Bargaining in Markets with Exclusion:  
An Analysis of Health Insurance Networks

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Abstract

This paper explores the common story that insurance companies exclude hospitals from their networks to gain bargaining leverage in contract negotiations. I propose a novel model of price formation in a bilateral oligopoly setting where the networks are endogenous. The endogeneity of its network allows the insurer to threaten to exclude hospitals. Exclusion is an equilibrium outcome; the insurer offsets the loss of premiums from a less valuable network by reimbursing hospitals less. I estimate this model using data from the Colorado All-Payer Claims Database. I find, using a counterfactual analysis, that restricting insurers' ability to exclude would lead to 50 percent higher prices negotiated between hospitals and insurers, while the Nash-in-Nash framework used in the hospital-insurer bargaining literature finds prices would fall by 36 percent.

1 Introduction

Spending on health care in the United States totals three trillion dollars per year, more than 350 billion dollars of which is spent by private insurance companies at hospitals[1]. Because of this high spending, policy makers and insurance companies have a considerable interest in controlling health care costs. One aspect of cost control used by insurance companies is to form networks. An insurance network is a list of providers which the insurance company incentivizes its patients

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to visit. Patients who visit a provider outside of their insurance network often face reduced or no
coverage for those services.\footnote{For example, out of network visits may have a higher copay, higher coinsurance or the payments do not factor into the deductible.}

This paper formalizes and explores the implications of a common story among health care
insiders: that the threat of exclusion from networks improves insurers’ bargaining leverage in their
negotiations with providers. \textcite{Howard2014} provides one example of this intuition: “Networks
give insurers leverage in their negotiations with providers over reimbursement rates. Insurers rely
on the threat of exclusion rather than the actual narrowness of their networks – providers that
do not face the threat of exclusion have little reason to temper their demands for higher prices.”
In my data, plans that exclude providers, often referred to as “narrow networks,” pay 23 percent
less at the same hospital for the same services. I present this result as suggestive evidence that
the bargaining leverage theory may account for substantial savings, while other mechanisms that
explain why narrow networks reduce insurers’ costs cannot easily explain this comparative static.\footnote{I discuss other mechanisms in section \ref{sec:conclusions}.}

Despite their cost savings, narrow-network health insurance plans are controversial.\footnote{See \textcite{Howard2014}, \textcite{Corlette2014}, or \textcite{Baicker2015} for more details on the policy discussion about restricting narrow networks.} The concern among regulators is that patients lack information about which conditions they will get in the future; without knowing what conditions they will have in the coming year, they may not check whether high quality providers are available in each specialty. This concern has grown due to the prevalence and popularity of narrow-network health plans in the insurance marketplace (referred to as “exchanges”) set up by the Affordable Care Act (ACA). In a national study, \textcite{Bauman2014} find that 45 percent of plans on the ACA health insurance exchanges have narrow networks, and in my sample 71 percent of patients are enrolled in a plan with a narrow network.\footnote{Bauman et al. (2014) define a narrow-network health plan as having less than 70 percent of that market’s hospitals in network. I follow their definition for this analysis. They find that roughly 90 percent of patients have access to narrow-network plans, but 90 percent also have access to broad-network health plans.} These plans are popular because, while they provide fewer options for care, they also charge lower premiums to consumers. For example, \textcite{Bauman2014} find that narrow-network plans charge premiums 13-17 percent lower than broad-network plans.\footnote{Their results control for metal level (a measure of the actuarial value of the plan), insurance company, plan type (e.g., HMO or PPO) and location.}

There is considerable policy interest around regulating these plans. The ACA included the
first federal “network adequacy” law, which sets standards that networks must meet, though it left
defining “adequate” to the states. Many states have since updated or are considering updating
their regulations.\footnote{Another common restriction on exclusion is an “any willing provider” law, which requires insurance companies to cover all medical providers willing to agree to the terms offered by the plan. In 2014, 27 states had passed some form of any willing provider law, though in many states this does not apply to hospitals. Source: \url{http://www.ncsl.org/research/health/any-willing-or-authorized-providers.aspx}}

However, careful regulation requires a trade off between the value of extra access to providers
and higher premiums due to reduced insurer bargaining leverage. One of the main contributions of this paper is to provide an empirical framework to better understand why, and how much, restricting insurers’ ability to exclude would raise costs. I argue that a structural model is needed to evaluate how much these laws would raise costs, since a reduced-form analysis may suffer from a bias due to the endogeneity of these networks.

To formalize how an insurer can use the threat of exclusion to gain leverage, I propose a novel model of price formation in a bilateral oligopoly setting where the networks are endogenous. My model nests the Nash-in-Nash bargaining model, which has become the workhorse model of vertical competition; when exclusion is assumed to be exogenous my model is identical to Ho and Lee (2017). Therefore, my model shares many of the advantages of the Nash-in-Nash model, it is in a bilateral oligopoly setting, allows for heterogeneity in the amount of available surplus and accounts for externalities and interdependencies between hospitals and insurers. However, allowing for the endogeneity of the networks allows me to capture two important institutional features of this market: the insurer uses the threat of exclusion to gain bargaining leverage, and exclusion is an equilibrium outcome of this model.

The model also allows for richer forms of competition between hospitals than the Nash-in-Nash model. In the spirit of Town and Vistnes (2001), my model allows excluded hospitals, which may be substitutes for those in the observed network, to effect the negotiations of hospitals who will reach an agreement. For example, an insurer’s threat to exclude a particular hospital may be more salient if there is a similar hospital to replace it with. A drawback of the Nash-in-Nash model is that negotiations are not affected by excluded hospitals.

To estimate this model, I use data from the Colorado All-Payer Claims Database (APCD), which is one of the few sources used in this literature that provides information on negotiated prices between all insurers and all hospitals. The setting for my study is the non-group market in the Denver, Colorado rating area. The non-group market is where individuals purchase insurance when it is not available through their employer and they are not eligible for government insurance (e.g., Medicare, Medicaid, Tricare, etc.). The ACA exchanges are included in the non-group market. As such, this is among the first papers which studies competition on the ACA exchanges.
Games with randomly ordered sequential agreements, which are commonly used in the literature where prices and networks are endogenous, can be difficult to estimate, especially when externalities between players are allowed. However, the main insight of the estimation section, and one reason for extending the Nash-in-Nash model, is that the networks form simultaneously, which simplifies estimation considerably. Extending the Nash-in-Nash model also allows me to compare my estimates with the hospital-insurer bargaining literature. This literature uses a rich model of the health insurance market to understand how consumer preferences over premiums, networks, and hospitals affect price formation. The bargaining model is only one stage of that broader model. I use the same model of consumer preferences over hospitals and health plans as Ho and Lee (2017) and Prager (2016) to isolate the contribution of the new bargaining stage from other features of this broader model.

While the role of exclusion is important for policies affecting how insurers form their networks, the Nash-in-Nash bargaining parameters are also policy relevant. If hospitals have a lot of relative bargaining power, then restricting one of the insurer’s tools to gain leverage may have a large effect on prices. On the other hand, if insurers have a lot of relative bargaining power, even without the use of exclusion, then these policies would not impact prices much.

To show that ignoring exclusion in estimation can be problematic, I analyze the effects of a counterfactual law where insurers are not allowed to exclude (i.e., a network adequacy law). The Nash-in-Nash model suggests that under the law prices would fall by 36 percent; plans that had narrow networks prior to the law now would distribute their enrollees across more hospitals, reducing the marginal surplus provided by any given hospital. However, by removing the bargaining leverage that exclusion provides, my model suggests that the law would increase the prices insurers pay by 50 percent, which is consistent with conventional wisdom that restricting narrow networks would increase costs for insurers.

The remainder of this paper is organized as follows. Section 2 discusses the related literature and other theories about why narrow-network plans lower costs for insurers. Sections 3 and 4 discuss the data I use and reduced-form evidence. Section 5 presents a stylized model to demonstrate how exclusion can lead to lower prices for the insurer and why it is an optimal strategy for the insurer. Section 6 discusses the computation of surplus and then, given the surplus values, estimation of the bargaining model. Sections 7 and 8 discuss the results and counterfactual estimates. Section 9 discusses limitations, extensions, and next steps. Section 10 concludes.

2 Literature Review

I highlight the contribution of my paper in three literatures: (1) a reduced-form literature on the savings from managed care, (2) theory on exclusion and bargaining over networks, and (3) the

\[^{12}\text{Abreu and Manea (2012), Manea (2015) and Elliott and Nava (2015) are examples of papers in this literature.}\]
Nash-in-Nash bargaining model. The final subsection discusses other proposed mechanisms for why narrow-network plans may save money for insurers.

2.1 Reduced-Form Estimates of Savings from Managed Care

Narrow networks are one strategy that “managed care” plans, such as health maintenance organizations (HMOs), use to reduce costs. Other strategies include incentivizing physicians to limit utilization, requiring a primary care gatekeeper to approve specialist visits, and more aggressive cost sharing. Much of the literature quantifying the savings from managed care do not separately account for the role of networks, which is a limitation of my paper as well.13 Most of the papers in the literature find large savings comparing managed care prices relative to fee-for-service. Gruber and Mcknight (2016), Cutler et al. (2000), and Altman et al. (2003) all look at per patient costs or cost per episode of care, and find savings around 30-40 percent, controlling for patient mix. However, cost per patient may include differences in utilization intensity.14 Wu (2009) and Dor et al. (2004) examine negotiated prices per procedure, which should not be affected by patient mix or utilization intensity, and is consistent with the unit being negotiated over. Wu (2009) and Dor et al. (2004) find effects of 26-50 percent and 20 percent, respectively. The estimates in my reduced-form analysis also use price per procedure and the magnitude of my findings are consistent with this literature. I also attempt to distinguish between lower negotiated prices and narrow-network plans shifting patients to cheaper hospitals.

2.2 Theory on Exclusion and Bargaining Over Networks

This paper is related to a broad theoretical literature on competition in vertical relationships and exclusive dealing.16 It is most closely related to Gal-Or (1997), who demonstrates in a stylized two-by-two model of hospital-insurer bargaining that exclusion can lead to insurers negotiating lower prices and can be an equilibrium outcome. Lee and Fong (2013) propose a dynamic model of hospital-insurer bargaining, where the networks are determined by a cost of agreement and dynamic considerations. This paper also contributes to the sparse empirical literature on exclusive dealing.17

This paper is also related to a recent literature on bargaining when prices and networks are endogenous. This includes Abreu and Manea (2012), Manea (2015) and Elliott and Nava (2015). Within this literature, my paper is closest to Camera and Selcuk (2010) who show how an endogenous capacity constraint can be used to negotiate lower prices. The models in this literature are

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13 Cost sharing refers to using copay or coinsurance to limit patients’ use of services.
14 As discussed in Cutler et al. (2000), these other strategies are primarily used to reduce utilization. However, Prager (2016) highlights how cost sharing may spillover into bargaining.
15 Patient mix refers to how sick patients are. Utilization refers to how many services a patient receives, conditional on how sick they are.
all very stylized; my model differs in that it allows for more heterogeneity and I use simultaneous agreement in order to simplify estimation.

2.3 Nash-in-Nash Bargaining Model

The literature on bargaining has a long history starting with the axiomatic approach to bargaining proposed by Nash (1950). Crawford and Yurukoglu (2012) extends the Nash bargaining solution to a bilateral oligopoly setting by invoking the bargaining protocol of Horn and Wolinsky (1988); each negotiation is modeled as a pairwise Nash bargaining solution, conditional on the outcome of all other negotiations. That is, it is a Nash equilibrium of Nash bargains, hence “Nash-in-Nash”. Collard-Wexler et al. (2016) provides non-cooperative foundations of the Nash-in-Nash model with an alternating offers, many-to-many, bargaining game similar to the pairwise bargaining game in Rubinstein (1982). Collard-Wexler et al. (2016) also provides sufficient conditions for when their non-cooperative model limits to the Nash-in-Nash model, analogous to Binmore et al. (1986) who show that Rubinstein (1982) limits to the pairwise Nash bargaining solution. To be precise, I propose a model which nests Collard-Wexler et al. (2016). When I compare my model to Nash-in-Nash, I am invoking their result that their non-cooperative solution limits to Nash-in-Nash.

The Nash-in-Nash model has been used extensively in the applied literature to model bilateral oligopoly settings because it allows for externalities and interdependencies between players, heterogeneity in surplus, and is relatively easy to estimate. The model has been used in a number of markets with vertical competition including: television (Crawford and Yurukoglu, 2012), medical devices (Grennan, 2013), bricks (Beckert et al., 2015), and gas stations (Soares, 2016). However, modeling a market with many firms on either side of the market as the outcome of pairwise Nash bargains ignores a lot of interesting economics (i.e., externalities from excluded players, punishment strategies, signaling, ordering of negotiations, informational asymmetries, etc.). This makes the model more tractable and in an applied setting data typically do not contain information about other aspects of negotiations. Furthermore, if these strategies or features of the market are present, they will be accounted for in the estimated bargaining parameters. This is consistent with the interpretation of the bargaining parameters. I extend this model by allowing another strategy, the threat of exclusion, which I have data on, to be incorporated into the model.

The Nash-in-Nash model can only explain exclusion if the incremental surplus from any agreement is negative. While they do not use the Nash-in-Nash model, Capps et al. (2003) and Ho (2009) provide intuition for what “exogenous exclusion” means in this setting. A plan may not reach an agreement with a hospital if the additional costs it incurs by including the hospital in the network is larger than the marginal benefit of including that hospital. While a number of other papers have attempted to account for exclusion in the Nash-in-Nash framework, in these papers the exclusion is exogenous and is due to firms’ surplus functions.\footnote{For example, Crawford and Yurukoglu (2012) uses this argument in the television market where the threat of}
Incorporating the threat of exclusion into the bargaining model is this paper’s contribution to the hospital-insurer bargaining literature. This particular literature began with Town and Vistnes (2001) and Capps et al. (2003) who specify a model of consumer valuation of hospital networks. Gowrisankaran et al. (2014) incorporated the Nash-in-Nash model into this literature. Other papers using the Capps et al. (2003) model of network valuation and the Nash-in-Nash model include Lewis and Pflum (2015), Ho and Lee (2017), and Prager (2016). While they do not use the Nash-in-Nash model, the following papers are also related. Shepard (2016) provides evidence that networks can reduce costs for insurers by excluding hospitals that attract high cost or high risk patients. Ho (2009) proposes a model of hospital networks using inequalities defined by what I refer to as exogenous exclusion. Finally, a current job market paper, Ghili (2016), proposes a bargaining model based on Jackson and Wolinsky (1996) to account for the endogeneity of the networks and the bargaining leverage that this may provide. Prager also develop a variant on the Nash-in-Nash model to account for the possibility of narrow networks.

### 2.4 Other Mechanisms for Savings from Narrow Networks

Finally, a number of other mechanisms have been proposed for why narrow-network plans have lower costs, including that they: (1) only use lower cost hospitals, (2) concentrate patient volume at fewer hospitals, and (3) avoid high cost patients who value broader networks. (1) This story would not explain variation in prices for the same services at the same hospital as I use in the reduced-form evidence section. (2) The standard assumptions made in the Nash-in-Nash hospital-insurer bargaining literature (constant marginal cost and declining marginal value of additional hospitals) implies that narrow networks should pay higher prices, all else constant. (3) Would lead to higher per patient costs, but would not explain lower negotiated prices per service. I believe these mechanisms are not mutually exclusive and my empirical model accounts for (1) and (2), while (3) is considered out of scope of this paper.
3 Data

The main data for this analysis is from the Colorado APCD. In addition, I supplement this data with information about premiums and networks from the Colorado Department of Insurance and company websites. I also use data from the American Hospital Association survey of hospitals.

The APCD is a collection of all the health insurance claims for (nearly) all insurance companies in Colorado. For enrollees of these plans, the claims reveal all their reimbursed encounters with health care providers. That is, the claims data contain detailed information about all reimbursed hospital visits, physician visits, prescription drug purchases, and other reimbursed medical care.

A claim is submitted by a health care provider in order to get reimbursed by an insurance company. Each claim contains person-level identifiers, information on what services were provided, the associated diagnosis, and, importantly, the negotiated price between the insurance company and the hospital. I use only outpatient hospital visits, where the object of a negotiation is typically the price per Current Procedural Terminology (CPT4) code.\textsuperscript{23} There are roughly 15,000 different CPT4 codes that represent very detailed services provided, for example a preventative doctor’s visit distinguishes between five different age groups and also between whether this was a first visit or not. The claims also contain diagnosis codes, represented by ICD-9 codes, which provide information on the conditions the patients have.\textsuperscript{24}

On each claim I observe many different prices, including the amount the insurance company reimburses the hospital, the copay, coinsurance, the deductible, etc. I use the allowed amount on the claim, which is the sum of all of these prices, and refer to this as the negotiated price between the hospital and insurer for the remainder of the paper. The data also contains an enrollment file, which provides information on every enrolled member regardless of whether they submitted a claim. These data contain the age, gender, and five-digit zip code of the enrollee. Observing all enrolled members, not just those who submit claims, allows me infer overall enrollments of the plans, which is used in plan-demand estimates.

The data is suited for my research question due to three features. First, it has the negotiated prices and quantities between many hospitals and many insurers. In many markets having prices negotiated between two businesses is competitive information. This data contains prices and quantities for (nearly) all firms in the market. Second, that I observe (nearly) the entire non-group market in Colorado allows me to estimate insurance demand, providing information about downstream competition as well. Finally, that I observe many hospitals allows me to estimate hospital demand.

\textsuperscript{23}While the rest of the literature uses inpatient admissions, the data are too thin to provide precise estimates.

\textsuperscript{24}There are roughly 14,000 different designations of conditions. In order to have many observations for each condition, I use the Clinical Classification Software (CCS), as defined by the Agency for Health Research and Quality, to reclassify diagnoses into 18 broad conditions represented by the body system they affect. CCS codes are available at: https://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp. The CCS also groups conditions into about 270 distinct categories. In future iterations of this paper, I plan to use those definitions and treat the 18 categories as a robustness check.
I focus my analysis on the ACA exchange and the off-exchange non-group market. The non-group market sells insurance to individuals who do not receive insurance through their employer or other means (e.g., Medicare, Medicaid). To sign up for insurance on the exchange, a consumer would go to http://connectforhealthco.com/, while to sign up off the exchange a consumer would usually work with a broker or with an insurance company directly. A few plans are available only on the exchange or only off the exchange; however, for the plans offered in both settings, I cannot distinguish how the plan was purchased. I treat the on-exchange market and the off-exchange non-group market as one market since consumers have both in their choice set.

There are many advantages of using the non-group market. First unlike many employers, premiums are paid by consumers (though some may receive government subsidies) and consumers are the decision makers about which plans to purchase. The other advantage is that the data on premiums and networks are more easily available because the plans are sold to the public.

While I have data from across the state, I only require one market to estimate bargaining parameters, so I focus my analysis on the rating area which includes Denver. A rating area is a state-defined collection of counties where, due to the ACA, an insurance company in the non-group market may not vary premiums, except by age and whether the person purchasing insurance is a tobacco user. There are 10 counties included in the rating area that includes Denver county and Arapahoe and Adams counties, where Aurora is located. It does not include Boulder or Colorado Springs. In each of these counties a 40-year-old, non-smoker must be offered the same premium regardless of other characteristics, like gender or past health history. I use the rating area to define the market, though roughly 20 percent of hospital visits leave the rating area. Finally, I only use data in 2014, the first year of the ACA exchanges and the last year I have APCD data for. I discuss the sample construction in more detail in Appendix A.

The first panel of Table 1 presents summary statistics where the unit of observation is a network. There are five narrow-network plans in my data and four broad-network plans. To be consistent with Bauman et al. (2014) I define a narrow-network as having less than 70 percent of hospitals in the rating area in network, however, in practice the broad-network plans all have fifteen hospitals, while the broadest narrow-network plan in my sample has eight hospitals. This suggests that the definition of narrow network is somewhat binary. Results would not change if I define a narrow-network as having 55% or having 95% of hospitals in the rating area. Conditional on being a

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25 A consumer might prefer to use the exchange to access premium subsidies for lower-income individuals. The subsidies are only available for those purchasing insurance through the exchange.

26 Most of the plans in the non-group market are offered both on and off the exchange and, when that happens, the plans are nearly identical.

27 Gowrisankaran et al. (2014) address many of the issues involved in estimating a Nash-in-Nash model in an employer-sponsored insurance setting.

28 In Colorado, the rating areas are defined by counties; however, other states use metropolitan statistical areas or zip-codes to determine their rating areas.

29 Furthermore, age adjustments are limited so that an insurer can charge a 64-year-old at most three times more than a 21-year-old.
narrow-network, the mean number of hospitals is 5.6. The average monthly premium (for a 40-
year-old on a silver plan) is $323, though this varies between $245 and $380. The average premium
for a narrow-network plan is $307.

The second panel of table 1 presents enrollee-level summary statistics. There are 130,000
members in the non-group market sample. The mean age is 37, and 55 percent of sample is female.
71 percent of the sample is in a narrow-network plan. Six percent of enrollees have a claim at an
in-network and in-sample hospital.

The third panel of table 1 presents summary statistics on the payments per visit. While only 6
percent of enrollees submitted a claim, there were 17,124 visits, since an enrollee can have multiple
visits. The first row of this panel is for all visits at hospitals in my sample, including those out-of-
network. For those visits the average payment was $1,736. There were 12,472 and 8,382 in-network
visits for all plans and narrow-network plans respectively, with average payments of $1,628 and
$1,543.

The final panel of table 1 presents summary statistics on the payments per claim line. These
values are what I refer to as the negotiated price. There are roughly four times as many claims
as visits because a single visit can result in multiple claims if multiple procedures are performed.
The first row of this panel is for all claims at hospitals in my sample, including those that were
out-of-network. There were 65,582 claims with an average payment of $453. There were 47,814
and 35,195 in-network claims for all plans and narrow-network plans respectively, with average
payments of $424 and $367. These final two panels demonstrate a few important points about
the data. First, the difference in claims between the first and second row of each panel shows
that about 30 percent of claims were coming from out-of-network hospitals. This suggests that the
networks are not necessarily binding, as many patients go out of network. Second, payments to the
hospitals are highest out of network, then lower at broad-network plans and finally the lowest at
narrow-network plans.

4 Reduced-Form Evidence

In this section, I (1) provide reduced-form evidence that narrow-network health plans get lower
prices, (2) distinguish between the theory about sending patients to lower-cost hospitals and im-
proved insurer bargaining leverage, and (3) provide a sense of the magnitude of savings for insurers.
Then, because consumer welfare may be impacted if insurers’ cost savings are passed through to
premiums, I provide evidence that health plans with narrow networks also charge lower premiums.

Because this paper takes a stand that the networks are endogenous, I caution that these are
simply correlations and do not provide a causal estimate of the effect of narrow-networks. The
concern is that plans which otherwise would not be able to negotiate low prices are the most likely
to use the tool of exclusion. This results in non-random selection into network size; if a narrow-
network plan were randomly assigned to be a broad-network plan, it would pay higher prices than
other broad-network plans. If my model is correct, the naive comparison between broad- and narrow-network plans would provide an estimate of the treatment effect (on the treated) that is biased towards zero. I discuss this issue more precisely at the end of the stylized model section.

To provide suggestive evidence of the bargaining leverage story, I look at variation, across network sizes, at the same hospital for the same service. For example, do narrow-network plans pay less for an x-ray at hospital A than broad-network plans? In the introduction, I argued that many of the other explanations for why narrow-network plans have lower costs would not explain this comparative static. Then, to account for the story about sending patients to cheaper hospitals, I provide results without controlling for the hospital. That is, do narrow-network plans pay less than broad-network plans for an x-ray on average? I find evidence that supports both stories and they are both incorporated into the modeling framework. Formally, the regression equation is:

\[ \log(price_{csjr}) = \beta \cdot 1(Narrow Network_r) + \alpha_s + \alpha_j + \epsilon_{csjr} \]

The unit of observation is a claim line \( c \), where \( s \) refers to the service (CPT4), \( r \) the insurer and \( j \) the hospital. \( 1(Narrow Network_r) \) is an indicator for whether the patient receiving the service was in a narrow-network health plan. \( \alpha_s \) and \( \alpha_j \) are service and hospital fixed effects, respectively. In all regressions I cluster standard errors by the network. I use the log of price due to the skewness in health expenditure data. I limit the sample to just in-network visits.

The first column of Table 2 suggests that narrow-networks pay 23 percent less than broad-networks, for the same service at the same hospital. The second column defines the service as a CPT4 code and modifier code, which is a more granular description of the services performed.\(^{30}\) The results are slightly larger in magnitude. In the third column, I drop \( \alpha_j \), the hospital fixed effect. This answers the question of how much less insurers pay for the same services, when allowing patients to go to different hospitals. The coefficient of \( -29 \) suggests that narrow-networks pay twenty-nine percent less for the same service. While 29 percent seems large, the magnitude is consistent with the literature.\(^{31}\) This result provides evidence that both theories are relevant. Column four presents results that do not drop out-of-network visits. That the coefficient is statistically indistinguishable from zero shows an important empirical issue in working with narrow-network health plan data: it is important to only use in-network providers, because narrow-network plans often pay more out-of-network than broad-network plans.\(^{32}\)

While conventional wisdom, and some empirical evidence, suggests that narrow-networks negotiate lower prices, there is less evidence of whether a narrow-network should be thought of as

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\(^{30}\) A CPT4 modifier code may or may not affect reimbursement. One example is to specify if a surgery was performed with or without anesthesia.

\(^{31}\) For example, Wu (2009) finds discounts of 26 to 50 percent while Dor et al. (2004) finds discounts of roughly 20 percent using per procedure data.

\(^{32}\) In some cases, the narrow-network plans pay the amount charged by the hospital for the out-of-network visits. This is typically more than the out-of-network plans pay, since those plans still negotiate their prices down.
binary or whether the narrowness of the network also matters. My model will imply that the
narrowness matters, though the effect is diminishes quickly. To explore this, I replace the narrow-
network indicator with a linear term for the number of hospitals in the network and only include
narrow-network plans.

Table 3 presents results using the number of hospitals in a network, another measure of network
narrowness, with the same controls as Table 2. I drop broad-network plans to distinguish the
source of variation from Table 2. The first column suggests that an extra hospital in the network
is correlated with 5 percent higher negotiated prices. The third column presents results without
controlling for the hospital. Again, the results are slightly larger than with the hospital controls.
The fourth column, which includes out-of-network claims now shows that smaller networks may
pay higher prices, this may be due to them excluding higher-cost hospitals and differentially paying
higher rates at those hospitals.

Finally, I provide evidence that narrow-network health plans also charge lower premiums. This
provides context about the effects on consumer surplus due to savings being passed through to
consumers. The analysis of premiums is simply a regression of the log of the premium on network
size. I only use data from the Denver rating area, so this is just a cross-sectional analysis across
plans. Table 4 presents the results from these regressions. In the first two columns, I use only the
lowest-cost silver plan for each network, which corresponds to the premiums I use in the structural
model. Because I observe the metal level in the premium data, I also present a specification which
includes them. The third and fourth columns include all metal levels, with an indicator for each.
The results are consistent with narrow-network plans having premiums that are 10-15 percent lower
than broad-network plans, which corresponds to roughly $30-45 per month. However, these results
are not statistically significant, which is not surprising given the limited number of observations.
These results are lower in magnitude than Bauman et al. (2014), who use a nationwide sample
and are also able to control for the company and plan type (PPO, HMO, etc.). They find narrow-
networks charge 15 percent lower premiums, on average.

One limitation of this analysis is that other aspects of plans, which may be correlated with a
narrow network, may affect the salience of “threat of exclusion” is. A narrow-network plan may
only charge a few dollars more for a visit out of network or may contract with doctors who have
incentives to send patients to certain hospitals. That is, the definition of exclusion is not binary or
one-dimensional. I argue this would bias the parameter of interest towards zero, because my model
treats exclusion as absolute (patients cannot go to an out-of-network hospital), while in practice
the threat of exclusion may not be as strong if the threat of exclusion is that copays are $10 higher.
That 30 percent of hospital visits are out-of-network, suggests that the networks are not binding.

33 That is, the two tables use distinct sources of variation. Table 2 compares broad- and narrow-networks, ignoring
the size of the narrow-network. Table 3 uses the size of the network dropping broad-network plans.
5 Stylized Bargaining Model

The previous section presented correlations that are most easily explained by the use of exclusion, providing bargaining leverage for the insurer. In this section I present a stylized version of my theoretical model, which aims to formalize the intuition behind these correlations. Following the industry intuition about why narrow-networks get lower prices, the mechanism I model is that a narrow network increases the threat of exclusion for the hospitals. I incorporate the threat of exclusion into an alternating-offers bargaining framework similar to [Rubinstein (1982)]. A hospital who rejects an offer from a narrow-network plan has a higher probability of being excluded from that network, than it would a broader network; there are more substitute hospitals remaining than when the network is smaller. The increased probability of exclusion reduces the continuation value for the hospitals, leading them to accept a lower price.

The bargaining protocol is adapted from Collard-Wexler et al. (2016), which provides foundations for the Nash-in-Nash bargaining model, to facilitate the comparison of my model with the empirical literature on hospital-insurer bargaining and to simplify estimation. There are two sides of the market, who alternate in making offers to the other side: In each period either hospitals make offers to the insurer or the insurer makes offers to hospitals. I incorporate the probability of exclusion by, in some periods, having Nature randomly choose hospitals to negotiate with the insurer. The insurer implicitly chooses the probability of exclusion by initially choosing a network size that may exclude hospitals.

I highlight three main results of my model. First, I contrast my model with Rubinstein (1982). If there is no exclusion, then the model suggests \(N\) agreements with the transfers suggested by Rubinstein (1982) in a pairwise setting. Second, I show that when the insurer decides to exclude, it will negotiate smaller transfers. Finally, I show that exclusion is an equilibrium outcome of the model. Even if exclusion shrinks the amount of surplus created, the insurer is able to make up for this by capturing a larger share of the surplus from hospitals.

The model is an alternating offers game between \(R\) insurers and \(N\) hospitals. Each player negotiates over surplus which represents the joint profits between insurer \(r\) and the hospitals insurer \(r\) contracts with. In the empirical model, this is the premiums that insurer \(r\) collects, minus the marginal cost to hospitals for treating insurer \(r\)'s patients. Insurer \(r\)'s payments to the hospital are the transfers they negotiate over. For the bargaining model, total surplus for insurer \(r\), \(\Pi_r(\mathcal{F}, x)\), is a primitive which depends on all insurers’ networks \((\mathcal{F})\) and all insurers’ transfers to hospitals \((x)\). I treat surplus as a primitive because all of the inputs are determined at other stages of the game, and are conditional on the outcome of the bargaining game. Payments to other hospitals affect surplus because they raise the insurer’s costs and may affect how they set their premiums. This is general enough to allow externalities and interdependencies between hospitals, and heterogeneity in

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34Surplus in this case ignores consumer surplus.
35Premiums are set in a separate stage of the game through Nash-Bertrand competition.
the value each hospital provides to consumers (which affects premium setting), and non-transferable utility between hospitals and insurers.

However, this generality complicates the discussion of how I incorporate the threat of exclusion and how it creates bargaining power for the insurer. Therefore, I now present a stylized version of the model, and I present the more general model, which I estimate, in section 3 of the appendix. These two discussions follow each other closely, so the reader may read either section and return at Section 5.4.3. In the stylized model I assume there is one insurer and the negotiation is over one unit of surplus. To relax these assumptions, in the general model, I assume the existence of an equilibrium and that players know which equilibria will be played. I also make informational assumptions, which rule out information asymmetries, similar to Crawford and Yurukoglu (2012).

5.1 Fundamentals

Consider a bargaining game between one insurer and \( N \) hospitals. Let \( \mathcal{N} \) denote the set of all hospitals. At \( t = 0 \), the insurer publicly commits to \( K \in \mathbb{N}^+, \) how many hospitals it would like to agree with, which remains a fixed constant for the remainder of the game. Figure 1 provides an example of a market with 3 hospitals. In panel (a), the insurer chooses to have a network size of 3. In panel (b), the insurer chooses to have a network size of 2.

Negotiations start at time period \( t = 1 \), step \( b \). Let \( \mathcal{F}_t \) and \( \mathcal{A}_t \) denote the sets of hospitals who have and have not reached an agreement before period \( t \). Let \( F_t = |\mathcal{F}_t| \) denote the number of hospitals who have reached an agreement by the beginning of period \( t \). In each period, every hospital \( j \) is either in \( \mathcal{F}_t \) or \( \mathcal{A}_t \), that is, \( \mathcal{F}_t \) and \( \mathcal{A}_t \) are a partition of \( \mathcal{N} \) for all \( t \). Each period, the set of hospitals who will either make or receive an offer that period is denoted \( \mathcal{K}_t \). I refer to \( \mathcal{K}_t \) as the “bargaining set”.

Either Nature or the insurer selects the set \( \mathcal{K}_t \) out of the set \( \mathcal{A}_t \), such that the number of hospitals selected, plus those who have already reached an agreement, equal the number of hospitals

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\[36\] Commitment is a key assumption; without commitment the insurer would not exclude and would lose the leverage gained from exclusion. In practice these contracts are renegotiated every year or every few years, and not all hospitals negotiate simultaneously. Furthermore, many of these insurance companies operate in many geographic markets, with different types of providers (hospitals, physicians, ambulatory care centers, etc.) and across many market segments (Medicare Advantage, health exchanges, individual and employer insurance, etc.). Reneging in one market could make the exclusion threat less credible in others.

\[37\] All periods after the first start with a step \( a \).
the insurer would like in the network, i.e., \( K = |F_t| + |K_t| \). In odd periods, the insurer chooses \( K_t \).
In even periods, Nature chooses \( K_t \) with equal probability among the hospitals in \( A_t \). I denote the probability of a hospital being picked as \( \mathbb{P}(F, K) = \frac{K - F}{N - F} = \frac{\# \text{ of Remaining Slots}}{\# \text{ of Remaining Hospitals}}. \)

Once the set \( K_t \) is specified, the game moves to the negotiation phase, step c, of period \( t \). For each agreement, the insurer receives one unit of surplus. The negotiation determines how much of that unit of surplus the insurer transfers to the hospital, denoted \( x_j \). When \( t \) is odd, the insurer makes offers to all hospitals in \( K_t \) simultaneously. When \( t \) is even, all hospitals in \( K_t \) make offers to the insurer simultaneously. A player who receives an offer has a binary choice to either accept or reject that offer. If the offer between hospital \( j \) and the insurer is accepted, hospital \( j \) joins the set \( F_{t+1} \) and remains in \( F \) for all subsequent periods. If an offer is rejected at period \( t \), that hospital joins the set \( A_{t+1} \). The game ends when \( K \) agreements have been made or when a breakdown occurs.

In order to have price determinacy, models of bargaining require a friction or cost of negotiating. I include an exogenous probability of breakdown, similar to Binmore et al. (1986). Starting in period \( t = 2 \) and in every following period, before \( K_t \) is set, Nature determines whether a breakdown occurs. I allow hospitals and the insurer to have asymmetric beliefs about the subjective probability of breakdown denoted by \( \rho_j^H \) and \( \rho_j^l \), respectively. When a breakdown occurs, the game ends and no further agreements can be made, though surplus created and transfers previously agreed to remain. All excluded hospitals, either due to the insurer reaching \( K \) agreements or breakdown receive zero surplus. Renegotiation of contracts is not allowed. The breakdown probabilities are assumed to be constant throughout time and do not vary based on which hospitals have reached agreements. Players do not discount the future.

For clarity, I respecify the timing of the model:

\( t=0 \). Insurer publicly commits to size of their network, \( K \).

\( t = 1, 3, 5, ... \) (if \( F < K \) agreements have been reached):

a. (Except period \( t = 1 \)) Nature decides whether there is a breakdown.

b. Insurer picks which hospitals to make an offer to \( K \).

c. Insurer makes simultaneous offers to the hospitals in \( K \).

d. Hospitals simultaneously decide whether to accept or reject their offer.

\( t = 2, 4, 6, ... \) (if \( F < K \) agreements have been reached):

a. Nature decides whether there is a breakdown.

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\[^{38}\] Asymmetric beliefs are allowed for in Binmore et al. (1986), with the assumption of some appropriate behavioral model, for example heterogenous priors. I follow Binmore et al. (1986) and do not specify this aspect of the model because it is not a key feature of the model. The main results of the model can be shown with symmetric beliefs. However, asymmetric beliefs help highlight the concerns endogenous networks raise for the reduced-form analysis and are an important feature of the empirical model where the interpretation of this parameter is different.
b. With equal probability \( \mathbb{P}(F, K) = \frac{K-F}{N-F} \), Nature chooses \( K - F \) hospitals to make an offer \( K \).

c. Hospitals in \( K \) make simultaneous offers to the insurer.

d. Insurer simultaneously decides whether to accept or reject each offer.

The game stops when \( K \) hospitals have reached agreement or breakdown occurs. Payments are made.

The structure of the game is common knowledge. Players know the surplus functions and all the parameters. At the end of \( t = 0 \), all the players know \( K \). At the beginning of each period \( t > 0 \), players know which players have agreed already, \( F_t \), and which remain active, \( A_t \). During period \( t \), once the bargaining set, \( K_t \), has been set but before offers are made, all players learn \( K_t \). That is, they all know which other hospitals are negotiating before offers are made. Because offers are made simultaneously, hospitals do not know what offers the others made/received. Likewise, similar to [Crawford and Yurukoglu 2012], I do not allow the insurer to use its information about what hospitals have offered or which hospitals have accepted to be used that period in decisions with other hospitals. That is, I rule out informational asymmetries for the insurer. Once all offers have been made and responded to, all players learn which agreements were reached so that at the beginning of period \( t + 1 \) the sets \( F_{t+1} \) and \( A_{t+1} \) will be known.

5.2 Equilibrium Strategy Profile

In this subsection, I propose a strategy profile which is a Markov-perfect equilibrium (MPE). The concept of an MPE restricts the set of equilibria to the subset of subgame-perfect Nash equilibria for which the only aspect of the history that influences strategies is the current state. In particular, this implies that if negotiations happen at \( t + 1 \), the probability that any hospital in \( A_{t+1} \) will be chosen to bargain at \( t + 1 \) is independent of the identity of the hospital which rejected an offer at \( t \).

In period \( t = 0 \), the insurer chooses the profit-maximizing size of the network. Let \( \hat{\Pi}^I(K) \) be the surplus the insurer receives in equilibrium when choosing size \( K \). In equilibrium the insurer chooses \( K \) such that \( \hat{\Pi}^I(K) \geq \hat{\Pi}^I(K') \) for all \( K' \leq N \).

In odd periods \( t = 1, \ldots, \infty \), step b, the insurer picks a bargaining set \( K_t \) such that \( |K_t| + |F_t| = K \). The insurer chooses their profit-maximizing network. Let \( \Pi^I(G_t; K) \) denote the expected surplus to the insurer given the equilibrium outcomes when the network \( G_t \) is chosen at \( t \). Then the insurer chooses the network \( G_t^I \) such that \( \Pi^I(G_t^I; K) \geq \Pi^I(G_t'; K) \) for all \( G_t' \) where \( |G_t'| = K \) and \( F_t \subset G_t \).

Let \( V_{j_{t+1}}(F_{t+1}, K) \) and \( W_{i_{t+1}}(F_{t+1}, K) \) respectively denote hospital \( j \)’s and the insurer’s expected value of being in the game at the beginning of period \( t + 1 \). Given that players know the bargaining set when making or receiving an offer, players can determine which hospitals will have reached agreements before receiving their offers in period \( t \). Therefore, in negotiations with hospital \( j \), the continuation value to the hospital and insurer during the offer stage of period \( t \) is
$V_{jt+1}(F_{t+1}, K)$ and $W_{t+1}(F_{t+1}, K)$, where $F_{t+1}$ takes into account those who have already reached an agreement ($F_t$) and those who are expected to reach an agreement (some subset of $K_t$). Because I use the MPE solution concept, the time period does not affect the value functions, except for whether the state is even or odd. I use $t$ subscripts to clarify timing. In periods $t = 1, \ldots, \infty$, step $c$, the players that make offers propose the offeree’s continuation value. When $t$ is odd, the insurer offers the hospital: $x_{jt} = V_{jt+1}(F_{t+1}, K)$. When $t$ is even, the hospital offers (to keep): $x_{jt} = 1 - W_{t+1}(F_{t+1}, K)$. The player who is offered their continuation value will accept.

Finally, I assume that in equilibrium there will be immediate agreement:

**Assumption 1.** Suppose the beliefs about breakdown probabilities are such that a possible equilibrium involves immediate agreement ($K_r$ agreements are reached in period $t = 1$ for each $r$) and that this equilibrium is played.

In the simplified model there are two reasons why it is unprofitable for the insurer to delay. First, as with many dynamic games of complete information delay is unprofitable for the insurer is that the expected costs of breakdown are higher if fewer hospitals have agreed at any point in time. Second, delay improves the continuation value of a hospital who reaches an agreement at $t = 1$ because the probability they are picked again if they deviate is higher than when all hospitals agree at period $t = 1$. Recall that $\mathbb{P} = \frac{K-F}{N-F}$. Because $K \leq N$, this probability is decreasing in $F$. Consider, for example, when $N = 9$ and $K = 3$. If $F_2 = 1$, (one hospital has already agreed at the beginning of period 2), $\mathbb{P} = .25$ (2 slots left divided by 8 hospitals left). If $F_2 = 2$, then $\mathbb{P} = .14$ (1 slot left divided by 7 hospitals left).

### 5.3 Determining Continuation Values

Now, I discuss the equilibrium outcomes and compute the continuation values, given the strategies specified in the previous section. While all hospitals agree in the first period, continuation values depend on the expected value for hospital $j$ after deviating from the equilibrium and rejecting the offer. Deviating hospital $j$’s expected value for period $t = 2$, given equilibrium strategies and immediate agreement, simplifies to:

$$V_{jt=2}(K - 1, K) = (1 - \rho_j^H) \cdot \mathbb{P}(K - 1, K) \cdot [1 - W_{t=3}(K - 1, K)] + \rho_j^H \cdot 0$$ \hspace{1cm} (1)$$

With probability $\rho_j^H$, breakdown occurs and the hospital gets nothing. With probability $(1 - \rho_j^H)$, agreements are made possible in period $t = 2$. In period $t = 2$, with probability $\mathbb{P} = \frac{1}{N-K+1}$, hospital $j$ will be chosen to make an offer. Because in equilibrium, all hospitals reach an agreement at $t = 1$, in considering the value of deviating, hospital $j$ expects the set of hospitals who have reached an agreement will consist of all the hospitals in the original bargaining set except itself, i.e.,

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\[^{39}\text{This is a similar argument to Möller (2007) who argues that when the timing of agreements is endogenous, there is an incentive for simultaneous agreements when the externalities between players weakens over time.}\]
\( F_2 = K - 1 \). It offers the insurer its continuation value for period \( t = 3 \) and keeps the remainder. The input to \( W_{t=3}(K - 1, K) \) is \((K - 1, K)\) because again we are considering a case where the insurer deviates to determine the continuation value.

Now I solve for the insurer’s continuation value by considering the case where it deviates at period \( t = 2 \). The insurer’s expected value in \( t = 3 \), given that the \( K - 1 \) hospitals have agreed is:

\[
W_{t=3}(K - 1, K) = (1 - \rho^I) [1 - V_{j=t=4}(K - 1, K)] + \rho^I \cdot 0
\]

With probability \( \rho^I \), breakdown occurs and the insurer gets nothing from this hospital, so it receives the values from other agreements (which I omit because they are sunk). With probability \( (1 - \rho^I) \), the game goes forward and the insurer offers hospital \( j \) its continuation value.

### 5.4 Bargaining Results

To calculate transfers, I consider a unilateral deviation by each hospital \( j \in K_1 \) separately. Because of immediate agreement, a unilateral deviation would imply there is only one additional agreement remaining. At this point the state of the game does not change from period \( t = 2 \) until an agreement is reached (conditional on the state being even or odd). Because the value functions only depend on the state, and the state only depends on whether the time is even or odd, \( V_{jt=2}(K - 1, K) = V_{jt=4}(K - 1, K) = \ldots = V_{j \text{ even}}(K - 1, K) \) and likewise for \( W_{t=3}(K - 1, K) = W_{t=5}(K - 1, K) = \ldots = W_{\text{ odd}}(K - 1, K) \). Therefore, for each insurer-hospital pair there are two unknowns \((V_{j \text{ even}}(K - 1, K)\) and \(W_{\text{ odd}}(K - 1, K))\) and two equations linear in the unknowns, so there exists a unique solution that can be represented with a closed form. Proposition 1 presents this solution:

**Proposition 1.** The equilibrium outcome of this game is given by:

\[
x_j(K) = \frac{\rho^I \cdot [(1 - \rho^I)^{\frac{1}{N - K + 1}}]}{1 - (1 - \rho^I) \cdot [(1 - \rho^H)^{\frac{1}{N - K + 1}}]}
\]

### 5.4.1 Relationship to Rubinstein Outcomes

Corollary 1 states that when \( K = N \), meaning the insurer chooses not to exclude, the model predicts \( N \) outcomes that match the outcomes in Rubinstein (1982).^40 In particular, \( K = N \) implies that \( P(\cdot) = 1 \), i.e., hospitals who reject an offer in the previous period will be picked with probability one. The solution reduces to:

---

^40 Technically these are Binmore et al. (1986) outcomes because the cost of negotiation is modeled as a risk of breakdown. However, the result would be the same as Rubinstein (1982) if I modeled it as a discount factor. I cite Rubinstein (1982) since it may be more familiar to a broader audience.
Corollary 1. When $K = N$ and $\mathbb{P}(\cdot) = 1$, the equilibrium outcome simplifies to:

$$x_j(N) = \frac{(1 - \rho^H_j) \cdot \rho^I_j}{1 - (1 - \rho^H_j) \cdot (1 - \rho^I_j)}$$

Allowing for exclusion, the results are the same as Rubinstein (1982), except that the hospitals’ risk of breakdown parameters are multiplied by their probability of being chosen, as highlighted by the brackets in Proposition 1. One way to interpret this is that my result is distinguishing the risk of breakdown from the risk of exclusion due to the narrow-network. This also demonstrates how my model nests the Nash-in-Nash solution. When there is no exclusion (or the probability of being picked after deviating equals 1), each negotiation becomes the outcome of a pairwise Rubinstein bargain, conditional on all the other negotiations. Collard-Wexler et al. (2016) provides sufficient conditions under which this limits to the Nash-in-Nash solution, similar to how Binmore et al. (1986) demonstrates that Rubinstein (1982) limits to the Nash solution. The remaining results show how my model extends the Nash-in-Nash model.

5.4.2 Narrow-Networks Negotiate Smaller Transfers

My next result shows that my model can imply smaller transfers when there is exclusion. This is a straightforward consequence of Proposition 1. Intuitively, the reason this occurs is that by excluding, the insurer is increasing the probability the hospital gets zero, which worsens the hospital’s continuation value. Why this worsens the continuation value is clear from Equation 1, as the value function is multiplied by $\mathbb{P}(K - 1, K) = \frac{1}{N-K+1}$. If hospital $j$ disagrees when many hospitals are excluded, the probability it gets nothing $(1 - \frac{1}{N-K+1})$ is large. When few hospitals are excluded, the probability of getting nothing is smaller, so the continuation value is larger.

While it may be intuitive that exclusion leads to smaller transfers, it is not obvious that exclusion can be optimal for the insurer. By narrowing the network, the insurer reduces total surplus, which would not be optimal if it did not get larger transfers.\(^{41}\)

5.4.3 Exclusion in Equilibrium

Figure 2 plots the value function at the beginning of the game for the insurer given different choices of $K$. I assume all hospitals have the same risk of breakdown probabilities. There are 7 hospitals in this game. $\rho^I = .75$, so the insurer expects a non-degenerate risk of breakdown. The top line, $\rho^H = 1$, shows that when the hospitals do not expect to have a chance to offer, and thus have no bargaining power, the insurer receives all the surplus. In this case, the insurer agrees with all 7 and they create 7 units of surplus which are all kept by the insurer. When $\rho^H = .25$, the insurer excludes 1 hospital in equilibrium, creating 6 total units of surplus and keeps roughly 4 of these

\(^{41}\)In my empirical setting, consumers prefer larger networks (more choice of hospitals, etc.) so a broad-network can charge higher premiums.
units. If it were to choose $K = 7$, it would create 7 total units of surplus, but would only keep 2 of these units. Finally, when $\rho^H = 0$, the insurer will exclude two hospitals. Instead, if it were to exclude no hospitals, the hospitals would capture all the surplus. The $K = N$ case matches the Rubinstein outcome (Corollary 1) times $N$, which is often not optimal for the insurer.

Figure 2: Insurer’s $t = 0$ expected value by network size.

Results are from simulated data, using the following parameters: $\rho^I = 0.75, \rho^H = 0.25, \Pi = 1, N = 7$

Finally, I discuss the endogeneity concern my model raises. In Figure 2, the insurer’s risk of breakdown parameter is fixed at $\rho^I = .75$. As $\rho^H$ increases, the insurer excludes fewer hospitals. This demonstrates that, as the insurer’s relative bargaining power increases, it is less likely to exclude.\[^{42}\] Intuitively, an insurer that will get less of the pie will not be affected as much by shrinking that pie. This raises a concern about selection into network size. If plans that are unable to negotiate low prices are the most likely to use the tool of exclusion, then observed broad-network prices are not an appropriate comparison. In Figure 2 when $\rho^H = 0$, the insurer chooses to exclude two hospitals, but if it had a broad network, it would transfer the entire unit of surplus to hospitals. In the other extreme, when $\rho^H = 1$, the insurer transfers no surplus to the hospitals.

6 Structural Model and Estimation

The estimation strategy amounts to matching the split of surplus predicted by the model to the “observed split of surplus.” While estimation of games with endogenous networks can be challenging, the key insight of this section is that estimation of a game with simultaneous agreement makes

\[^{42}\]This result is also shown in Gal-Or (1999).
estimation feasible. This is a feature of the Nash-in-Nash model; however, it is not standard in the literature where prices and the networks are endogenous, which uses randomly ordered sequential matching. I begin by discussing how I estimate the surplus over which the hospitals and insurers negotiate. Then I discuss how I estimate the bargaining parameters.

There are two important distinctions between the theoretical model and the empirical model. I allow for hospitals and insurers to negotiate over a linear prices and the interpretation of the risk of breakdown parameter changes. I back out the linear price that is consistent with the lump-sum transfer that is implied by the model. This is also done in [Gowrisankaran et al. (2014), Ho and Lee (2017), and Prager (2016)]. Since I do not observe the price for each hospital-insurer-service combination, I assume that insurers negotiate a constant markup above a CPT4 code’s relative weight. Throughout the paper, I refer to lump-sum payments as transfers and payments based on a linear price schedule as prices.

In the previous theory section, the cost of negotiation is represented by an exogenous risk of breakdown due to the regulator ending the game. This parameter explains how surplus is split between parties and therefore is often referred to as a “bargaining parameter.” In the empirical literature, the bargaining parameters are estimated as the residuals that explain the split of surplus beyond other aspects of the model and data. That is, the bargaining parameters are interpreted as reduced-form parameters which explain how surplus is divided between hospitals and insurers. This does not preclude the risk of breakdown as an aspect of price formation, but accounts for many other stories (for which data are not available) that effect price formation.

6.1 Defining Surplus

In order to estimate the bargaining model from the previous section, I require estimates of the surplus at stake in each negotiation. Surplus is defined as the sum of profits to each insurer and the providers they contract with, which are determined by consumers’ choices over which hospitals to use and which plans to enroll in. This allows insurers’ valuation of hospitals to depend on how its enrollees value those hospitals. This section presents a five-stage model which describes how consumers make these choices, how the insurers set their premiums, and how prices and the network are negotiated.

Stage 1: Prices and the network are negotiated between insurers and hospitals.

Stage 2: Insurers set their premiums.

Stage 3: Consumers choose which health plan to join.

Stage 4: Nature determines which consumers get sick.

Stage 5: Consumers who got sick choose which hospital to attend.

Besides the bargaining stage, the framework in this section is standard in the literature, for example 43 For those who have read the appendix, I change notation from $x$, which represents transfers, to $p$, which represents prices.
it follows [Ho and Lee (2017)] closely, facilitating comparison between the bargaining models. As is typical with these models, I solve the game backwards.

### 6.1.1 Stage 5 - Provider Choice

Consumer $i$, who lives in county $m$, is enrolled in health plan $r$, and gets sick with condition $d$, has to choose a hospital in its health plan’s network. To simplify the model, I assume consumers cannot go out of network, while in practice many do but have to pay higher copays or coinsurance. Conditional on being sick enough to go to a hospital, the utility of hospital $j$ for a consumer is given by:

$$u_{imjd} = \gamma \text{distance}_{mj} + \delta^H_{jd} + \epsilon^H_{imjd}$$

$\delta^H_{jd}$ denotes the mean value of hospital $j$ to a patient with disease $d$. The mean value can include out-of-pocket prices the consumer would have to pay for that hospitalization, hospital quality, patient preferences, etc. I avoid parameterizing these aspects of the model to remain agnostic on functional form and to avoid the need for instruments. This parameterization is also used in [Ericson and Stanc (2015)] $\text{distance}_{mj}$ is the distance from the patient’s county to hospital $j$. The distance coefficient is identified by variation in hospital choice probabilities across counties. $\epsilon^H_{imjd}$ is an idiosyncratic taste for hospital $j$ and is i.i.d Type 1 extreme value. The outside option is using a hospital that is outside the rating area; I observe this occurs for roughly 20 percent of visits. I normalize the mean value of the outside option to zero, $u_{im0} = \epsilon^H_{im0}$.

This parameterization limits market shares and substitution patterns to a single index that depends on $\delta^H_{jd}$ and distance, which along with the logit structure implies the independence of irrelevant alternatives (IIA) property. Also, if patients of different health status choose hospitals differently, as shown in [Shepard (2016)], then my model would overestimate the value (to the insurer) of hospitals that attract the costliest patients. In order to account for these concerns, I include age-hospital interactions to allow individual’s preferences for hospitals to vary by age as well.

I estimate hospital choice parameters by inverting the age-gender-county-condition specific market shares and running OLS, as shown in [Berry (1994)]. Because of the distributional assumption of $\epsilon^H_{imjd}$, the expected probability of going to a hospital, in a particular plan, conditional on a consumer getting sick is:

$$\sigma_{imjd}(F_r) = \frac{\exp \left( \gamma \text{distance}_{mj} + \delta^H_{jd} \right)}{1 + \sum_{k \in F_r} \exp \left( \gamma \text{distance}_{mk} + \delta^H_{kd} \right)}$$

\[44\] To compute the distance measure, I take the centroid of the patient’s zip code to the centroid of the hospital’s zip code, then take an average weighted by the number of patients in each zip code to get the mean distance at the county level.
6.1.2 Stage 4 - Nature Determines Which Consumers Get Sick

In stage 4, there are no strategic decisions to be made, as Nature determines which consumers get sick. Let the probability of getting sick with disease \( d \) be given by \( f_{id} \). I calculate \( f_{id} \) by using the observed probability that an enrollee has a hospital visit, for disease \( d \), in my sample. I compute the number of enrollees in 12 groups, (six age categories times gender).\(^{45}\) I estimate this probability across the entire rating area.

6.1.3 Stage 3 - Consumers Choose health plans

In stage 3, consumers choose their health plan. Following Town and Vistnes (2001) and Capps et al. (2003), I model utility as the value of premiums, the expected value of the network, and other plan characteristics:

\[
U_{imr} = \alpha_1 r \text{ premium}_{ir} + \alpha_2 E(u_{imr}) + \xi_{mr} + \epsilon^P_{imr}
\]

\( \text{premium}_{ir} \) is the premium that consumer \( i \) would face, which is, by law, constant across counties within a rating area, except by age. \( \xi_{mr} \) is other unobserved plan characteristics which can vary by county. \( \epsilon^P_{imr} \) represents idiosyncratic consumer preferences over plan characteristics that are assumed to be i.i.d Type 1 extreme value. \( \alpha_1 r \) is a health plan specific premium-sensitivity parameter. \( E(u_{imr}) \) is the expected utility of the providers in health plan \( r \)’s network. This is also referred to as willingness to pay (WTP) for the network.\(^{46}\) This value, as shown in Capps et al. (2003) is given by the familiar inclusive value formula, incorporating the probability of getting sick with disease \( d \):

\[
E(u_{imr}) = \sum_{d \in D} f_{id} \ln \left( \sum_{j \in F_r} \exp \left( \gamma \text{ distance}_{mj} + \delta_{jd}^H \right) \right)
\]

Prager (2016), Ericson and Starc (2015), and Ho and Lee (2017) use variation in premiums offered for individual versus family plans to account for the endogeneity of premiums. My data does not have information on which enrollees are in which families. Furthermore, many enrollees receive unobserved subsidies for premiums, which creates measurement error in the observed premium that is paid by an enrollee. To handle these concerns, rather than estimating \( \alpha_1 r \) directly, I back out \( \alpha_1 r \) using first-order conditions implied by optimal premium setting.\(^{47}\) This similar to how Rosse (1970) or Berry (1994) use optimal pricing to back out marginal costs. First, I estimate \( \alpha_2 \) separately by defining \( \delta^P_{imr} = \alpha_1 r \text{ premium}_{ir} + \xi_{mr} \) as the mean value of the plan, net of the value of the network in each county. Then I rewrite the utility function as:

\(^{45}\) Age categories are: 0-18, 19-25, 26-35, 36-45, 46-55, 56-65

\(^{46}\) This varies from the rest of the literature; because I do not estimate the copay sensitivity, I do not rescale the WTP term. Therefore, it is measured in units of utils, rather than dollars.

\(^{47}\) The supply-side premium elasticity is more relevant because the main purpose of this stage is to understand how insurers update premiums. This also avoids the measurement concern due to subsidies. While I have not computed welfare results, I will need to account for consumers facing different premiums.
\[ U_{imr} = \alpha_2 E(u_{imr}) + \delta^{P}_{imr} + \epsilon_{imr} \]

I estimate \( \alpha_2 \) by inverting the market shares for each plan, in each county, for each demographic group. There are two sources of identifying variation: consumer demographics and geographic variation. Each demographic group values the network differently, so if those who value networks more (typically older patients) choose broader networks, one would expect a positive \( \alpha_2 \). Likewise, plans vary in terms of the location of their in-network hospitals. \( \alpha_2 \) will be positive if consumers are more likely to choose plans which include nearby hospitals. The outside option is being uninsured. I use the estimates from Panhans (2016), who calculates the insurance take-up rate by age in Colorado. The uninsured rate varies from 30 percent to 60 percent, mostly declining by age.48

Denote the probability that consumer \( i \), in county \( m \), signs up for insurance plan \( r \) as \( S_{imr}(\text{premium}(F, p), F) \). \( F \) represents the set of all observed networks. The functional form is due to the distributional assumption on \( \epsilon^{P}_{imr} \):

\[
S_{imr}(\text{premium}, F) = \frac{\exp (\alpha_1 r \text{ premium}_{ir} + \alpha_2 E(u_{imr}) + \xi_r)}{1 + \sum_{k \in R} \exp (\alpha_1 k \text{ premium}_{ik} + \alpha_2 E(u_{ink}) + \xi_k)}
\]

(3)

Because the market shares take into account premiums and networks from each insurer in the market, I omit the \( r \) subscript on \( \text{premium} \) and \( F \). This equation defines how cross-insurer competition is accounted for in the model; plans engage in Nash-Bertrand competition over premiums, after the networks and prices are set.

6.1.4 Stage 2 - Insurers Choose Premiums

Insurer \( r \)'s expected profits consist of the premiums it receives, minus the expected amount it must reimburse the hospitals in its network. The expected amount it must pay for consumer \( i \) is the probability of the consumer being sick with disease \( d \) \( (f_{id}) \) times the expected value of the payments (weighted by the probability of going to each hospital, conditional on having disease \( d \), \( \sum_{j \in F_r} p_{jdr}(F, \Pi_r, K) \sigma_{imjd}(F_r) \)) times the probability that the consumer chooses that health plan \( (S_{imr}(\text{premium}(F, p), F)) \).

\[
\Pi_r'(F, p, K) = \sum_i \left[ \text{premium}_{ir}(F, p_r) - \sum_{d \in D} f_{id} \sum_{j \in F_r} p_{jdr}(F, \Pi_r, K) \cdot \sigma_{imjd}(F_r) - \text{other costs}_i \right] S_{imr}(\text{premium}(F, p), F)
\]

(4)

I also include \( \text{other costs}_i \) that account for each consumer’s expected costs for the insurer in other settings, such as inpatient hospitals and physician visits. To back out plan-specific premium sensitivities, \( \alpha_{1r} \), I take the derivative of Equation 4 with respect to premiums. I solve for it \( \alpha_{1r} \), since all other terms in this equation are observed or estimated. I use the estimated market share

48Under the ACA regulations, there is an “individual mandate” that requires all individuals eligible for the exchanges to have insurance. In 2014, those who do not purchase insurance and were not exempt were liable for a “shared responsibility payment” of $95 or one percent of household income, whichever was greater for an individual.
values, since the model suggests that plans set premiums based on expected costs not observed costs.

6.2 Stage 1 - Providers and Insurers Bargain over Prices and the Network

For the remainder of the paper, I refer to the subjective beliefs about the risk of breakdown, $\rho_j^H$ and $\rho_r^I$, as “generic bargaining parameters” to differentiate the bargaining power they provide from the threat of exclusion and highlight how all other sources of bargaining power are accounted for in these parameters. In this section, I discuss the estimation of the generic bargaining parameters, $\rho_j^H$ and $\rho_r^I$, and the effect of exclusion $P_r$. While I have focused on the effect of exclusion, the generic bargaining parameters are relevant for network adequacy policies as well. If hospitals have a lot of relative bargaining power, then restricting one of the insurer’s tools to gain leverage may raise prices a lot. On the other hand, if insurers have a lot of relative bargaining power, even without the use of exclusion, then these policies would not impact prices much.

To estimate these parameters, I match the model’s prediction of the split of surplus to the observed split of surplus. The observed split of surplus is the hospital’s profits divided by the marginal surplus hospital $j$ contributes to network $r$, $(\Pi^{MARG}_{jr}(\mathcal{F}, \mathcal{F}_r \setminus \{j\}, p(\mathcal{F}), K))$. The marginal surplus contains three terms: (1) the surplus the insurer receives with the observed network $(\Pi_r^I(\mathcal{F}, p, K))$ (2) the surplus captured by hospital $j$, given the observed network $(\Pi^H_{jr}(\mathcal{F}, p, K))$ (3) minus the surplus the insurer would obtain if they made offers to the observed network, but hospital $j$ (and only hospital $j$) deviates, followed by a breakdown $(\Pi^{IB}_{jr}(\mathcal{F}, \mathcal{F}_r \setminus \{j\}, p(\mathcal{F}), K))$. Formally, the marginal surplus can be written:

$$\Pi^{MARG}_{jr}(\mathcal{F}, \mathcal{F}_r \setminus \{j\}, p(\mathcal{F}), K) = \Pi_r^I(\mathcal{F}, p, K) + \Pi^H_{jr}(\mathcal{F}, p, K) - \Pi^{IB}_{jr}(\mathcal{F}, \mathcal{F}_r \setminus \{j\}, p(\mathcal{F}), K)$$

(5)

Note that marginal surplus is not a value that I am assuming, but rather this is derived in the appendix.

The surplus captured by the insurer, $(\Pi_r^I(\mathcal{F}, p, K))$, is given in Equation 4. The surplus captured by hospital $j$ from insurance company $r$ is defined as the price that the hospital receives for each service minus the marginal cost of the service, times the number of services the hospital provides. The number of services is defined as the probability of patient $i$ joining insurer $r$’s plan, times the probability of being sick with disease $d$, times the probability of using hospital $j$, conditional on having disease $d$:

49 Due to the linearity of the surplus functions, this is an equivalent way of writing the equation in the appendix. $\Pi_r^I = \Pi_r - \sum \Pi^H_{jr}$, then I add back in $\Pi^{IB}_{jr}$ because it is not subtracted off.
\[\Pi^H_{jr}(F, p, K) = \sum_i \sum_{d \in D} f_{id} [p_{jd}(F, \Pi_j, K) - mc_{jd}] \sigma_{mj}(F_j) \cdot S_{imr}(premium_i(F, p) F) \quad (6)\]

For both hospital and insurer surplus, prices, probabilities of being sick, and premiums are observed in the data. I use estimated, rather than observed, insurer and hospital market shares because the timing of the model suggests prices are negotiated over expected surplus. For now I assume that marginal costs are zero. I plan to follow Ho and Lee (2017) in defining marginal costs using costs reported in the AHA data. Without accounting for costs, my coefficient estimates will be biased to suggest that hospitals have more bargaining power than they would if marginal costs were positive.

I compute the insurer’s profit during breakdown after hospital \( j \) unilaterally deviates from the equilibrium, \( \Pi^{IB}_{jr}(F, F_r \{ j \}, p(F), K) \), for each hospital-insurer pair separately:

\[
\Pi^{IB}_{jr}(F, F_r \{ j \}, p(F), K) = \sum_i \left[ \text{premium}_i(F_r \{ j \}, F_{-r}, p) - \sum_{d \in D} f_{id} \sum_{k \in F_r \{ j \}} p_{kd}(F, \Pi_j, K) \sigma_{mk}(F_r \{ j \}) - \text{other cost}_i \right] 
\cdot S_{imr}(premium_i(F_r \{ j \}, F_{-r}, p), F_r \{ j \}, F_{-r})
\]

The breakdown value depends on the premiums, insurer \( r \)’s market share and remaining hospitals’ market shares (from insurer \( r \)’s enrollees) that would occur when hospital \( j \) is omitted from insurer \( r \)’s network but the other hospitals in insurer \( r \)’s network remain. I use the estimates from stages 2-5 of the game to compute these values for the network where hospital \( j \) is excluded. For other plans, I use the observed premiums. Finally, I use the observed prices for the non-deviating hospitals: hospitals \( i \in F_r \{ j \} \) agree to prices with the expectation that the network \( F_r \) will be formed. They only learn about the deviation after agreeing to a price. I include \( F \) in \( p(\cdot) \) to specify the expectations of the network realization used to form prices.

That negotiated prices during breakdown and prices negotiated by other hospital-insurer pairs (and hence other insurers’ premiums) all depend on the equilibrium network is the key simplification of simultaneous agreement that makes estimation feasible. Because I only use observed prices, the values \( \Pi^{MARG}_{jr}(F, F_r \{ j \}, p(F), K) \) and \( \Pi^H_{jr}(F, p, K) \) can be computed in a separate step from the estimation of bargaining parameters.

Now I discuss the split of surplus predicted by the model. In Appendix B, I derive the transfer to the hospital, which is the generalized version of Proposition 1 (which gave the split of surplus). The equation includes multiple insurers, and a more general form for the probability hospital \( j \) is chosen to negotiate after deviating and is multiplied by the marginal surplus value:

\footnote{This is because I assume that plans do not learn about others’ networks until after the premiums are set.}

\footnote{Using observed prices is consistent with negotiating a linear price, not a lump-sum transfer. If lump-sum transfers were made, under breakdown, because more patients visit each in-network hospital (due to the IIA property of the Type 1 extreme value error terms) the linear price would need to fall to keep the lump-sum transfer constant.}
\begin{equation}
x_j^r(\mathcal{F}; \rho^H, \rho^I, \theta) = \Pi_{j^r}^{MARG}(\mathcal{F}, \mathcal{F}_r \backslash \{j\}, p(\mathcal{F}), K) \cdot \frac{\rho^I^j \cdot (1 - \rho^H^j) \cdot \mathbb{P}_r(j \in \mathcal{F}_r^2 | \mathcal{F}_r \backslash \{j\})}{1 - (1 - \rho^H^j) \cdot (1 - \rho^I^j) \cdot \mathbb{P}_r(j \in \mathcal{F}_r^2 | \mathcal{F}_r \backslash \{j\})}
\end{equation}

\(\mathbb{P}_r(j \in \mathcal{F}_r^2 | \mathcal{F}_r \backslash \{j\})\) represents the probability that hospital \(j\) is chosen to negotiate in period \(t = 2\) (resulting in the network of \(\mathcal{F}_r^2\), conditional on no breakdown, after deviating and rejecting an offer during period \(t = 1\). \(\rho^I^j\) is identified by within-hospital across-insurer variation in prices. For example, do some insurance companies negotiate lower prices at all hospitals? \(\rho^H^j\) is identified by within-insurer across-hospital variation, conditional on those hospital’s marginal surplus. For example, do certain hospitals negotiate higher prices across all insurance companies, conditional on the marginal surplus they provide? That negotiated prices are not included in the estimation of other stages helps to clarify the variation in the data that identifies these parameters.

One difference between my model and the Nash-in-Nash model is that hospitals which are excluded from the network may have an effect on hospitals who are included. Town and Vistnes (2001) describes why excluded hospitals may affect a hospital’s bargaining leverage: “With HMOs contracting with multiple hospitals to form networks, a hospital’s bargaining leverage depends both on its own characteristics and on the characteristics of other hospitals inside and outside the network. In particular, if the HMO’s best alternative to contracting with a high-priced hospital is to replace that hospital with another, the high-priced hospital’s bargaining leverage depends on the hospital’s incremental value to the network relative to other hospitals that could replace it.” This is incorporated into my theoretical model through the probability of being picked after deviating. If hospital \(j\)’s probability of being picked in the period after deviating is affected by how many (or which) hospitals are excluded, then that would effect the continuation value of hospital \(j\).

However, the probability of being chosen to make an offer after deviating is not observable, since by definition it does not occur in equilibrium. This may require a more complete model of network formation which might depend on factors like insurers’ interactions with hospitals in other markets (e.g., does an insurer contract with a hospital in a plan it offers in its employer-sponsored insurance or its Medicare Advantage line of business?) and dynamic factors (e.g., did its network include that hospital in previous years?). While an interesting avenue of research, I consider this outside the scope of this paper.

The assumption of hospitals being chosen with equal probability after deviating is arbitrary and likely to be an unrealistic measure of the competitive effect of excluded hospitals. Therefore, in some specifications, I include a reduced-form parameter, \(\theta\), which captures the correlation between the substitutability of excluded hospitals and the negotiated prices of hospitals in the network. I also present a specification without this parameter, since it is not structural parameter.

To measure the substitutability of excluded hospitals, I calculate the number of “acceptable replacement” hospitals that are excluded from the observed network but would provide sufficient surplus to be able to reach an agreement with the insurer after a hospital in the observed network.
deviates. For example, in a market where hospitals A and B are within one mile of each other and hospital C is fifty miles away, an insurer may only need one of A and B, but require C. Suppose the insurer selects \{A, C\}; then if C deviates, it will have probability one of being picked again, while A has a one-half probability of being picked because B is an acceptable replacement for it.

Given the number of acceptable replacement hospitals, I parameterize the probability of hospital \(j\) being selected after deviating with insurer \(r\) as follows:

\[
\hat{P}_r(j \in F_r^2|F_r^1\{j\}; \rho^H, \rho^I, \theta) = \exp(\theta \cdot \log(\hat{P}_r(j \in F_r^2|F_r^1\{j\}; \rho^H, \rho^I))
\]

where \(\hat{P}_r(j \in K_2|K_1\{j\}; \rho^H, \rho^I)\) represents the equal probability chance of being picked to offer after deviating, which is one divided by the number of acceptable hospitals plus one for hospital \(j\) itself. The advantage of this functional form is, if there are no replacement hospitals (i.e., if this is a broad-network), then \(\hat{P} = 1\), because \(P = 1\) (and \(\log(P) = 0\)). If \(P < 1\) and \(\theta = 0\), then \(\hat{P} = 1\) and there is no correlation between negotiated price and the number of excluded hospitals. If \(P < 1\) and \(\theta = 1\), then \(\hat{P} = P\), which is consistent with the naive assumption of equal probability among acceptable hospitals. \(\theta \in (0, 1)\) implies a correlation between these two extremes.

\(\theta\) captures the reduced-form effect of having excluded hospitals that are close substitutes. \(\theta\) is identified by variation in the number of acceptable replacement hospitals which may vary across hospitals within a network, as in the case of hospitals \{A, C\} given above. That is, this parameter is identified by variation in each in-network hospital’s characteristics and how they compare to excluded hospitals, conditional on the observed networks. To test the sensitivity of this parameter, I present four parameterizations. (1) I do not include this parameter. (2) I include one \(\theta\) which does not vary across hospital-insurer pairs. (3) I include an insurer-specific \(\theta_r\). (4) I include a hospital-specific \(\theta_j\). Including an insurer-specific \(\theta_r\) might be preferred if certain insurers can use the threat of exclusion more effectively than others. For example, if they contract with a hospital in another market, such as the employer-sponsored insurance market, the threat of exclusion may carry extra weight or other hospitals may be worse substitutes than implied by the model. Likewise, a hospital-specific \(\theta_j\) may be preferred if certain hospitals are more difficult to exclude. For example, a star hospital may not be a close substitute for others. The reduced-form parameter would capture these effects. I leave the details of computing the number of acceptable replacement hospitals to Appendix C.

To estimate this model once I have computed \(\hat{P}_r(j \in K_r^2|K_r^1\{j\}; \rho^H, \rho^I, \theta)\), for that draw of parameters, I can compute the transfer implied by the model:

\[
\frac{x_{jr}(F; \rho^H, \rho^I, \theta)}{\Pi_{jr}^{MARG}(F, F_r\{j\}, p(F), K)}
\]

\(^{52}\)I cannot include a \(\theta_r\) because the variation needed to identify this parameter is based on either within-hospital or within-insurer variation in the number of acceptable replacement hospitals.
where $x_{jr}(\mathcal{F}; \rho^H, \rho^I, \theta)$ is given by Equation 7 (except using $\hat{P}$). I find the set of parameter values $\rho^H, \rho^I, \theta$ that minimize the distance between the model-predicted split of surplus and the observed split of surplus given by:

$$
\frac{\Pi_{jr}^H(\mathcal{F})}{\Pi_{jr}^MARG(\mathcal{F}, \mathcal{F}_r \setminus \{j\}, p(\mathcal{F}), K)}
$$

7 Results

This section presents the estimation results of my model. I show that consumers value closer hospitals, broader networks, and lower premiums, as expected. The main point of these results are that they are all similar to those in the literature, which facilitates the comparison of the bargaining models. Then I discuss the estimation results for the bargaining parameters, which are the focus of this paper. I present results for the model with and without allowing for exclusion. I use these results in the counterfactual and use the counterfactual to aid the interpretation of the bargaining parameters.

7.1 Demand Estimation Results

In Stage 5, consumers who got sick choose which hospital to attend. Table 5 shows the results of the hospital demand regressions. The first column does not include age-hospital interactions, while the second does. In both, the coefficient on distance in miles is roughly $-0.016$. This implies an elasticity of $-0.16$, meaning that a one-percent increase in distance to a hospital leads to a .16 percent lower chance of attending that hospital. The negative coefficient on distance is common in the literature, for example Town and Vistnes (2001), Prager (2016), and Ho and Lee (2017) all find negative coefficients on distance.

In Stage 4, Nature decides which consumers get sick and what conditions they get. I determine the probability of being treated for condition $d$ for a given gender-age group. Table 6 presents the probability of an individual being treated for condition $d$. Injuries, diseases of the musculoskeletal system, and neoplasms were the most common conditions. Roughly 2.25 percent of the sample had an outpatient visit in 2014 for an injury, and 1 percent for neoplasms. Table 7 presents the probability of having a hospital visit by age category. The probability of having a condition is rising in the age of the patient. A person age 56-65 has an average of .2 hospital visits.

In Stage 3, consumers choose their health plans, based on the premiums, networks, and other plan characteristics. I present results for the willingness to pay (WTP) for the networks first, since it was estimated separately. Table 8 presents summary statistics on the WTP measure. The first row shows the mean WTP for all plans, then breaks out WTP for narrow and broad-network plans. Narrow-network plans have lower WTP than broad-network plans since they have fewer hospitals.

53 Neoplasms are abnormal growths of tissue. Much of the spending in this category is associated with cancer.
The later rows show WTP by age group. Older patients have higher WTP because they are more likely to get sick, and, conditional on getting sick, they are more likely to use popular hospitals.

Table 9 presents the results for the WTP for the network. The coefficient is a statistically significant .5, which corresponds to an elasticity of .09. This coefficient is of the expected sign, which Prager (2016), Ho and Lee (2017), and Ericson and Stanc (2015) find as well. Since I did not estimate a copay elasticity, the interpretation differs from the other papers in the literature, as I do not rescale the WTP measure into dollars.

Table 10 presents the insurer-specific premium sensitivities. The second column provides an indicator for whether that plan had a broad or narrow network. The third column presents the parameter estimates, that are all between $-0.0009$ and $-0.00025$. I also present elasticities because the parameter estimates are difficult to interpret. Each consumer type (defined by their age-gender-county) will have their own elasticity since the market share of each plan varies by type. The fourth column presents the unweighted across-types mean market share-premium elasticity for each insurer. The market share-premium elasticities are all between $-1.5$ and $-3$. These results in line with the literature, Ho and Lee (2017) find $-1.2$, Cutler and Reber (1998) find $-2$ and Prager (2016) finds from $-0.4$ to $-0.6$. The elasticities may be larger than others in the literature due to fiercer competition in this market; the Colorado market has more insurers than any of the other papers cited.

### 7.2 Bargaining Estimation Results

Table 11 and Table 12 list the generic bargaining parameter results for each hospital and insurer, respectively. The specification I report uses the insurer-specific $\theta_r$, though the qualitative results in this section do not change based on the specification I use. In each table, I present the model assuming the networks are endogenously and exogenously formed. Assuming the networks are exogenous in this case is equivalent to setting $\hat{P} = 1$.

Because the model assumed the generic bargaining parameters represent subjective beliefs about the risk of breakdown, larger values correspond to less bargaining power. The level of the parameters are difficult to interpret, transfers depend on an insurer’s parameter relative to a hospital’s parameter. In both tables when exclusion is assumed endogenous the generic bargaining parameters are larger, but for narrow-network plans the magnitude of that difference is much larger than for broad-network plans or hospitals. The model with exogenous exclusion overstates narrow-network plans’ relative bargaining power, because a narrow-network plan’s use of the threat of exclusion is accounted for in its generic bargaining parameter; their strategic choice is being treated as a characteristic of the plan.

To aide the interpretation of the generic bargaining parameters, the fifth and sixth columns of Table 12 present the split of surplus assuming $\hat{P} = 1$ for both models. I use hospital 6 and plug the parameters into Equation 7 (and set $\Pi^{MARG}_{jt} = 1$). This shows how the endogenous and
exogenous models differ in how they split surplus, as only determined by the generic bargaining parameters. The broad-network plans have similar splits of surplus across both models, while the narrow-network plans have much larger transfers for the model with endogenous networks.

Table 13 presents the results for the insurer-specific $\theta_r$ values. I still need to compute standard errors. All the values are closer to .5 than 0 or 1. If these values are statistically different than 0, that would suggest that insurer-hospital pairs negotiate lower prices when there are more acceptable replacement hospitals excluded from that insurer’s network. This would provide some evidence of a negative correlation between the number of substitutable hospitals and negotiated prices. If the parameter estimates are statistically different than 1, that would suggest that equal probability of choosing replacement hospitals is too extreme. To interpret the coefficients, consider the case with three acceptable replacement hospitals. Including the deviating hospital implies an equiprobability value of $P = .25$. When $\theta = .5$, the implied probability would be $\hat{P} = .75$. I use the counterfactual analysis to interpret the magnitude of this effect.

8 Counterfactuals

Throughout this paper I have argued that exclusion is an important aspect of competition in health care markets. In this section I show how incorporating exclusion into the model can produce different counterfactual estimates than the Nash-in-Nash model. The counterfactual I compute is that there is a law that restricts exclusion, so each insurer chooses to have a broad network. I assume that breakdown under the counterfactual is to simply have one deviating player be excluded. Unlike in estimation, this requires computing counterfactual prices. I compute new prices, then update the surplus values and repeat in a fixed-point algorithm. I do this for both endogenous and exogenous networks. In the counterfactual, $\hat{P} = 1$ because there are no longer acceptable replacement hospitals.

Table 14 presents the ratio of prices before and after the law, at hospitals included in the observed networks. These results do not include the effect of shifting patients to different hospitals. That is, the results should be interpreted as the mean change in price for the same services at the same hospital, similar to the reduced-form analysis. In the model where the networks are assumed exogenous, if the marginal surplus is constant, the prices will remain constant; the generic bargaining parameters are held fixed, while the other two determinants of prices, the threat of exclusion and the marginal surplus, are assumed constant. However, the marginal surplus declines in the counterfactual, because the insurer is distributing its patients across more hospitals. In the counterfactual the model with exogenous networks has 36 percent lower prices.

\[\hat{P} = \exp(0.5 \cdot \log(0.25)).\]

If exclusion is not allowed, then an insurer might not be allowed to market their plan under breakdown. However, this makes marginal surplus very large for each negotiation (as the hospitals can destroy all of the insurer’s profit). This has a large effect on broad-network plans, which is an unrealistic feature of that counterfactual and distracts from the analysis of bargaining power.
In the model with endogenous networks, while the marginal surplus falls, the insurers also lose the bargaining leverage due to exclusion in the counterfactual. The difference between the columns demonstrates the magnitudes of the effect of bargaining leverage. The first row presents the case that $\theta = 1$, which assumes that hospitals are chosen with equiprobability by Nature. In this case the endogenous exclusion result suggests prices will rise by 110 percent due to the law. The second row shows when there is one common $\theta$ for all hospitals and insurers. The third and fourth rows show when there are insurer- and hospital-specific $\theta$ values. All three rows show prices rising roughly 50 percent under the counterfactual law. I believe these results are overstated because I have not yet accounted for hospital marginal costs. This overstates hospital bargaining power, because they appear to have larger profits. Removing the threat of exclusion increases prices for hospitals with a lot of bargaining power more than those with little bargaining power who would not negotiate high prices even without exclusion.

To summarize, I have showed that restricting insurers’ ability to exclude hospitals may lead to higher negotiated prices, which is in line with conventional wisdom. I am still working on a full welfare analysis, but the results for negotiated prices suggest that restricting insurers’ ability to exclude may raise premiums for consumers and potentially hurt welfare, in some settings.

9 Limitations and Extensions

I believe the main limitation of this paper is how it accounts for the benefits of a network adequacy policy (in the welfare analysis I plan to provide). Regulators worry that consumers, not knowing which conditions they will get in the following year, will not account for these diseases when choosing a plan. A thorough welfare analysis of network adequacy policy should account for the fact that consumers often do not search over providers, do not account for uncertainty in the way my model assumes, and provider lists are often wrong, difficult to find, or misleading. Indeed, the literature on consumer choice of health insurance has found considerable evidence of consumer inconsistencies, inertia, inattention, and other “behavioral hazards”. Without these features, restricting plan choice is difficult to justify, given that broad-network plans are also available in my setting.

External validity is also a concern for this study. While my results are consistent with the health policy literature, which has argued that limiting an insurer’s ability to exclude may increase health care costs, the magnitude of the effect depends on the characteristics of each market. Markets vary in the amount of insurer competition, hospital competition, and bargaining power between insurers and hospitals. Each of these factors will effect the costs of a network adequacy policy. In 2014, Denver’s non-group market was especially competitive, there were 12 insurers present.

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56 Haeder et al. (2016) provide evidence of misleading physician network lists.
57 For example, see Abaluck and Gruber (2011), Handel (2013), Handel and Kolstad (2015), Handel et al. (2015), Ho et al. (2015), Baicker et al. (2015), and Dalton et al. (2015).
Furthermore, in rural areas with fewer hospitals exclusion may not be possible.

Finally, I abstract away from selection in this paper to focus on the contribution to the bargaining model used in the hospital-insurer bargaining literature. However, adverse selection may be a concern for policy regarding networks. For example, Shepard (2016) provides evidence that networks may also be used to avoid high cost patients. In a follow-up paper Liebman and Panhans (2016) explores the interaction between hospital-insurer bargaining and adverse selection.

10 Conclusion

Health care spending accounts for roughly 17 percent of gross domestic product in the United States. Because of this, there is considerable policy interest in cost control. One aspect of cost control used by insurance companies is to form networks. While there are a number of reasons networks reduce insurance costs, I focus on the role of bargaining leverage. I present empirical evidence consistent with this story. Then, I model the role of exclusion by using the intuitive idea that the threat of exclusion limits a hospital’s ability to ask for higher prices. I use this model to evaluate a counterfactual network adequacy law and find that consistent with the health policy community’s warnings, these laws may increase costs.

This paper also shows how failing to incorporate the threat of exclusion into the Nash-in-Nash bargaining framework can be problematic. The Nash-in-Nash bargaining model is very general and allows for rich models of bilateral oligopoly that can be feasibly estimated. Because of this, it is growing in popularity, and it has been used to model many different markets. The standard Nash-in-Nash model may be reasonable in other settings, where the threat of exclusion is not an institutional feature of the market or excluded firms are not good substitutes for included firms. However, in cases like hospital-insurer bargaining, where the threat of exclusion is an institutional feature of the market, my model shows that it may be important to account for the networks and the bargaining leverage they provide.

References


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Prager, E., 2016. Tiered Hospital Networks, Health Care Demand, and Prices.


Table 1: Summary Statistics

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</tr>
<tr>
<td>Payment (Narrow Networks)</td>
<td>8382</td>
<td>1543</td>
<td>3129</td>
</tr>
<tr>
<td>Payment (All Claims)</td>
<td>65582</td>
<td>453</td>
<td>1544</td>
</tr>
<tr>
<td>Payment (In Network Hosp)</td>
<td>47814</td>
<td>424</td>
<td>1520</td>
</tr>
<tr>
<td>Payment (Narrow Networks)</td>
<td>35195</td>
<td>367</td>
<td>1091</td>
</tr>
</tbody>
</table>

The first panel presents plan-level data and only includes plans I was able to match with the CO APCD data. Premiums and network data are from the CO Department of Insurance. All subsequent data are from the CO APCD. The second, third, and fourth panel present data at the enrollee, visit, and claim level, respectively. Visits and claims are only from outpatient hospital settings.
Table 2: Correlations between Network Size and Prices
Dependent Variable: Log Price

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Narrow Indicator</td>
<td>-0.236***</td>
<td>-0.266***</td>
<td>-0.289**</td>
<td>-0.111</td>
</tr>
<tr>
<td>(0.0396)</td>
<td>(0.0465)</td>
<td>(0.120)</td>
<td>(0.103)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>47814</td>
<td>47814</td>
<td>47814</td>
<td>65582</td>
</tr>
<tr>
<td># Networks</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Hospital Fixed Effect</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Service Fixed Effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>In-Network Only</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01

Standard errors, in parentheses, are clustered by network. The unit of observation is a claim line. The dependent variable is log price per claim. Narrow indicates that the network includes less than 70% of hospitals in my sample. All columns have service fixed effects. Columns (1) and (2) have fixed effects for the hospital and vary the definition of service (CPT4 code versus CPT4 code and modifier). Column (3) omits the hospital fixed effect. Column (4) includes out-of-network claims.

Table 3: Correlations between Network Size and Prices
Dependent Variable: Log Price

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Hospitals</td>
<td>0.0491**</td>
<td>0.0508**</td>
<td>0.0782***</td>
<td>-0.0774***</td>
</tr>
<tr>
<td>(0.0175)</td>
<td>(0.0167)</td>
<td>(0.0183)</td>
<td>(0.0155)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>35195</td>
<td>35195</td>
<td>35195</td>
<td>52963</td>
</tr>
<tr>
<td># Networks</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Hospital Fixed Effect</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Service Fixed Effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>In-Network Only</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01

Standard errors, in parentheses, are clustered by network. The unit of observation is a claim line. The dependent variable is log price per claim. Hospitals represent the number of hospitals in network. Only narrow-network plans were included in this regression. All columns have service fixed effects. Columns (1) and (2) have fixed effects for the hospital and vary the definition of service (CPT4 code versus CPT4 code and modifier). Column (3) omits the hospital fixed effect. Column (4) includes out-of-network claims.
Table 4: Correlations between Network Size and Premiums
Dependent Variable: Log Premium

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Narrow Indicator</td>
<td>-0.119</td>
<td>-0.165</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0967)</td>
<td>(0.101)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Hospitals</td>
<td>0.0163</td>
<td>0.0218*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00992)</td>
<td>(0.00946)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Silver Indicator</td>
<td>0.166***</td>
<td>0.166***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0180)</td>
<td>(0.0180)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gold Indicator</td>
<td>0.316***</td>
<td>0.316***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0639)</td>
<td>(0.0627)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>9</td>
<td>9</td>
<td>24</td>
<td>24</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01

Standard errors, in parentheses, are clustered by network. The dependent variable is the monthly premium for a 40-year-old non-smoker. The unit of observation is a plan-metal value. Metal levels are from the CO Department of Insurance and are not available in the CO APCD data. Narrow indicates that the network includes less than 70% of hospitals in my sample. Columns (1) and (2) only use the silver plan premium, which matches the rest of the analysis. Columns (3) and (4) include bronze- and gold-level premiums, with controls for the metal level. This regression only includes data from the Denver, CO rating area.

Table 5: Demand for Hospitals

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance (Miles)</td>
<td>-0.0167***</td>
<td>-0.0159***</td>
</tr>
<tr>
<td></td>
<td>(0.00280)</td>
<td>(0.00263)</td>
</tr>
<tr>
<td>Mean Elasticity</td>
<td>-0.168</td>
<td>-0.160</td>
</tr>
<tr>
<td>Std Dev Elasticity</td>
<td>0.103</td>
<td>0.0979</td>
</tr>
<tr>
<td>Observations</td>
<td>3927</td>
<td>3927</td>
</tr>
<tr>
<td>Disease-Hospital FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Age-Hospital FE</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01

Standard errors are in parentheses. The unit of observation is a county-disease-age-sex-hospital. The dependent variable is the difference in the log market share of each hospital and the log market share of the outside option. Both columns include disease-hospital fixed effects. Column (2) includes age-hospital fixed effects.
Table 6: Prevalence of Condition Categories

<table>
<thead>
<tr>
<th>Condition Category</th>
<th>mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Certain Conditions Originating in the Perinatal Period</td>
<td>0.01</td>
</tr>
<tr>
<td>Complications from Pregnancy, Childbirth and the Puerperium</td>
<td>0.29</td>
</tr>
<tr>
<td>Congenital Anomalies</td>
<td>0.05</td>
</tr>
<tr>
<td>Diseases of Genitourinary System</td>
<td>0.88</td>
</tr>
<tr>
<td>Diseases of the Blood and Blood-forming Organs</td>
<td>0.10</td>
</tr>
<tr>
<td>Diseases of the Circulatory System</td>
<td>0.49</td>
</tr>
<tr>
<td>Diseases of the Digestive System</td>
<td>0.69</td>
</tr>
<tr>
<td>Diseases of the Musculoskeletal System</td>
<td>1.36</td>
</tr>
<tr>
<td>Diseases of the Nervous System</td>
<td>0.63</td>
</tr>
<tr>
<td>Diseases of the Respiratory System</td>
<td>0.38</td>
</tr>
<tr>
<td>Diseases of the Skin and Subcutaneous Tissue</td>
<td>0.16</td>
</tr>
<tr>
<td>Endocrine, Nutritional and Metabolic Diseases</td>
<td>0.34</td>
</tr>
<tr>
<td>Infectious and Parasitic Diseases</td>
<td>0.13</td>
</tr>
<tr>
<td>Injury and Poisoning</td>
<td>2.25</td>
</tr>
<tr>
<td>Mental Illness</td>
<td>0.15</td>
</tr>
<tr>
<td>Neoplasms</td>
<td>1.00</td>
</tr>
<tr>
<td>Residual Codes, Unclassified</td>
<td>2.93</td>
</tr>
<tr>
<td>Symptoms, Signs and Other Ill-defined Conditions</td>
<td>1.07</td>
</tr>
</tbody>
</table>

Conditions are defined as CCS codes. Prevalence is the number of visits per enrollee. Numbers are percentages.

Table 7: Prevalence of Conditions by Age

<table>
<thead>
<tr>
<th>Age</th>
<th>mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-18</td>
<td>2.67</td>
</tr>
<tr>
<td>19-25</td>
<td>7.62</td>
</tr>
<tr>
<td>26-35</td>
<td>11.18</td>
</tr>
<tr>
<td>36-45</td>
<td>14.58</td>
</tr>
<tr>
<td>46-55</td>
<td>16.87</td>
</tr>
<tr>
<td>56-65</td>
<td>21.50</td>
</tr>
<tr>
<td>Total</td>
<td>12.40</td>
</tr>
</tbody>
</table>

This table displays the average number of visits per enrollee in each age group. Numbers are percentages.
Table 8: Summary Statistics for WTP for Networks

<table>
<thead>
<tr>
<th></th>
<th>Both mean</th>
<th>sd</th>
<th>Narrow mean</th>
<th>sd</th>
<th>Broad mean</th>
<th>sd</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Enrollees</td>
<td>0.16</td>
<td>0.10</td>
<td>0.11</td>
<td>0.06</td>
<td>0.21</td>
<td>0.11</td>
</tr>
<tr>
<td>Age 0-18</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>Age 19-25</td>
<td>0.11</td>
<td>0.05</td>
<td>0.08</td>
<td>0.03</td>
<td>0.14</td>
<td>0.04</td>
</tr>
<tr>
<td>Age 26-35</td>
<td>0.16</td>
<td>0.05</td>
<td>0.11</td>
<td>0.03</td>
<td>0.21</td>
<td>0.03</td>
</tr>
<tr>
<td>Age 36-45</td>
<td>0.22</td>
<td>0.07</td>
<td>0.16</td>
<td>0.04</td>
<td>0.29</td>
<td>0.03</td>
</tr>
<tr>
<td>Age 46-55</td>
<td>0.22</td>
<td>0.07</td>
<td>0.16</td>
<td>0.04</td>
<td>0.29</td>
<td>0.03</td>
</tr>
<tr>
<td>Age 56-65</td>
<td>0.22</td>
<td>0.08</td>
<td>0.16</td>
<td>0.04</td>
<td>0.30</td>
<td>0.04</td>
</tr>
<tr>
<td>Observations</td>
<td>19440</td>
<td>10800</td>
<td>8640</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The unit of observation is age-gender-county-network. Summary statistics are unweighted means, standard deviations of WTP measure.

Table 9: Demand for Networks

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTP for Network</td>
<td>0.505**</td>
</tr>
<tr>
<td></td>
<td>(0.204)</td>
</tr>
<tr>
<td>County-Network Fixed Effect</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean Elasticity</td>
<td>0.0896</td>
</tr>
<tr>
<td>Std Dev Elasticity</td>
<td>0.0402</td>
</tr>
<tr>
<td>Observations</td>
<td>742</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

The unit of observation is age-gender-county-network. Dependent variable is the log of aggregate market share minus log of number uninsured. OLS regression includes county and network fixed effects.
Table 10: Premium Sensitivity

<table>
<thead>
<tr>
<th>Network Id</th>
<th>Narrow Ind</th>
<th>$\alpha_{1r}$</th>
<th>Mean Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>-0.00032</td>
<td>-1.88</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>-0.00028</td>
<td>-1.70</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>-0.00038</td>
<td>-2.12</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>-0.00033</td>
<td>-1.92</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>-0.00027</td>
<td>-1.78</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>-0.00062</td>
<td>-2.76</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>-0.00086</td>
<td>-2.97</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>-0.00029</td>
<td>-1.85</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>-0.00043</td>
<td>-1.93</td>
</tr>
</tbody>
</table>

The unit of observation is age-gender-county-network. Plan specific premium sensitivities are determined using first-order condition for optimal premium setting, then solving for $\alpha_{1r}$, the premium-sensitivity parameter. Observed premiums and prices are used. Estimated, rather than observed, hospital and plan market shares are used. First four rows correspond to broad-network plans, last five narrow-network plans. Elasticities vary by age-gender-county because the market shares vary, elasticity column presents the unweighted mean across each type.

Table 11: Hospital-Specific Bargaining Parameters, $\rho_{jH}$

<table>
<thead>
<tr>
<th>Hospital Id</th>
<th>Endogenous Exclusion</th>
<th>Exogenous Exclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.93</td>
<td>0.87</td>
</tr>
<tr>
<td>2</td>
<td>0.84</td>
<td>0.73</td>
</tr>
<tr>
<td>3</td>
<td>0.60</td>
<td>0.44</td>
</tr>
<tr>
<td>4</td>
<td>0.84</td>
<td>0.71</td>
</tr>
<tr>
<td>5</td>
<td>0.83</td>
<td>0.70</td>
</tr>
<tr>
<td>6</td>
<td>0.50</td>
<td>0.35</td>
</tr>
<tr>
<td>7</td>
<td>0.62</td>
<td>0.45</td>
</tr>
<tr>
<td>8</td>
<td>0.58</td>
<td>0.42</td>
</tr>
<tr>
<td>9</td>
<td>0.61</td>
<td>0.49</td>
</tr>
<tr>
<td>10</td>
<td>0.68</td>
<td>0.51</td>
</tr>
<tr>
<td>11</td>
<td>0.49</td>
<td>0.30</td>
</tr>
<tr>
<td>12</td>
<td>0.66</td>
<td>0.50</td>
</tr>
<tr>
<td>13</td>
<td>0.22</td>
<td>0.16</td>
</tr>
<tr>
<td>14</td>
<td>0.65</td>
<td>0.48</td>
</tr>
</tbody>
</table>

The second and third columns are hospital-specific generic bargaining parameters, $\rho_{jH}$. Smaller values mean more bargaining power (smaller belief about subjective probability of breakdown). Interpretation depends on value relative to insurer bargaining parameter. This specification allows the $\theta_r$ to vary by insurer. The exogenous exclusion model sets $\mathbb{P} = 1$. 

43
Table 12: Insurer-Specific Bargaining Parameters, $\rho_r^I$

<table>
<thead>
<tr>
<th>Network Id</th>
<th>Narrow Ind.</th>
<th>Endogenous Excl. Parameter</th>
<th>Exogenous Excl. Parameter</th>
<th>Endogenous Split</th>
<th>Exogenous Split</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0.59</td>
<td>0.29</td>
<td>0.37</td>
<td>0.35</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0.10</td>
<td>0.02</td>
<td>0.09</td>
<td>0.03</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0.29</td>
<td>0.16</td>
<td>0.22</td>
<td>0.23</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>0.12</td>
<td>0.07</td>
<td>0.10</td>
<td>0.12</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>0.74</td>
<td>0.14</td>
<td>0.42</td>
<td>0.21</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>0.81</td>
<td>0.20</td>
<td>0.44</td>
<td>0.27</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>0.72</td>
<td>0.04</td>
<td>0.41</td>
<td>0.07</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>0.35</td>
<td>0.10</td>
<td>0.26</td>
<td>0.15</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>0.74</td>
<td>0.06</td>
<td>0.42</td>
<td>0.10</td>
</tr>
</tbody>
</table>

The third and fourth columns are insurer-specific generic bargaining parameters, $\rho_r^I$. Smaller values mean more bargaining power (smaller belief about subjective probability of breakdown). This specification allows the $\theta_r$ to vary by insurer. The exogenous exclusion model sets $\hat{P} = 1$. The fifth and sixth columns display the split of surplus, given by Equation 7, with hospital 6 to demonstrate how the parameters interact.

Table 13: Insurer-Specific Exclusion Parameters $\theta_r$

<table>
<thead>
<tr>
<th>Network Id</th>
<th>Parameter Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0.35</td>
</tr>
<tr>
<td>6</td>
<td>0.25</td>
</tr>
<tr>
<td>7</td>
<td>0.56</td>
</tr>
<tr>
<td>8</td>
<td>0.67</td>
</tr>
<tr>
<td>9</td>
<td>0.57</td>
</tr>
</tbody>
</table>

Larger values correspond to stronger (negative) relationship between number of acceptable replacement hospitals and hospital’s share of surplus. 0 would correspond to no correlation, while 1 would correspond to equiprobability of a deviating hospital being picked.
Table 14: Counterfactual Negotiated Prices

<table>
<thead>
<tr>
<th>Type of Variation</th>
<th>With Exclusion</th>
<th>Nash-in-Nash</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta = 1$</td>
<td>1.56</td>
<td>0.62</td>
</tr>
<tr>
<td>One $\theta$</td>
<td>0.99</td>
<td>0.62</td>
</tr>
<tr>
<td>$\theta_r$ by Ins.</td>
<td>1.27</td>
<td>0.62</td>
</tr>
<tr>
<td>$\theta_j$ by Hosp.</td>
<td>1.20</td>
<td>0.62</td>
</tr>
</tbody>
</table>

This table reports the results of different counterfactual simulations where exclusion is not allowed. Each row presents a different set of $\theta$ parameters which capture the relationship between number of acceptable replacement hospitals and hospital’s share of surplus. The first row assumes $\theta = 1$ which corresponds to assuming equiprobability of a deviating hospital being picked. The second row allows for one $\theta$ value. The third and fourth rows allow the $\theta$ to vary by insurer and hospital, respectively. Breakdown has one hospital dropped from the network. The exogenous exclusion model sets $\mathbb{P} = 1$. 
A  Data Appendix

Data on premiums and networks are collected from the CO Department of Insurance website and insurance company websites. There are 12 companies in the market who offer 22 different networks. The claims data always indicate the insurance company, but only a few companies indicate which network the consumer has enrolled in. Of these 12 companies, four companies in the data either did not submit their claims or had too few enrollees for me to use their claims with any sort of precision. These companies corresponded to six networks. Three other networks, while technically offered in the Denver rating area were focused in other parts of the state and had very little enrollment. For one company, I could not determine which of their claims corresponded to the individual market. Finally, three companies offered a pair of networks which I could not distinguish in the claims data. However, for only one of the networks were the set of hospitals different. For these three pairs networks, I treat the two networks as one, and for the one with different hospitals, I use the smaller network to avoid characterizing out-of-network visits as in-network. This leaves me with nine networks total, across seven companies. For simplicity, I treat the two companies with observably different networks as different companies and use the terms network, insurer and company interchangeably.

The premium data are by company, network and metal level (metal levels: bronze, silver, gold and platinum correspond to the actuarial value of the plans). In the claims I do not observe the metal level, but the networks and negotiated prices do not vary by metal level. Throughout the draft I use the cheapest silver plan offered for that network as the premium.

The sample of hospitals I use is the set of hospitals classified in the American Hospital Association directory as General Medical/Surgical hospitals. This excludes rehabilitation hospitals and children’s hospitals. I also exclude Veterans Affairs hospitals. This leaves 17 hospitals and I drop two others since they have very few claims. I match the hospitals using a fuzzy match by name, with the claims data, then hand check them with their National Provider Identifier (NPI) in the national database of providers.

B  Complete Bargaining Model

In this section, I propose the complete version of my bargaining model. Compared to the stylized version, I allow for many insurers and heterogeneity of surplus. The discussion in this section closely follows the discussion of the stylized version, with changes made as appropriate. This model is meant to provide foundations for the empirical framework, so many of the assumptions were made with the five-stage model in mind, however, I make a few modifications to keep this section self-contained and highlight points which concern later stages of the game or estimation in footnotes.

58 In future work, I plan to account for within company competition.
59 By law, plans are allowed to charge different premiums for each age group, but only up to a three-to-one ratio (that is, a plan may charge a 64-year-old only three times higher premiums than a 21-year-old). I adjust premiums for each age group accordingly, using a table from ... in their insurance filings.
60 https://npiregistry.cms.hhs.gov/
B.1 Fundamentals

Consider a bargaining game between \( R \) insurers and \( N \) hospitals. Let \( \mathcal{R} \) and \( \mathcal{N} \) denote the set of insurers and hospitals, respectively. At \( t = 0 \), each insurer \( r \) publicly commits to \( K_r \in \mathbb{N}^* \), how many hospitals it would like to agree with, which remains a fixed constant for the remainder of the game.\(^{61}\)

Negotiations start at time period \( t = 1 \), step \( b \). Let \( \mathcal{F}_{rt} \) and \( \mathcal{A}_{rt} \) denote the sets of hospitals who have and have not reached an agreement before period \( t \). In each period, every hospital \( j \) is either in \( \mathcal{F}_{rt} \) or \( \mathcal{A}_{rt} \) for each insurer. That is, \( \mathcal{F}_{rt} \) and \( \mathcal{A}_{rt} \) are a partition of \( \mathcal{N} \) for all \( t \). At the beginning of each period, the set of hospitals who will either make or receive an offer is chosen. I refer to this set of hospitals as the “bargaining set,” denoted \( \mathcal{K}_{rt} \). Either Nature or the insurer selects the set \( \mathcal{K}_{rt} \) out of the set \( \mathcal{A}_{rt} \) such that the number of hospitals selected, plus those who have already reached an agreement, equal the number of hospitals the insurer would like in the network, i.e., \( K_r = |\mathcal{F}_{rt}| + |\mathcal{K}_{rt}| \). To simplify the model, I assume that Nature will only choose hospitals that create enough surplus so that the hospital-insurer pair could potentially reach an agreement.\(^{62}\)

Once the set \( \mathcal{K}_{rt} \) is specified, the game moves to the negotiation phase, step \( c \), of period \( t \). When \( t \) is odd, the insurer makes offers to all hospitals in \( \mathcal{K}_{rt} \) simultaneously. When \( t \) is even, all hospitals in \( \mathcal{K}_{rt} \) make offers, denoted \( x_{jr} \), to the insurer simultaneously. A player who receives an offer has a binary choice to either accept or reject that offer. If the offer between hospital \( j \) and the insurer is accepted, hospital \( j \) joins the set \( \mathcal{F}_{rt+1} \) and remains in \( \mathcal{F}_r \) for all subsequent periods. If an offer is rejected at period \( t \), that hospital joins the set \( \mathcal{A}_{rt+1} \). The game ends for insurer \( r \) when \( K_r \) agreements have been made. Transfers are made at the end of the game.\(^{63}\)

In order to have price determinacy, models of bargaining require a friction or cost of negotiating. I include an exogenous probability of breakdown, similar to Binmore et al. (1986). Starting in period \( t = 2 \) and in every following period, before \( \mathcal{K}_{rt} \) is set, in step \( a \), Nature determines whether a breakdown occurs. I allow hospitals and insurers to have asymmetric beliefs about the subjective probability of breakdown denoted by \( \rho^H_j \) and \( \rho^I_r \), respectively.\(^{64}\) When a breakdown occurs, the

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\(^{61}\)Commitment is a key assumption; without commitment the insurer would not exclude and would lose the leverage gained from exclusion. In practice these contracts are renegotiated every year or every few years, and not all hospitals negotiate simultaneously. Furthermore, many of these insurance companies operate in many geographic markets, with different types of providers (hospitals, physicians, ambulatory care centers, etc.) and across many market segments (Medicare Advantage, health exchanges, individual and employer insurance, etc.). Reneging in one market could make the exclusion threat less credible in others.

\(^{62}\)All periods after the first start with a step \( a \).

\(^{63}\)Exclusion is exogenous when a hospital does not have enough surplus to reach an agreement. As Capps et al. (2003) point out, this will occur if added cost of a hospital (due to substitution towards that hospital and its marginal cost of treating patients) is higher than the marginal benefit of including that hospital.

\(^{64}\)Because I allow for externalities between hospitals, it is possible that if Nature is picking one hospital at a time then an earlier picked hospital may not provide enough surplus for the pair to reach an agreement. Instead, Nature determines all the sets of hospitals where each hospital could reach an agreement, then randomly chooses one of those sets.

\(^{65}\)For the purposes of the bargaining game, I assume that surplus is paid at the end of the period. In the full model, surplus is paid to the insurer (through premiums) in Stage 3, and the insurer makes transfers to hospitals in Stage 5. As I highlight later, players are negotiating over expected surplus in this stage.

\(^{66}\)Asymmetric beliefs are allowed for in Binmore et al. (1986), with the assumption of some appropriate behavioral model, for example heterogenous priors. I follow Binmore et al. (1986) and do not specify this aspect of the model because it is not a key feature of the model. The main results of the model can be shown with symmetric beliefs. However, asymmetric beliefs help highlight the concerns endogenous networks raise for the reduced-form analysis and are an important feature of the empirical model where the interpretation of this parameter is different.
game ends and no further agreements can be made, though the surplus created and transfers previously agreed to remain. All excluded hospitals, either due to the insurer reaching $K_r$ agreements or breakdown, receive zero surplus from that insurer. Renegotiation of contracts is not allowed. The beliefs about the probability of breakdown are assumed to be constant throughout time and do not vary based on which hospitals have reached agreements. Players do not discount future surplus or transfers.

For clarity, I respecify the timing of the model:

t=0. Each insurer $r$ publicly commits to size of their network, $K_r$.

t = 1, 3, 5, ... (if $|F_r| < K_r$ agreements have been reached):

a. (Except period $t = 1$) Nature decides whether there is a breakdown.

b. Each insurer $r$ picks which hospitals to make an offer to $K_r$.

c. Each insurer $r$ makes simultaneous offers to the hospitals in $K_r$.

d. Hospitals in $K_r$ simultaneously decide whether to accept or reject their offer(s).

t = 2, 4, 6, ... (if $|F_r| < K_r$ agreements have been reached):

a. Nature decides whether there is a breakdown.

b. With equal probability $P(\cdot)$ Nature chooses $K_r - |F_r|$ hospitals to make an offer $K_r$ to each insurer $r$.

c. Hospitals in $K_r$ make simultaneous offers to each insurer $r$.

d. Insurers simultaneously decide whether to accept or reject each offer.

The game stops when $K$ hospitals have reached agreement or breakdown occurs. Then payments are made.

I treat surplus as a primitive that takes as an input the network of hospitals and transfers agreed upon by all hospital-insurer pairs and returns a dollar amount. That is, for any network $G_r$ and set of transfers $x$, $\Pi_r(G, x)$ is the total surplus generated. I omit the $r$ subscript for $G$ and the $jr$ subscript for $x$ because this function depends on the networks of all insurers and transfers for all hospital-insurer pairs. That surplus depends on the networks and transfers of all players allows for flexibility in the externalities between hospitals and insurers. I include transfers in this section because they affect the optimal premium setting for an insurer and insurers compete over premiums. I assume that surplus is declining in transfers and that adding any hospital to the network, holding transfers to all hospitals fixed, will increase surplus. I assume all players are risk neutral.

The surplus functions allow for non-transferable utility because the surplus depend on the transfers. Neither Binmore et al. (1986) nor Collard-Wexler et al. (2016) allow for non-transferable

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67 In the empirical section I specify the surplus function. I treat surplus as a primitive here because all of the inputs are determined at other stages of the game, conditional on the outcome of the bargaining game. Therefore, hospitals and insurers can determine the expected surplus values at any state of the world. Intuitively, this is the value of the expected premiums that the insurer takes as revenue, minus the expected sum of marginal costs of the services provided to all the hospitals in network.

68 In the five-stage model, transfers effect surplus through premiums. Therefore, the sum of expected costs across all hospitals, not the transfer to any particular hospital, is the object of interest.
utility, but Crawford and Yurukoglu (2012) does. I do not have an analytic solution with non-transferable utility, but can solve the model numerically. For this section, I assume transferable utility, that is, hospital $j$’s negotiated transfer with insurer $r$ does not affect the total surplus created by insurer $r$’s network in its negotiations with hospital $j$. In practice if a hospital negotiates a larger transfer, that may increase the insurer’s premiums, reducing the total surplus available. This precludes a closed-form solution because larger transfers would reduce surplus, which would lower the agreed-upon transfer. This assumption is simply expositional, in the empirical analysis, I use a fixed-point algorithm to solve for each premium-transfer pair.

Throughout this section, I refer to surplus kept by insurers or hospitals and also allow for these values to differ in the case of a breakdown.\footnote{Again, these terms will all be explicitly specified in the empirical section, but for expositional simplicity these values are taken as primitives in the bargaining game.} The term $\Pi^I_r(G, x, K)$ will represent the surplus insurer $r$ captures, which is the total surplus, minus the markups to the hospitals. Likewise, $\Pi^H_j(G, x, K)$ represents the surplus hospital $j$ receives from patients enrolled in insurer $r$’s plan. Finally, I use $\Pi^B_r(G, x, K)$ and $\Pi^{IB}_r(G, x, K)$ to denote the total surplus created and the surplus kept by insurer $r$ during a breakdown, respectively.

I assume an equilibrium exists and that all players know which equilibrium will be played. I assume that players know the surplus functions, $\Pi$, and beliefs about the probability of breakdown, $\rho$, for all the players. Throughout the bargaining stage, insurers do not know the outcomes of decisions that other insurers make (including the size of the networks, $K$, the bargaining sets, $\mathcal{K}$, the set of agreements reached, $\mathcal{F}$, or transfers, $x$).\footnote{For the purposes of the bargaining game, I assumed that surplus was paid at the end of the period. Information about other insurer’s networks and premiums are not known until after Stage 2, when premiums are set. These informational assumptions may be realistic if insurers do not reveal information about their networks to others prior to selling their products. My empirical setting is the first year of the exchange marketplace, which may restrict insurers’ ability to look at the networks in the previous year. Information about other insurers’ prices are proprietary.} That is, insurers do not update their information about other insurers once decisions are made.

During negotiations, hospitals know the size of the network, $K$, the bargaining set, $\mathcal{K}$, and any agreements that have been made, $\mathcal{F}$. Hospitals never learn the transfers other hospitals are offered, offer, or agree to throughout the game.\footnote{Other hospital’s negotiated prices are proprietary.} To rule out informational asymmetries, I assume that the hospitals do not use their information with one insurer when negotiating with a different insurer. Likewise, I do not allow insurers to use information about their negotiations with other hospitals.

To give an example of these informational assumptions, consider a multilateral negotiation where each hospital sends a delegate to negotiate with a delegate from each insurer. Each insurer is located in a separate building, so delegates from different insurers cannot communicate, nor can delegates from one hospital negotiating with different insurers. Once in the building, there is a waiting room where the insurer announces the size of the network, $K_r$.\footnote{The hospital delegates in the waiting room are $A_{ir}$.} Then, the insurer lists all the hospital delegates who will be called to negotiate, so all the delegates at that building know which hospital delegates were included in the bargaining set. Then all the hospital delegates in the bargaining set go into separate offices, each with a separate insurer delegate. Offers are made without any communication outside of the pair of delegates negotiating. Finally, after offers are accepted or rejected in that period, which agreements are made is announced to all the delegates at that building.
the drawback is that it increases the number of strategies available and the number of resulting equilibria. This requires strong assumptions to regain tractability. However, even if this was a less restrictive framework, I do not have data on whether other strategies are used in practice, and if they are, they will be accounted for in the bargaining parameters of the empirical model. While these are strong restrictions on the model, this is a critique of the Nash-in-Nash model generally. One interpretation of my paper is as a constructive criticism of these restrictions: I am allowing for an additional strategy (the threat of exclusion) for which data are available and demonstrating how to incorporate it into the tractable and rich empirical framework the Nash-in-Nash model provides.

B.2 Equilibrium Strategy Profile

In this subsection, I propose a strategy profile which is a Markov-perfect equilibrium (MPE). The concept of an MPE restricts the set of equilibria to the subset of subgame-perfect Nash equilibria for which the only aspect of the history that influences strategies is the current state. In particular, this implies that if negotiations happen at $t+1$, the probability of any hospital in $A_{rt+1}$ to be chosen to bargain at $t+1$ is independent of the identity of hospitals which rejected an offer at $t$.

In period $t = 0$, each insurer chooses its profit-maximizing size of the network, given its expectation about the network sizes of other insurers. Let $\Pi_r^t(K_r; K_{-r})$ be the surplus the insurer receives in equilibrium when choosing network size $K_r$, given that they expect other insurers to choose size $K_{-r}$. In equilibrium each insurer chooses $K_r$ such that $\Pi_r^t(K_r; K_{-r}) \geq \Pi_r^t(K_r'; K_{-r})$ for all $K_r' \leq N$.

In odd periods $t = 1, \ldots, \infty$, step b, the insurer picks a bargaining set $K_{rt}$ such that $|K_{rt}| + |F_{rt}| = K_r$. When making this choice, the insurer chooses its profit-maximizing network. Let $\Pi_r^t(G_{rt}, G_{-rt}, x, K)$ denote the expected surplus to the insurer given the equilibrium outcomes when insurer $r$ chooses network $G_{rt}$ and expects all other insurers to choose the networks $G_{-r}$, and transfers $x$ at $t$. Then the insurer chooses the network $G_{rt}$ such that $\Pi_r^t(G_{rt}, G_{-r}, x, K) \geq \Pi_r^t(G_{rt}', G_{-r}, x, K)$ for all $G_{rt}'$ such that $|G_{rt}'| = K_r$ and $F_{rt} \subset G_{rt}$.

Let $V_{jrt+1}(F_{rt+1}, F_{-r}, x, K)$ and $W_{rt+1}(F_{rt+1}, F_{-r}, x, K)$ denote hospital $j$’s and insurer $r$’s expected value of having not reached an agreement before the beginning of period $t+1$, conditional on expectations about future agreements with insurer $r$, $F_{rt+1}$, networks formed by other insurers, $F_{-r}$, and expectations about others’ transfers $x$. Given that players know the bargaining set when making or receiving an offer, players can determine which hospitals will have reached agreements before receiving their offers in period $t$. Therefore, in negotiations with hospital $j$, the continuation value to the hospital and insurer during the offer stage of period $t$ is $V_{jrt+1}(F_{rt+1}\{j\}, F_{-r}, x, K)$ and $W_{rt+1}(F_{rt+1}\{j\}, F_{-r}, x, K)$, where $F_{rt+1}$ takes into account those who have already reached an agreement ($F_{rt+1}$) and those who are expected to reach an agreement (some subset of $K_{rt}$). This excludes hospital $j$ because the negotiation including hospital $j$ is the one where a deviation is being considered. Because I use the MPE solution concept, the time period does not affect the value functions, except for whether the state is even or odd. However, I use $t$ subscripts to clarify timing. In periods, $t = 1, \ldots, \infty$, step c, the players which make offers propose their counterpart’s continuation value. The player who is offered their continuation value will accept.

I assume that in equilibrium there will be immediate agreement.

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74 The condition $F_{rt} \subset G_{rt}$ simply means that they are choosing the entire network, conditional on $F_{rt}$ having already agreed.

75 Because $A_{rt+1}$ and $F_{rt+1}$ partition $N$, it is sufficient to just use $F_{rt+1}$ as the state space.

76 Without Assumption A, ImmAgg, the model is not fully specified. In particular, expectations about the network in
**Assumption ImmAgg** (Immediate Agreement). Suppose the value of the primitives is such that a possible equilibrium involves immediate agreement ($K_r$ agreements are reached in period $t = 1$ for each $r$) and that this equilibrium is played.

In the simplified model there are two reasons why it is unprofitable for the insurer to delay. First, the expected costs of breakdown are higher if fewer hospitals have agreed at any point in time. Second, at least in the stylized model delay improves the continuation value of a hospital who reaches an agreement at $t = 1$ because the probability they are picked again if they deviate is higher than when all hospitals agree at period $t = 1$. This is a similar argument to Möller (2007) who argues that when the timing of agreements is endogenous, there is an incentive for simultaneous agreements when the externalities between players weakens over time. Finally, in the more general model, the insurer may also be left with a less profitable network if they allow Nature to choose which hospitals remain.

### B.3 Determining Continuation Values

Now, I discuss the equilibrium outcomes and compute the continuation values, given the strategies specified in the previous section. While all hospitals agree in the first period, continuation values depend on the expected value for hospital $j$ after deviating from the equilibrium and rejecting the offer. Consider hospital $j$’s decision to deviate from the equilibrium and reject the offer (in period $t = 1$ only). Deviating hospital $j$’s expected value for period $t = 2$, given equilibrium strategies, simplifies to:

$$
V_{jrt=2}(K_{r}\setminus\{j\}) = \rho_j^H \cdot 0 \\
+ \left[ \Pi_r(K_{r1}, x(K_{r1})) - \sum_{i \in (K_{r1}\setminus\{j\})} \Pi_r^H(K_{r1}, x(K_{r1})) - W_{t=3}(K_{r1}\setminus\{j\}, x(K_{r1})) \right] \cdot (1 - \rho_j^H) \cdot \mathbb{P}(j \in K_{r2}|K_{r1}\setminus\{j\})
$$

where $\mathbb{P}(j \in \hat{F}_r|F_r, K_r)$ denotes the probability that hospital $j$ is included in network $\hat{F}_r$, given that the hospitals in $F_r$ have already reached an agreement and that $K_r$ hospitals will ultimately reach an agreement (barring a breakdown). I drop notation for other networks (both $F_{-r}$ and $K$) because the player’s expectations about these values are unchanging. With probability $\rho_j^H$, breakdown occurs and the hospital gets nothing. With probability $(1 - \rho_j^H)$, agreements are made possible in period $t = 2$. In period $t = 2$, with probability $\mathbb{P}(j \in K_{r2}|K_{r1}\setminus\{j\})$, hospital $j$ will be chosen to make an offer. The most the hospital can ask for is all the surplus the insurance company receives, net of what it pays out to other hospitals and the insurer’s continuation value. Because in equilibrium all hospitals reach an agreement at $t = 1$, in considering the value of deviating, hospital $j$ expects the payments to all other hospitals are formed with the expectation that all hospitals in $K_{r1}$ will reach an agreement at $t = 1$.

If hospital $j$ were to deviate, then the network would consist of all the hospitals in the original bargaining set except hospital $j$, i.e., $\hat{F}_{r2} = K_{r1}\setminus\{j\}$. Since I am computing hospital $j$’s value of deviation, I focus on the case where it is picked in the following period. Therefore, the input to future periods and whether there is enough surplus available to reach agreements need to be considered. Expectations no longer matter because the case where the deviating hospital is chosen is the only relevant case. Assuming immediate agreement also assumes that each hospital in the network provides enough surplus to be included.

\[77\] Since I am focusing on a hospital that deviated, by definition $j \in K_{r1}$.
\(\Pi_r(\cdot)\) is \(\mathcal{K}_{r1}\) because, conditional on hospital \(j\)’s offer being accepted, the final state will be \(\mathcal{K}_{r1}\)\(^{78}\).

Finally, the input to \(W_{rt=3}(\cdot)\) is \(\mathcal{K}_{r1}\{j\}\) because if the offer is not accepted, then the state going into period \(t = 3\) will be \(\mathcal{K}_{r1}\{j\}\). However, all other transfers will have been agreed upon under the expectation that \(\mathcal{K}_{r1}\) would have been the outcome of the negotiations in \(t = 1\). Notice that until the final agreement is made, the set of hospitals which will have agreed at any given period remains unchanged at \(\mathcal{K}_{r1}\{j\}\).

Now, I solve for the insurer’s value function by considering the case where it deviates at period \(t = 2\). In this case, the insurer will pick the most profitable network \(\mathcal{K}_{r1}\) again, so it chooses the same hospital \(j\) which deviated previously. The insurer’s expected value in \(t = 3\), given that the hospitals in \(\mathcal{K}_{r1}\{j\}\) have agreed, is:

\[
W_{rt=3}(\mathcal{K}_{r1}\{j\}) = (1 - \rho^r_1) \left[ \Pi_r(\mathcal{K}_{r1}, x(\mathcal{K}_{r1})) - \sum_{i \in (\mathcal{K}_{r1}\{j\})} \Pi^H_r(\mathcal{K}_{r1}, x(\mathcal{K}_{r1})) - V_{jr=t=4}(\mathcal{K}_{r1}\{j\}, x(\mathcal{K}_{r1})) \right] (9)
+ \rho^r_1 W^B_r(\mathcal{K}_{r1}\{j\}, x(\mathcal{K}_{r1}))
\]

With probability \((1 - \rho^r_1)\), the game goes forward and the insurer offers hospital \(j\) its continuation value, keeping the remainder of the surplus that was not paid out to other players. With probability \(\rho^r_1\), breakdown occurs and the insurer receives \(\Pi^B_r(\mathcal{K}_{r1}\{j\}, x(\mathcal{K}_{r1}))\). Notice that transfers are determined based on the expectation that \(\mathcal{K}_{r1}\) will have been formed, since these were the expectations of other hospitals in \(\mathcal{K}_{r1}\), besides deviating hospital \(j\).

### B.4 Bargaining Results

To calculate transfers, I consider a unilateral deviation by each hospital \(j \in \mathcal{K}_{r1}\) separately. Because of immediate agreement, a unilateral deviation would imply there is only one additional agreement remaining. At this point the state of the game does not change from period \(t = 2\) until an agreement is reached (conditional on the state being even or odd). Because the value functions only depend on the state, and the state only depends on whether the time is even or odd, \(V_{jr=t=2}(\mathcal{K}_{r1}\{j\}, x(\mathcal{K}_{r1})) = V_{jr even}(\mathcal{K}_{r1}\{j\}, x(\mathcal{K}_{r1})) = \ldots = V_{jr even}(\mathcal{K}_{r1}\{j\}, x(\mathcal{K}_{r1}))\) and likewise \(W_{rt=3}(\mathcal{K}_{r1}\{j\}, x(\mathcal{K}_{r1})) = W_{r odd}(\mathcal{K}_{r1}\{j\}, x(\mathcal{K}_{r1}))\). Therefore, for each insurer-hospital pair I have two unknowns \(V_{jr even}(\cdot)\) and \(W_{r odd}(\cdot)\) and two equations linear in the unknowns, so there exists a unique solution that can be represented with a closed form (conditional on \(P(j \in \mathcal{K}_{r2}|\mathcal{K}_{r1}\{j\})\)). Proposition \(^2\) presents this solution:

**Proposition 2.** The equilibrium outcome of this game is given by:

\[
x_{jr}(\mathcal{K}_{r1}) = \frac{\Pi^{j\text{ARG}}_r(\mathcal{K}_{r1}) \cdot P(j \in \mathcal{K}_{r2}|\mathcal{K}_{r1}\{j\}) \cdot (1 - \rho^H_j) \cdot (\rho^r_1)}{1 - (1 - \rho^r_1) \cdot (1 - \rho^H_j) \cdot P(j \in \mathcal{K}_{r2}|\mathcal{K}_{r1}\{j\})}
\]

Where the marginal surplus is defined as:

\(^{78}\)Note that in this case all transfers would be the same as if it happened in period \(t = 1\), since the other hospitals reached this agreement with an expectation that all hospitals would reach an agreement. The strategic situation is the same for hospital \(j\) as it was in period \(t = 1\).
\[
\Pi_{jr}^{\text{MARG}}(K_{r1}) = \Pi_r(K_{r1}, x(K_{r1})) - \sum_{i \in (K_{r1} \setminus \{j\})} \Pi_r^H(K_{r1}, x(K_{r1})) - \Pi_r^I(B(K_{r1} \setminus \{j\}, x(K_{r1}))
\]

Note that marginal surplus is not a value that I am assuming, but rather this is a derived value.

### B.4.1 Relationship to Rubinstein Outcomes

My first result states that when \(K_r = N\), meaning the insurer chooses not to exclude, the model predicts \(N\) outcomes that match the outcomes in Rubinstein (1982). In particular, \(K_r = N\) implies that \(\mathbb{P}(\cdot) = 1\), i.e., hospitals who reject an offer in the previous period will be picked with probability one. The solution reduces to:

**Corollary 2.** When \(K = N\) and \(\mathbb{P}(\cdot) = 1\), the equilibrium outcome simplifies to:

\[
x_{jr}(N) = \frac{\Pi_{jr}^{\text{MARG}}(N) \cdot (1 - \rho_j^H) \cdot \rho_r^l}{1 - (1 - \rho_j^H) \cdot (1 - \rho_r^l)}
\]

Allowing for exclusion, the results are the same as the Rubinstein result, except that the hospitals’ risk of breakdown parameters are multiplied by their probability of being chosen, as highlighted by the brackets in Proposition 2. One way to interpret this is that my result is distinguishing the risk of breakdown from the risk of exclusion due to the narrow-network. This also demonstrates how my model nests the Nash-in-Nash solution. When there is no exclusion (or the probability of being picked after deviating equals 1), each negotiation becomes the outcome of a pairwise Rubinstein bargain, conditional on all the other negotiations. Collard-Wexler et al. (2016) provides sufficient conditions under which this limits to the Nash-in-Nash solution, similar to how Binmore et al. (1986) demonstrates that Rubinstein (1982) limits to the Nash solution. The remaining results show how my model extends the Nash-in-Nash model.

### B.4.2 Narrow Networks Negotiate Smaller Transfers

My next result shows that the model with exclusion can imply smaller transfers. This will be true if the following assumptions hold:

**Assumption SN (Smaller Network).** For positive numbers \(l\):

\[
\mathbb{P}(\cdot; K) \leq \mathbb{P}(\cdot; K + l)
\]

Assumption SN (A.SN) states that the probability of a hospital being selected in the following period is smaller compared to the case where the insurer chose a smaller network size in period \(t = 0\). In a setting where hospitals are all acceptable and have equal probability of being chosen, this is a natural property. A smaller network, holding \(N\) constant, means more hospitals are excluded. Therefore, if a hospital deviates, there are more available hospitals to fill their slot, so the deviating hospital has a lower chance of being picked again.

As a counterexample, suppose there are four hospitals and one insurer. If the network size is \(K = 2\), then the following networks are chosen with equal probability \(\{1, 2\}, \{2, 3\}, \{2, 4\}\). If the network size is \(K = 3\) then the following networks are chosen with equal probability \(\{1, 3, 4\}, \{1, 2, 3\}, \{1, 2, 4\}\). Consider hospital 2’s decision to deviate when \(K = 2\) and after \(\{2, 3\}\) has been offered. In this case, hospital 2 knows with probability 1 it will be selected to negotiate in
the following period. Now, suppose that $K = 3$ and $\{1, 2, 4\}$ have been offered to. After deviating, hospital 2 has a one-half probability of being included in the following period.

**Assumption CMS (Constant Marginal Surplus).** For positive numbers $l$: $\Pi^{MARG}_{jr}(K; K) = \Pi^{MARG}_{jr}(K; K + l)$

Assumption CMS (A CMS) states that the marginal surplus generated by a hospital is constant in the size of the network. While the functional form in the empirical section will imply lower marginal surplus, A CMS isolates the role of bargaining leverage from changing the amount of surplus to be split. Without accounting for the changing probability of exclusion, lower marginal surplus would imply that insurers with larger networks negotiate smaller transfers. I argue that this effect is offset by the exclusion effect, which is why in the data insurers with larger networks are observed paying larger transfers.

**Proposition 3.** Under assumptions A SN and A CMS, insurers with smaller networks negotiate smaller transfers.

This is a straightforward consequence of Proposition 2. Intuitively, the reason this occurs is that by excluding, the insurer is increasing the probability the hospital gets zero, which worsens the hospital’s continuation value. Why this worsens the continuation value is clear from equation as the value function is multiplied by $\mathbb{P}(j \in K_{T2} | K_{T1} \{j\})$. If hospital $j$ disagrees when many hospitals are excluded, the probability it gets nothing $(1 - \mathbb{P}(j \in K_{T2} | K_{T1} \{j\}))$ is large. When few hospitals are excluded, the probability of getting nothing is smaller, so the value of deviating is larger.

### C Defining Acceptable Replacement Hospitals

To determine the probability that hospital $j$ is picked after deviating in period $t = 1$, I calculate the number of otherwise excluded hospitals that provide enough surplus to make agreement with the insurer feasible. I refer to these as “acceptable replacement” hospitals. For hospitals not in $K_{T1}$, their continuation in even periods is zero: In equilibrium they do not maximize the insurer’s profit, so they will not be picked again in $t = 3$. Therefore, any surplus they can extract at period $t = 2$ from the insurer would make them better off. This simplifies checking which hospitals are acceptable because I only need to check whether:

$$\Pi^I_{jr}(\mathcal{F}_r \cup \{i\} \{j\}, \mathcal{F}_{-r}, p(\mathcal{F}), K) > (1 - \rho^I)\Pi^I_{jr}(\mathcal{F}, p, K) + \rho^I\Pi^{LB}_{jr}(\mathcal{F}, \mathcal{F}_r \{j\}, p(\mathcal{F}), K)$$

That is, hospital $i$ is acceptable if they provide enough surplus such that the insurer would be better off paying them their marginal cost, rather than offering nothing and waiting until the following period, where with probability $\rho^I$ the insurer receives their breakdown value and with probability $(1 - \rho^I)$ it matches with hospital $j$.

As with the breakdown case, because this is after a deviation from hospital $j$ in period $t = 1$, the other hospitals in network have negotiated with the expectation that $\mathcal{F}$ would form, so I use observed prices for all other hospitals and price equal to marginal cost for hospital $i$. Therefore, $\Pi^I_{jr}(\mathcal{F}_r \cup \{i\} \{j\}, \mathcal{F}_{-r}, p(\mathcal{F}), K)$ is defined as:

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That is the insurer decides whether to make an offer to hospital $i$ or wait to match with hospital $j$ in the following period.
\[ \Pi_I^i(F_r \cup \{i\}\setminus\{j\}, F_{-r}, p(F), K) = \sum_i \left[ \text{premium}_i(F_r \cup \{i\}\setminus\{j\}, F_{-r}, p) - \sum_{d \in D} \sum_{k \in F_r \cup \{i\}\setminus\{j\}} p_{kd}(F, \Pi_r, K) \sigma_{id}(F_r \cup \{i\}\setminus\{j\}) \right] \cdot S_{imm}(\text{premium}_i(F_r \cup \{i\}\setminus\{j\}, F_{-r}, p), F_r \cup \{i\}\setminus\{j\}, F_{-r}) \]

Premiums and the market share values depend on the observed network, minus hospital \(j\) and plus hospital \(i\). Because all prices are observed (including for hospital \(i\) where it equals marginal cost), \(\Pi_I^i(F_r \cup \{i\}\setminus\{j\}, F_{-r}, p(F), K)\) can be computed prior to estimation. For every insurer and every hospital \(j\) in that insurer’s observed network, I compute this value for every hospital \(i\) excluded from the observed network to check whether \(i\) is an acceptable replacement.