

Dafny, Leemore; Hendel, Igal; Wilson, Nathan

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# Narrow Networks on the Health Insurance Exchanges: What Do They Look Like and How Do They Affect Pricing? A Case Study of Texas

*By Leemore Dafny, Igal Hendel, and Nathan Wilson\**

\* Dafny: Kellogg, Northwestern University, Evanston, IL 60208, (e-mail: [l-dafny@kellogg.northwestern.edu](mailto:l-dafny@kellogg.northwestern.edu)); Hendel: Department of Economics, Northwestern University, Evanston, IL 60208 (e-mail: [igal@northwestern.edu](mailto:igal@northwestern.edu)); Wilson: Bureau of Economics, Federal Trade Commission, Washington DC, 20580 (e-mail: [nwilson@ftc.gov](mailto:nwilson@ftc.gov)). The views expressed in this article are those of the author. They do not necessarily represent those of the Federal Trade Commission, and the work was not prepared as part of the author's work for the FTC. We thank Mariano Irace, David Benson and Chris Ody for tremendous assistance.

The health insurance exchanges established by the Affordable Care Act opened in October 2013, potentially auguring a new era for the insurance industry and American health care overall. Myriad insurance market regulations were simultaneously implemented, most notably the requirements that insurers take all comers (“guaranteed issue”), and vary

premiums only by location, household structure, age, and smoking status. The vast majority of legal residents ineligible for public insurance and lacking access to “affordable” coverage through an employer or spouse became eligible for income-based subsidies to purchase plans on the exchange.<sup>1</sup>

The new exchanges (or “marketplaces” in government parlance) offer plans classified by “metal tiers.” These tiers are distinguished by actuarial value (AV), defined as the share of healthcare spending that an insurance plan pays for a typical enrollee. However, even within a given tier, plans may vary in several financial

<sup>1</sup> The exception are individuals between 100 and 133% of the federal poverty line, who do not qualify for subsidies or Medicaid in states that did not elect to expand Medicaid. The Kaiser Family Foundation estimates 4.8 million individuals fall in this category. Source: “The Coverage Gap: Uninsured Poor Adults in States that Do Not Expand Medicaid,” *Kaiser Family Foundation Issue Brief*, March

2014. [http://kaiserfamilyfoundation.files.wordpress.com/2014/04/8505-the-coverage-gap\\_uninsured-poor-adults-in-states-that-do-not-expand-medicaid.pdf](http://kaiserfamilyfoundation.files.wordpress.com/2014/04/8505-the-coverage-gap_uninsured-poor-adults-in-states-that-do-not-expand-medicaid.pdf)

and nonfinancial dimensions. We focus on the dimension of network breadth or value, specifically with respect to hospitals. “Narrow” or “limited” networks - which are much more prevalent in plans offered on the exchanges than off, have generated significant public debate (e.g., Howard, NEJM, 2014). We have three primary objectives: (1) to describe networks on offer on the exchanges; (2) to construct measures of network breadth and value; and (3) to explore the link between price and network value, and, in so doing, gain insights into the validity of choice models commonly used in provider merger analyses (next draft). Our data is at present restricted to the state of Texas, the largest state with a federally-facilitated marketplace.

## **I. The Texas Health Insurance**

### **Marketplace**

The Texas Health Insurance Marketplace is operated by the federal government. The state is divided into 26 markets called “ratings areas.” 25 of these areas consist of a county or contiguous counties encompassing a city or town; the 26<sup>th</sup> (which accounts for 11.5% of the state’s population) is a hodgepodge of all remaining counties.<sup>2</sup> Whereas insurers’ participation decision may vary at the county level (i.e. a plan need not be available to residents of all counties within a given ratings areas), pricing can vary only at the ratings area level. We restrict attention to plans in the “silver” tier (corresponding to an AV of 70 percent), as all participating insurers must offer at least one silver plan, and all insurer-network configurations are represented in this tier.<sup>3</sup>

<sup>2</sup> We exclude ratings area 26 from our analyses owing to difficulties in gathering data on in-network hospitals.

<sup>3</sup> This need not be true in other states, and/or in 2015 and beyond; in other words, we are unaware of a regulation requiring all networks

offered by an insurer to be offered within the silver tier. Note that “plan” refers to a choice available on the exchange.

Ten insurers offered plans in at least 1 ratings area in 2014. Three of these insurers participated in 1-2 ratings areas. Blue Cross and Blue Shield of Texas (BCBS-TX) was the only carrier to offer a plan in all ratings areas.

BCBS-TX also offered two distinct networks in each ratings area, a narrow one in conjunction with an HMO product, and a very broad one linked to a PPO product. No other carrier offered more than one network in the same ratings area. Online Appendix Table 1 provides additional detail on insurer participation and networks by area.

## II. Network Breadth and Value

We consider a simple measure of network breadth and a more complex measure of network value (derived from a model of hospital demand):

**Discharge Shares:** Discharge shares are defined at the network-ratings area level, and then matched to the plans utilizing that network. (For example, Blue Cross offers 2 silver HMO plans in Houston, both of which utilize the Blue Advantage HMO network.) We calculate the discharge share as the ratio of patient discharges in hospitals belonging to a network over the total number of discharges to patients residing in the ratings area.<sup>4</sup> Online Appendix Figure 1 illustrates the variation in breadth as measured by discharge shares.

**Expected Utility:** We construct a measure of the expected utility associated with a network by estimating a discrete choice model of hospital demand, and aggregating across the predicted utilities of admissions for each patient location-diagnosis-network combination using the actual data on patient locations and statewide probabilities of

<sup>4</sup> For plans only offered in a subset of counties within a ratings area, we construct the discharge share (and expected utility measure) using data for residents in those counties.

admissions in an exhaustive set of diagnosis categories. Additional details on the data source and estimation are described in the Data Appendix.

We find the correlation between discharge shares and expected utility is high ( $r=0.86$ ), but as Online Appendix Figure 1 illustrates, there is significant variation in expected utility for the broadest networks (in which share of discharges is at or close to 1).

### **III. Which Hospitals Are Included in Networks?**

To gain a better understanding of which hospitals are included in narrow networks, we constructed a dataset using the hospital-insurer-network-ratings area as the unit of observation. In every ratings area, observations are generated for all general acute-care hospitals located in that area that are also included in at least one network offered in

that ratings area. We define an “in network” indicator that takes a value of “1” if a hospital is included in the relevant hospital-insurer-network-ratings area. Descriptive statistics are presented in Online Appendix Table 2. The mean value for “in network” is 0.57 – considerably lower than the mean of 0.83 reported by Ho (2009) study of HMO/POS networks in 43 U.S. markets. That is, the average network on the Texas exchange is considerably narrower than the networks utilized by managed care plans in 2002 (the year of Ho’s data).

Online Appendix Table 3 reports the results of linear probability models of network inclusion.<sup>5</sup> Our first specification includes only hospital characteristics (such as case-mix index, and a dummy for system membership of different types). We progressively add insurer fixed effects (column 2), and ratings areas fixed effects (column 3). The insurer dummies are

<sup>5</sup> Probit models yielded qualitatively similar results; we use linear probability models for ease of interpretation.

highly predictive, with all insurers apart from Cigna having less inclusive networks (on average) than the narrow Blue Cross network (the omitted category). However, there appears to be a common preference for hospitals with more beds, lower case-mix indices, and critical access designations. Interestingly, we do not find non-Medicare price to be predictive of network inclusion. (In future work, we plan to consider additional hospital and market characteristics in these models, e.g. service lines.)

#### **IV. How Does Network Breadth Affect Premiums?**

To explore the relationship between network breadth/value and plan premiums, we estimate hedonic pricing models. The unit of observation is the plan-ratings area, and our regressand is the log of plan premium for a 27-

year-old single policyholder.<sup>6</sup> Descriptive statistics are available in Online Appendix Table 4. Table 1 presents results obtained using the discharge ratio as the regressor of interest, and Online Appendix Table 5 presents results using expected utility. All models include control variables designed to account for non-network related variation in the different plans. In particular, we include an indicator variable for whether there is a deductible, the log of the deductible if it is non-zero, the log of the maximum out of pocket expenses a patient might bear, and a set of ratings area fixed effects. In all models, we report standard errors that are clustered at the insurer-ratings area level. We weight observations to reflect the relevant population in counties with access to the plan; details are provided in the table notes.<sup>7</sup>

<TABLE 1 HERE>

<sup>6</sup> Plan premiums for other ages and family structures are a constant percentage of the 27-year-old single premium.

<sup>7</sup> The results are qualitatively similar when we do not weight observations. Details are available upon request.

As previously noted, BCBS was the only carrier to simultaneously offer both broad and narrow networks. Therefore, absent another source of variation in network coverage, we would have to rely on variation across rather than within insurance carriers to identify the coefficient of interest. Fortunately, the fact that most carriers operate in a number of markets enables us to estimate models that control for insurer fixed effects and to exploit within-insurer variation in network breadth and value across markets.

We begin by estimating a model including all the variables described above as well as a dummy for BCBS, which is a low-priced carrier in most markets. The results, displayed in Column 1 in Table 1 and Online Appendix Table 5, show no relationship between network breadth and premiums. However, once we include fixed effects for all insurance carriers (Column 2), we find a positive and significant relationship: a one-standard deviation increase in discharge ratio (expected utility) is

associated with a premium increase of 10 percent (8 percent). Separating the sample into non-BCBS (Column 3) and BCBS plans (Column 4) shows the association between price and network breadth is driven by the latter.

Column 5 adds a dummy for HMO (which is collinear with insurer dummies in the non-BCBS sample). The results reveal that our estimate of the price effect of network breadth/value is largely due to lower across-the-board prices for BCBS' HMO/narrow network plan. The relative narrowness of the Blue Advantage HMO network across markets is a small and mildly significant predictor of premiums. This result is confirmed by a simple examination of BCBS' pricing. BCBS priced its (narrow) Blue Advantage HMO plans roughly 22% lower than its (broad) Blue Choice PPO plans in all markets; the exact ratio for each market is given in Online Appendix Table 1.

We conclude that, at least in year 1 of the Texas Health Insurance Marketplace, network narrowness and consumer valuation of networks does not seem to explain much of the observed premium variation. It is likely that these measures reflect information that is difficult for individual insurance purchasers to access and to process. (Certainly the process to gather the data from insurers was arduous even for trained research assistants, requiring multiple web searches and repeat phone calls.)

#### **IV. Discussion**

The data and analysis we present in this paper suggest the projected consumer valuation of the network affiliated with a particular insurance product may not be as directly related to pricing as some of the discussion surrounding narrow networks has suggested. However, it is difficult to separately identify insurer and network effects in hedonic models of premiums in Texas markets. To the extent

network breadth/value predicts price, a simpler measure (discharge share) does not do measurably worse, and may in fact be superior in terms of fit than a measure derived from patient choice models. These findings suggest that insurers and consumers may rely on simple heuristics for pricing (and valuing) different providers. Other markets may provide richer data with which to test alternative measures of network value. In future drafts, we aspire to identify those markets where such measures are more strongly correlated with premiums, and to understand the drivers of this correlation and the implications for models of hospital choice and hospital-insurer bargaining.

#### **Online Data Appendix**

To construct our estimates of the expected utility associated with every network-ratings area pair, we estimated a discrete choice model of hospital demand using inpatient discharge data from the Texas Department of State Health Services Center for Health Statistics for 2010.



We cleaned the data to focus on the decision-making of patients receiving referred non-urgent care at general acute care facilities. We exclude admissions to facilities focusing on rehabilitation, specialty services, and the provision of long term acute care, as well as admissions missing key data elements (e.g., age, patient residence, admission diagnosis).

With the cleaned Texas data, we construct our measure of the expected utility that a consumer will gain from choosing a given network following the approach laid out in the existing literature (Capps et al., 2002; Ho, 2006, 2009). The first step is to estimate a discrete choice model for hospitals allowing for differences across individuals. We do this using the flexible semiparametric estimator

<sup>8</sup> Our categorizing variables are as follows. Our initial categorizing variable is patients' zip code of residence. This should capture a large degree of variation in location, income and other patient characteristics affecting provider choice. In addition, we use three age groups: under 18; 18-64; and 65 and over. For conditions, we use the combination of seven disease categories based off of the HCFA's Major Diagnosis Categories: respiratory; circulatory; digestive; orthopedic; endocrine and kidney; reproductive and obstetric; and all others. We further subdivide these categories by degree of condition acuity as proxied by the weight attributed to their diagnosis-related group (DRG). We use three such groups: low (weight under 1); medium (weight between 1 and 2); and high (weight above 2).

described in Carlson, et al. (2012). This approach involves first partitioning patients into mutually exhaustive bins based around their demographic characteristics and conditions.<sup>8</sup> Then we use the empirical probabilities that observationally equivalent individuals within these bins go to different hospitals to form predicted choice probabilities for the relevant set of hospitals for each bin. These predicted probabilities are merged back to the patient-level data so that we have a predicted probability for each relevant hospital for each patient in our sample.<sup>9</sup>

In order to turn these predicted probabilities into estimates of expected utility, we use the nonlinear inversion of shares to recover the underlying value of consumers' expected

<sup>9</sup> In an effort to avoid the problems posed by "thin" bins, we implement a modest extension of the approach described in Carlson et al. This involves iteratively dropping categorizing variables, and forming new estimated choice probabilities. The choice probability from the richest model will be kept if calculated for a bin of at least a certain threshold size (in our case 20). If not, the choice probability will be taken from the second richest model, provided that it was calculated for a bin of at least the threshold size. This process was repeated until all observations had choice probabilities.

utility for each hospital (Berry 1994). However, instead of normalizing by the value of the outside option, we focus on a large provider utilized by many consumers state wide: Medical City Dallas Hospital.<sup>10</sup> In those cohorts where this choice was never utilized, we impose that it nonetheless had a very small chance of being chosen so that the normalization utility was well-defined.

To form estimates of the ex-ante desirability of insurer networks, we follow the same approach as Ho (2006, 2009), aggregating over consumers within ratings areas. A key part of this aggregation process relates to consumers' ex ante expectations of suffering different conditions. We construct these expectations based around the realized outcomes within age group state-wide. In other words, conditional on age group, we assume that heart disease equally afflicts consumers in Lubbock and Austin. This broadly adheres to

the approach taken by Ho (who separated consumers further by gender).

The usefulness of our expected utility metric relies on our ability to match the hospitals in the discharge data to the hospitals in the insurer network data. The latter was gathered manually from insurer websites by our research assistants. We begin by identifying AHA IDs for hospitals appearing in each data source. We then match the two datasets by AHA ID. As a test of the accuracy of our process, we calculated the share of beds in a ratings area (according to the AHA) that is accounted for by hospitals appearing in at least one network for that ratings area. We find that ratings area 26 has a relatively low “share captured” (64%), and this is among the reasons we exclude ratings area 26 from our estimation sample. The other semi-outlier is ratings area 1, with a share captured of 75%. Across the

<sup>10</sup> The choice of facility was largely arbitrary. A general hospital appearing in many choice sets was chosen.

remaining areas (2-25), the lowest share captured was 92%, and the average was 99%.

#### REFERENCES (HEADING)

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- Howard, D. H. 2014. "Adverse effects of prohibiting narrow provider networks," *New England Journal of Medicine*, 371, 7, 591-593.
- Ho, Kate. 2009. "Insurer-Provider Networks in the Medical Care Market," *American Economic Review*, 99, 1, 293-330.

TABLE 2: RELATIONSHIP BETWEEN NETWORK BREADTH AND PLAN PREMIUMS

Sample	All plans		Non-BCBS plans	BCBS plans	
	(1)	(2)	(3)	(4)	(5)
discharge ratio	0.0227 [0.0796]	0.268 [0.0504]***	-0.0362 [0.0456]	0.421 [0.0132]***	0.0260 [0.0135]*
deductible is 0	0.149 [0.362]	-0.401 [0.154]**	-0.388 [0.295]		
ln(deductible   >0)	0.00993 [0.0484]	-0.0659 [0.0200]***	-0.0639 [0.0379]*	-0.0444 [0.0000878]***	-0.0444 [0.0000884]***
ln(max OOP)	0.349 [0.310]	-0.291 [0.0874]***	-0.278 [0.123]**		
Insurer fixed effects	N	Y	Y	N	N
R-sq	0.398	0.734	0.822	0.851	0.997
Observations	251	251	151	100	100

Notes: Sample excludes metal colors other than Silver, ratings area 26, multi-state plans, one observation with an Exclusive Provider Network (EPO), and the sole plans offered by Sendero and Community First remaining after the other restrictions. Two insurers, Community Health Choice and Molina Marketplace have zero deductibles: ln(deductible) is coded as zero in this cases. All specifications include ratings area fixed effects. Observations are weighted using the county population divided by the number of plans offered in the county, summed over the counties within the ratings area in which the plan is offered. Standard errors are clustered by ratings area x insurer network. Standard errors are listed in [].  
\* p<0.10, \*\* p<0.05, \*\*\* p<.01