal{J}_k}$; consumer i in market k enrolls insurer j with probability:

$$s_{ijk}(H_k) = \frac{\exp\left(\beta_i^D \sum_m \gamma_{\theta lmk} H_{jmk} - \alpha_i c_{\theta lyjk} + \phi_j\right)}{\sum_{g\in\mathcal{J}_k} \exp\left(\beta_i^D \sum_m \gamma_{\theta lmk} H_{gmk} - \alpha_i c_{\theta lyjk} + \phi_g\right)}$$

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 and negotiated prices also entail strategic interactions across insurers that may introduce correlation with unobserved characteristics. My identification strategy follows Nevo (2000) and Shepard (2022) in the use of fixed effects that absorb the endogenous variation in these two variables.

For network breadth, note that my demand specification aggregates H_{jmk} across services, which eliminates the variation in that dimension. The demand function also includes insurer fixed effects, ϕ_j, that capture unobserved insurer-level characteristics that may be correlated with network breadth. Insurer fixed effects, however, do not capture unobserved quality that varies *within* insurer. To show that this type of variation is not concerning, appendix table 18 provides a robustness check where I include additional insurer-level quality measures that vary across markets. These measures are obtained from the Ministry of Health's enrollee satisfaction surveys and contain average waiting time to schedule an appointment with the doctor and likert measure of patient satisfaction with their insurer. Results in the appendix show that preference for network breadth is robust to the inclusion of these quality measures. Therefore, β_i^D in my main specification is identified from variation in market demographics within insurer, which generates exogenous variation in $\gamma_{\theta lmk}$.

For average out-of-pocket costs, recall that coinsurance rates, copayments, and required contributions to the system are regulated by the government and standardized across insurers, hospitals, and services. This helps correct part of the endogeneity problem of negotiated service prices that enter out-of-pocket costs through coinsurance payments. Negotiated prices are also unobserved to consumers before making their enrollment decisions. But it is possible that consumers choose their insurer based on unobserved quality that is correlated with negotiated prices, even if prices themselves are unobserved. A clear example of unobserved quality in this model is the insurer's coverage of star hospitals. If consumers disproportionately enroll 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 the null. To address this issue, appendix table 19 presents a robustness check where demand includes an indicator for whether the insurer covers any star hospital per service in each market. My main estimate of α_i does not change with inclusion of this measure of quality.

Besides negotiated prices being unobserved and cost-sharing being standardized, average out-of-pocket costs include copayments and tax contributions to the health care system, which are orthogonal to negotiated prices. Copayments and tax contributions represent on average 82% of an individual's total out-of-pocket expenses, while negotiated prices account for the remaining 18%.[10] Hence, two types of variation identify α_i: variation in cost-sharing rules across patients, within insurer, and variation in choice sets across markets.

To address any other endogeneity concerns, appendix table 16 also provides an alternative demand estimation that uses instrumental variables for average out-of-pocket costs in a control function approach. The instrument is the reference price per service created by government in 2005, explained in more detail in the next subsection. Results in the appendix show that the magnitude of the coefficient on average out-of-pocket costs increases 19% relative to my main specification in section 5.1. But counterfactual simulations remain virtually unchanged. My preferred demand model is one without a control function for average out-of-pocket costs because the variation in reference prices across insurers comes entirely from γ. Finally, insurer fixed effects ϕ_j are identified from variation in insurer market shares across markets.

4.2 Insurer Average Costs per Enrollee

Following Shepard (2022), I assume the realized annual health care cost of consumer i of type (θ, l) under the observed service-specific networks, $C^{obs}_{ijk}(H_{jk})$, equals the cost of a type-(θ, l) consumer plus a random shock: $C^{obs}_{ijk}(H_{jmk}) = AC_{\theta ljk}(H_{jmk}) + \omega_{ijk}$. If sex, age, and diagnoses are observable or predictable by the insurer before the cost shock is realized, then ω_{ijk} is orthogonal to $AC_{\theta ljk}(H_{jmk})$ conditional on (θ, l) and I can recover this cost directly from the data by taking the average of observed costs across individuals of type (θ, l): $AC_{\theta ljk}(H_{jmk}) = \frac{1}{N_{\theta ljk}} \sum_{\theta(i)=\theta, l(i)=l} C_{ijk}(H_{jmk})$. 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:

$$\log(AC_{\theta ljk}(H_{jk})) = \beta^S_0 \Big(\sum_m \gamma_{\theta lmk} A_m \Big) + \beta^S_1 \Big(\sum_m \gamma_{\theta lmk} H_{jmk} \Big) + \frac{1}{2M_k} \beta^S_2 \sum_m \sum_{n \neq m} \gamma_{\theta lmk} \gamma_{\theta lnk} H_{jmk} H_{jnk} + \lambda_{\theta l} + \delta_j + \eta_k \tag{3}$$

where M_k is the number of service categories available in market k, that is, services that existing hospitals in the market can provide. A_m is the average reference price for service m explained in more detail below, $\lambda_{\theta l}$ is a consumer type (θ, l) fixed effect, δ_j is an insurer fixed effect, and η_k

[10] The extent to which negotiated prices respond to risk adjustment and premium deregulation through changes in the service-specific hospital networks is an interesting avenue for future research.

is a market fixed effect. In appendix 7, I show that this average cost function per enrollee has a direct relation to a model where consumers choose a hospital to receive service m. In my case, the average cost function per enrollee need only capture the relation between costs and hospital networks, so a complete model of consumer choice of hospital is not needed. My specification imposes fewer assumptions than a discrete hospital choice model, but is flexible enough to allow for cost variation across consumer types and network breadth, so it can be understood as a reduced-form approximation of an equilibrium where insurers and hospitals engage in bilateral negotiation over service prices and then consumers make claims for those services.

The coefficient β_1^S represents the elasticity of average costs with respect to insurer j's network breadth. β_2^S captures the average degree of complementarity between pairs of services. If $\beta_2^S < 0$, then insurer j exhibits economies of scope across services, so greater coverage for service $n \neq m$ makes it more attractive to the insurer to provide higher coverage for service m. If $\beta_2^S \geq 0$, then insurer j's coverage decisions across services are at least independent. I include this measure of scope economies to rationalize the fact that I observe insurers that have a broad network in one service, offering 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 the board of services. My specification with two-way interactions between services is the simplest way to capture economies of scope. Any evidence of economies of scope between pairs of services will likely hold for higher-order interactions. Scope economies can come from insurers either offering different services at different hospitals or from insurers covering different services at the same hospital. My model of average costs can not tell these two interpretations apart.

The first two terms in the right-hand side of equation (3) are multiplied by $\gamma_{\theta lmk}$ 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.

$\lambda_{\theta l}$ measures the average degree of selection by type-(θ, l) consumers and provides a test for the type of selection occurring in this market, in the lines of Einav et al. (2010). In the presence of adverse selection, insurer j's average costs would be increasing with consumer type and thus with preferences for network breadth. In this case, the competitive equilibrium in network breadth would be below the efficient coverage level. On the contrary, if the market exhibits advantageous selection, average costs and consumer types would be negatively correlated, such that the competitive equilibrium in network coverage would be above the efficient level. If the Colombian health insurance market is characterized by adverse selection, then my counterfactual analyses will shed light on whether alternative risk adjustment formulae or premium deregulation can bring network breadth closer to efficiency.

Identification. As noted in the descriptive exercises, consumers select into carriers based on how broad the network is in services they need. This type of selection introduces potential biases in the coefficients of the average cost function per enrollee. Adverse selection can make it look as if broad network insurers have much higher costs per enrollee than they would in absence of selection, leading to an upwards bias in the β^S coefficients. If selection happens mostly on observables, then consumer type fixed effects in equation (3) 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 types. One way to check if this is case is to test whether estimates are robust to a more granular definition of consumer type. Appendix table 22 presents results of a specification where average cost is calculated over consumer types defined as a combination of sex, age (instead of age group), and 30 (instead of 7) exhaustive and mutually exclusive diagnoses listed in appendix table 31. Except for β_0^S, the coefficients of the average cost function per enrollee are robust to this alternative definition.

The parameters of equation (3) are, hence, identified from variation in average costs within consumer types across insurers that are identical except for their network coverage 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 to absorb most of the endogenous variation across and within insurers due to selection. I estimate the average cost function using OLS, which generates a measurement error $\nu_{\theta ljk}$ that is unobserved to insurers and to the econometrician. The estimating equation is:

$$\log(AC_{\theta ljk}(H_{jk})) = f(A_m, H_{jmk}, \gamma_{\theta lmk}; \beta) + \nu_{\theta ljk}$$

where $f(A_m, H_{jmk}, \gamma_{\theta lmk}; \beta)$ equals the right-hand side of equation (3).

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. These lists were determined 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 (Decree 2423 of 1996).[11] 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 m in the insurers' average cost function. This means that β_0^S will adjust up or down depending on whether insurers bargain markups or markdowns with hospitals for the average service. Figure 6 shows the average total claim cost for service m calculated directly from the claims data in black and the price instrument in red. The correlation between these two measures equals 0.77.[12]

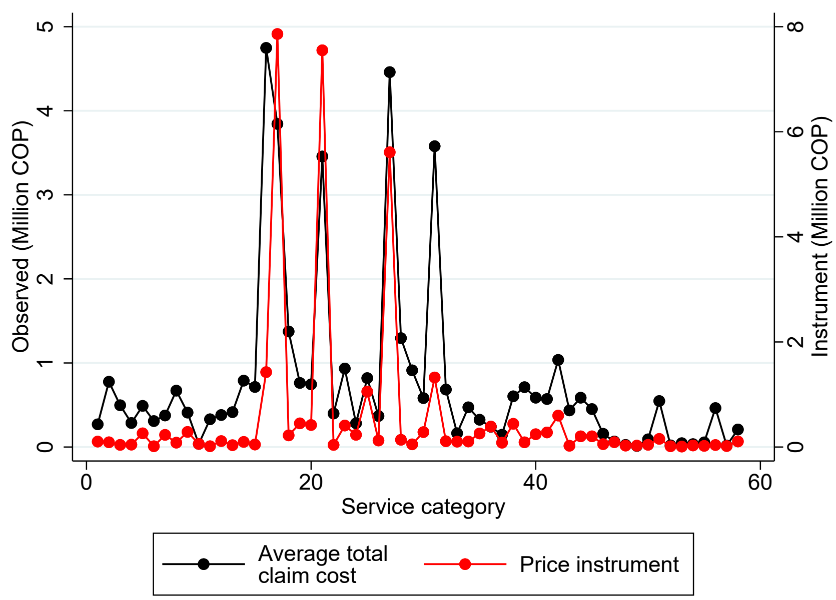


Figure 6: Average claims cost and reference prices

4.3 Competition in Network Coverage

Insurers compete separately in every market choosing their degree of service-specific network breadth after taking expectations of demand and costs, with Nash equilibrium as solution concept. Let

[11] The lists are known as the Compulsory Traffic Accident Insurance Tariffs Manual and the Social Security Institute Tariffs Manual.

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

$\pi_{ijk}(H_k, \theta, l)$ be insurer j's short-run per-enrollee profit in market k, which depends on j's network breadth and its rivals', H_k, as well as on the enrollee's type (θ, l). The short-run per-enrollee profit is given by:

$$\pi_{ijk}(H_k, \theta, l) = (R_{\theta k} - (1 - r_y)AC_{\theta ljk}(H_{jk}))s_{ijk}(H_k)$$

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

I focus on a steady state Nash equilibrium in which insurers choose networks to maximize the sum of short-run profits and long-run discounted profits per enrollee minus the cost of network formation:

$$\Pi_{jk}(H_k) = \sum_{\theta,l} \Big(\underbrace{\pi_{ijk}(H_k, \theta, l)N_{\theta lk}}_{short-run\ profit} + \underbrace{\sum_{s=t+1}^{T} \beta^s \sum_{\theta',l'} (1 - \rho_{\theta' l' k})\mathcal{P}(l'|\theta, l)\pi_{ijk}(H_k, \theta', l')N_{\theta' l' k}}_{long-run\ profit} \Big)$$
$$- \underbrace{\sum_m \Big(\omega H_{jmk} + \xi_{jmk}\Big) H_{jmk}}_{network\ formation\ cost}$$

Insurers take into account the future profits associated to each enrollee since, after making their first enrollment choice, individuals experience infinite inertia. $N_{\theta lk}$ is the market size of consumers type (θ, l), which is fixed over time, so there are no dynamics introduced by changes in population. In the expression for long-run profits, I assume that the probability of switching across carriers is zero. $\rho_{\theta lk}$ represents the probability that type (θ, l) 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 in unemployment. $\mathcal{P}(l'|\theta, l)$ is the transition probability from type (θ, l) in period t to diagnosis l' in period $t + 1$ (the transition across θ is deterministic). Future profits at year t are discounted by a factor of β^t, and I set β equal to 0.95.[13]

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:

[13] In the formulation of insurer profits, I use θ to denote sex-age combinations as opposed to sex-age groups, to avoid introducing more notation, but to be consistent between transition probabilities and periods over which future profits are calculated (years).

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

This network formation cost is non-linear in network breadth, ω capturing the convexity of the cost function. The network formation cost is also heterogeneous across insurers, markets, and services, with ξ_j, ξ_k, and ξ_m representing the insurer-, market-, and service-specific cost components, respectively.

I assume $\Delta\xi_{jmk}$ 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. An example of this can be that the insurer has 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 to providing broad network coverage for a given service is that it increases both demand and costs. By doing so, not only does the insurer attract more consumers overall, but disproportionately attracts those with a high likelihood of claiming the service, which evidences vertical differentiation. Rivals' choices of network breadth also affect insurer j's profits, which evidences horizontal differentiation. Insurer j's demand elasticities are a function of own and rival network breadth choices; and, given that there is no outside option, rival network breadth also affects insurer j's total average cost through its effect on the composition of insurer j's enrollee types.

If consumers were forward looking and could anticipate their future diagnoses, the equilibrium would be one where all insurers choose broad networks. Consumer myopia in this model helps explain why narrow network carriers exist in equilibrium and, thus, allows for the possibility that consumers adversely select into insurers based on network breadth. While this might be a strong assumption, it is worth noting that 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 coverage and co-existence of broad and narrow network carriers in equilibrium.

My model of competition in service-specific network breadth can be understood as expanding on the first stage of the game in Liebman (2018), where insurers commit to network size before negotiating prices with hospitals and the solution concept is Markov-perfect equilibrium. I reinterpret network size as a continuous measure in the unit interval per service and focus on a simultaneous-move game with Nash equilibrium as solution concept. I do not model price negotiations as my focus is on the network formation stage. My model of insurer competition also 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 insurer competition in network breadth accounting for future profits, although I ignore hospital identity.

Profit maximization involves a set of $J \times M$ FOCs in each market, which assuming an interior solution, is given by:

$$\sum_i \left(\frac{\partial \pi_{ijk}}{\partial H_{jmk}} N_{\theta lk} + \sum_{s=t+1}^{T} \beta^s \sum_{\theta', l'} (1 - \rho_{\theta lk}) \mathcal{P}(l'|\theta, l) \frac{\partial \pi'_{ijk}}{\partial H_{jmk}} N_{\theta' l' k} \right) = 2\omega H_{jmk} + \xi_{jmk} \tag{4}$$

The left-hand side of equation (4) represents the marginal variable profit MVP_{jmk} and the right-hand side is the marginal cost of network formation.

Identification. Rewriting the FOC as:

$$MVP_{jmk}(H_{jmk}) = 2\omega H_{jmk} + \xi_j + \xi_k + \xi_m + \Delta\xi_{jmk}, \quad \forall\ H_{jmk} \in (0,1) \tag{5}$$

makes explicit the endogeneity between H_{jmk} and $\Delta\xi_{jmk}$. Insurance companies observe $\Delta\xi_{jmk}$ before or simultaneously with their network breadth choices. 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 $E[\Delta\xi_{jmk}|H_{jmk}] < 0,\ \forall\ H_{jmk} \in (0,1)$ and OLS estimation of (5) would result in ω that is biased towards the null.[14] Identification of network formation cost parameters, thus, relies on instrumental variables Z_{jmk} 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 $E[\Delta\xi_{jmk} Z_{jmk}] = 0,\quad \forall\ H_{jmk} \in (0,1)$.

The instrument set is populated as follows. First, I include the set of insurer, market, and

[14]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.

service fixed effects in equation (5). Second, because I use data from 2011 in estimating the model and $\Delta\xi_{jmk}$ 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 diseases make a claim for service m in market k. These probabilities are calculated as the average prediction of equation (2) 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 $E[\Delta\xi_{jmk}Z_{jmk}] = 0$, 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_{jmk}, $\forall\ m, k$. 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.[15]

5 Estimation

5.1 Insurer Demand

I proceed with the estimation of demand for insurance carriers using a conditional logit with insurer fixed effects. For computational simplicity, I estimate equation (1) in a random sample of 500,000 new enrollees. Results are reported in table 8. I find that demand for insurers is decreasing in average out-of-pocket payments, suggestive of patient moral hazard; and increasing in network breadth, suggestive of positive selection into health insurance. In particular, an increase of one million pesos in the average out-of-pocket spending reduces demand for carriers by 6.64 percentage

[15] More generally, without dropping observations at the corners, the parameters of the network formation cost are partially identified. Note that the FOC at $H_{jmk} = 0$ is $MVP_{jmk} - \xi_j - \xi_k - \xi_m - \Delta\xi_{jmk} < 0$, and at $H_{jmk} = 1$, is $MVP_{jmk} - \tilde{\omega} - \xi_j - \xi_k - \xi_m - \Delta\xi_{jmk} > 0$. 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.

points. An increase of one percentage point in network coverage increases the probability of choosing an insurer by 2.37 percentage points.

I find that interactions between demographics and diagnoses with carrier characteristics also matter for enrollment decisions. Males are as sensitive to out-of-pocket expenses as females but have a stronger taste for network breadth. Older patients are less likely to enroll broad network carriers and are more sensitive to out-of-pocket expenses, while younger patients have a higher preference for network coverage and their insurance demand is more inelastic. These findings are consistent with the idea that older patients have had more interaction with the health care system, which makes them more likely to concentrate their care in a few providers.

Findings also show that patients 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 expenses. On the one hand, the interaction between network breadth and indicators for each of the chronic diseases are all negative and significant compared to individuals without diagnoses. On the other hand, interactions between average out-of-pocket spending and diagnosis indicators are all positive and significant. In fact, for individuals with renal disease, the effective demand elasticity with respect to the out-of-pocket expenditure is nearly zero. Finally, relative to people living in urban areas, I find that those who live in special peripheral municipalities characterized by fewer providers and more difficult access to care, have stronger preferences for coverage and a relatively inelastic demand with respect to out-of-pocket expenses.

Estimators on the preference for network breadth and out-of-pocket expenses are robust to an alternative demand specification where consumers are uncertain about their diagnoses and maximize utility over expected diagnoses and service utilization (see appendix table 13). In appendix table 17, I also provide results of a robustness check dropping markets 05, 08, 11, and 76, with the main capital cities where hospital identity might be an issue. Results there are consistent with my main finding that consumers care about broader networks and lower out-of-pocket expenditures, and that willingness-to-pay for an additional percentage of coverage is greater for individuals with chronic conditions than for healthy ones.

Because my measure of network coverage might be correlated with other insurer-market level quality measures that may induce bias and are not captured by the insurer fixed effect, I estimate demand with additional quality controls as a robustness check. Using enrollee satisfaction survey data from the Ministry of Health, I obtain a measure of average waiting times for a doctor appointment through the insurer and average insurer quality as measured by a likert scale. Results of this

Table 8: Insurer demand

Insurer choice		Coefficient	Std. Error
Network		2.37***	0.01
OOP spending	(million COP)	-6.64***	0.21
Interactions			
Network	Demographics		
	Male	0.30***	0.01
	Age	-0.01***	0.00
	Diagnoses		
	Cancer	-0.34***	0.02
	Cardiovascular	-0.33***	0.01
	Diabetes	-0.44***	0.04
	Renal	-0.61***	0.08
	Other	-0.53***	0.02
	>=2 diseases	-0.64***	0.02
	Healthy	(ref)	(ref)
	Location		
	Normal	0.05***	0.01
	Special	0.73***	0.04
	Urban	(ref)	(ref)
OOP spending	Demographics		
	Male	0.05	0.09
	Age	-0.01***	0.00
	Diagnoses		
	Cancer	5.36***	0.22
	Cardiovascular	5.89***	0.18
	Diabetes	5.77***	0.31
	Renal	6.27***	0.22
	Other	5.56***	0.20
	>=2 diseases	5.89***	0.18
	Healthy	(ref)	(ref)
	Location		
	Normal	1.15***	0.11
	Special	0.67	0.43
	Urban	(ref)	(ref)
N		5,800,610	
N enrollees		500,000	
Pseudo-R^2		0.17	

Note: This table reports results of the insurer choice model estimated on a random sample of 500,000 new enrollees. Network coverage per service is weighted by the probability of claiming the service. Includes insurer fixed effects. Robust standard errors reported. ***p<0.01, **p<0.05, *p<0.1.

Table 9: Average willingness-to-pay per consumer type

Characteristic	Willingness-to-pay
Diagnosis	
Cancer	0.07
Cardiovascular	0.63
Diabetes	0.48
Renal	0.08
Other	0.37
>=2 diseases	0.57
Healthy	0.01
Sex	
Female	0.27
Male	0.35
Age group	
<1	0.04
1-4	0.13
5-14	0.30
15-18	0.31
19-44	0.23
45-49	0.54
50-54	0.19
55-59	0.77
60-64	0.73
65-69	0.17
70-74	0.08
>=75	0.06

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 $\frac{1}{\alpha_i}\frac{\partial s_{ijk}}{\partial H_{jmk}}\frac{H_{jmk}}{s_{ijk}} = \frac{1}{\alpha_i}\beta_i^D\gamma_{\theta lmk}(1-s_{ijk})H_{jmk}$ and is measured in millions of COP.

exercise are provided in appendix table 18 and show that my estimators are robust to the inclusion of additional quality measures that vary within insurer.

In appendix table 20, I re-estimate demand calculating network breadth on the sample of 316 largest hospitals in the country and on the entire sample of providers, to see whether my hospital sample selection criteria matters for final results. The coefficients of interest associated to preference for network breadth and out-of-pocket spending are robust to these alternative network measures as well. Finally, in appendix table 21, I conduct a robustness check estimating demand on the sample of adults aged 19 or older, to get at the issue that children themselves may not be making informed insurance carrier choices but parents in their behalf. Including children could potentially lead to overestimation of the preference for network breadth given that I do not observe households nor head of household. My results are, nonetheless, robust to limiting the sample to only adults.

Using the estimates for network breadth preference and disutility of average out-of-pocket payments, I recover the patients' willingness-to-pay for an additional percentage of network coverage per service. Willingness-to-pay is calculated as $\frac{1}{\alpha_i}\frac{\partial s_{ijk}}{\partial H_{jmk}}\frac{H_{jmk}}{s_{ijk}}$ and is measured in millions of pesos. Differences in willingness-to-pay across consumer types will be suggestive of adverse selection from the demand side. Consumers with higher willingness-to-pay for a particular service category will tend to sort into carriers with high coverage for that service.

Table 9 presents the average willingness-to-pay across services, insurers, and markets, conditional on consumer observable characteristics. I find that patients with chronic conditions have a higher willingness-to-pay than individuals without diseases, overall. Within the group of patients with diseases, there is heterogeneity in willingness-to-pay across conditions as well. For instance, patients with cardiovascular disease are willing to pay 0.56 million pesos more for an additional percentage point of coverage across all services compared to patients with cancer. This is because individuals with cardiovascular conditions require a broader array of services than patients with cancer, for whom care is mostly concentrated in services like chemotherapy and radiotherapy. To put these numbers in context, the monthly minimum wage in Colombia during 2011 was 0.53 million pesos or \$271. Findings also show that willingness-to-pay is 80 thousand pesos higher for males than for females, the first of which also have a relatively high prevalence of long-term diseases. Moreover, average willingness-to-pay is non-monotonic with respect to age. Consumers aged 55-59 have the highest willingness-to-pay equal to \$0.77 million pesos, an increase of \$0.23 million pesos from individuals aged 45-49.

5.2 Insurer Average Costs Per Enrollee

I estimate equation (3) for the logarithm of insurers' average cost per consumer type-(θ, l) and market in the sample of new *and* current enrollees, conditional on observed choices in 2010 and 2011. Table 10 shows the results and appendix figure 7 presents the estimated consumer type fixed effects and their corresponding 95% confidence intervals. Average costs are increasing in network breadth and decreasing in the correlation between network coverage 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 m decreases the average cost of providing service $n \neq m$ by 0.51% per enrollee.[16] The effect of scope economies is smaller in magnitude than the direct effect of network breadth. My estimates show that a 1% increase in network breadth, raises average costs

[16] This effect is calculated as the average of $100 \times \frac{1}{2M_k}\hat{\beta}_2^S \sum_{n\neq m} \gamma_{\theta lmk}\gamma_{\theta lnk} H_{jnk}$

by 1.93%.[17] Findings also show that average costs decrease with service m's reference price, which is due to cheaper services, like consultations and laboratory, having a higher likelihood of being claimed.

Table 10: 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.

Figure 7 better depicts the magnitude of scope economies by service. The figure plots the predicted average cost against observed average network breadth in different service categories including: procedures in cardiac vessels, stomach, intestines; imaging; consultations; laboratory; nuclear medicine; and hospital admissions. In general, average costs are hump-shaped with respect to network breadth. In the left side panel of the figure, going from 20% to 30% coverage of procedures in stomach, raises the average cost per enrollee by $0.16 million pesos; while going from 70% to 80% network breadth, reduces the average cost per enrollee by $0.27 million pesos. In the right side panel, average cost reductions associated to coverage of nuclear medicine occur only at levels of network breadth exceeding 70%. While for consultations, laboratory, hospital admissions, and procedures in cardiac vessels the average cost per enrollee is increasing at all values of the average network breadth.

[17] This effect is calculated as the average of $100 \times \hat{\beta}_1^S \gamma_{\theta l j m k}$

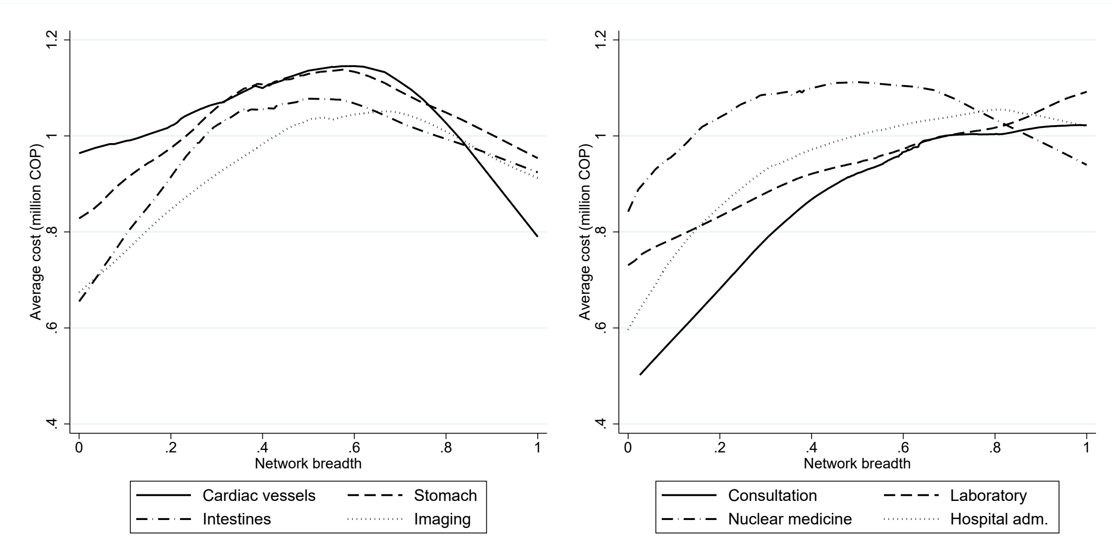


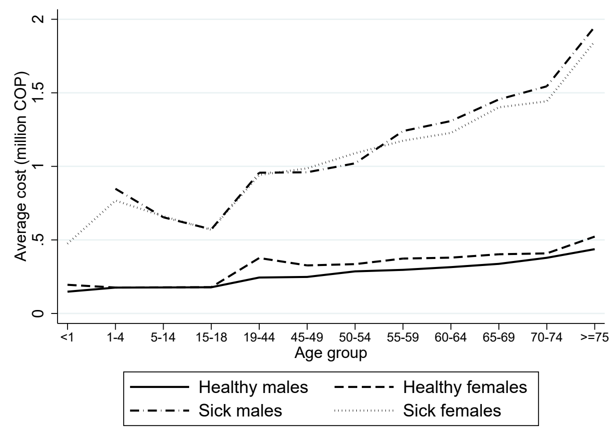
Figure 7: Average cost function per service

Note: This figure shows the predicted average cost conditional on observed levels of network breadth separately for 8 service categories: procedures in cardiac vessels, stomach, intestines, and imaging, consultations, laboratory, nuclear medicine, and hospital admissions.

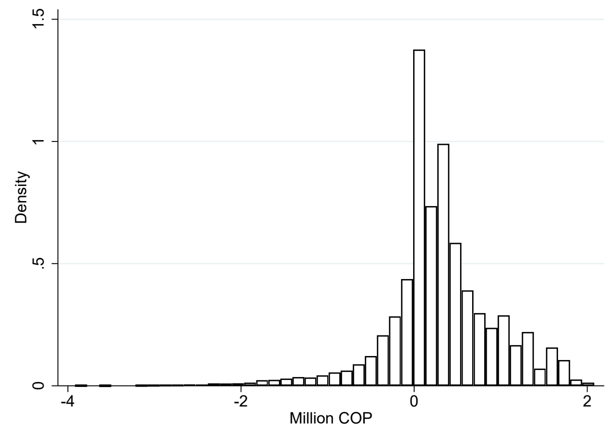
Scope economies also vary across consumer types. Appendix table 23 shows the change in the average cost of healthy females aged 19-44 and the average cost of females aged 19-44 with cancer, following a 10% increase in network breadth for the service in each row, separately for narrow and broad network carriers. I define a broad network carrier for service m as an insurer with average network breadth across all services $n \neq m$ above 80%, and a narrow network carrier as the opposite.

Following a 10% increase in network breadth for consultations, results in the appendix show that the average cost of healthy adult females enrolled to a narrow network carrier increases $1,343 pesos more than for those enrolled to a broad network carrier. There is no evidence of scope economies among females with chronic diseases. For example, a 10% increase in network breadth for laboratory services, raises the average cost of adult females with cancer at a narrow network carrier by $14,711 pesos and at a broad network carrier by $17,086 pesos. Appendix table 24 presents similar comparisons across broad and narrow network carriers in the case of males aged 19-44 with diabetes and males aged 19-44 without diseases.

Panel (a) of figure 8 shows that, in the sample of new enrollees, the predicted average cost per consumer type 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. These predictions are consistent with the descriptive evidence of section 3. Between



(a) Predicted average cost



(b) Predicted profit per consumer type

Figure 8: 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.

the ages of 19-44, healthy females are 55% more expensive than healthy males, because of the costs associated to childbirth. Among enrollees with chronic conditions aged 19-44, males are 2% more expensive than females, and this difference in costs increases with age.

Differences in average costs generate significant variation in profits per consumer type as seen in panel (b) of figure 8. Profits per new enrollee are calculated as the average risk-adjusted transfers (ex-ante and ex-post) minus the 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 per consumer type comes from differences in cost across diagnoses and network breadth.[18] 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 to avoid these enrollees.

5.3 Competition in Network Breadth

With the insurer demand and average cost estimations, I compute the left-hand side of equation (4) denoting total marginal variable profits. Appendix 9 presents summary statistics of this variable as well as of dropout probabilities and transition probabilities needed to recover marginal revenues and

[18]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.

marginal costs. The average marginal variable profit per service and market ranges between $248 million pesos for EPS005 and $1,302 million pesos for EPS016. There is significant dispersion in this variable within insurers as its standard deviation exceeds $900 millions for the majority of carriers. The fact that marginal variable profits are positive for all insurer-service-market combinations, suggests a role for network formation costs in explaining profit maximizing choices of network breadth.

Table 11 presents the results of a 2-step GMM estimation for equation (5) on the subsample of four largest markets and 10 largest insurers in these markets, where the observed equilibrium is an interior solution.[19] 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 the level of network breadth. The coefficient associated to this variable is positive and significant. The first-stage F-statistic for the endogenous variable, network breadth, is greater than the 1% critical value. Appendix table 28 presents the first-stage regression, where the sign of the coefficients associated with each instrument are as expected.

Convexity of the average cost and the network formation cost with concavity of demand, guarantee that the insurer's profit function is concave in the level of network breadth. While concavity would be violated in presence of scope economies as those included in the insurer average cost function, the magnitude of these scope economies is small enough relative to the direct effect of network breadth on average costs, so as to not pose concerns about existence of an equilibrium in counterfactual. Existence of this counterfactual equilibrium also relies on the continuity and differentiability of the profit function at an interior solution.

Using the estimators for the FOC, I calculate the average total network formation cost across markets per insurer in column (1) of appendix table 29. Column (2) reports the network formation cost as a percentage of total variable profits. For 7 out of the 10 insurers, network formation costs represent at least 80% of an insurer's total variable profits. These percentages almost match the ratio of administrative expenses to accounting profits calculated from insurers' balance sheets and income statements.[20]

Changes in network breadth generate variation in profits that can be decomposed into its portions explained by variations in demand, average costs, and network formation costs. How much of the variation in profits comes from changes in demand and changes in the composition of enrollee

[19] Appendix figure 8 reports the distribution of network breadth in this subsample.

[20] See https://docs.supersalud.gov.co/PortalWeb/SupervisionRiesgos/EstadisticasEPSRegimenContributivo/RC%20Estados%20financieros%20Dic%202011-CT2011.pdf

Table 11: Model of insurer network formation costs

MVP_{jmk}	Coefficient	Std. Error
Network	3,139***	335
Insurer FEs		
EPS001	-37	189
EPS002	-9	171
EPS003	-25	184
EPS005	-490***	173
EPS010	410**	181
EPS013	-300*	168
EPS016	-235	173
EPS017	180	182
EPS018	18	197
EPS037	(ref)	(ref)
Market FEs		
Market 05	(ref)	(ref)
Market 08	-354***	110
Market 11	381***	108
Market 76	-77	106
First stage F-stat	929.7	
N	2,262	
R^2	0.63	

Note: This table presents a 2-step GMM estimation of equation (5) 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.

types per insurer evidence the extent of adverse selection from the demand-side. The change in networks induced by changes in the regulatory environment that affect insurers but not consumers, instead, evidence risk selection from supply.

To decompose short-run profit changes following an increase in network coverage, I conduct an exercise where I allow each insurer to unilaterally increase its network breadth for service m by 10%, while holding its competitors' choices fixed. In this exercise, I do not impose the FOC, so predictions of network formation costs are in absence of the cost shock, or $(\hat{\omega} H_{jmk} + \hat{\xi}_j + \hat{\xi}_k + \hat{\xi}_m)H_{jmk}$. This decomposition can be understood as a partial equilibrium exercise where each insurer engages in a one-shot deviation. If my model is able to rationalize the choices of network breadth observed in the data, then the decomposition exercise should show that there are no profitable deviations, or that changes in total costs overcompensate changes in revenues when these changes are positive.

Table 12 presents the average percentage change in short-run demand ($\%\Delta s_{ijk}$), total revenues ($\%\Delta R_{\theta t} s_{ijk}$), total average costs ($\%\Delta AC_{\theta ljk} s_{ijk}$), average cost per enrollee ($\%\Delta AC_{\theta ljk}$), and network formation costs ($\%\Delta F_{jk}$) 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 the increase in total average costs plus the increase in network formation costs is greater than the increase in total revenues, so there are no profitable one-shot deviations.

Second, because changes in network breadth are weighted by $\gamma_{\theta lmk}$, I find that a 10% increase in coverage of consultations generates the largest variations in demand and costs relative to other services. For this service, demand increases 12.70% relative to observed levels, while total average costs and network formation costs increase 14.20% and 7.18%, respectively. In the case of hospital admissions, I find that insurers that increase coverage by 10%, experience a 0.69% increase in demand, a 0.74% increase in total average costs and a 0.47% increase in network formation costs.

For the services in this table, the change in demand explains on average 46% of the change in insurer total costs (total average costs plus network formation costs), while the change in networks, which directly affects average costs per enrollee and network formation costs, explains the remaining 54%. This means that the effect of demand-side selection generated from insurers' network breadth choices is substantial. Moreover, because transfers from the government are fixed, the change in total revenues equals the change demand.

Table 12: Decomposition of short-run profit changes after network breadth increase

Service	$\%\Delta s_{ijk}$	$\%\Delta R_{\theta t} s_{ijk}$	$\%\Delta AC_{\theta ljk} s_{ijk}$	$\%\Delta AC_{\theta ljk}$	$\%\Delta F_{jk}$
Cardiac vessels	0.01	0.01	0.01	0.00	0.08
Stomach	0.01	0.01	0.02	0.00	0.10
Intestines	0.27	0.27	0.29	0.02	0.20
Imaging	3.91	3.91	4.25	0.32	2.21
Consultations	12.70	12.70	14.20	1.31	7.18
Laboratory	5.71	5.71	6.24	0.49	3.12
Nuclear medicine	0.09	0.09	0.10	0.01	0.10
Hospital admissions	0.69	0.69	0.74	0.05	0.47

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

In appendix table 30, I show that most of the variation in demand and costs following a 10% increase in coverage of consultations comes from individuals with chronic conditions other than renal disease, particularly from those with cardiovascular diseases. Broader networks for consultations increases the demand from individuals with diseases and changes the composition of enrollee types within each insurer. The latter effect explains why insurer's average costs per enrollee increase 1.01% relative to observed levels for people with conditions other than renal disease. In the case of hospital admissions, I find that a 10% increase in network breadth attracts more patients with renal disease, followed by patients with other diseases, and lastly by healthy consumers. Raising network breadth for imaging and laboratory services generates similar effects on demand from sick and healthy individuals.

6 The Effect of Risk Adjustment on Network Breadth

I use my model estimates to conduct two types of counterfactual exercises that help understand the effect of risk adjustment on service-level hospital network breadth and its welfare implications. In view of the growing network adequacy rules in countries like the US and concerns about access to health care in Colombia, 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 to higher health care costs. Quantifying the extent to which hospital networks respond to risk adjustment and the pass-through to health care costs can help policymakers in the design of public health insurance systems.

In the first counterfactual exercise, I eliminate the observed risk adjustment mechanisms and impose a uniform transfer across all consumer types, This transfer equals the national average cost per enrollee. 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. Potential variation in service prices and consumption of health care are captured by my average cost function, which is a reduced-form approximation to a bargaining equilibrium between insurers and hospitals. Dropout probabilities are mostly determined by the event of becoming unemployed rather than by the individual choosing not to enroll due to changes in the network. Moreover, risk adjustment does not impact consumers' tax contribution to the health care system. Therefore, it is reasonable to assume that dropout probabilities are fixed under alternative risk adjustment formulae. Finally, I assume that the probability of transitioning to new diagnoses depends mostly on the natural disease and age progression rather than on network breadth.

In my counterfactual analyses I also assume that choice sets and utility and cost parameters remain fixed, so other than through changes in networks and demand, insurers will not incur costs in addition to their average costs per enrollee and total network formation costs. This means that the set of insurers that participate in every market is fixed. Insurers can drop coverage of specific services altogether as long as coverage is non-zero for at least one service in each market where the insurer is present. For computational simplicity, I conduct my counterfactual analyses in the largest market in the country, the capital city of Bogotá. This market represents 28.7% of all continuously enrolled individuals in the contributory regime and has presence of all 14 insurers.

With the rich preference and cost heterogeneity in the model one might worry that multiple equilibria arise under counterfactual market conditions. For instance, my measure of scope economies, which generates a non-monotonic average cost function with respect to network breadth, can make it such that either every firm chooses complete networks or no coverage at all. Whether there are multiple equilibria in this market depends on the shape of the insurers' profit function and, thus, on the shape of the best response function. While a direct proof of uniqueness in the model is challenging given insurers' strategic interactions and the 58 dimensions of network breadth, in appendix 10 I provide intuition for the sign of the second partial derivative of the insurers' profit function with respect to network breadth, all else equal. Results in the appendix suggest that for every insurer, the profit function is likely concave in each dimension of the choice variable, and thus their best response function well-behaved. In computing the counterfactual analyses, I also use 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 table 1 times an adjustment factor λ calibrated to match observed short-run government spending:

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

The counterfactual transfer eliminates variation across sex and age groups, but is designed so that short-run government spending and, thus, insurer revenues are the same as in the observed scenario. Failure to compensate for individuals' health risk should exacerbate risk selection, which would incentivize insurers to narrow their networks in services that baseline costlier patients require. Appendix figure 9 shows the distribution of the difference between the counterfactual transfer without risk adjustment and the observed transfer per consumer type. Insurers receive lower payments for old individuals with chronic conditions and higher payments for young, healthy consumers, relative to the observed scenario. For example, for males aged 19-44 with cancer in Bogotá, 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 and market, insurers receive \$236 thousand pesos more than the observed transfer of \$347 thousand pesos.

Using the FOC condition of the insurer's profit maximization problem, I conduct an iterative procedure until convergence up to a tolerance level of 10^{-5} in the vector of service-specific network breadth. Because estimation of the FOC uses data from the 10 largest insurance companies in the 4 largest markets, a fair comparison of counterfactual results to the observed equilibrium requires using my model to predict network breadth under the observed risk adjustment when these 10 insurers instead of 14 compete in the market.

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 costs per enrollee, and short-run consumer welfare separately for healthy and sick individuals.[21] My findings show that under no risk adjustment, average network breadth falls 4.2%. The reduction in coverage explains the 2.0% decrease in insurer total average costs relative to the observed risk adjustment. This corresponds to a 1.2% reduction in average costs per enrollee. The fall in network breadth means insurers do not enjoy the cost savings from scope economies, but the direct effect of lower network breadth on average costs overcompensates the effect on scope economies.

While the reduction in average network breadth seems small in magnitude, it has substantial effects on consumer welfare. Eliminating the risk adjustment systems results in a 3.9% decrease in short-run consumer welfare for individuals without diseases. Consumer welfare falls 3.6% for individuals with chronic conditions who use health care services more often. A back-of-the-envelope calculation shows that the overall decrease in welfare equals 73,312 pesos (\$38.6) per capita per year. This is because with lower network breadth, access to and quality of care worsen in counterfactual, which differentially impacts those with a higher likelihood of making claims.

Panel B of table 13 shows that the reduction in average network breadth happens across the board of services. I collapse the 58 service categories into 15 broader groups that describe medical procedures in certain parts of the body. When they are not compensated for their enrollees' health risk, insurers drop coverage of relatively expensive services like hospital admissions by 26.4% and procedures in skull and spine by 5.0%. For less expensive services, the reduction in average network

[21] Insurer total average costs are calculated as:
$\sum_{ij}\left(AC_{\theta ljk}s_{ij}+\sum_{s=t+1}^{T}\beta^{s}\sum_{\theta',l'}(1-\rho_{\theta l})\mathcal{P}(l'|\theta,l)AC_{\theta'l'jk}s'_{ij}\right)$,
Short-run average cost per enrollee is $(1/N)\sum_{ij}AC_{\theta lj}$,
and short-run consumer welfare is $\sum_i|\alpha_i|^{-1}\log(\sum_j exp(\beta_i^D\sum_m\gamma_{\theta lm}H_{jm}-\alpha_i c_{\theta jy}+\delta_j))$

breadth is smaller but still sizable. For instance, average coverage of procedures in joints and bones falls by only 2.8%. Figure 9 shows the correlation between changes in service-level network breadth and the difference between the probability that a sick consumer and a healthy consumer make a claim for that service. When this difference is small, insurers tend to broaden their networks for that particular service to attract healthy individuals. When this difference is large, the correlation is negative, suggesting that insurers drop coverage of services that sick individuals are differentially more likely to claim.

Table 13: Counterfactual changes in networks, costs, and welfare under no risk adjustment

Variable	%Δ in CF
Panel A. Overall	
Avg. Network	-4.2
Total avg. cost	-2.0
Avg. cost per enrollee	-1.2
Consumer welfare (healthy)	-3.9
Consumer welfare (sick)	-3.6
Panel B. Avg. network per service	
Skull, spine, nerves, glands	-5.0
Eyes, ears, nose, mouth	-5.4
Pharynx, lungs	-1.6
Heart and cardiac vessels	-1.4
Lymph nodes, bone marrow	3.1
Esophagus, stomach and intestines	0.0
Liver, biliary tract	-7.0
Abdominal wall	-1.6
Urinary system	-2.1
Reproductive system	-3.0
Bones and facial joints	-2.8
Joints, bones, muscles, tendons	-2.8
Skin	-11.4
Imaging, lab, consultation	-6.2
Hospital admission	-26.4

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 per 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.

Consistent with adverse selection, insurers for which average network breadth falls by a greater percentage in counterfactual see a decrease in total short-run demand from healthy and sick individuals as seen in appendix figure 11. The figure shows the correlation between the change in average network breadth and the change in total demand across insurers. Under no risk adjustment, healthy

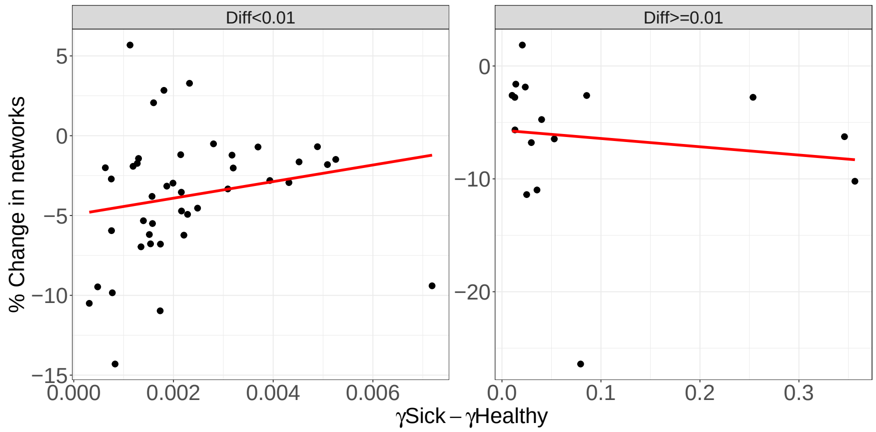


Figure 9: Network changes per service and likelihood of making claims under no risk adjustment

Note: This figure shows the correlation between changes in average network breadth per insurer under the no risk adjustment counterfactual and the average difference between the probability that a sick consumer and a healthy consumer make a claim for the service. Every black dot corresponds to an insurer and the red line is a linear fit. The left panel conditions the difference between claim probabilities to be less that 0.01 and the right panel conditions this difference to be greater than or equal to 0.01.

individuals substitute away mostly from EPS005 into EPS001, EPS010, and EPS037, given that EPS005 has the largest reduction in average network breadth equal to 7.7%. The pattern is similar for demand from consumers with chronic diseases. This suggests that health risk becomes more concentrated relative to the observed scenario, since the baseline largest insurers end up receiving most of the switchers with diseases.

Overall, panel A of appendix figure 14 shows that in a situation where all insurers choose narrow networks, those that reduce their network breadth by a larger percentage have increases in total long-run profits, as opposed to those that drop network coverage by a small amount. The figure presents the correlation between the change in average total profits and the change in average network breadth, across insurers. The red line corresponding to a linear fit, shows that this correlation is negative, which implies that the reduction in costs from lower network breadth overcompensates the reduction in demand.

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

$$R^{cf}_{\theta lk} = \lambda \times a_k \times 360 \times \frac{\sum_{i \in \theta l} X_i}{\sum_{i \in \theta l} d_i}$$

where X_i is the total health care cost of individual i of type (θ, l), d_i is the number of days enrolled to the contributory system during a year, a_k is the market multiplier from 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 l. 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 31. These conditions are obtained by grouping the ICD-10 codes accompanying an individual's claims following Riascos et al. (2014).[22,23] In both cases, when the prediction of the annualized health care cost equals zero for a consumer type, I replace it for the value in the observed risk adjustment system which conditions on sex, age group, and location.

For the second approach, the capitated transfer is:

$$R^{cf}_i = \lambda \times AC_{\theta ljk}$$

where λ is an adjustment factor as before and $AC_{\theta ljk}$ is the individual's average cost conditional on observed networks.

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. Unlike the observed risk adjustment system, the counterfactual payments allow for variation within θ and k, while keeping short-run government spending fixed. Appendix figure 10 presents the distribution of the difference between counterfactual payments and observed risk adjusted transfers per consumer type. In Bogotá, with compensations that control for the list of 7 diseases, insurers receive \$1.8 million pesos more for males aged 19-44 with cancer compared to the observed transfer, but receive only \$0.4 million pesos more for females with cancer aged 19-44.

Table 14 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

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

[23] 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.

network breadth, costs, and welfare are higher the more detailed is the risk adjustment mechanism. Average network breadth increases 1.6% relative to the observed scenario in column (1), while it increases 3.2% in column (2) and 9.2% in column (3). Network breadth increases across the board of services as seen in panel B of the table, but disproportionately so for services that mostly sick patients tend to claim, which is consistent with weakened selection incentives. Focusing on column (3), for example, average network breadth for hospital admissions increases 24.3%, while for primary care or consultations it increases only 9.4%.

Table 14: Counterfactual changes in networks, costs, and welfare under improved risk adjustment

	%Δ in CF		
Variable	(1) 7 diseases	(2) 30 diseases	(3) "Perfect"
Panel A. Overall			
Avg. Network	1.6	3.2	9.2
Total avg. cost	0.9	2.1	3.3
Avg. cost per enrollee	0.4	1.0	1.4
Consumer welfare (healthy)	1.6	3.7	5.3
Consumer welfare (sick)	1.3	3.1	4.8
Panel B. Avg. network per service			
Skull, spine, nerves, glands	1.2	1.8	6.6
Eyes, ears, nose, mouth	1.9	2.7	-1.2
Pharynx, lungs	0.5	0.6	2.1
Heart and cardiac vessels	1.2	2.9	13.0
Lymph nodes, bone marrow	1.6	6.1	20.8
Esophagus, stomach and intestines	1.7	3.6	8.9
Liver, biliary tract	1.8	3.0	-6.1
Abdominal wall	0.9	3.4	22.1
Urinary system	1.0	1.7	32.4
Reproductive system	1.3	2.3	9.5
Bones and facial joints	0.6	0.4	1.6
Joints, bones, muscles, tendons	1.0	2.1	5.0
Skin	6.3	24.1	41.1
Imaging, lab, consultation	2.1	4.3	9.4
Hospital admission	4.6	4.3	24.3

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 per 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.

Figure 10 confirms that changes in network breadth after compensating for the list of 30 disease categories are positively correlated with the difference between the probability that a sick consumer and a healthy one make a claim for that service, when this difference is large. But there is a negative correlation when the difference in claim probabilities is small. This suggests that compensating

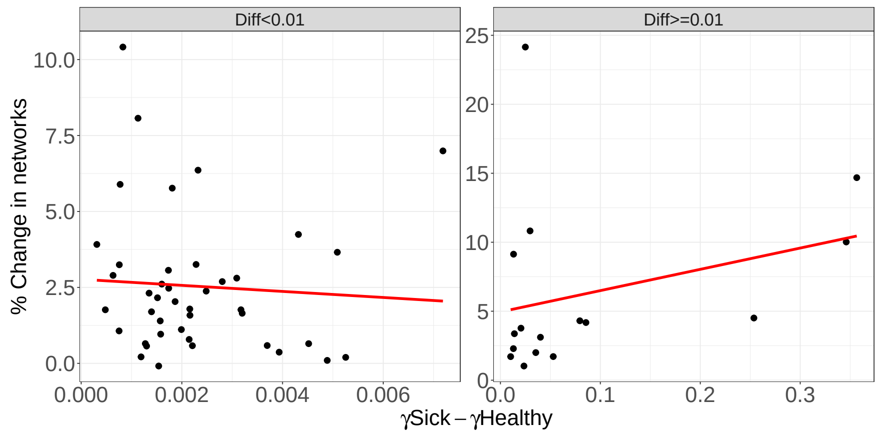


Figure 10: Network changes per service and likelihood of making claims under improved risk adjustment

Note: This figure shows the correlation between changes in average network breadth per insurer under the improved risk adjustment formula with 30 disease categories and the average difference between the probability that a sick consumer and a healthy consumer make a claim for the service. Every black dot corresponds to an insurer and the red line is a linear fit. The left panel conditions the difference between claim probabilities to be less that 0.01 and the right panel conditions this difference to be greater than or equal to 0.01.

insurers ex-ante for chronic diseases improves access to care in services that patients with those diseases are significantly more likely to claim relative to healthy consumers.

Because enrollees prefer broader networks on average, insurers that expand their network breadth by a larger amount in counterfactual have higher demand as well. Appendix figure 12 shows a positive correlation between changes in networks and changes in demand from both healthy and sick individuals. Panel (b) of appendix figure 14 also shows a positive correlation between changes in networks and changes in profits. This is consistent with broad network carriers attracting more consumers overall, a higher share of which are healthy. It also suggests that the direct effect of expanding the networks on total variable costs and network formation costs is smaller than the effect of scope economies and changes in demand composition. Column (2) of table 14 shows that across insurers and markets, total short-run average costs increase only 2.1% in counterfactual, while total revenue for insurers EPS005 and EPS017, for example, increases 17.9% and 13.8%, respectively; changes that can only stem from demand.

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 3.1% relative to the observed scenario. For consumers without diseases, welfare increases 3.7%. The overall effect on consumer welfare equals 68,418 pesos ($36.0) per capita per year. These effects are larger in magnitude with "perfect" risk adjustment in column (3). Results show that consumer welfare increases 5.3% for the healthy and 4.8% for the sick, which overall represents a 98,309 pesos ($51.8) increase per capita per year.

If allowing diagnoses to enter the ex-ante risk adjustment formula results in higher network coverage and higher 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.

7 The effect of Premiums on Network Breadth

In this section, I study the effect of deregulating premiums on market outcomes. I assume insurers compete on prices and are allowed to price discriminate based on the enrollee's income level, sex, and age group, similar to their pricing rules in supplementary health insurance plans. Insurers engage in Bertrand competition in premiums separately by market. In the observed scenario, the monthly contribution to the health care system equals 12% of the enrollee's monthly income. 1/3 of this contribution is paid by the enrollee and the remaining 2/3 by her employer. Under counterfactual premiums, I assume the same split of the cost of enrollment.[24] Premiums replace the government's risk-adjusted transfers and insurers receive premium revenues directly, so government spending is zero in counterfactual.

More formally, in the observed scenario, total average out-of-pocket expenses equal average coinsurance payments, plus average copayments and average contributions to the health care system as seen below.

$$c_{\theta lyjk} = \text{Coins}_{\theta lyjk} + \text{Copay}_{\theta lyjk} + \text{Contribution}_y$$

Allowing insurers to compete in premiums means that the counterfactual measure of total average out-of-pocket spending is:

$$\tilde{c}_{\theta lyjk} = \text{Coins}_{\theta lyjk} + \text{Copay}_{\theta lyjk} + (1/3) * \tilde{P}_{\theta yjk}$$

[24] 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.

where $\tilde{P}_{\theta yjk}$ is insurer j's total premium in market k for consumer type θ with income level y. Because premiums are paid instead of the required contributions to the health care system in the observed scenario, I assume that dropout probabilities remain 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 disenroll and remain uncovered in counterfactual. This provides a natural test of the assumption of fixed dropout probabilities, where the null hypothesis is equality of the conditional distribution of premiums and contributions, conditional on networks.

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

$$s_{ijk}(H_k) = \frac{\exp\left(\beta_i^D \sum_m \gamma_{\theta lmk} H_{jmk} - \alpha_i \tilde{c}_{\theta lyjk} + \phi_j\right)}{\sum_{g \in \mathcal{J}_k} \exp\left(\beta_i^D \sum_m \gamma_{\theta lmk} H_{gmk} - \alpha_i \tilde{c}_{\theta lyjk} + \phi_g\right)} \tag{6}$$

Equation (6) implicitly assumes that the marginal disutility of premiums is the same as the marginal disutility of contributions, coinsurance payments, and copays, which is equal to α_i. This assumption is based on the fact that consumers should not care whether increases in out-of-pocket costs come from premiums or cost-sharing if they are making rational choices (Abaluck and Gruber, 2011).

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

$$\pi_{ijk}(H_k, P_k, \theta, l) = (\tilde{P}_{\theta yjk} - (1 - r_y) AC_{\theta lj}(H_{jk})) s_{ijk}(H_k, P_k)$$

The insurer now has two choice variables per market: the network breadth per service and the premium per consumer type. Notice that the average cost function is the same as in the observed scenario, that is, I do not model the relation between premiums and average costs. While some papers use that relation to test for adverse selection (Tebaldi, 2017; Einav et al., 2010), in my case it is more difficult to argue what the functional form of average cost is with respect to premiums than to assume that the average cost function does not change in counterfactual. Moreover, because I allow insurers to discriminate premiums along income level, sex, and age group, selection in this market can now happen both through premiums and service-level network breadth.

Insurers simultaneously choose premiums and service-level network breadth in period $t = 0$ and commit to this choice thereafter. The solution concept in counterfactual is a full commitment Nash equilibrium. Insurers simultaneously choose premiums and networks to maximize:

$$\Pi_{jk}(H_k,P_k)=\sum_{\theta,l}\Big(\pi_{ijk}(H_k,P_k,\theta,l)N_{\theta lk}+\sum_{s=t+1}^{T}\beta^s\sum_{\theta',l'}(1-\rho_{\theta lk})\mathcal{P}(l'|\theta,l)\pi_{ijk}(H_k,P_k,\theta',l')N_{\theta'l'k}\Big)$$
$$-\sum_m\Big(\omega_0 H_{jmk}+\xi_{jmk}\Big)H_{jmk}$$

The FOC with respect to premiums is:

$$\frac{\partial\Pi_{jk}}{\partial P_{\theta yjk}}=\sum_i\left(\frac{\partial\pi_{ijk}}{\partial P_{\theta yjk}}N_{\theta lk}+\sum_{s=t+1}^{T}\beta^t\sum_{\theta',l'}(1-\rho_{\theta lk})\mathcal{P}(l'|\theta,l)\frac{\partial\pi'_{ijk}}{\partial P_{\theta yjk}}N_{\theta'l'k}\right)=0$$

where,

$$\frac{\partial\pi_{ijk}}{\partial P_{\theta yjk}}=\Omega\Big(\tilde{P}_{\theta yjk}-(1-r_y)AC_{\theta ljk}\Big)+s_{ijk}(H_k,P_k)$$

and,

$$\Omega(j,g)=\begin{cases}-s_{ijk}(1-s_{ijk})\alpha_i & \text{if}\quad j=g\\ s_{ijk}s_{igk}\alpha_i & \text{if}\quad j\neq g\end{cases}$$

Note that the short-run premium level can be solved for from the premium FOC. This determines a function of the form $\tilde{P}_{\theta yjk}=f(\tilde{P}_{\theta yjk})$, that can be used to obtain equilibrium premiums in a fixed point manner.

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

$$\frac{\partial\Pi_{jk}}{\partial H_{jmk}}=\sum_i\left(\frac{\partial\pi_{ijk}}{\partial H_{jmk}}N_{\theta lk}+\sum_{s=t+1}^{T}\beta^t\sum_{\theta',l'}(1-\rho_{\theta lk})\mathcal{P}(l'|\theta,l)\frac{\partial\pi'_{ijk}}{\partial H_{jmk}}N_{\theta'l'k}\right)$$
$$-\Big(2\omega_0 H_{jmk}+\xi_{jmk}\Big)=0$$

I estimate this counterfactual in data from Bogotá only for simplicity. Computation proceeds as a nested fixed point. For every vector of network breadth, I solve for the fixed point in premiums. Then, I solve for the fixed point in network breadth. Figure 11 presents the distribution of observed contributions to the health care system, total premiums, and premium pass-through to consumers, which equals 1/3 of total premiums. First of all, with deregulation, I find that insurers will charge non-zero premiums. These premiums are significantly greater than observed contributions to the system, but have a higher dispersion across consumer types. On the one hand, the average contribution equals \$50.8 thousand pesos and its standard deviation across consumer types is \$17.7 thousand pesos. On the other hand, the average consumer premium equals \$351.7 thousand pesos and its standard deviation is \$158.5 thousand pesos.

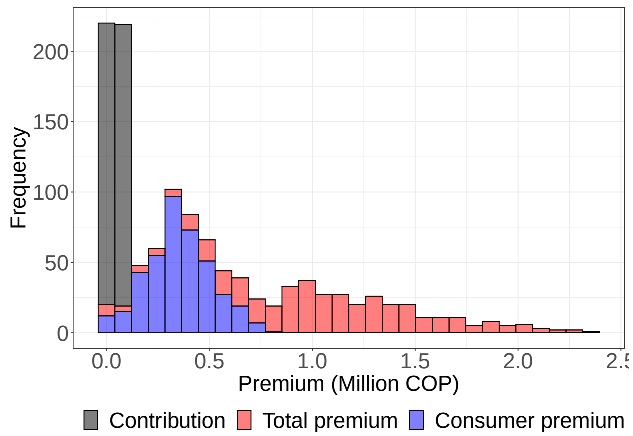


Figure 11: Distribution of counterfactual premiums

Note: This figure shows the distribution of observed tax contribution to the health care system in black, the distribution of total counterfactual premiums in red, and the distribution of premium pass-through to consumers in blue, which equals 1/3 of total premiums.

Table 15 presents the average total premium across demographics and insurers in millions of pesos. I find that average premiums are \$100 thousand pesos higher for males than female, which is consistent with men being more likely to develop chronic diseases compared to women. The breakdown across age groups shows that average total premiums are generally U-shaped with respect to age. For children aged 5-14, the average premium equals \$1.26 million pesos, which decreases by nearly half for individuals aged 45-49. Finally, the average premium for individuals aged 75 or older is \$1.14 million pesos. My findings show that counterfactual premiums weakly increase with the enrollee's income level. People earning between 2 and 5 times the monthly minimum wage pay premiums that are \$10 thousand pesos higher than individuals who make less that 2 times the minimum monthly wage. Across insurers, I find a positive correlation between premiums and insurer size. Relatively large insurers such as EPS037 have higher premiums than smaller insurers such as EPS002 and EPS003.

Counterfactual premiums are higher than observed contributions to the health care system, because insurers significantly expand their networks relative to the observed scenario. This means that there is a large pass-through of insurance coverage to premiums as noted in Cabral et al. (2018). Panel A of table 16 presents the percentage change in counterfactual of average network breadth, insurer total average costs, short-run average cost per enrollee, insurer total revenue, and short-

Table 15: Average premium per consumer characteristics and insurer

Variable	Avg. premium
Sex	
Female	1.01
Male	1.10
Age group	
<1	—
1-4	—
5-14	1.26
15-18	1.34
19-44	1.53
45-49	0.63
50-54	0.51
55-59	1.05
60-64	0.98
65-69	1.00
70-74	1.11
>=75	1.14
Income group	
$<$ 2 x MMW	1.05
$[2, 5]$ x MMW	1.06
$>$ 5 x MMW	—
Insurer	
EPS001	1.46
EPS002	0.66
EPS003	0.93
EPS005	1.82
EPS010	1.00
EPS013	0.70
EPS016	0.62
EPS017	1.17
EPS018	0.97
EPS037	1.22

Note: This table presents the counterfactual average total premium per sex, age category, income group, and insurer. Measured in million COP.

run consumer welfare for healthy and sick individuals. Allowing insurers to compete in premiums, increases average network breadth by 46.0%. This increase in coverage happens across all services as seen in panel B of the table. While relatively 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 as procedures in skin or abdominal wall, the effect is substantial.

Given that average network breadth expands considerably, and that the direct effect of network breadth on average costs is greater than the effect of scope economies, I find that the short-run per-enrollee average cost increases 9.1% relative to observed predictions. However, weighting by demand in the long-run, total insurer average costs fall 0.5%. The effect on insurers' total costs is

Table 16: Changes in networks, costs, and welfare under premium deregulation

Variable	%Δ in CF
Panel A. Overall	
Avg. Network	46.0
Total avg. cost	-0.5
Avg. cost per enrollee	9.1
Total revenue	108.9
Consumer welfare (healthy)	-73.7
Consumer welfare (sick)	13.3
Panel B. Avg. network per service	
Skull, spine, nerves, glands	34.3
Eyes, ears, nose, mouth	54.2
Pharynx, lungs	60.6
Heart and cardiac vessels	85.8
Lymph nodes, bone marrow	30.7
Esophagus, stomach and intestines	26.6
Liver, biliary tract	38.3
Abdominal wall	54.4
Urinary system	43.7
Reproductive system	41.3
Bones and facial joints	23.7
Joints, bones, muscles, tendons	60.4
Skin	272.6
Imaging, lab, consultation	32.7
Hospital admission	26.2

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 across insurers, 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 per 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.

explained entirely by risk selection. If average cost per enrollee increases, only large increases in demand from relatively cheap individuals, such as those without diseases, can explain the fall in insurer's total costs in the long-run.

Appendix figure 13 in fact shows that under premium deregulation, demand from healthy individuals sees large changes across insurers compared to demand from sick patients, conditional on network breadth changes. Since on average all insurers expand their networks, such that there is less network heterogeneity across carriers, risk selection in this counterfactual happens mostly on the premium level. This translates into a low correlation between changes in network breadth and changes in profits as seen in panel C of appendix figure 14.

Panel A of table 16 also shows that insurer total revenues double in counterfactual. But, this effect is completely at the expense of consumers without diseases, for whom welfare falls 73.7%. For healthy individuals, who have a low willingness-to-pay for network breadth and a high sensitivity to out-of-pocket expenses, welfare losses due to out-of-pocket premium payments overcompensate the welfare gains from greater network breadth in every service. Instead, for consumers with chronic diseases who have a high willingness-to-pay for coverage and who are relatively inelastic to out-of-pocket expenditures, welfare increases 13.3% relative to the observed scenario.

The substantial decrease in welfare for healthy consumers is problematic. If individuals without chronic diseases could drop out of the market, a premium deregulation policy could unravel the market by making the healthy disproportionately choose uninsurance and broad network carriers face higher uninsurable costs from those with chronic diseases. Market equilibrium under premium deregulation could be restored not only by making enrollment mandatory, but also by having the government pay premiums in a way that spending matches what the government would spend with risk adjustment.

8 Conclusions

Risk selection is a main concern in public health insurance systems with regulated competition, where governments make risk adjusted transfers 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 in premiums, but less explored is the interaction of risk selection with non-price competition. I model insurer competition in hospital networks in the context of Colombian health care system, where the government sets premiums to zero and compensates private insurers with a coarse risk adjustment formula that controls only for sex, age, and location.

In Colombia, insurers have discretion only over which services to cover at which hospitals, so hospital networks are service specific. This is similar to allowing insurers to include specialized hospitals in their networks as in the United States. Conditional on risk adjustment, I find that insurers engage in risk selection by narrowing their networks in services that costly patients, usually with chronic conditions, tend to demand the most. This strategy either disincentivizes enrollment from these costly individuals or selects those with lower baseline health care costs conditional on risk adjustment.

The increasing popularity of network adequacy rules in countries like the United States and the policy debate surrounding access to care in Colombia, raises the question of how to incentivize insurers to expand their networks, while containing health care costs. I use my model to answer this question by measuring the effect of risk adjustment and premium setting on service-level hospital 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. This implies lower quality of and access to care, which is why consumer welfare falls by $49.0 per capita per year relative to the observed scenario. Improving the risk adjustment formula by compensating for sex, age, location, and a list of 30 exhaustive and mutually exclusive diagnoses all ex-ante, results in service-level networks that are broader on average, particularly for services that individuals with chronic diseases are differentially more likely to claim. With an improved risk adjustment formula, the welfare of patients with chronic diseases increases between $48.7 and $68.2 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 this improved risk adjustment is difficult because of information frictions between hospitals, insurers, and the regulator. Allowing insurers to compete in premiums results in nearly complete hospital networks for every insurer and service. This network expansion comes at the expense of higher out-of-pocket costs, which significantly reduces welfare for consumers without diseases but increases it for individuals with chronic conditions who are less elastic with respect to out-of-pocket expenses.

The findings of this paper provide evidence of the trade-off between better access to care through broader hospital networks and lower health care costs. In quantifying the extent to which networks respond to risk adjustment and premiums, the findings here help policymakers in the design of public health systems with private provision of health insurance. Policy implications, nonetheless, extend beyond these types markets, to ones where private insurers actively engage in risk selection using the non-price elements of their health insurance plans.

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