Disagreement Payoffs and Negotiated Prices: Evidence from Out-of-Network Hospital Payments*

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Abstract

Disagreement payoffs are a key determinant of the surplus split in bargaining equilibria. The bulk of existing empirical work on Nash bargaining assumes zero disagreement payoffs: when two parties fail to arrive at a contract, their ties completely sever and no transactions occur between them. In this paper, we study the impacts of nonzero disagreement payoffs on negotiated prices between health insurers and hospitals in New Hampshire. We propose and operationalize a measure of off-contract prices based on institutional details of health insurers' out-of-network payment policies. We then estimate hospital marginal costs and other bargaining model parameters, and show how these estimates change from the canonical Nash-in-Nash framework when we vary the level of the disagreement payoff. Finally, we conduct a series of policy-relevant counterfactuals based on current federal and state policy proposals to cap out-of-network reimbursements. Policies that reduce off-contract prices closer to Medicare rates result in considerably lower negotiated prices with in-network hospitals, but narrower networks.

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1 Introduction

A recent wave of policy proposals aims to reduce health care spending by regulating disagreement payoffs in price negotiations between health insurers and health care providers. Such regulations are meaningful because the lack of a formal contract between insurers and providers does not completely eliminate transactions between them. Instead, consumers whose health insurer lacks a negotiated contract with a provider can—and often do—still obtain out-of-network care from that provider. In many of these cases, the insurer reimburses a portion of the claim at a prespecified out-of-network rate. Expectations about these off-contract prices may, in part, determine network decisions and in-network prices.

In this paper, we estimate the impact of disagreement payoffs on equilibrium networks and negotiated prices, and quantify the impacts of policy proposals designed to regulate out-of-network reimbursements. These proposals come from both major political parties. The Republican-sponsored Lower Health Care Costs Act of 2019 proposes to cap insurers' off-contract payments at median in-network rates in a given market (Alexander 2019). One of the leading Democratic candidates for the 2020 presidential election proposes capping out-of-network reimbursements 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). These caps are designed in part to reduce patients' exposure to high "surprise medical bills" when treated by out-of-network providers, but proponents also see them as a mechanism for reducing negotiated in-network prices by dampening providers' bargaining leverage (Kane 2019; Chernew et al. 2019). For similar reasons, 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).

We begin by proposing a practical solution to the empirical challenge of measuring the off-contract prices actually paid to hospitals by health insurers. We then estimate a structural model of Nash bargaining and network formation that explicitly incorporates off-contract transactions and off-contract prices, and show how the predictions of this model deviate from the canonical Nash-in-Nash framework. To operationalize the demand inputs into the Nash bargaining model, we estimate a model of hospital demand for a set of non-emergent outpatient procedures, with out-of-network hospitals included in consumers' choice sets. On the supply side, we estimate hospitals' marginal costs, Nash bargaining weights, and other determinants of hospital and insurer surplus. We then use the estimates of our model to simulate outcomes of policies that either cap or increase out-of-network reimbursements, and show the trade-offs involved in each.

The empirical setting for this paper is the hospital market in New Hampshire, a suitable setting for several reasons. First, some health insurers serve the New Hampshire market even though most of their enrollees reside in the neighboring state of Massachusetts. This generates substantial variation in the contract status of New Hampshire hospitals across insurers, partly driven by variation in the distribution of enrollees across New Hampshire and the New Hampshire–Massachusetts border. Second, we document nontrivial volumes at out-of-network New Hampshire providers. In our sample, out-of-network hospitals account for 14.2 percent of transactions for a large New England insurer. Within this insurer, a typical out-of-network hospital has approximately one tenth of the volume of a typical contracted in-network hospital. This volume is quite high relative to the small size of the out-of-network hospitals, which only make up 20.4 percent of all insurers' total hospital volume in the market. Finally, out-of-network care in this market is nearly always paid for in part or in whole by insurers.

The paper's first contribution is to provide a detailed and realistic assessment of out-of-network prices paid by insurers. Empirical work faces a practical barrier to accounting for these out-of-network, or off-contract, transactions. It is challenging to measure prices in a non-posted price market in the absence of a price contract, hindering the accurate estimation of disagreement values. Moreover, off-contract prices in health care markets often 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. 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 typically available to researchers. The resulting measure yields a reasonable approximation of observed out-of-network hospital payments by insurers in New Hampshire.

Our second contribution is extending the Nash-in-Nash framework and showing how the predictions of our model improve upon the canonical 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 2017b; 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 disagreement is equal to the loss of profit associated with the transactions that occur under agreement.[2] As discussed above, the assumption of zero off-contract volume is clearly violated in the health care context, because insured consumers receive out-of-network care. This violation is not unique to health care. 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 associated directly 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.[3] Therefore, the importance of defining surplus from agreement more flexibly than the direct value of a contract extends to a variety of industries.

Our model departs from the existing empirical literature by allowing patients to obtain care at out-of-network providers, and allowing insurers to pay those providers strictly positive off-contract prices. We show that consumers do strongly prefer to receive care at in-network hospitals, but that there is a non-negligible set of cases where the model predicts use of an out-of-network hospital for the outpatient procedures we consider. We then show, both theoretically and using our measure of off-contract prices, that estimates of marginal costs are biased upward when these off-contract volumes are not taken into account. Specifically, we find that ignoring positive volumes and payoffs from disagreement results in overstating hospital marginal costs by more than ten percent. 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 ordinarily 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 that assumes zero disagreement values, our model predict both broader networks and lower equilibrium prices at every level of out-of-network reimbursement.

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

[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 2017a; Ghili 2017), define the surplus from agreement more flexibly. However, those papers maintain the assumption of zero off-contract transactions.

[3]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).

We next consider two main counterfactual simulations designed to regulate off-contract prices. The first 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 to benchmarks to the point where hospitals are nearly paid their full charge price. The second proposal, reflective of current federal and state legislation, considers capping out-of-network reimbursements at multiples of Medicare rates. We find that in all these counterfactual simulations, our model predicts increasing the off-contract prices gives hospitals significant bargaining leverage to raise negotiated prices considerably above costs. Specifically, raising the current charge price benchmark by 50 percent results in an approximate 38 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 250 percent of Medicare rates (an approximate 30 percent decline from current reimbursements) is projected to reduce negotiated prices by close to half.

However, while capping out-of-network reimbursements reduces equilibrium prices, it also imposes a trade-off against reduced in-network access to providers. For an insurer currently observed to cover 27 percent of the hospitals in New Hampshire, imposing off-contract prices equal to 250 percent of Medicare rates reduces the share of hospitals covered to 14 percent of the market. These predictions depart from predictions using the canonical Nash-in-Nash model. Under our counterfactual simulations, the price predictions from the canonical framework are 10 to 20 percent higher than our model with non-zero disagreement values. Moreover, whereas our model predicts reducing off-contract prices to 125 percent of Medicare rates still leaves 12 percent of the hospitals covered in equilibrium, the estimates from the canonical Nash-in-Nash model predict a near-complete unraveling of the entire network, with only one hospital remaining in the network.

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 (2017a); Ghili (2017); Liebman (2017). We view our approach as complementing these important advances by providing a computationally simple alternative for dealing with disagreement values. Another strand of 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). We contribute to this literature by formally incorporating out-of-network reimbursements into a model designed to predict their impact on in-network prices.

The paper proceeds as follows. Section 2 discusses the details of our algorithm to measure off-contract prices. Section 3 discusses our theoretical model and predictions of the impacts of nonzero disagreement values. Section 4 describes our empirical context, data, and sample. Section 5 outlines our empirical strategy. Section 6 presents the parameter estimates, and Section 7 presents counterfactual simulations. Finally, Section 8 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 demand-side incentives 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.[4]

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. 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, they 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 privately insured and fee-for-service Medicare claims. Among its flagship products are the FH Charge Benchmarks, which many insurers use as

[4]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.

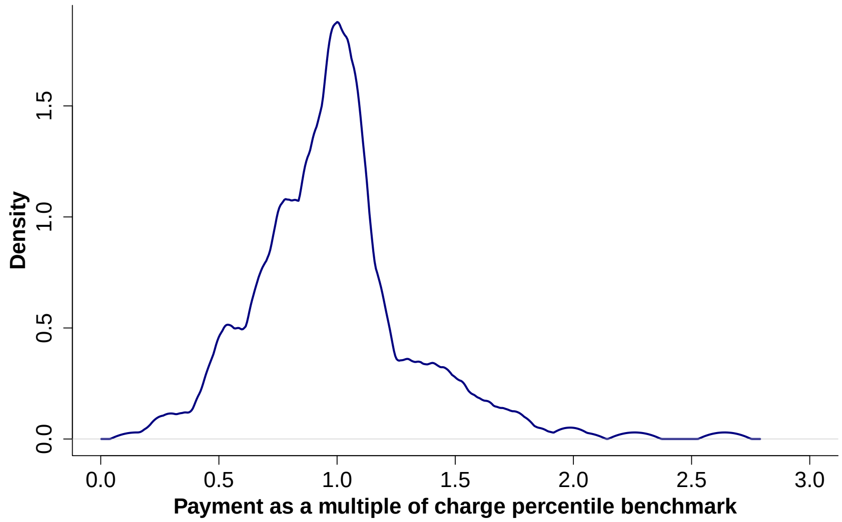
Table 1: Insurer Policies on Out-of-Network Payments

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

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. It is updated twice a year using a rolling twelve-month window of claims data. Insurers that purchase the Charge Benchmarks can then use a given 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.

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 and is described in detail in Appendix B. Each 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

Figure 1: Out-of-Network Payments in a Sample Plan



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.

the paid amount to the benchmarks.

Figure 1 shows the distribution of the ratio of paid amounts to the 60th percentile benchmarks for one of our key insurer's large PPO plans. This plan typically pays for out-of-network care at 100 percent of the 60th percentile benchmark, as indicated by the spike in the distribution at 1. 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. 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.[5]

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, this requires examining its claims from other markets. These out-of-network policy inferences are facilitated by comprehensive data on insurers' networks, described in Section 4.3. We then use the inferred policies to construct off-contract prices for pairs of insurers and hospitals that do not necessarily have

[5] We are in the process of negotiating a purchase of the proprietary FAIR Health data.

a contract. These off-contract price measures are a key input to estimating our Nash bargaining model with nonzero disagreement values, to which we now turn.

3 Model

In this section, we outline the bargaining model with positive disagreement volumes and show how its predictions depart from a model with zero volume in case of disagreement. The discussion is kept at a general level. We defer the detailed definitions of several model objects, especially those related to demand, until Section 5, after first discussing the data in Section 4.

3.1 Bargaining Model

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 pair-wise Nash bargaining interactions, but depart from the hospital bargaining literature by specifying strictly positive off-contract prices and volumes.

A negotiated contract between insurer m and hospital h 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.[6] 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, and 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. The out-of-network payment rates depend only on the services provided, not the identity or cost structure of the hospital.

Hospital objectives. We model hospitals as profit maximizers. Hospital h's surplus from a contract with insurer m at a negotiated price p_{mh} is given by

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

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

where c_h is the hospital's marginal cost of treating a typical patient, and $\sigma^1_{mh} > \sigma^0_{mh}$ are the hospital's patient volumes from insurer m in the case of agreement and disagreement, respectively. 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. The term b_h represents the hospital's cost of negotiating with an insurer, which we call its contracting cost. Contract negotiations in this industry are notoriously resource-intensive, often taking months and requiring hospitals to have a dedicated division for provider contracting. We interpret the b_h parameter as a flavor of Coasian transaction cost. A hospital whose expected gains from a contract do not exceed the contracting cost will not engage in negotiations and instead elect to remain out of network.

Insurer objectives. We follow Gowrisankaran et al. (2015) in defining 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 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 use the model of the insurer as an imperfect agent for its enrollees from Gowrisankaran et al. (2015). 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 3.2 obtain for both sets of insurer objectives.

Insurer m's surplus from a contract with hospital h at a negotiated price p_{mh} is given by

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

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, $\psi^1_{mh} = \sum_{h' \neq h} \sigma_{mh'} p_{mh'}$. Finally, b_m denotes the insurer's per-hospital contracting cost. When the insurer's expected gains from a contract with a given hospital do not exceed the per-hospital contracting cost, the insurer will not negotiate with that hospital and relegate it to out-of-network status.

Equilibrium. An equilibrium consists of a set of indicators for which hospital-insurer pairs come to an agreement, and a negotiated price p^*_{mh} for each contracting pair. Hospital h and insurer m will come to an agreement that puts the hospital in the insurer's network only if both parties have (weakly) positive gains from trade from agreement. That is, the two inequalities

$$\begin{aligned} S_h(h, p^*_{mh}) \geq& 0\,, \\ S_m(h, p^*_{mh}) \geq& 0 \end{aligned} \tag{3}$$

must hold at the expected negotiated price. If either or both of these conditions are violated, there is no agreement and hospital h remains outside insurer m's network.

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

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

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

$$\begin{aligned} &\gamma \frac{-\sigma^1_{mh}}{\alpha_m W^1_{mh} - p^*_{mh}\sigma^1_{mh} - \psi^1_{mh} - \left[\alpha_m W^0_{mh} - p^0_m \sigma^0_{mh} - \psi^0_{mh}\right] - b_m} \\ =& -(1-\gamma)\frac{\sigma^1_{mh}}{\left(p^*_{mh} - c_h\right)\sigma^1_{mh} - \left(p^0_m - c_h\right)\sigma^0_{mh} - b_h} \end{aligned}$$

which yields an equilibrium price of

$$p^*_{mh} = \frac{1}{\sigma^1_{mh}} \left[\begin{array}{l} (1-\gamma)\,\alpha_m \left(W^1_{mh} - W^0_{mh}\right) + p^0_m \sigma^0_{mh} + \gamma c_h \left(\sigma^1_{mh} - \sigma^0_{mh}\right) \\ -(1-\gamma)\left(\psi^1_{mh} - \psi^0_{mh}\right) - (1-\gamma)\, b_m + \gamma b_h \end{array} \right] \tag{4}$$

In the empirical application, we use both the first-order conditions on equilibrium prices (Equation 4) and the inequality constraints from the network inclusion conditions (Equation 3) to identify parameters of interest.

3.2 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. Here, we illustrate the bias arising from assuming that disagreement volume is zero when estimating hospital marginal costs c_h.

Consider a simplified empirical setup where all quantities except c_h are observed, and there is some insurer m that has a negotiated contract with hospital h. It is then straightforward to solve for an unbiased estimate $\hat{c}_h$ by rearranging Equation 4:

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

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

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

Since $\gamma \leq 1$, setting disagreement volume to zero induces a positive bias and $\tilde{c}_h > \hat{c}_h$. That is, understating the true volume under disagreement results in overstating hospitals' costs.

This bias has important implications for counterfactual exercises. When hospital 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.[7]

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

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. We then proceed to Section 5, which outlines the empirical implementation of the bargaining model from Section 3.1 and describes the estimation procedure used to recover its structural parameters.

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 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 regional insurers and small local affiliates of national insurers, such as Aetna and United.

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 volumes of Massachusetts residents or locals who are insured by Massachusetts insurers. For example, Harvard Pilgrim was 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.

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 2009–2012 Massachusetts All-Payer Claims Database (APCD). Private health insurers contribute data for the APCD to the state agency that manages the data and uses it for policy-relevant analysis, the Center for Health Information and Analysis (CHIA) (CHIA 2014). The data include privately managed Medicare Part C and Medicaid Managed Care plans, but not traditional Medicare or Medicaid.

The APCD contains approximately 150 million health care claims per year. These include claims originating both within and outside of Massachusetts, as long as they are attributable to enrollees of Massachusetts insurers that contribute data. 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 APCD. Charge prices measure what the provider bills the insurer or the patient. 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; or the amount the insurer pays the provider off-contract, in case of an out-of-network provider. We use the allowed and paid amounts to construct measures of equilibrium negotiated prices for use with the first-order conditions in Equation 4. We use the ratio of paid amount to charge price to infer insurer's out-of-network payment policies. Also reported in the data are amounts for which patients are directly responsible under their insurance plan: deductibles, copays, and coinsurance.

We supplement the APCD 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

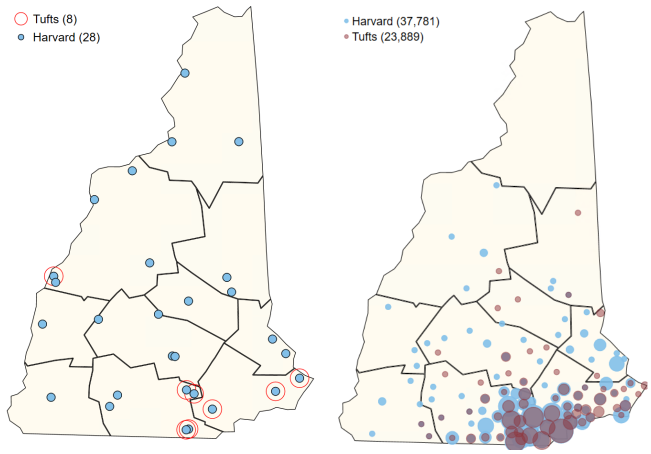
To determine which hospital-insurer pairs have a negotiated contract, we use data on insurers' hospital networks. These data were hand-collected from New England insurers' current and archived plan documentation, as described in Prager (2018).[8]

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. If a hospital is not classified as in-network even in the insurer's broadest-network plans, then it is defined as lacking a contract with the insurer. As described in Section 4.1, the largest insurer with an incomplete hospital network in New Hampshire is Tufts Health Plan.

Figure 2 shows the hospital networks and distribution of enrollees for two carriers in New Hampshire: Harvard Pilgrim and Tufts Health Plan. Figure 2a shows that Harvard Pilgrim has full coverage in the state, whereas Tufts' largest PPO network only covers 8 hospitals. Those hospitals tend to be clustered in the southeastern part of the state, while several counties in the mid-to-northern part of the state have zero coverage. Figure 2b shows the geographic distribution of enrollees for each of those plans, pulled from a random sample of 5000 members. Harvard's enrollees are widely distributed across the state, whereas Tufts members are concentrated in the southeast, matching the

[8] Many claims databases, including the one used in this paper, 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 2: Hospital Networks and Enrollees by Health Plan in New Hampshire



(a) Hospital Networks (b) Enrollees

Notes: Panel (a) plots the hospital networks for Harvard Pilgrim and Tufts Health Plan in New Hampshire. Small blue circles represent Harvard's hospital network and large red circles represent Tufts' hospital network. Panel (b) plots the distribution of enrollees for each health plan from a random sample of members in the state, by 5-digit zip code. Blue circles represent Harvard's enrollees and red circles represent Tufts enrollees.

geographic distribution of hospitals covered. However, Tufts also does have some enrollees residing in counties in the northern and western part of New Hampshire, where network coverage is much sparser.

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 APCD. Reconstructing DRG classifications from the data without proprietary software would introduce additional noise into our off-contract price measures. In addition, focusing on this narrow set of related procedures allows us to weaken our assumptions about the structure of price contracts, as described below. Therefore, we are better able to estimate both demand for out-of-network care and accurately forecast out-of-network reimbursements from carriers to providers at the outpatient setting.

We focus on a set of outpatient procedures that are foreseeable rather than emergent and that are frequently performed in a hospital setting (i.e. an outpatient center that is owned by or affiliated with an acute care hospital). We avoid emergency health care because insurers frequently reimburse out-of-network emergency care more generously than non-emergent care. Moreover, insurers' definitions of what constitutes an emergency vary across insurers and over time, and the decision to classify a given out-of-network claim as emergent or non-emergent is often made on an ad hoc basis.[9] Our focus on procedures primarily performed in hospital settings allows us to make the simplifying assumption that patients choose to receive care from one of the acute care hospitals in New Hampshire, as opposed to a broad set of physicians and physician practices in the state. This allows us to significantly reduce the dimensionality of our demand and bargaining estimation.[10]

We focus on five procedures: upper GI endoscopies and related biopsies, diagnostic colonoscopies, colonoscopies and related biopsies, lesion removal colonoscopies, and knee arthroscopies. We restrict the data to patients who have had any of these procedures, but who have not had an inpatient hospital admission or an emergency department (ED) visits in the last 5 days.[11] Restricting to patients without a recent hospitalization or ED history helps to rule out cases of diagnostic procedures arising directly from a recent diagnosis or episode of care, that would be likely to be performed in the same hospital and therefore bias our demand estimates. For each procedure, we assign a measure of resource intensity by merging in Medicare Relative-Value-Units (RVUs) from the Center for Medicare and Medicaid Services (CMS).[12] RVUs are updated annually by CMS and are used to determine Medicare payment rates for professional services in Part B.[13] RVUs also vary geographically to reflect local variation in resource utilization for particular procedures. As such, a patient living in Boston may have a different RVU weight for a colonoscopy than a patient living in New Hampshire. In our setting, we use RVU as a continuous measure of severity in our demand model.

We make some additional sample restrictions to construct our final sample for the demand

[9]These observations were shared with us by a third-party consultant specializing in health insurance.

[10]Tilipman (2018) describes this dimensionality problem in more detail.

[11]In a robustness check, we restrict the data to patients who have not had an inpatient admission or ED visit within the last 30 days, and obtain similar estimates.

[12]The RVU data can be downloaded from https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeeSched/PFS-Relative-Value-Files.html.

[13]In this way, they are analogous to DRGs, but for physician services.

model. First, we limit the data to only patients insured by Harvard Pilgrim, Tufts Health Plan, or Blue Cross Blue Shield of Massachusetts (BCBSMA). We do so both because we have data on the hospital networks of each of those carriers and so that we can ensure a sizable sample of patients receiving care in New Hampshire. In our bargaining estimation, we only focus on Harvard Pilgrim and Tufts. Second, 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. As such, we include a full set of 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. We hereafter refer to these as "border zip codes." 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.

Table 2 shows the summary statistics for our final outpatient sample. The first two columns reflect average characteristics for the full sample. Patients in our sample are, on average, 52 years old and seek care for an RVU weight of 7.22. Approximately 47 percent of our sample are insured by Blue Cross Blue Shield, with the remainder evenly split between Harvard and Tufts. On average, patients travel about 11 miles for one of our selected procedures. Column 1 also displays the average hospital characteristics where patients sought care. On average, hospitals have about 200 beds, about 40 percent have a cardiac catheterization lab (often a signal of expensive service lines), about 54 percent have a NICU, and about 40 percent are teaching hospitals. In the full sample, 99 percent of patients seek care from an in-network hospital for our selected services. This pattern changes, however, when limiting the sample to only Tufts enrollees and only those residing in New Hampshire (the second two columns). Here, patients travel somewhat smaller distances to receive care (about 8 miles), seek care for somewhat lower-intensity procedures, and from hospitals that are notably smaller with fewer expensive service lines. For example, the share of patients going to hospitals with a cardiac catheterization lab in this Tufts sample is only 7 percent. Most importantly, however, the share of procedures performed in-network hospitals drops from 99 percent to 93 percent. This variation is critical for identifying patient disutility from out-of-network hospitals in our demand

Table 2: Outpatient Sample Summary Statistics

	Full Sample		Tufts NH Sample	
	Mean	Std Dev	Mean	Std Dev
	Patient Characteristics			
Age	52.46	16.85	50.04	11.28
Female	0.50	0.50	0.48	0.50
RVU Weight	7.22	2.89	6.75	2.27
BCBS	0.47	0.50	–	–
Tufts	0.26	0.44	–	–
Harvard	0.27	0.44	–	–
Distance in Miles	11.12	10.82	8.27	9.99
In Network Hospital	0.99	0.09	0.93	0.24
	Hospital Characteristics			
Beds	207.83	101.61	178.02	65.18
CathLab	0.39	0.49	0.07	0.25
NICU	0.54	0.50	0.50	0.50
Neuro	0.98	0.14	0.99	0.11
MRI	0.87	0.34	0.99	0.11
Critcal Access	0.04	0.19	0.01	0.12
Teaching	0.38	0.49	0.29	0.45

Notes: Outpatient sample summary statistics 2009-2013. First two columns reflect the full sample, including Massachusetts residents on the border of New Hampshire and New Hampshire residents. Second two columns reflect only New Hampshire residents who are insured by Tufts Health Plan.

model.

4.5 Constructing Price and Cost Indices

To operationalize the bargaining model in 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 (2017b), 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.[14] 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 4 linear in hospital marginal costs.

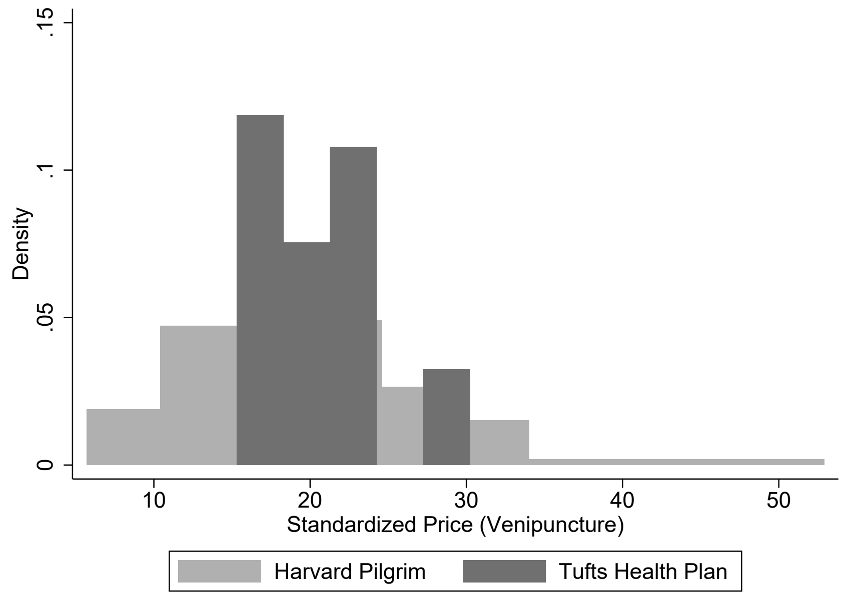
Existing work on hospital-insurer bargaining has generally restricted the analysis to inpatient hospital care. In an inpatient setting, a natural choice for the resource weights w_d are DRG weights, which are weights specifically designed to measure the relative resource intensity of various types of 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.[15] We normalize the weights such that $w_d = 1$ for venipuncture (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. Figure 3 plots the price indices computed for our two focal insurers across in-network hospitals in New Hampshire. The prices reflect estimated reimbursements for a routine venipuncture. The distribution for Harvard Pilgrim is considerably wider than the distribution for Tufts: certain hospitals are reimbursed as little as $5 for procedures with intensity equivalent to a venipuncture, while at the top end of the

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

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

Figure 3: Distribution of Standardized In-Network Prices, By Carrier



This figure plots the price indices for Harvard Pilgrim and Tufts Health Plan across years and in-network hospitals in New Hampshire. Dark bars indicate Tufts Health Plan, while light bars indicate Harvard Pilgrim.

distribution, hospitals are reimbursed upwards of \$40 for the same intensity. The distribution for Tufts is less dispersed, with most hospitals being reimbursed between \$15 and \$20 for procedures with the same intensity.

5 Estimation

We begin by estimating a model of hospital choice, and then use the results as inputs to estimating the insurer-hospital bargaining model outlined in Section 3.1.

5.1 Hospital Choice

In the final stage of the model, 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):

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

where λ_h are hospital fixed effects, 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), and interactions between patient characteristics and service availability at hospital h. Here, d is defined at the level of specific medical procedures (CPT codes), and we proxy for it with the RVU weight 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. The coefficient δ includes the demand effect of higher expected out-of-pocket payment for out-of-network hospitals.[16] We do not include a finer measure of 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.

This specification 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 4). 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.[17] 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

[16] The implicit assumption in this specification is that consumers know that they are likely to incur *some* cost for receiving out-of-network care, though they do not necessarily observe what those specific costs are.

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

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 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.

These quantities constructed from the hospital demand model form the observables that enter into estimating the bargaining model, to which we now turn.

5.2 Insurer-Hospital Bargaining and Network Formation with Nonzero Disagreement Payoffs

Using the quantities constructed from the demand model as data, we are left with four sets of parameters to estimate from the bargaining model: hospitals' marginal costs of treating patients c_h; insurers' weighting of enrollee expected utility relative to hospital expenditures α_m; the Nash bargaining parameter γ; and insurers' and hospitals' contracting costs b_m and b_h. We estimate these parameters using the generalized method of moments. There are two sets of moments: equality moments from the first-order conditions in Equation 4, and inequalities from the gains-from-trade conditions in Equation 3. We discuss each of these in turn.

Hospital-insurer pairs that have a negotiated contract contribute equality moments from the first-order conditions on negotiated price. Prices are observed, whereas hospital marginal costs are not. We express hospital h's marginal cost for treating a patient with resource intensity $w_d = 1$ as a function of observables g_h

$$c_h = \theta g_h + \nu_h \tag{5}$$

where θ 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 4. That is, we define the econometric error for a hospital-insurer pair as

$$\xi_{mh} = \theta g_h - \frac{1}{\gamma\left(\sigma^1_{mh} - \sigma^0_{mh}\right)}\left[\begin{array}{l} p^*_{mh}\sigma^1_{mh} - (1-\gamma)\,\alpha_m\left(W^1_{mh} - W^0_{mh}\right) - p^0_m\sigma^0_{mh} \\ +\,(1-\gamma)\left(\psi^1_{mh} - \psi^0_{mh}\right) + (1-\gamma)\,b_m - \gamma b_h \end{array}\right] \tag{6}$$

We then follow Gowrisankaran et al. (2015) in searching for parameters θ 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

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

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.

So far, the estimation procedure has followed closely to the Nash-in-Nash approach outlined in Gowrisankaran et al. (2015). However, our model deviates in two important ways. First, our primary interest in the paper is examining 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.[18] Second and relatedly, the estimation procedure must account for the fact that in our setting, network status is endogenously determined.

The estimation ought therefore to incorporate additional moments from the network status determination decisions. Formally, in addition to the equality moments in Equation 7, each hospital-insurer-year observation must additionally contributes an inequality from the network inclusion conditions. This estimation is currently in progress, following the procedure is outlined in Appendix C.

However, in its current form, our model instead calibrates the contracting costs by approximating them through an iterative grid search. Specifically, we iterate our bargaining estimation using our moment condition in Equation 6 over 100 different possible values of $b_m$and b_h, where each ranges from \$0 to \$1,000,000. We then choose the parameters that minimize the GMM objective function over those iterations. More formally, let $\boldsymbol{\theta} = [\theta, \gamma, \alpha]$ be the set of parameters (excluding the contracting costs) that we search for from the equality moments. Then our estimated $\hat{\boldsymbol{\theta}}$, $\hat{b_m}$, and $\hat{b_h}$ become:

$$[\hat{\boldsymbol{\theta}}, \hat{b_m}, \hat{b_h}] = \min_{\hat{b_m}, \hat{b_h}} (\min_{\hat{\boldsymbol{\theta}}} \xi'_{mh} Z_{mh} Z'_{mh} \xi_{mh}) \tag{8}$$

where $b_m, b_h \in [0, 5000, 10000, 25000, 50000, 75000, 100000, 200000, 500000, 1000000]$.

6 Results

6.1 Hospital Demand Estimates

Table 3 shows the results of the hospital demand model for outpatient care. Consistent with the literature on hospital and physician demand, distance enters negatively and significantly into the utility function. Older patients are less willing to travel for colonoscopies, endoscopies, and arthroscopies, but patients in need of procedures with higher RVU weights (particularly the arthroscopies) are more willing to travel farther distances.

[18] See Ho and Lee (2017a); Ghili (2017); Liebman (2017) for recent examples of this.

Table 3: Results of Hospital Demand

Variable	Utility Parameter	Standard Error
Distance	-0.1525***	0.0066
Distance^2	0.0008***	0.0000
DistxAge	-0.0011***	0.0000
DistxRVU	0.0011*	0.0002
In Network	1.1641***	0.1237
BedsxAge	-0.0001***	0.0000
BedsxRVU	0.0004***	0.0000
BedsxDist	0.0001***	0.0000
CathLabxAge	0.0247***	0.0018
CathLabxRVU	0.0351***	0.0078
CathLabxDist	0.0097***	0.0022
NICUxDist	-0.0094***	0.0016
NICUxFemale	0.1369***	0.0256
NeuroxAge	-0.0091	0.0057
NeuroxRVU	-0.0379*	0.0222
NeuroxDist	-0.0531***	0.0058
MRIxAge	-0.0086***	0.0019
MRIxRVU	-0.0411***	0.0080
MRIxDist	-0.0264***	0.0022
CritAccessxAge	-0.0079*	0.0047
CritAccessxRVU	0.0767***	0.0206
CritAccessxDist	0.0318***	0.0057
TeachingxAge	0.0012	0.0012
TeachingxRVU	-0.0541***	0.0051
TeachingxDist	0.0393***	0.0021
Hospital FE	Yes	
Obs.	1,157,062	
Pseudo R2	0.52	

Notes: ***p<0.01, **p<0.05, *p<0.10. Results from hospital demand model from years 2009-2013. Each observation reflects a visit x hospital pair. “CathLab” refers to whether the hospital has a cardiac catheterization lab. “Neuro” refers to whether the hospital has a neurology unit. “CritAccess” refers to whether the hospital is a critical access hospital.

Most of the interactions between patients and hospital characteristics follow the expected signs. 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. Female patients receive more utility from hospitals with neonatal intensive care units.

The key 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 a four additional miles to receive care from an in-network facility as opposed to an out-of-network facility, or about 36 percent farther than the average distance traveled in our sample (11 miles). This preference for hospitals to be in the insurer's network generates positive consumer willingness-to-pay, which then enters into the insurer objective function (Equation 2).

6.2 Hospital Costs and Bargaining Parameters

The first column of Table 4 shows the results of the bargaining estimation. The estimated hospital costs for routine venipunctures (the baseline procedure with weight $w_d = 1$) in 2010 are all positive, ranging from a low of \$1.62 to a high of \$11.83, with most cost estimates in the \$11–12 range. These estimates are quite reasonable. For example, Dartmouth Hitchock lists its professional charge for a routine venipuncture at \$29. If private insurers reimbursed the full charge price, then our estimated \$11.44 cost would imply that Dartmouth Hitchock is making a margin of 162 percent for this procedure. However, private insurers almost always reimburse hospitals at prices considerably lower than charge prices.

Harvard Pilgrim's estimated Nash bargaining weight is 0.99, while Tufts' is 0.49, 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

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

Variable	Non-Zero Volumes	Traditional N-i-N
Hospital Costs (c_h)		
Alice Peck Day Memorial Hospital	1.62	1.83
Androscoggin Valley Hospital	11.92	13.42
Catholic Medical Center	10.75	15.05
Cheshire Medical Center	11.62	13.34
Concord Hospital	11.72	12.95
Cottage Hospital	11.82	12.70
Dartmouth Hitchcock Medical Center	11.44	17.19
Elliot Hospital	7.51	11.79
Exeter Hospital	8.78	10.83
Franklin Regional Hospital	11.80	12.72
Frisbie Memorial Hospital	11.38	14.06
Huggins Hospital	11.75	12.98
Lakes Region General Hospital	11.77	12.78
Littleton Regional Hospital	11.80	13.31
Memorial Hospital	11.72	13.21
Monadnock Community Hospital	11.30	14.18
New London Hospital	11.63	13.21
Parkland Medical Center	7.85	10.91
Portsmouth Regional Hospital	10.73	15.53
Southern New Hampshire Medical Center	5.67	7.21
Speare Memorial Hospital	11.79	12.84
St. Joseph Hospital	4.00	5.27
Upper Connecticut Valley Hospital	11.78	12.79
Valley Regional Hospital	11.83	12.81
Weeks Medical Center	11.83	12.80
Wentworth Douglas Hospital	11.23	14.17
Bargaining Weights		
$\gamma_{Harvard}$	0.99	0.99
γ_{Tufts}	0.49	0.49
Bargaining Fixed Costs		
b_m	50,000	50,000
b_h	0	0
MCO weight on WTP		
α	18.13	18.13
Obs.	34	34

Results from bargaining estimation 2010. First column reflects estimates from a 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_m at \$50,000, b_h at \$0, and the second column fixes $\gamma_{Harvard}$ and γ_{Tufts} to the values estimated in the first column. 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.

and enrollment. The estimated MCO weight on consumer surplus relative to spending, α, is 18.13. Though the magnitude of the estimate is difficult to interpret, as our WTP is in utils rather than dollars, its direction is informative.

The estimated bargaining fixed costs for insurers and hospitals, b_m and b_h, are \$50,000 and \$0, respectively. This implies that the fixed costs of forming and maintaining contracts falls largely on the carrier, consistent with prior literature (Ghili 2017). The estimate for b_m is quite a bit higher than existing literature. For instance, Ghili (2017) finds that the contracting costs per hospital range from about \$800 per year to about \$1,400 per year for a 200-bed hospital. Our higher estimate as largely driven by Tufts' small presence in the New Hampshire market, and reflective of the the fact that our contracting costs would therefore not only include the fixed cost annual bargaining, but the costs that would be incurred with forming a contract with hospitals *in a different market* (e.g. market research, credentialing providers, etc.).[19] The hospital contracting costs, conversely, are an order of magnitude lower, which aligns with the fact that every hospital is observed to contract with Harvard (suggesting that hospital contracting costs are likely smaller).

6.3 Estimates Under Zero Disagreement Volumes

We now turn to the impact that nonzero disagreement volumes have on the estimated cost parameters of the model. To do so, we hold fixed the estimated contracting fixed costs (b_m and b_h), as well as the estimated bargaining weights ($\gamma_{Harvard}$ and γ_{Tufts}) and re-estimate the hospital marginal costs (c_h) and MCO weights on consumer surplus (α) under the standard Nash-in-Nash framework.[20] 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. Finally, we re-estimate hospital costs from the supply side of the model. For this exercise, we run the bargaining model on a single year (2010, midway through our sample), as this is sufficient to empirically illustrate the implications of nonzero disagreement values that were first discussed in Section 3.2.

[19] This is analagous to the cost of market entry.

[20] We re-estimate α since re-estimating our WTP measure under a different choice set would rescale our utility parameters, hence we want to allow the MCO weight on surplus to reflect this change.

The bargaining model estimates for 2010 using the standard Nash-in-Nash model are reported in Table 4 column 2. Incorporating nonzero volumes into the estimation, as predicted by the theoretical model outlined in 3.2, yields substantially lower hospital marginal cost estimates than assuming that volumes are zero to out-of-network hospitals. In fact, the magnitudes of the change are quite dramatic: on average, standardized marginal costs are estimated to be approximately 15 percent lower under a model with nonzero payoffs. Indeed, this suggests that prior models may have been systematically overestimating these costs, limiting the scope of potential policy interventions to reduce hospital reimbursement prices without resulting in closure or market exit. We turn to detailing how these overestimates may affect changes in negotiated rates through a series of counterfactual policy experiments in the next section.

7 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. One of the leading Democratic candidates for the 2020 presidential election proposes capping out-of-network reimbursements 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. It is therefore not surprising that these proposals have drawn considerable scrutiny from hospital and physician groups, however, with some providers arguing that accepting lower out-of-network payments jeopardizes 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 2010, using our estimates from Column 2 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, coupled with the presence of contracting costs, 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 4 to simulate in-network negotiated rates p_{mh}^t given the set of estimated $\hat{\boldsymbol{\theta}}$, $\hat{b_m}$, $\hat{b_h}$, when we set p_m^0 to the counterfactual reimbursement.

2. Given the new in-network prices in Step 1, use the profitability conditions (described in detail in Appendix C) 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.

Based on the first-order condition for equilibrium prices (Equation 4), equilibrium in-network prices are linear in counterfactual out-of-network reimbursements. This is because, conditional on which hospitals are in the insurer's network, transaction volumes to each hospital are fixed. Our counterfactual simulations shift p_m^0 for all hospitals simultaneously, which will shift a given hospital h's equilibrium price by $\sigma_{mh}^0/\sigma_{mh}^1 + (1-\gamma)\psi_{mh}^0$. This linearity is a consequence of hospital demand being independent of price, conditional on network structure. As discussed in Section 5, this is a sensible approximation for the majority of consumers in our sample. However, if consumers were

Figure 4: 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-netowrk (volume-weighted average prices). Plot is for Tufts Health Plan in 2010. Gaps represent counterfactuals for which no equilibrium was found.

responsive to price, then p_{mh} would be nonlinear in p_m^0 even conditional on the network.[21] Without consumer price responsiveness, nonlinearities in the relationship between p_m^0 and p_{mh} can only occur due to changes in the networks themselves.

7.1 Alternate Multiples of Charge Price Benchmarks

We first consider rescaling the disagreement values to be 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.

The solid blue dots in Figure 4 plot the results of this simulation. In-network negotiated rise with increases in the off-contract prices that insurers pay to out-of-network hospitals. By increasing off-contract prices, hospitals disagreement value is improved, while the insurer's disagreement value worsens. Hospitals and therefore they gain considerable bargaining leverage to raise prices. The

[21] A counterfactual simulation allowing for consumer price responsiveness is in progress.

slope is quite dramatic.[22] At current off-contract prices (multiple of 1.0 on the horizontal axis), the average predicted in-network price is \$10.85 (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 70 percent to an average of about \$18.20. On the other hand, reducing the benchmark to half of the current benchmark would drive predicted in-network rates to below \$6, substantially below the median hospital's marginal cost.[23]

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.1, which adds equilibrium networks to the plot, these goals are in direct competition. As negotiated prices fall, so too does the fraction of hospitals that are in the equilibrium network.

Figure 4 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 at each multiple of current off-contract prices, as shown in Appendix Figure A.1.[24] This is a good illustration of the importance of accurately estimating hospital costs 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 both spending and access to care.

7.2 Medicare-Based Out-of-Network Payment Caps

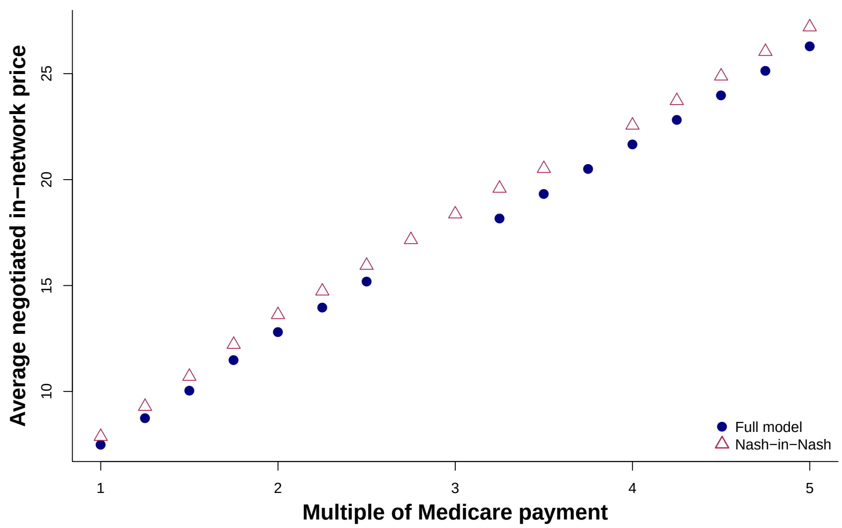
Next, we consider policy proposals that peg insurer reimbursements to out-of-network hospitals at multiples of Medicare reimbursement rates. Medicare reimbursements for the outpatient procedures we study are approximately one quarter of the in-network prices we observe in New Hampshire (see Figure 3), and for many hospitals, less than half of the marginal costs estimated in Table 4. It

[22] Note that in the vicinities of equilibrium network transitions, an equilibrium cannot always be found; this is the source of the gaps in Figure 4.

[23] Such agreements are still possible in equilibrium because the hospital's outside option is to remain out-of-network but still treat some of the insurer's patients at an even lower off-contract price.

[24] The predicted networks also change more abruptly.

Figure 5: 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-netowrk (volume-weighted average prices). Plot is for Tufts Health Plan in 2010. Gaps represent counterfactuals for which no equilibrium was found.

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 strictly above one.

Figure 5 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 4 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 400 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.2, equilibrium networks are generally broader using estimates from our model. At 250 percent of Medicare, the equilibrium network using our model includes only three of New Hampshire's 26 hospitals. Even more starkly, at 125 percent of Medicare, the equilibrium network includes only one hospital when we use the cost estimates from the Nash-in-Nash model assuming zero disagreement values.

These results suggest that proposals to peg out-of-network reimbursements to as low as 125 percent of Medicare would likely cause substantial disruptions to provider networks and prices. Equilibrium prices may fall below hospitals' marginal costs, inducing exits or reducing hospitals' capital investment, service availability, and quality of care. While predicting hospitals' decisions on these margins is outside the scope of this paper, our results provide suggestive evidence of potentially large changes in the market.

8 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.

Consistent with our theoretical prediction, incorporating out-of-network transactions into the empirical model results in substantially lower estimates of hospital costs. 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 severely reduce network breadth, 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.

References

Alexander, Lamar (2019) "Lower Health Care Costs Act," July.

Becerra, Xavier, Kathleen Foote, Michael Jorgenson, Cheryl Lee Johnson, Esther La, and Emilio Varanini (2018) "Complaint for Vilations of the Cartwright Act."

Berry, Steven, Martin Gaynor, and Fiona Scott Morton (2019) "Do Increasing Markups Matter? Lessons from Empirical Industrial Organization," *Journal of Economic Perspectives*, Vol. 33, No. 3, pp. 44–68.

Chernew, Michael, Maximilian Pany, and Richard Frank (2019) "The Case For Market-Based Price Caps," September.

CHIA, (Massachusetts Center for Health Information and Analysis) (2014) *All-Payer Claims Database*: Massachusetts Center for Health Information and Analysis.

Cooper, Zach, Stuart Craig, Martin Gaynor, Nir Harish, Harlan Krumholz, and john Van Reehen (2019a) "The Price Ain't Right? Hospital Prices and Health Spending on the Privately Insured," *Quarterly Journal of Economics*, Vol. 134.

Cooper, Zach, Fiona Scott Morton, and Nathan Shekita (2019b) "Surprise! Out-of-Network Billing for Emergency Care in the United States," *Working Paper*.

Cooper, Zack, Hao Nguyen, Nathan Shekita, and Fiona Scott Morton (2019c) "Out-Of-Network Billing And Negotiated Payments For Hospital-Based Physicians," *Health Affairs*, Vol. 39, No. 1, p. 10.1377/hlthaff.

Craig, Stuart, Keith Ericson, and Amanda Starc (2019) "How Important is Price Variation Between Health Insurers?" *Working Paper*.

Crawford, Gregory S. and Ali Yurukoglu (2012) "The Welfare Effects of Bundling in Multichannel Television Markets," *American Economic Review*, Vol. 102, No. 2.

Creswell, Julie, Barry Meier, and Jo Craven McGinty (2013) "New Jersey Hospital Has Highest Billing Rates in the Nation," *The New York Times*.

Ellison, Alia (2018) "California files antitrust suit against Sutter Health: 5 things to know," *Becker's Hospital Review*.

Ghili, Soheil (2017) "Network Formation and Bargaining in Vertical markets: The Case of Narrow Networks in Health Insurance," *Working Paper*.

Gowrisankaran, Gautam, Aviv Nevo, and Robert Town (2015) "Mergers When Prices are Negotiated: Evidence from the Hospital Industry," *American Economic Review*, Vol. 105, No. 1, pp. 172–203.

Hanbury, Mark (2019) "Nike stops selling on Amazon, kills deal after 2 years," *Business Insider*.

Ho, Kate (2009) "Insurer-Provider Networks in the Medical Care Market," *American Economic Review*, Vol. 99, No. 1, pp. 393–430.

Ho, Kate and Robin Lee (2017a) "Equilibrium Provider Networks: Bargaining and Exclusion in Health Care Markets," *Working Paper*.

——— (2017b) "Insurer Competition in Health Care Markets," *Econometrica*, Vol. 85, No. 2, pp. 379–417.

Horn, Henrick and Asher Wolinsky (1988) "Bilateral Monopolies and Incentives for Merger," *The RAND Journal of Economics*, Vol. 19, No. 3, p. 408.

Kane, Arielle (2019) "Affordable Health Care for All: An American Solution to High Costs and Coverage Gaps," September.

Liebman, Eli (2017) "Bargaining in Markets with Exclusion: An Analysis of Health Insurance Networks," *Working Paper*.

Luthi, Susannah (2019) "Doctors, hospital groups gear up for surprise medical bill fight," *Modern Healthcare*.

Pakes, Ariel (2010) "Alternative Models for Moment Inequalities," *Econometrica*, Vol. 78, No. 6.

Pakes, Ariel, Jack Porter, Kate Ho, and Joy Ishii (2015) "Moment Inequalities and their Applications," *Econometrica*, Vol. 83, No. 1.

Pete For America, Campaign (2019) "Medicare for All Who Want It," September.

Prager, Elena (2016) "Tiered Hospital Networks, Health Care Demand, and Prices," *Working Paper*.

——— (2018) "Consumer Reponsiveness to Simple Health Care Prices: Evidence from Tiered Hospital Networks," *Working Paper*.

Prager, Elena and Nicholas Tilipman (2019) "Hospitals Are Paid Their Charemaster Prices By Some Health Insurers," *Working Paper*.

Reinhardt, Uwe E. (2006) "The Pricing of U.S. Hospital Services: Chaos Behind a Veil," *Health Affairs*, Vol. 25, No. 1, pp. 57–69.

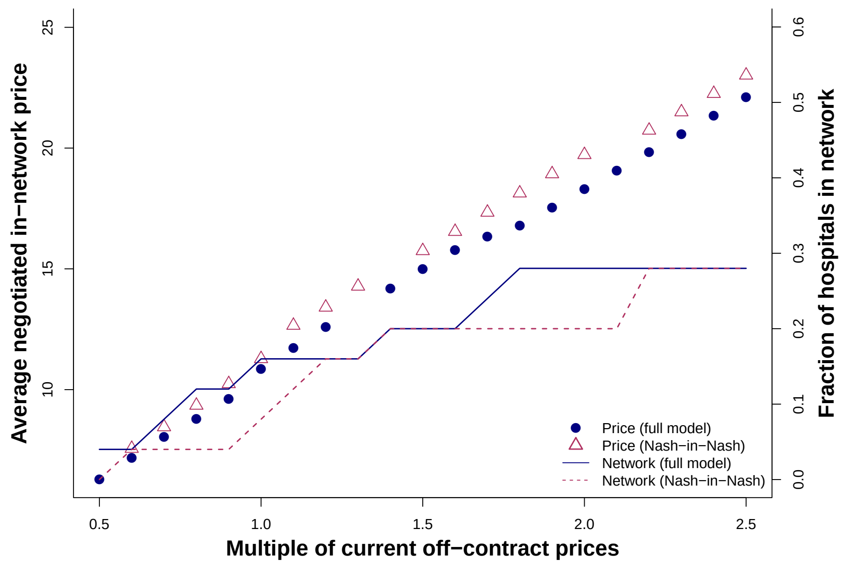
Shepard, Mark (2016) "Hospital Network Competition and Adverse Selection," *NBER Working Paper Series, 22600*.

Tilipman, Nicholas (2018) "Narrow Physician Networks, Switching Costs, and Product Variety in Employer Markets," *Working Paper*.

Appendices

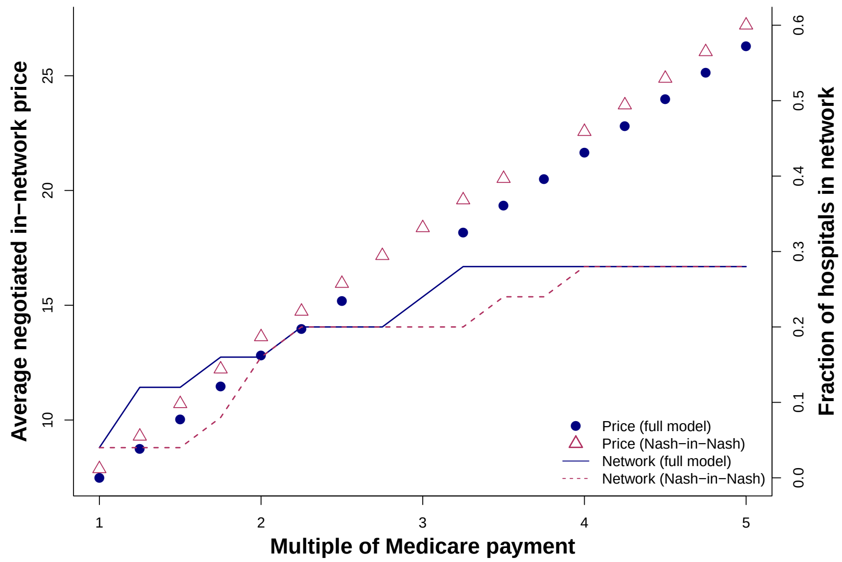
A Additional Tables and Figures

Figure A.1: 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-netowrk (volume-weighted average prices). Plot is for Tufts Health Plan in 2010. Gaps represent counterfactuals for which no equilibrium was found.

Figure A.2: 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-netowrk (volume-weighted average prices). Plot is for Tufts Health Plan in 2010. 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 Moment Inequality Estimation of Contracting Costs

We therefore incorporate into the estimation additional moments from the network status determination decisions. Formally, in addition to the equality moments in Equation 7, each hospital-insurer-year additionally contributes an inequality from the network inclusion conditions.

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, relative to the outside option of the hospital remaining out-of-network. To construct these moments, we follow closely the literature on moment inequalities (Ho 2009; Pakes 2010; Pakes et al. 2015). More formally, consider an insurer m and define its surplus from agreement with hospital h as:

$$S_h^m(\boldsymbol{\theta}) = \alpha_m W_{mh}^1 - p_{mh}^* \sigma_{mh}^1 - \psi_{mh}^1 - \left[\alpha_m W_{mh}^0 - p_m^0 \sigma_{mh}^0 - \psi_{mh}^0\right]$$

We assume that insurers have expectations over their surplus for any contract and that they predict these gains with error.[25] Let ω_{mh} be the difference between the insurer's expected surplus from agreement with hospital h and the realized surplus, and let $E[\omega_{mh}|\mathcal{J}] = 0$, where $\mathcal{J}$ is the insurer's information set at the time of contracting decision. Then:

$$E[S_h^m(\boldsymbol{\theta})|\mathcal{J}] = S_h^m(\boldsymbol{\theta}) - \omega_{mh}$$

An analogous expression can be constructed for each hospital's expected gains-from-trade with insurer m such that:

$$E[\pi_m^h(\boldsymbol{\theta})|\mathcal{I}] = \pi_m^h(\boldsymbol{\theta}) - v_{hm} = (p_{mh}^* - c_h)\, \sigma_{mh}^1 - \left(p_m^0 - c_h\right) \sigma_{mh}^0 - v_{hm}$$

where π_m^h are the observed profits for hospital h from contracting with insurer m, v_{hm} is a mean-zero error term for hospital h and c_h is projected from Equation 5.

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

[25] For example, insurers 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.

two inequalities that impose lower bounds on the insurer's and hospital's surpluses from agreement:

$$\begin{aligned}
0 \leq & E[S_h^m(\boldsymbol{\theta})|\mathcal{J}] = S_h^m(\boldsymbol{\theta}) - \omega_{mh} \\
0 \leq & E[\pi_m^h(\boldsymbol{\theta})|\mathcal{I}] = \pi_m^h(\boldsymbol{\theta}) - \upsilon_{hm}
\end{aligned} \tag{9}$$

We refer to these inequalities as network inclusion moments.

For hospital-insurer pairs that are observed not to have a contract, it must be the case 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, one or both of the network inclusion inequalities for the pair must be violated. In the raw data, we do not observe which party's network inclusion condition is violated, so in the estimation we only impose that at the current parameter guesses $\hat{\boldsymbol{\theta}}$, there exists no price that would make both parties' surpluses positive. 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, denoted $p_{mh}^+(m)$, is less than the lowest price that h would be willing to accept while still maintaining a positive surplus, denoted $p_{mh}^-(h)$. These prices are given by

$$\begin{aligned}
p_{mh}^+(m) = & \arg\max_{p_{mh}} \left[\left(\alpha_m W_{mh}^1 - p_{mh}\sigma_{mh}^1 - \psi_{mh}^1 \right) - \left(\alpha_m W_{mh}^0 - p_m^0 \sigma_{mh}^0 - \psi_{mh}^0 \right) \right] \\
& \text{s.t.} \;\; \left(\alpha_m W_{mh}^1 - p_{mh}\sigma_{mh}^1 - \psi_{mh}^1 \right) > \left(\alpha_m W_{mh}^0 - p_m^0 \sigma_{mh}^0 - \psi_{mh}^0 \right) \\
= & \frac{1}{\sigma_{mh}^1} \left[\alpha_m \left(W_{mh}^1 - W_{mh}^0 \right) + p_m^0 \sigma_{mh}^0 - \psi_{mh}^1 + \psi_{mh}^0 \right]
\end{aligned}$$

for the insurer's maximum price and

$$\begin{aligned}
p_{mh}^-(h) = & \arg\min_{p_{mh}} \left[\left(p_{mh} - c_h \right) \sigma_{mh}^1 - \left(p_m^0 - c_h \right) \sigma_{mh}^0 \right] \\
& \text{s.t.} \;\; \left(p_{mh} - c_h \right) \sigma_{mh}^1 > \left(p_m^0 - c_h \right) \sigma_{mh}^0 \\
= & \frac{1}{\sigma_{mh}^1} \left[p_m^0 \sigma_{mh}^0 + \left(\sigma_{mh}^1 - \sigma_{mh}^0 \right) c_h \right]
\end{aligned}$$

for the hospital's minimum price.

Each hospital-insurer pair that is observed not to have a negotiated contract therefore contributes a single inequality that imposes upper bounds on the surpluses from agreement:

$$p_{mh}^{-}(h) - p_{mh}^{+}(m) < 0 \tag{10}$$

We refer to these inequalities as network exclusion moments.[26]

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. As such, we can use sample analogs, similar to Ho (2009) to estimate the bounds on the hospital and insurer surpluses from agreement. Specifically, for instruments $z \in \boldsymbol{J}$ and $z \in \boldsymbol{I}$, our estimating equations for the network inclusion conditions become:

$$0 \leq \frac{1}{H} \sum_{h} \pi_{m}^{h}(\boldsymbol{\theta})|(z) \tag{11}$$

$$0 \leq \frac{1}{M} \sum_{m} S_{h}^{m}(\boldsymbol{\theta})(z) \tag{12}$$

Analogous expressions can be created for the network exclusion conditions. If no set of parameters satisfies all of inequalities, we construct a moment equation that minimizes the absolute deviations for any inequality violated. We then stack these moments together with the equality moments from the bargaining first-order conditions (equation 7) and search for parameters $\boldsymbol{\theta}$ that minimize the weighted sum of the network inclusion, network exclusion, and bargaining first-order condition moments.

[26]The inequality in equation 10 can be further simplified to $\alpha_m \left(W_{mh}^{1} - W_{mh}^{0}\right) - \psi_{mh}^{1} + \psi_{mh}^{0} > \left(\sigma_{mh}^{1} - \sigma_{mh}^{0}\right) c_h$.