Non-Price Competition and Risk Selection Through Hospital Networks

Natalia Serna*

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Abstract

Health insurers can engage in risk selection through the design of their hospital networks. I measure the impact of risk selection incentives on hospital network breadth using a model of insurer competition in networks applied to data from Colombia's health care system. Every aspect of the Colombian national insurance plan is regulated by the government except for hospital networks, which insurers can choose separately for different services. I find that insurers risk-select by providing narrow networks in services that unprofitable patients require. Eliminating risk adjustment reduces average network breadth by 6.7% and consumer welfare by 2.2%. Improving the risk adjustment formula increases average network breadth by 4.6%-28.0% and consumer welfare by 2.9%-8.0%, depending on how many risk factors are included. Price and non-price competition are substitutes for risk selection as a zero-premium policy exacerbates underprovision of hospital 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.

*Department of Economics, University of Wisconsin-Madison. E-mail: nserna@wisc.edu. I want to thank the Colombian Ministry of Health and Alvaro Riascos at Quantil for providing the data for this research. I am deeply grateful to my dissertation committee members Alan Sorensen, Ken Hendricks, Corina Mommaerts, and Dan Quint, as well as Naoki Aizawa, JF Houde, Lorenzo Magnolfi, Christopher Sullivan, and Ashley Swanson for their invaluable mentorship and thoughtful advice at UW Madison. I also thank Zarek Brot-Goldberg, Ignacio Cuesta, Gastón Illanes, Cici McNamara, Mark Shepard, and Benjamin Vatter, for their useful feedback. This research has benefited from comments from participants at the Stanford Institute of Theoretical Economics, the IO Workshop at UW-Madison, ASHEcon, MEA, and the Quantil Seminar in Colombia.

1 Introduction

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

Most prior studies have focused on risk selection through premiums, holding other aspects of the insurance plan fixed (e.g, Ho and Lee, 2017; Dafny et al., 2015). These studies have motivated policies such as premium subsidies, open enrollment, or informational nudges to contain selection incentives (Polyakova, 2016; Nuscheler and Knaus, 2005). Less attention has been paid to whether insurers strategically choose the non-price characteristics of their plans to cream-skim the market. In this paper I study how insurers can engage in risk selection through the design of their hospital networks. I measure the impact of risk selection incentives on the breadth of hospital networks, and simulate the effects of policies like risk adjustment that aim to reduce insurers' incentives to risk-select.

I analyze data from Colombia, where private insurers provide a national health insurance plan in a system similar to the Medicare Advantage program in the United States. However, a key difference is that almost all aspects of the insurance contract are closely regulated: premiums, coinsurance rates, copays, and maximum out-of-pocket amounts are all set by the government. The only element of the public health insurance plan that is unregulated is hospital networks, which insurers can choose separately for different services. In other words, insurers have discretion over which services to cover at which hospitals, so they can use their service-specific hospital networks as a mechanism to select risks and minimize costs. By offering a narrow network in services that costly patients demand the most, insurers can effectively discourage enrollment from these patients. This kind of non-price, service-level risk selection has been studied from a theoretical perspective by Cao and McGuire (2003) and Frank et al. (2000), and documented by Park et al. (2017), who find that insurers in Medicare Advantage engage in risk selection by placing services that sick individuals need in higher cost-sharing tiers.[1]

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

I start by showing that incentives for risk selection at the service level exist because the government's risk adjustment formula is very coarse and fails to compensate insurers for enrollee characteristics that predict the use of health services. This generates variation in service profitability to which insurers' hospital network choices respond: networks are narrower for less profitable services. The positive correlation between service profitability and hospital network breadth is driven by patients adversely selecting insurers that have relatively broad networks in services they need. For example, insurers with broad networks of dialysis enroll a larger share of patients with renal disease. The likelihood of making a dialysis claim is also higher the broader is the network for dialysis, an effect that is unlikely the result of moral hazard. To more systematically quantify the impact of risk selection I simplify hospital networks to a single index of network breadth per service denoting the fraction of all hospitals in a market that can provide the service that are covered by the insurer. This measure of network breadth is positively correlated with insurers' star hospital coverage and negatively correlated with distance to the nearest hospital. So although changes in network breadth can be interpreted directly as changes in the number of hospitals covered, they also represent changes in the quality of in-network hospitals and in patient proximity to the nearest in-network hospital.

This paper is the first to quantify the effect of risk adjustment and premium setting on network breadth, health care costs, and consumer welfare, but it is not the first to consider the potential of networks to serve as a tool for risk selection.[2] 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 exclusion incentives are exacerbated under coarse risk adjustment and zero premiums.

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 breadth, conditional on their rivals' choices. My solution concept is a steady state Nash equilibrium where insurers compete for the set of new enrollees who are then locked into their initial insurer choice for subsequent periods. This model resembles the first stage of the game in Liebman (2018), where insurers commit to network size before entering price negotiations with hospitals. But unlike existing methods that seek to endogeneize hospital networks in a Nash-in-Nash bargaining framework (Prager and Tilipman,

[2]See Geruso and Layton (2017) for a review of how adverse selection affects the design of health insurance contracts including hospital networks.

2020; Ghili, 2020; Ho and Lee, 2019), I take a reduced-form approach to the price bargaining game and focus on modelling insurers dynamic incentives to choose network breadth per service, which considerably simplifies computation of counterfactual networks.

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 weighted by the probability that the patient makes a claim for that service, and a function of average out-of-pocket payments. I allow for sufficient observed heterogeneity in the preference for network breadth and out-of-pocket costs to capture adverse selection, but there is no unobserved consumer heterogeneity that is common across alternatives. Therefore selection in my model occurs only on observable, un-reimbursed (or poorly reimbursed) consumer characteristics like diagnoses. I also allow for moral hazard in insurer demand by making out-of-pocket costs a function of network breadth.

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. The average cost 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. With this approximation I won't be able to separate how much of the change in average costs per enrollee comes from the effect of network breadth on negotiated prices versus its effect on healthcare utilization. But this distinction is irrelevant from the point of view of the insurers' profit maximization problem. 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 who are continuously enrolled during the sample period (9 million) and their claims (250 million). This isolates consumers whose choices are not conflated by variation income, job loss, or informality, which generate variation in enrollment spells. 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 costs, 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 in a partial equilibrium exercise where 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 half of the variation in total health care costs.

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 service-level 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 10.1%, and of relatively cheap services such as consultations and laboratory by 6.2%. In the short-run, eliminating risk adjustment reduces consumer welfare by only 3.3% or 13,753 pesos ($7.2) per capita per year for those with chronic conditions since out-of-pocket cost savings partially compensate reductions in coverage.

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 4.6%-28.0% relative to the observed scenario depending on how many risk factors are included in the formula, and the effects on network breadth are larger for services that mostly sick patients tend to claim. Broader network coverage increases consumer welfare for enrollees with chronic diseases by 3.4%-11.1%, which in the case of "perfect" risk adjustment is equivalent to an increase of 49,161 pesos ($25.9) 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 in counterfactual. I find that premiums are U-shaped with respect to the enrollee's age, higher for males than for females, and higher for low-income individuals, reflecting the correlation between these demographic characteristics and health status. Deregulating premiums incentivizes insurers to more than double their network breadth per service. Thus, price and non-price competition are substitutes from the point of view of risk selection. Put differently, a zero-premium policy may exacerbate the underprovision of hospital coverage. Broader networks under premium competition increase consumer welfare by 13.1% only for individuals with chronic conditions and under certain assumptions on the sensitivity of demand to premiums. But welfare falls consistently for those without diseases, who have low willingness-to-pay for network breadth and high elasticity with respect to out-of-pocket costs.

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 United States. 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 literature 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). While other papers deal with alternative selection mechanisms such as 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. 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 hospital 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. This model can generate predictions of market structure in health insurance systems where insurers compete mainly on the non-price characteristics of their insurance plans.

2 Institutional Background and Data

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 states 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 fraction of their monthly income.[3] The national plan covers a comprehensive list of more than 7,000 services or procedures and 673 medications as of 2010. The government sets

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

premiums for the national plan to zero and sets cost-sharing rules as functions of the enrollee's income level, but they are standardized across insurers and providers.[4] 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.[5] 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. Insurers then engage in bilateral negotiations over service prices and types of contract (capitation or fee-for-service) with in-network hospitals.

At the end of every year, insurers report to the government all health claims made through the national insurance plan that they reimbursed hospitals in their network for. The data for this paper are the enrollment files of all enrollees to the contributory system during 2010 and 2011 (25 million), and their claims reports to the government (650 million). I focus on the sample of individuals with continuous enrollment spells or no gaps in enrollment per year (9 million) and their associated claims (270 million). This distinguishes consumers whose choices are not conflated by variation in income across time, job loss, or informality, which are the main reasons for variation in enrollment spells.[6] Of the continuously enrolled, 2/3 are *current enrollees* or individuals who are enrolled throughout 2010 and 2011. The remaining 1/3 are *new enrollees* or individuals who enroll for the first time in 2011. Because there is near universal coverage, new enrollees to the contributory system can be individuals who move from the subsidized system after they find a job, or those who for some reason were uninsured for 12 continuous months and then enroll the health care system.[7] In the sample

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

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

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

[7]Even if new enrollees in 2011 had enrollment before the start of my sample period in 2010, decree 806 of 1998 and decree 1703 of 2002 established that after three continuous months of non-payment of tax contributions to the

of current enrollees, only 0.06% switch their insurance carrier from 2010 to 2011, which evidences the extent of consumer inertia in this market. Even conditional on patients whose diagnoses change from one year to the other, the switching rate equals 0.1%.

The enrollment files have basic demographic characteristics like sex, age, municipality of residence, and enrollment spell length in the year. Although I do not observe individual income per month, using aggregate income data from enrollees to the contributory system I assign each individual the average income in its municipality, sex, and age group. The health claims 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.

Every claim is associated to a 6-digit service code from the national insurance plan, which I assign to one of 58 service categories ("service" for short) describing surgical and non-surgical procedures in parts of the body.[8] Examples of these service categories are procedures in cardiac vessels, procedures in stomach, procedures in intestines, imaging, consultations, and hospital admissions. Each category, in turn, covers more detailed medical procedures. For instance, procedures in cardiac vessels includes angioplasty, pericardiotomy, heart transplant, and aneurysm excision. Procedures in intestines includes colonoscopy, duodenectomy, and colectomy. Hospital admissions includes ICU admission, NICU admission, and general acute care admission by type of hospital room. The complete list of services is provided in appendix 2.

Health claims reports to the government come from the 23 private insurers that participated in Colombia's contributory health care system during my sample period. I focus on the 14 largest insurers that account for over 97% of enrollees. Insurers compete for enrollees separately in every market, which I define as a Colombian state (similar to an MSA in the US), there are 32 markets in my data. The Colombian insurance market is highly concentrated, the top 3 companies cover over 50% of individuals (see appendix table 3). All insurers have presence in the central region of the country but peripheral markets, characterized by difficult geographical access, have fewer insurers, the smallest of which has a duopoly of carriers (see panel A of appendix figure 1).

Health claims can be provided either by in-network stand-alone doctors, clinics, or hospitals. In 2011, Colombia's health care system had around 11,200 hospitals and small clinics, that comprised only 1/6 of all providers in the country. I focus on the sample of hospitals and clinics ("hospitals" for

system, a person would be disenrolled and would lose any information so far reported to the health care system.

[8] 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 from the Ministry of Health.

short) that provide inpatient, surgical, urgent care, and diagnostic services, which are in the upper tail of the distribution of health care costs, where variance is high and risk selection incentives are more salient. My hospital sample selection criteria matters because I recover the insurers' service-level hospital network from observed claims. This can be problematic, particularly for small providers, because it may be the case that there zero claims rendered for a service that they are actually contracted to provide under an insurer's network. To avoid this type of measurement error, my sample focuses on relatively large hospitals for which there are sufficient claims in each service category to infer them as being part of an insurer's network. Appendix figure 2 shows the distribution of number of claims per hospital, insurer, and service as well as per insurer and service.

Obtaining networks from observed claims can also 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 address these issues, I conduct robustness checks on my definition of networks later in document, where I focus only on the largest hospitals in the country defined by the number of beds and where I use all providers reported in the claims data.

I obtain the list of 1,663 hospitals in 2011 and 1,453 in 2010 that satisfy my sample definition from the Ministry of Health's Registry of Health Care Providers.[9] I match hospitals in my claims data to the registry and end up with a 97% match rate in 2010 and an 87% match rate in 2011. The matched sample of hospitals, which represents 3% of all providers in the country, accounts for 32% of total health care costs and 27% of total claims in the contributory system. It also accounts for 40% of total costs and claims per insurer on average. Panel B of appendix figure 1 shows the total number of hospitals per market. The largest market has 196 hospitals and the smallest market has 7 of them.

3 Descriptive Evidence

Private insurers in the contributory system are reimbursed by the government at the beginning of every year (ex-ante) with capitated risk-adjusted transfers, and at the end of every year (ex-post) with the High-Cost Account. The ex-ante risk adjustment formula controls for sex, age group, and municipality of residence. The formula does not include information about a patient's previous

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

diagnoses. For year t, the base un-adjusted capitated transfer is calculated using the claims data from all insurers from year $t-2$. This transfer is roughly equal to the present value of the average annual health care cost per enrollee. Then, for each risk pool defined by a combination of sex, 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 the government's formula is only 1.65% ! Using the demographic information contained in the 2010 and 2011 enrollment files, I am able to recover the ex-ante risk-adjusted transfer that each insurer received for each of its enrollees. Ex-ante reimbursements range from 162.2 thousand pesos (males aged 15-18) to 2.2 million pesos (for females aged 75 or older), with an average of 650.8 thousand pesos.

The High-Cost Account, on the other hand, compensates insurers that enroll an above-average share of people with any of the following chronic diseases: cervical cancer, breast cancer, stomach cancer, colon cancer, prostate cancer, lymphoid leukemia, myeloid leukemia, hodgkin lymphoma, non-hodgkin lymphoma, epilepsy, rheumatoid arthritis, and HIV/AIDS. The per-patient reimbursement equals the average cost of treatment for each disease. These reimbursements come from insurers that enroll a below-average share of individuals with those diseases.[10] My data contains total High-Cost Account transfers that each insurer received per year. Total ex-post transfers represent only 0.4% of total ex-ante transfers per insurer during the sample period. Despite compensating insurers for a few diagnoses, selection incentives are still present after ex-post risk adjustment as shown in Riascos (2013) and Riascos and Camelo (2017).

Selection incentives exist because annual health care costs exhibit an enormous variation across patients within an age group relative to government reimbursements. Figure 1 shows that the mean and variance of health care costs increase with age. The variance is measured by the difference between the 10th and 90th percentiles depicted in the figure. For 80% of enrollees in their early 20s, annual health care costs range from 0 to 0.5 million pesos. While for 80% of those in their early 70s, costs range between 0 and 2.5 million pesos.

The rising trend in total costs suggests that insurers have incentives to engage in selection against old individuals if age is not appropriately controlled for in the risk adjustment formula. The rising trend in variance suggests that there is scope to select consumers in the upper tail of

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

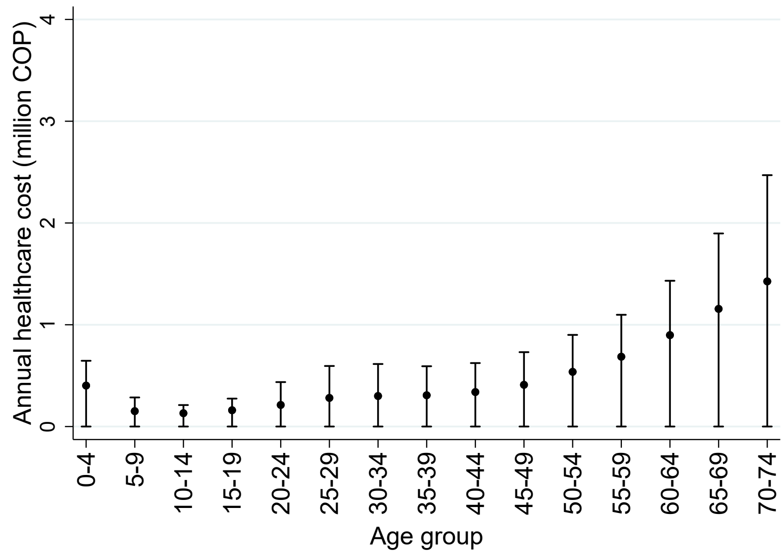


Figure 1: Total health care cost by age group

Note: Figure presents the mean, 10th, and 90th percentiles of annual health care cost by age group.

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 because the current risk adjustment systems include very coarse age groups and do not use information from a patient's diagnoses to calculate ex-ante reimbursements.

The coarse nature of the risk adjustment formula and the high variance in health care costs generate large variation profits per enrollee that incentivizes risk selection. Table 1 presents the mean, 1st and 99th percentiles of profits per capita in the sample of current enrollees and new enrollees during 2011. The profit is calculated as the government's ex-ante and ex-post transfers, plus revenues from copayments and coinsurance rates, minus total 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 current enrollees, resulting in the highest 99th percentile across insurers equal to 2.15 million pesos. The formulas also severely undercompensate costs for this insurer's most expensive current enrollees, 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 current enrollees, 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 1: Distribution of profit per enrollee

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

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

3.1 Measuring network breadth

This paper is focused on insurers' incentives to use provider networks to risk-select. Every aspect of the national insurance plan is regulated by the government except for hospital networks that are established at the service level. Insurers can choose 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 determine whether insurers respond to cream skimming incentives in their hospital coverage choices, in this section I provide descriptive evidence of variation in network breadth consistent with risk selection efforts.

Insurers in Colombia have discretion over the number of hospitals to cover for each service, but it is mandatory to cover all services in the national insurance plan. Network breadth is thus defined over the number of hospitals *conditional on the service*, but not over services. Although insurers' coverage choices per service are in part determined by differences in hospital specialty and available capacity, these choices also depend on the type of consumers that insurance companies want to risk select upon. As an example of 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 hospitals located in the main cities: 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 appear as differences in network breadth. I define network breadth as the fraction of all hospitals in a market offering a particular service that are covered by the insurer. Table 2 shows that there is significant heterogeneity in network breadth per service across insurers and markets. EPS013 and EPS016 have relatively broad networks in almost all markets, covering an average of 49.7% and 55.0% of hospitals per service during 2011, respectively. 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 Ministry of Health show that narrow networks is one of the top three reasons for dissatisfaction with an insurance company (see appendix figure 3). Patients enrolled with insurers that have low network breadth typically have to travel longer distances to seek care, therefore network breadth can be interpreted as a measure of proximity to hospitals. Going from network breadth of 60% to 90%, reduces travel time to the nearest hospital by 7 minutes on average (see appendix figure 4).

By collapsing networks to one dimension for each service, I am effectively assuming hospital quality as constant and treating hospital coverage as a first-order problem motivated by the enrollment satisfaction surveys. While there is extensive literature documenting consumer preference

Table 2: Distribution of network breadth per service

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

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

heterogeneity over hospitals using models of hospital choice (e.g., Ho, 2006), this preference for hospital quality is only problematic for the purpose of this paper if network breadth and hospital quality are negatively correlated. In that case, policies aiming to incentivize broader networks can result in insurers dropping star hospitals from their networks and increasing coverage of low-quality providers, which can be detrimental for patients. A negative correlation would also suggest that focusing on the choice of network breadth alone would misrepresent the insurers' optimization problem.

In appendix table 7 I find a strong positive correlation between network breadth and measures of hospital quality such as star hospital coverage, patient satisfaction, and inverse inpatient 48-hour mortality rate. Nonetheless, a positive correlation does not imply that estimates of consumers' preference for network breadth will be unbiased, given that network breadth represents the probability that *any* hospital is included in the network. If certain hospitals are significantly more or less likely to be included in the network because of their quality, then my network breadth measure would fail to capture a relevant source of heterogeneity across hospitals that could bias my results.

To check for differences across hospitals, I regress an indicator for whether the hospital is in network, on hospital and insurer-by-service fixed effects, separately for every market. The insurer-by-service fixed effects capture the average probability that any hospital is included in the service network, while the hospital fixed effects capture deviations from that average probability. Appendix figure 5 shows that for 5 of the largest markets in the country, all of which account for 76% of the continuously enrolled, more than 80% of hospital fixed effects are insignificant in every market.

In section 5 I provide additional evidence that network breadth is not inconsistent with consumers having preferences for hospital quality by conducting robustness checks on my insurer demand model. In the robustness checks I include an indicator of star hospital coverage at the service level. The finding that estimates of the preference for network breadth are robust to different specifications of the model suggests that network breadth itself is a relevant dimension of insurer choice.

3.2 Network breadth as a means of risk selection

The descriptive statistics show that there is substantial variation in service-level network breadth and profits per enrollee across insurers and markets that are suggestive of differences in selection efforts. In this subsection I link profits per enrollee with service utilization to characterize selection incentives at the service level by replicating figures in Geruso et al. (2019). 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. Patients who make claims for several services will be represented in several dots, while patients who make zero claims and are the most profitable are not represented in this figure. The red line is the 45 degree line, which splits the space into services that are overcompensated by the risk-adjusted transfers (above the line) and those that are undercompensated (below the line).

The 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 data from all individuals enrolled to the contributory system without constraining enrollment to be continuous in panel (a) of appendix figure 6.

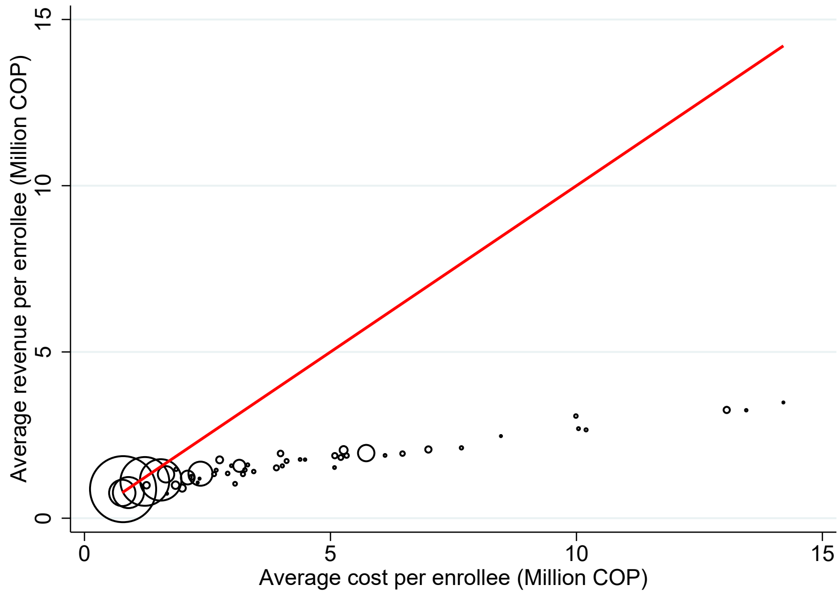


Figure 2: Service-level selection incentives after risk adjustment

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.

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 appendix figure 7. 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 3 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 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

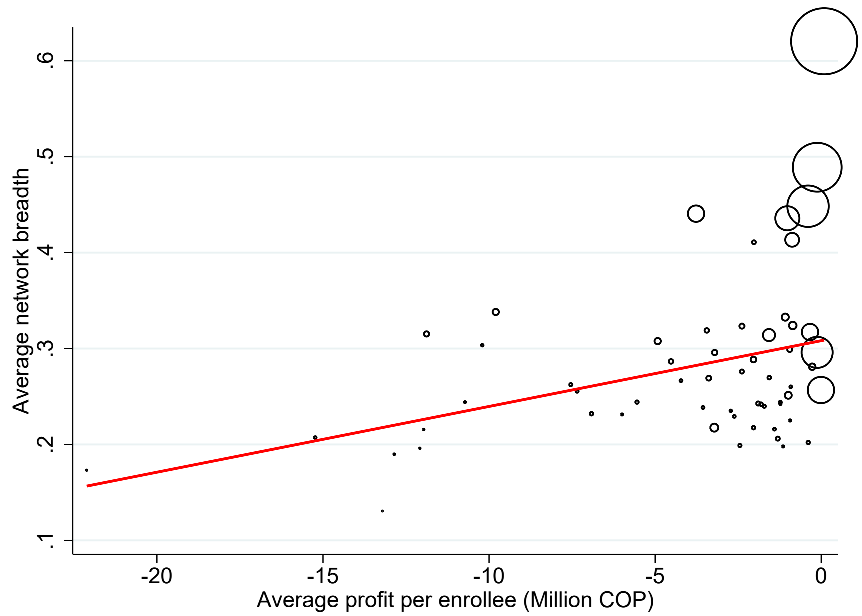


Figure 3: Correlation between network breadth and service profitability

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.

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 6, as well as within insurer and market as seen in appendix table 8, where I regress network breadth on average profit per enrollee using different sets of fixed effects.

Figure 3 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 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.

3.3 Selection vs. Moral Hazard

Variation in service profitability stems primarily from variation in service-level health care costs that is not accounted for by the risk adjustment mechanisms. Health care cost variation, in turn, can be due either to selection of consumers into carriers that have high coverage for the services they need or to differences in the consumption of health services across consumers. Previous descriptive evidence conflates these effects of selection and moral hazard in health insurance demand. In this section I assess how much of the variation in costs can be explained by adverse selection and cream skimming alone.

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

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

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

Results presented in table 3 are suggestive of this source of selection. 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 probability of dialysis claims, antirheumatic drug claims, and chemotherapy claims are also positively correlated with network breadth for dialysis, procedures in bones and joints, and chemotherapy, respectively. For instance, a percentage point increase in network breadth for dialysis is related to a 3% increase in the probability of a dialysis claim 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.

While the positive correlation between network breadth and number of claims conditional on 2010 health status could be explained by moral hazard rather than by selection, the correlation with the likelihood of making claims is unlikely the result of moral hazard. A person is not more

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

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

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

likely to develop renal disease, cancer, or arthritis just because their insurer has a broad network in services those diseases need for treatment. The positive correlation may also be unlikely to reflect adverse selection as it requires individuals knowing if and when they will develop a disease. However, focusing on the admittedly small sample of switchers, appendix table 9 shows that the probability of switching carriers in 2011 is higher among individuals whose health status changes from 2010 to 2011 than their counterparts. These can be people who were healthy and unpredictably developed a chronic disease or people who had additional health conditions predictably diagnosed to them in 2011, for example, a patient with diabetes developing cardiovascular disease, or a patient with diabetes developing renal disease.

Conditional on health status and total health care costs in 2010, appendix table 10 also shows that patients enrolled to insurers with higher network breadth among common services like hospital admissions, consultations, and laboratory in 2010 are less likely to switch. But if they switch, consumers whose health status changes over time tend to switch towards the insurer that has the greatest network breadth for services they need given their newly diagnosed conditions relative to their incumbent insurer, which is consistent with selection into moral hazard. Appendix table 11 shows, for example, that women who switch and were in childbearing ages in 2010 are 2.77 percentage points more likely to choose the insurer with higher network breadth for delivery services relative to their incumbent insurer. The table also shows that individuals who were healthy in 2010, develop a chronic disease in 2011, and switch their carrier are 1.94 percentage points more likely to choose the insurer with higher network breadth for hospital admissions than their incumbent insurer. Results are similar for patients who switch but were diagnosed in 2010 as seen in appendix table 12.

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 have strong carrier inertia even after their insurer changes its service-level network breadth and potentially becomes suboptimal for the enrollee, does not mean that 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:

$$\begin{aligned} y_{ikm}^{2010} =& \beta_0 + \beta_1 (H_{j'km}^{2010} - H_{j'km}^{2011}) + \beta_2 Switch_{im} + \beta_3 Switch_{im} \times (H_{j'km}^{2010} - H_{j'km}^{2011}) \\ & + \mathbf{d}_i \beta_4 + \lambda_k + \delta_{j'} + \eta_m + \varepsilon_{ikm} \end{aligned}$$

Here y_{ikm}^{2010} is either the logarithm of total health care cost of individual i in service k during 2010 or an indicator for having non-zero claims for service k in 2010. $Switch_{im}$ is an indicator for whether the consumer switched carriers from one year to the other. The subscript j' denotes the insurer chosen in 2011, so $H^{2010}_{j'km}$ is the 2010 network breadth of insurer j' and $H^{2011}_{j'km}$ is the 2011 network breadth of insurer j'. $\mathbf{d}_i$ is a vector of demographics and diagnoses, λ_k is a service fixed effect, $\delta_{j'}$ is an insurer fixed effect, and η_m 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 4 shows that individuals who switch into carriers that reduce their network coverage over time tend to be less costly in that service than individuals who do not switch. 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.[11]

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:

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

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

[11]Results in column (1) of table 4 are robust to alternative modelling specifications. Appendix table 16 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 stage log-linear regression conditional on having non-zero cost.

In the main specification, the change in network breadth across time is defined within 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 17.

Appendix table 18 also provides results of the main specification using only the sample of switchers.

Table 4: Selection on baseline costs and risk

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

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

in column (3) of table 4. Appendix table 19 also shows results of a specification that correlates 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.

3.4 Trade-offs to Broad vs. Narrow Networks

The descriptive analysis of the previous subsection showed that consumers' decisions over insurance carriers and insurers' choices of network breadth per service are characterized by substantial adverse selection. Whether adverse selection is sufficient to generate an asymmetric equilibrium in network breadth per service in absence of price competition is still an unanswered question. 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. However, I find 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-offs also arise from differences in the composition of consumer types in demand across insurers. I find that greater network breadth over a particular service is associated with higher annual health care costs in that service even after controlling for patient demographics and diagnoses (see appendix 6). The fact 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). I also find 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 (see appendix 7). Insurers that offer broad networks across all services on average tend to have greater market share in the number of healthy individuals as well, which evidences a strong consumer preference for network breadth. Appendix 8 shows that these findings are robust to different modelling choices.

Put together the correlations imply that, relative to narrow network carriers, insurers that offer broad networks have higher demand from healthy individuals who are usually profitable, and from 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, which prevents the equilibrium from being one where all insurers choose complete network coverage.

4 Econometric Model

The descriptive analysis presented evidence of outstanding risk selection incentives per service and variation in service-level network breadth that responds to those incentives. In this section I put together the descriptive findings to model insurer competition in hospital networks per service. The timing is as follows:

1. Insurers set their vector of service-specific network breadth, $H_m = \{H_{jm}\}_{j=1}^{\#\mathcal{J}_m}$, where $H_{jm} = \{H_{jkm}\}_{k=1}^{K_m}$, $\mathcal{J}_m$ is the set of insurers in market m, and K_m is the set of services in market m.

2. Given insurers' network breadth per service, consumers make enrollment decisions.

The model of insurer demand will focus on the sample of new enrollees in 2011 for which selection efforts are stronger. New enrollees 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, since they have relatively lower preference for network breadth but 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 and 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 networks 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. Insurers maximize the sum of current and future discounted profits by simultaneously choosing their vector of network breadth conditional on their rivals' choices. I allow insurers to be heterogeneous in their average cost per enrollee and network formation cost, which in addition to preference heterogeneity help rationalize the asymmetric equilibrium in network breadth observed in the data.

4.1 Insurer Demand

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

I assume the individual knows her 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 preferred demand specification is one where new enrollees know their health condition because selection occurs on observable, un-reimbursed (or poorly reimbursed) consumer characteristics such as those associated to health status. The consumer observes each insurer's network breadth in service k and market m, H_{jkm}; weights each service by the probability of claiming it $\gamma_{\theta km}$, conditional on the diagnosis; and then makes a one-time myopic choice of carrier. Denote by u_{ijm} the indirect utility of a new enrollee i in market m for insurer j, which takes the following form:

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

where,

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

The vector x_i includes consumer demographics such as sex, age (continuous), indicators for the diagnoses in L, municipality category indicators, and an intercept.[12] The vector y_i includes income level indicators. $c_{\theta jm}$ is the average out-of-pocket cost of consumer type θ at insurer j, which depends on the insurer's vector of network breadth H_{jm}. The coefficient ϕ_j is an insurer fixed effect that captures unobserved insurer quality and ε_{ijm} is an iid unobserved shock to preferences assumed to be distributed T1EV. In terms of parameters, β_i^D represents the preference for network breadth, and α_i represents the marginal disutility of a one million pesos increase in out-of-pocket costs.

Average out-of-pocket costs are the sum of coinsurance payments, copays, and tax contributions

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

to the health system as seen below:

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

The tax contribution equals 12% of the enrollee's monthly income y, 1/3 of which is paid by the enrollee and 2/3 by her employer. Tax contributions vary only across income categories, while coinsurance payments and copays depend not only on income but also on the insurer's negotiated service prices with hospitals and on the individual's health care utilization. Prices and utilization are correlated with the insurer's choice of service-level network breadth because of insurer-hospital price bargaining and because of patient moral hazard. Appendix figure 9 shows that out-of-pocket costs in fact vary substantially across insurers and across consumer types. To capture this correlation, I assume that out-of-pocket payments are a linear function of the insurers' average cost per enrollee $AC_{\theta jm}$, which in turn depends on network breadth as follows:

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

where $\epsilon_{\theta jm}$ is a standard normal error term. I estimate equation (2) separately by income group to recover $\hat{\mu}_y$; results are presented in appendix table 20. If out-of-pocket costs were composed of only coinsurance payments, then μ_y would be equal to the coinsurance rate. But because these out-of-pocket costs involve payments (tax contributions) that individuals make directly to the health care system and that insurers *do not cover*, μ_y will diverge or will be larger than the coinsurance rate. A more detailed description of insurers' average cost per enrollee is provided in the next subsection.

The first term on the right side of equation (1) can be interpreted as a reduced-form approximation to the consumer's expected utility for the network obtained from a 2-step model, in which first the individual chooses an insurer and then chooses an in-network hospital, as in Ho and Lee (2017). In the case of Ho and Lee (2017), the insurer offers the same network of hospitals to consumers of different medical conditions. In my case, variation in network breadth across services and variation in the likelihood of making claims for those services, 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, $\gamma_{\theta km}$, is the average prediction per consumer type, service, and market, of a logistic regression estimated at the patient level given by:

$$1\{Claim_{ikm}\} = \psi_k + \psi_\theta + \psi_m + \psi_{ikm} \tag{3}$$

The dependent variable is an indicator for whether consumer i living in market m made a claim in service category k. On the right side, ψ_k, ψ_θ, and ψ_m are service, consumer type, and market fixed effects, respectively. ψ_{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 over the type of services they will need conditional on their initial health condition are correct on average, and that these expectations do not depend on the insurer they enroll with. I estimate equation (3) on data from both current and new enrollees in 2010 and 2011. Appendix figure 8 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_{ijm} 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.[13]

The second term to the right of equation (1) captures differences in prices and utilization across insurers to generate consumer sorting based on out-of-pocket payments. This sorting is needed to rationalize the existence of narrow network carriers in the *observed* equilibrium since myopic, healthy new enrollees disproportionately choose narrow network carriers with lower implied out-of-pocket costs. I allow out-of-pocket costs to depend on network breadth to capture the extent of moral hazard in health insurance demand and to reflect the price-coverage trade-off that consumers face when making enrollment decisions.

Out-of-pocket costs are aggregated across services for several reasons. First, negotiated service prices are unobserved to consumers at the time of enrollment, so there is no reason to believe they would weight out-of-pocket costs in one service more heavily than in another service. Second,

[13] 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 21).

calculating out-of-pocket costs as ex-post averages from observed claims at the service level would introduce a strong mechanical bias: insurers with narrow networks would seem even cheaper to consumers because I do not observe enough claims per service as opposed to a case where these costs are aggregated across services. Calculating out-of-pocket costs at the service level would require imputing costs for consumer-insurer combinations for which I do not observe claims being rendered for a service, so measurement errors would be much more likely. Aggregating out-of-pocket costs partially solves this source bias. I discuss identification of my demand model next.

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

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

Identification and model specification. 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 for network breadth follows Nevo (2000) and Shepard (2022) in the use of fixed effects that absorb the endogenous variation in this variable. Identification of out-of-pocket costs relies on Petrin and Train (2010)'s control function approach.

For network breadth, note that my demand specification aggregates H_{jkm} across services, eliminating the variation in that dimension. The demand function also includes insurer fixed effects that control for unobserved insurer-level characteristics that may be correlated with network breadth. These fixed effects do not capture unobserved quality that varies *within* insurers nor *within* markets. However appendix tables 24-26 illustrate that this type of variation is not concerning for identification purposes. The tables provide robustness checks of demand that include additional insurer-level quality measures that vary across markets and consumer types, or that use a measure of network breadth that assigns higher weight to higher-quality hospitals. A more detailed discussion of these exercises is provided in section 5.1. Results in the appendix show that the preference for network breadth is robust to the inclusion of different insurer and hospital quality measures. Therefore β_i^D in my main specification is identified from variation in market demographics within insurer, which generates exogenous variation in $\gamma_{\theta km}$. Intuitively, for exogenous reasons some markets will have a higher prevalence of respiratory diseases, which makes insurers offer broader hospital coverage for procedures in lungs than they would in markets with lower prevalence of the disease.

For average out-of-pocket costs, recall that coinsurance rates, copayments, and required tax 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 when making enrollment choices. 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. An example of unobserved quality in this model could be 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 24 presents a robustness check where demand includes an indicator of star hospital coverage interacted with the probability of making claims for each service. My main estimate of α_i does not change with the inclusion of this measure of hospital quality.

Finally, even though out-of-pocket costs are aggregated to the consumer type-insurer level, it is possible that calculating this variable as an ex-post average from observed claims introduces a mechanical bias. To address this source of endogeneity and correlation of prices with unobserved quality mentioned above, my preferred demand estimation is one that uses an instrument for out-of-pocket costs in a control function approach (Petrin and Train, 2010). The instrument is the reference price per service created by government in 2005 –explained in more detail in the next subsection– interacted with the probability of making claims for the service. My main results as well as robustness checks in the appendix use this instrument.[14]

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

$$c_{\theta(i)jm} = \beta_0 + \beta_1(1 - r_i)\sum_k \gamma_{\theta km} A_k + \lambda_\theta + \delta_j + \eta_m + \mu_{\theta(i)jm}$$

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

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

The maintained assumption is that $\hat{\mu}^z_{\theta jm}$ is correlated with ε_{ijm} but that, conditional on $\hat{\mu}^z_{\theta jm}$, ε_{ijm} is independent of $c_{\theta jm}$. First stage results are presented in appendix table 22.

4.2 Insurer Average Costs per Enrollee

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

$$\log(AC_{\theta jm}(H_{jm})) = \beta^S_0 \Big(\sum_k \gamma_{\theta km} A_k \Big) + \beta^S_1 \Big(\sum_k \gamma_{\theta km} H_{jkm} \Big) + \frac{1}{2K_m} \beta^S_2 \sum_k \sum_{l \neq k} \gamma_{\theta km} \gamma_{\theta lm} H_{jkm} H_{jlm} + \lambda_\theta + \delta_j + \eta_m \quad (4)$$

where K_m is the number of service categories available in market m, that is, services that existing hospitals in the market can provide. A_k is the reference price for service k explained in more detail below, λ_θ is a consumer type fixed effect, δ_j is an insurer fixed effect, and η_m is a market fixed effect. In appendix 11 I show that this average cost function per enrollee has a direct relation to a model where consumers choose a hospital to receive service k. In my case, the average cost function per enrollee need only capture the relation between costs and network breadth, 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, 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^S_1 represents the elasticity of average costs with respect to insurer j's network breadth. β^S_2 captures the average degree of complementarity between pairs of services. If $\beta^S_2 < 0$, then insurer j exhibits economies of scope across services, so greater coverage for service $l \neq k$ makes it more attractive to the insurer to provide higher coverage for service k. If $\beta^S_2 \geq 0$, 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 10). For instance, EPS013, EPS016, and EPS037 tend to have generous coverage across all services and markets, while EPS008, EPS009, and EPS012 tend to have narrower networks across all services. Scope economies can come from insurers 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 (4) are multiplied by $\gamma_{\theta km}$ to capture the fact that increasing network breadth for one service does not increase the average cost of all consumer types by the same magnitude. The effect on average costs will depend on how likely it is that the consumer makes a claim in that service category, which is known by insurance companies before making coverage decisions. For example, increasing network breadth for c-sections is likely going to increase the average cost of women in childbearing ages but not the average cost of men.

λ_θ measures the average degree of selection by type-θ 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 willingness-to-pay 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 or anticipate needing. 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 (4) help correct the endogenous variation in network breadth across enrollees. If selection happens mostly on unobservables, then it should be the case that there is unobserved cost variation within consumer types. One way to check if this is case is to test whether estimates are robust to a more granular definition of consumer type. I conduct two exercises to this end: first, in appendix table 29 I present results of a specification where average cost is calculated over consumer types defined as the combination of sex, age (instead of age group), and 30 (instead of 7) exhaustive and mutually exclusive diagnoses (listed in appendix table 39). Second, in appendix table 30 I show an average cost estimation on patient-level data from all continuously enrolled individuals in 2011. In both exercises, the coefficients of the average cost function have the same order of magnitude and direction as my main estimates. My preferred specification is one that aggregates total healthcare cost to the consumer type level to avoid econometric issues that arise from the overwhelming amount of zeros in health care costs at the patient-level.

The parameters of equation (4) are hence identified from variation in average costs within consumer types across insurers that are identical except for their network breadth per service. My source of identification does not rely on different consumers implying different costs for similar insurers as in Tebaldi (2017) but, *conditional* on the composition of enrollee pools, for different coverage levels per service to imply different costs to the insurer. The average cost specification aggregates network breadth across services and includes a rich set of fixed effects that absorb the endogenous variation of network breadth across and within insurers due to selection. I estimate the average cost function using OLS, which generates a measurement error $\nu_{\theta jm}$ that is unobserved to insurers and to the econometrician. The estimating equation is:

$$\log(AC_{\theta jm}(H_{jm})) = f(A_k, H_{jm}, \gamma_{\theta m}; \beta^S) + \nu_{\theta jm}$$

where $f(A_k, H_{jm}, \gamma_{\theta m}; \beta)$ equals the right-hand side of equation (4) and represents the structural average cost per enrollee.

Service reference prices. In 2005, the Colombian government published a list of reference prices for all the services included in the national health insurance plan. The list was created by a group of government officials and medical experts with the purpose of reimbursing hospitals in the event of terrorist attacks, natural disasters, and car accidents (Decree 2423 of 1996).[15] 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 4 shows the average total claim cost for service m calculated directly from the claims data in black and the price

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

instrument in red. The correlation between these two measures equals 0.77.[16]

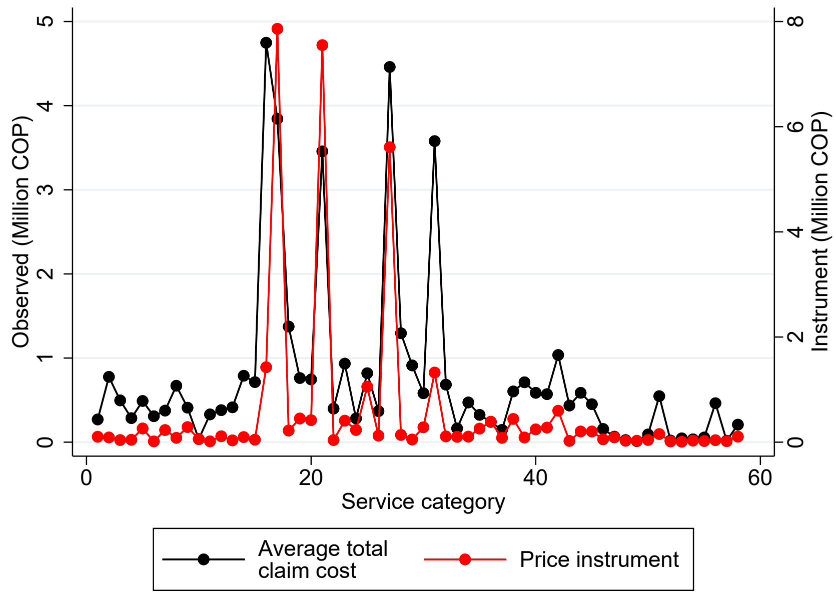


Figure 4: Average claims cost and reference prices

4.3 Competition in Network Coverage

Insurers compete separately in every market choosing their service-specific network breadth after taking expectations of demand and costs, with Nash equilibrium as solution concept. Let $\pi_{ijm}(H_m, \theta)$ be insurer j's short-run per-enrollee profit in market m, which depends on j's network breadth and its rivals', all collected in the vector H_m, as well as on the enrollee's type θ. The short-run per-enrollee profit is given by:

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

where $R_{\theta m}$ is the per-capita revenue including ex-ante and ex-post risk-adjusted transfers from the government and average copayments, $AC_{\theta jm}$ is the average cost of a type-θ consumer net of patients' coinsurance payments with r_i denoting the coinsurance rate, and s_{ijm} is consumer i's choice probability for insurer j in market m. Although ex-post risk adjustment depends on the type of consumers that insurers enroll, total ex-post transfers represent on average only 0.4% of total ex-ante transfers across insurers. Thus, having ex-post transfers be orthogonal to network breadth

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

is a reasonable assumption.

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 minus the cost of network formation:

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

Insurers take into account the future profits associated to each enrollee since, after making their first enrollment choice, individuals experience infinite inertia. $N_{\theta m}$ is the market size of consumers type θ, which is fixed over time, so there are no dynamics introduced by changes in population. In the expression for long-run profits, I assume that the probability of switching across carriers is zero. $\rho_{\theta m}$ represents the probability that type θ drops out of the contributory system. This probability is (assumed) exogenous to the choice of network breadth as it is mostly governed by the event of falling in unemployment. $\mathcal{P}(\theta'|\theta)$ is the transition probability from type θ in period t to type θ' in period $t+1$. Future profits at year t are discounted by a factor of β^t, and I set β equal to 0.95.[17]

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

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

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

I assume $\Delta\xi_{jkm}$ is a network formation cost shock that is *iid* across insurers, services, and markets, as well as over time. This cost shock is observed by insurers but unobserved to the econometrician, and it is mean independent of insurers' network formation cost shifters. By making

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

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 a broad network for a given service is that it increases both demand and costs. By doing so, not only does the insurer attract more consumers overall, but disproportionately attracts those with a high likelihood of claiming the service. The positive relation between network breadth and demand creates vertical differentiation in this model. Rivals' choices of network breadth also affect insurer j's profits. Willingness-to-pay for insurer j or its demand derivatives are a function of own and rival network breadth. Moreover, given that there is no outside option, rival network breadth affects insurer j's total average cost through its effect on the composition of insurer j's enrollee types. Variation in willingness-to-pay across consumer types and rivals generates horizontal differentiation in this model.

Notice that 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 narrow network carriers. While myopia can be a strong assumption, its equilibrium implications are similar to a model where consumers are forward looking but (wrongly) believe that switching costs are zero, so they can re-optimize every period. Equilibrium implications of myopia are also similar to a model where consumers heavily discount the future and therefore choose their insurer based on current preferences and characteristics. This means that even without myopia, the model would generate adverse selection on network breadth and co-existence of broad and narrow network carriers in equilibrium.

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 in an alternating-offers bargaining game. In Liebman (2018) the solution concept is a Markov-perfect equilibrium. I reinterpret network size as a continuous measure in the unit interval for every service and focus on a simultaneous-move game with Nash equilibrium as solution concept. I do not model price negotiations between insurers and hospitals because 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 the dynamic incentives that insurers face when setting up their networks. However, unlike Shepard (2022) I assume hospital quality is constant.

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

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

The left-hand side of equation (5) represents the marginal variable profit MVP_{jmk} and the right-hand side is the marginal cost of network formation.

Identification. Rewriting the FOC as:

$$MVP_{jkm}(H_{jkm}) = 2\omega H_{jkm} + \xi_j + \xi_k + \xi_m + \Delta\xi_{jkm}, \quad \forall\ H_{jkm} \in (0,1) \tag{6}$$

makes explicit the endogeneity between H_{jkm} and $\Delta\xi_{jkm}$. Insurance companies observe $\Delta\xi_{jkm}$ before or at the same time as they are deciding on their network breadth per service. For instance, if an insurer hires a highly trained manager to bargain with hospitals or if an insurance company is vertically integrated with its network, then $E[\Delta\xi_{jkm}|H_{jkm}] < 0, \ \forall\ H_{jkm} \in (0,1)$ and OLS estimation of (6) would result in ω that is biased towards the null.[18] Identification of network formation cost parameters, thus, relies on instrumental variables Z_{jkm} that are correlated with network breadth but not with the cost shock, and that are correlated with marginal variable profits only through network breadth, such that $E[\Delta\xi_{jkm} Z_{jkm}] = 0, \ \forall\ H_{jkm} \in (0,1)$.

The instrument set is populated as follows. First, I include the set of insurer, market, and service fixed effects in equation (6). Second, because I use data from 2011 in estimating the model and $\Delta\xi_{jkm}$ is assumed *iid* over time, I use the service-specific network breadth in 2010. Third, I include the average probability that a female, a person aged 19-44, and an individual without diseases make a claim for service k in market m. These probabilities are calculated as the average prediction of equation (3) across consumers that share the demographic traits above. Finally, I include the interaction between 2010 network breadth and the average service claim probability of a person aged 19-44.

The moment conditions at an interior solution, given by $E[\Delta\xi_{jkm} Z_{jkm}] = 0$, can only rationalize

[18] 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.

the observed equilibrium in markets where no insurer chooses a corner solution in any of the services. In other words, the model is rejected by the data in markets where insurers choose service-level network breadth equal to zero or one. Thus, to estimate the parameters of the network formation cost as described by the FOC, I restrict my sample to the four largest markets in the country (Antioquia 05, Atlántico 08, Bogotá 11, and Valle de Cauca 76) that cover 60% of the population in the contributory regime, and to the top 10 insurers in these markets that cover 87% of enrollees (EPS001, EPS002, EPS003, EPS005, EPS010, EPS013, EPS016, EPS017, EPS018, EPS037). In this final sample, all insurers choose an interior solution in H_{jkm}, $\forall\ k, m$. In dropping the smallest insurers I am assuming that only competition among the largest carriers determines their network breadth choices, and that small insurers move only after the top companies make their choices.[19]

5 Estimation

5.1 Insurer Demand

I proceed to estimate insurer demand with a conditional logit by maximum likelihood. For computational simplicity, I estimate equation (1) on a random sample of 500,000 new enrollees. First stage control function results for out-of-pocket costs are presented in appendix table 22. Results in table 5 show that insurer demand is decreasing in out-of-pocket costs, suggestive of patient moral hazard; and increasing in network breadth, suggestive of positive selection into health insurance. A one million pesos increase in out-of-pocket costs reduces demand for carriers by 7.52 percentage points on average, corresponding to an average elasticity of -0.51.[20] A one percentage point increase in network breadth across all services increases the choice probability by 5.64 percentage points on average.[21]

Interactions between consumer and insurer characteristics matter for enrollment decisions. Males are less sensitive to out-of-pocket expenses than females but have a stronger taste for network breadth. Older patients are both less likely to enroll broad network carriers and more sensitive to

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

[20]The elasticity with respect to out-of-pocket costs is $\frac{\partial s_{ijm}}{\partial c_{\theta jm}} \frac{c_{\theta jm}}{s_{ijm}}$, which is averaged across consumers and insurers. Failure to correct for endogeneity of out-of-pocket costs results in underestimation of the price sensitivity of demand as seen in appendix table 23.

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

out-of-pocket costs compared to younger patients. One explanation for this is that old individuals have had more contact with the health care system and more likely concentrate their care in a few providers. Given that old consumers tend to have higher out-of-pocket costs, findings also imply that the average demand elasticity for patients aged 65 or older (-0.84) is almost twice that of patients aged 19-44 (-0.46). Preference for network breadth is also decreasing with income. Results show that increasing network breadth has a larger positive effect on demand from individuals earning less than 2 times the monthly minimum wage than on demand from those with incomes greater than 5 times the monthly minimum wage.

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 costs. Interactions between network breadth and indicators for each chronic disease are all negative and significant compared to individuals without diagnoses. Instead, interactions between average out-of-pocket spending and diagnosis indicators are all positive and significant. Despite these patterns in preferences, the implied average elasticity for individuals without diseases (-0.50) is smaller than for patients with renal disease (-1.49) because their out-of-pocket costs are relatively low. Results also show that compared to people living in urban areas, those who live in special peripheral municipalities, characterized by fewer providers and more difficult access to care, have stronger preferences for coverage but low sensitivity to out-of-pocket expenses. For individuals living in these peripheral municipalities, the average elasticity with respect to out-of-pocket costs equals -0.16, while for those living in urban areas it equals -0.74.

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

Table 6 presents the average willingness-to-pay across services, insurers, and markets, conditional on consumer observable characteristics. Patients with chronic conditions have a higher willingness-to-pay for network breadth than individuals without diagnoses consistent with strong adverse selection. For instance, patients with cancer are willing to pay 22.0 thousand pesos for an additional percentage point of coverage in the average service while healthy individuals are willing to pay only 2.1 thousand pesos. Willingness-to-pay also varies across diseases because of their different likeli-

Table 5: Insurer demand

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

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

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

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

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

hoods of making claims for each service. To put these numbers in context, the monthly minimum wage in Colombia during 2011 was 535.6 thousand pesos ($271), so patients with cancer are willing to pay 4% of a month's income for better coverage in the average service. Findings also show that willingness-to-pay is around one thousand pesos higher for males than for females, the first of which have a relatively high prevalence of long-term diseases. Average willingness-to-pay is also non-monotonic with respect to age. Consumers aged 55-59 are willing to pay 3.8 thousand pesos on average for an additional percentage point of coverage in a service, which corresponds to an increase of nearly 2 thousand pesos from people aged 45-49.

Robustness checks. Although insurer fixed effects in the demand function control for insurer-level unobserved quality that may be correlated with network breadth or out-of-pocket costs, this unobserved quality could vary within insurers or across consumer types in ways that are not captured by the fixed effects. I show that this type of unobserved quality does not pose a threat to identification by conducting several robustness checks. In the first exercise reported in appendix table 24, I estimate a demand function that includes an indicator of star hospital coverage per insurer, market, and service, interacted with the probability of making claims for the service. In the second exercise in appendix table 25, I estimate demand in the subsample of markets without star hospitals to show that hospital quality does not affect my estimates of the preference for network breadth. In the third exercise reported in appendix table 26, I use enrollee satisfaction survey data from the Ministry of Health to obtain two measures of quality that vary across insurers and markets: average waiting times for a doctor appointment and average insurer quality from a likert scale. I interact these measures with the probability of making claims for a service to introduce variation across consumer types as well. Results in these exercises show that my estimators on network breadth and out-of-pocket costs are overall robust to the inclusion of insurer and hospital quality measures, although the coefficient on out-of-pocket decreases in magnitude in the second exercise.

Appendix table 27 presents robustness checks on my network measure, since recovering service-level hospital coverage from observed claims can both create mechanical bias and introduce measurement error. I re-estimate demand defining network breadth over the sample of 316 largest hospitals in the country and over the entire sample of providers in the claims data. The coefficients of interest associated to preference for network breadth and out-of-pocket spending are robust to these alternative network definitions.

Finally, appendix table 28 presents a robustness check where demand is estimated on the sample of adults aged 19 or older. This gets at the issue that children themselves may not be making informed insurance carrier choices but parents in their behalf. Given that I do not observe households nor head of household to control for family enrollment, including children in the estimation sample could potentially lead to overestimation of the preference for network breadth. My results however are not sensitive to limiting the sample to only adults.

5.2 Insurer Average Costs Per Enrollee

I estimate equation (4) for the logarithm of insurers' average cost per consumer type-θ and market in the sample of new and current enrollees, conditional on observed choices in 2010 and 2011. Table 7 shows the results and appendix figure 11 presents the estimated consumer type fixed effects with their corresponding 95% confidence intervals. Average costs are increasing in network breadth and decreasing in the correlation between network breadth for different pairs of services. This suggests that insurer coverage decisions are characterized by economies of scope. A 1% increase in network breadth for service k decreases the average cost of providing service $l \neq k$ by 0.51% per enrollee.[22] 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 by 1.93% per enrollee.[23] 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 7: Insurer average costs per enrollee

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

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

Figure 5 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,

[22] This effect is calculated as the average of $100 \times \frac{1}{2K_m}\hat{\beta}_2^S \sum_{l \neq k} \gamma_{\theta km}\gamma_{\theta lm}H_{jlm}$

[23] This effect is calculated as the average of $100 \times \hat{\beta}_1^S \gamma_{\theta km}$

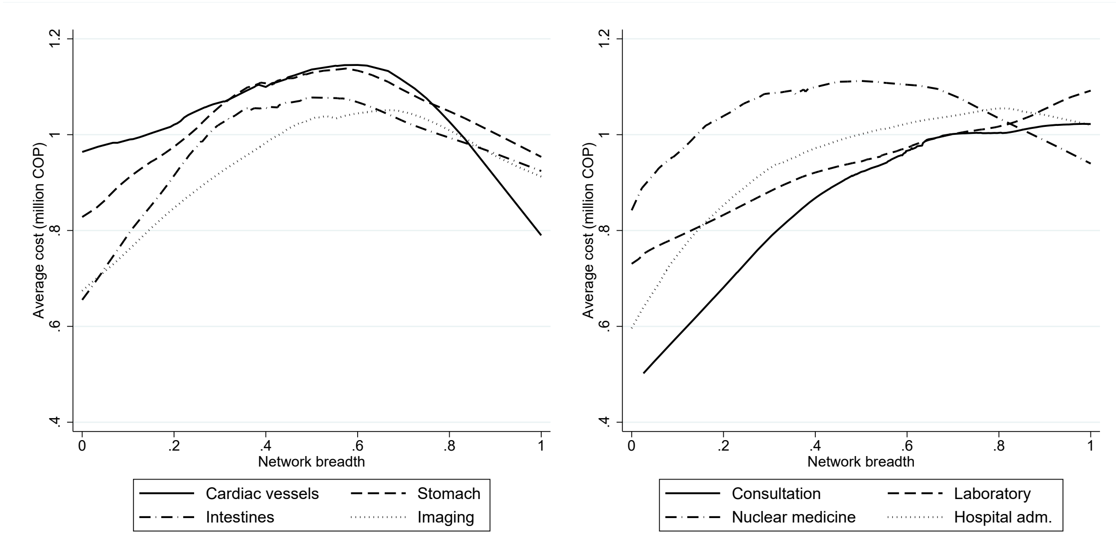


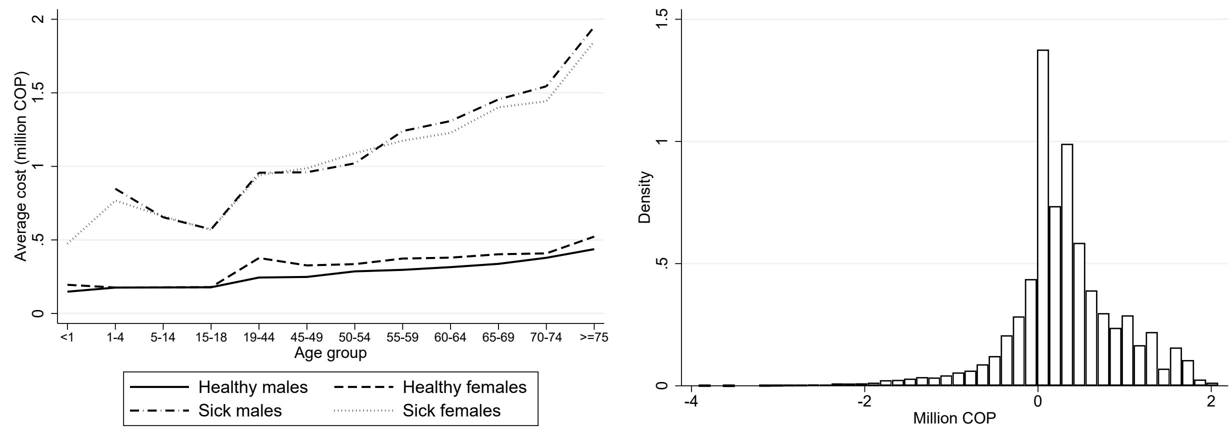
Figure 5: Average cost function per service

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.

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 monotonically increasing in network breadth.

The magnitude of scope economies also varies across consumer types. Appendix table 31 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 k as an insurer with average network breadth across all services $l \neq k$ above 80%, and a narrow network carrier as the opposite.

Results in the appendix show that following a 10% increase in network breadth for consultations, the average cost of healthy adult females enrolled to a narrow network carrier increases 1,343 pesos more than the average cost of 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, 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 32 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.



(a) Predicted average cost

(b) Predicted profit per consumer type

Figure 6: 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.

Panel (a) of figure 6 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. Between 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 6. Profits per new enrollee are calculated as the average risk-adjusted transfers (ex-ante and ex-post) minus the predicted average cost. Since the ex-ante risk adjustment formula controls for only sex, age category, and municipality of residence, most of the variation in profits across consumer type comes from differences in diagnoses and network breadth.[24] 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.

Model-based evidence of adverse selection. The existence of adverse selection over service-level networks in absence of premiums implies that consumers who have the highest willingness-to-pay for

[24] 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.

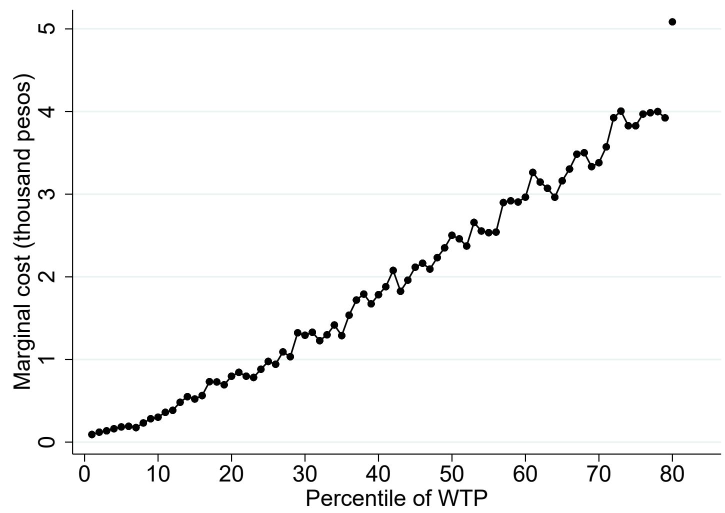


Figure 7: Model-based adverse selection

Note: This figure plots the average marginal cost across all services by percentile of willingness-to-pay (WTP) for network breadth. Marginal costs for service k are given by $\frac{\partial(AC(H_{jkm})s_{ijm}(H_{jkm}))}{\partial H_{jkm}}$. These costs are first averaged (arithmetically) across services, and then across enrollees based on their percentile of WTP. Willingness-to-pay for service k is given by $\frac{1}{|\alpha_i|}\frac{\partial s_{ijm}(H_{jkm})}{\partial H_{jkm}}$, and averaged across services. The positive correlation between marginal costs and WTP is consistent with adverse selection on service-level networks.

network breadth are also the ones that represent the highest cost to the insurer. With my demand and average costs estimates I can test for the presence of adverse selection by plotting marginal cost against willingness-to-pay in the lines of Einav et al. (2010). Marginal costs for service m are given by $\frac{\partial(AC(H_{jkm})s_{ijm}(H_{jkm}))}{\partial H_{jkm}}$, while willingness-to-pay for network breadth over service k is $\frac{1}{|\alpha_i|}\frac{\partial s_{ijm}(H_{jkm})}{\partial H_{jkm}}$. Averaging across services, figure 7 presents the average marginal cost by percentile of willingness-to-pay. Across the distribution, there is a positive correlation between willingness-to-pay and marginal costs of the endogenously selected enrollees, consistent with strong adverse selection over service-level networks.

5.3 Competition in Network Breadth

The third piece of the insurers' profit function left to estimate is the network formation cost. To recover the network formation cost I use the FOC from the insurers' profit maximization problem. Demand and average cost estimates allow me to compute the left-hand side of equation (5) denoting marginal variable profits (MVP). Appendix 13 presents some summary statistics of this variable as well as of dropout probabilities and transition probabilities, which are calculated off-line non-parametrically from the data. There is significant profit heterogeneity across and within insurers.

The average MVP per service and market ranges between 222 million pesos for EPS005 and 1,276 million pesos for EPS016, while the standard deviation exceeds 900 million pesos for all carriers. The fact that MVPs are positive for all insurer-service-market triplets suggests a role for network formation costs in explaining the profit maximizing choices of network breadth.

Table 8 presents the results of a 2-step GMM estimation for log MVP in equation (6) on the subsample of four largest markets and 10 largest insurers in those markets, where the observed equilibrium is an interior solution.[25] The specification includes insurer, market, and service fixed effects, but only the first two are reported for exposition. I find that network formation costs are strictly convex in network breadth. A one percentage point increase in network breadth for service m raises marginal variable profits for that service by 34% on average. The first-stage F-statistic for the endogenous variable is greater than the 1% critical value, thus, lagged network breadth and average market demographics are strong predictors of the observed equilibrium. Appendix table 36, which presents first-stage regression results, shows that the coefficients associated with each instrument all have their expected sign.

Using the estimators for the FOC, I recover each insurer's network formation cost per market and report the mean and the ratio to total variable profits in columns (1) and (2) of appendix table 37, respectively. Network formation costs range between 60% and 90% of total variable profits. The model's predicted ratio of total costs to total revenues per insurer closely match the ratio of obtained from insurers' balance sheets and income statements, even though information contained in these public records is not used for estimation (see appendix figure 13).

Magnitude of adverse selection. Changes in network breadth generate profit variation that can be decomposed into its portions explained by variations in demand, average costs, and network formation costs. How much of the variation in profits comes from changes in demand and in the composition of consumer types evidence the extent of adverse selection. Changes in networks induced by regulation that is specific to insurers evidence risk selection in supply. To quantify the magnitude of adverse selection, I decompose profit changes that result from a partial equilibrium exercise where each insurer is allowed to unilaterally increase its network breadth for service m by 10%, while holding its rivals fixed. If my model is able to rationalize the choices of network breadth observed in the data, the decomposition exercise should show that there are no profitable one-shot deviations.[26]

[25] Appendix figure 12 reports the distribution of network breadth in this subsample.

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

Table 8: Model of insurer network formation costs

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

Note: This table presents a 2-step GMM estimation of equation (6) 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.

Table 9 presents the average percentage change in short-run demand ($\%\Delta s_{ijm}$), total revenues ($\%\Delta R_{\theta m} s_{ijm}$), total average costs ($\%\Delta AC_{\theta jm} s_{ijm}$), average cost per enrollee ($\%\Delta AC_{\theta jm}$), and network formation costs ($\%\Delta F_{jm}$) across insurers and markets, following a 10% increase in network breadth for the service in the row. First of all, I find that for every service 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 deviations.

Second, because changes in network breadth are weighted by the probability of making claims for each service, I find that a 10% increase in coverage of consultations generates the largest variations in demand and costs compared to other services. Demand increases 11.13% relative to observed levels, while total average costs and network formation costs increase 12.61% and 7.47%, respectively. In the case of hospital admissions, insurers that increase coverage by 10% see only a 0.58% increase in demand, a 0.63% increase in total average costs, and a 0.57% increase in network formation costs.

For the services in this table, the change in demand explains on average 48% of the change in insurer total costs. Changes in average costs per enrollee and network formation costs explain the remaining 52%. This means that adverse selection on network breadth is substantial, accounting for nearly half of the variation in total health care costs.

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

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

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

Appendix table 38 shows that most of the variation in demand following a 10% increase in coverage of consultations comes from healthy individuals, followed by consumers with chronic diseases other than renal disease. Increasing network breadth for imaging and laboratory services generates similar effects on demand from the sick and the healthy. But results are quite opposite for hospital admissions. A 10% increase in network breadth for admissions tends to attract more patients with renal disease, followed by patients with other diseases, and lastly by healthy consumers. These heterogeneous effects on demand across services are further evidence of the extent of adverse selection in this market.

6 The Effect of Risk Adjustment on Network Breadth

In this section, 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 United States and concerns about narrow networks 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 that is equal to the national average cost per capita. In the second exercise, I improve the government's risk adjustment formula by reimbursing diagnoses ex-ante. In both scenarios, I hold short-run government spending, dropout probabilities, and transition probabilities fixed. Keeping government spending fixed allows changes in networks to be determined only by changes in how resources are redistributed across insurers but not by the level of the transfer itself. Dropout probabilities are mostly determined by the event of becoming unemployed rather than by the individual choosing not to enroll with a particular insurer due to changes in the network. Because risk adjustment does not impact consumers' tax contribution to the health care system, it is also reasonable to assume that dropout probabilities are fixed under alternative risk adjustment formulae. I assume that the probability of transitioning to new diagnoses depends mostly on the natural disease and age progression rather than on network breadth. But health care consumption and service prices are allowed to vary in counterfactual, with changes captured in a reduced-form way by the insurers' average cost function per enrollee.

In my counterfactual analyses I also assume that choice sets and utility and cost parameters are fixed, so that the set of insurers that participate in every market does not change. 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.

The rich preference and cost heterogeneity in my model could generate multiple equilibria under the counterfactual market conditions considered in this section. 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 every firm choosing complete networks or no coverage at all are both feasible equilibria. In the case of the insurers' average cost function, the magnitude of scope economies is small enough relative to the direct effect of network breadth on average costs per enrollee so as to not pose concerns about uniqueness.

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 14 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 vector, and thus their best response function potentially well-behaved. Although having well-behaved best response functions is not sufficient for uniqueness either, it is at least informative of how likely the problem of multiple equilibria is in this context. In computing the counterfactual analyses, I also use several different starting values for the vector of service-level network breadth and confirm that they all converge to the same equilibrium.

6.1 No Risk Adjustment

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

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

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, incentivizing insurers to drop coverage in services that unprofitable patients require. Appendix figure 15 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. 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 10 presents the percentage change in counterfactual relative to the observed scenario, of average network breadth, insurer total average costs, short-run average costs per enrollee, and short-run consumer welfare for healthy and sick individuals.[27] Under no risk adjustment, average network breadth falls by 6.7%. This reduction in coverage explains the 0.9% decrease in average costs per enrollee and the resulting 0.7% decrease in insurers' total average costs. The fact that total average costs fall with the reduction in coverage indicates that the direct effect of network breadth on costs is larger than its effect on scope economies.

While the reduction in average network breadth is relatively large, its effect on consumer welfare is muted by reductions in out-of-pocket costs, that is, by patient moral hazard. The average elasticity with respect to out-of-pocket costs goes from -0.51 in the observed scenario to -0.69 in counterfactual. Eliminating the risk adjustment systems results in a 2.1% decrease in short-run consumer welfare for individuals without diseases and in a 3.3% decrease in welfare for those with chronic conditions. The welfare effect on patients with diseases is greater in magnitude because access to and quality of care worsen in particular for services that these patients a more likely to claim. A back-of-the-envelope calculation indicates that the overall reduction in welfare is equivalent to 13,753 pesos ($7.2) per capita per year.

Panel B of table 10 shows that the reduction in average network breadth happens across all services. For exposition purposes, I collapse the 58 service categories into 15 broader groups 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 10.1% and procedures in skull and spine by 7.5%. For less expensive services, the reduction in average network breadth is smaller but still sizable. For instance, average coverage of imaging, lab, and consultations falls by 6.2%.

Figure 8 plots 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 the service. When this difference is small, insurers tend to narrow their networks to attract healthy individuals for whom the reduction in out-of-pocket costs overcompensates the reduction in network breadth. When this difference is large, the correlation is positive, suggesting that insurers expand coverage of services that sick individuals are differentially more likely to claim because they are able to pass-through higher out-of-pocket costs to these consumers.

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

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

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

Note: Panel A of this table presents the percentage change in counterfactual under no risk adjustment relative to predictions at observed risk adjustment, of average network breadth across insurers, insurer total average costs, short-run average cost per enrollee, and short-run consumer welfare for the healthy and sick. Panel B presents the percentage change in counterfactual of average network breadth 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 magnitude in counterfactual see larger declines in total short-run demand from the healthy and the sick as seen in appendix figure 17. The figure presents the correlation between changes in average network breadth and changes in total demand per health status across insurers. Healthy individuals tend to substitute away from EPS001 into EPS037, given that the former reduces its average network breadth by 7.1%, a greater-than-average reduction. The pattern is similar for demand from consumers with chronic diseases.

Overall, panel A of appendix figure 20 shows that in a situation where all insurers choose narrow networks, those that reduce their network breadth by a greater magnitude have greater long-run profits compared to those that drop network coverage by a small amount. The figure presents the correlation between changes in average total profits and changes in average network breadth across insurers. The red line corresponding to a linear fit, shows that this correlation is negative, so cost

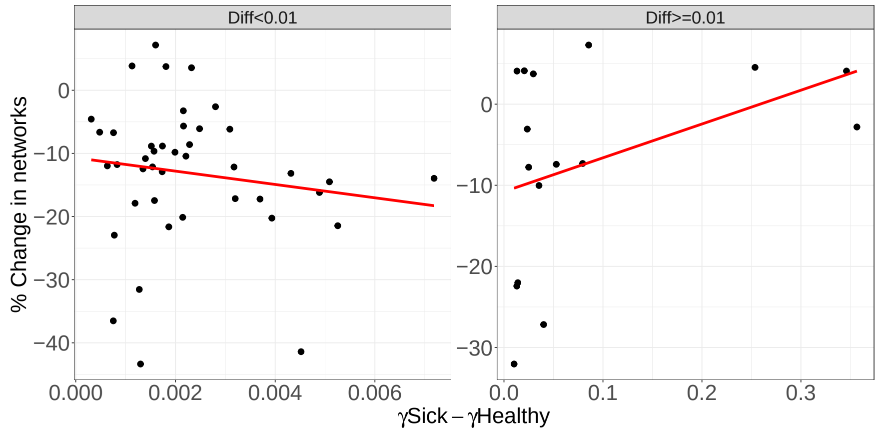


Figure 8: Network changes per service and likelihood of making claims under no risk adjustment

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.

reductions stemming from lower network breadth overcompensate reductions 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:

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

where T_i is the total health care cost of individual i of type θ, b_i is the number of days enrolled to the contributory system during the year, a_m is the market multiplier from appendix table 1, and λ is an adjustment factor calibrated to match observed short-run government spending. I use two sets of exhaustive and mutually exclusive diseases to compensate for ex-ante. The first is the list of 7 diseases used in the model of section 4. The second is a more granular list of 30 health conditions presented in appendix table 39. These conditions are obtained by grouping the ICD-10 codes accompanying an individual's claims following Riascos et al. (2014).[28,29] 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:

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

where λ is an adjustment factor as before and $\widehat{AC}^{obs}_{\theta jm}$ is the individual's predicted average cost conditional on observed networks.

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, counterfactual payments allow for variation within θ and m, while keeping short-run government spending fixed. Appendix figure 16 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, but receive only 0.4 million pesos more for females aged 19-44 with the same health condition.

Table 11 shows the percentage change in network breadth, insurer costs, and consumer welfare under the improved risk adjustment formula with 7 disease categories in column (1), with the list of 30 disease categories in column (2), and with "perfect" risk adjustment in column (3). Effects on network breadth, costs, and welfare are greater the more detailed the risk adjustment formula is. Average network breadth increases 4.6% relative to the observed scenario in column (1), 10.9% in column (2), and 28.0% in column (3). Network breadth increases across all services as seen in panel B of the table, but disproportionately for services that mostly sick patients tend to claim, which is consistent with weakened selection incentives. Focusing on column (2), for example, average network breadth for procedures in abdominal wall increases 37.9%, while for primary care or consultations it increases only 10.0%. Figure 9 confirms that when compensating insurers for a list of 30 diseases ex-ante, service-level network breadth is positively correlated with the difference between the probability that a sick consumer and a healthy one make a claim for that service. Thus, improving the risk adjustment formula to account for some measure of health status improves access

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

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

to care in services that patients with chronic conditions are significantly more likely to claim.

Table 11: 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	4.6	10.9	28.0
Total avg. cost	1.0	3.6	2.9
Avg. cost per enrollee	1.1	3.7	3.0
Consumer welfare (healthy)	2.8	9.9	7.7
Consumer welfare (sick)	3.4	10.7	11.1
Panel B. Avg. network per service			
Skull, spine, nerves, glands	-2.0	-7.3	14.9
Eyes, ears, nose, mouth	8.0	13.3	7.1
Pharynx, lungs	11.4	18.5	62.4
Heart and cardiac vessels	6.4	15.6	52.3
Lymph nodes, bone marrow	6.5	19.4	59.0
Esophagus, stomach and intestines	4.0	13.5	31.2
Liver, biliary tract	1.8	7.3	-0.6
Abdominal wall	19.0	37.9	106.7
Urinary system	13.2	26.9	76.2
Reproductive system	5.9	11.5	25.6
Bones and facial joints	4.6	7.6	19.3
Joints, bones, muscles, tendons	6.2	13.4	21.3
Skin	5.0	12.1	18.9
Imaging, lab, consultation	2.9	10.0	21.3
Hospital admission	0.5	1.0	37.5

Note: Panel A of this table presents the percentage change in counterfactual under improved risk adjustment relative to predictions at observed risk adjustment, of average network breadth, insurer total average costs, short-run average cost per enrollee, and short-run consumer welfare for the healthy and sick. Panel B presents the percentage change in counterfactual of average network breadth 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.

Insurers that expand their network breadth by a greater amount in counterfactual also see large increases in demand. Appendix figure 18 shows that changes in networks and changes in demand from both healthy and sick individuals are positively correlated in counterfactual. However greater demand does not translate into higher profits as seen in panel (b) of appendix figure 20. The negative correlation between changes in networks and changes in profits suggests that the direct effect of expanding the networks on average costs per enrollee and network formation costs is greater than the effect on demand and on the composition of enrollee pools. In fact column (2) of table 11 shows that insurers' total short-run average costs increase 3.6% in counterfactual, while total revenues increase by an average of 2.7% across insurers; variation that can only stem from changes in demand. Consumer out-of-pocket costs also increase in counterfactual due to changes in the

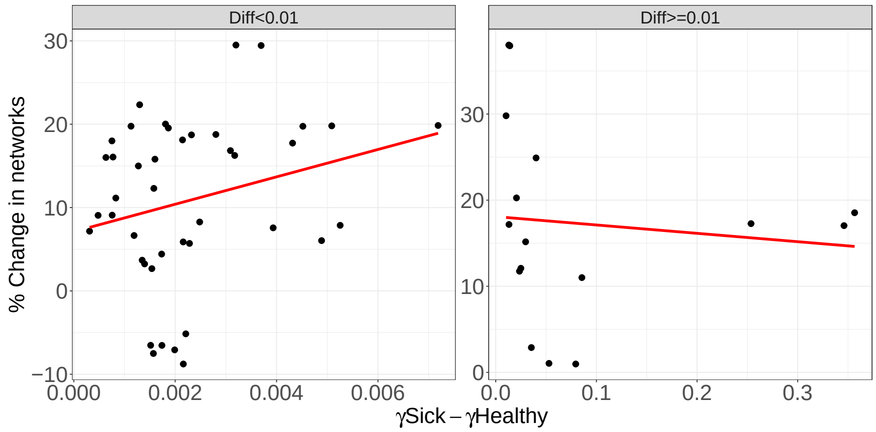


Figure 9: Network changes per service and likelihood of making claims under improved risk adjustment

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.

average cost per enrollee. In the case of "perfect" risk adjustment, these changes imply an average elasticity of -0.66, which represents a 29% increase (in absolute value) from baseline.

With the improved risk adjustment formula that uses the list of 30 disease categories, I find that consumer welfare for patients with any chronic condition increases 10.7% relative to the observed scenario. For consumers without diseases, welfare increases by a smaller magnitude equal to 9.9%. The overall effect on consumer welfare is 62,442 pesos ($32.9) per capita per year. With "perfect" risk adjustment in column (3), consumer welfare increases 7.7% for the healthy and 11.1% for the sick, which overall represents a 49,161 pesos ($25.9) increase per capita per year. Welfare effects from improved risk adjustment are greater for patients with chronic diseases because their willingness-to-pay for network breadth, which is a function of the likelihood of making claims, is greater than that of healthy individuals. Note that even though greater network breadth increases consumers' out-of-pocket costs, the resulting marginal disutility is averaged-out with insurer competition. The direct effect of network breadth on welfare thus dominates the effect of out-of-pocket costs.

If allowing diagnoses to enter the ex-ante risk adjustment formula results in greater network coverage and welfare for patients most at need of care, at no extra cost for the government, why hasn't this formula been implemented in Colombia? First, there are information frictions that prevent a diagnosis-specific risk adjustment to have positive hospital network effects. Recall that risk-adjusted transfers for year t are calculated using claims data from year $t-2$, which might not be informative about the prevalence of diseases in t. Second, allowing for variation across diagnoses could incentivize insurers to engage in upcoding practices, which are difficult to observe and therefore penalize. Despite these challenges, the Colombian government is currently undergoing a modification of the risk adjustment system that consists of reimbursing insurers for bundles of services that, according to medical experts, patients with certain health conditions, such as diabetes, need during the course of treatment. While this new reimbursement does not involve changes to the risk adjustment formula itself nor does it keep government spending fixed given that reimbursements would be made in addition to the existing transfers, it does involve compensating insurers for currently unprofitable services, which should reduce selection incentives. If and after these changes are fully implemented, my model predicts that hospital networks should expand.

7 The effect of Premiums on Network Breadth

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

I assume insurers compete on prices and are allowed to price discriminate based on the enrollee's income level, sex, and age group. Insurers engage in Nash-Bertrand competition in premiums separately by market. Recall that in the observed scenario the monthly contribution to the health care system equals 12% of the enrollee's monthly income, 1/3 of which is paid by the enrollee and 2/3 by her employer. Under counterfactual premiums, I assume the same split of the cost of enrollment between consumers and their employers.[30] Premiums replace the government's risk-adjusted transfers in the insurers' profit function and replace consumers' tax contributions to the system, so government spending is zero in counterfactual and out-of-pocket costs now involve premium payments.

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

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

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

where $\tilde{P}_{\theta jm}$ is insurer j's total premium in market m for consumer type θ. Because premiums are paid instead of the required tax contributions to the health care system, I also assume that dropout probabilities are fixed in counterfactual conditional on network breadth. To the extent that premiums are not significantly greater than observed contributions to the system, conditional on network coverage, an individual is not necessarily more likely to dropout of the system. 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 $P_{\theta jm} = (1/3) \times \tilde{P}_{\theta jm}$, individual i's choice probability for insurer j in market m is:

$$s_{ijm}(H_m) = \frac{\exp\left(\beta_i^D \sum_k \gamma_{\theta km} H_{jkm} - \alpha_i P_{\theta jm} - \alpha_i \tilde{c}_{\theta jm} + \phi_j\right)}{\sum_{j' \in \mathcal{J}_m} \exp\left(\beta_i^D \sum_k \gamma_{\theta km} H_{j'km} - \alpha_i P_{\theta j'm} - \alpha_i \tilde{c}_{\theta j'm} + \phi_{j'}\right)} \tag{7}$$

While equation (7) implicitly assumes that the sensitivity of demand to premiums is the same as to coinsurance payments and copays, I conduct analyses allowing the average component of α_i across patients to be greater for premiums than for out-of-pocket costs. This is following Abaluck and Gruber (2011) who find that consumers are more responsive to premiums than to other measures of cost-sharing in the context of prescription drug coverage in Medicare Part D. I calibrate the fixed component of α_i associated to premiums in a way that generates similar average premium elasticities as in Abaluck and Gruber (2011), equal to -1.17, and as in Shepard (2022), equal to -1.48.

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

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

The insurer has two choice variables per market: the network breadth per service and the premium per consumer type. I assume that the average cost function per enrollee is the same as in the observed scenario. Even though some papers use the relation between average costs and premiums 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 costs 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 network breadth per service taking into account the future profits associated to each new consumer that enrolls with it. The solution concept is a steady state Nash equilibrium. Insurers choose premiums and networks to maximize:

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

The FOC with respect to premiums is:

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

where,

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

and,

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

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

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

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

I estimate this counterfactual exercise in data from Bogotá for simplicity. Computation proceeds as a nested fixed point. For every guess of the equilibrium vector of network breadth, I solve for the fixed point in premiums in an inner loop. Then, in the outer loop, I solve for the fixed point in network breadth. Figure 10 presents the distribution of observed monthly contributions to the health care system and monthly premium pass-through to consumers, when the coefficient on premiums equals the coefficient on out-of-pocket costs in demand. I find that premiums are not greater than observed contributions to the system but exhibit similar dispersion across consumer types. This pattern holds regardless of how the average component of α_i is calibrated. The average monthly contribution equals 50.8 thousand pesos with a standard deviation of 17.7 thousand pesos, while the average consumer monthly premium equals 34.8 thousand pesos with a standard deviation of 10.9 thousand pesos.

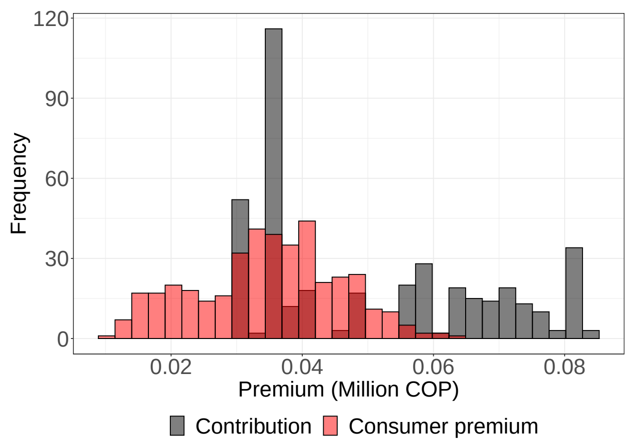


Figure 10: Distribution of counterfactual monthly premium

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

Table 12 presents average total premiums conditional on consumer demographics and insurer. The average component of α_i for premiums is set to 1 and 1.5 times the average component for out-of-pocket costs in columns (1) and (2), respectively. Focusing on column (2), total premiums are 138 thousand pesos higher for males than for females, reflecting men's higher likelihood of developing chronic diseases compared to women. Average total premiums are U-shaped in age following the pattern of expected health care costs. For children aged 5-14, the annual premium equals 1.496 million pesos on average. This premium decreases to 0.729 million pesos for people aged 45-49, and then it increases to 1.323 million pesos for those aged 70-74. Counterfactual annual premiums also weakly decrease with the enrollee's income level because high income individuals have both lower willingness-to-pay for network breadth and better health status compared to low income individuals. The annual premium for people earning between 2 and 5 times the monthly minimum wage is on average 50 thousand pesos lower than for individuals who make less that 2 times the minimum monthly wage. Findings also show a negative correlation between total premiums and insurer market share in the number of enrollees. For example, EPS037 which has a market share of 7.1% in counterfactual charges an average annual premium that is 503 thousand pesos higher than that of EPS002 which has a market share of 18.5%.

Table 12: Average premium per consumer characteristics and insurer

Variable	Avg. total premium	
	(1) 1.0α	(2) 1.5α
Sex		
Female	1.183	1.180
Male	1.325	1.318
Age group		
<1	—	—
1-4	—	—
5-14	1.502	1.496
15-18	1.581	1.575
19-44	1.789	1.784
45-49	0.734	0.729
50-54	0.612	0.608
55-59	1.271	1.265
60-64	1.168	1.162
65-69	1.203	1.197
70-74	1.329	1.323
>=75	1.355	1.349
Income group		
$< 2\times$ MMW	1.282	1.274
$[2,5]\times$ MMW	1.227	1.224
$> 5\times$ MMW	—	—
Insurer		
EPS001	1.368	1.358
EPS002	0.944	0.960
EPS003	1.113	1.152
EPS005	1.410	1.405
EPS010	1.314	1.269
EPS013	1.245	1.264
EPS016	1.164	1.176
EPS017	1.157	1.150
EPS018	1.324	1.291
EPS037	1.505	1.463

Note: Table presents the counterfactual average total premium conditional on consumer demographics and insurer, measured in millions of pesos. Columns (1) and (2) set the average component of α_i for premiums equal to 1 and 1.5 times the average component for out-of-pocket costs, respectively.

Average monthly premiums are significantly smaller than average monthly contributions to the health care system even when insurers substantially expand their networks. This suggests that there is a small pass-through of insurance coverage to premiums that is explained by insurer competition, a finding opposite to Cabral et al. (2018). Panel A of table 13 presents the percentage change in counterfactual relative to the observed scenario of average network breadth, insurer total average costs, short-run average cost per enrollee, insurer total revenue, and short-run consumer welfare for healthy and sick individuals. The panel also shows the implied average elasticity with respect to monthly total premiums.[31] Consumer welfare in counterfactual is monetized using the estimate of consumer sensitivity to out-of-pocket costs rather than the estimate for premiums, to allow a fair comparison with the observed scenario. The fixed component of demand sensitivity to premiums is set to 1 and 1.5 times the fixed component of out-of-pocket costs in columns (1) and (2), respectively.

Deregulating premiums incentivizes insurers to more than double their average network breadth. Price and non-price competition in this market are thus substitutes from the point of view of risk selection. If allowed to charge premiums, insurers would cream-skim the market using premiums rather than service-level networks. The effect of premium competition on average network breadth decreases with the implied demand elasticity to premiums, which goes from -0.81 in column (1) to -1.22 in column (2). The 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 imaging, lab, consultations, or procedures in skin, the effect is still substantial.

Given that the direct effect of network breadth is greater than the effect of scope economies on average costs, short-run average cost per-enrollee increases 9.0% relative to the observed scenario in column (2). Total insurer average costs also increase 13.9% but most of this variation is explained by the direct effect of networks on average costs rather than by selection or changes in demand. With all insurers choosing broad networks, service-level network breadth exhibits less heterogeneity across carriers. As a result, findings show smaller variations in demand from sick individuals than from healthy ones. Appendix figure 19 shows that the correlation between changes in demand from the sick and changes in network breadth is smaller than the correlation with changes in demand from the healthy. These small selection effects explain why variation in network breadth is mostly orthogonal to variation in insurer profits as seen in panel C of appendix figure 20.

Premium deregulation generates a significant transfer of surplus from consumers to insurers. Panel A of table 13 shows that insurer total revenues more double in counterfactual. Revenues

[31] The individual elasticity with respect to monthly total premiums is calculated as $\frac{1}{12} \times \frac{\partial s_{ijm}}{\partial P_{\theta jm}} \frac{P_{\theta jm}}{s_{ijm}}$ and then averaged across individuals.

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

Variable	%Change in CF	
	(1) 1.0α	(2) 1.5α
Panel A. Overall		
Avg. Network	111.2	107.3
Total avg. cost	17.7	13.9
Avg. cost per enrollee	22.7	9.0
Total revenue	146.9	110.7
Consumer welfare (healthy)	-22.6	-77.3
Consumer welfare (sick)	13.1	-47.8
Panel B. Avg. network per service		
Skull, spine, nerves, glands	75.8	65.9
Eyes, ears, nose, mouth	172.6	197.5
Pharynx, lungs	272.8	276.2
Heart and cardiac vessels	127.5	127.7
Lymph nodes, bone marrow	82.5	82.2
Esophagus, stomach and intestines	92.7	89.8
Liver, biliary tract	98.9	94.0
Abdominal wall	210.5	183.8
Urinary system	152.0	133.1
Reproductive system	115.0	112.2
Bones and facial joints	122.5	120.1
Joints, bones, muscles, tendons	112.0	114.0
Skin	104.6	107.3
Imaging, lab, consultation	91.1	78.0
Hospital admission	72.4	50.7

Note: Panel A of this table presents the percentage change in counterfactual under premium deregulation relative to predictions at observed risk adjustment, of average network breadth, insurer total average costs, short-run average cost per enrollee, insurer total revenue, and short-run consumer welfare for the healthy and sick. Panel B presents the percentage change in counterfactual of average network breadth 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. The average component of α_i for premiums is set to 1 and 1.5 times the average component for out-of-pocket costs in columns (1) and (2), respectively.

increase completely at the expense of consumers without diseases, for whom welfare falls 22.6% in column (1) and 77.3% in column (2). For healthy individuals, who have a low willingness-to-pay for network breadth and a high sensitivity to out-of-pocket costs, welfare losses due to premium payments overcompensate welfare gains from broader networks 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 effects are either positive or negative but smaller in magnitude. For these individuals welfare increases 13.1% relative to the observed scenario in column (1) but decreases 47.8% in column (2) when sensitivity to premiums is 50% greater than sensitivity to out-of-pocket costs.

The substantial decrease in welfare for healthy consumers is problematic. If individuals without chronic diseases could drop out of the health care system, a premium deregulation policy could unravel the market. By making the healthy disproportionately choose uninsurance, broad network carriers could face significant uninsurable costs from the remaining enrollees with chronic diseases. Market equilibria under premium deregulation could be restored not only by making enrollment mandatory, but also by having the government pay a fraction of premiums such that total spending matches current risk adjustment spending.

8 Conclusions

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

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

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 reducing selection incentives and containing health care costs. I use my model of insurer competition to answer this question by measuring the effect of typical policies used to combat risk selection, such as risk adjustment and premium setting, on service-level network breadth while holding government spending fixed.

I find that eliminating risk adjustment makes insurer competition a race to the bottom in terms of network breadth. Average network breadth falls 6.7% but the reduction is larger in services that sick individuals require the most. As a result consumer welfare falls by \$7.2 per capita per year relative to the observed scenario. Improving the risk adjustment formula by compensating insurers for sex, age, location, and a list diagnoses results in service-level networks that are broader on average, particularly for services that individuals with chronic diseases are more likely to claim. With an improved risk adjustment formula, average network breadth increases between 4.6% and 28% and consumer welfare increases between \$9.3 and \$32.9 per capita per year depending on how many risk factors are included in the formula. Despite the positive welfare gains at no additional cost to the government, implementing an improved risk adjustment system is difficult because of information frictions between hospitals, insurers, and the regulator. Allowing insurers to compete Nash-Bertrand in premiums results in nearly complete hospital networks for every insurer and service. Thus price and non-price competition are substitutes from the point of view of risk selection. The increase in service-level network breadth comes at the expense of higher out-of-pocket costs, which significantly reduces welfare for consumers without diseases who are more sensitive to out-of-pocket costs compared to individuals with chronic conditions.

This paper provides new evidence of the ways in which insurers can use their hospital network to select risks and the type of policies that can be used to mitigate risk selection through hospital networks. In quantifying the extent to which networks respond to risk adjustment and premiums, the findings of this paper speak to the trade-off between having better access to care and containing health care costs. Findings can help policymakers in the design of public health systems with private provision of health insurance. But policy implications extend beyond these types markets to ones where private insurers compete on the non-price characteristics of their health insurance plans.

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