Regulating Out-of-Network Hospital Payments: Disagreement Payoffs, Negotiated Prices, and Access*

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Abstract

Recent policy proposals seek to regulate the prices that hospitals can levy for care delivered outside of a patient's insurance network. In this paper, we study the potential effects of such regulations on equilibrium in-network prices and access. We first describe how out-of-network reimbursements affect negotiations over in-network prices and network status. We then conduct a series of counterfactuals to empirically evaluate current policy proposals that would cap out-of-network reimbursements. To do so, we estimate a model of insurer-hospital bargaining that explicitly allows for transactions in the absence of a contract. We operationalize the model using a novel, data-driven measure of out-of-network prices paid by insurers to hospitals. Our results suggest that reducing out-of-network reimbursements would have the intended effect of lowering negotiated prices with in-network hospitals. Aggressive regulation, however, would reduce access to care as a result of narrower networks and some outright service line closures.

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1 Introduction

Policy-makers have recently sought to regulate the prices that hospitals can levy when they are not in an insurer's provider network. Proponents tout these out-of-network price caps as a mechanism for not only reducing patients' exposure to surprise medical bills outside their insurer's network, but also reducing negotiated prices with in-network providers (Kane 2019; Chernew et al. 2019). If successful, these reductions may also have the unintended—and under-discussed—effect of pushing insurers to drop hospitals from their networks. In extreme cases, the price reductions may push hospitals to close altogether. This paper evaluates empirically the effects of out-of-network price caps on equilibrium negotiated in-network prices, network breadth, and provider closures.

The paper's first contribution is to propose a practical solution to the empirical challenge of measuring the out-of-network prices actually paid to hospitals by health insurers. The literature recognizes the importance of correctly accounting for disagreement values in the estimation of bargaining models (Ho and Lee 2019). Nevertheless, existing papers on hospital-insurer bargaining have assumed away the presence of transactions in the case of disagreement, owing in part to the difficulty of measuring off-contract prices. Beyond the fact that health care markets lack posted prices, off-contract prices can vary by insurer, geography, type of service, and institutional features or laws governing a particular market. To circumvent these issues, we leverage the institutional details of health insurers' out-of-network payment policies to construct a measure of off-contract prices. To our knowledge, this paper is the first to incorporate a data-driven measure of out-of-network prices. We leverage the fact that many insurers base their out-of-network reimbursement policies on third-party benchmarks constructed from hospital charge prices in a given geographic market. We replicate the third-party methodology for constructing these benchmarks using the type of data that are readily available to researchers. The resulting measure yields a reasonable approximation of observed out-of-network hospital payments in our data.

Our second contribution is to use our measure of off-contract prices to extend the canonical Nash-in-Nash bargaining framework. The bulk of the existing work defines the disagreement outcome of a negotiation as severing that pair's link outright (Crawford and Yurukoglu 2012; Ho and Lee 2017; Gowrisankaran et al. 2015; Prager 2016).[1] This setup implies an assumption that no transactions occur between the two non-contracting parties, and the loss in surplus from disagree-

[1] This is the Nash-in-Nash structure introduced by Horn and Wolinsky (1988).

ment is equal to the loss of profit associated with the transactions that occur under agreement.[2] In health care, however, the lack of a formal contract between an insurer and a provider does not completely eliminate transactions between them. Instead, that insurer's patients can—and, in our data, often do—still obtain out-of-network care from such providers.

Our model departs from the existing empirical literature by allowing patients to obtain care from out-of-network providers, and allowing insurers to pay those providers strictly positive off-contract prices. We operationalize the model empirically in the context of the hospital market in New Hampshire, a suitable setting for several reasons. First, New Hampshire has insurer-hospital pairs that truly lack contracts. In some markets, insurers that offer narrow-network health maintenance organization (HMO) plans still have negotiated contracts with every hospital because they use complete networks for their preferred provider organization (PPO) plans. This paper studies regulation of cases where there exists no negotiated price to fall back on, and so requires a setting with true narrow networks, where some hospitals are out of network for *all* of an insurer's plans. An advantage of studying the New Hampshire market is that multiple insurers have true narrow networks. These are regional insurers with a large presence in neighboring states and low enrollment in New Hampshire itself. Second, we document nontrivial volumes at out-of-network New Hampshire providers. In our sample, out-of-network hospitals account for half of transactions across two insurers with true narrow networks. Finally, out-of-network care in this market is nearly always paid for in part or in whole by insurers.

We show, both theoretically and using our measure of off-contract prices, that estimates of marginal costs are biased when hospitals are assumed to have no out-of-network volumes. Under commonly satisfied empirical conditions, the bias results in underestimating the ability of policy to drive down prices without triggering provider exit. The bias is larger when the true off-contract volume and price are larger. While the bias can affect any of the model's parameters, its effects are most easily illustrated by fixing all parameters besides hospital marginal costs. This results in an upward bias in the marginal cost estimates, thereby reducing estimated hospital margins and resulting in policy counterfactuals that understate the maximum price reduction achievable without hospital exit. Empirically, we find that allowing out-of-network payoffs from disagreement results

[2] Papers that allow for more than a single deviation from the observed equilibrium, such as those using a Nash-in-Nash model with threat of replacement (Ho and Lee 2019; Ghili 2017), define the surplus from agreement more flexibly. However, those papers maintain the assumption of zero off-contract transactions.

in estimating hospital marginal costs that are 39.5 percent lower on average. This overestimation of marginal costs in the standard model ultimately results in overly pessimistic evaluations of two policy goals: access to health care providers and prices. Ordinarily, these two policy goals require a trade-off, since a simple method for reducing prices is to exclude high-priced providers from the network. However, compared to estimates from the canonical model with zero disagreement values, estimates from our model predict both broader networks and lower equilibrium prices at low levels of out-of-network prices.

We next consider counterfactual simulations that mimic proposed regulations. Current proposals to cap out-of-network prices come from both major political parties. The Republican-sponsored Lower Health Care Costs Act of 2019 proposes capping insurers' off-contract payments at median in-network rates within each market (Alexander 2019). During his campaign for the 2020 Democratic presidential nomination, Pete Buttigieg proposed setting the cap at 200 percent of Medicare (Pete For America 2019). Other third-party proposals have called for rates as low as 120 percent of Medicare (Kane 2019). Notably, out-of-network payments are also a subject of antitrust cases against hospitals. For example, California's high-profile complaint against Sutter Health describes Sutter's out-of-network prices as "punitively high" (Becerra et al. 2018; Ellison 2018).[3]

Our first set of counterfactuals varies the charge price benchmarks from which most insurers in our sample determine their current out-of-network payments. We consider policies that reduce the benchmarks and policies that expand the benchmarks to the point where hospitals are paid nearly their full charge price. The second set of counterfactuals considers capping out-of-network reimbursements at multiples of Medicare rates. In both sets of counterfactual simulations, our model predicts increasing the off-contract prices gives hospitals bargaining leverage to negotiate above-cost prices. Specifically, doubling the current off-contract price benchmark percent results in a 22 percent increase in average volume-weighted in-network prices. Conversely, reducing off-contract prices to the vicinity of Medicare reimbursements substantially reduces negotiated prices. Pegging off-contract prices to 100 percent of Medicare rates is projected to reduce negotiated prices by more than half. Importantly, we find substantial effects on negotiated prices regardless of whether hospitals are allowed to improve their disagreement value by refusing to treat out-of-

[3]Another high-profile example involves insurers in New Jersey citing high out-of-network reimbursements as responsible for rapid premium growth in the state (Avalere 2015). Similarly, New Jersey's Bayonne Medical Center was accused of strategically going out of network with insurers in order to receive higher reimbursements (Creswell et al. 2013).

network patients.

However, while capping out-of-network reimbursements reduces equilibrium prices, it also imposes a trade-off against reduced access to providers. In equilibrium, lower out-of-network prices can reduce the joint surplus from agreement available for splitting by the insurer and the hospital, resulting in fewer in-network agreements. Reductions in the joint surplus are a result of a reduction in the savings available to the insurer from bringing a given hospital into its network, which is in turn due to the insurer paying lower equilibrium prices to other hospitals. In our counterfactuals, cutting off-contract prices by half reduces the share of hospitals covered by 15 percentage points, or 39.5 percent below baseline. These predictions depart from predictions using the canonical Nash-in-Nash model. Under our counterfactual simulations, the price predictions from the canonical framework are more than 10 percent higher than our model with nonzero disagreement values. The predicted networks under the canonical framework are also weakly narrower than in our model. Finally, our counterfactual simulations suggest that reducing off-contract prices to near the level of Medicare rates would drive substantial hospital exit as in-network prices begin to drop below hospital marginal costs. With out-of-network reimbursements pegged to 100 percent of Medicare, the counterfactuals predict that more than 40 percent of hospitals would close the service lines in our sample.

Finally, our third set of counterfactuals mimics the proposed Lower Health Care Costs Act by pegging out-of-network prices at the median negotiated price among in-network providers in a geographic market. Unlike the other proposals, this policy would create subsequent adjustments over time because it calls for the out-of-network benchmark to be recalculated each year on the basis of the preceding year's negotiated prices. Our simulations suggest that this would lead to more dramatic changes in prices and access than other proposals over the course of a few years. This policy would generate a cycle in which out-of-network benchmark fall each year, followed by the high-priced hospitals in insurers' networks being dropped, followed by a subsequent decrease in the median negotiated price among remaining hospitals. Within five years of implementation, our simulations predict that half of hospitals would close. This stark prediction highlights the potentially high stakes of regulating out-of-network prices.

Our paper relates to several strands of literature. Several recent papers have proposed approaches to relaxing the Nash assumption that in case of disagreement, all other parties' contracts remain the same (Ho and Lee 2019; Ghili 2017; Liebman 2017). We view our approach as complementing these important advances by providing a computationally simple alternative for dealing with misspecified disagreement values. Another strand of the literature has recently begun investigating the prevalence and impact of out-of-network reimbursement structures and other determinants of insurer-hospital negotiated rates, especially in the context of surprise out-of-network bills (Cooper et al. 2019a; Craig et al. 2019; Cooper et al. 2019c,b; Fiedler 2020). We contribute to this literature by formally incorporating out-of-network reimbursements into a model designed to predict their impact on in-network prices, network breadth, and hospital service line closures.

Our main conceptual point carries over to other industries. In television markets, for example, content providers receive revenue directly from advertisers as well as from cable companies. The loss of a contract with a cable company therefore reduces surplus not just by the fees directly associated with that contract, but also by the reduced fees advertisers will be willing to pay as a result of losing access to that cable company's subscribers. In a similar vein, a two-sided platform that loses a brand from among its sellers will likely see an increase in purchases of that brand's products from third-party sellers.[4] In short, the importance of defining surplus from agreement more flexibly than the direct value of a contract extends to a variety of contexts.

The paper proceeds as follows. Section 2 discusses the details of our algorithm to measure off-contract prices. Section 3 presents our theoretical model and empirical strategy. That section also includes discussion of the direction and magnitude of bias arising from assuming zero out-of-network volumes. Section 4 describes our empirical context, data, and sample. Section 5 presents the parameter estimates, and Section 6 presents counterfactual simulations. Finally, Section 7 concludes.

2 Measuring Off-Contract Prices

Health insurers do not contract with every health care provider in the United States. Because the U.S. health care system lacks posted prices (Reinhardt 2006), insurers typically put in place explicit policies governing how much they will pay non-contracted providers. While insurers could in principle refuse to pay non-contracted providers at all, in practice they face pressure from the

[4] A high-profile example of this is Nike's withdrawal from its contract with Amazon in fall 2019, following Nike's dissatisfaction with Amazon's handling of counterfeit and third-party merchandise (Hanbury 2019).

demand side to provide some coverage for out-of-network care. For example, employers may want to ensure coverage for employees who need care while traveling for work or for employees or dependents who do not live near headquarters. Insurers often pay some portion of the bill for out-of-network care, and these payments can be substantial.[5]

Most insurers have policies that rely on "usual and customary" rates to determine payment for out-of-network services. The definition of usual and customary may vary across insurers or even within an insurer's product portfolio, but typically relies on some notion of the prevailing market rate for a given service, although it is occasionally pegged to fee-for-service Medicare payment rates. Measuring out-of-network payment rates has historically presented a challenge for health economists. It requires inferring payment policies in a market that lacks posted prices, among transacting pairs that lack contracts and frequently have low transaction volumes. Driven in part by these measurement difficulties, existing work on insurer-provider negotiations has assumed away the possibility of out-of-network transactions. This assumption may be a reasonable simplification in the settings typically studied by existing hospital-insurer bargaining papers, which use a sample of health care services that are rarely obtained out of network (inpatient hospital care). In the case of the outpatient care sample studied in this paper, however, out-of-network transaction volume can be substantial. Outpatient care has grown from less than one third of hospital revenues in 1994 to nearly half, highlighting the importance of understanding out-of-network prices for the hospital market as a whole.

Measuring out-of-network prices is integral to this paper. We therefore begin by inferring the structure of out-of-network payments from insurers' public documents, and then turn to the data for specific parameter values. Table 1 quotes the relevant language from several insurers' policy documents.

Insurers are not always explicit about how they define the prevailing market rate, but when they are explicit, their definitions often refer to FAIR Health benchmarks. FAIR Health is a private health analytics firm that sells health care data products to health insurers, providers, employers, and other entities. Its products are based on a near-universal sample of claims from fee-for-service Medicare and privately insured patients. Among its flagship products are the FH

[5]See Creswell et al. (2013) for anectodal evidence that insurers in certain markets pay substantial amounts in the form of chargemaster prices to out-of-network hospitals. Prager and Tilipman (2019) discuss this further in the context of regional Massachusetts carriers.

Charge Benchmarks, which many insurers use as an input to determining out-of-network payment rates. This product reports quantiles summarizing the distribution of charge prices at the level of a geographic area-treatment type pair. Charge prices are sticker prices that are billed by hospitals but are typically substantially higher than the prices actually paid by insurers, which negotiate price contracts with hospitals, and by most patients. The Charge Benchmarks product is updated twice a year using a rolling twelve-month window of claims data. Insurers that purchase the Charge Benchmarks can then use a predetermined percentile of the charge price distribution as an input to their determination of out-of-network rates, as indicated by the quotes from Aetna's, Cigna's, and United's policies in Table 1. Although FAIR Health products are not intended to be used as suggested appropriate payment amounts, insurers' payment policies are often informed by them. Prior to FAIR Health's entry in late 2011, many insurers used benchmarks produced by the United Healthcare-owned firm Ingenix, whose benchmark products were calculated using a nearly identical algorithm to FAIR Health's but are now defunct (Bernstein 2012). We therefore restrict our analyses to 2012 onward, when FAIR Health benchmarks became widely used.

We infer insurers' policies with respect to the charge benchmarks by comparing payments for services rendered by out-of-network providers to the commonly used charge benchmark percentiles. We construct the analog of the FAIR Health benchmarks from our data by closely following FAIR Health's algorithm. The algorithm is public; we describe it in detail in Appendix B. Each out-of-network claim is matched to its benchmark based on procedure code (CPT code), geographic area, and date of most recent benchmark release. We then examine the distribution of the ratio of the paid amount to the benchmarks.

Figure 1a shows the distribution of the ratio of paid amounts to the 60th percentile benchmarks for out-of-network facility claims by one of the insurers in our sample, Tufts Health Plan. When the hospital bills the insurer for more than the benchmark (charge > benchmark), the insurer typically only pays the 60th percentile benchmark, as indicated by the spike in the solid line distribution at 1.[6] When the hospital bills less than the benchmark (charge < benchmark), the

[6] Although the bulk of the mass is clustered near 1, many out-of-network claims are not paid based on this multiple. This is partially attributable to noise in our measure of the benchmarks for facility-based claims. Whereas FAIR Health uses the near-universe of privately insured claims and the universe of fee-for-service Medicare claims, our all-payer claims databases only capture the near-universe of privately insured claims. Our measure of the benchmark percentiles is therefore necessarily noisy. Appendix Figure A.1 shows that our constructed measure provides a good approximation of the proprietary FAIR Health data for professional claims, where we have data directly from FAIR Health.

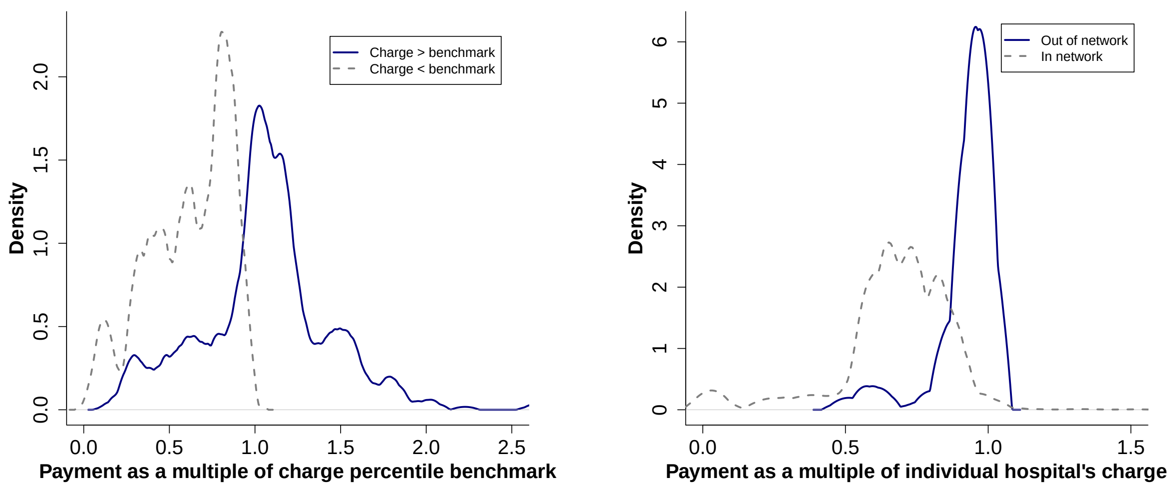
Table 1: Insurer Policies on Out-of-Network Payments

Insurer	Relevant Quote From Policy
Aetna	We get information from FAIR Health [...] For most of our health plans, we use the 80th percentile to calculate how much to pay for out-of-network services
Blue Cross Blue Shield of Massachusetts	Reimbursement for out-of-network providers will be based on a usual and customary fee schedule
Cigna	Under this option, a data base compiled by FAIR Health, Inc. (an independent non-profit company) is used to determine the billed charges made by health care professionals or facilities in the same geographic area for the same procedure codes using data. The maximum reimbursable amount is then determined by applying a percentile (typically the 70th or 80th percentile) of billed charges, based upon the FAIR Health, Inc. data
Harvard Pilgrim	When using Non-Plan Providers, the Plan pays only a percentage of the cost of the care you receive up to the Usual, Customary and Reasonable Charge for the service
Tufts	Reasonable Charge is the lesser of the: amount charged; or amount that we determine to be reasonable, based upon nationally accepted means and amounts of claims payment
United	Affiliates of UnitedHealth Group frequently use the 80th percentile of the FAIR Health Benchmark Databases

insurer nearly always pays precisely the entire billed amount, as shown by the solid line in Figure 1b. We therefore model Tufts Health Plan as paying the minimum of the hospital's billed charges and the 60th percentile charge benchmarks for out-of-network claims. This means that although the few hospitals whose charge prices are below the benchmark may be able to raise their out-of-network payments from Tufts by increasing their charge prices, they will still be constrained by Tufts' out-of-network payment policy once charge prices equal or exceed the benchmarks.

We use the procedure that underlies Figure 1 to infer insurers' policies for out-of-network payments. If an insurer has a complete provider network within our primary sample, as is the case for Harvard Pilgrim, this requires examining its claims from other markets in which it has a narrow network. These out-of-network policy inferences are facilitated by comprehensive data on insurers' networks, described in Section 4.3. If an insurer has a complete provider network across our entire sample, we use the insurer's stated policies, relying on the same documents as Table 1. We then

Figure 1: Out-of-Network Payments by Tufts



(a) Payment Relative to Benchmark, by Charge $\gtrless$ Benchmark

(b) Payment Relative to Charge When Charge $<$ Benchmark, by Network Status

Tufts Health Plan's payment amounts for out-of-network outpatient hospital transactions in a flagship PPO plan, as a multiple of the 60th percentile charge benchmark for the corresponding procedure code. This plan typically pays out-of-network hospitals at 100 percent of the 60th percentile benchmark.

use the inferred policies to construct off-contract prices for pairs of insurers and hospitals that do not necessarily have a contract. These off-contract price measures are a key input to estimating our Nash bargaining model with nonzero disagreement volumes, to which we now turn.

3 Model and Estimation

The goal of the model is to make inferences from the equilibrium network status and equilibrium in-network prices observed in the data. Hospitals do not have posted prices that are systematically paid by purchasers of their services. Instead, health insurers negotiate with hospitals to arrive at a contracted price that the hospitals will be paid for providing services to the insurers' enrollees. We model these negotiations as pairwise Nash bargaining interactions, but depart from the hospital bargaining literature by specifying strictly positive off-contract prices and volumes.

The model proceeds in three stages:

1. Insurer m and hospital h decide whether to enter into negotiations. If so, a contracting cost b is incurred.

2. If they have decided to enter into negotiations, insurer m and hospital h engage in bilateral negotiations that, if successful, determine the in-network price p_{mh}.

3. With some probability f_{id}, patient i enrolled in insurer m's plan gets sick and requires procedure d. The patient chooses a hospital from among the hospitals in the market, which may or may not be in insurer m's network.

The estimation proceeds in two steps. First, we estimate a model of hospital choice corresponding to Stage 3. Second, we estimate the insurer-hospital bargaining model corresponding to Stages 1 and 2 using objects constructed from the hospital choice model estimates and our measure of off-contract prices. There are five sets of parameters to estimate from the bargaining model: hospitals' marginal costs of treating patients; hospitals' average recouped fraction of balance bills; insurers' weighting of enrollee expected utility relative to hospital expenditures; Nash bargaining weights; and contracting costs. We estimate these parameters using the generalized method of moments.

In the sections that follow, we discuss the model and estimation pertaining to Stages 1 and 2. The discussion of Stage 3 is relegated to Appendix C, as we follow a well-established literature that models hospital demand using discrete choice models. The only departure we make from the literature is to allow hospital choices to be a function of the patient's expected balance bill, or out-of-pocket payment in the case of going to an out-of-network hospital. The balance bill is a function of the insurer's out-of-network payment policy, the hospital's charge price, and (in counterfactuals) regulation.

The remainder of this section is structured as follows. Section 3.1 derives the equilibrium prices in case of agreement, conditional on entering into negotiations. Section 3.2 then discusses how an insurer and a hospital decide whether to enter into negotiations in the first place. Section 3.3 describes how we use the equilibrium price conditions from Section 3.1 and the network status conditions from Section 3.2 for estimation. Section 3.4 then shows how the predictions of the bargaining model with positive disagreement volumes depart from the predictions of a model with zero volume in case of disagreement. Finally, Section 3.5 discusses identification.

3.1 Model Setup: Price Negotiation Stage

In Stage 2 of the model, insurer m and hospital h negotiate over the in-network prices if they decided in Stage 1 to enter into negotiations. A negotiated contract between them specifies a price p_{mh}

that hospital h will be paid for treating insurer m's enrollees, and assigns the hospital to be in the insurer's network.[7] In-network status grants the hospital a larger volume of the insurer's patients than out-of-network status. In the absence of a negotiated contract, the hospital remains out of network. The relatively few services it does provide to insurer m's patients are paid according to the insurer's out-of-network payment policy, denoted by price p_m^0, plus any portion μ of the balance bill the hospital successfully collects from the patient. The insurer's out-of-network payment rates depend only on the services provided, not the identity or cost structure of the hospital.[8]

Hospital Objectives

We model hospitals as profit maximizers. Conditional on entering into the negotating process, hospital h's surplus from a contract with insurer m at a negotiated price p_{mh} is given by

$$S_h(m, p_{mh}) = (p_{mh} - c_h)\,\sigma_{mh}^1 - \left(p_m^0 + \mu\left(p_h^c - p_m^0\right) - c_h\right)\sigma_{mh}^0 \tag{1}$$

where c_h is the hospital's marginal cost of treating a typical patient, p_h^c is its charge price, μ is the average fraction of balance bills recouped by hospitals, and $\sigma_{mh}^1 > \sigma_{mh}^0$ are the hospital's patient volumes from insurer m in the case of agreement and disagreement, respectively. The balance bill is equal to the charge price billed by the hospital when it is out of network less the out-of-network price paid by the insurer according to the insurer's policy. A hospital's volume under a given network configuration is predicted from the hospital demand model discussed in Appendix C. In the empirical application, we weight patient volumes by a measure of resource intensity associated with the services provided, and assume that the price and the hospital's cost both scale linearly by the resource intensity.

Insurer Objectives

We define insurers as maximizing a weighted difference of their enrollees' expected utility and their costs of paying for health care. Insurer m's enrollees' expected utility is a function of which hospitals are in its network: enrollees prefer to have more hospitals in the network. An alternative

[7] Hospital-insurer contracts are regularly updated with new prices. Throughout the paper, we omit time subscripts from the notation for brevity.

[8] In practice, each insurer's out-of-network payment rates also vary across geographic markets that typically have multiple hospitals in each market (see Appendix B). We omit the geographic market subscripts from the notation for simplicity, but calculate the out-of-network prices separately within each market in the empirical application.

specification of insurers' objectives is profit maximization, which requires a model of health insurance plan choice. Because our data do not allow us to construct plan choice sets for the majority of patients, this is not feasible in our empirical application. We instead follow Gowrisankaran et al. (2015) in modeling the insurer as an imperfect agent for its enrollees. We note, however, that the qualitative differences between models assuming zero disagreement volumes and models accounting for positive disagreement volumes that we outline in Section 3.4 obtain for both sets of insurer objectives.

Conditional on entering into negotiations, insurer m's surplus from a contract with hospital h at a negotiated price p_{mh} is given by

$$S_m(h, p_{mh}) = \left(\alpha_m W^1_{mh} - p_{mh}\sigma^1_{mh} - \psi^1_{mh}\right) - \left(\alpha_m W^0_{mh} - p^0_m \sigma^0_{mh} - \psi^0_{mh}\right) \tag{2}$$

where α_m is the insurer's weight on enrollee expected utility, and $W^1_{mh} > W^0_{mh}$ are the expected utilities in the case of agreement and disagreement, respectively. The terms ψ^1_{mh} and ψ^0_{mh} denote the insurer's payments to other hospitals in the case of agreement and disagreement with hospital h, respectively. For example, $\psi^1_{mh} = \sum_{h' \neq h} \sigma_{mh'} p_{mh'}$, where other hospitals' volumes $\sigma_{mh'}$ are computed for the case where hospital h is in the network.

Equilibrium Negotiated Prices

In case of agreement, the negotiated price p^*_{mh} is the one that maximizes the Nash bargaining product:

$$p^*_{mh} = \arg\max_{p_{mh}} S_m(h, p_{mh})^{\gamma_m} S_h(h, p_{mh})^{1-\gamma_m}$$

where $\gamma_m \in [0, 1]$ is insurer m's Nash bargaining parameter. Taking the derivative of the logged Nash product with respect to price, the first-order condition describing p^*_{mh} becomes

$$\gamma_m \frac{-\sigma^1_{mh}}{\alpha_m W^1_{mh} - p^*_{mh}\sigma^1_{mh} - \psi^1_{mh} - [\alpha_m W^0_{mh} - p^0_m \sigma^0_{mh} - \psi^0_{mh}]}$$

$$=$$

$$-(1-\gamma_m) \frac{\sigma^1_{mh}}{\left(p^*_{mh} - c_h\right)\sigma^1_{mh} - \left(p^0_m + \mu\left(p^c_h - p^0_m\right) - c_h\right)\sigma^0_{mh}}$$

which yields an equilibrium price of

$$p_{mh}^{*} = \frac{1}{\sigma_{mh}^{1}} \left[\begin{array}{l} (1-\gamma_m)\,\alpha_m \left(W_{mh}^{1} - W_{mh}^{0}\right) + (1-\gamma_m\mu)\, p_m^0 \sigma_{mh}^0 + \gamma_m \mu p_h^c \sigma_{mh}^0 \\ +\gamma_m c_h \left(\sigma_{mh}^{1} - \sigma_{mh}^{0}\right) - (1-\gamma_m)\left(\psi_{mh}^{1} - \psi_{mh}^{0}\right) \end{array} \right] \tag{3}$$

The first-order condition in Equation 3 contributes a set of moments used in estimation.

3.2 Model Setup: Network Formation Stage

The price negotiations discussed in Section 3.1 take place only if an insurer and a hospital decide in Stage 1 of the model to enter into negotiations. Insurer m and hospital h will enter into negotiations if the expected joint surplus from agreement, relative to the outside option of the hospital remaining out-of-network, is weakly positive. If the expected joint surplus is negative, then there can exist no price that would induce positive surplus for both parties individually. The parties will then anticipate that no agreement will be reached in Stage 2, and therefore will decide in Stage 1 not to enter into negotiations.

We model negotiations as costly: the insurer and hospital must jointly pay a contracting cost b for each pairwise negotiation. This modeling assumption is motivated by the institutional details of the health care industry. Contract negotiations in this industry are notoriously resource-intensive, often lasting for months and requiring insurers to have a dedicated division for provider contracting.[9] We interpret the b parameter as a flavor of Coasian transaction cost. Once the contracting cost is paid, it is sunk. Therefore, the contracting cost does not enter into the price negotiations in Stage 2. This setup implies the assumption that both parties can commit to transferring surplus in Stage 2 in order to guarantee weakly positive surplus from agreement for the other party. While we do not microfound this assumption, it can be loosely interpreted as arising from the repeated nature of the game that insurers and hospitals are playing in practice.

The condition for entering into negotiations is that insurer m's and hospital h's ex ante joint surplus from agreement is weakly positive. The ex ante joint surplus is simply the sum of the

[9] It is likely that contracting costs vary across hospitals and insurers. Ideally, we would estimate them as separate parameters using each insurer and hospital's network inclusion conditions *separately.* However, we do not have sufficient variation in our data to separately identify these parameters, along with our other parameters of interest. We therefore estimate the network inclusion moments as maximizing a *joint* surplus and interpret the contracting costs as a combination of insurer and hospital negotiating costs.

surplus available for splitting, less the contracting cost:

$$E_{mh} = \alpha_m W^1_{mh} - \psi^1_{mh} - \left(\alpha_m W^0_{mh} - p^0_m \sigma^0_{mh} - \psi^0_{mh}\right) - c_h \sigma^1_{mh} - \left(p^0_m + \mu \left(p^c_h - p^0_m\right) - c_h\right) \sigma^0_{mh} - b \quad (4)$$

Together with the assumption of commitment, the Nash-in-Nash structure of Stage 2 guarantees that, if $E_{mh} \geq 0$ and the pair enters negotiations, then an agreement will be reached in Stage 2. We leverage this in the estimation by inferring a weakly positive joint surplus in Stage 1 if and only if an agreement is observed. Note that the negotiated price p_{mh} does not enter into E_{mh} because its negative effect on the insurer's portion of the surplus, $-p_{mh}\sigma^1_{mh}$, is precisely offset by its positive effect on the hospital's surplus, $p_{mh}\sigma^1_{mh}$.

3.3 Estimation of Model Parameters

We use the model conditions from the price negotiation stage and the network formation stage to form moments for estimation. There are five sets of parameters to estimate from the model: the insurers' weights on expected utility α_m, the insurers' Nash bargaining weights γ_m, the average fraction of balance bills recouped by hospitals μ, the hospital marginal costs c_h, and the joint contracting cost b. All other objects in the model are predicted from the hospital demand model (see Appendix C) and treated as data. This section describes the two sets of moments that enter into our generalized method of moments estimation. The price negotiation stage contributes equality moments, and the network formation stage contributes inequality moments. We defer the discussion of identification to Section 3.5.

Equality Moments from Price Negotiation

Hospital-insurer pairs that have a negotiated contract contribute equality moments from the first-order conditions on negotiated price. In our equilibrium condition for Stage 2, equation 3, prices are observed, whereas hospital marginal costs, c_h, are parameters to be identified. We express hospital h's marginal cost for treating a patient with resource intensity $w_d = 1$ as a function of observables g_h:

$$c_h = \lambda g_h + \nu_h \quad (5)$$

where λ is a parameter vector and ν_h is the unobservable component of hospital costs. The observable characteristics in g_h on which we project costs include hospital fixed effects, which subsume hospital characteristics that remain fixed over the course of our sample period, such as teaching status and system status; and year fixed effects, which allow for flexible statewide trends in cost growth.

The econometric error for the GMM estimator is then defined as the difference between the projected cost from Equation 5 and the cost implied by the first-order conditions on equilibrium prices from Equation 3. That is, we define the econometric error for a hospital-insurer pair as

$$\xi_{mh} = \lambda g_h - \frac{1}{\gamma_m\left(\sigma^1_{mh} - \sigma^0_{mh}\right)} \left[\begin{array}{l} p^*_{mh}\sigma^1_{mh} - (1-\gamma_m)\,\alpha_m\left(W^1_{mh} - W^0_{mh}\right) \\ -\left(1-\gamma_m\mu\right)p^0_m\sigma^0_{mh} - \gamma_m\mu p^c_h\sigma^0_{mh} + (1-\gamma_m)\left(\psi^1_{mh} - \psi^0_{mh}\right) \end{array} \right] \quad (6)$$

We then search for parameters λ to set the vector of ξ_{mh} across pairs orthogonal to a set of assumed exogenous variables z_{mh}. Following Gowrisankaran et al. (2015), we include in z_{mh}: a hospital's predicted contribution to enrollees' expected utility, $W^1_{mh} - W^0_{mh}$; its expected per-enrollee contribution to expected utility; and predicted hospital quantity. The equality moment that enters into the GMM estimation is then

$$\mathbb{E}\left[\xi_{mh} | z_{mh}\right] = 0 \quad (7)$$

This gives us one moment per hospital-insurer pair in each year that the pair has a negotiated contract. Out-of-network hospitals do not contribute to this set of moments, as the Nash bargaining first-order condition on which the moments are based is not defined in the absence of a negotiated price contract.

Inequality Moments from Network Formation

In addition to the equality moments contributed by hospital-insurer-years in which we observe an agreement (Equation 7), each hospital-insurer-year contributes an inequality from the network formation conditions discussed in Section 3.2. We require these conditions for two reasons. First, a primary goal of the paper is to examine how negotiated prices change with different assumptions about the magnitudes of disagreement volumes and out-of-network reimbursement benchmarks. However, varying the level of out-of-network payments may result in carriers or hospitals deciding it is more profitable to enter into a formal contract (and negotiate an in-network rate) rather than remain out-of-network under counterfactual policies. As such, our model needs to incorporate carrier and hospital decisions surrounding network formation with currently out-of-network hospitals, as several recent papers have done (Ghili 2017; Liebman 2017; Ho and Lee 2019). Second, the estimation procedure must account for the fact that in our setting, network status is endogenously determined. Since some networks are incomplete, using only the first-order conditions from in-network hospitals would lead to biased parameter estimates.

We therefore incorporate into the estimation additional moments from the network status determination decisions discussed in Section 3.2. To construct these moments, we follow closely the literature on moment inequalities (Ho 2009; Pakes 2010; Pakes et al. 2015). Formally, we define insurer m's and hospital h's ex ante joint surplus from agreement as:

$$
\begin{aligned}
E_{mh}(\boldsymbol{\theta}) &= \alpha_m W^1_{mh} - \psi^1_{mh} - \left(\alpha_m W^0_{mh} - p^0_m \sigma^0_{mh} - \psi^0_{mh}\right) - c_h \sigma^1_{mh} - \left(p^0_m + \mu\left(p^c_h - p^0_m\right) - c_h\right)\sigma^0_{mh} - b \\
&= \alpha_m\left(W^1_{mh} - W^0_{mh}\right) - \psi^1_{mh} + \psi^0_{mh} + \left(-\sigma^1_{mh} + \sigma^0_{mh}\right) c_h + \mu\left(p^c_h - p^0_m\right)\sigma^0_{mh} - b
\end{aligned}
$$

where c_h is projected from Equation 5, and $\sigma^1_{mh}, \sigma^0_{mh}, W^1_{mh}, W^0_{mh}, \psi^1_{mh}, \psi^0_{mh}$ are predicted from the demand model. If hospital h is in insurer m's network, then both parties must have positive gains from trade at the observed negotiated price and at the current parameter guesses $\hat{\boldsymbol{\theta}}$, relative to the outside option of the hospital remaining out-of-network.

We assume that insurers and hospitals have expectations over their surplus for any contract and that they predict these gains with error.[10] Let ω_{mh} be the difference between the parties' expected total surplus from agreement and the realized surplus, and let $\mathbb{E}[\omega_{mh}|\mathcal{J}] = 0$, where $\mathcal{J}$ is the insurer's and hospital's information set at the time of contracting decision.[11] Then:

$$
\begin{aligned}
\mathbb{E}[E_{mh}(\boldsymbol{\theta})|\mathcal{J}] &= E_{mh}(\boldsymbol{\theta}) - \omega_{mh} \\
&= \left[\alpha_m\left(W^1_{mh} - W^0_{mh}\right) - \psi^1_{mh} + \psi^0_{mh} + \left(-\sigma^1_{mh} + \sigma^0_{mh}\right) c_h + \mu\left(p^c_h - p^0_m\right)\sigma^0_{mh} - b\right] - \omega_{mh}
\end{aligned}
$$

Each hospital-insurer pair that is observed to have a negotiated contract therefore contributes

[10] For example, they may be uncertain as to how other insurers or hospitals might react to any contracting decision, which would impact the ultimate negotiated rates and estimates of gains from trade.

[11] Recall that the Nash-in-Nash setup assumes that all bargaining parties have the same information set.

one inequality that imposes a lower bound on the total available surplus from agreement:

$$0 \leq \mathbb{E}[E_{mh}(\boldsymbol{\theta})|\mathcal{J}] = E_{mh}(\boldsymbol{\theta}) - \omega_{mh} \tag{8}$$

We refer to these inequalities as network inclusion moments.

For hospital-insurer pairs that are observed not to have a contract, our model requires that there exists no price that would make both the hospital and the insurer better off than if they do not have a negotiated contract. Thus, in the estimation, we impose that at the current parameter guesses $\hat{\boldsymbol{\theta}}$, there exists no price that would make both parties' surpluses positive.[12] The resulting inequality for estimation is given by:

$$0 > \mathbb{E}[E_{mh}(\boldsymbol{\theta})|\mathcal{J}] = E_{mh}(\boldsymbol{\theta}) - \omega_{mh} \tag{9}$$

Each hospital-insurer pair that is observed not to have a negotiated contract therefore contributes a single inequality, defined by Equation 9, that imposes upper bounds on the surpluses from agreement. We refer to these inequalities as network exclusion moments. In the estimation, if insurer m and hospital h are observed not to have a network but Equation 9 is violated—that is, if the implied total surplus at the current parameter values is positive—we penalize the objective function by the magnitude of the violation.

Collectively, the network inclusion and exclusion conditions are what Ghili (2017) calls network stability conditions. Because of the mean-zero assumptions on ω and v conditional on insurer and hospital information sets, when the sample of inequalities grows large, the errors tend to zero in the limit. Given instruments $z \in \boldsymbol{J}$, our estimating equations for the network inclusion conditions become:

$$0 \leq E_{mh}(\boldsymbol{\theta})(z)$$

We search for a full set of parameters, $\boldsymbol{\theta}$,that satisfies this full system of inequalities. If no set of parameters satisfies all of inequalities, we construct a moment equation that minimizes the absolute

[12] Equivalently, if h is observed not to be in m's network, then we assume that the highest price that m would be willing to pay while still maintaining a positive surplus is less than the lowest price that h would be willing to accept while still maintaining a positive surplus. This is because the insurer's surplus is monotonically decreasing in price and the hospital's surplus is monotonically increasing in price.

deviations for any inequality violated. We then stack these moments together with the equality moments from the bargaining first-order conditions (Section 3.1) and search for parameters $\boldsymbol{\theta}$ that minimize the weighted sum of the network inclusion, network exclusion, and bargaining first-order condition moments.

3.4 Implications of Nonzero Disagreement Values

Empirical work on bargaining typically observes negotiated prices as an equilibrium outcome, and uses them to infer a set of structural parameters pertaining to costs (marginal or fixed) and Nash bargaining weights. Misspecification of the disagreement volume σ^0_{mh} and the disagreement payments $p^0_m\sigma^0_{mh}$ biases these structural parameters. Any of the parameters may be biased due to misspecification of the disagreement payments. To ease interpretation, it is therefore helpful to consider all but one set of parameters as being fixed at known values, and derive the bias on one set of free parameters. Here, we illustrate the bias arising from assuming that disagreement volume is zero when estimating hospital marginal costs c_h and fixing all other parameters. Biases in marginal cost estimates are of interest to antitrust regulators due to their direct relationship with margins, which are used in merger evaluation.

Consider a simplified empirical setup where the parameters γ_m, α_m, μ, and b are known, leaving only the hospital costs c_h as parameters to estimate. Take an insurer m that has a negotiated contract with hospital h. An expression for the unbiased estimate, $\hat{c}_h$, can be obtained by rearranging Equation 3:

$$\hat{c}_h = \frac{p^*_{mh}\sigma^1_{mh} - (1-\gamma_m)\,\alpha_m\left(W^1_{mh} - W^0_{mh}\right) + (1-\gamma_m)\left(\psi^1_{mh} - \psi^0_{mh}\right) - (1-\gamma_m\mu)\,p^0_m\sigma^0_{mh} - \gamma_m\mu p^c_h\sigma^0_{mh}}{\gamma_m\left(\sigma^1_{mh} - \sigma^0_{mh}\right)}$$

If disagreement volume is instead assumed to be zero, then we will obtain a biased estimated of hospital marginal cost, $\tilde{c}_h$:

$$\tilde{c}_h = \frac{p^*_{mh}\tilde{\sigma}^1_{mh} - (1-\gamma_m)\,\alpha_m\left(\tilde{W}^1_{mh} - \tilde{W}^0_{mh}\right) + (1-\gamma_m)\left(\tilde{\psi}^1_{mh} - \tilde{\psi}^0_{mh}\right)}{\gamma_m\tilde{\sigma}^1_{mh}}$$

where the tilde notation represents quantities calculated from the demand model assuming zero volumes for all out-of-network hospitals. If the insurer has an incomplete network that excludes at least one other hospital $h' \neq h$, then $\tilde{\sigma}^1_{mh} \neq \sigma^1_{mh}$, $\tilde{W}^1_{mh} \neq W^1_{mh}$, and $\tilde{\psi}^1_{mh} \neq \psi^1_{mh}$. That is, the quantities corresponding to hospital h being in the insurer's network under the model assuming zero disagreement volumes depart from the full model.

Regardless of the network configuration, as long as the true disagreement volumes are not equal to zero, the estimated costs will not be equal across the two models. The estimated hospital cost under the assumption of zero disagreement values will be biased upward, i.e. $\tilde{c}_h > \hat{c}_h$, if and only if:

$$\alpha_m \left(W^1_{mh} - W^0_{mh}\right) - \left(\psi^1_{mh} - \psi^0_{mh}\right) + \frac{\left(1-\gamma_m\mu\right) p^0_m + \gamma_m \mu p^c_h - p^*_{mh}}{1-\gamma_m} \sigma^0_{mh}$$
$$>$$
$$\frac{\left(\sigma^1_{mh} - \sigma^0_{mh}\right)}{\tilde{\sigma}^1_{mh}} \left[\alpha_m \left(\tilde{W}^1_{mh} - \tilde{W}^0_{mh}\right) - \left(\tilde{\psi}^1_{mh} - \tilde{\psi}^0_{mh}\right)\right] \quad (10)$$

This inequality states that hospital cost estimates will be biased upward if the true payments from the insurer to the hospital in the event of disagreement are "large enough." It is a necessary and sufficient condition for upward bias. For ease of exposition, we present the underlying intuition by discussing two comparative statics rather than the inequality as a whole. The discussion is presented in terms of conditions for the hospital cost estimate being biased upward due to an assumption of zero disagreement volumes, because this is what we believe to be more common empirically; the statements hold in reverse for downward bias.

The first point to note is that, all else equal, the larger is the true out-of-network volume σ^0_{mh}, the larger the upward bias on the hospital cost estimate.[13] To see this, note that the right-hand side of the inequality is scaled by $\left(\sigma^1_{mh} - \sigma^0_{mh}\right)/\tilde{\sigma}^1_{mh} \in [0,1]$. This is the ratio of the hospital's true volume gain from being in-network to its volume gain under the assumption of zero out-of-network volume. The true out-of-network volume σ^0_{mh} also appears on the left-hand side of the inequality (multiplied by a positive constant). The underlying intuition is that, when the true out-of-network volume is large, the hospital's true disagreement value is also relatively large as a result of out-of-network payments. The assumption of zero disagreement volumes therefore overstates the

[13] This is more easily seen when the inequality is rewritten with respect to the ratio of volume gains:

$$\frac{\left(\sigma^1_{mh} - \sigma^0_{mh}\right)}{\tilde{\sigma}^1_{mh}} < \left[\alpha_m \left(W^1_{mh} - W^0_{mh}\right) - \left(\psi^1_{mh} - \psi^0_{mh}\right) + \frac{\left(1-\gamma_m\mu\right) p^0_m + \gamma_m \mu p^c_h - p^*_{mh}}{1-\gamma_m} \sigma^0_{mh}\right] \Big/ \left[\alpha_m \left(\tilde{W}^1_{mh} - \tilde{W}^0_{mh}\right) - \left(\tilde{\psi}^1_{mh} - \tilde{\psi}^0_{mh}\right)\right]$$

hospital's true surplus from agreement. As a result, the surplus implied by the observed negotiated price p^*_{mh} must instead be rationalized by a high cost estimate $\tilde{c}_h$.

The second comparative static is that, all else equal, the higher is the out-of-network price, the larger the upward bias on the hospital cost estimate. The last term on the left-hand side of the inequality is the product of the true out-of-network volume σ^0_{mh} and the difference between the out-of-network price p^0_m and the negotiated in-network price p^*_{mh}, scaled by the inverse of the hospital's Nash bargaining weight.[14] If the out-of-network price is higher than what the negotiated price would be under agreement, as is typically the case in practice, then this term is positive. The underlying intuition is analogous to the previous paragraph. The higher is the true out-of-network price, the more severely the assumption of zero disagreement volumes will overstate the hospital's true surplus. The surplus implied by the observed price must instead be rationalized by a high cost estimate.

The remaining terms in the inequality measure the insurer's surplus from including hospital h in the network, modulo the change in spending on that hospital itself. On the left-hand side, the term $\alpha_m \left(W^1_{mh} - W^0_{mh}\right) > 0$ is enrollees' willingness-to-pay to include hospital h in the network, scaled by its contribution to the insurer's surplus. This term is typically smaller than its right-hand side analog $\alpha_m \left(\tilde{W}^1_{mh} - \tilde{W}^0_{mh}\right)$, because the WTP gain from an included hospital is smaller when consumers can still seek care at that hospital even if it is out of network. The term $\left(\psi^1_{mh} - \psi^0_{mh}\right)$ is the change in the insurer's payments to other hospitals $h' \neq h$ as a result of including h and having consumers re-sort across hospitals. This difference is negative, because hospital h loses volume to other hospitals when it is out of network. The terms in brackets on the right-hand side of the inequality are the analogs calculated under the assumption of zero volume for all out-of-network hospitals (scaled by the the volume gain ratio discussed above). The calculated savings in payments to other hospitals will be larger on the right-hand side, $\tilde{\psi}^0_{mh} - \tilde{\psi}^1_{mh} > \psi^0_{mh} - \psi^1_{mh}$, because the assumption of zero disagreement volume will mean there is more of hospital h's volume to be reallocated to other hospitals in the event of disagreement.[15] Therefore, upward bias in the hospital cost estimates cannot result from the WTP and other-hospital savings alone, as the sum of these terms is greater on the right-hand side.

[14] Recall that γ_m is the insurer's bargaining weight, and the two parties' weights sum to one.

[15] Both components of the $\left(\tilde{\psi}^1_{mh} - \tilde{\psi}^0_{mh}\right)$ term may depart from their right-hand side analogs, because if any hospitals besides h are out-of-network, then the right-hand-side will assume they have zero volumes.

Instead, the assumption of zero disagreement volumes will only bias the hospital cost estimates upward if the true disagreement payments are large enough to reverse the inequality. As discussed above, this can obtain from a combination of large out-of-network volumes σ^0_{mh} and high out-of-network prices p^0_m. In our setting, it is usually the case that $p^0_m > p^*_{mh}$ and $\sigma^0_{mh} > 0$, so we expect the majority of the cost estimates to be biased upward under the model that assumes zero disagreement volumes. Figure 6 shows how this expectation plays out in the data: the bias is of the same sign as $p^0_m - p^*_{mh}$ for most hospitals, and is increasing in $p^0_m - p^*_{mh}$.

Bias in hospital cost estimates has important implications for counterfactual exercises. When cost estimates are biased upward, counterfactual simulations of policies whose goal is to reduce negotiated prices will understate the true magnitude of price reductions. This arises from an understatement of true hospital markups due to the upward-biased cost estimates. The downward-biased estimate of hospital markups gives the impression that there is little room to reduce prices without inducing hospital exit. Moreover, if policy-makers rely on economists' estimates of markups, they may craft policies that erroneously assume hospitals are capturing little producer surplus.[16] In Section 6, we show how the biased cost estimates affect the predicted effects of counterfacual policies.

3.5 Identification of Bargaining Parameters and Contracting Costs

Identification of hospital marginal costs, c_h, and bargaining weights, γ_m, is similar to Gowrisankaran et al. (2015). The equality moments from Stage 2 of the model (Equation 6) help pin down these parameters. Estimation of these moments relies on exogenous instruments, z_{mh}. We use all the fixed effects included in the cost equation (Equation 5) as well as the the instruments described above. Hospital marginal costs c_h are identified primarily through variation in observed prices within insurer across hospitals. Intuitively, for given guesses of γ_m, α_m, μ, and b, hospitals that have higher observed negotiated prices, p_{mh}, will be predicted to have higher marginal costs. Figure 2 displays the type of variation in negotiated prices observed in the data that helps to identify c_h. The figure shows that there is substantial within-insurer variation in negotiated prices. Figure 3 also shows that hospitals that have high negotiated prices with one insurer tend to have high negotiated prices with other insurers.

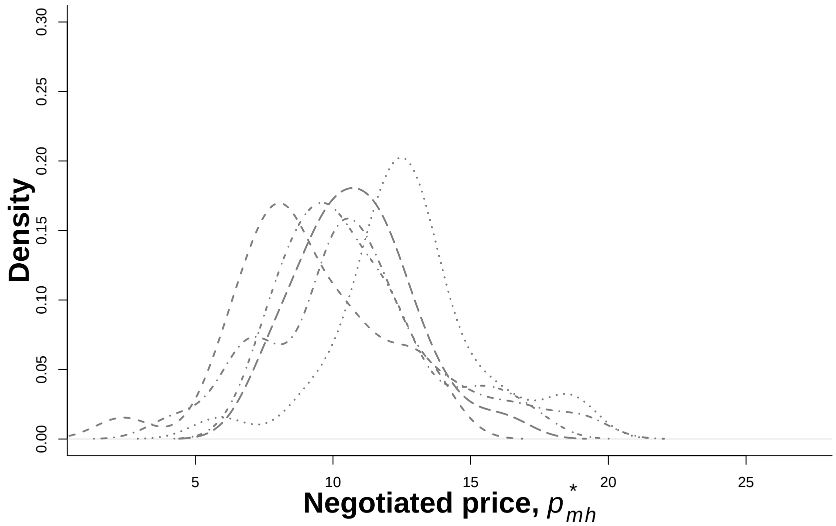
[16] See Berry et al. (2019) for a forceful argument in favor of careful estimation of markups.

Conversely, the bargaining weights γ_m are identified primarily from variation in observed prices within hospitals, across insurers. Suppose, for instance, that two insurers have enrollee distributions with similar WTP for a particular hospital, but those insurers negotiated very different prices with that hospital. This variation would map into different values of γ_m for each insurer, reflecting their differential ability to extract surplus from negotiations. Figure 4 shows that for most hospitals, the (anonymous) insurer on the horizontal axis negotiates lower prices than the competing insurer on the vertical axis. All else equal, these price differences will map into a higher estimated γ_m for the insurer on the horizontal axis.

Identification of μ, the average share of the potential balance that hospitals are able to recoup, also largely comes from the equality moments. However, in addition to relying on variation in observed in-network prices across hospitals and insurers, we rely on variation in observed *charge* prices, p_h^c, across hospitals and out-of-network reimbursement prices, p_m^0, across insurers. Intuitively, different hospitals' surpluses from agreement will have different sensitivities to changes in the guess of μ. A hospital's surplus will be more sensitive the larger is its predicted out-of-network volume and the larger is its balance bill, $p_h^c - p_m^0$. Similarly, the surplus will be more sensitive the lower is the insurer's out-of-network payment, p_m^0.

Identification of the insurer's weight on enrollee surplus, α_m, and the contracting cost, b, relies largely on the inequality moments from Stage 1 of the model in Equations 8 and 9. Since we estimate both γ_m and α_m at the insurer level, it is empirically difficult to separately identify them using the same variation from the equality moments. For example, if one insurer negotiates a higher price with a particular hospital relative to another insurer, this may be because that insurer's bargaining ability is greater or because that insurer places higher weight on enrollee surplus. The network inclusion moments help to separate these. If, conditional on a guess of γ_m, an insurer is observed to include a hospital in its network despite that inclusion increasing costs more than it increases enrollees' WTP (scaled by the current guess of α_m), then the implication is that this insurer values its enrollees' surplus more than the current guess of α_m. Figure 5 suggests that insurers are indeed responsive to their enrollees' surplus. Harvard Pilgrim, which has a relatively large number of enrollees in the northern part of New Hampshire, includes many more northern hospitals in its network than does Tufts, whose enrollees are clustered near the southern border. MVP, which has a lumpier distribution of enrollees throughout New Hampshire and additional enrollees to the west

Figure 2: Distributions of In-Network Prices by Insurer



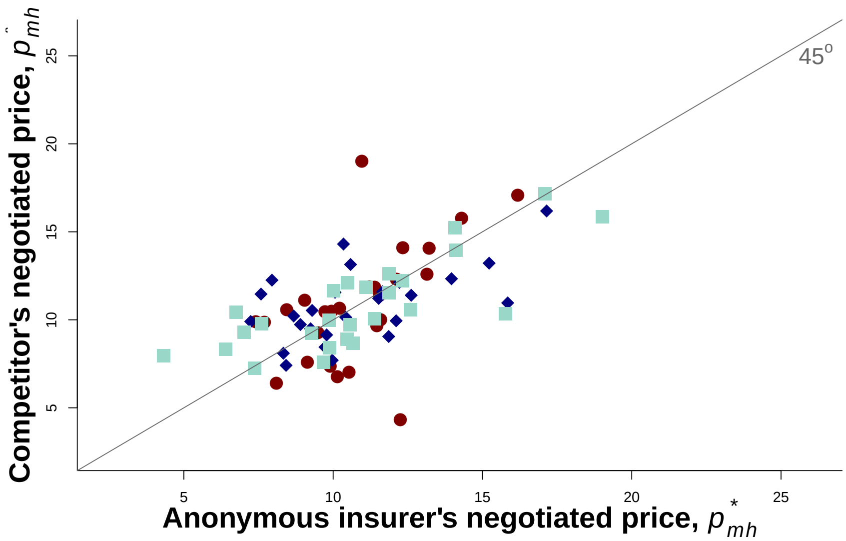
This figure plots the price indices for the five insurers with complete networks across hospitals in New Hampshire in 2012. Each curve represents the distribution of one insurer's negotiated hospital prices. The variation in negotiated prices within an insurer across hospitals contributes to the identification of the hospital marginal cost estimates.

in Vermont (not pictured), includes hospitals near its enrollee clusters and some hospitals near the Vermont border. All three insurers include the premier academic medical center in the state, Dartmouth-Hitchcock Medical Center, which patients value highly.

To identify contracting costs, b, we require additional assumptions. The first assumption is that the contracting costs are identical across all insurer-hospital pairs in our data. This assumption aids in identification in two ways. First, given the limited number of insurers in our sample, it allows us to use information estimated from moment conditions from one insurer in order to inform guesses for other insurers. Second, it implicitly assumes away any structural errors that might bias the estimate of b. This problem is discussed at length in Eizenberg (2014) and Pakes (2010). In our setting, by assuming that the contracting costs are the same across hospitals, we rule out the possibility that coverage decisions depend on private information indicating heterogeneity in contracting costs across hospitals. Similar assumptions have been made in Ho (2009) and Nosko (2014). Once the cost of entering into the negotiation is paid, that cost becomes sunk regardless of whether agreement is reached.[17]

[17] This implication does not require any further assumptions. In the model, an insurer-hospital pair will not enter

Figure 3: Hospitals' In-Network Prices Across Large Insurers



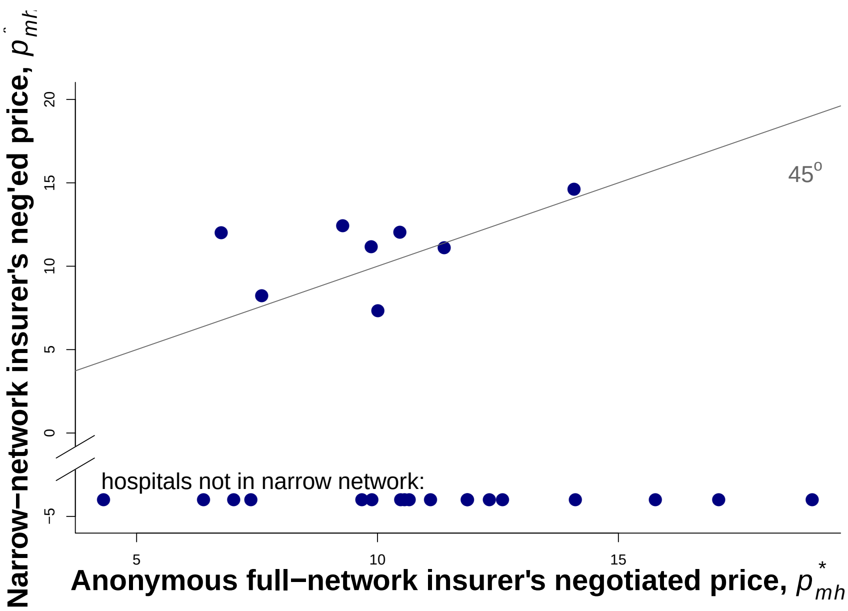
This figure plots the relationship between the three largest insurers' (by market share) negotiated prices. Each dot represents a hospital. Each dot type represents a single (anonymous) pair of insurers. Hospitals that have a high negotiated price with one insurer typically also have high prices with other insurers. This within-hospital correlation contributes to the identification of the hospital marginal cost estimates.

A second assumption we make is that b reflects annual *fixed* costs of negotiation that are incurred irrespective of whether an insurer had a contract with a hospital in prior years. That is, we assume that the negotiating process is costly, even for renegotiations of existing contracts. This is motivated by two facts. First, insurers and hospitals employ dedicated staff for contract negotiations with the other party. Second, existing evidence has shown that the administrative burden of dealing with contract negotiations adds considerable expense and complexity on both the insurer and provider sides (Wikler et al. 2012). Contracting disputes sometimes arise between parties that have a history of successful negotiations. Such disputes can require prolonged and costly negotiating before the parties ultimately agree.

While these are not innocuous assumptions, our primary interest in this paper is demonstrating the impact of disagreement values on prices and equilibrium networks. As we argue in Section 3.4, the primary mechanism for this effect is through model estimates of hospital marginal costs and bargaining parameters. Therefore, while precise estimates of contracting costs do help to

into negotiations in the first place if the expected surplus from agreement (relative to disagreement) is not large enough to offset the bargaining cost.

Figure 4: Hospitals' In-Network Prices Across Complete- Vs. Narrow-Network Insurers



This figure plots the relationship between the 2012 negotiated prices of a high-market share insurer with a complete hospital network (horizontal axis) and the negotiated prices of one of the two narrow-network insurers (vertical axis). Each dot represents a hospital. The insurer on the horizontal axis typically negotiates a lower price than the insurer on the vertical axis with the same hospital. The hospitals excluded from the narrow-network insurer's network have disproportionately high negotiated prices with complete-network insurers. This type of variation across insurers contributes to the identification of the Nash bargaining weight estimates.

rationalize the observed networks in the data at baseline, our counterfactual predictions of the effect of regulating out-of-network reimbursements are largely invariant to our estimates of b. Appendix A reports a robustness check in which we set $b = 0$ and re-estimate all other parameters of the bargaining model. The estimates of the remaining key parameters c_h and γ_m remain quite similar, suggesting that our results are robust to the value of b.

4 Data

In this section, we provide context for our empirical application: the private health insurance market in New Hampshire. We then describe the data used in estimation and the details of sample construction.

4.1 Empirical Setting

Our empirical setting is large New England insurers' negotiations with hospitals in New Hampshire. The insurance market is highly concentrated, with the largest three insurers accounting for at least 85 percent of commercial enrollment throughout our sample period. Two of the top three insurers are large national insurers. As in many states, the top insurer is the local Blue Cross Blue Shield (BCBS) carrier, which is Anthem. Depending on the year, Cigna, another large national carrier, is in second or third place. The third of the top three is Harvard Pilgrim, a smaller, regional carrier that draws the bulk of its enrollment from New England (Prager and Tilipman 2019). The remainder of the insurance market is divided between a number of other local affiliates of national insurers, notably Aetna and United; and regional insurers, notably Tufts Health Plan and MVP Health Care. Our sample consists of the top six insurers in the state by market share (Anthem, Harvard Pilgrim, Cigna, United, Aetna, and MVP), plus an additional regional insurer (Tufts) that provides additional variation in hospital networks.

New Hampshire has 32 hospitals, including a Veterans Affairs hospital and five rehabilitation or psychiatric hospitals. We focus on the remaining 26 acute care hospitals, including the state's premier academic hospital, Dartmouth-Hitchcock Medical Center. With more than a third of its population classified as rural, and mountainous terrain that impedes travel, fully half of New Hampshire's hospitals are designated as Critical Access Hospitals by CMS. Because New Hampshire is geographically small and shares a relatively densely populated border with Massachusetts, many hospitals in the southern part of the state have substantial patient volumes from Massachusetts residents or New Hampshire locals who are insured by Massachusetts insurers. For example, Harvard Pilgrim and Tufts were originally based in Massachusetts.

Most insurers with substantial operations in New Hampshire have complete hospital networks within the state. That is, they have negotiated contracts with each of the state's 26 acute care hospitals. Unsurprisingly, among the insurers with complete networks are the three top insurers in the state. This pattern is not peculiar to New Hampshire; it is common for insurers to have locally complete hospital networks for their broadest-network plans.

Outside of New Hampshire's top three insurers, however, some hospital networks are incomplete. Notably, Massachusetts-based Tufts Health Plan, which is among the smaller insurers in the state throughout our sample period, has negotiated contracts with only eight of the state's 26 hospitals.

The Tufts network includes four of the five highest-volume hospitals in the state, among them the Dartmouth-Hitchcock flagship hospital. The other four hospitals within Tufts' network are all within a 35-minute drive of the state's southern border with Massachusetts, where the bulk of Tufts' enrollees are located. None of the hospitals in the northern half of New Hampshire is in Tufts' network. The fact that Tufts' network only covers a small share of the New Hampshire market, despite having enrollees residing in the state, plays an important role in identifying parameters in our demand and bargaining models. We similarly leverage variation in network coverage by MVP, which operates primarily in upstate New York and Vermont, and covers a minority of New Hampshire hospitals.

4.2 Health Care Claims Data

Data for estimating the hospital choice model and constructing other inputs to the bargaining model are drawn from the 2010–2012 New Hampshire All-Payer Claims Database (APCD) and the Massachusetts APCD. Private health insurers contribute data for the APCDs to the state agency that manages the data and uses it for policy-relevant analysis. In New Hampshire, this is the Comprehensive Health Care Information System (CHIS); in Massachusetts, it is the Center for Health Information and Analysis (CHIA) (CHIA 2014).

The New Hampshire and Massachusetts APCDs contain claims originating both within and outside of their respective states, as long as they are claims for services to enrollees of health insurance plans headquartered in the state. For example, a resident of Rhode Island who is employed by and purchases health insurance through a Massachusetts-based employer will be included in the Massachusetts APCD. A New Hampshire resident who is insured through a New Hampshire employer will be included in the New Hampshire APCD, even when obtaining health care services out of state. Each claim contains information on the patient's demographics, the insurance plan, the identity of the health care provider, the diagnosis, the services rendered, and prices.

There are multiple price variables in the APCDs, all of which are required for our analysis. Charge prices measure what the provider bills the insurer or the patient. As discussed in the introduction, charge prices are irrelevant for the vast majority of health care services obtained; importantly, they do not dictate payment amounts when an insurer and a hospital have a contract. Instead, allowed amounts and insurer paid amounts measure the insurer's contracted price with the provider in case of an in-network provider with a negotiated price contract. In the case of an out-of-network provider, these variable measure the amount the insurer agrees to pay the provider off-contract. We use the allowed and paid amounts to construct measures of equilibrium negotiated prices for use with the first-order conditions in Equation 3. We also compare them to additional data, described in Section 2, to infer insurers' out-of-network payment policies. Finally, also reported in the data are amounts for which patients are directly responsible under their insurance plan: deductibles, copays, and coinsurance.

We supplement the APCDs with hospital characteristics drawn from the American Hospital Association (AHA) Annual Survey Database and from the Centers for Medicare and Medicaid Services (CMS). Characteristics used in the analysis include teaching status, bed count, and the presence of certain service lines such as neonatal intensive care units. In addition, we calculate driving distances from patient five-digit zip codes to hospitals for use in the hospital demand model.

4.3 Hospital Networks Data

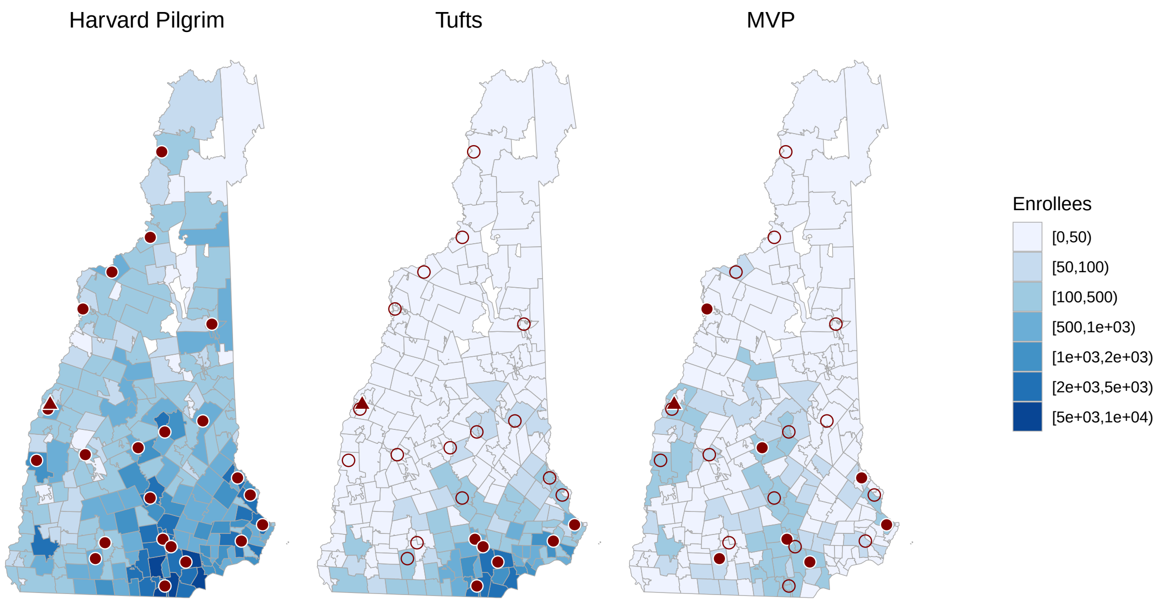
To determine which hospital-insurer pairs have a negotiated contract, we use data on insurers' hospital networks. These data were hand-collected from New England insurers' current and archived plan documentation, as described in Prager (2018).[18]

In some cases, an insurer may classify a hospital as an in-network provider for its generous plans (such as PPO plans) while classifying it as an out-of-network provider for its narrow-network plans (mainly HMO plans). The analysis needs to capture whether an insurer-hospital pair has *any* negotiated price contract that an insurer can invoke if its enrollees get care at the hospital. We therefore define a hospital that is classified by an insurer as in-network in at least one plan type as having a negotiated price contract with that insurer. Only if a hospital is not classified as in-network even in the insurer's broadest-network plans do we consider it a true out-of-network hospital. As described in Section 4.1, the largest insurers with incomplete hospital networks in New Hampshire are MVP and Tufts.

Figure 5 shows the hospital networks and distribution of enrollees for three carriers in New

[18]Many claims databases, including the Massachusetts APCD, include a variable for a provider's network status. However, these variables are reported unreliably; for example, Harvard Pilgrim does not populate the field at all. We therefore view the network information collected directly from insurers' plan documentation as substantially more reliable.

Figure 5: Hospital Networks and Enrollees by Health Plan in New Hampshire



Notes: Figure plots the New Hampshire enrollments of three key insurers at the 5-digit zip code level. Solid red circles represent in-network hospitals; the solid red triangle near the center of the state represents Dartmouth-Hitchcock Medical Center, the premier academic hospital in the state. Hollow circles represent out-of-network hospitals. For the two narrow-network insurers, Tufts and MVP, in-network hospitals are located near large masses of enrollees.

Hampshire: Harvard Pilgrim, Tufts, and MVP. Figure 5a shows that Harvard Pilgrim has full coverage in the state, whereas Tufts' and MVP's largest PPO network cover only 8 hospitals each. Tufts' in-network hospitals tend to be clustered in the southeastern part of the state, where the majority of Tufts' New Hampshire enrollees live, and near to its primary market of Massachusetts. MVP, which operates primarily in New York State and Vermont, has multiple pockets of enrollees in New Hampshire. The majority of MVP's in-network hospitals are also located near the enrollee masses. Both Tufts and MVP also cover Dartmouth-Hitchcock Medical Center, which, although geographically distant from the bulk of their enrollees, commands high willingness to pay due its status as the state's premier academic hospital. Finally, Harvard Pilgrim has substantially higher enrollment in New Hampshire than either Tufts or MVP, with relatively high enrollment counts throughout the state. All New Hampshire hospitals are in Harvard Pilgrim's network.

4.4 Outpatient Hospital Sample

In the empirical implementation, we restrict our attention to health care services that are performed in an outpatient, rather than inpatient, setting. We do this for two primary reasons. First, in our sample, out-of-network inpatient hospitalizations are rarer than out-of-network claims for outpatient services. Second, the data we use to construct off-contract prices is based on the FAIR Health outpatient benchmark data (see Appendix B). To infer inpatient benchmarks for out-of-network reimbursements would require use of diagnosis-related groups (DRGs), which are not reliably reported in the APCDs. Reconstructing DRG classifications from the data without proprietary software would introduce additional noise into our off-contract price measures.

We restrict our sample to outpatient procedures that plausibly constitute the primary reason for a patient's choice of provider. This requires dropping procedure codes that are incidental to the main treatment or procedure. We drop the following classes CPT codes: pathology and laboratory services (codes beginning with 8 or P); codes specific to the emergency department (codes 99281–99288); anesthesia (codes 00100–01999, 99100–99150); modifier codes for visits or services that are already reported separately (Category III CPT codes); temporary codes for emerging technologies (Category III CPT codes); ambulance and other transportation (codes beginning with A); durable medical equipment (codes beginning with E or K); dental procedures (codes beginning with D); and other temporary and miscellaneous codes (codes beginning with Q or S). The vast majority of volume among the dropped categories belongs to pathology and laboratory services. We refer to the remaining CPT codes as "primary" procedure codes.

We subset the primary procedure codes to the top 1,000 codes by hospital revenue. These top 1,000 codes account for 96.7 percent of hospital outpatient revenue and 98.5 percent of hospital outpatient volume among primary codes. The top ten of these codes, which account for 17.2 percent of revenue and 65.4 percent of volume, are dominated by generic visit codes and diagnostic procedures. Two of them are outpatient or physician office visits by established patients; six are the diagnostic procedures of diagnostic colonoscopies, head MRI scans, mammograms, echocardiograms, abdominal CT scans, and biopsies of the upper digestive tract; one is the injection of the drug infliximab, which is used to treat autoimmune conditions including arthritis and Crohn's disease; and one is physical therapy exercises.

We make some additional sample restrictions to construct our final sample for the demand model. First, we limit the data to only patients insured by Anthem/BCBS, Harvard Pilgrim, Cigna, United, Aetna, MVP, or Tufts. These insurers collectively account for 97 percent of commercial health insurance enrollment in New Hampshire in 2012. The top three, Anthem, Harvard Pilgrim, and Cigna, account for 89 percent. Although our primary focus is on New Hampshire, we observe patients who reside in Massachusetts who cross the border to seek care in New Hampshire. Similarly, we observe patients residing in New Hampshire who seek care in Massachusetts. We include in the sample all enrollees who live in New Hampshire as well as those who live in Massachusetts near the New Hampshire border. Specifically, we include any enrollee living in any Massachusetts zip code within the 75th percentile of distance traveled to a New Hampshire hospital. For every enrollee, we include in the choice set all 26 acute care hospitals in New Hampshire, as well as any Massachusetts hospital within the 75th percentile of distance traveled from any border zip code. The final choice set consists of 40 hospitals, 26 from New Hampshire and 14 from Massachusetts.

For computational feasibility, we take a random sample of approximately 101,000 visits (a 0.5 percent sample) to use in the maximum likelihood estimation. Visits to hospitals or hospital-affiliated providers comprise 31.5 percent of the sample; the majority of the sample consists of visits to standalone physician offices and other providers not affiliated with a hospital. The final sample, including both hospital visits and non-hospital visits, consists of visits from Anthem/BCBS at 55.3 percent, Harvard Pilgrim at 16.9 percent, Tufts at 10.9 percent, Cigna at 8.0 percent, United at 4.7 percent, Aetna at 3.4 percent, and MVP at 0.8 percent. Table 2 shows the summary statistics for our demand estimation sample, subsetting just to hospital visits. Anthem's share is higher, 61.3 percent, when subsetting to hospital visits. Tufts' sample share is substantially larger than its New Hampshire market share because Tufts is among the top three insurers in Massachusetts, from which we also draw data. Among visits to hospitals and their affiliated providers, 68.0 percent are to New Hampshire hospitals and the remaining 32.0 percent are to Massachusetts hospitals.

In the demand estimation sample, less than 1 percent of visits are to out-of-network providers. This is because the majority of visits in the sample are by patients who have access to complete networks; these are all to in-network providers. When subsetting to patients insured through narrow-network insurance plans based in New Hampshire, 63.0 percent of MVP's hospital visits and 1.5 percent of Tufts' hospital visits are to out-of-network hospitals. These out-of-network shares rise by about half of a percentage point when further subsetting to hospitals in New Hampshire.

Table 2: Demand Sample Summary Statistics

	Full Sample		NH Narrow Plans	
	Mean	SD	Mean	SD
Patient Characteristics				
Age	49.012	19.256	41.501	17.469
Female	0.592	0.491	0.601	0.490
FAIR Health Weight	39.076	135.782	41.180	113.913
Anthem/BCBS	0.613	0.487	0.000	0.000
Cigna	0.100	0.300	0.000	0.000
Harvard Pilgrim	0.133	0.339	0.000	0.000
Tufts	0.093	0.290	0.299	0.458
United	0.016	0.127	0.000	0.000
Aetna	0.036	0.185	0.000	0.000
MVP	0.010	0.099	0.701	0.458
Distance (Miles)	10.487	13.361	13.972	16.855
Hospital Characteristics				
In Network	0.992	0.088	0.561	0.497
Beds	196.121	107.371	192.632	106.048
Cath Lab	0.802	0.398	0.820	0.384
NICU	0.285	0.451	0.335	0.472
Neuro	0.898	0.303	0.907	0.291
MRI	0.823	0.382	0.863	0.345
Critical Access	0.099	0.299	0.146	0.354
Teaching	0.180	0.384	0.162	0.369

Notes: Summary statistics for demand estimation sample of 2011–2012 outpatient visits. Columns 1–2 summarize the full sample of hospital visits, including Massachusetts residents near the New Hampshire border as well as New Hampshire residents. Columns 3–4 subset to enrollees in New Hampshire-based insurance plans with narrow networks (Tufts and MVP).

These patients travel somewhat smaller distances to receive care: the mean distance traveled to an out-of-network hospital is 10.5 miles, compared to 16.9 miles to in-network hospitals. Patients appear to trade off disutility from seeking care out of network against the utility of traveling a shorter distance. We leverage this type of variation for estimating the demand model. The out-of-network hospitals comprising these visits are smaller than hospitals comprising in-network visits, with a mean bed count of 160.4 compared to 217.8. The intensity of care obtained at out-of-network hospitals is similar to that in in-network hospitals.

To estimate the bargaining model, we construct the quantities in Section 3.3 from a random sample of 5,000 households. For each household member, we merge in the annual prevalence of health care services in each decile of severity. Severity is measured by weights w_d, described below in Section 4.5. Severity quantiles and their associated prevalences are calculated from all commercially insured patients in the New Hampshire APCD, separately by sex and five-year age band. We use these prevalences to construct, for each patient, the predicted WTP and hospital volumes under each network configuration. In the bargaining estimation, each patient from the 5,000-household sample is then scaled up by the appropriate sample weight to represent the insurers' complete enrollment panel.

4.5 Constructing Price and Cost Indices

To operationalize the bargaining model from Section 3.1, we adopt from the literature a key simplifying assumption about how prices and marginal costs are scaled. Following Gowrisankaran et al. (2015) and Ho and Lee (2017), we assume that each hospital-insurer pair negotiates a single price index p_{mh} that is then scaled multiplicatively to determine the price for a given diagnosis or service.[19] The multiplicative scaling w_d is based on the resource intensity of the diagnosis or service, so that the price that insurer m pays to hospital h for service d is given by $w_d p_{mh}$. In our empirical application, this becomes a weaker assumption, requiring that prices are scaled in this manner only for the relatively narrow range of services we consider. We make the same scaling assumption about hospital marginal costs c_h, as in those papers. This makes the Nash bargaining first-order conditions in Equation 3 linear in hospital marginal costs.

Existing work on hospital-insurer bargaining has generally restricted the analysis to inpatient

[19] Other papers making analogous assumptions include Shepard (2016), Ghili (2017) and our own work in Prager (2018) and Tilipman (2018).

hospital care. In an inpatient setting, a natural choice for the resource weights w_d are DRG weights, which are weights specifically designed to measure the relative resource intensity of various types of inpatient care. Since our analysis focuses instead on outpatient hospital care, we turn to a different measure of w_d. We select a measure that achieves internal consistency with our algorithm for measuring off-contract prices, described in Section 2: the FAIR Health charge benchmark percentiles.[20] For each procedure in the sample, we assign a measure of resource intensity constructed from FAIR Health weights. We normalize the weights such that $w_d = 1$ for venipuncture (i.e., a blood draw; CPT code 36415), chosen because it is both common and a fairly uniform procedure. Thus, the prices and costs we report should be scaled by the resource intensity of a given type of care relative to the resource intensity of venipuncture. We have validated our price measure against DRG-deflated inpatient prices for the same hospital-insurer pairs, and found similar patterns over time across the two price measures.

In the demand model, the weights act as a measure of severity, allowing patients seeking care for more complex bundles of care to choose different providers than otherwise similar patients who require simpler care. In the bargaining model, the weights serve as a multiplier for scaling hospital volumes. A higher weight w_d will increase both the hospital's marginal cost of treating a patient and the price paid to the hospital by the same multiplicative factor.

Figure 2, first described in Section 3.5, plots the price indices computed for the five insurers with complete hospital networks in New Hampshire: Anthem, Harvard Pilgrim, Cigna, United, and Aetna. The price indices reflect negotiated prices for procedures with the resource intensity of a routine venipuncture. Negotiated prices fall primarily in the \$6 to \$13 range.

5 Results

5.1 Hospital Demand Estimates

Table 3 shows the results of the hospital demand model for outpatient care. Our preferred specification is Column 2, in which we instrument for the in-network hospital indicator using enrollee geography as described in Appendix C. Consistent with the literature on hospital and physician demand, distance enters negatively and significantly into the utility function. Patients dislike ex-

[20]The benchmark construction algorithm is described in detail in Appendix B.

posure to higher balance bills.

Most of the interactions between patients and hospital characteristics follow the expected signs. Older patients are less willing to travel. Patients are more willing to travel for hospitals with a cardiac catheterization lab, larger hospitals, and teaching hospitals. More puzzling is that patients are more willing to travel to critical access hospitals. This is partially, but not entirely, explained by multicollinearity between critical access status and bed size, as critical access hospitals are small: the majority of the ones in our sample have 25 beds. Patients requiring more resource-intensive procedures are also more willing to travel to larger hospitals and hospitals with cardiac catheterization labs and also, again, critical access hospitals.

We include two key terms in the model to capture patient disutility from seeking out-of-network care. The first is an in-network indicator and the second is the potential "balance bill" a consumer might incur from the hospital. The latter is calculated as the difference between a hospital's posted list price (i.e. its charge price, p_h^c) and the amount that insurer reimburses for out-of-network care (p_m^0). It is meant to capture the fact that patients may have expectations over their out-of-pocket burden at any particular hospital, which may dissuade them from seeking care at that hospital. The key assumption we make here is that patients are broadly aware of their *potential* out-of-network bill, but are uncertain as to the charge the hospital will *actually* levy. In other words, when p_m^0 is regulated downwards, patients may incur additional disutility from going to an out-of-network hospital, as they may expect that the hospital will pass an additional cost burden onto them. However, this does not necessarily mean that the hospital will pass on the full amount.[21] We interpret the former term as a hassle cost that patients pay for seeking out-of-network care that does not vary by hospital. Such costs can include, for instance, receiving prior authorization from the insurer or the cost of acquiring price information from the hospital.

The coefficient on the hospital's in-network indicator is positive and significant, confirming that patients receive significant disutility from getting outpatient care out-of-network. The estimate translates to an average patient willing to travel about five additional miles to receive care from an

[21] These assumptions are motivate by institutional details. First, given that we focus on voluntary care——as opposed to emergent care——consumers are more likely to make a price assessment before agreeing to seek care out-of-network. Second, while hospitals technically do have the ability to fully balance-bill patients for out-of-network care, patients rarely actually do receive bills for the full charge amounts. In fact, the portion of a balance bill that hospitals typically collect is not well documented (Duffy et al. 2020). As such, while there may be a correlation between a patient's expectation of their balance bill and their actual ultimate out-of-pocket price burden, the correlation is not necessarily strong.

in-network facility as opposed to an out-of-network facility, or about one third farther farther than the average distance traveled in our sample (13.2 miles). The combination of both of these forces results in positive consumer willingness-to-pay for hospitals to be part of an insurer's network, which then enters into the insurer objective function (Equation 2).

5.2 Hospital Costs and Bargaining Parameters

The first column of Table 4 shows the results of the bargaining estimation. The results that follow are from an intermediate version from an older sample definition; updates are in progress as of the date of this draft. We report the results for 2012, the first year that FAIR Health is fully operational. The estimated hospital costs for routine venipunctures (the baseline procedure with weight $w_d = 1$) in 2012 are all positive and exhibit substantial variation, ranging from a low of \$0 to a high of \$18.41, with most cost estimates in the \$3–11 range. These are largely sensible magnitudes. Given that most hospitals in New Hampshire are reimbursed between \$15 and \$20 for this procedure, this suggests that hospitals are, on average, making a markup of 150–300 percent relative to estimated costs, with substantial heterogeneity. For example, Dartmouth-Hitchcock Medical Center, a prestigious academic hospital, is estimated to make a markup of about 500 percent in our model, on the higher end of the spectrum.

Harvard Pilgrim Health Care's estimated Nash bargaining weight is 1, while Tufts Health Plan's is 0.67, suggesting that on average Harvard Pilgrim is able to extract more surplus from New Hampshire hospitals relative to Tufts. This aligns closely with the fact that for the same procedures, Harvard Pilgrim is observed to pay lower prices than Tufts to the same hospitals. Moreover, Harvard Pilgrim maintains a larger presence in the New Hampshire market than Tufts, both in terms of number of hospitals in-network and enrollment. The estimated MCO weight on consumer surplus relative to spending, α, is 23.40. Though the magnitude of the estimate is difficult to interpret, as our WTP is in utils rather than dollars, its direction is informative. Insurers are estimated to place strictly positive weights on enrollee surplus relative to costs arising from hospital expenditures.

Finally, the estimated contracting cost, b, is approximately \$21,883,suggesting that the fixed cost of forming and maintaining contracts is considerable. Two factors modify this seemingly large estimate. First, recall that this reflects the *joint* contracting cost between insurers and hospitals, as specified in 3. Second, the contracting cost is not a key driver of our core parameter estimates

Table 3: Hospital Demand Estimates

	(1) No IV		(2) IV Deg 1	
In-Network Hospital	1.0990***	(0.1642)	2.4109***	(0.1745)
Other In-Network Provider	2.7371***	(0.0607)	2.7774***	(0.0607)
Balance Bill ($)	-0.0060	(0.0039)	-0.0056	(0.0040)
Distance (miles)	-0.2995***	(0.0059)	-0.2995***	(0.0059)
Distance^2	0.0007***	(0.0000)	0.0007***	(0.0000)
Distance × Age	0.0000	(0.0000)	-0.0000	(0.0000)
Distance × Intensity Weight	-0.0000	(0.0000)	-0.0000	(0.0000)
Beds × Age	0.0000***	(0.0000)	0.0000***	(0.0000)
Beds × Intensity Weight	0.0000***	(0.0000)	0.0000***	(0.0000)
Beds × Distance	-0.0000*	(0.0000)	-0.0000*	(0.0000)
Beds × Female	0.0000	(.)	0.0000	(.)
Critical Access × Age	0.0008	(0.0014)	0.0004	(0.0014)
Critical Access × Intensity Weight	0.0052***	(0.0004)	0.0052***	(0.0004)
Critical Access × Distance	0.0942***	(0.0059)	0.0970***	(0.0059)
Critical Access × Female	0.0000	(.)	0.0000	(.)
Teaching × Age	-0.0110***	(0.0014)	-0.0105***	(0.0014)
Teaching × Intensity Weight	-0.0021***	(0.0003)	-0.0021***	(0.0003)
Teaching × Distance	0.0561***	(0.0026)	0.0559***	(0.0026)
Teaching × Female	0.0000	(.)	0.0000	(.)
Cath Lab × Age	0.0063***	(0.0014)	0.0060***	(0.0014)
Cath Lab × Intensity Weight	0.0068***	(0.0004)	0.0068***	(0.0004)
Cath Lab × Distance	0.0976***	(0.0058)	0.0982***	(0.0058)
Cath Lab × Female	0.0000	(.)	0.0000	(.)
MRI × Age	0.0025**	(0.0009)	0.0025**	(0.0009)
MRI × Intensity Weight	0.0008***	(0.0002)	0.0008***	(0.0002)
MRI × Distance	0.0253***	(0.0024)	0.0256***	(0.0024)
MRI × Female	0.0000	(.)	0.0000	(.)
NICU × Age	0.0000	(.)	0.0000	(.)
NICU × Intensity Weight	0.0000	(.)	0.0000	(.)
NICU × Distance	-0.0005	(0.0024)	-0.0002	(0.0024)
NICU × Female	0.0088	(0.0231)	0.0086	(0.0231)
Neuro × Age	-0.0003	(0.0013)	-0.0003	(0.0013)
Neuro × Intensity Weight	0.0003	(0.0003)	0.0003	(0.0003)
Neuro × Distance	-0.0057*	(0.0027)	-0.0057*	(0.0027)
Neuro × Female	0.0000	(.)	0.0000	(.)
Hospital FEs	Yes		Yes	
Up to Deg 1 of 1st Stage Resid	No		Yes	
Pseudo R^2	0.696		0.697	
Choices	77961		77961	

Notes: ***p<0.01, **p<0.05, *p<0.10. Results from multinomial logit provider choice model from years 2011–2012. IV columns estimated using a control function with boostrapped standard errors with replications. *Choices* is the number of choice sets used in estimation. *In-Network Hospital* and *Other In-Network Provider* are indicators for whether the provider is in the patient's insurer's network and is a hospital or non-hospital provider, respectively. *Balance Bill* is the potential (maximum) dollar amount a patient would be charged out-of-pocket in cases where the hospital is out of network. Results for other polynomial degrees of the first-stage residual are reported in Table C.1.

(the hospital marginal costs and bargaining weights). When we re-estimate the model assuming that the bargaining costs are 0, the marginal cost estimates remain very similar.

5.3 Estimates Under Zero Disagreement Volumes

We now turn to the impact that allowing for out-of-network transactions and non-zero disagreement volumes have on the estimated cost parameters of the model. To do so, we hold fixed the estimated MCO weight on enrollee surplus (α), and contracting costs (b), and re-estimate the hospital marginal costs (c_h) and bargaining weights (γ_m) under the standard Nash-in-Nash framework. To implement the version that shuts down out-of-network transactions, we first remove all out-of-network hospitals from each individual's choice set, and then use the demand model from Table 3 to recompute predicted hospital shares and WTP from the demand model parameters. The predicted demand quantities are then used to generate new predictions for total spending under the assumption that volumes and payments to out-of-network hospitals are zero. This, in essence, shuts down the channel where patients can seek care out-of-network if a hospital and insurer were to not form a contract. Finally, we re-estimate hospital marginal costs and bargaining weights from the supply side of the model.

The bargaining model estimates for 2012 using the canonical Nash-in-Nash framework are reported in Table 4 column 2. In most cases, the full model (column 1) yields substantially lower hospital marginal cost estimates than the model that shuts down the out-of-network channel. The magnitude of the bias is large: on average, standardized marginal costs are estimated to be 39.5 percent lower under the full model with nonzero disagreement volumes. Moreover, the direction and magnitude of the bias are consistent with the comparative statics discussed in Section 3.4. Figure 6 plots the empirical analog of the comparative static on prices. It shows that, as out-of-network prices p_m^0 rise above negotiated prices p_{mh}^*, the standard Nash-in-Nash model tends to overestimate hospital marginal costs to a greater degree. Because out-of-network prices are greater than negotiated prices in most markets, the majority of standard Nash-in-Nash estimates of hospital costs are biased upward.

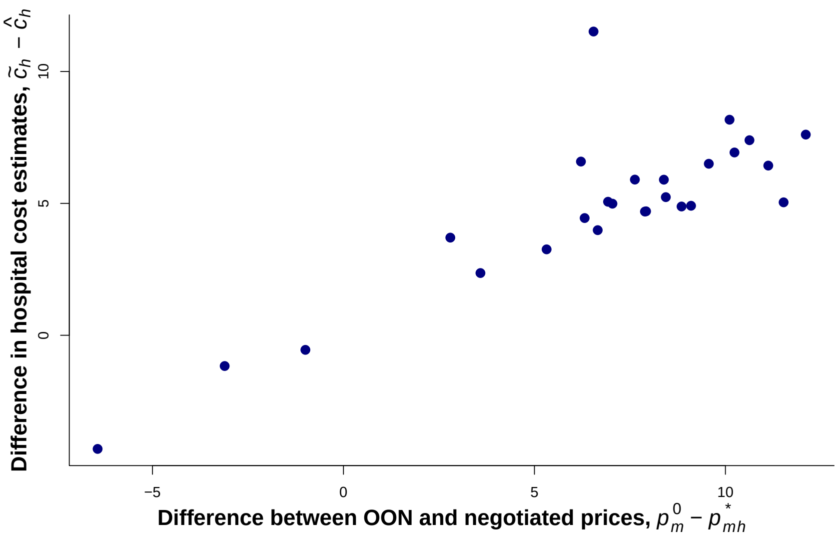
Returning to the example of Dartmouth-Hitchcock, for instance, the full model predicts marginal costs that are 10 percent lower than the predictions of a model with no out-of-network volumes. This result makes sense: since Dartmouth-Hitchcock is a high-demand hospital, the model predicts

Table 4: Hospital Cost Estimates With and Without Non-Zero Disagreement Volumes

Variable	With OON	No OON
Selected hospital costs (c_h):		
Alice Peck Day Memorial Hospital	13.74	11.17
Androscoggin Valley Hospital	11.45	17.07
Catholic Medical Center	11.36	11.69
Cheshire Medical Center	0.00	6.28
Concord Hospital	7.09	10.53
Cottage Hospital	0.00	7.26
Dartmouth-Hitchcock Medical Center	8.47	9.42
Elliot Hospital	6.88	10.91
Exeter Hospital	13.31	15.05
Franklin Regional Hospital	0.00	4.20
Frisbie Memorial Hospital	2.68	10.58
Huggins Hospital	10.11	11.87
Lakes Region General Hospital	0.95	6.96
Littleton Regional Hospital	11.22	14.11
Memorial Hospital	17.89	19.01
Monadnock Community Hospital	11.21	12.28
New London Hospital	2.48	9.62
Parkland Medical Center	5.09	6.12
Portsmouth Regional Hospital	8.81	10.42
Southern New Hampshire Medical Center	0.04	6.53
Speare Memorial Hospital	3.87	12.54
St. Joseph Hospital	0.00	8.37
Upper Connecticut Valley Hospital	7.46	11.77
Valley Regional Hospital	18.41	15.84
Weeks Medical Center	9.82	10.49
Wentworth Douglass Hospital	8.80	9.82
Insurer parameters:		
Bargaining weight $\gamma_{Harvard}$	1.00	1.00
Bargaining weight γ_{Tufts}	0.67	0.67
Insurer weight on WTP α	23.40	23.40
Contracting Cost b	\$21,883	\$21,883

Results from bargaining estimation 2010. First column reflects estimates from the full model, allowing for non-zero disagreement volumes and payoffs constructed from Fair Health benchmarks. Second column reflects estimates with disagreement volumes set to zero, as in canonical Nash-in-Nash estimation. All models fix b, γ, and α at their estimated values from the full model. Each observation reflects an insurer-hospital pair. Sample is limited to Harvard Pilgrim, Tufts Health Plan, and only New Hampshire hospitals. Hospital marginal costs reflect a "standardized" cost measure for performing a routine venipuncture.

Figure 6: Bias in Hospital Cost Estimates Under Zero Disagreement Volumes



This figure illustrates the direction of the bias arising from assuming zero disagreement volumes using our estimates for 2012. The horizontal axis is the difference between the hospital's out-of-network price and its negotiated price with Harvard Pilgrim, which has a complete network. The vertical axis is the difference between the hospital cost estimates from the standard Nash-in-Nash framework (assuming zero disagreement volumes) and the hospital cost estimates from the full model with nonzero disagreement values. The bias of the Nash-in-Nash estimates increases with the difference between the out-of-network and in-network prices.

it would retain considerable out-of-network volume should it exit an insurer's network. This outside option allows it to negotiate a higher price. In the absence of this phenomenon, the model without out-of-network transactions rationalizes Dartmouth-Hitchcock's high price by loading it onto a high estimate of its marginal cost. In other words, allowing for out-of-network transactions implies a considerably higher hospital mark-up than would be estimated in their absence. This leaves more room for price regulation without sending hospitals to their shut-down conditions, a point we return to in 6 below.

6 Policies to Reduce Negotiated Prices

We conduct a series of policy counterfactual simulations using our bargaining model estimates by imposing various restrictions on the out-of-network reimbursement policies and then simulating equilibrium *in-network* negotiated rates between insurers and providers in our sample.

One set of counterfactuals mirrors current federal legislation surrounding surprise out-of-network billing, but applies them more broadly to all out-of-network payments. The Lower Health Care Costs Act of 2019 proposes to regulate surprise out-of-network billing by capping insurers' off-contract payments at median in-network rates in a given market, while also establishing strong balance-billing protections for patients (Alexander 2019). Other policy proposals include fixing out-of-network reimbursements to multiples of Medicare payment rates. A high-profile candidate for the 2020 Democratic presidential nomination proposed setting the cap at 200 percent of Medicare (Pete For America 2019). Other proposals have called for rates as low as 120 percent of Medicare (Kane 2019).

Medicare rates are substantially lower than the current standard based on FAIR Health benchmarks. For example, Tufts' current benchmark is approximately three times Medicare rates. These proposals have consequently drawn considerable scrutiny from hospital and physician groups, with some warning that reducing out-of-network payments would jeopardize their long-run financial viability. Some groups have proposed requiring insurers and providers to settle disputes over out-of-network reimbursement through binding arbitration. Others have proposed *increasing* the standard by which providers are reimbursed to the full charge amount (Luthi 2019). As such, we also simulate policies that vary the multiples of the FAIR Health benchmark themselves.

In order to predict the impacts of these policies, we focus specifically on Tufts Health Plan (which has an incomplete network in New Hampshire) and on the year 2012, using our estimates from Column 1 of Table 4. Under standard Nash-in-Nash, the procedure would involve using our estimated parameters and computing in-network rates, p_{mh}, for every hospital-insurer pair under the different out-of-network reimbursement structures. However, our analysis is complicated by the fact that imposing alternate disagreement payoffs may result in different networks being formed in equilibrium. To incorporate this feature, our iterative simulation proceeds in a series of steps at each iteration t:

1. Use the bargaining first-order conditions in Equation 3 to simulate in-network negotiated rates p_{mh}^t given the set of estimated $\hat{\boldsymbol{\theta}}$ when we set p_m^0 to the counterfactual reimbursement.

2. Given the new in-network prices in Step 1, use the network inclusion and exclusion conditions (equations 8 and 9) to check whether any new networks form or whether any existing networks sever. Denote each network link by I_{mh}^t.

3. If a new link forms, assign the predicted in-network price p_{mh}^t from Step 1. If a link severs, assign the counterfactual out-of-network reimbursement p_m^0 to the severed link.

4. If $\max_{m,h} \left| p_{mh}^t - p_{mh}^{t-1} \right| < \epsilon$ and $\max_{m,h} \left| I_{mh}^t - I_{mh}^{t-1} \right| = 0$, stop. Otherwise, return to Step 1 using the updated p_{mh}^t, I_{mh}^t.

The convergence criterion requires that network links do not change between iterations $t-1$ and t, and that prices change by no more than \$0.01 ($\epsilon = 0.01$). Because network links are allowed to change, finding an equilibrium is not guaranteed.

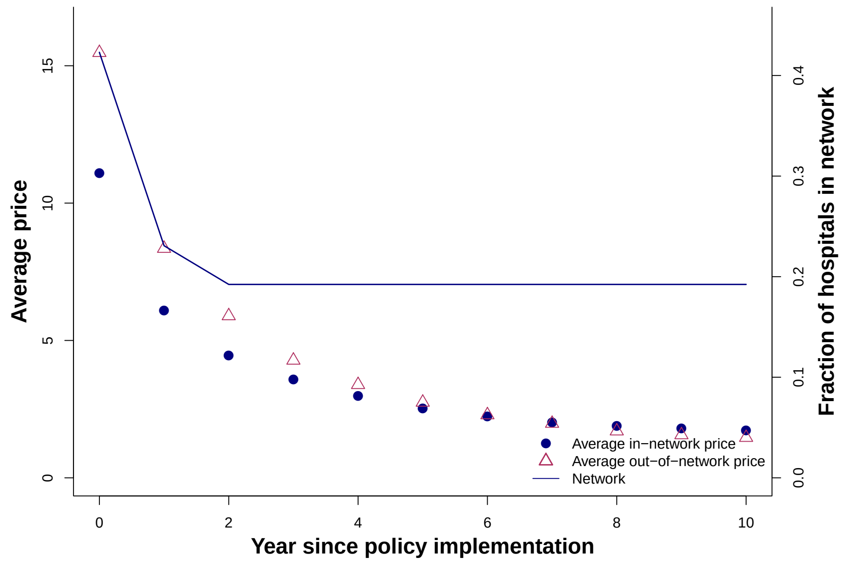
Reducing the out-of-network reimbursement via regulation would have several effects. Most immediately, it would worsen hospitals' outside option, driving them to accept lower in-network prices from insurers. In some cases, the out-of-network prices would drop sufficiently low that insurers will prefer to leave the hospitals out of network, accepting lower total consumer WTP in exchange for lower costs. Marginal consumer WTP for adding a hospital to the network will also change as patients' expected balance bill changes with the insurer's regulated out-of-network payment. Finally, if prices drop below marginal costs, hospitals may stop accepting patients if they are permitted to do so, or they may exit the market altogether.

6.1 Negotiated Prices as Out-of-Network Payment Caps

We begin by considering the Alexander (2019) proposal to peg out-of-network prices to median negotiated in-network prices in the corresponding geographic market. In the majority of markets, median negotiated prices are substantially lower than current out-of-network prices. Forcing hospitals to accept the median in-network price when they are out of network would therefore amount to worsening their bargaining leverage vis-à-vis insurers in the majority of markets. This is precisely the mechanism that the policy proposal is designed to leverage in order to reduce negotiated in-network prices.

However, the designers may not have considered the self-reinforcing effects of such a policy. As written, the policy would peg the current year's out-of-network prices to the preceding year's median negotiated prices. In the first year of implementation, this would reduce in-network prices due to the worsening of hospitals' bargaining leverage. The following year, the median will be calculated from a negotiated price distribution that has shifted to the left, further reducing negotiated in-network prices. For hospitals with relatively high marginal costs, these reductions may suffice to push both

Figure 7: Predicted Negotiated Prices Against Multiples of Current Off-Contract Prices



This figure plots results of counterfactual simulations pegging out-of-network prices to the median of the prior year's negotiated in-network prices. The left vertical axis plots the counterfactual average prices, weighted by volume. Plot is for Tufts Health Plan in 2012. Gaps represent counterfactuals for which no equilibrium was found.

the out-of-network price and the in-network price they could negotiate below their marginal costs. Those hospitals may then prefer to minimize their volumes by leaving insurers' networks, or even by exiting the market altogether. Over time, patients may retain in-network access only to a small set of hospitals with low marginal costs.

Figure 7 simulates these effects over the first ten years following policy implementation. Both negotiated and out-of-network prices drop substantially, particularly in the first two years, but so too does network breadth. Policy-makers have not stated spiraling reductions in access to care as a policy goal. It is therefore arguably unlikely that a policy like the one simulated in Figure 7 would be knowingly adopted. We therefore turn next to proposed regulations that would avoid such self-reinforcing effects.

6.2 Alternate Multiples of Charge Price Benchmarks

In this section, we consider rescaling the out-of-network prices to alternate multiples of the current benchmarks (the current benchmark for Tufts Health Plan is the 60th percentile of charges, as described in Appendix B). This is meant to approximate the impact on in-network hospital prices of proposals to set out-of-network reimbursements closer to hospitals' current charge prices. Unlike in Section 6.1, these policy proposals do not have a dynamic element because current out-of-network prices do not directly affect the following year's out-of-network price calculations. We therefore simulate the effects for a single contemporaneous year.

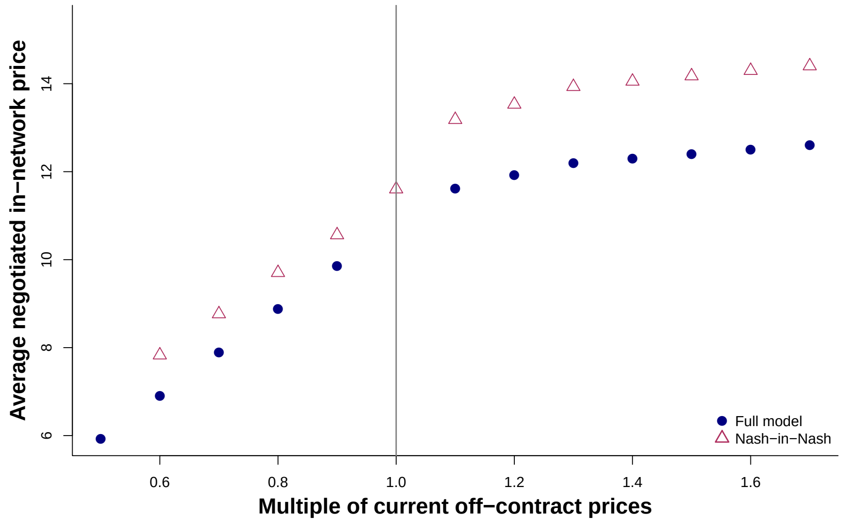
Two forces moderate the magnitude of the effect of regulating out-of-network prices. First, for the few hospitals whose charge prices are lower than the current benchmarks, the counterfactuals have no impact on the out-of-network price until the benchmark drops below the charge price. Similarly, in counterfactuals involving very high out-of-network prices, the majority of hospitals' charge prices are below the out-of-network prices, blunting the effects of further increases in the regulated out-of-network price. Second, for this set of counterfactuals and the ones in Section 6.3, we allow hospitals to turn away patients of insurers with which they are out of network. This means that when out-of-network prices drop below hospitals' marginal costs, hospitals can effectively impose zero disagreement volumes, collapsing the model to the standard Nash-in-Nash one.[22] Some have argued that out-of-network price regulation will not effectively reduce negotiated prices unless it is paired with a requirement for providers to accept all patients (Fiedler 2020). This set of counterfactuals suggests otherwise. In Section 6.4, which evaluates the effect of out-of-network price regulation on hospital closures, we shut down hospitals' ability to turn away unprofitable patients. However, we first describe the results under the assumption that hospitals can turn away unprofitable out-of-network patients.

The solid blue dots in Figure 8 plot the results of this simulation. In-network negotiated prices rise with increases in the off-contract prices that insurers pay to out-of-network hospitals. By increasing off-contract prices, the hospital's disagreement value is improved, while the insurer's disagreement value worsens. Hospitals therefore gain considerable bargaining leverage to raise prices.[23] At current off-contract prices (multiple of 1.0 on the horizontal axis), the average predicted in-network price is \$11.09 (for a routine venipuncture). However, if off-contract prices were to increase to twice the current benchmark, then average negotiated prices are predicted to increase by approximately 7 percent to an average of \$11.86. On the other hand, reducing the benchmark to half of the current benchmark would drive average predicted in-network prices down by approximately

[22] More precisely, hospitals turn away patients when the sum of p_m^0 and whatever the hospital expects to recoup from the average patient is below marginal cost. For simplicity, we omit this from the main text.

[23] Note that in the vicinities of equilibrium network transitions, an equilibrium cannot always be found; this is the source of the gaps in Figure 8.

Figure 8: Predicted Negotiated Prices Against Multiples of Current Off-Contract Prices



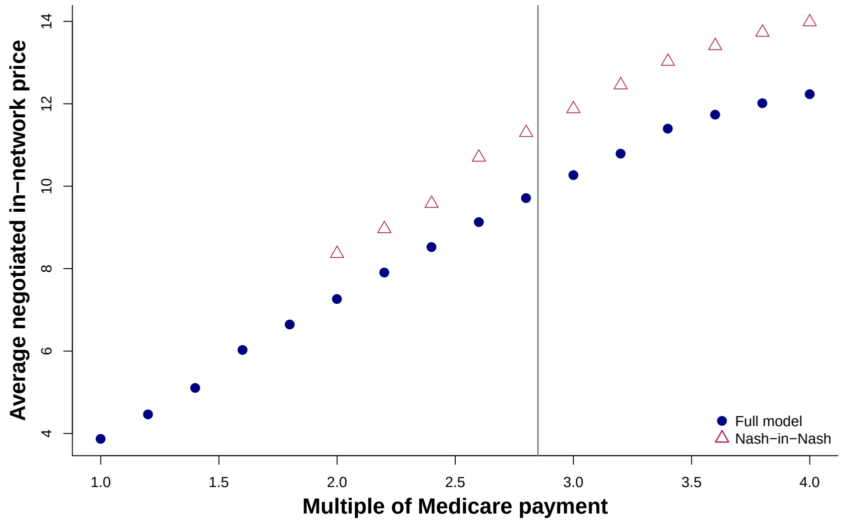
This figure plots results of counterfactual simulations varying out-of-network prices to be various multiples of current out-of-network payments. The vertical axis plots the counterfactual negotiated price for hospitals predicted to be in-network (volume-weighted average prices). Gray vertical line is value of observed out-of-network payments. Plot is for Tufts Health Plan in 2012. Gaps represent counterfactuals for which no equilibrium was found.

47 percent to \$5.92.

While equilibrium price reductions are desirable to policy-makers, access to health care is also an important policy goal. As shown in Appendix Figure A.2, which adds equilibrium networks to the plot, these goals are in direct competition. As negotiated prices fall, the fraction of hospitals that are in the equilibrium network also falls, albeit at a much slower rate. Reducing the benchmark to half the current benchmark would cause Tufts' network breadth to fall by 15 percentage points, from a baseline of 38 percent of hospitals being in network to 23 percent.

Figure 8 also illustrates how conclusions about the counterfactual policies would differ under estimates from the standard Nash-in-Nash model that assumes zero disagreement volumes. The hollow red triangles plot the results of the same simulation, but using our bargaining model estimates from the last column of Table 4. Due to the higher estimated hospital marginal costs, the counterfactual in-network prices are always higher than those using our baseline model. Moreover, despite the higher prices, the equilibrium networks are (weakly) narrower, as shown in Appendix Figure A.2. This is a good illustration of the importance of accurately estimating hospital costs

Figure 9: Predicted Negotiated Prices Against Multiples of Medicare Reimbursements



This figure plots results of counterfactual simulations varying out-of-network prices to be various multiples of Medicare reimbursements. The vertical axis plots the counterfactual negotiated price for hospitals predicted to be in-network (volume-weighted average prices). Gray vertical line is approximate value of observed out-of-network payments. Plot is for Tufts Health Plan in 2012. Gaps represent counterfactuals for which no equilibrium was found.

when conducting policy simulations whose goal is to reduce equilibrium prices. The standard Nash-in-Nash model both overstates equilibrium prices and understates network breadth. In evaluating a policy proposal, this would cause overly pessimistic predictions about spending and, under some parameter values, about access to care.

6.3 Medicare-Based Out-of-Network Payment Caps

Next, we consider policy proposals that peg out-of-network prices to multiples of Medicare reimbursement rates. Medicare reimbursements for the outpatient procedures we study are approximately one quarter of the in-network prices we observe in New Hampshire (see Figure 2), and for many hospitals, less than half of the marginal costs estimated in Table 4. It is therefore not surprising that most proposals use multiples of Medicare reimbursements greater than one. We simulate the counterfactual equilibrium in-network prices and networks for a range of multipliers no smaller than one.

Figure 9 plots the results of this simulation. As before, the solid blue dots represent simulations using the hospital cost estimates that take nonzero disagreement values into account, while the hollow red triangles represent simulations using estimates from the standard Nash-in-Nash model. It is clear from comparing these counterfactuals to Figure 8 that Medicare reimbursements are substantially lower than current off-contract reimbursements: current equilibrium prices are achieved when out-of-network prices are pegged to approximately 300 percent of Medicare.

Negotiated prices are lower using the smaller hospital cost estimates from the model with nonzero disagreement values. As shown in Appendix Figure A.3, equilibrium network breadth is sometimes slightly reduced as out-of-network reimbursements approach Medicare rates.

These results suggest that proposals to peg out-of-network reimbursements to as low as 125 percent of Medicare would likely cause substantial reductions in provider prices with minimal network disruptions. Under the assumptions we have used in the counterfactuals thus far, regulating out-of-network prices may not reduce access to care. Since hospitals are given the option to refuse treatment to out-of-network patients if the out-of-network price is regulated too low, hospitals effectively have a lower bound to their disagreement payoff at zero. This places pressure on insurers to offer higher prices than they would if hospitals were compelled to accept all patients. We next turn to a set of counterfactuals that add the mechanism of hospitals being required to treat all patients. We use these counterfactual to evaluate a potential additional channel for access reductions: hospital exits.

6.4 Forecasting Hospital Closures

The counterfactual simulations discussed in Sections 6.2 and 6.3 allow hospitals to leave insurers' networks in equilibrium. The narrowing of networks that we document is a central concern raised by opponents of regulation to cap out-of-network reimbursements. By contrast, the possibility of outright closures of hospital service lines—or, in extreme cases, of entire hospitals—has received little attention. If reductions in out-of-network reimbursements prompt sufficient reductions in in-network prices, some hospitals may be forced to exit service lines for which prices fall below their marginal costs. In existing models of hospital-insurer bargaining, the assumption of zero out-of-network volumes precludes the possibility of care being reimbursed at below marginal cost. On one hand, a hospital will only enter into a contract if the in-network price exceeds its marginal cost; on the other hand, remaining out-of-network means no marginal costs are incurred. This section evaluates the impact of regulating out-of-network prices on hospital exit.

We proceed by amending the counterfactual simulation algorithm to allow hospitals to exit when marginal profits fall below zero. The amended algorithm iterates through the following steps at each iteration t:

1. Use the bargaining first-order conditions in Equation 3 to simulate in-network negotiated rates p^t_{mh} given the set of estimated $\hat{\boldsymbol{\theta}}$, when we set p^0_m to the counterfactual reimbursement.

2. Given the new in-network prices in Step 1, use the network inclusion and exclusion conditions (equations 8 and 9) to check whether any new networks form or whether any existing networks sever. Denote each network link by I^t_{mh}.

3. If a new link forms, assign the predicted in-network price p^t_{mh} from Step 1. If a link severs, assign the counterfactual out-of-network reimbursement p^0_m to the severed link.

4. Calculate each hospital's total profit across insurers. If total profit is negative, assign hospital h to exit the market. Denote each closure by C^t_{mh}.

5. Given the price assignments from Step 3 and the exits from Step 4, check whether any exited hospital can profitably re-enter the market. If so, add it back to the set of hospitals negotiating in the next iteration.

6. If $\max_{m,h}\left|p^t_{mh} - p^{t-1}_{mh}\right| < \epsilon$, $\max_{m,h}\left|I^t_{mh} - I^{t-1}_{mh}\right| = 0$, and $\max_{m,h}\left|C^t_{mh} - C^{t-1}_{mh}\right| = 0$, stop. Otherwise, return to Step 1 using the updated p^t_{mh} from Step 1, I^t_{mh} from Step 2, and updated C^t_{mh} from Step 4.

The convergence criterion requires that market exit status and network links do not change between iterations $t-1$ and t, and that prices change by no more than \$0.01 ($\epsilon = 0.01$). Because exit, entry, and network links are allowed to change, finding an equilibrium is not guaranteed.

Modeling hospital exit in the counterfactuals requires several assumptions. First, we assume that the hospital service lines used in our empirical analyses are separable from hospitals' other service lines (see Section 4.4 for a detailed description of the sample). If that is the case, then price dropping below marginal cost for these service lines is a sufficient condition for a hospital to close the affected service lines. We therefore interpret our hospital closure results as pertaining only to the service lines included in our sample.

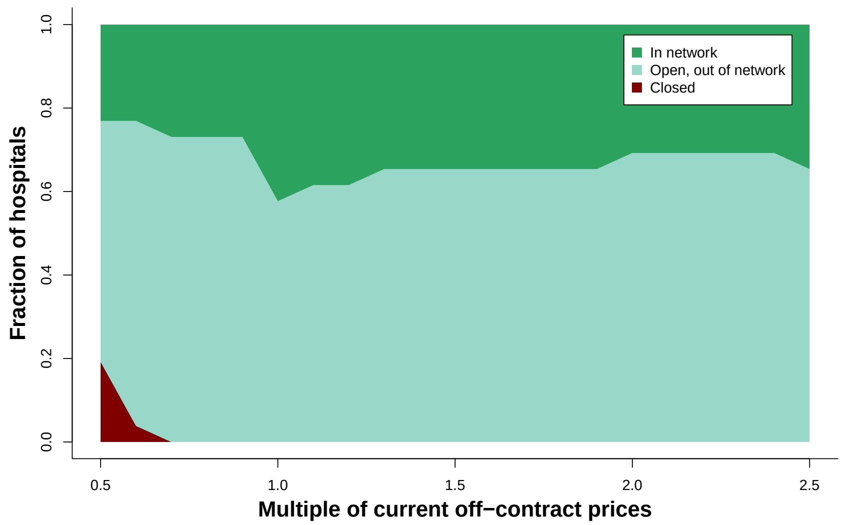
Second, we do not account for hospitals' ability to reduce their marginal costs by changing their production technology. A hospital whose marginal revenue falls below marginal cost due to regulation is effectively assumed to be powerless to return to positive marginal profits. In reality, hospitals can make (costly) investments to reduce costs or can reduce costs by reducing quality. This set of counterfactual results should therefore be interpreted as static.

Third, we assume for this set of counterfactuals that hospitals cannot turn away patients, regardless of the hospital's network status with a patient's insurer. We impose this assumption in order to generate a notion of exit. If hospitals can turn away out-of-network patients, then they need never accept prices below marginal cost. Imposing the requirement that hospitals must treat even those out-of-network patients for whom $p_m^0 + \mu(p_h^c - p_m^o) < c_h$ produces scenarios in which a hospital can make strictly negative profits by remaining open. This assumption is motivated by similar regulation that applies to emergency health care: the Emergency Medical Treatment and Active Labor Act (EMTALA) requires hospitals to accept and treat patients until they are stable, regardless of insurance status. In this set of counterfactuals, we effectively impose a form of EMTALA on our non-emergency outpatient care sample.

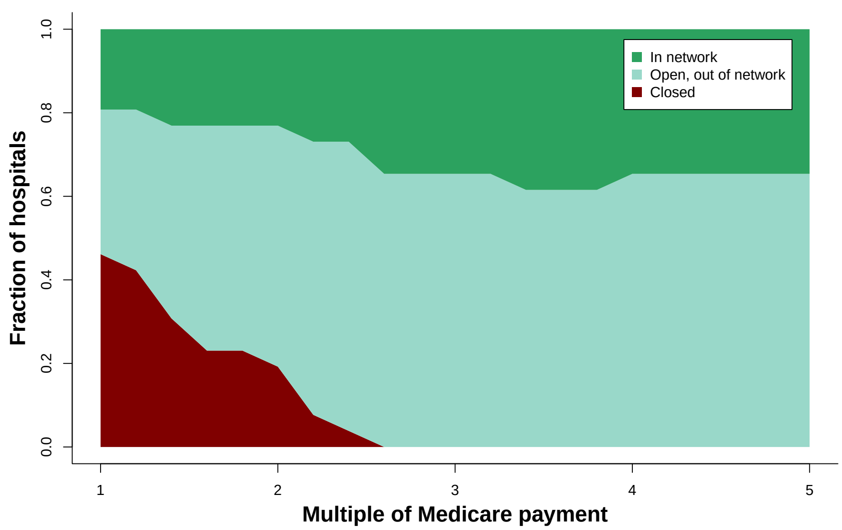
Finally, we assume that if the hospital's total profit summed across insurers is negative, that induces the hospital to exit. A necessary condition for exit is therefore that at least one insurer m's price drops below the hospital's marginal cost. This assumption is a simplification, in that we check profits only among the insurers for which have bargaining model estimates. In reality, hospitals derive revenues from public payers in addition to private insurers. Even if private insurers' prices drop below cost, a hospital may be able to stay open profitably if Medicare or Medicaid profits exceed the losses from private patients. Since Medicare rates are generally lower than private insurers' prices (see Section 6.3) and Medicaid is less generous than Medicare in most states, we do not view this potential cross-subsidization as a serious threat to our assumptions. However, it remains true that hospitals may cross-subsidize losses from one private insurer's patients using higher prices from a different private insurer. Our counterfactuals do not account for this possibility.

Figure 10 plots the results of the counterfactuals from Sections 6.2 and 6.3, now accounting for hospital exit. Consistent with the earlier results, the fraction of hospitals that remain in the insurer's network (dark green in the figure) drops slightly as out-of-network reimbursements p_m^0 drop and in-network negotiated prices p_{mh}^* follow. Beyond the narrowing networks, however, Figure 10b also makes clear that severe price reductions will also induce some hospitals to close service lines. While regulating out-of-network prices from their current value of approximately 300 percent of Medicare rates to 250 percent of Medicare rates would not affect the incidence of exits (or network breadth), we find that regulating beyond this point may begin to affect access. Indeed, capping out-of-network reimbursements at Medicare rates is predicted to induce more than forty percent of all hospitals to exit the market for in-sample service lines. While evaluating the relative welfare impacts of large price reductions against hospital closures is beyond the scope of this paper, these counterfactual simulations lend credence to concerns about providers exiting in response to various payment-reducing policy proposals.

Figure 10: Predicted Networks and Hospital Service Line Closures



(a) Under Multiples of Current Off-Contract Prices



(b) Under Multiples of Medicare Reimbursements

This figure plots results of counterfactual simulations varying out-of-network prices to be various multiples of current out-of-network payments (Figure 10a) or Medicare reimbursements (Figure 10b). The vertical axis plots the fraction of hospitals whose service lines are open and that are in network (dark green), open but out of network (light green), or exited from the market (red). Plot is for Tufts Health Plan in 2012, using the estimates from the full bargaining model.

7 Conclusion

Nash-in-Nash bargaining models are a workhorse tool of empirical work studying markets with negotiated prices. While the importance of correctly specifying disagreement values in these models is well understood, there is a practical barrier to measuring prices and transaction volumes in the absence of an agreed-upon contract. This paper proposes a tractable measure of off-contract prices in the context of hospital-insurer negotiations, and uses the measure to evaluate policy proposals surrounding out-of-network hospital reimbursements. Those policy evaluations require a new modeling feature relative to the existing literature: without a way for out-of-network reimbursement rates to enter into the bargaining model, it is not possible to simulate the effects of changing those rates on equilibrium prices and networks.

Incorporating out-of-network transactions into the empirical model results in substantially lower estimates of hospital costs for the majority of hospitals in our data. Because our proposed measure of out-of-network prices is simple to implement in the types of datasets used in the insurer-hospital bargaining literature, it should be straightforward for researchers to correct for this bias in future empirical work without an additional computational burden. This difference in costs also has important implications for the predicted effects of proposed policies. Under a range of counterfactual policies, cost estimates from our model predict lower equilibrium prices and broader equilibrium networks than do cost estimates from the standard model. The counterfactual simulations suggest that policies that cap out-of-network payments at prices close to Medicare rates would reduce access to care, and may even cause hospitals to exit in equilibrium due to in-network prices dropping below marginal costs. Policies that set *all* prices in the health care market to Medicare rates, such as some versions of Medicare For All proposals, may generate even more dramatic market adjustments.

Regulation of health insurers' out-of-network payments is currently limited to a small handful of jurisdictions. As a result, insurers are free to change their policies determining out-of-network prices. If, for instance, hospitals in a market strategically inflate their charge prices in order to raise the benchmark charge prices on which insurers often base out-of-network payments, then insurers can amend their policy to pay a smaller fraction of the benchmark. Policy-makers should therefore consider pairing any regulation of out-of-network payments with regulations that take determination of the benchmark price out of the hands of providers. Pegging to a (large) multiple of Medicare would achieve this goal, whereas pegging to any form of charge prices would not.

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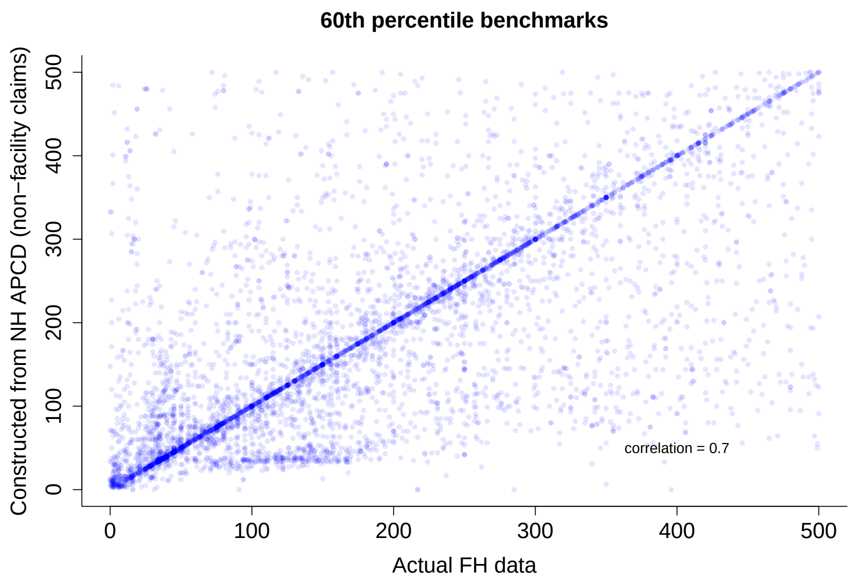
Appendices

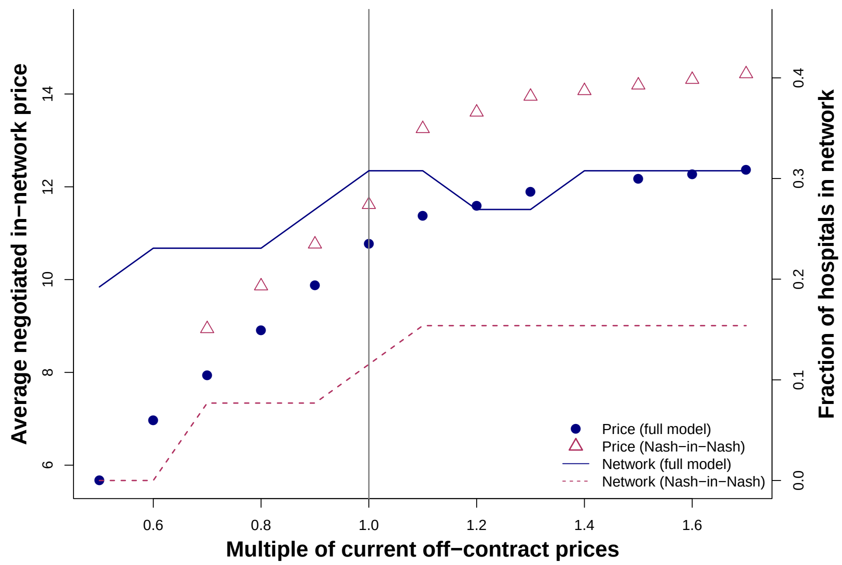
A Additional Tables and Figures

Figure A.1: Comparison of Benchmarks Reconstructed From Data Against Actual FAIR Health Benchmarks



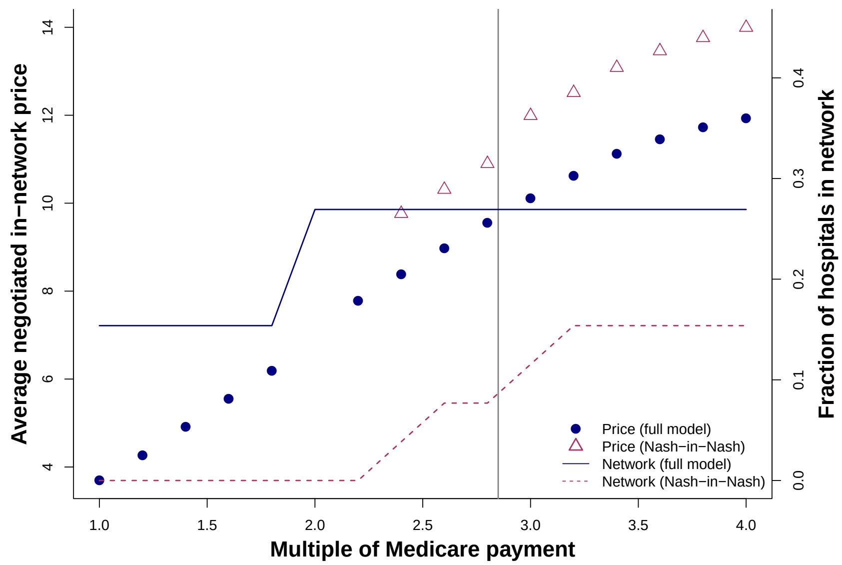
This figure plots our approximation of the FAIR Health Charge Benchmarks, calculated from the New Hampshire APCD, against the actual benchmark product purchased from FAIR Health. Each point is a CPT code-geographic market pair. Plot is for outpatient claims.

Figure A.2: Predicted Negotiated Prices Against Multiples of Current Off-Contract Prices



This figure plots results of counterfactual simulations varying out-of-network prices to be various multiples of current out-of-network payments. The vertical axis plots the counterfactual negotiated price for hospitals predicted to be in-network (volume-weighted average prices). Gray vertical line is value of observed out-of-network payments. Plot is for Tufts Health Plan in 2012. Gaps represent counterfactuals for which no equilibrium was found.

Figure A.3: Predicted Negotiated Prices Against Multiples of Medicare Reimbursements



This figure plots results of counterfactual simulations varying out-of-network prices to be various multiples of Medicare reimbursements. The vertical axis plots the counterfactual negotiated price for hospitals predicted to be in-network (volume-weighted average prices). Gray vertical line is approximate value of observed out-of-network payments. Plot is for Tufts Health Plan in 2012. Gaps represent counterfactuals for which no equilibrium was found.

B Constructing Price Benchmarks

This appendix section describes in detail the price benchmarks used to construct the off-contract prices first described in Section 2.

B.1 The FAIR Health Algorithm

FAIR Health is the source of charge price benchmarks for many insurers (see Table 1). For each type of health care service, FAIR Health calculates the distribution of charge prices within a geographic region over the course of one year. The geographic regions chiefly correspond to three-digit zip codes, although in low-density areas a handful of three-digit zips might be aggregated into one geographic unit of analysis (typically no more than three, but up to a maximum of twelve). The country is partitioned into 493 such geographic regions. Four of these are in New Hampshire.

FAIR Health has multiple benchmark price products: hospital inpatient benchmarks, based on ICD diagnosis codes or bundled DRG diagnosis codes; hospital outpatient benchmarks, based on CPT procedure codes; anesthesia benchmarks, based on CPT procedure codes; professional services benchmarks, based on HCPCS/CPT codes; and others. As our empirical exercise is limited to outpatient hospital demand, we are interested in the CPT-based benchmarks.

For each CPT code in each geographic unit, FAIR Health starts with all health care claims in that CPT-geography pair. This includes both claims from their large sample of private insurers and the universe of fee-for-service Medicare claims. It then calculates for each claim the absolute distance from the median charge price for that CPT-geography pair. The median of those distances is then computed. Next, extreme outliers are dropped: any claim whose distance from the median charge price is more than 5.92 times the median distance (in either direction) is dropped from the sample. Finally, the remaining claims are used to calculate charge price percentiles within each CPT-geography pair.

The standard FAIR Health benchmark products report the 50th, 60th, 70th, 75th, 80th, 85th, 90th, and 95th percentiles, but insurers can also purchase custom products reporting other quantiles of the distribution. The benchmarks are updated every six months based on a rolling one-year sample of claims. There is a May release based on data from the prior March through the most recent February, and a November release based on data from the prior September through the most recent August.

B.2 Approximating FAIR Health Benchmarks

We approximate the outpatient price benchmarks using the near-universe of private insurance claims in New Hampshire from the state's All-Payer Claims Database. As the FAIR Health benchmarks additionally use the universe of fee-for-service Medicare claims, our measure of the benchmark percentiles is somewhat noisy.

However, we follow the FAIR Health benchmark algorithm as faithfully as possible within the available data. We match the geographic units exactly using FAIR Health's crosswalk between three-digit zip codes and their definition of the four geographic units in New Hampshire. We also match the level of the procedure code by using CPT codes (without modifiers). Finally, we match the rolling one-year windows and their release dates in May and September.

We are in the process of negotiating a purchase of the proprietary FAIR Health data. If that purchase succeeds, we will update the paper to use the benchmarks from FAIR Health instead of our approximations.

C Hospital Choice

The bargaining model in Section 3 relies on estimates from a model of hospital demand. This section describes the underlying demand estimation, which follows what is now standard in the literature.

Consumers enrolled in health insurance get sick and require health care with some probability. A consumer insured by insurer m and needing procedure d gets the following utility from seeking outpatient care at hospital h (for convenience, we omit time subscript t):

$$u_{imhd} = \lambda_h + \delta\eta_{mh} + \beta x_{ihd} + \varepsilon_{imhd} \tag{11}$$

where λ_h are hospital fixed effects (separate for the hospital's main campus or a secondary location), η_{mh} is an indicator for whether hospital h is in insurer m's network, and x_{ihd} is a vector of observable characteristics of the patient and the hospital. x_{ihd} includes the distance between consumer i's home and hospital h, hospital characteristics, such as its teaching status, patient demographics (in our setting, age, RVU weights of the procedure, and gender), the expected balance bill (calculated as the hospital's charge price less the insurer's out-of-network paid price), and interactions between patient characteristics and service availability at hospital h. Here, d is defined at the level of specific medical procedures (CPT codes). We proxy for its severity with the weights constructed from FAIR Health data for the particular procedure, as described in Section 4.5. If consumers prefer to seek care at in-network hospitals, we expect a positive coefficient estimate δ for the in-network indicator. We do not include a finer measure of in-network out-of-pocket price in x_{ihd} because consumers in most plans are not subject to the type of out-of-pocket price structure that results in price-shopping (Prager 2018). The error term ε_{imhd} is assumed to be Type 1 Extreme Value, yielding a discrete choice multinomial logit structure.

We estimate the hospital demand model using maximum likelihood and use it to construct the inputs to the bargaining model. The coefficient on the in-network indicator η_{mh} plays a key role in constructing the expected hospital volumes and willingnesses-to-pay under the observed and unobserved network configurations used to estimate the bargaining model. We therefore instrument for the in-network hospital hospital indicator to address concerns that insurers may differentially include in their networks the hospitals for which their enrollees have an unobservable preference. For example, if insurers differentially including unobservably higher-quality hospitals and the quality heterogeneity is not adequately captured by the hospital fixed effects, then the coefficient on the in-network indicator will be biased upward. We leverage a feature of this market shown in Figure 5: insurer networks are highly correlated with the geographic distribution of their enrollees. This is likely due to the fact that the fixed cost of entering negotiation in Equation 4 is only recouped when a sufficient number of enrollees highly value access to the hospital. We therefore instrument for network status using the logarithm of the count of enrollees within 20 miles of the hospital. (The 20-mile radius produces the strongest first stage of distances we have tested.)

Because the multinomial logit second stage is nonlinear, we use a control function approach. The control function corrects for the correlation between the endogenous regressor and the error term by approximating the component of the error that is correlated with the endogenous regressor and including it as a separate regressor . In practice, in the first stage, we regress the in-network hospital indicator on the exogenous variables and the enrollee count "instrument," and include the residuals from this first-stage regression in the second-stage multinomial logit. Under the exclusion restriction, there exists some function of the first-stage residuals that produces consistent coefficient estimates in the second stage. Because the true functional form is unknown, we allow the first-stage residuals to enter flexibly into the hospital choice model using up to a fifth-degree polynomial expansion. To deal with instability arising from the correlation between lower- and higher-order polynomial terms, we use an orthogonal basis for the polynomial expansion. Table C.1 shows the results, including the coefficients on the first-stage residual terms. Our preferred specification is the control function with the fourth-degree polynomial. Adding higher-order polynomial terms beyond the fourth causes the included residual terms to lose significance, and the point estimates on the variables of interest are relatively stable from the fourth to higher degrees. The final two columns of Table C.1 show this pattern.

The demand specification in Equation 11 yields a probability that hospital h is chosen that is given by:

$$\sigma_{imhd} = \frac{\exp\left(\lambda_h + \delta\eta_{mh} + \beta x_{ihd}\right)}{\sum_j \exp\left(\lambda_j + \delta\eta_{mj} + \beta x_{ijd}\right)}$$

where j enumerates the set of all hospitals available to patients (all New Hampshire hospitals and 14 Massachusetts hospitals, as discussed in Section 4.3).

The predicted shares σ_{imhd} from the demand model are used to construct an insurer's volume of patients for each hospital, used in the bargaining model (Equation 3). If hospital h is in insurer m's network, its predicted volume is given by

$$\sigma^1_{mh} = \sum_{i \in I_m} \sum_d w_d f_{id} \sigma_{imhd}$$

where f_{id} is the probability that a consumer of type i requires care for procedure d over the course of a plan-year.[24] The term w_d is the resource utilization multiplier used to construct a weighted sum of hospital volume. The terms $\sigma^0_{mh}, \psi^1_{mh}, \psi^0_{mh}$ are defined analogously. These enter into the insurer's bargaining surplus (Equation 2) and the hospital's bargaining surplus (Equation 1) and are used for estimating the bargaining model.

Consumers' expected utility from insurer m's network also enters into the bargaining model. This expected utility is a function of the probability of getting sick and needing care, the set of hospitals that are in the network, and the strength of the preference for in-network hospitals. We

[24] In specifying f_{id}, we allow for individual consumers to require procedure d more than once in a plan-year.

Table C.1: Hospital Demand Estimates

	(1) No IV	(2) IV Deg 1	(3) IV Deg 2	(4) IV Deg 3	(5) IV Deg 4	(6) IV Deg 5
In-Network Hospital	1.0990***	2.4109***	1.2963***	1.2993***	2.7822***	2.3228***
	(0.1642)	(0.1745)	(0.2212)	(0.2431)	(0.3561)	(0.4675)
Other In-Network Provider	2.7371***	2.7774***	2.7662***	2.7662***	2.7669***	2.7676***
	(0.0607)	(0.0607)	(0.0607)	(0.0607)	(0.0607)	(0.0607)
Balance Bill ($)	-0.0060	-0.0056	-0.0074**	-0.0074**	-0.0070**	-0.0074**
	(0.0039)	(0.0040)	(0.0026)	(0.0026)	(0.0027)	(0.0027)
Distance (miles)	-0.2995***	-0.2995***	-0.2991***	-0.2991***	-0.2991***	-0.2991***
	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0059)
Distance^2	0.0007***	0.0007***	0.0007***	0.0007***	0.0007***	0.0007***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Distance × Age	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Distance × Intensity Weight	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Beds × Intensity Weight	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Critical Access × Intensity Weight	0.0052***	0.0052***	0.0053***	0.0053***	0.0052***	0.0052***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Teaching × Intensity Weight	-0.0021***	-0.0021***	-0.0021***	-0.0021***	-0.0021***	-0.0021***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Cath Lab × Intensity Weight	0.0068***	0.0068***	0.0069***	0.0069***	0.0069***	0.0069***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
MRI × Intensity Weight	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
NICU × Intensity Weight	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
Neuro × Intensity Weight	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
1st Stage Residual[1]		-0.2594***	-0.2346***	-0.2352***	-1.3007***	-3.3195*
		(0.0118)	(0.0229)	(0.0305)	(0.1709)	(1.3886)
1st Stage Residual[2]			-0.0284	-0.0302	-7.7191***	-26.1096*
			(0.0316)	(0.0692)	(1.2425)	(12.6066)
1st Stage Residual[3]				-0.0030	-11.1727***	-38.6411*
				(0.1007)	(1.7951)	(18.8085)
1st Stage Residual[4]					-2.8144***	-13.3527
					(0.4539)	(7.1645)
1st Stage Residual[5]						-2.9254
						(1.9638)
Hospital FEs	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.696	0.697	0.696	0.696	0.696	0.696
Choices	77961	77961	78754	78754	78754	78754

Notes: ***p<0.01, **p<0.05, *p<0.10. Results from multinomial logit provider choice model from years 2011–2012. IV columns estimated using a control function with boostrapped standard errors with replications. *Choices* is the number of choice sets used in estimation. *In-Network Hospital* and *Other In-Network Provider* are indicators for whether the provider is in the patient's insurer's network and is a hospital or non-hospital provider, respectively. *Balance Bill* is the potential (maximum) dollar amount a patient would be charged out-of-pocket in cases where the hospital is out of network.

denote an individual consumer's expected utility for insurer m's network as

$$W_{im} = \sum_{d} f_{id} \log \left(\sum_{j} \exp\left(\lambda_j + \delta\eta_{mj} + \beta x_{ijd}\right) \right)$$

The W_{im} terms are summed across an insurer's enrollees to obtain the insurer-wide expected utility of a network that enters into the insurer's bargaining surplus, as defined in Equation 2. When hospital h is in the network, this becomes

$$W^1_{mh} = \sum_{i \in I_m} \sum_{d} f_{id} \log \left(\exp\left(\lambda_h + \delta \cdot 1 + \beta x_{ihd}\right) + \sum_{j \neq h} \exp\left(\lambda_j + \delta\eta_{mj} + \beta x_{ijd}\right) \right)$$

and W^0_{mh} is defined analogously when the hospital is out of network.