Non-Price Competition and Risk Selection Through Hospital Networks

Natalia Serna[*]

October 7, 2022

Click here for latest version

Click here for appendix

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.

1 Introduction

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

Most prior studies have focused on how risk selection affects premiums, holding other aspects of the insurance plan fixed (e.g, Cabral et al., 2018; Ho and Lee, 2017; Dafny et al., 2015). Less attention has been paid to whether insurers strategically choose the non-price characteristics of their plans to cream-skim the market. In this paper I study how insurers 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.

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

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

---

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

I start by providing several pieces of evidence that insurers risk-select using their service-level hospital networks. First, I show 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, which generates variation in service profitability. Then, I provide evidence that insurers' service-level hospital networks respond to those incentives, by showing that networks tend to be narrower for less profitable services. Finally, I find that 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, patients are more likely to make dialysis claims the broader is the network for dialysis or women are more likely to have a baby the broader is the network for delivery services.

To further study risk selection through networks, I develop and estimate a model of insurer competition in service-level hospital network breadth and consumer demand for insurance. The model is able to rationalize an asymmetric equilibrium in network breadth with demand-side adverse selection alone, though it also incorporates rich cost heterogeneity across insurers. The model allows me to quantify how hospital network breadth, health care costs, and consumer welfare respond to changes in the regulatory environment. This question has become increasingly relevant in view of the growing regulation regarding network adequacy rules (Mattocks et al., 2021; Haeder et al., 2015). In the model, 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 simplification directly addresses the question of existence of narrow networks in health insurance, while also facilitating tractability in counterfactual simulations.

For consumer demand, I model new enrollees' myopic and static discrete choices of insurance carrier. The enrollees' indirect utility is a function of insurers' network breadth per service and out-of-pocket costs. The demand function incorporates sufficient observed heterogeneity in the preference for network breadth and the marginal disutility for out-of-pocket costs to capture adverse selection, but there is no unobserved heterogeneity that is common across choice alternatives. This means that selection in my model occurs only on observable, un-reimbursed (or poorly reimbursed) consumer characteristics like diagnoses. I endogeneize out-of-pocket costs to the choice of network breadth per service, allowing for moral hazard, to capture the cost-coverage trade-off that consumers face when making enrollment decisions. Consumers may have strong preferences for broader networks, but enrolling with a broad network carrier is associated with higher out-of-pocket costs. To the extent that healthy consumers have lower willingness-to-pay for network

breadth relative to sick consumers, insurers will be able to screen healthy individuals by choosing narrow networks at the service level.

For supply, I start by modelling insurers' average cost per enrollee as a non-linear function of service-level network breadth and enrollee characteristics. 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. This approximation allows me to focus on insurers' dynamic incentives to choose network breadth, while still capturing effects on negotiated prices and health care utilization when simulating counterfactual policies. In that sense, my average cost model diverges from existing literature on endogenous hospital network formation in a Nash-in-Nash bargaining framework (Prager and Tilipman, 2020; Ghili, 2020; Ho and Lee, 2019; Liebman, 2018).

Insurers maximize total profits by choosing their vector of service-level network breadth, conditional on rivals' choices. Total profits are given by the sum of short-run profits and long-run discounted profits, minus the cost of network formation. Insurers' network formation cost is a service-specific administrative cost associated with inclusion of an additional hospital to the network. Network formation cost shocks are observed by insurance companies but unobserved to the econometrician. When making coverage choices, insurers internalize the dynamic incentives introduced by infinite consumer inertia. Once a new enrollee chooses an insurance company, this enrollee does not switch, which implies insurers can reap-off the long-run profits associated with this individual. With infinite consumer inertia, the dynamic programming problem of choosing network breadth every period can be approached as a static problem in steady state. My solution concept is thus a steady state Nash equilibrium.

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 would 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 overall have a strong preference for broader networks, a narrow network carrier will attract fewer sick enrollees who are unprofitable, but also fewer healthy enrollees who are profitable conditional on risk adjustment.

I estimate the model on a novel administrative dataset that encompasses all enrollees to the

contributory health care system in Colombia during 2010 and 2011, which represents nearly half of the population in the country (25 million individuals) and their medical claims (650 million). 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 in 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.

Consumer preference for service-level network breadth is identified from exogenous variation in market demographics. Intuitively, some markets will have higher prevalence of a disease, which generates exogenous variation in the probability of making claims and thus in insurers' decisions to offer network breadth in services required for treatment of the disease. Consumer marginal disutility for out-of-pocket costs is identified from exogenous variation in government's service reference prices, which I implement using a control function approach (Petrin and Train, 2010). Service reference prices are supply shifters and are unobserved by consumers, but they affect consumer demand only through their effect on out-of-pocket costs. The insurer's average cost function is identified from variation in insurer characteristics within consumer type, while network formation costs are identified from exogenous variation in the probability of making claims and in previous years' network breadth choices under the assumption that network formation cost shocks are independent across time.

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. A decomposition of profit changes in a partial equilibrium exercise where an insurer unilaterally increases network breadth for a service shows that adverse selection explains on average half of the variation in insurers' total costs, while the rest is explained by cost heterogeneity.

I use my model to quantify how hospital networks respond to changes in the regulatory envi-

ronment and how these network breadth changes affect health care costs and consumer welfare. 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 compensation 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 the absence of risk adjustment, insurers reduce coverage of relatively expensive services such as hospital admissions by 10.1%, and reduce coverage 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 from smaller network breadth 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 in every market. 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 under-provision 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.

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. Although Shepard (2022) in the context of the Massachusetts Exchange shows that sick individuals' strong preferences for one star hospital incentivizes insurers to drop this hospital from their networks, I show that selection can happen on insurers' multidimensional choice of service-level 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). Other papers deal with alternative selection mechanisms such as insurer advertising (Aizawa and Kim, 2018) and drug formulary design (Geruso et al., 2019).

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.

In what follows I will describe the Colombian health care system (section 2), provide descriptive evidence of risk selection through networks (section 3), introduce my model of insurer competition (section 4), and provide estimation results (section 5) and counterfactual simulations (sections 6 and 7). Section 8 concludes.

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

At the end of every year, insurers report to the government all health claims made through the national insurance plan that they reimbursed hospitals in their network for. The data for this paper are the enrollment files of all enrollees to the contributory system during 2010 and 2011 (25 million), and their claims reports to the government (650 million). I focus on the sample of individuals with continuous enrollment spells or no gaps in enrollment 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.[5] Of the continuously enrolled, 2/3 are *current enrollees* or individuals who are enrolled throughout 2010 and 2011. The remaining 1/3 are *new enrollees* or individuals who enroll for the first time in 2011. Because there is near universal coverage, new enrollees to the contributory system can be individuals who move from the subsidized system after they find a job, or those who for some reason

---

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

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

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

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

were uninsured for 12 continuous months and then enroll in the health care system.[6] In the sample of current enrollees, only 0.06% switch their insurance carrier from 2010 to 2011, which 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. The health claims data reports, among others, date of provision, service description, service price, provider, insurer, and ICD-10 diagnosis code.

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

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

---

[6]Even if new enrollees in 2011 had enrollment before the start of my sample period in 2010, decree 806 of 1998 and decree 1703 of 2002 established that after three continuous months of non-payment of tax contributions to the health care system, a person would be disenrolled and lose any information so far reported to the system. Moreover, because the subsidized regime has more insurers than the contributory regime, a new enrollee that switches from the former to the latter would likely switch insurers.

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

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

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

3   Descriptive Evidence

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

---

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

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 enrollment files, I can recover the ex-ante risk-adjusted transfer that each insurer received for each of its enrollees. Ex-ante reimbursements range from 162.2 thousand pesos (males aged 15-18) to 2.2 million pesos (for females aged 75 or older), with an average of 650.8 thousand pesos.

The High-Cost Account compensates insurers that enroll an above-average share of people with any of the following chronic diseases: cervical cancer, breast cancer, stomach cancer, colon cancer, prostate cancer, lymphoid leukemia, myeloid leukemia, hodgkin lymphoma, non-hodgkin lymphoma, epilepsy, rheumatoid arthritis, and HIV/AIDS. The per-patient reimbursement equals the average cost of treatment for each disease. These reimbursements come from insurers that enroll a below-average share of individuals with those diseases.[9] My data 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, suggesting these ex-post transfers do not provide much risk adjustment. Despite compensating insurers for a few diagnoses, selection incentives are still present after ex-post risk adjustment as shown in Riascos (2013) and Riascos and Camelo (2017).

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

The coarse nature of the risk adjustment formula and the high variance in health care costs generate large variation 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

---

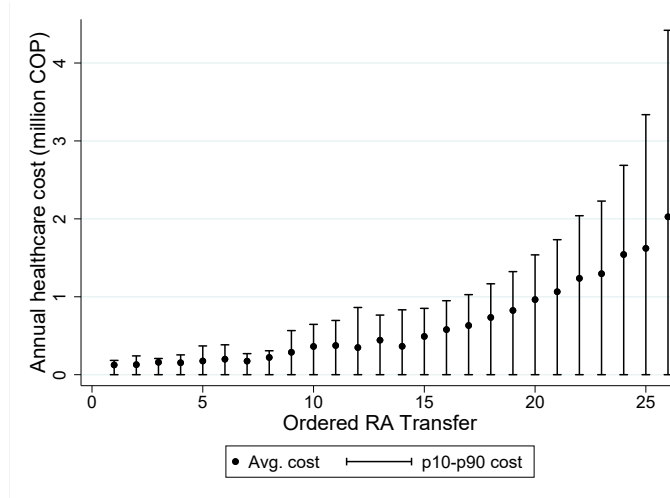[9]See Resolution 000248 of 2014 from the Ministry of Health.

Figure 1: Health care cost by risk-adjusted transfer

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

adjustment formulas were able to completely eliminate risk selection incentives, the variance in the distribution of profits per enrollee should be similar across insurers, but this is not the case. The table also shows that new enrollees' average profit is significantly higher than that of current enrollees, and their distribution of profits per capita less skewed to the left. Thus selection efforts should be stronger among new enrollees.

3.1   Measuring network breadth

Insurers in Colombia have discretion over how many hospitals to cover for each service, but it is mandatory that they cover at least one hospital for every service in the national insurance plan. This means that network breadth is defined over the number of hospitals *conditional on the service*, but not over services. Although insurers' coverage choices are in part determined by differences in hospital specialty and available capacity, these choices also depend on the type of consumers that insurance companies want to risk select upon. As an example of these service-level networks, appendix table 4 shows which insurers covered the services of cardiology, dialysis, and hospital admissions at three hospitals in the country. The table shows for example that at Fundación Valle del Lili, EPS010 covers cardiology, but not admissions. EPS002 covers dialysis, but not cardiology nor admissions. While EPS005 covers admissions, but not dialysis nor cardiology.

If insurers use their service-level hospital networks to select risks, then differences in risk selection efforts should appear as differences in network breadth. I define network breadth as the fraction of

Table 1: Distribution of profit per enrollee

Insurer	Current			New		
	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.

all hospitals in a market offering a particular service that are covered by the insurer. Table 2 shows that there is significant heterogeneity in network breadth per service across insurers and markets. EPS013 and EPS016 have relatively broad networks in almost all markets, covering an average of 49.7% and 55.0% of hospitals per service during 2011, respectively; while smaller insurers, like EPS008 and EPS023, tend to cover between 12.6% and 10.0% of hospitals per service in the average market. For the majority of insurance companies, network breadth exhibits small declines from 2010 to 2011 due to hospital entry.

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

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 both the enrollment satisfaction surveys and the fact that star hospitals are not as common in Colombia as they are for example in the United States. While there is extensive literature documenting

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.

consumer preference 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 insurers' choice of network breadth alone would be misleading.

In appendix table 5 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, suggesting that network breadth is not inconsistent with consumer preference for star hospitals. In section 5 I provide additional evidence that hospital quality does not bias my estimates by conducting robustness checks on my insurer demand model.

3.2 Network breadth as a means of risk selection

The descriptive statistics show that there is substantial variation in service-level network breadth and profits per enrollee across insurers and markets that are suggestive of differences in selection efforts. In this subsection I link profits per enrollee with service utilization to characterize selection incentives at the service level by replicating figures in Geruso et al. (2019) with my data. In figure 2 I show whether the current risk adjustment systems are effective at neutralizing service-level risk selection. The figure plots the average cost per enrollee against the average revenue per enrollee
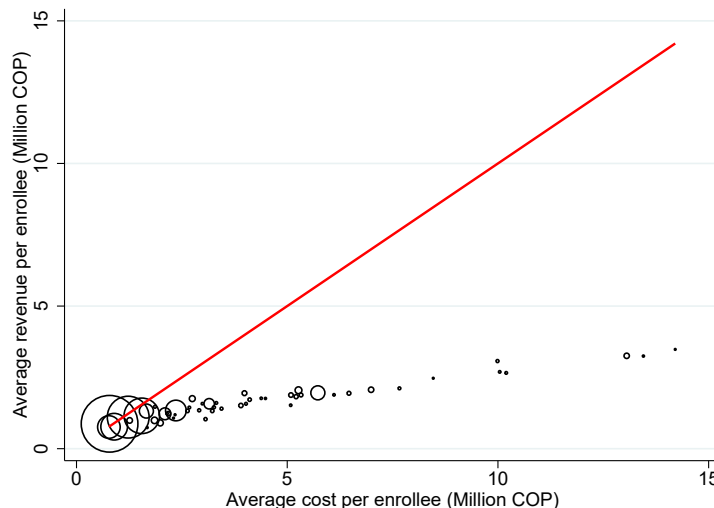
Figure 2: Service-level selection incentives after risk adjustment

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

conditional on patients who make claims for each service. Every dot in the figure represents a service weighted by the number of patients who make claims for it. Patients who make claims for several services will be represented in several dots, while patients who make zero claims and are the most profitable are not represented in this figure. The red line is the 45 degree line, which splits the space into services that are overcompensated by the risk-adjusted transfers (above the line) and those that are undercompensated (below the line).

The most commonly utilized services, such as consultations, imaging, and laboratory, are located around the 45 degree line, so risk-adjusted compensation succeeds 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.[10]

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

---

[10]These findings hold when using information from all individuals enrolled to the contributory system without constraining enrollment to be continuous.
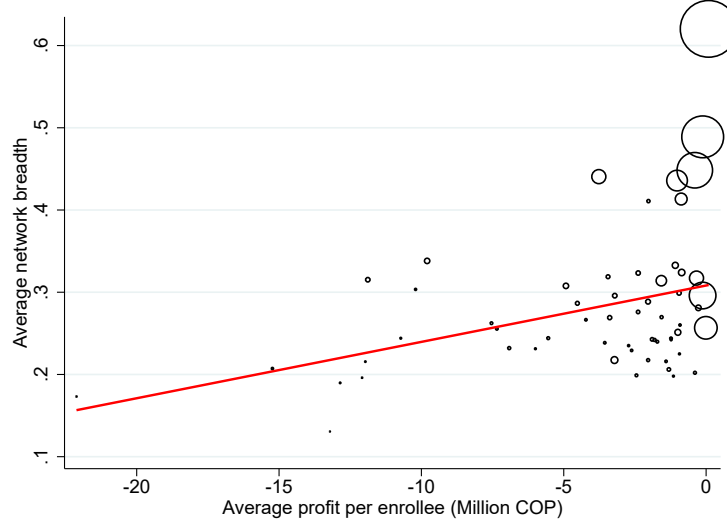
Figure 3: Correlation between network breadth and service profitability

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

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

3.3 Selection vs. Moral Hazard

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

To separate selection from moral hazard, I start by estimating a regression on the sample of

current enrollees who received a diagnosis in 2010. The dependent variable is the number of claims or an indicator for making a claim during 2011 in a service that is associated with treatment of their health condition diagnosed in 2010. The regression specification is given by:

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

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

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

While the positive correlation between network breadth and number of claims conditional on 2010 health status could be explained by moral hazard rather than by selection, the correlation with the likelihood of making claims is unlikely the result of moral hazard. A person is not more 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 6 shows that 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. Results are similar for patients who switched but received a diagnosis in 2010 as seen in appendix table 7.

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

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

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

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

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

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

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

Here y_{ikm}^{2010} is either the logarithm of total health care cost of individual i in service k and market m during 2010 or an indicator for having non-zero claims. S_{im} is an indicator for whether the

consumer switched carriers from one year to the other. The subscript j' denotes the insurer chosen in 2011, so $H^{2010}_{j'km}$ 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.

Table 4: Selection on baseline costs and risk

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

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

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

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

---

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

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

3.4 Trade-offs to Broad vs. Narrow Networks

Whether adverse selection is sufficient to generate an asymmetric equilibrium in network breadth per service is still an outstanding question. If insurers can not charge higher prices for greater coverage, then in absence of premium competition we would predict that all insurers choose narrow networks across all services. However, the data suggests that there are trade-offs to the provision of a narrow and a broad network that are consistent with an asymmetric equilibrium. Naturally, these trade-offs arise from differences in costs and demand across insurers. But more importantly, trade-offs also arise from differences in the *composition* of consumer types in demand.

Network breadth for a particular service is positively correlated with health care costs in that service (see appendix 6) and with 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 overall also tend to have greater market share in the number of healthy individuals given that consumers have strong preferences for broader networks.[13] Put together the correlations imply that, relative to narrow network carriers, insurers that offer broad networks have relatively higher demand from patients with chronic diseases who are usually unprofitable conditional on risk adjustment, but their level of demand from healthy individuals who are profitable is meaningful as well.

4 Model

In this section I put together the descriptive findings to model insurer competition in hospital networks per service. The timing of the model 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.

---

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

[13]These findings are robust to different modelling choices like using a two-part model for health care 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.

2. Given insurers' network breadth per service, consumers realize health shocks and 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 demographics and diagnoses, on the insurers' network breadth per service, and on their implied out-of-pocket costs.

The demand model captures the cost-coverage trade-off that consumers face when making enrollment choices by endogeneizing out-of-pocket costs to network breadth or, in other words, allowing for moral hazard. Consumers may have strong preferences for broader networks, but enrolling broad network carriers implies making higher out-of-pocket payments. To the extent that healthy consumers care more about out-of-pocket costs than network breadth relative to sick consumers, insurers will be able to screen healthy individuals by choosing narrow networks at the service level. I also assume that 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 maps into the near-zero fraction of enrollees in the data that switch their insurance carrier from one year to the other.

Consumers' cost-coverage trade-off, myopia, and inertia, generate 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. 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 by choosing their vector of network breadth per service. In making coverage choices, insurers internalize the dynamic incentives introduced by consumers facing infinite inertia. With infinite inertia, the dynamic programming problem of network formation can be approached as a static problem in steady state. Insurers maximize the sum of current and future discounted profits by simultaneously choosing their vector of network breadth conditional on their rivals' choices, so the solution concept is a steady state Nash equilibrium.

I allow insurers to be heterogeneous in their average cost per enrollee and network formation cost, which in addition to preference heterogeneity can help rationalize the asymmetric equilibrium in

network breadth observed in the data. Because asymmetries in network breadth could be generated by this cost heterogeneity alone rather than by adverse selection in demand, the supply model is needed to assess the relative importance of these two factors.

4.1 Insurer Demand

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

I assume the individual knows her diagnoses before making her first enrollment choice. This could be either because of medical family history or because, 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 $q_{\theta km}$, conditional on the diagnosis; and then makes a one-time myopic choice of carrier. Denote by u_{ijm} the indirect utility of a new enrollee i in market m for insurer j, which takes the following form:

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

where,

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

22

The vector x_i includes consumer demographics such as sex, age (continuous), indicators for the diagnoses in L, type of municipality indicators, and an intercept.[14] 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 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, $1/3$ of which is paid by the enrollee and $2/3$ by her employer. Tax contributions vary only across income categories y, while coinsurance payments and copays depend not only on income but also on the insurer's negotiated service prices with hospitals and on the individual's health care utilization. Prices and utilization are correlated with the insurer's choice of service-level network breadth because of insurer-hospital price bargaining and because of patient moral hazard. Appendix figure 5 shows that out-of-pocket costs in fact vary substantially across insurers and across consumer types. To capture this correlation, I assume that out-of-pocket payments are a linear function of the insurers' average cost per enrollee $AC_{\theta jm}$, which in turn depends on network breadth as follows:

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

where $\epsilon_{\theta jm}$ is a standard normal error term. I estimate equation (2) separately by income group to recover μ_y; results are presented in appendix table 10. If out-of-pocket costs were composed of only coinsurance payments, then μ_y would be equal to the coinsurance rate. But because these out-of-pocket costs involve payments (tax contributions) that individuals make directly to the health care system and that insurers *do not cover*, μ_y will be different from the coinsurance rate. A more detailed description of insurers' average cost per enrollee is provided in the next subsection.

The first term on the right side of equation (1) can be interpreted as a reduced-form approxi-

---

[14]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.

mation 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, $q_{\theta km}$, is the average prediction per consumer type, service, and market, of a logistic regression estimated at the patient level given by:

$$1\{\text{Claim}_{ikm}\} = \psi_k + \psi_\theta + \psi_m + \psi_{ikm} \tag{3}$$

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 4 presents the distribution of $q_{\theta km}$ separately for healthy and sick individuals, and for a few service categories.

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

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 cost-coverage trade-off that consumers face when making enrollment decisions. Out-of-pocket costs are aggregated across services because a service-level calculation would require imputing costs for consumer-insurer combinations for which I do not observe claims being provided for a service, so measurement errors and mechanical bias would be much more likely.

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

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

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

For network breadth, my demand specification aggregates H_{jkm} across services, eliminating the endogenous variation in that dimension. The demand function also includes insurer fixed effects that control for unobserved insurer-level characteristics that may be correlated with network breadth. These fixed effects do not capture unobserved quality that varies *within* insurers nor *within* markets. However appendix tables 14-16 illustrate that this type of variation is not concerning for identification purposes. The tables provide robustness checks of my demand model that include additional insurer-level quality measures that vary across markets and consumer types. A more detailed discussion of these exercises is provided in section 5.1. β_i in my main specification is therefore identified from variation in market demographics, which generates exogenous variation in $q_{\theta km}$. 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 in these markets than they would in markets with lower prevalence of the disease.

Identification of the marginal disutility for out-of-pocket costs relies on exogeneity of coinsurance rates, copayments, and required tax contributions to the system. This helps correct part of the bias introduced by negotiated service prices, which affect coinsurance payments. Nonetheless, it is

possible that consumers choose their insurer based on unobserved quality that is correlated with negotiated prices and that the coinsurance rates and copayments do not account for as they are standardized across insurers.

An example of unobserved quality that can bias my estimates is the insurer's coverage of star hospitals. If consumers disproportionately enroll with carriers that cover star hospitals and these carriers in turn negotiate higher prices with those hospitals, then my model would interpret consumers as having low sensitivity to out-of-pocket costs, biasing α_i towards the null. To address this issue, my preferred demand specification is one that uses an instrument for out-of-pocket costs in a control function approach (Petrin and Train, 2010). The instrument is the reference price per service created by government in 2005 –explained in more detail in the next subsection. Reference prices are supply shifters; they affect insurer-hospital negotiations but are unobserved by consumers. Moreover, reference prices only affect demand through their effect on out-of-pocket costs. [15] I also conduct additional robustness checks to verify that star hospital coverage is not a meaningful source of bias.

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, $C_{ijm}^{obs}(H_{jm})$, equals the average cost of a type-θ consumer plus a random shock: $C_{ijm}^{obs}(H_{jkm}) = AC_{\theta jm}(H_{jkm}) + \omega_{ijm}$. 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

---

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

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

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

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

The maintained assumption is that $\hat{\varphi}_{\theta jm}^z$ is correlated with ε_{ijm} but that, conditional on $\hat{\varphi}_{\theta jm}^z$, ε_{ijm} is independent of $c_{\theta jm}$. First stage results are presented in appendix table 11.

logarithm of average cost per consumer type as a function of network breadth, as follows:

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

where K_m is the number of service categories available in market m, that is, services that existing hospitals in the market can provide. A_k is the reference price for service k explained in more detail below, λ_θ is a consumer type fixed effect, δ_j is an insurer fixed effect, and η_m is a market fixed effect. In appendix 10 I show that this average cost function per enrollee has a direct relation to a model where consumers choose a hospital to receive service k.

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

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

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

endogenous variation of network breadth across and within insurers due to selection.

If selection happens mostly on observables, then consumer type fixed effects in equation (4) help correct the endogenous variation in network breadth across enrollees. If selection happens mostly on unobservables, then it should be the case that there is unobserved cost variation within consumer types. One way to check this is to test whether estimates are robust to a more granular definition of consumer type. I conduct robustness checks of this style in appendix table 18 using patient-level data.[16] I estimate the average cost function using OLS, which generates a measurement error that is unobserved to insurers and to the econometrician.

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.[17] Although they were not meant to guide price negotiations between insurers and hospitals, there is evidence that insurers use these reference prices as starting points in their negotiations with hospitals (Ruiz et al., 2008). I use the reference prices as a measure of average claim cost for service K in the insurers' average cost function and as an instrument for demand. Figure 4 shows the average total claim cost for each service in the horizontal axis calculated directly from the claims data in black and the price instrument in red. The correlation between these two measures equals 0.77.[18]

4.3 Competition in Network Coverage

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

---

[16]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.

[17]Decree 2423 of 1996

[18]Let p_k^R be the reference price for service k and f the average inflation rate from 2005 to 2011, then $A_k = p_k^R \times (1 + f)^6$.
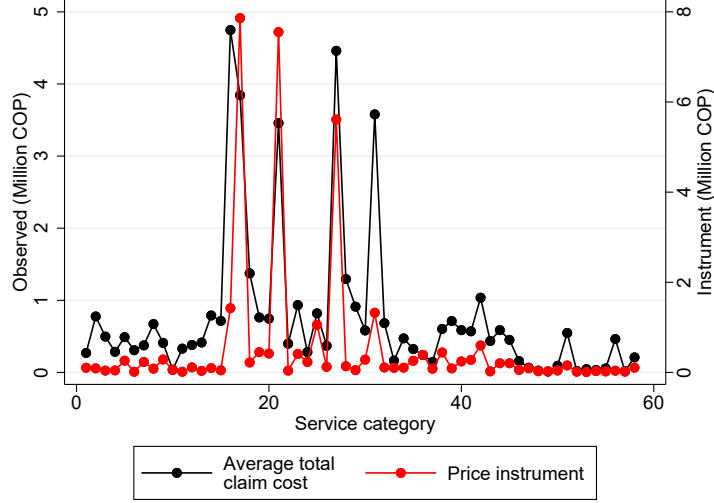
Figure 4: Average claims cost and reference prices

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

patients' coinsurance payments with r_i denoting the coinsurance rate, and s_{ijm} is consumer i's choice probability for insurer j in market m.

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

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

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 into unemployment. $\mathcal{P}(\theta'|\theta)$ is the transition probability from type θ in period t to type θ'

in period $t+1$. Future profits at year t are discounted by a factor of ζ^t, and I set ζ equal to 0.95. [19]

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

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

Profit maximization involves a set of $J \times K$ first-order conditions (FOC) in each market, which

---

[19]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).

assuming an interior solution in network breadth, is given by:

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

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

$$\frac{\partial \pi_{ijm}}{\partial H_{jkm}} = \underbrace{\overbrace{R_{\theta m} \frac{\partial s_{ijm}}{\partial H_{jkm}}}^{\text{Selection}} - \overbrace{R_{\theta m} \left| \frac{\partial s_{ijm}}{\partial AC_{\theta jm}} \right| \frac{\partial AC_{\theta jm}}{\partial H_{jkm}}}^{\text{Moral hazard}}}_{\text{Marginal revenue}} \qquad (6)$$

$$- \underbrace{(1-r_i) \left(\overbrace{AC_{\theta jm} \frac{\partial s_{ijm}}{\partial H_{jkm}} + s_{ijm} \frac{\partial AC_{\theta jm}}{\partial H_{jkm}}}^{\text{Selection}} - \overbrace{AC_{\theta jm} \left| \frac{\partial s_{ijm}}{\partial AC_{jm}} \right| \frac{\partial AC_{\theta jm}}{\partial H_{jkm}}}^{\text{Moral hazard}} \right)}_{\text{Marginal cost}}$$

Equation (6) shows the effect of adverse selection and moral hazard on insurers' network breadth choices. If the insurer increases its network breadth for a particular service, marginal revenues will increase due to selection because individuals prefer broader networks overall, so insurer demand increases. Selection also increases insurers' marginal cost because a broader network for a service attracts expensive consumers who are more likely to claim the service, and because changes in network breadth increase the cost of the average consumer. Moral hazard has opposite effects on marginal revenues and marginal costs. Moral hazard reduces marginal revenues because broader networks, which incentivize individuals to consume more health care, increase the individual's out-of-pocket cost and thus put a downward pressure on the insurer's demand. Moral hazard also reduces insurers' marginal cost because individuals whose out-of-pocket costs increase and whose enrollment is therefore discouraged, are also the ones who are the most expensive to the insurer in that service category.

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

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

Identification. Rewriting the FOC as:

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

makes explicit the endogeneity between H_{jkm} and the network formation cost shocks, $\Delta\xi_{jkm}$. Insurance companies observe $\Delta\xi_{jkm}$ before or at the same time as they are deciding on their network breadth per service. For instance, if an insurer hires a highly trained manager to bargain with hospitals or if an insurance company is vertically integrated with its network, then $E[\Delta\xi_{jkm}|H_{jkm}] < 0, \ \forall\, H_{jkm} \in (0,1)$ and OLS estimation of (7) would result in ω that is biased towards the null.[20] Identification of network formation cost parameters, thus, relies on instrumental variables Z_{jkm} that are correlated with network breadth but not with the cost shock, and that are correlated with marginal variable profits only through network breadth, such that $E[\Delta\xi_{jkm}Z_{jkm}] = 0, \ \forall\, H_{jkm} \in (0,1)$.

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

---

[20]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.

include the interaction between 2010 network breadth and the average service claim probability of a person aged 19-44.

The moment conditions at an interior solution, given by $E[\Delta\xi_{jkm}Z_{jkm}] = 0$, can only rationalize the observed equilibrium in markets where no insurer chooses a corner solution in any of the services. In other words, the model is rejected by the data in markets where insurers choose service-level network breadth equal to zero or one. Thus, to estimate the parameters of the network formation cost as described by the FOC, I restrict my sample to the four largest markets in the country (Antioquia 05, Atlántico 08, Bogotá 11, and Valle de Cauca 76) that cover 60% of the population in the contributory regime, and to the top 10 insurers in these markets that cover 87% of enrollees (EPS001, EPS002, EPS003, EPS005, EPS010, EPS013, EPS016, EPS017, EPS018, EPS037). In this final sample, all insurers choose an interior solution in H_{jkm}, $\forall\ k, m$. In dropping the smallest insurers I am assuming that only competition among the largest carriers determines their network breadth choices, and that small insurers move only after the top companies make their choices.[21]

5 Estimation

5.1 Insurer Demand

I 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 11. 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.[22] A one percentage point increase in network breadth across all services increases the choice probability by 5.64 percentage points on average.[23]

Interactions between consumer and insurer characteristics matter for enrollment decisions. Males

---

[21]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.

[22]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.

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

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 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).

Individuals with chronic conditions do not necessarily have stronger preferences for network breadth than their healthy peers but they are significantly less responsive to out-of-pocket costs. Interactions between network breadth and indicators for each chronic disease are all negative and significant compared to individuals without diagnoses. Instead, interactions between average out-of-pocket spending and diagnosis indicators are all positive and significant. Despite these patterns in preferences, the implied average elasticity for individuals without diseases (−0.50) is smaller than for patients with renal disease (−1.49) because their out-of-pocket costs are relatively low. Appendix 9.3 presents some measures of the in-sample model fit.

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 (4% of monthly income) for an additional hospital in the average service (or roughly a 10-minute reduction in travel time), which corresponds to a one percentage point increase in network breadth; while healthy individuals are willing to pay only 2.1 thousand pesos. Willingness-to-pay is higher for males than for females, the first of which have a relatively high prevalence of long-term diseases. Average willingness-to-pay is also non-monotonic with respect to age.

Robustness checks. Although insurer fixed effects in the demand function control for insurer-level unobserved quality that may be correlated with network breadth or out-of-pocket costs, this

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.

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 14, I estimate a demand function that includes an indicator of star hospital coverage per insurer, market, and service. In the second exercise in appendix table 15, I estimate demand in the subsample of markets without star hospitals. In the third exercise reported in appendix table 16, I use enrollee satisfaction survey data from the Ministry of Health to obtain two measures of insurer quality that vary across markets: average waiting times for a doctor appointment and average insurer quality from a likert scale. Results in these exercises show that my estimates are robust to the inclusion of insurer and hospital quality measures, although the coefficient on out-of-pocket decreases in magnitude in the second exercise. Results are also robust to the use of different provider

samples for constructing my measure of network breadth as seen in appendix table 17.

5.2 Insurer Average Costs Per Enrollee

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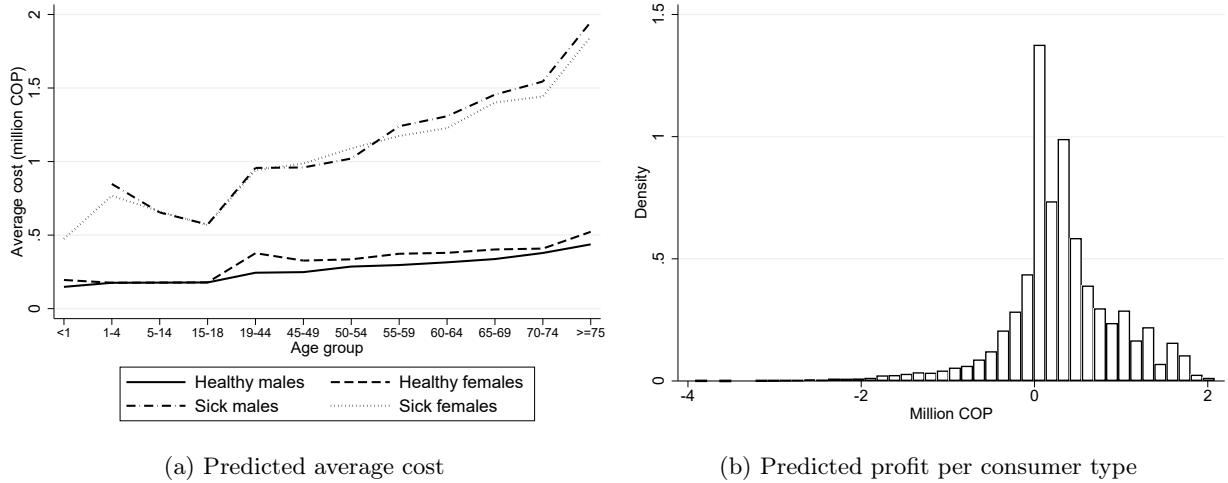

(a) Predicted average cost

(b) Predicted profit per consumer type

Figure 5: Predicted average cost and surplus per consumer type

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

Panel (a) of figure 5 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

---

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

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

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.

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

Model-based evidence of adverse selection. With my demand and average costs estimates I can test for the presence of adverse selection by plotting marginal cost against willingness-to-pay for network breadth along the lines of Einav et al. (2010). Marginal costs for service k are given by $\frac{\partial(AC(H_{jkm})s_{ijm}(H_{jkm}))}{\partial H_{jkm}}$, and willingness-to-pay for network breadth over service k is $\frac{1}{|\alpha_i|}\frac{\partial s_{ijm}(H_{jkm})}{\partial H_{jkm}}$. Averaging across services, figure 6 presents the average marginal cost in the vertical axis by percentile

---

[26]Profit variation per enrollee can also be partly explained by differences in sex, age, and location if the risk adjustment formula imperfectly compensates insurers in these dimensions.
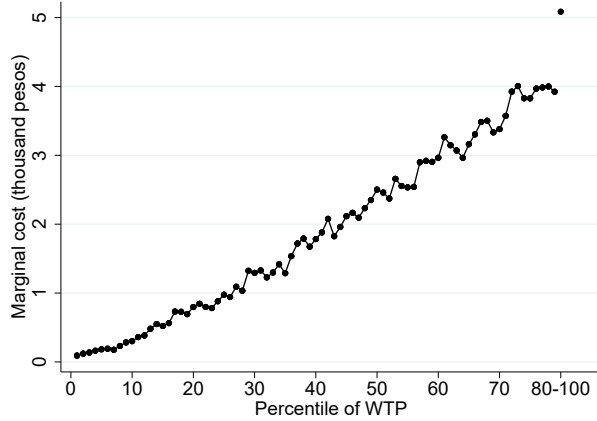
Figure 6: Model-based adverse selection

Note: This figure plots the average marginal cost by percentile of average willingness-to-pay for network breadth, where averages are calculated across services. Marginal costs for service k are given by $\frac{\partial (AC(H_{jkm})s_{ijm}(H_{jkm}))}{\partial H_{jkm}}$. Willingness-to-pay for service k is given by $\frac{1}{|\alpha_i|}\frac{\partial s_{ijm}(H_{jkm})}{\partial H_{jkm}}$.

of willingness-to-pay for network breadth in the horizontal axis. The positive correlation between these two variables indicates that endogenously selected patients with the highest willingness-to-pay for network breadth are also the most expensive to the insurer.

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 12 presents some summary statistics of this variable as well as of dropout probabilities and transition probabilities, which are calculated off-line non-parametrically from the data. The fact that MVPs are positive for all insurer-service-market triplets suggests a role for network formation costs in explaining the profit maximizing choices of network breadth.

Table 8 presents the results of a 2-step GMM estimation for log MVP in equation (7) on the subsample of four largest markets and 10 largest insurers in those markets, where the observed equilibrium is an interior solution. The specification includes insurer, market, and service fixed effects, but only the first two are reported for exposition. I find that network formation costs are strictly convex in network breadth. A one percentage point increase in network breadth for service k 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 (see appendix table 23). As a measure of out-of-sample fit, appendix figure 9 compares the model's predicted ratio of total costs to total revenues per insurer to the ratio obtained from insurers' public income statements.

Table 8: Model of insurer network formation costs

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

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

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 unilaterally increases network breadth for service k by 10%, while holding its rivals fixed. If my model is able to rationalize the choices of network breadth observed in the data, the decomposition exercise should show that there are no profitable one-shot

deviations.[27]

Table 9 presents the average percentage change in short-run demand ($\%\Delta s_{ijm}$), total revenues ($\%\Delta R_{\theta m}s_{ijm}$), total average costs ($\%\Delta AC_{\theta jm}s_{ijm}$), average cost per enrollee ($\%\Delta AC_{\theta jm}$), and network formation costs ($\%\Delta F_{jm}$) across insurers and markets, following a 10% increase in network breadth for the service in the row. First of all, I find that for every service total costs increase by a greater magnitude than total revenues, so there are no profitable deviations. Second, because changes in network breadth are weighted by the probability of making claims for each service, a 10% increase in coverage of consultations generates the largest variations in demand and costs compared to other services. Finally, findings indicate that the change in demand explains on average 48% of the change in insurer total costs, while cost heterogeneity explains the remaining 52%.

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 $\Delta\xi_{jkm} = 0$.

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 with 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 health insurance

---

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

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. I also assume that choice sets and utility and cost parameters are fixed, so that the set of insurers that participate in every market does not change. For computational tractability, I conduct my counterfactual analyses in 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 dimensionality of insurer choices in my model could generate multiple equilibria under the counterfactual market conditions considered in this section. For instance, my measure of scope economies can make it such that every firm choosing complete networks or no coverage at all are both feasible equilibria. In the case of the insurers' average cost function, the magnitude of scope economies is small enough relative to the direct effect of network breadth on average costs per enrollee so as to not pose concerns about uniqueness. The rich preference and cost heterogeneity also prevent multiple equilibria from arising.

Whether there are multiple equilibria in this market depends on the shape of the insurers' profit 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. In computing the

counterfactual analyses, I also use several different starting values for the vector of service-level network breadth and confirm that they all converge to the same equilibrium.

6.1 No Risk Adjustment

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

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

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

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 rather than 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.[28] Under no risk adjustment, average network breadth falls by 6.7%. This reduction in coverage explains the 0.9% decrease in average costs per enrollee and the resulting 0.7% decrease in insurers' total average costs. The fact

---

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

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

Variable	%Δ in CF
Panel A. Overall	
Avg. network breadth	-6.7
Total avg. cost	-0.7
Avg. cost per enrollee	-0.9
Consumer welfare (healthy)	-2.1
Consumer welfare (sick)	-3.3
Panel B. Avg. network 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.

that total average costs fall with the reduction in coverage indicates that the direct effect of network breadth on costs is larger than its effect on scope economies.

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

Panel B of table 10 shows that the reduction in average network breadth happens across all services. For exposition purposes, I collapse the 58 service categories into 15 broader groups. When

they are not compensated for their enrollees' health risk, insurers reduce coverage of relatively expensive services like hospital admissions by 10.1% and procedures in skull and spine by 7.5%. For less expensive services, the reduction in average network breadth is smaller but still sizable. For instance, average coverage of imaging, lab, and consultations falls by 6.2%. Consistent with adverse selection, insurers for which average network breadth falls by a greater magnitude see larger declines in total short-run demand from the healthy than the sick as seen in appendix figure 13. Panel A of appendix figure 16 also shows that insurers that reduce their network breadth by a greater magnitude have greater long-run profits compared to those that drop network coverage by a small amount.

6.2   Improved Risk Adjustment

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

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

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

where T_i is the total health care cost of individual i of type θ, b_i is the number of days enrolled to the contributory system during the year, a_m is the market multiplier from appendix table 1, and λ is an adjustment factor calibrated to match observed short-run government spending. I use two sets of exhaustive and mutually exclusive diseases to compensate for ex-ante. The first is the list of 7 diseases used in the model of section 4. The second is a more granular list of 30 health conditions presented in appendix table 24.[29] These conditions are obtained by grouping the ICD-10 codes accompanying an individual's claims following Riascos et al. (2014).[30] In both cases, when

---

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

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

the 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. Appendix figure 12 presents the distribution of the difference between counterfactual payments and observed risk adjusted transfers per consumer type. With compensations that control for the list of 7 diseases, insurers receive 1.8 million pesos more for males aged 19-44 with cancer, but receive only 0.4 million pesos more for females aged 19-44 with the same health condition.

Table 11 shows the percentage change in network breadth, insurer costs, and consumer welfare under the improved risk adjustment formula with 7 disease categories in column (1), with the list of 30 disease categories in column (2), and with "perfect" risk adjustment in column (3). Effects on each of these variables are greater the more 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. This is consistent with weakened selection incentives and with demand-side adverse selection being a main factor in determining narrow networks and an asymmetric equilibrium in network breadth.

Insurers that expand their network breadth by a greater amount in counterfactual also see large increases in demand from sick individuals (see appendix figure 14). However greater demand does not translate into higher profits (see panel (b) of appendix figure 16). Column (2) of table 11 shows that insurers' total short-run average costs increase 3.6% in counterfactual, while total revenues increase by an average of 2.7% across insurers; variation that can only stem from changes in demand. Consumer out-of-pocket costs also increase in counterfactual due to changes in the average cost per enrollee. In the case of "perfect" risk adjustment, these changes imply an average elasticity of -0.66, which represents a 29% increase (in absolute value) from baseline.

With the improved risk adjustment formula that uses the list of 30 disease categories, I find

46

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 breadth	4.6	10.9	28.0
Total avg. cost	1.0	3.6	2.9
Avg. cost per enrollee	1.1	3.7	3.0
Consumer welfare (healthy)	2.8	9.9	7.7
Consumer welfare (sick)	3.4	10.7	11.1
Panel B. Avg. network 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.

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

If allowing diagnoses to enter the ex-ante risk adjustment formula results in greater network coverage and welfare for patients most at need of care, at no extra cost for the government, why hasn't this formula been implemented in Colombia? First, there are information frictions that

prevent a diagnosis-specific risk adjustment to have positive hospital network effects. Recall that risk-adjusted transfers for year t are calculated using claims data from year $t - 2$, which might not be informative about the prevalence of diseases in t. Second, allowing for variation across diagnoses could incentivize insurers to engage in upcoding practices, which are difficult to observe and therefore penalize. Despite these challenges, the Colombian government is currently undergoing a modification of the risk adjustment system that consists of reimbursing insurers for bundles of services that, according to medical experts, patients with certain health conditions, such as diabetes, need during the course of treatment. While this new reimbursement will not keep government spending fixed, it will involve compensating insurers for currently unprofitable services. If and after these changes are fully implemented, my model predicts that hospital networks should expand.

7 The effect of Premiums on Network Breadth

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

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

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

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

---

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

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

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

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

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

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

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

Insurers simultaneously choose premiums and network breadth per service taking into account the future profits associated to each new consumer that enrolls with it. The solution concept is a steady state Nash equilibrium. Insurers choose premiums and networks to maximize:

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

The FOC with respect to premiums is:

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

---

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

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,

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

The short-run annual premium level can be solved for from the premium FOC, which determines a fixed point iteration.

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 7 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 is independent of how the average component of α_i is calibrated. The average monthly contribution equals 50.8 thousand pesos with a standard deviation of 17.7 thousand pesos, while the average consumer monthly premium equals 34.8 thousand pesos with a standard deviation of 10.9 thousand pesos.

Table 12 presents the average premium received by insurers in a year conditional on consumer demographics. 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. Counterfactual premiums are correlated with enrollees' underlying health. Focusing on column (2), average premiums are 138 thousand pesos higher for males than for females, reflecting men's higher likelihood of developing chronic diseases. Premiums are also U-shaped in age following the pattern of average health care costs, and weakly decreasing in income because high-income individuals tend to be healthier than
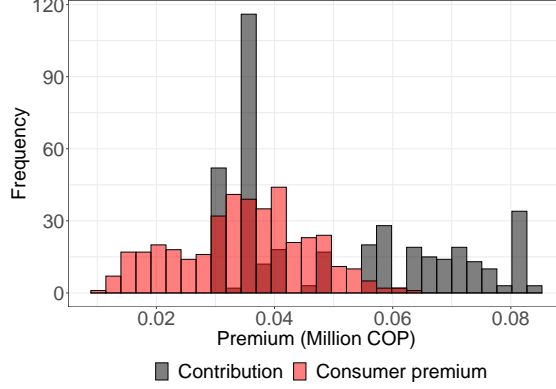
Figure 7: Distribution of counterfactual monthly premium

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.

low-income individuals. Findings 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%.

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.[33] Consumer welfare in counterfactual is monetized using the estimate of consumer sensitivity to out-of-pocket costs rather than the estimate for premiums, to allow for a fair comparison with the 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 and discriminate premiums, insurers would cream-skim the market using premiums rather than service-level networks. The effect of premium competition on average

---

[33]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 12: Average premium per consumer characteristics and insurer

Variable		Avg. premium	
		1.0α	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 average premiums received by insurers in a year 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.

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.

Total insurer average costs increase 13.9% in column (2), a finding that is explained by the direct effect of networks on average costs being larger that the effect of selection or changes in demand. With all insurers choosing broad networks, service-level network breadth exhibits less heterogeneity across carriers. As a result, variations in demand from sick individuals are relatively small compared to variations in demand from healthy individuals as seen in appendix figure 15.

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

Variable	%Change in CF	
	(1) 1.0α	(2) 1.5α
Panel A. Overall		
Avg. network breadth	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.

These small selection effects also explain network breadth is mostly orthogonal to insurer profits in panel (c) of appendix figure 16.

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 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 higher out-of-pocket payments overcompensate welfare gains from having broader networks in every service. The increase in out-of-pocket costs comes from increases in coinsurance payments, which are affected by

network breadth; but not from premiums, which are smaller than tax contributions in the observed scenario. 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 depend on how the sensitivity of demand to premiums is calibrated.

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 would face significant uninsurable costs from the remaining enrollees with chronic diseases. Market equilibria under premium deregulation could be restored not only by making enrollment mandatory, but also by having the government pay a fraction of premiums 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.

References

Abaluck, J. and Gruber, J. (2011). Choice Inconsistencies Among the Elderly: Evidence from Plan Choice in the Medicare Part D Program. *American Economic Review*, 101(4):1180–1210.

Aizawa, N. and Kim, Y. (2018). Advertising and Risk Selection in Health Insurance Markets. *American Economic Review*, 108(3):828–867.

Brown, J., Duggan, M., Kuziemko, I., and Woolston, W. (2014). How Does Risk Selection Respond to Risk Adjustment? New Evidence from the Medicare Advantage Program. *American Economic Review*, 104(10):3335–3364.

Cabral, M., Geruso, M., and Mahoney, N. (2018). Do Larger Health Insurance Subsidies Benefit Patients or Producers? Evidence from Medicare Advantage. *American Economic Review*, 108(8):2048–2087.

Cao, Z. and McGuire, T. (2003). Service-Level Selection by HMOs in Medicare. *Journal of Health Economics*, 22(6):915–931.

Capps, C., Dranove, D., and Satterthwaite, M. (2003). Competition and market power in option demand markets. *RAND Journal of Economics*, pages 737–763.

Chiappori, P. and Salanie, B. (2000). Testing for Asymmetric Information in Insurance Markets. *Journal of Political Economy*, 108(1):56–78.

Dafny, L., Hendel, I., and Wilson, N. (2015). Narrow Networks on the Health Insurance Exchanges: What do they Look Like and How do they Affect Pricing? A Case Study of Texas. *American Economic Review*, 105(5):110–14.

Decarolis, F. (2015). Medicare Part D: Are Insurers Gaming the Low Income Subsidy Design? *American Economic Review*, 105(4):1547–1580.

Einav, L., Finkelstein, A., and Cullen, M. (2010). Estimating Welfare in Insurance Markets Using Variation in Prices. *Quarterly Journal of Economics*, 125(3):877–921.

Einav, L., Finkelstein, A., Ryan, P., Schrimpf, D., and Cullen, M. (2013). Selection on Moral Hazard in Health Insurance. *American Economic Review*, 103(1):178–219.

Einav, L., Finkelstein, A., and Tebaldi, P. (2019). Market Design in Regulated Health Insurance Markets: Risk Adjustment vs. Subsidies.

Ellis, R. and McGuire, T. (2007). Predictability and Predictiveness in Health Care Spending. *Journal of Health Economics*, 26(1):25–48.

Finkelstein, A., Hendren, N., and Shepard, M. (2019). Subsidizing Health Insurance for Low-Income Adults: Evidence from Massachusetts. *American Economic Review*, 109(4):1530–1567.

Frank, R., Glazer, J., and McGuire, T. (2000). Measuring adverse selection in managed health care. *Journal of Health Economics*, 19(6):829–854.

Geruso, M., Layton, T., and Prinz, D. (2019). Screening in Contract Design: Evidence from the ACA Health Insurance Exchanges. *American Economic Journal: Applied Economics*, 11(2):64–107.

Ghili, S. (2020). Network Formation and Bargaining in Vertical Markets: The Case of Narrow Networks in Health Insurance.

Gowrisankaran, G., Nevo, A., and Town, R. (2015). Mergers When Prices Are Negotiated: Evidence from the Hospital Industry. *American Economic Review*, 105(1):172–203.

Haeder, S., Weimer, D., and Mukamel, D. (2015). California hospital networks are narrower in marketplace than in commercial plans, but access and quality are similar. *Health Affairs*, 34(5):741–748.

Ho, K. (2006). The Welfare Effects of Restricted Hospital Choice in the US Medical Care Market. *Journal of Applied Econometrics*, 21(7):1039–1079.

Ho, K. and Lee, R. (2017). Insurer Competition in Health Care Markets. *Econometrica*, 85(2):379–417.

Ho, K. and Lee, R. (2019). Equilibrium provider networks: Bargaining and exclusion in health care markets. *American Economic Review*, 109(2):473–522.

Kong, E., Layton, T., and Shepard, M. (2022). Adverse Selection Pricing and Unraveling of Competition in Insurance Markets.

Lavetti, K. and Simon, K. (2018). Strategic Formulary Design in Medicare Part D Plans. *American Economic Journal: Economic Policy*, 10(3):154–92.

Liebman, E. (2018). Bargaining in Markets with Exclusion: An Analysis of Health Insurance Networks.

Mattocks, K., Elwy, A., Yano, E., Giovannelli, J., Adelberg, M., Mengeling, M., Cunningham, K., and Matthews, K. (2021). Developing network adequacy standards for va community care. *Health Services Research*, 56(3):400–408.

McGuire, T., Glazer, J., Newhouse, J., Normand, S., Shi, J., Sinaiko, A., and Zuvekas, S. (2013). Integrating risk adjustment and enrollee premiums in health plan payment. *Journal of Health Economics*, 32(6):1263–1277.

McWilliams, J., Hsu, J., and Newhouse, J. (2012). New Risk-Adjustment System Was Associated With Reduced Favorable Selection In Medicare Advantage. *Health Affairs*, 31(12):2630–2640.

Nevo, A. (2000). Mergers with Differentiated Products: The Case of the Ready-To-Eat Cereal Industry. *The RAND Journal of Economics*, pages 395–421.

Nicholson, S., Bundorf, K., Stein, R., and Polsky, D. (2004). The Magnitude and Nature of Risk Selection in Employer-Sponsored Health Plans. *Health Services Research*, 39(6):1817–1838.

Pakes, A., Porter, J., Ho, K., and Ishii, J. (2015). Moment Inequalities and their Application. *Econometrica*, 83(1):315–334.

Park, S., Basu, A., Coe, N., and Khalil, F. (2017). Service-level Selection: Strategic Risk Selection in Medicare Advantage in Response to Risk Adjustment. *NBER Working Paper*, (24038).

Pauly, M. and Herring, B. (2007). Risk Pooling and Regulation: Policy and Reality in Today's Individual Health Insurance Market. *Health Affairs*, 26(3):770–779.

Petrin, A. and Train, K. (2010). A Control Function Approach to Endogeneity in Consumer Choice Models. *Journal of Marketing Research*, 47(1):3–13.

Polyakova, M. (2016). Regulation of Insurance with Adverse Selection and Switching Costs: Evidence from Medicare Part D. *American Economic Journal: Applied Economics*, 8(3):165–195.

Prager, E. and Tilipman, N. (2020). Regulating Out-of-Network Hospital Payments: Disagreement Payoffs, Negotiated Prices, and Access.

Riascos, A. (2013). Complementary compensating mechanisms of ex ante risk adjustment in colombian competitive health insurance market. *Revista Desarrollo Y Sociedad*, 71(1):165–191.

Riascos, A., Alfonso, E., and Romero, M. (2014). The performance of risk adjustment models in colombian competitive health insurance market. *Documentos CEDE*, (33).

Riascos, A. and Camelo, S. (2017). A note on risk-sharing mechanisms for the colombian health insurance system. *Documentos CEDE*, (30):1–14.

Riascos, A., Romero, M., and Serna, N. (2017). Risk Adjustment Revisited using Machine Learning Techniques. *Documentos CEDE*, (27).

Ruiz, F., Amaya, L., Garavito, L., and Ramírez, J. (2008). *Precios y Contratos en Salud: Estudio Indicativo de Precios y Análisis Cualitativo de Contratos*. Ministerio de la Protección Social.

Shepard, M. (2022). Hospital Network Competition and Adverse Selection: Evidence from the Massachusetts Health Insurance Exchange. *American Economic Review*, 112(2):578–615.

Tebaldi, P. (2017). Estimating Equilibrium in Health Insurance Exchanges: Price Competition and Subsidy Design under the ACA.