Dynamic Bargaining between Hospitals and Insurers

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Abstract

This paper quantifies the role of government-driven benchmark rate inflation in spending on behalf of privately insured patients. When contracts are formed simultaneously, anticipated price inflation has no effect in net present value terms. When contracts are multiyear and staggered and negotiators discount future payments, anticipated inflation is passed through to real spending due to the asymmetric discounting from the perspective of negotiation and the market. I leverage panel data on hospitalinsurer contracts from West Virginia to show that contracts are multiyear and staggered, with even short-lived contracts remaining in place for three years or more. I estimate a structural model of bargaining with staggered contracts to characterize the degree to which negotiators discount future profits. I find that negotiators were substantially, but incompletely, forward-looking: I reject the null hypothesis of myopia and estimate an annual discounting rate of $\beta = 0.899$. I use the estimated dynamic model to quantify the forward-looking response to a proposed government-driven reform that would have increased private payment inflation between negotiations. The reform would not have any effect under a static model. I find that the reform would increase private spending after nine years by \$4.98 billion, while a myopic model lacking forward-looking responses would overestimate the effect by \$2.35 billion and miss short-term dynamics, including the possibility of payment decreases.

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1 Introduction

Each year, trillions of dollars of payments are made under agreements whose price cannot be changed as quickly as market conditions. The divergence between realized and hypothetical prices between negotiations is especially acute in American healthcare, where firms rely on externally-set benchmarks to dictate price dynamics.

This paper studies the impact of government-driven price dynamics on private insurer spending. In the era that I study, it is understood that hundreds of billions of dollars of payments were negotiated as fixed markups over government-set Medicare payment formulas and Medicare rate increases trailed private insurers' negotiated increases.

Under the static prevailing wisdom for considering this market, Medicare rate levels have direct no role in real payments. Most work on private spending has leveraged static models (Gowrisankaran et al., 2015, Ho and Lee, 2017) and focused on Medicare's relevance to static incentives (Cooper et al., 2019, Clemens and Gottlieb, 2017). From a static perspective, Medicare's only role in these contracts is as a numeraire that prices relative services. However, price negotiated markups were only revised every few years, while Medicare rates were revised annually, leaving a direct role of Medicare policy in the evolution of private price dynamics between negotiations.

In fact, Medicare dynamics could have a role in net present value terms if contracts are staggered and negotiators discount future periods. Imagine for simplicity a world with twoperiod contracts chosen to target a net present value payment $p_t + \beta p_{t+1}$ equal to $P(1 + \beta)$, with constant inflation rate ϕ . If contracting is simultaneous, then there is neutrality in net present value (NPV) terms: the NPV payment beginning in a contracting period t is $\sum_{h=0}^{\infty} \beta^{2h}(p_t + \beta p_{t+1}) = 2\frac{P}{1-\beta}$. If contracting is staggered, then the long-run net present value payment is $\left(2 + \frac{(1-\beta)\phi}{1+\beta(1+\phi)}\right)\frac{P}{1-\beta}$, which generates passthrough of ϕ to payments as long as the discounting rate β is below one. This is because when negotiators discount future profits, the payment increase for old contracts must be larger than the payment decrease for new contracts to achieve neutrality in net present value terms. Neutrality is restored in NPV terms if inflation reform is announced in advance, but removed by accounting for externalities of prices across contracts.

A full accounting of the role of Medicare dynamics in private spending requires data on contract duration, timing, and benchmark usage, as well a model of how negotiators respond to anticipated inflation. The data is a public record administrative dataset on hospital– insurer contracts from West Virginia between 2006 and 2015. Negotiated agreements would consistently remain in place for three years or longer, and contracts were meaningfully staggered both across years and within a given year, yielding scope for benchmark dynamics to have real effects. I estimate that 46.74% of payments were likely benchmarked to Medicare, with these payments associated with the largest insurer, Highmark BCBS, yielding important scope for Medicare dynamics in particular to affect private insurer spending.

The model of negotiation is a dynamic extension of the Ho and Lee (2017) model. Hospitals agree to receive reduced prices in exchange for an insurer offering favorable cost-sharing. Insurers leverage their network of hospitals to offer higher-quality insurance to consumers. Consumers trade off between the insurer's premiums and the value of the insurer's network if sick, and some of those consumers get sick and receive care at a hospital.

It is known in this setting that prices have mutually reinforcing externalities: if an insurer and hospital disagree, some consumers will substitute to competing insurers with the hospital in-network, and some patients will retain the insurer and substitute to other in-network hospitals. As a result, higher prices paid to local competitors make disagreement more costly to the insurer and more favorable to the hospital, pushing negotiated prices upward.

Unlike the Ho and Lee model, I allow contracts to be staggered, future conditions to be uncertain, and negotiators to discount future profits. I do so with the Nash-in-Kalai model, which agrees with Nash-in-Nash in transferable utility models like Ho and Lee (2017), but which the companion paper Dorn (2025a) shows enables identification and general method of moments (GMM) estimation in dynamic models. Kalai proportional negotiators choose a contract to maximize joint gains from trade, subject to splitting gains from trade in proportion to fixed bargaining weights τ . Negotiators trade off between current and future profits with a shared annual post-inflation discounting rate $\beta \in [0, 1)$.

To quantify the effect of Medicare dynamics on equilibrium private spending, I estimate the empirical model with the data from West Virginia. Gains from trade are mainly driven by consumers' substitution patterns across insurers and hospitals. As is standard, I assume consumers choose insurance plans based on the expected utility of the network over hypothetical diagnoses, and patients choose and value hospitals according to a logit model. Consistent with the substantial cost-sharing in this market, I model patients as facing an equal monetary cost across hospitals when choosing care. I estimate hospital choice with logistic maximum likelihood as a function of diagnosis category and location, using Highmark BCBS patients that are in-network at all West Virginia hospitals. I estimate insurer demand based on the correlation of insurer sales and network quality within Affordable Care Act (ACA) rating areas that control for most sources of premium variation. I calibrate consumers' price-sensitivity based on Ho (2006)'s estimated own-price elasticity of -1.4.

The estimated hospital and insurer demand functions are key inputs to the bargaining model. I estimate bargaining parameters based on GMM for a model-derived moment on expected NPV gains from trade at the moment of bargaining. I impose a five-year finite horizon model as an approximation to an infinite-horizon model that includes the bulk of gains from trade within my ten years of data. The finite horizon allows me to permit $\beta = 1$ as an improper limit in estimation. The discounting rate β is estimated using insurer dummy variables and hospital size groups as instruments: smaller insurers and larger hospitals were more likely to reach agreements with longer terms and faster price growth, so that increases in the discounting rate have a larger effect on NPV payments for these firms.

I find that negotiators value an inflation-adjusted dollar next year equivalently to ninety cents in the current year. The estimated discounting rate corresponds to a four-year discounting rate of 66%. I overwhelmingly reject the null hypothesis of myopia that would correspond to a static-type model, but also reject the null hypothesis of $\beta = 1$ that would correspond to zero inflation passthrough. I also estimate that when negotiating with a medium-sized hospital, all insurers retain between 85% and 89% of the joint surplus, but I find substantial heterogeneity by hospital, with large hospitals receiving a near-even split and small hospitals receiving roughly take-it-or-leave-it offers.

I use the estimated structural model to quantify the anticipatory response to a Medicare dynamics. American hospitals have often argued that the payments they receive from Medicare have failed to keep pace with costs. To simulate a more favorable dynamic, I consider a one percentage point annual increase in Medicare rates, roughly counteracting observed deflation relative to reported costs. The change is implemented as a surprise announcement at the end of 2006 that is fully known in every subsequent period. The key mechanism to quantify is the offsetting forward-looking response, although contractual externalities also adjust in equilibrium. I am conservative and do not include the reinforcing interaction between premiums and payments.

I find that persistent Medicare payment increases would have real effects on the payments negotiated by commercial insurers, even after accounting for forward-looking offsets. I estimate that after nine years, this change to Medicare rates would increase spending on behalf of the commercially insured by 1.319%. This effect is 25.4% of the predicted increase if negotiators did not adjust their contracted multiples. Extrapolated nationally in 2015 and converted to 2019 dollars, the effect corresponds to a \$4.98-billion increase in spending. I find that forward-looking price reductions are an important mechanism, to the point that I estimate spending in one year would decrease. Approaches based on the static literature would predict incorrect effects. A myopic model that corresponds to static-type estimation with accurate dynamic timing would overestimate the 2015 effect by \$2.35 billion and miss those short-run dynamics. A static model with single-period contracting would fail to capture any effect at all.

An important caveat is that the available data does not indicate Medicare benchmarks

directly. Secondary sources indicate that at the start of the period, Highmark BCBS used Medicare rates directly at least for outpatient care at hospitals. Public disclosures of prices beginning in 2021 indicate that current prices are based on Medicare Diagnosis Related Group (DRG) codes, but use an independent formula. As a result, I cannot speak with certainty about the role of Medicare in payments today. However, the results here immediately carry over to proposals to regulate the levels and inflation of hospital list prices (Chernew et al., 2020, Duffy et al., 2020, Liu et al., 2021, Prager and Tilipman, 2022, Berenson and Murray, 2022), which I can say definitively were used as benchmarks in West Virginia in the era that I study and nationally today (Koos et al., 2024). In non-healthcare markets with negotiated nominal prices, the real-price-increase parameter ϕ corresponds to the inverse of nominal price inflation, so that the analysis here is likely to carry over, with signs reverse, to the effect of anticipated monetary inflation on real spending in other markets.

The analysis here is most directly related to the broad literature on healthcare spending in the United States. American healthcare prices are an international outlier (Reinhardt, 2006), and substantial attention has been paid to the details and drivers of spending. Considerable attention has been paid to the role of market power and bargaining in dictating these prices (Capps et al., 2003, Gowrisankaran et al., 2015, Ho and Lee, 2017, 2019, Ghili et al., 2023). My analysis builds on analysis of claims data that characterizes price structure (Weber et al., 2019), in particular the work of Cooper et al. (2019) that I discuss further in Appendix B.2. Of particular note are Clemens and Gottlieb (2017), who study the role of Medicare as an outside option in bargaining (which I abstract from), and Clemens et al. (2017), who study the role of Medicare in physician price dynamics.

The mechanism that I study is closer to work on price-setting in macroeconomics. My empirical model is in many ways similar to a Taylor (1980) model of staggered price-setting, but with prices that are negotiated rather than set unilaterally, and with persistent rather than one-off price increases. As a result, my work is related to a Calvo (1983) model of random price updating. For more on the macroeconomic literature, see Werning (2022). There is also work on regulation of pharmaceutical inflation (Abbott, 1995, Ridley and Zhang, 2017) and dynamic medical price effects (Ji and Rogers, 2023, Acquatella et al., 2023), but without externalities of prices across products.

The plan of the paper is as follows. Section 2 characterizes the effect of benchmark inflation in simple triangular markets and describes the Kalai proportional bargaining solution that I use to tractably incorporate staggered bargaining. Section 3 presents the key descriptive evidence, that contracts in West Virginia were multiyear, staggered, and substantially affected by Medicare rate dynamics. Section 4 describes my empirical model. Section 5 describes estimation and Section 6 presents my counterfactual results. Section 7 concludes.

2 Stylized Models of Benchmark Inflation Passthrough

I show that in the absence of contractual externalities, benchmark inflation has no effect on the net present value of simultaneously-formed payments, but does have long-run effect on payments that are negotiated at staggered moments. I then describe my solution concept for incorporating contractual externalities with staggered contracts, the Nash-in-Kalai model of bargaining. In the presence of contractual externalities, I show that the NPV-constant model's characterization of the sign of long-run behavior holds, but benchmark inflation can also affect a given contract's NPV payments through contractual externalities.

2.1 Passthrough with no Contractual Externalities

Imagine a highly stylized world with two hospital–insurer pairs that independently target net present value payments.

Pairs negotiate payments p_t as a fixed multiple α applied to a benchmark rate b_t for two periods. The benchmark rate is known to follow the constant inflation rate $\phi > 0$, so that $b_t = b_0(1 + \phi)^t$. The benchmark b is known at the time of negotiation, so negotiating over the initial multiple m is equivalent to negotiating over the initial payment p.

In periods $t_0 = 1, 3, 5, \ldots$, and so on, pair one chooses a starting payment $p_{t_0}^{(1)}$, knowing that the period $t_0 + 1$, the payment will be $p_{t_0+1}^{(1)} = (1+\phi)p_{t_0}^{(1)}$. $\phi > -1$ is the known inflation rate. The negotiators value next-period profits at a rate $\beta \in [0, 1]$; in this stylized world, behavior at $\beta = 1$ is well-defined. The negotiators target a net present value of payment $P(1 + \beta)$. Simple algebra yields that $p_{t_0}^{(1)} = P \frac{1+\beta}{1+\beta(1+\phi)}$.

In periods $t_0 = 1 + u, 3 + u, 5 + u, \ldots$, pair two chooses a starting payment $p_{t_0}^{(2)}$. There are no externalities across contracts, so $p_{t_0}^{(2)} = P \frac{1+\beta}{1+\beta(1+\phi)}$ as well. By construction, inflation ϕ has no effect on the net present value payment under a given contract at the time of formation.

Proposition 1 (Staggering + Discounting Implies Passthrough). Let $S_t = p_t^{(1)} + p_t^{(2)}$ be the total spending in period t. Suppose contracts are simultaneous (u = 0). Then the NPV of total payments from the first negotiation is $\sum_{t=0}^{\infty} \beta^t S_t = 2\frac{P}{1-\beta}$. Alternatively, suppose contracts are alternating (u = 1). Then the NPV of payments is $\sum_{t=0}^{\infty} \beta^t S_t = \left(2 + \frac{(1-\beta)\phi}{1+\beta(1+\phi)}\right) \frac{P}{1-\beta}$.

Proof. Suppose u = 0. Total payments are $S_t = 2P \frac{1+\beta}{1+\beta(1+\phi)}$ in periods 1, 3, 5, ... and are $S_t = 2P \frac{(1+\beta)(1+\phi)}{1+\beta(1+\phi)}$ in periods 2, 4, 6, By inspection, the net present value payment beginning in period t_0 is $2\frac{P}{1-\beta}$.

Alternatively, suppose u = 1. Suppose that t is odd-numbered, so that firm one's payment is $p_t^{(1)} = P \frac{1+\beta}{1+\beta(1+\phi)}$, and firm two's payment is $p_{t-1}^{(2)} = P \frac{1+\beta}{1+\beta(1+\phi)}(1+\phi)$. By addition, the

total payment is $S_t = \frac{1+1(1+\phi)}{1+\beta(1+\phi)}P(1+\beta) = \left(2 + \frac{(1-\beta)\phi}{1+\beta(1+\phi)}\right)P$. By symmetry, this holds for every period t, so that if $\beta < 1$, ϕ is passed through to long-run spending.

Intuitively, under time discounting, the initial forward-looking response to ϕ is smaller than the later realized effect. Negotiators offset anticipated ϕ -driven future price increases by reducing starting prices. If $\beta < 1$, then the future increases must be larger than the starting decreases in absolute terms to arrive at the same net present value payment. At a market level, old and new contracts get equal weight, generating passthrough of ϕ to payments.

Note that in a model with a surprise announcement before period t of inflation beginning in period $t_0 > t$, then there would be exact neutrality of ϕ . This generates neutrality in NPV terms: there is no effect of ϕ on NPV payments, though it does have a long-run effect. This neutrality is specific to an anticipated shock without externalities. If the inflation shock is a surprise change, as in my counterfactual, then ϕ has a larger effect in the short-run than the long-run, so that passthrough is unambiguously positive.

This very simple model holds NPV payments constant for each contract. It is known from static models of healthcare bargaining that there are contractual externalities, in the sense that bilateral prices have a mutually reinforcing effect (Ho and Lee, 2017). Virtually all models of bargaining with contractual externalities have involved single-period agreements (Lee et al., 2021). I characterize bargaining with contractual externalities under a particular extension of static Nash bargaining: the recursive Kalai proportional bargaining solution.

2.2 Recursive Kalai Proportional Bargaining

I assume negotiators follow Kalai proportional bargaining. The companion paper Dorn (2025a) argues that this solution concept is uniquely tracable in the presence of uncertainty or staggered contracting.

The Nash-in-Kalai solution is a Nash equilibrium in Kalai proportional bargains. The Kalai proportional bargaining solution with player-j bargaining weight τ_{ij} chooses the contract \mathbb{C}_{ijt} that maximizes gains from trade among the ray of agreements that generate positive gains and give player j a τ_{ij} share of the joint gains from trade. That is, if the Kalai proportional solution predicts gains GFT_i for player i and GFT_j for player j, then the gains must satisfy $\tau_{ij}GFT_i = (1 - \tau_{ij})GFT_j$. This immediately permits a moment in the presence of uncertainty, which would not hold under most bargaining solutions (Dorn, 2025a). The bilateral solution concept is presented graphically in Figure 1(a).

The unique feature of the static Kalai proportional bargaining solution that I exploit is the *step-by-step* (Kalai, 1977) or *path independence* (Roth, 1979) property. I demonstrate this property in Figure 1(b). If $f(S, v^D)$ is a bargaining solution over feasible utility sets S with



Figure 1: Left: The Kalai proportional bargaining solution for choosing an agreement V_{Kalai}^A (blue) on a Pareto frontier PF relative to the value of disagreement v^D (red), with proportional split illustrated by dashed blue line. Right: the step-by-step agreement $V_{\text{Step 1}}^A$ (blue) recursively defined through bargaining relative to a first-step agreement $V_{\text{Step 2}}^D$ (red), chosen through applying the bargaining solution to negotiations over some smaller Pareto frontier PF' (pink, with dashed line indicating gains) relative to the full disagreement v^D (omitted).

disagreement points v_D , then the step-by-step property is that for any $S' \subseteq S$ that generates a valid bargaining problem, $f(S, f(S', v^D)) = f(S, v^D)$.¹ Graphically, moving the disagreement value upwards along the proportional-split ray does not change the predicted agreement. Kalai (1977) shows that this feature is unique to Kalai proportional bargaining in games with free disposal, and Roth (1979) shows that this feature is unique to bargaining solutions with "proportional character" in games that may lack free disposal. Dorn (2025a) shows that this property can be used to derive simple representations of the outcome of recursive bargaining problems in dynamic games, as merges with interacting staggered contracts.

2.3 Passthrough with Contractual Externalities

I now show that simultaneous-payment neutrality carries through to Nash-in-Kalai bargaining with interacting contracts. With staggered contracts, the long-run passthrough of Section 2.1 carries on, but with a twist: even a single contract's net present value payment

 $^{^1\}mathrm{I}$ modify the notation slightly from Kalai and Roth in order to avoid imposing a disagreement point normalization.

is affected by ϕ .

A monopolist insurer bargains two-period contracts with two symmetric downstream hospitals. The monopolist insurer sells insurance for \$10,000 per life. The insurer will sell 6,000 units of insurance with both hospitals in their network, 4,000 units with one hospital in their network, and no one will purchase insurance with an empty hospital network. After choosing insurance, enrollees become patients and distribute evenly among hospitals in the insurer's network. The number of patients at a hospital depends on the realized network, so contracts are over a price per patient rather than a payment directly.

A contract takes the form of a multiple α on the benchmark price per patient that will remain in place for ℓ periods. The price per unit of care is b_t and continues to inflate at a rate of ϕ . I write $\mathbb{C}_t = (\mathbb{C}_{1t}, \mathbb{C}_{2t})$ for the realized period t contracts, where $\mathbb{C}_{ht} = (\ell_{ht}, p_{ht})$ is hospital h's contract in period t (the number of remaining periods ℓ_{ht} and the current period price per patient $p_{ht} = \alpha_{ht}b_t$). If hospital h fails to agree to a contract in period t, I write $\mathbb{C}_{ht} = (0, 0)$. The insurer and hospital flow profits in terms of insurer demand D^M and hospital patient count D_h^H is as follows:

$$\pi^{M}(\mathbb{C}_{t}) = D^{M}(\mathbb{C}_{t}) - \sum_{h} D^{H}_{h}(\mathbb{C}_{t}) p_{ht} \text{ and } \pi^{H}_{h}(\mathbb{C}_{t}) = D^{H}_{h}(\mathbb{C}_{t}) p_{ht}.$$

All firms play Markov (memoryless) strategies and maximize NPV profits. Negotiators follow Kalai proportional bargaining relative to one-period disagreement. Hospital one bargains in odd-numbered periods t_0 , and hospital two bargains in periods $t_0 + u$. In the interest of simplicity I keep regularity conditions implicit in this toy model.

Contracts in this setting have externalities. Suppose the insurer expects hospital -h will agree to a multiple $\alpha_{-ht} = p_{-ht}/b_t$ whether the bargain with hospital h succeeds or fails. With an agreement, the insurer will earn \$60m in premium revenue, pay 3,000 p_{ht} to hospital h, and pay 3,000 p_{-ht} to hospital -h. With a failed bargain with hospital h, the insurer will earn \$40m in premium revenue and pay 4,000 p_{-ht} to hospital -h. The insurer's flow gains are equal to $20m - 3,000p_{ht} + 1,000p_{-ht}$, which are increasing in the price they will agree to pay hospital -h: the more the insurer agrees to pay hospital -h, the more the insurer will be willing to pay to hospital h to divert patients from the more expensive hospital.

I write $p_{Static}^* = \$20,000\frac{(1-\tau)}{2+\tau}$ as the unique equilibrium in the simultaneous one-period contracting game where prices are $p_{ht}^* = (1-\tau)(\$20m+1,000p_{-h,t})$.

Now imagine that contracts remain in place for two periods, as in the model with no contractual externality. Equilibrium payments are as follows.

Proposition 2. Suppose $\tau \in (0,1)$ and $\beta > 0$. If u = 0, then the initial prices $p_{t_0}^{(1)} = p_{t_0}^{(2)}$ at the moment of simultaneous negotiation are equal to $p_{Static}^* \frac{1+\beta}{1+\beta(1+\phi)}$, generating neutrality

from the first negotiation. If u = 1, then the long-run negotiated starting price is

$$p_{t_0}^{(1)} = p_{t_0+1}^{(2)} = \$20,000 \frac{1-\tau}{2+\tau} \frac{(1+\beta)(2+\tau+4\beta(1-\tau))}{(1-\tau)(3\beta(1+\beta(1+\phi)) - (1-\beta)^2(1+\phi)) + 3(1+\beta(1+\phi))}$$
(1)

If $\beta < 1$, then long-run payments $3,000(2+\phi)p_{t_0}^{(1)}$ and a given contract's net present value payment $3,000(1+\beta(1+\phi))p_{t_0}^{(1)}$ are strictly increasing in ϕ .

Proof. See Appendix A.2.

The neutrality from Section 2.1 carries through when bargaining is conducted simultaneously under Kalai proportional bargaining, despite the presence of contractual externalities.

With staggered contracts, there is a nonneutral twist. The effect on market payments from asymmetric discounting relevance from the no-externality model remains in place. However, with contractual spillovers, benchmark inflation also changes a given contract's net present value payment. Consider the insurer negotiating with hospital 1 in period t_0 , knowing that the hospital-2 price will be revised next period. As ϕ increases, the hospital 2 price is higher in period t_0 and lower in period $t_0 + 1$. Under discounting, the period- $t_0 + 1$ price decrease is lower in absolute terms than the period- t_0+1 price increase. Further, the period- t_0 negotiators discount the period- $t_0 + 1$ price decrease by β , so that ϕ has a real effect on NPV payments even for a given agreement. As a result, even announced-in-advance changes in ϕ can have real effects.

This stylized models highlight that for benchmark inflation to have real effects, contracts must be multiyear, agreements must be staggered, benchmarks must be used, and negotiators must discount future payments. The bulk of this paper will be estimating the discounting rate β in one market. The first three stylized facts are easier to establish.

3 Key Descriptive Evidence

I quantify contract timing and dynamics using a public record dataset on West Virginia hospital-insurer contracts between 2006 and 2015. Static models are used in part because it is rare to see the data on contract timing (Sorensen, 2003, Reinhardt, 2006, Gudiksen et al., 2019), making the setting an exciting opportunity to understand contractual dynamics.

I am able to amass a panel dataset on hospital-insurer contracts because West Virginia made the contracts public records. The contract disclosure was a byproduct of a "corridor" rate regulation system. The state mandated a dynamic ceiling on hospital list prices and an average-cost floor on private insurer payments. The regulator in charge of certifying



Figure 2: Contracts are multiyear. Distribution of reported contract lengths for fixed-term contracts in general (left panel) and auto-renew contracts with reported formation dates as-of fiscal 2015 (right panel). Colors indicates insurer. The two nonmodeled contracts correspond to Wheeling–Pittsburgh Steel.

the average-cost floor made the regulated contracts public records. The state destroyed the contracts at the end of the corridor system in 2016, but retained scans of contract summary information that I leverage in my analysis.

The contract dataset I use includes Discount Contract Lists (DCLs) and Detailed Contract (DC) forms. The DCLs are a panel dataset of projected discounts relative to list prices by contract for 2006–2015. Appendix Figure 8 gives one example.² I use these reports to observe payment rates and infer some negotiation times. The DC reports are supplemental information for contracts that either constituted at least 5% of a hospital's projected utilization or which fell into certain rare exceptions, and were retained beginning midway through 2010. Appendix Figure 9 presents one example. The DC data includes detailed information on scale, as well as further information on formation and expiration dates (if applicable).³

The contract data is public record, so I am able to reference specific firms and provide the data for other researchers to use. I ultimately focus my estimation on six insurers that were more likely to report retrospective formation dates: Highmark BCBS, the largest insurer;

²The reports exclude Medicare Advantage contracts. Medicare Advantage is a large and ostensibly commercial insurance product that is funded by Medicare and often included with traditional Medicare (CMS, 2022).

³There are also reported submission dates. I use contract approval date, rather than submission date, as a measure of contract negotiation and start date because approval was generally quick, while contract submission date is sometimes used to refer to a recent resubmission of an extant contract.



Figure 3: Contracts are formed at different times. Histogram of contract start dates for contracts used in the estimation sample and introduced in 2007–2014 for Highmark BCBS (blue) and other modeled insurers (pink). Vertical lines indicate January 1 of a given year. Contracts were not systematically introduced on the same dates.

HPUOV, a regional insurer; Aetna, Carelink, Cigna, and UnitedHealth, the four largest for-profit firms.⁴ I refer to these insurers as "modeled" and group the remaining tail of small insurers into a "nonmodeled" category. The cleaned dataset is available at https://jacobdorn.info/files/ContractData.zip. For more on the state's rate review system, see Murray and Berenson (2015). For more on the setting and the data, see the companion paper Dorn (2025b).

Figure 2 demonstrates that hospital-insurer contracts in West Virginia were multiyear. Figure 2(a) includes contracts with reported formal expiration dates. These contracts were associated with Highmark BCBS, and corresponded to standard lengths of three or five years. The right panel includes "auto-renew" contracts: contracts with an annual commitment that would automatically renew until one side requested termination. Auto-renew contracts were associated with smaller contracts that would rarely be reported in the DC data, and so I can generally only infer the formation dates for a selected sample of auto-renew contracts. Figure 2(b) shows that even for the auto-renew contracts with reported formation dates in 2015, a sample highly selected towards shorter tenures, most agreements had been formed at least a decade previously. In companion work, Dorn (2025b) estimates that the average auto-renew renewal probability in this era was 93.4%.

Figure 3 demonstrates that contracts were staggered. The figure plots contract start dates for contracts used in the estimation sample. These are bargains with reliable start and

 $^{^4\}mathrm{Carelink}$ was a regional subsidiary of Coventry between 1999 and Aetna's acquisition of Coventry at the end of 2014.

end date information in my sample. Contracts were visually formed in many years and all throughout a given year. This pattern of staggered formation held both across hospitals for Highmark BCBS and across insurers.

| MCO | Prospective | Share of Charges |
|---------------|-------------|------------------|
| All | 46.74 | 53.26 |
| Modeled MCOs | 60.20 | 39.80 |
| Highmark BCBS | 72.27 | 27.73 |
| HPUOV | 56.24 | 43.76 |
| Other Modeled | 13.14 | 86.86 |
| Nonmodeled | 3.03 | 96.97 |

Table 1: The estimated share of inpatient payments by benchmark type for fiscal years 2011– 16. Prospective contracts were common, especially for Highmark BCBS.

I establish the usage of benchmarks over time using the panel data on payment rates. I classify contracts as either likely list-price-linked "share of charges" contracts or likely-Medicare-linked "prospective" contracts. This notation follows Cooper et al. (2019). See Appendix B.1 for more on the algorithm and Appendix B.2 for more on the logic.⁵ Weber et al. (2019) indicate that in Colorado, maternity care is more likely to be paid on a per diem basis. The West Virginia administrative data suggests that few contracts, if any, used a combination of share of charges and per diem payments, and I exclude newborn care in estimation and counterfactuals to assuage any concerns on this point. I present estimated frequencies in Table 1. I classify an estimated 46.7% of inpatient spending as prospective, and find that prospective contracts were especially common for the largest insurer Highmark BCBS, as well as for HPUOV in the regions in which it was a larger actor.

The choice of benchmark had an important consequence on how prices would evolve after a contract was formed. Figure 4 presents the ratio of incurred list prices and received payments to hospital reported costs among patients with Medicare and private insurance based on data that I describe later in Section 5.1. List prices increased quickly, roughly three percentage points faster than hospital reported costs. Medicare rates depreciated relative to hospital reported costs, roughly by one percentage point annually. As a result, if insurer A formed a contract with a hospital paying a fixed multiple of charges, and insurer B formed a contract at the same time with the same average initial payment calculated as a fixed fraction of Medicare rates, then after five years, insurer A could easily pay 20% more. The associated divergence in payments between negotiations was an important driver of the divergence in payments between Highmark BCBS and other insurers in this era (Dorn, 2025b).

⁵Note that some charges are based on diagnoses, and are therefore also prospective. The key difference is that Medicare-linked prices evolve based on a national formula.



Figure 4: The ratio of list price charges (top) and real payments (bottom) to reported costs by Medicare (red) and private payors (blue) for West Virginia hospitals. Dashed lines represent Medicare 2006 values extrapolated based on three ppt. and negative one ppt. annual changes.

I have established that in West Virginia, contracts were multiyear and staggered, and there was important variation in price inflation based on choice of benchmark. In the next section, I present an empirical model of how forward-looking negotiators would respond to anticipated benchmark inflation in the presence of a larger and interacting market.

4 Empirical Nash-in-Kalai Bargaining Model

I now describe the empirical bargaining model, which is an extension of the Ho and Lee (2017) model to allow contracts to be multiyear and staggered. I leverage the Nash-in-Kalai model, which aligns with a Nash-in-Nash in Ho and Lee's static setting, but which is more tractable when contracts are staggered. For more on the model, see the companion paper Dorn (2025a).

Time is indexed by t. One year is a single unit of time, which is further divided at least daily, with time at period s indicated as t_s or t. The annual discounting rate is equal to $\beta \in [0, 1)$, with myopia corresponding to $\beta = 0$. I will allow the model to tend to continuous time in the sense of the division of time tending to infinity; Dorn (2025a) applied to the model I discuss shows that further division of time within a day has no effect on payments.

The timing in each period t_s is as follows:

1. Information is revealed, premiums may be set, and auto-renew decisions are made. Information \mathcal{I}_{t_s} is revealed, which reflects several subgames.

- 2. Contracts are bargained. For hospital-insurer pairs ij with more than one feasible contract, new contracts $\hat{\mathbb{C}}_{ijt_s}$ are chosen through bilateral Kalai proportional bargaining relative to the null contract, with j receiving bargaining weight $\tau_{ij} \in [0, 1]$. I write the number of new contracts formed by firm i as \hat{R}_{it_s} .
- 3. Flow profits are formed. Flow profits for agent *i* at contract state $\hat{\mathbb{C}}_{t_s}$ with associated *j*-to-*i* prices $\hat{p}_{ijt_s} = -\hat{p}_{jit_s}$ and network of firms with agreements \mathcal{G}_{it_s} are equal to

$$\pi_{tsi}(\hat{\mathbb{C}}_{ts}) + \sum_{j \in \mathcal{G}_{its}} \hat{p}_{ijts} D_{ts,ij}(\hat{\mathbb{C}}_{ts}) - r_i \hat{R}_{its}$$

where $r_i \ge 0$ is the cost of validating a new contract to firm *i*.

Flow profits are adapted from Ho and Lee. Contracts can be formed between hospitals and insurers (also known as managed care organizations, or MCOs). I adapt their notation and refer to hospitals with subscripts i or h and with superscripts H, and refer to insurers with subscripts j or n and with superscripts M. I discuss each stage in further detail.

4.1 Information is Revealed

In this model, the information updating stage 1 includes information that is unobserved by me; benchmark rates, which I infer from the payment data; premiums, which are updated in the first period of the year; and auto-renew decisions, which are made annually for each contract.

In the first period of each year (t = u for an integer u), bencmark rates and premiums are updated and demand unobservables for the year are determined. I write the sequence of benchmark prices of benchmark b at hospital i as p_{it}^b . I assume that benchmark prices move exogenously from the contracts I model, which is innocuous for prospective contracts, and leverages the small size of share of charges contracts. I assume that firms engage in Nash-Bertrand competition based on demand at equilibrium networks without internalizing the effect of premiums on subsequent negotiations. Internalized premium externalities could be accommodated into the model, but the available premium data is coarse and premium effects are not at the center of the mechanism that I model.

Auto-renew contracts can be revised annually. For an auto-renew contract between ij negotiated at time t_0 , then in periods $t = t_0 + u$ for integers u, both sides have the opportunity to request the contract not renew. If the contract is not renewed, then it must either be negotiated from scratch or no contract will be in place.

After auto-renew decisions are made, there is a set of feasible bilateral contracting states C_{ijts} . For any pair ij, a feasible state can be either the single renewal contract, a single

null contract, or a set of feasible agreements. Only hospitals and insurers can reach nonnull agreements. A contract between hospital i and insurer j includes p_{ijt_s} , the net i-to-jtransfer per unit of equilibrium demand $D_{t_s,ij}(\mathbb{C}_{t_s})$ provided in period t_s , and some other characteristics that I will describe later in this section.

One could just as easily imagine strategic interactions after bargaining rather than before bargaining. Such a change could be accommodated at the cost of additional notation to track the outcome of the end-of-period response. I will eventually imagine a period to be arbitrarily short, so that a single period is almost irrelevant. A more substantive change would be if non-bargaining competition occurred at the same time as bargaining in stage 2. Such simultaneous competition would be insubstantial if it occurred only at specific times, but difficult to model if the strategic response was revisited in every period while a pair remained in impasse.

4.2 Contracts are Bargained

The core of my analysis is the bargaining Stage 2.

Contracts are negotiated as a benchmark (either a prospective or share of charges price), a fixed benchmark price multiple (or equivalently initial price), and expiration (either a fixed expiration date or an auto-renew contract that can renew on January 1 of each year). I assume that firms that enter impasse continually attempt to reach a contract in good faith to avoid further painful exclusion, formalized as Good-Faith Disagreement in Appendix Assumption 2.

I assume that a bilateral pair chooses a contract taking as given past decisions and current and future strategies. The assumption on future strategies is to my knowledge innocuous. The restriction on simultaneous strategies is the standard passive beliefs assumption that if i or j defects and changes their behavior, neither party adjusts their behavior in, or expectations about, other strategic decisions taken at the same time (Lee et al., 2021). This decision is relatively innocuous in a dynamic market: I will have in mind a model where the length of a period tends to zero, so that the simultaneous negotiations will typically have no importance in the limit.

I assume in estimation and counterfactuals that equilibrium networks, benchmarks, and lengths are known: pairs that do not form an agreement will not form an agreement for any realization of demand unobservables. For estimation, this is stronger than necessary. I only need anticipated prices under a pair's agreement and impasse paths generate the same sequence of other-pair contract structures. For counterfactuals, this is a more substantive assumption that Medicare reform would not lead to adjustment of benchmark usage or networks, which I discuss later.

4.3 Flow Profits are Formed

I write insurer j's network in period t as $\mathcal{G}_{jt}^M = \{\text{hospitals } i \mid \mathbb{C}_{ijt} \neq \mathbb{C}_{0,ijt}\}$. I write a hospital i's network \mathcal{G}_{it}^H analogously, and write $\mathcal{G}_t = \{ij \mid \mathbb{C}_{ijt} \neq \mathbb{C}_{0,ijt}\}$ for the full network. The insurer charges premiums ϕ_{jt} , which I assume are set simultaneously during stage 1 of every January 1. (This is a slight abuse of notation from the stylized model's inflation rate, which is not applicable in the empirical model.) I write the vector of premiums in the market as ϕ_t . The transfer demand function is hospital inpatient units of care, $D_{ijt}(\mathbb{C}_t) = D_{ijt}^H(\mathcal{G}_t, \phi_t)$, which is zero for ij that reach the null contract.

If i is a hospital and j is an insurer, then the pre-transfer profit functions are:

$$\pi_{it}^{H}(\mathbb{C}_{t}) = -\sum_{n \in \mathcal{G}_{it}^{H}} D_{int}^{H}(\mathbb{C}_{t})c_{i} \text{ and } \pi_{jt}^{M}(\mathbb{C}_{t}) = D_{jt}^{M}(\mathcal{G}_{t},\phi_{t})(\phi_{jt}-\eta_{j}),$$

where c_i is the hospital's per-unit cost, D_{jt}^M is the insurer j demand function, η_j is insurer j's per-enrollee noninpatient costs. I describe the demand function specifications in Section 5.1.

The associated flow pre-transfer gains from trade for a hospital *i* and insurer *j* at the equilibrium contracts $\hat{\mathbb{C}}_t$, networks $\hat{\mathcal{G}}_t$, and premiums $\hat{\phi}_t$ are:

$$\begin{bmatrix} \Delta_{ij} \pi_{it}^{H} \end{bmatrix} = -c_{i} D_{ijt} \left(\hat{\mathbb{C}}_{t} \right) - c_{i} \sum_{n \in \mathcal{G}_{it}^{H}} \left(D_{int} \left(\hat{\mathbb{C}}_{t} \right) - D_{int} \left(\left(\hat{\mathbb{C}}_{t,-ij}, \mathbb{C}_{0,ijt} \right) \right) \right)$$

$$\begin{bmatrix} \Delta_{ij} \pi_{it}^{M} \end{bmatrix} = \left(D_{jt}^{M} \left(\hat{\mathcal{G}}_{t}, \hat{\phi}_{t} \right) - D_{jt}^{M} \left(\hat{\mathcal{G}}_{t}/ij, \hat{\phi}_{t} \right) \right) \left(\hat{\phi}_{jt} - \eta_{j} \right),$$

$$(2)$$

where $\hat{\mathcal{G}}_t/ij$ removes ij from the equilibrium networks.

I set the hospital negotiation cost r_i to zero because it is not clear the parameter is separately-identified from the insurer costs r_j (see Dorn (2025a)), and I assume the insurer costs r_j are constant for non-Highmark-BCBS insurers to increase statistical power.

The representation of profits in stage 3 as the sum of a pre-transfer flow profit function and negotiated transfers generalizes many, but not all, conceivable dynamic markets.

I implicitly rule out payments under null contracts. One could imagine modifying the game to include payments outside of a contract, for example through out-of-contract purchasing (Prager and Tilipman, 2022). I rule that out for conciseness. One could extend the Nash-in-Kalai model to cover these cases at the cost of yet more notation.

I model a negotiation cost borne after bargaining succeeds. Real negotiation costs are

borne both at the stage of preparing for negotiations (Gooch, 2019, ECG, 2020, Fletcher, 2020, Beier, 2020) and at the stage of carefully checking the terms of a potential agreement (STD TAC and Moss, 2014, PMMC, 2019, Fletcher, 2020). I model the bargaining friction as only the ex post cost to validate a potential agreement. Some work includes a sunk negotiation cost (Prager and Tilipman, 2022). Sunk costs can prevent firms from forming Pareto-efficient contracts. In a static model, sunk costs have the advantage of not entering into payments. In a forward-looking model, future sunk costs enter into current payments in a challenging way.

4.4 NPV Payment Moment

The dynamic Nash-in-Kalai bargaining model yields a moment on expected NPV payments, and as a result the econometrician can construct moments on payments for estimation. The moment naturally generalizes the static Nash-in-Nash bargaining moment to incorporate multiple periods of gains from trade.

I maintain some regularity conditions.

Assumption 1. (Regularity conditions)

Players are risk-neutral, share rational expectations, and follow Markov strategies. If ij reach their null contract in t_s and do not negotiate a new contract in t_{s+1} then ij reach their null contract in t_{s+1} . There is a uniform transversality condition: if $\mathcal{F}_{t_r|t_s}(\mathcal{I}_{t_s})$ is the set of feasible information sets in period $t_r \geq t_s$ after information \mathcal{I}_{t_s} is reached in period t_s , then

$$\lim_{h \to \infty} \sup_{\mathcal{I}_{t_s}} \sup_{\mathcal{I}_{t_{s+h}} \in \mathcal{F}_{t_{s+h}|t_s}(\mathcal{I}_{t_s})} \sup_{i} \beta^{h/m} \left| V_{i,t_{s+h}}^{(1)}(\mathcal{I})(\mathcal{I}_{t_{s+h}}) \right| = 0.$$

I will assume a Nash-in-Kalai equilibrium.

Definition 1 (Nash-in-Kalai equilibrium). A Nash-in-Kalai equilibrium is a conditional random variable distribution $\mathcal{I}_{t_s} \mid (\mathcal{I}_{t_{s-1}}, \mathbb{C}_{t-1})$, a bilateral contract choice distribution $\hat{\mathbb{C}}_{t_s,ij}(\mathcal{I}_{t_s})$, and recursive value functions such that (i) all strategies are Markov strategies, (ii) any strategies in the formation of \mathcal{I}_{t_s} are in the appropriate equilibrium, and (iii) for every ij and every subgame, the expected NPV profit of the distribution of $\hat{\mathbb{C}}_{t_s,ij}(\mathcal{I}_{t_s}) \mid \mathcal{I}_{t_s}$ when taking other strategies as given solves the Kalai proportional bargaining problem over value functions with bargaining weight $\tau_{ij} \in [0, 1]$ on player j > i.

The expected NPV payment is as follows.

Theorem 1 (Nash-in-Kalai Moment). Consider a dynamic Nash-in-Kalai equilibrium that satisfies Assumption 1. Suppose players i < j form a contract in a subgame time t_0 that remains in place through the (potentially random) terminal time t^{*} with (potentially random) realized prices p_{ijt}^* . Then the expected NPV of realized payments $D_{t_s,ij}p_{ijt_s}^*$ at the moment of contract formation is equal to the sum of the expected NPV of flow period Nash-in-Nash payments, a negotiation cost payment, and an impasse repricing payment term:

$$\mathbb{E}_{t_0}\left[\sum_{t_0 \le t_s \le t^*} \beta^{\frac{t_s - t_0}{m}} D_{t_s, ij} p^*_{ijt_s}\right] = \operatorname{Pay}_{NiN} + \operatorname{Pay}_{NC} + \operatorname{Pay}_{IRT},\tag{3}$$

where the expected NPV of static Nash-in-Nash payments is:

$$\operatorname{Pay}_{NiN} = \mathbb{E}_{t_0} \left[\sum_{t_0 \le t_s \le t^*} \beta^{\frac{t_s - t_0}{m}} \left(\begin{array}{cc} -\tau_{ij} & ([\Delta_{ij} \pi_{it_s}] + [\Delta_{ij} T_{it_s, -j}]) \\ + (1 - \tau_{ij}) & ([\Delta_{ij} \pi_{jt_s}] + [\Delta_{ij} T_{jt_s, -i}]) \end{array} \right) \right],$$
(4)

the negotiation cost payment Pay_{NC} is equal to $\tau_{ij}r_i - (1 - \tau_{ij})r_j$, and the impasse repricing payment Pay_{IRT} is:

$$\operatorname{Pay}_{IRT} = E_{t_0} \left[\sum_{t_s \ge t_0} \beta^{\frac{t_s - t_0}{m}} \left\{ \begin{array}{cc} -\tau_{ij} & \left(\hat{\pi}^A_{it_s} + \hat{T}^A_{it_s} - \hat{\pi}^D_{it_s} - \hat{T}^D_{it_s} \right) \\ + (1 - \tau_{ij}) & \left(\hat{\pi}^A_{jt_s} + \hat{T}^A_{jt_s} - \hat{\pi}^D_{jt_s} - \hat{T}^D_{jt_s} \right) \end{array} \right\} \right],$$
(5)

where $\hat{\pi}_{t_s,k}^A$ and $\hat{T}_{t_s,k}^A$ correspond to the (potentially random) path of profits and net transfers if ij enter their impasse point beginning in period $t^* + 1$ and the ij equilibrium contract is replaced with the ij null contract in periods t_0 through t^* , and where $\hat{\pi}_{t_s,k}^D$ and $\hat{T}_{t_s,k}^D$ correspond to those paths if ij enter their impasse point beginning in period t_0 .

Proof. Dorn (2025a).

This is a generalization of the static Nash-in-Nash bargaining payment, which corresponds to the case of no uncertainty and myopia ($\beta = 0$). In many empirical applications, the realized payments $D_{t_s,ij}p_{ijt_s}^*$ can be observed, the flow Nash-in-Nash payments in Pay_{NiN} depend on estimable demand functions and a small number of bargaining parameters, and Pay_{NC} depends on only a few parameters.

The term Pay_{IRT} accounts for the fact that in future periods, the Nash-in-Nash disagreement point differs from the Nash-in-Kalai impasse point. The static Nash-in-Nash gains used in Pay_{IRT} are calculated relative to disagreement under the non-*ij* contracts formed in equilibrium, while the Nash-in-Kalai gains are calculated relative to disagreement under the non-*ij* contracts formed when continually expecting expecting *ij* to exit impasse. I approximate Pay_{IRT} to zero; it is zero in steady state (Dorn, 2025a).

Based on Theorem 1, the initial price $p_{ijt_0}^*$ given expectations over the distribution of

benchmark prices $p_{it}^{B_{ijt}}$ and expiration t^* solves:

$$p_{ijt_0}^* \mathbb{E}_{t_0} \left[\sum_{t=t_0}^{t^*} \beta^{t-t_0} D_{ijt}^H (\mathcal{G}_t, \phi_t) \frac{p_{it}^{B_{ijt}}}{p_{it_0}^{B_{ijt}}} \right] = \mathbb{E}_{t_0} \left[\sum_{t=t_0}^{t^*} \beta^{t-t_0} \left(-\tau_{ij} \left[\Delta_{ij} \pi_{it}^H \right] + (1 - \tau_{ij}) \left[\Delta_{ij} \pi_{jt}^M \right] \right) \right] - (1 - \tau_{ij}) r_j.$$

The left-hand side is observed up to the patience parameter β . The right-hand side depends on the insurer's bargaining weight τ_{ij} , negotiation costs r_j , hospital demand D^H , insurer demand D^M , hospital costs c_i , insurer noninpatient costs η_j , and prices per unit of care p.

I parameterize the bargaining weights as an insurer fixed effect with hospital size effects on a logit scale:

$$\log\left(\tau_{ij}/(1-\tau_{ij})\right) = \log(\tau_j/(1-\tau_j)) + \tau^{Size}\log(HospSize_{i,2006}/MeanHospSize_{2006}), \quad (6)$$

where hospital size is measured as the size of the bargaining system in my first year of 2006 and τ_j is insurer bargaining power measured at the average-sized hospital system. Larger hospitals have more bargaining weight if τ^{Size} is negative. I assume that the insurer bargaining weight parameter τ_j is shared for the for-profit insurers I model (Aetna, Cigna, Carelink, and UnitedHealth). In estimation, I allow τ_j to be below 0 or above 1 as a plausibility test; if that happens, then I take $\tau_{ij} = \tau_j$.

5 Estimation of Bargaining Model

Unlike the previous static literature, I estimate bargaining parameters with only new contracts and allow negotiators to balance gains from trade over multiple periods. I find that a forward-looking model is more accurate than the existing static or myopic approaches: I estimate a discounting rate of $\beta = 0.899$ and clearly reject the null hypothesis of myopia that corresponds to the static model's one-period estimation with accurate contract timing.

5.1 Estimation

In the interest of brevity, I include only a high-level summary of my estimation procedure here.

Table 2 presents count statistics for the full contract data, the contract data involving the six modeled insurers, and the 63 contracts used in bargaining estimation.

I complement the novel contract data with more standard data on hospital and insurer quantities demanded. I use 2016 uniform billing (UB) data to estimate hospital and insurer

Table 2: Count statistics for all hospital-insurer years (All Contracts), hospital-insurer years with modeled insurers (Modeled Contracts), and hospital-insurer years used in bargaining estimation (Estimation Bargains).

| Data | Hospitals | Hosp. Systems | MCOs | System-MCO Pairs | System-MCO Years | Bargain Count |
|---------------------|-----------|---------------|------|------------------|------------------|---------------|
| All Contracts | 38 | 33 | 168 | 613 | 5108 | |
| Modeled Contracts | 35 | 30 | 6 | 159 | 1482 | |
| Estimation Bargains | 32 | 27 | 6 | 53 | 289 | 63 |

quantities demanded for identified insurers. The UB data is discharge data on every inpatient stay in West Virginia, and identifies primary payor if the primary payor is one of Aetna, Highmark BCBS, or HPUOV. The data is not claims data, because it does not include negotiated or realized payments. I estimate insurance demand for previous years and other modeled insurers using data on annual sales and premiums in the West Virginia fully insured market. The insurer fully insured sales data is digitized from state-level accident and health reports like Offices of the Insurance Commissioner (2016). The reports cover every plan sold in which an insurer is paid a premium to provide comprehensive medical insurance. I also use state financial reports on Medicare rates in supplemental analyses.

I estimate hospital demand with maximum likelihood. I group diagnoses into one of six main categories based on Ho (2006)'s International Classification of Diseases (ICD) categories (see Appendix Table 5 for frequencies). I adapt the notation of Ho (2006), but similar models are widely used (Capps et al., 2003, Gowrisankaran et al., 2015, Ho and Lee, 2017, Prager and Tilipman, 2022). I assume that the utility of a potential hospital is a function of the patient's diagnosis, the hospital's quality, and the patient's location. In particular, I assume the utility of consumer i visiting in-network hospital h with diagnosis ℓ (cancer, cardiac, digestive, labor, neurological, or other) is:

$$u_{i,h,\ell}^H = \delta_{h,\ell}^H + \nu_{i,h,\ell}\rho + \varepsilon_{i,h,\ell}$$

where $\delta_{h,\ell}^{H}$ is a hospital-diagnosis fixed effect, $\nu_{i,h,\ell}$ are patient-hospital characteristics (distance in miles, distance squared, and distance interacted with emergency), and ε is a type 1 extreme value shock. I estimate the model with Blue Cross patients in 2016, as all hospitals are in-network for Blue Cross.

Hospital demand is identified by selection on observables. If consumers are highly likely to choose Charleston Area Medical Center (CAMC) relative to Saint Francis Hospital one mile away, my estimates will infer that CAMC offers more utility to consumers after adjusting for location. The degree to which patients with similar diagnoses choose closer hospitals identifies the ρ distance coefficients. There are three key assumptions for the hospital demand model to be accurate for bargaining estimation. First, Blue Cross hospital choice should be

representative of the generic patient's hospital choice decision conditional on location and diagnosis (i.e., no endogeneity of insurance choice with respect to hospital value). Second, observed choices should identify counterfactual choice probabilities with different hospital choice sets (i.e., unconfoundedness and correct functional form). Third, the observed hospital choices should capture the value of hypothetical hospital networks when choosing an insurer before the realization of diagnosis.

I estimate insurer demand mainly using cross-sectional data from 2016, the year in which I have estimates of local sales. I leverage Affordable Care Act (ACA) premium restrictions, which prevented insurers from differentiating premiums within geographic rating areas beyond a limited set of homogeneously incorporated factors. I use these rating areas to control for most sources premium variation, and use the correlation of sales with network quality within rating areas to identify the effect of network quality on insurer sales. I assume that the utility of insurer j to consumer i in county c in ACA rating area m in year t is

$$u_{i,j,c,m,t}^{M} = \gamma_k WTP_{j,k,c,t} + \tilde{\delta}_{j,m,t}^{M} - \alpha \phi_{j,t} + \xi_{j,k,c,t} + \varepsilon_{i,j,c,m,t}$$

where $\delta_{j,k,m}^{M}$ is an insurer-rating-area fixed effect that includes premium levels, $WTP_{j,k,c}$ (Capps et al., 2003) is the ex ante expected utility of insurer j's network to an individual of age-group k in county c, γ_k are age-group-dependent coefficients on WTP, $\xi_{j,k,c}$ is an age-county unobservable, and ε is a type 1 extreme value shock. Similar models have been used by Ho and Lee (2017) and Ghili (2022). The equation is estimated using the moment $E[WTP_{j,k,c,2016}\xi_{j,k,c,2016}] = 0$, matching observed county-age shares for insurers identified in the inpatient data, and matching state-level sales for all modeled insurers in each year. I assume that the insurer-rating area fixed effects $\delta_{j,m}^{M}$ are constant across markets for the two insurers that are not identified in the inpatient data, Cigna and UnitedHealth.

Insurer demand is identified based on variation in network quality conditional on premiums. Insurer regional coverage was heterogeneous within West Virginia's 11 market rating areas (see Figure 5). The γ_k coefficients are identified by the degree to which consumers are more likely to choose an insurer with better coverage within a rating area that standardizes premiums. The key identification assumption is exogeneity: the market-level unobservables should be uncorrelated with network quality itself. The premium sensitivity is calculated to match the average premium elasticity from Ho (2006), which corresponds to a coefficient on premiums of $\alpha = -0.00032$. The main threat to identification is variation in large-group employer premiums within rating area, which were likely to be small, and variation in selfinsured employers' expected costs, which I abstract from based on data limitations. I discuss these and some other caveats in demand estimation in Appendix B.4.



0% 25% 50% 75% 100%

Figure 5: Percent of 2016 inpatient discharges by county of residence that are in the 2015 reported network of (clockwise from top-left) Aetna, Cigna, UnitedHealth, and the Health Plan of the Upper Ohio Valley. Highmark BCBS (omitted) is in-network in all West Virginia hospital reports. The large cities of Charleston, Huntington, Morgantown, Wheeling, and Pittsburgh, PA are indicated by letter labels.

I estimate bargaining parameters through GMM on estimated and predicted net present value payments. Unlike existing static approaches, I allow negotiators to balance gains from trade over the multiple years in which their contract remains in place, and I only use new contracts with reliable start and end dates in estimation. I estimate a finite-horizon bargaining model, because West Virginia was nonstationary which precludes estimating a compelling infinite-horizon model. I consider the first T = 5 years of gains from trade, which I take as an approximation to an infinite-length model. Because of the finite horizon model, I allow for a discounting rate of one in estimation as an improper limit.

My bargaining instruments are insurer and grouped-hospital-size dummy variables. Larger insurers and smaller hospitals were more likely to reach contract with shorter duration and slower price growth. As a result, increases in the discounting rate β have a larger effect on NPV payments for these firms. Both instruments also identify the bargaining weight heterogeneity. The key identifying assumption is an exclusion restriction for the effect of hospital and insurer identity on payments. I identify insurer noninpatient costs η_j using moments on reported medical spending, which come from Centers for Medicare & Medicaid Services reports. My main specification uses hospital reported costs as a proxy for the opportunity cost of inpatient care, although I consider other cost models as robustness checks. I bootstrap standard errors by resampling inpatient cases and state-level sales.

Identification of bargaining parameters comes from various sources. The η_j insurer noninpatient costs are identified primarily from the CMS medical loss ratio reports but are shifted by the GMM procedure based on observed payments. The flow gains from trade $[\Delta_{ij}\pi]$ are identified from estimated demand, noninpatient costs η_j , and calibrated hospital costs c. The τ_{ij} bargaining weights are identified by average realized gains from trade by hospital and insurer. The β discounting rate is identified by the correlation of anticipated benchmark inflation and starting prices conditional on average gains from trade. The r^M negotiation costs are identified from any remaining differences in the levels of payments and the levels of predicted payments. I discuss potential biases in Appendix

See Appendix B.1 for more on estimation, Appendix B.3 for a detailed description of the data analysis, and Appendix B.4 for key caveats.

5.2 Parameter Estimates

I estimate an annual patience parameter of $\beta = 0.899$ and overwhelmingly reject the null hypothesis of myopia ($\beta = 0$). My estimated hospital and insurer demand systems are generally plausible, with parameter estimates presented in Appendix B.6.

I present bargaining estimates under two models, both of which use the same hospital and insurer demand estimates. The first strategy is a *myopic* approach that estimates bargaining parameters for contracts with confirmed start and end dates, but constrains the discount rate β to zero to recover a static-type estimation strategy. The second strategy is a *forwardlooking* approach described above, which allows the annual discount rate β to take on any value between zero (myopia) and one (no discounting after CPI inflation).

The bargaining estimates are presented in Table 3. The staggered nature of contracting in Section 3 rejects a truly static model, and the forward-looking estimates reject a myopic

| | | | Parameter | | |
|-----------------------------------|-------------------------|---|---|---|---|
| | eta | $	au_{BCBS}$ | $	au_{HPUOV}$ | $	au_{FP}$ | $-\tau^{Size}$ |
| Myopic (Nash/Kalai) | \cdot (\cdot) | $\begin{array}{c} 0.876^{***} \\ (0.012) \end{array}$ | $\begin{array}{c} 0.825^{***} \\ (0.232) \end{array}$ | $\begin{array}{c} 0.861^{***} \\ (0.034) \end{array}$ | $\begin{array}{c} 1.037^{***} \\ (0.199) \end{array}$ |
| Forward-Looking $(Pay_{IRT} = 0)$ | 0.899^{***} (0.03) | $\begin{array}{c} 0.854^{***} \\ (0.006) \end{array}$ | $\begin{array}{c} 0.877^{***} \\ (0.026) \end{array}$ | 0.889^{***} (0.005) | $\begin{array}{c} 0.989^{***} \\ (0.028) \end{array}$ |
| Note: | | | *p<0. | 1; **p<0.05; | ***p<0.01 |

Table 3: Estimated bargaining and patience weights for the myopic (first row) and more general forward-looking (second row) bargaining models. The MCO τ_j bargaining weights are estimated for Highmark BCBS (BCBS), HPUOV, and the modeled for-profit insurers (FP) and represent the insurer's predicted share of gains from trade at the average bargain's hospital bargaining system log 2006 size. I present estimates of noninpatient costs (η) and net negotiation costs (r_j) in Appendix Table 9. Estimates under alternative bargaining models are presented in Appendix Table 4.

model in which negotiators only value one period of gains from trade. My estimated model overwhelmingly rejects a null hypothesis of myopia. My estimated patience parameter of $\beta = 0.899$ also rejects a null hypothesis of one. These indicate that firms care about future period profits ($\beta > 0$) but value a dollar today less than a dollar tomorrow ($\beta < 1$). I find excellent model fit (Appendix Figure 10). The results are qualitatively similar under most other specifications (Appendix Table 4).

The forward-looking model does a better job of predicting initial rates than the myopic model, even though the forward-looking model targets payments in later contract years. For example, the correlation between forward-looking and myopic predicted and real starting share of list prices is 0.521 and 0.452, respectively (Appendix Figure 11).

The estimated bargaining weights are generally empirically plausible. I find little heterogeneity in bargaining power across insurers: I estimate that insurers keep 85%–89% of the joint surplus when bargaining with a medium-sized hospital system (Table 3). The estimated weights are somewhat larger than other estimates in the literature based on claims data (Ho and Lee, 2017, Ghili, 2022). There is no restriction in my estimation procedure that both sides must gain from the negotiated contracts, so it is reassuring that the myopic and forward-looking models estimate bargaining weights τ_{ij} between zero and one.

6 Counterfactual Analysis

Medicare pays hospitals at rates that the American Hospital Association argues have deflated related to costs (AHA, 2022). I ask how a counterfactual change in Medicare rates to roughly track West Virginia hospital reported cost growth would affect spending in the private insurer market. I apply the estimated model to quantify this effect. I find that Medicare benchmark dynamics have an important role in private insurer spending, but a myopic model lacking forward-looking responses would both substantially overstate the effects and miss important short-run dynamics.

The exact counterfactual is an additional one-percentage-point annual increase in hospital prospective prices, announced at the end of 2006 to begin in 2007. The one-percentage-point increase would roughly offset the divergence between West Virginia Medicare rates and hospital costs in this era. The change would correspond to a \$26.5-billion increase in 2015 Medicare hospital expenditures (CMS, 2022, expressed in 2019 dollars). I do not have access to the DRG weight schemes used in the construction of payments, so I assume all prices imputed as prospective would increase one percentage point faster annually beginning in 2007. My counterfactual can also be interpreted as quantifying the impact of requiring these contract prices to inflate one percentage point faster annually.

Counterfactual payments are calculated as follows. I first calculate counterfactual contract prices holding benchmark choice, contract length, premiums, and NPV residual payment fixed, and using plug-in estimates of counterfactual benchmark price growth. This forms a linear price system, which can be solved in closed-form. I then estimate downstream premium effects based on the Nash-Bertrand premium competition model. I do not estimate the reinforcing effects between prices and premiums, which is conservative. I discuss these choices further in Appendix B.1.

I summarize the effects by year under a hypothetical static model, the estimated forwardlooking model, and the estimated myopic model in Figure 6. The effects are presented as a percentage of modeled insurer spending, which is roughly three-quarters of all private insurer spending (Dorn, 2025b). A static model with one-period contracts (black) would fail to estimate any effect: even if Medicare doubled rates annually, Medicare-benchmarking negotiators could cut their contracted multiples in half and arrive at the same real outcomes. I find that contracts are multiyear, so that the reform will at least have a short-run effect.

Under the forward-looking model (blue), I estimate quantitatively meaningful spending effects and important short-run dynamics. In 2007–2009, many prospective contracts remained in place, so that Medicare's reform mechanically increases payments. Highmark BCBS and HPUOV revised many of these contracts in 2009, leading to a forward-looking



Figure 6: Estimated counterfactual spending effects from a one-percentage-point increase in Medicare rates from a myopic (blue) and dynamic (red) bargaining model. The dashed line indicates 0.20 percentage point additional annual spending increases starting in 2009.

price reduction to the point that spending would decrease. There is a similar dip in 2012 when Highmark BCBS revised the three-year contracts formed in 2009. In later years, contracts remain in place and effects compound. After nine years, the estimated increase in spending is 1.3%. The estimated increase in West Virginia spending in the commercially insured inpatient market would be \$7.1 million. The percent change in spending after nine years, if extrapolated to the 2015 national hospital market and inflation-adjusted to 2019 dollars, corresponds to a \$4.98-billion effect. I present effects on insurer payments, hospital payments, and premiums in Appendix Figures 12, 13, and 14, respectively.

A myopic model (blue) would miss these short-run dynamics. In the middle of the panel, when the reform would have a small or negative effect, the myopic model incorrectly predicts a substantial spending increase. In the longer-term, the myopic model overestimate the effects by 45% or more. The reason the myopic bargaining model overestimates the effects of benchmark price increases is because forward-looking bargainers respond to anticipated future increases, while myopic bargainers only care about accumulated increases so far. In contrast, a static model of period-by-period contracting would be biased in the opposite direction, by ruling out any effect at all.

The estimated 2015 spending increase of 1.319% is below the compounded benchmark price increase of 9.37% for three main reasons: many payments were benchmarked to unaffected list prices, the Medicare-benchmarked contracts were renegotiated every few years, and forward-looking bargainers revise starting prices downward based on the anticipated future benchmark price increases. I measure the importance of the first mechanism by considering

a same-multiple model, wherein the firms keep their original negotiated benchmark multiples α in place. Appendix Figure 15 presents the different estimated effects. The mechanical model that leaves benchmarks and multiples in place accounts for only the first response, and would estimate a massive nine-year effect that corresponds to nine compounded 0.564 percentage point spending increases. As seen in Figure 6, the myopic model is not nearly so extreme by allowing negotiators to respond to accumulated benchmark increases and adjusted contractual externalities, but still substantially overestimates the effect and misses important dynamics like a spending reduction in 2009.

7 Discussion

This paper studies the effect of benchmark inflation on real spending. For this question, the key empirical quantities are whether contracts are multiyear and staggered and whether negotiators discount future profits. This work leverages new public record data on hospital– insurer contracts to demonstrate that real-world contracts are multiyear and staggered and to test whether negotiators care about future periods as much as current periods, if at all. I overwhelmingly reject the null hypothesis of myopia that corresponds to static-type estimation with accurate dynamic timing, but also find that negotiators discount future profits.

I leverage the estimated empirical Nash-in-Kalai bargaining model to quantify the effect of proposed government-set rate increases. I find that forward-looking responses would offset 32% of the increase after nine years, and lead to a payment reduction in one year. Nevertheless, I find that the proposed dynamic increase to Medicare rates would have significant effects on private insurer spending — a mechanism that existing static models cannot capture.

The empirical analysis here opens up exciting new avenues for future empirical work. In the West Virginia context, my companion paper Dorn (2025b) documents that smaller insurers experienced rapid price increases under long-lived contracts. A forward-looking model is needed to quantify the impact of these contracts on competition, spending, and premiums. Further, static approaches to antitrust questions, such as merger effects, typically assume that all contracts in a market were recently formed. In West Virginia, such static models would underestimate smaller insurers' bargaining power by misattributing fast ex post price increases to a lack of ex ante bargaining power. Future work can explore the implications of staggered contracting and predictable price dynamics for antitrust analysis and other questions around market power.

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A Additional Theoretical Content

A.1 Additional Assumptions

The good-faith disagreement assumption is as follows.

Assumption 2 (Good-faith disagreement). Let $G_{t:T|t-1}^{(3)}$ be the distribution function of equilibrium networks $\hat{\mathcal{G}}_t, \ldots \hat{\mathcal{G}}_T$ in stage 2 of period t as a function of the history h^{t-1} reached at the end of stage 3 of period t-1. Consider some subgame period t_0 in stage 2. Let h^{t_0} be a draw from the support of the t_0 subgame equilibrium of stage 2. Let \hat{h}^{t_0} be the history formed by replacing the ij contract with the null contract. Then for all finite T, $G_{t:T|t-1}^{(3)}(h^{t_0}) = G_{t:T|t-1}^{(3)}(\hat{h}^{t_0})$.

Assumption 2 essentially says that bargainers attempt to exit impasse as soon as possible: if ij bargaining fails in period t_0 , then i returns to j's network as soon as they would have been in-network in equilibrium. Future networks are assumed to be unaffected by ij disagreement because everyone continues to expect ij to reach a contract.⁶ Good-faith disagreement is in line with the empirical rarity of disagreement, which suggests disagreement is painful and consistently avoided. The good-faith assumption is also in line with the Nash-in-Nash bargaining model's Nash equilibrium assumption: under single-period Nash-in-Nash bargaining, contracts are formed assuming other bargains will succeed. I implicitly rule out any effect of current networks on subsequent future demand. If Assumption 2 did not hold and disagreement affected subsequent networks, as in Lee and Fong (2013)'s model, then the form of payments would be modified to incorporate the effect of impasse on subsequent network formation.

A.2 Appendix Proofs

Proof of Proposition 2. I begin with Kalai proportional bargaining with two periods of exclusion when u = 0. Two-period bargaining with two periods of exclusion is equivalent to

⁶The assumption only refers to one disagreement, but Assumption 2 rules out continued impasse affecting subsequent networks by inductively applying the following argument to construct $t_0 + 2$ networks under impasse. First draw $t_0 + 1$ networks from $G^{t_0(3),t+1:\infty}(\hat{h}^{t_0(3)})$, which by Assumption 2 is the same as drawing from $G^{t_0(3),t+1:\infty}(h^{t_0(3)})$; then draw $h^{t_0+1(3)}$ from the distribution of t_0+1 histories conditional on $\hat{h}^{t_0(3)}$ and $t_0 + 1$ networks; and then substitute the null contract for $ijt_0 + 1$. This process generates the distribution of $(\mathcal{G}_{t_0+1}, \mathcal{G}_{t_0+2})$ under impasse. By Assumption 2 applied to both draws, this process generates the same distribution as drawing $(\mathcal{G}_{t_0+1}, \mathcal{G}_{t_0+2})$ from $G^{t_0(3),t+1:\infty}(h^{t_0(3)})$.

static bargaining but prices are scaled by $1 + \beta(1 + \pi)$ and insurer gains are scaled by $1 + \pi$. The proposed bargaining solution is a Kalai proportional solution when $p \ge 0$ so that both sides get weakly positive gains from trade. Any higher (lower) price would produce lower (higher) gains for the insurer and higher (lower) gains for the hospital and not be a Kalai proportional bargaining solution. Therefore this is the unique bargaining solution.

Continuing in the u = 0 case, Kalai proportional bargaining solution with one period of exclusion has the same solution by the step-by-step property, which I now verify. Suppose the insurer bargains with hospital h in period t_0 relative to negotiating in period t_0+1 . Write $V^{(d),H}(p_0, p_1, p_2)$ and $V^{(d),M}(p_0, p_1, p_2)$ as the value of disagreeing d times with anticipated hospital h prices p_0, p_1, p_2 . Let \hat{p}_0 be the proposed price and $\hat{p}_1^{(1)}$ be the Kalai proportional response after one disagreement. By construction, the proposed price satisfies

$$(1-\tau)\left(V^{(0),M}(\hat{p}_{0},\hat{p}_{1}^{(1)},p_{Simult}^{*})-V^{(2),M}(\hat{p}_{0},\hat{p}_{1}^{(1)},p_{Simult}^{*})\right)$$
$$= (\tau)\left(V^{(0),H}(\hat{p}_{0},\hat{p}_{1}^{(1)},p_{Simult}^{*})-V^{(2),H}(\hat{p}_{0},\hat{p}_{1}^{(1)},p_{Simult}^{*})\right).$$

By definition, the Kalai proportional bargaining price after 1 disagreement satisfies:

$$(1 - \tau) \left(V^{(1),M}(\hat{p}_0, \hat{p}_1^{(1)}, p^*_{Simult}) - V^{(2),M}(\hat{p}_0, \hat{p}_1^{(1)}, p^*_{Simult}) \right)$$

= $(\tau) \left(V^{(1),H}(\hat{p}_0, \hat{p}_1^{(1)}, p^*_{Simult}) - V^{(2),H}(\hat{p}_0, \hat{p}_1^{(1)}, p^*_{Simult}) \right).$

By subtraction:

$$(1-\tau) \left(V^{(0),M}(\hat{p}_0, \hat{p}_1^{(1)}, p_{Simult}^*) - V^{(1),M}(\hat{p}_0, \hat{p}_1^{(1)}, p_{Simult}^*) \right) = (\tau) \left(V^{(0),H}(\hat{p}_0, \hat{p}_1^{(1)}, p_{Simult}^*) - V^{(1),H}(\hat{p}_0, \hat{p}_1^{(1)}, p_{Simult}^*) \right),$$

so that $p_{Simult}^* = \hat{p}_0$ is a Kalai proportional bargaining solution. It is the unique simultaneous bargaining solution by the same arguments as the two-period exclusion case.

Now consider the u = 1 case. Suppose hospital 1 bargains with the insurer after hospital 2 reached the price p_{Alt}^* last period. In the current period, hospital 2's price is $(1 + \pi)p_{Alt}^*$.

With an agreement, the insurer will gain \$20m + 1,000 p_{Alt}^* this period and pay 3,000 $p_{Alt}^*(2+\pi)$ in every period. With a disagreement, the insurer will pay 4,000 $(1+\pi)p_{Alt}^*$ this period and 6,000 p_{Simult}^* in all future periods, where 3,000 $p_{Simult}^* = \frac{1-\tau}{1+\beta(1+\pi)}(\$20m(1+\beta)) + 1,000(1-\tau)p_{Simult}^*$ by Proposition 2.

With an agreement, the hospital will receive a net present value payment of $3,000p_{Alt}^*/(1-\beta)$. With disagreement, the hospital will receive a net present value payment of $3,000p_{Simult}^*\beta/(1-\beta)$.

The remainder of the proof is algebra to verify the proposed form of p_{Alt}^* splits gains from trade proportionally. I omit the details for brevity.

B Additional Empirical Content

B.1 Estimation Overview, Continued

I infer contract benchmarks based on the contract data. I infer that a payor with the same reported discount of list prices (or a difference of 0.01% after rounding) in consecutive hospital reports was a share of charges (list-price-benchmarked) contract that paid as a fixed discount of list prices. For the first observation of a hospital–payor pair, I infer that a round-number discount followed by a change of payor or a new share of charges contract was the final year of an expiring share of charges contract. I infer all other contracts were prospective and used Medicare as the benchmark.

I estimate a finite horizon model: I consider only the first T years of a contract in calculating gains from trade, where T = 5 for my current analysis. I cannot estimate a compelling infinite horizon model because West Virginia is nonstationary. I take T = 5 as an approximation: as the length of available data goes to infinity, T would go to infinity slowly to enable the number of bargains in estimation to go to infinity as well. The finite horizon makes a constant patience parameter β at best an approximation because the fifth year in should principle best approximate later years. The finite horizon model also calls for care in modeling how impasse affects other bargainers near the end of the horizon. I calculate gains from trade through 2016. Contracts in 2016 are calculated by linearly extrapolating list price levels from calendar year 2015 contract reports and extrapolating contract list price shares from 2015.

The utility equation includes only aggregate premium variation. Since 2014, the Affordable Care Act (ACA) restricts insurer premium setting substantially (CMS, 2023). Insurers set premiums (outside the large-group market) by geographic rating area defined by the state of West Virginia.⁷ Premium variation in 2016 is essentially subsumed into the $\tilde{\delta}_{j,m}^{M}$ insurer-rating-area fixed effects.

My counterfactual analysis must account for changes in insurer attractiveness and premiums over time. For years before 2016, I include an insurer-time fixed effect $\tilde{\delta}_{j,t}^M$. The fixed effect $\tilde{\delta}_{j,t}^M$ captures systematic changes in insurer value and premiums in previous years. I

⁷Insurers also have a limited ability to adjust premiums based on tobacco use, family size, and age. In practice, insurers applied at most a small adjustment for tobacco use, a similar adjustment for large families, and the same age multipliers. I hold these multiples fixed in my analysis.

solve for the values to match state-level sales by year after adjusting for changes in networks and local population. I discuss other estimation details in Appendix B.3.

The bargaining model is estimated based on observed and predicted payments for observed bargains. I use the estimated hospital and insurer demand systems as inputs to gains from trade in bargaining, with other bargaining parameters like the bargaining weights τ_{ij} and discounting rate β estimating through GMM. I define $\omega_{ijt}(\bar{\theta})$ to be the normalized NPV residual payment from ij negotiating in period t at parameters $\bar{\theta}$:

$$\omega_{ijt}^{p}(\bar{\theta}) = \frac{\sum_{t=t_{0}}^{t^{*}} \bar{\beta}^{t-t_{0}} \left(D_{ijt}^{H} p_{ijt}^{H} - \left\{ -\bar{\tau}_{ij} [\Delta_{ij} \bar{\pi}_{it}^{H}] + (1 - \bar{\tau}_{ij}) [\Delta_{ij} \bar{\pi}_{jt}^{M}] \right\} \right) - (1 - \bar{\tau}_{ij}) \bar{r}_{j}^{M}}{\sum_{t=t_{0}}^{\lfloor mean(t-t_{0}) \rfloor} \bar{\beta}^{t-t_{0}} + (mean(t-t_{0}) - \lfloor mean(t-t_{0}) \rfloor) \bar{\beta}^{\lceil mean(t-t_{0}) \rceil}}, \quad (7)$$

where a bar denotes a parameter that is estimating in my bargaining model and $mean(t-t_0)$ is the average bargain's number of years elapsed. The denominator is added to express ω_{ijt} in terms of the ij NPV payment and an aggregate normalization to avoid attenuating the estimated patience parameter β . (As seen in Appendix Table 4, I would estimate a similar $\hat{\beta}$ if I instead normalized by the average value of $\sum \beta^t$ across bargains used in model estimation.) My main specification calibrates hospital costs from reported hospital average costs, which should roughly track the outside option of Medicare rates if hospitals are near capacity, and adjust hospital costs in robustness tests. The parameters to estimate are the τ_j insurer bargaining weights, τ^{Size} contribution of size to hospital bargaining weight, β patience parameter, η_j insurer noninpatient costs, and payment-equivalent negotiation costs r_j .

Bargaining moments are constructed as follows. I take the NPV payment residual $\omega_{ijt}^p(\bar{\theta})$ from Equation (7). I define $\omega_{jt}^M(\bar{\theta}) = \sum_{t=2011}^{2016} \frac{\bar{\eta}_j D_{jt}^M + \sum_h D_{hjt}^h p_{hjt}}{\phi_{jt} D_{jt}^M} - MLR_{j,t}$ as the difference between model-implied medical loss ratio and the medical loss ratios $MLR_{j,t}$ reported to CMS for years 2011 and later. My moments are $E[Z^p \omega^p] = 0$ and $E[Z^M \omega^M] = 0$. The hospital-insurer payment instruments Z^p are insurer dummies and indicators for hospital size in six groups. The insurer medical loss ratio instruments Z^M are insurer dummies.

Similar strategies have been used with various datasets in static models, though there are important differences. Some notable papers with similar identification strategies are Grennan (2013), Gowrisankaran et al. (2015), Ho and Lee (2017, 2019), Ghili (2022), Liebman (2022) and Prager and Tilipman (2022). Gowrisankaran et al. (2015) and Prager and Tilipman (2022) assume insurers maximize a criterion other than profits. Grennan (2013) and Ghili (2022) have a non-zero-sum downstream response to negotiated prices, which could be partially captured in levels by my flexible hospital-insurer bargaining weight specification (Equation (6)). However, such time-varying NTU bargaining cannot fit into my Kalai proportional bargaining model for reasons discussed in (Dorn, 2025a). Ho and Lee (2019) and Ghili (2022) consider network formation in response to disagreement, which is at odds with my good-faith disagreement and simultaneous bargaining Assumptions 1 and 2. Many of these works estimate premium responsiveness (Gowrisankaran et al., 2015, Ho and Lee, 2017, 2019, Liebman, 2022, Ghili, 2022). I instead use market premium regulations to estimate demand given observed premiums and focus on price counterfactual effects that can be conservatively bounded without an estimate of premium responsiveness.

I interpret the ω^p NPV payment residuals as counterfactual-invariant unobserved components of gains from trade, and estimate starting payments that in counterfactuals leave ω^p unchanged. There may be slight bias from benchmark uncertainty via Jensen's inequality, which is likely to be second-order in my setting but could be accounted for by adapting tools from the time series literature.

The counterfactual assumes that benchmark choices would be unaffected, which is plausible for the narrowing counterfactual I consider. The choice of benchmark is highly associated with bargaining power and likely to be at most moderately affected by the change in benchmark dynamics. Most fixed-length contracts were formed by Highmark BCBS, so holding lengths constant mostly corresponds to assuming that Highmark BCBS would not change which contract terms were formed on a three-year or five-year basis and that the other insurers would not change their share of charges renewal strategies.

B.2 Discussion of Cooper et al.'s Work on Prospective Contracts

This work owes a tremendous debt to Cooper et al. (2019). In this section, I discuss how their work on prospective contracts relates to my analysis.

Cooper et al. (2019) estimate 74% of large for-profit insurers' prospective contract cases are paid as a fixed markup over Medicare and find that Medicare benchmarks are associated with larger hospitals. Negotiations of prospective contracts in West Virginia were more likely and more important at larger hospitals, both of which are associated with Medicare benchmark usage in Cooper et al. (2019)'s analysis. Reinhardt (2006) also claims that heterogeneous DRG weights were more typical. I cannot directly compare payment schemes in West Virginia to Medicare rates without access to claims or pricing data by insurer, but Highmark BCBS often used customized DRG weights in inpatient prices disclosed after my dataset ended, but used Medicare rates directly in outpatient calculations at the start of the era I study.

I do not have service-level price disclosures in the era I look at or reliable measures of Highmark BCBS price increases during the post-2021 price disclosure era. I therefore proceed in my main analysis assuming that Highmark BCBS DRG weight increases tracked Medicare rates whether Highmark directly used Medicare weights or used customized weights in the era I study. My analysis can also be interpreted as a counterfactual in which Highmark BCBS payment rates were required to increase one percentage point faster annually than in the status quo, regardless of how the payments were calculated. The choice of benchmark only enters the bargaining model through the realized prices. The distinction between Medicare as a benchmark and Medicare-based benchmarks with heterogeneous weights does matter to comparing services (that I aggregate into a generic unit of care) and the interpretation of the counterfactual for policy purposes.

Cooper et al. also argue that Medicare-benchmarked contracts were likely to be boilerplate take it or leave it offers. Cooper et al. do not directly measure boilerplate usage, but large insurers often make such offers to physicians (Abbey, 2012) and Highmark BCBS used shared markups over Medicare for outpatient care at some hospitals (Highmark West Virginia, 2011). That said, stakeholders did not recall boilerplate Highmark BCBS contracts, I have found qualitatively that Highmark BCBS prices disclosed under post-2021 regulations are often calculated as hospital-specific markups over a shared diagnosis-based schedule, and Highmark BCBS contracts were typically implemented at different times (Figure 3). I therefore conclude the use of boilerplate contracts in West Virginia was likely limited.

B.3 Detailed Data Description

The first step of data processing is cleaning the contract reports. I discuss this cleaning in Dorn (2025b). Networks are inferred by calendar year of submission, with missing years inferred from the closest report breaking ties to previous reports. There is a small amount of manual network handling. I drop contracts for nonstandard care like psychiatric care, lab fees, or professional fees. When an insurer reports multiple contracts (for example Highmark BCBS separately reports their indemnity and PPO contracts), I aggregate payments using the closest available reported number of discharges where possible. (I take an unweighted average if I never have estimated number of discharges per contract.) In this paper, I include First Health contracts as HPUOV contracts based on HPUOV's description of First Health as a "strategic partner" (Wayback Machine, 2021).

I focus on the regulated hospitals and treat the remote Critical Access Hospitals (CAHs) that were deregulated after 2000 as negligible. The state also allowed border hospitals to keep their contracts private. I use the fiscal year 2016 report to infer list price payment rates for Weirton Medical Center, and treat the small Williamson Memorial Hospital as equivalent to a CAH.

The estimation sample of bargains was identified manually. The main source was reported contract start and end dates in the panel contract dataset, but regulator contract decisions were also used as a supplement. I mitigate the bias introduced by Aetna's acquisition of Carelink at the start of 2015 by not including any contracts which lasted into 2016 (under the finite horizon) in bargaining estimation. I identify likely bargains for use in counterfactuals but not estimation based on remaining occasions on which either a contract was introduced, a share of charges contract was changed or replaced, a first year after expiration (with a change in discount rates), manual research suggests a change in payments, or the year after a contract was reported as being expected to expire, so long as the automatic processing identification does not happen in the last period in which I observe the contract. I treat the effective date as January 1 (except for one case in which other data suggests the contract began January 2).

In the inpatient data, I exclude rehab, long-term, and psychiatric hospitals; exclude newborns, residents of other states, and noncommercially insured patients (but including public employees who chose HPUOV to align with the fully insured sales data); take the hospital's main location from Medicare cost reports; and identify systems that reported joint contracts based on manual research. I assign patients locations by county geographic centroid. I estimate probabilities of patients having misclassified insurance status based on reported care frequencies where typos seem likely.

I infer diagnosis categories based on Ho (2006)'s classification of ICD-9 codes. The West Virginia inpatient data lacks ICD-9 codes and only has ICD-10 codes for 59% of discharges, so I convert the data's MS-DRG codes to ICD-10 codes using CMS (2020) and then into ICD-9 codes using NBER (2021). I supplement this conversion with manual research for common DRG codes this method fails to classify. I drop the 2% of cases for which the DRG conversion did not yield an ICD code and I did not reach an active category determination. Where this process maps multiple ICD-9 codes to the same DRG category, I choose the most common ICD-9 code's category.

I calculate Medicare payment-to-cost ratios from state uniform financial reports (UFRs) and linearly interpolate payment-to-cost ratios where missing in the available data.

I convert premiums and other monetary data to 2019 dollars based on consumer price index (CPI) inflation. Federal regulations precluded the state from collecting data on sales in the self-funded market. I infer self-funded sales in 2016 to match estimated combined sales in the UB data and use the fully insured market to infer premiums and insurer values before 2016.

There are some subtleties to my insurer data. Fully insured sales by insurer and selffunded sales estimates come from reports like Offices of the Insurance Commissioner (2008, 2016) for the comprehensive market. Insurer sales are aggregated by group code where possible and outliers are cleaned. In 2008–2009, sales were not reported. As a result, I linearly interpolate the missing lives and inflation-adjusted premiums. I similarly linearly interpolate the sales estimates for the ERISA (self-funded) market for missing years. I calculate MLRs from 2011–2018 CMS reports for West Virginia business in the individual, small-group, and large-group markets. I aggregate MLRs by NAIC company code where available and by name where NAIC codes are not available and take the numerators and denominators from the MLR_NUMERATOR and MLR_DENOMINATOR variables in part 5 (for 2011–13) or part 3 (for 2014 and later) of the reports. I aggregate medical loss and premium revenue across insurance products by group code. Inflation rates are calculated using World Bank CPI inflation over years relative to 2019 from the priceR package: 2017 nominal payments are inflation-adjusted based on the inflation rates reported for 2017 and 2018.

Hospital demand and ex ante WTP are calculated as follows. I calculate the probability of any diagnosis in the inpatient data in 2016 conditional on age, assuming each person has at most one inpatient discharge per year. I then obtain the potential hospitals each Highmark BCBS patient could have visited and run a weighted logit regression of choice on hospital and ν characteristics by diagnosis. The regression is weighted to include probability-of-Blue-Cross-weighted choices at hospitals that misclassified Blue Cross care. I then extrapolate the estimates to calculate the ex post willingness to pay for every conceivable county-agehospital combination conditional on diagnosis and aggregate the measure into an ex ante WTP measure for every hospital-insurer-age-location-year combination. The WTP measure is calculated as follows:

$$WTP_{j,k,c} = \sum_{\ell} \mathbb{P}(\text{Diagnosis } \ell \mid \text{Age group } k) \log \left(\sum_{h \in \mathcal{G}_j^M} exp(u_{c,h,\ell}^H) \right),$$

where the $u_{c,h,\ell}$ ex ante hospital utility to a consumer in county c with diagnosis ℓ is from the hospital choice model.

Insurer demand estimation is an involved process involving substantial data cleaning for 2016 alone. I first estimate insurer sales based on the fraction of commercially insured inpatient diagnoses from an age group in a county in the inpatient data. The county commercially insured population is taken as the Census intercensal population estimate multiplied by the state estimated fraction of age group with commercial insurance in the inpatient data. I then adjust the inpatient data to ensure every insurer has at least one estimated sale per age-county (taking the needed population from other sales estimates proportionally) and then include non-Highmark (other state) Blue Cross in the outside option. I infer state-level insurer sales in the self-funded market in 2016 for Aetna, Highmark BCBS, and HPUOV based on the difference between state-level sales estimates and state-level fully insured sales. I extrapolated self-funded sales for the two insurers not identified in the inpatient data, Cigna and UnitedHealth, by assuming the sales ratio between the markets is equal to the median estimated ratio. I scale down estimated sales to insure the modeled insurers never exceed 85% of a county-age group's estimated sales individually or exceed 90% in aggregate.

Once sales are estimated, I estimate insurer demand with an outer loop-inner loop algorithm. I An outer loop proposes Cigna and UnitedHealth δ^M fixed effects (including statelevel premiums) and an inner loop produces county-age-insurer implied values of $\gamma_k WTP_k + \xi$ to fit age-insurer-county ales estimates for the modeled insurers. I then iteratively update the Cigna and UnitedHealth fixed effects based on the current WTP coefficient estimates until conversion. The WTP coefficients are calculated by market-size-weighted regression of $\gamma_k WTP_k + \xi$ (inferred from 2016 sales estimates) on WTP_k (from hospital demand and sickness probabilities). To calculate pre-2016 demand, I calculate pre-2016 WTP in utility by insurer, county, and age. I solve for changes to state-level insurer value (inclusive of state-level premiums) to match state-level sales after adjusting for county-level population changes and ASO market size changes changes. I assume that Carelink's ξ values before its acquisition by Aetna at the end of 2014 were equal to Aetna's values in those same markets.

For bargaining, I estimate the effect of insurer network on hospital and insurer sales as follows. I predict sales under both the observed networks and under counterfactual networks that drop the insurer–system pair at the observed premiums. (Premium changes would be measured in Pay_{IRT}, which estimation currently sets to zero.) I measure the effects for a bargain year as a weighted average of calendar years: if a bargain began 3/4 of the way through 2010, then the first year of gains from trade under the bargain will be a weighted average of 1/4 of the gains from 2010 and 3/4 of the gains from 2011. I calculate the inputs to gains from trade, like the change in hospital costs, for the bargaining estimator. For calculating τ_{ij} hospital heterogeneity, I calculate hospital costs incurred in 2006 as the sum of reported list prices multiplied by the estimated cost-to-charge ratio. I calculate demand estimates from the estimated models to mitigate reporting endogeneity.

The bargaining optimization proceeds as follows. For constructing τ_{ij} , I normalize log hospital system size by the mean log system size in bargaining to report τ_j at the mean. The hospital groups in the price instruments Z^p are chosen to group hospitals by approximate size while ensuring a reasonable number of bargains for each hospital group: the hospitals are first ordered by the quantity of NPV realized payments in estimation bargains if β were equal to 0.8, and then split into six groups based on quantiles of payments taken to the power of 0.3, a quantity which was chosen to balance information with group size. Bargaining parameters are optimized over a simple moment weighting that tries to make the scales roughly comparable across moments: it weights MLR squared moments by 10^5 and normalized payment squared moments by the average NPV payment if β were equal to 0.8 (with the ω -style denominator normalization) by the relevant hospital group or insurer. The optimization attempts to reoptimize 10 times before returning the estimated parameters. Standard errors are calculated by bootstrap by resampling inpatient cases and state-level insurance choices 100 times. The bootstrapped confidence intervals for counterfactuals take the estimated demand functions as fixed and incorporate the uncertainty in bargaining parameters.

The counterfactual calculation process is as follows. I take the estimated $\hat{\tau}_{ij}$ from the relevant bargaining models, calculate payment multiples to infer the realized counterfactual ratio of starting price to NPV payment, and add 2016 data based on 2015 for computing counterfactual effects on late inferred bargains. There is some further data handling around the Aetna-Carelink acquisition at Davis Medical Center, which had a contract with Carelink but not Aetna before the acquisition. On the rare occasion that a midyear negotiation led to a change of benchmark, I infer the smaller starting price, which increases the forward-looking offsets slightly. I construct realized price transition matrices and matrices of the expost effect of future prices on bargained prices, calculate the realized residual (including demand-driven components of gains from trade) which is held fixed in counterfactuals, confirm that geometric-sum estimates would converge, calculate counterfactuals by matrix inversion, and calculate some summary statistics for later analysis.

The specific implementation of counterfactuals involves substantial data cleaning. I calculate when contract terms were changed under a modeled or inferred bargain. Counterfactual prices are adjusted at the start the year of negotiation or inferred change. Negotiations inferred from an expected expiration date past the final contract report are implemented at the start of the next calendar year to allow for potential roll-over. There is further data cleaning, for example ensuring that new bargains are not inferred during years that are a part of an estimation sample bargain, ensuring inferred benchmark choice by year is consistent with the inferred negotiation dates around the Aetna/Carelink acquisition, and holding fixed some small hospitals that did not provide inpatient data in 2016 that was used to estimate hospital demand.

I estimate downstream premium effects based on Ho (2006)'s estimated own-price elasticity. I calibrate a coefficient on inflation-adjusted premiums to match the estimated average own-price elasticity of -1.4. I solve for the wedge in insurer-year marginal cost needed to make realized premiums optimal under simultaneous annual Nash-Bertrand premium-setting. I then find the new equilibrium premiums under that change in insurer-year marginal cost and the new predicted negotiated premiums, inclusive of any patient reallocation in response to the new premiums. I am conservative and do not quantify the reinforcing effect between new premiums and prices.

B.4 Caveats and Limitations

My hospital demand model abstracts from various features to focus on price-setting. Insurers can differ systematically and between plans based on cost-sharing and can put hospitals in separate tiers, but the effects of inpatient cost-sharing at common American levels are generally small (Gowrisankaran et al., 2015). I assume 2016 hospital demand was equal to previous hospital demand and as a result do not capture historical hospital investment or changes in patient steering through physician integration. Discussions with stakeholders suggest hospital perceptions were mostly time-invariant. I do not model separate hospital demand by sex, which leads to less precision and could introduce bias by missing premium discrimination before 2014. I do not capture any supply incentives introduced by the choice between prospective Medicare-based payments (which pay based on diagnosis) and list-price-based payments (which pay based on services) or the level of prices, though I hold benchmark choice constant in counterfactuals.

I only model hospital demand by West Virginia residents for West Virginia hospitals. Some degree of state bias at borders is inevitable when data ends at state lines that real humans can cross, and I likely miss some competition in the state's northern panhandle (due to the proximity of Pittsburgh area hospitals), eastern panhandle (due to the proximity of larger cities in Maryland and Virginia), in Wheeling (due to the proximity of East Ohio Regional Hospital in Ohio), in Huntington (due to the proximity of King's Daughters hospital in Kentucky), and for the Health Plan of the Upper Ohio Valley (which had a comparable line of business in Ohio).

I abstract away from some small potential responses to dropping a contract. I assume there was no out-of-network care by insured patients in West Virginia. Out-of-network care is more common for outpatient care, but can happen for emergency inpatient care and might have become more common if a desirable hospital left an insurer's network. I model consumer substitution to small rural critical access hospitals in response to an insurer dropping a modeled hospital, but treat those payments (which by construction are small) as zero.

The premium data is limited relative to other settings. Large-group premiums were not regulated by the ACA and could reflect different age-based price discrimination or idiosyncratic rating areas than in the ACA-regulated market. It is possible for there to be an unmodeled interaction of age-based premiums with market area that is not captured by market-insurer fixed effects; residual correlation of outpatient and inpatient networks; unmodeled heterogeneity in Cigna, UnitedHealth, and small insurer quality across rating areas; variation in insurer entry in the individual market within rating areas; and variation within rating area in the self-insured market. Aetna premiums in 2015 and 2016 may be mismeasured due to misalignment of premium payments and insurance dates after the insurer acquired Carelink in 2015. I only observe premiums annually. Intrayear premium-setting could be accommodated in the model with appropriate data. I model a static premium-setting process. Dynamic premium-setting to incorporate incentives like inertia is an interesting avenue for future work.

My insurer demand model is stylized. I do not have data on choices by family or by employer, so I model the reduced-form selection of insurance by individual based on individual diagnoses probabilities. The model of plan choice allows selection only on observables and I treat self-funded and fully insured plans as equally profitable to insurers despite their different business practices. I do not precisely measure outside options across multiple insurers due to lack of identifiers of small insurers. For example, the simplification to modeled insurers likely misspecifies the disagreement point of Charleston Area Medical Center in any hypothetical 2007 negotiation, because the hospital only reported contracts with BCBS and nonmodeled insurers in that year. I also do not model the outside option of no insurance or how insurance rates might vary across different areas in West Virginia. I do not model "BlueCard" incentives created by Blue Cross pooling networks: in a border hospital, part of the hospital's value of contracting with Highmark Blue Cross might include the value of additional consumers from CareFirst (Maryland and Virginia) and Anthem (Kentucky and parts of Ohio) Blue Cross in a way that Highmark does not value. There also may be asymmetric value created in other states, but the insurers I model are present on the other sides of West Virginia's more populous Ohio and Pennsylvania borders. I also estimate a model of logistic choice within age-county due to data limitations. That said, the key goal of my model is accurately capturing dynamic bargaining incentives, so the largest concerns reflect any unmodeled changes in these incentives over time during the era I study.

I capture benchmark usage imperfectly. Both one-off repeated discounts and one-off round-number discounts can reflect coincidence or typographical errors, so each imputation approach has tradeoffs. I generate similar estimated benchmark usage whether I use my main definition or alternatively infer share of charges contracts from round-number discounts. I summarize the concordance across measures in Appendix Figure 7. Both approaches treat as fully prospective any contracts that were benchmarked to list prices with different discounts within inpatient care, which may have included a few Highmark BCBS contracts in early years of my data (Rivard, 2010); any use of per diems for subsets of care like labor cases (Weber et al., 2019); or any use of list prices in outlier payments.



Figure 7: Estimated concordance of benchmark classification by insurer and fiscal year starting with larger contract scale reports in 2011. Blue and red contracts are classified by my algorithm as prospective and share of charges, respectively. Dark colors correspond to roundnumber discounts reaching the opposite conclusion. An estimated 94.2% of inpatient payments have the same imputation across methods, 1.1% are assigned as share of charges by only repeating non-round-number discounts, and 4.8% are assigned as prospective by only reporting varying round-number discounts (driven by Highmark BCBS-Cabell Huntington in 2011–13).

My stylized approach to hospital pricing is standard but abstracts from the relative prices of services. For example, insurers could use list prices for different services to pricediscriminate between share of charges payors, though I found no evidence they actually did so. I assume that units of care are proportional to hospital list prices to align with the reported contract data. I inflation-adjust based on CPI which is imperfectly aligned with both hospital care and specific West Virginia conditions. The CPI inflation adjustment may be particularly problematic for noninpatient costs (η) and hospital costs (c), with offsetting effects. It is unclear how these offsetting issues would bias estimates of the patience parameter β , if at all.

I treat benchmark prices as stylized prices per unit of care and treat them as updated annually. It is standard in this literature to aggregate multiple services to a generic unit of care. Firms could apply separate multiples to different care aggregates within a contract, but the average should be a reasonable summary statistic. Firms could commit to time-varying multiples, but to my knowledge they rarely (if ever) do so in practice. List price multiples are theoretically bounded above by one, but generally list prices are intentionally set far above what any contract could reach. I abstract from some other roles of benchmark prices to focus on price negotiation dynamics (Clemens and Gottlieb, 2017). I do not model chargemaster and Medicare timing within a calendar year. List prices governed by the chargemaster could be updated at frequencies other than annually, though such higher frequencies are not standard (Reinhardt, 2006, Tompkins et al., 2006, Jahn, 2017). In principle, chargemasters can be used to price discriminate among insurers that use list prices as a benchmark, but I found no indication that hospitals do so (Reinhardt, 2006, Abbey, 2012, Kidder, 2013).

The model abstracts from many potential aspects of bargaining. I impose a finite horizon model under the view that it is part of an increasingly long-term approximation to a true infinite horizon model. The finite horizon is an approximation — for example, it might be more appropriate to place extra weight on the fifth year as a proxy for subsequent profits. The theoretical arguments deriving estimation moments would not hold if the negotiators had asymmetric patience parameters, risk aversion, or different expectations of the future. Whether these sorts of informational differences can be incorporated in dynamic bargaining is an interesting avenue for future work. It is possible for the bargainers to implicitly or explicitly bargain over nonprice objects like adjudication processes or cooperation, although such objects are generally viewed as secondary (Abbey, 2012, Vega, 2013, Gooch, 2019). I assume that disagreement does not affect subsequent demand functions; disagreement is a dynamic process that affects consumer inertia which I hope to explore in future work.

My estimation procedure implicitly rules out selection of networks on unobservable components of utility. That said, I see limited variation in networks over time, so that any bias would likely occur through selection on contract length rather than selection on contract existence. Such hypothetical selection bias is an interesting direction for future work.

The model's timing abstracts from many real-world subtleties around timing in the service of empirical tractability. I model bargaining as succeeding at the start of the day on which it was accepted by the regulator and ending on an unambiguous day of the year. In practice, contracts are agreed to before they go into effect and occasionally expired contracts would remain in place on a short-term basis while negotiations remained ongoing. Short-term extensions are equivalent to auto-renew contracts in my model, but I will miss extensions that began and ended between contract reports. Impasse is assumed to affect insurer demand in a static process throughout the year; insurance contracts with employers and individuals are reached at staggered times, a process that does not correspond perfectly with this paper's static insurer demand model. I attempt to capture annual patience with an annual patience parameter, using contract dates within a year when estimating the bargaining model but treating profits as equally profitable within a year, which is a convenient but unrealistic simplification. For counterfactuals, I simplify prices and treat bargaining as being conducted at the start of the year to focus on the counterfactual effects at the cost of some precision.

There are also a few other places wherein the bargaining model is currently simplified for convenience. The bargaining model is estimated with a high-dimensional optimization that may not reach a global optimum. The estimation procedure is somewhat affect by initial conditions; most notably, negotiation cost contributions to payments do not always move much from their initial value of \$10,000; identification of these terms is subtle (Dorn, 2025a). I use state-level premiums to calculate insurer gains from trade, which may introduce some bias from relative age discrimination between insurers. I model hospitals as negotiating by contract reporting unit. For example, in this era, the WVU Medicine system included Berkeley Medical Center and Jefferson Medical Center, but these hospitals negotiated contracts as a separate Eastern Panhandle delivery system. As discussed, I do not estimate an impasse repricing transfer term (with unclear effect) and hold premiums constant in counterfactuals (with conservative effect).

I do not model the network formation process. A frictionless Nash-in-Nash bargaining model rarely speaks persuasively to why networks are incomplete — for example, an insurer might exclude a hospital to increase their leverage in other negotiations. In my model, networks are theoretically restricted by hospital costs and negotiation costs. I do not view those bargaining frictions as a fully compelling model of network formation. I also abstract from any monitoring costs associated with auto-renew contracts. An equivalent perspective on auto-renew frictions is to view the investment in monitoring staff as fixed. Other disagreement models could be accommodated by adjusting the impasse repricing transfer term to include other disagreement effects. I focus on changes to benchmark price increases that are comparable to normal levels of benchmark price increases. As a result, the counterfactuals would be unlikely to affect network formation substantially.

There are various limitations on counterfactuals. The one percentage point payment increase is based on West Virginia data, but a national equivalent might be closer to 0.7 percentage point annual increase. It is possible that my deterministic stance on uncertainty in counterfactuals introduces bias if the uncertainty over benchmark prices was first-order relative to the changes that would be incurred in the counterfactual I consider. I do not model any effects on how much care would be reported or how hospital investment might change in counterfactuals due to the limited effects of three- or five-year price commitments on longer-term investment decisions. The set of benchmarks used has changed over time and has shifted towards prospective payments, making out-of-sample extrapolation unclear but potentially meaning national effects of Medicare-based benchmark prices would be larger in years after 2015. West Virginia is a small market, so it is possible that bargaining is less frequent than in large markets that constitute a lot of, but by no means all of, American healthcare. The contract data I use is partial in the earliest and latest years, and as a result I may miss some bargains that were not reported. The downstream estimates of effects on premiums are highly stylized.

B.5 Other Bargaining Models

The rows in Appendix Table 4 are as follows. The first two rows are the main myopic and forward-looking model estimates, as presented in Table 3. The third row normalizes payments by the average value of $\sum \beta^t$. The fourth row estimated hospital costs as a multiple of list prices rather than calibrating hospital costs. (The estimated multiple is 1.45.) The fifth, sixth, and, seventh rows multiply hospital costs by a fixed scalar. The eighth row multiplies hospital costs by the hospital's reported Medicare payment-to-cost ratio to proxy for the outside option of Medicare patients if hospitals are capacity-constrained. The ninth row takes η values to fit MLR reports rather than calculating them. The tenth row multiplies insurer gains from trade by the hospital's reported share of commercial costs from inpatient care. The eleventh row fixes β . Rows twelve, thirteen, and fourteen fix τ . Rows fifteen and sixteen are versions of the main model estimates, but without τ^{Size} size interactions. Rows seventeen and eighteen are "only-2015" model estimates that use 2015 payments and treat all 2015 contracts as new, with and without hospital size interactions, respectively.

Note also that the estimated discount parameter β is somewhat dependent on the exact split of hospital groups in constructing instruments: bootstrapped β standard errors with reestimated hospital groups increase from 0.03 to 0.109, driven by the 18% of bootstraps in which United Hospital Center's assignment changes.

| | Parameter | | | | | |
|---|---|---|---|--|---|--|
| | β | τ_{BCBS} | $	au_{HPUOV}$ | $	au_{FP}$ | $-\tau^{Size}$ | |
| Myopic (Baseline) | \cdot (·) | 0.876^{***} (0.012) | $\begin{array}{c} 0.825^{***} \\ (0.232) \end{array}$ | 0.861^{***} (0.034) | 1.037^{***} (0.199) | |
| Forward-Looking (Baseline) | 0.899^{***} (0.03) | 0.854^{***} (0.006) | 0.877^{***} (0.026) | 0.889^{***} (0.005) | 0.989^{***} (0.028) | |
| Forward-Looking (Mean $\sum \beta^t$ normalization) | $0.925 \ (\cdot)$ | $0.854 \\ (\cdot)$ | $0.876 \\ (\cdot)$ | $\begin{array}{c} 0.89 \\ (\cdot) \end{array}$ | $0.991 \\ (\cdot)$ | |
| Forward-Looking (Estimate Hospital Costs) | $0.497 \\ (\cdot)$ | $\begin{array}{c} 0.939 \\ (\cdot) \end{array}$ | $\begin{array}{c} 0.938 \\ (\cdot) \end{array}$ | $0.942 \\ (\cdot)$ | $1.009 \\ (\cdot)$ | |
| Forward-Looking (Hospital Costs * 2) | $\begin{array}{c} 1 \\ (\cdot) \end{array}$ | $\begin{array}{c} 1 \\ (\cdot) \end{array}$ | $\begin{array}{c} 1 \\ (\cdot) \end{array}$ | $\begin{array}{c} 1 \\ (\cdot) \end{array}$ | -0.276 (·) | |
| Forward-Looking (Hospital Costs * 0.9) | $0.931 \\ (\cdot)$ | $\begin{array}{c} 0.838 \\ (\cdot) \end{array}$ | $0.858 \\ (\cdot)$ | $0.875 \\ (\cdot)$ | $0.969 \\ (\cdot)$ | |
| Forward-Looking (Hospital Costs $* 1/2$) | $\begin{array}{c} 1 \\ (\cdot) \end{array}$ | $0.778 \\ (\cdot)$ | $0.781 \\ (\cdot)$ | $0.821 \\ (\cdot)$ | $\begin{array}{c} 0.903 \\ (\cdot) \end{array}$ | |
| Forward-Looking (Medicare Costs) | $0.895 \\ (\cdot)$ | $0.834 \\ (\cdot)$ | $0.847 \\ (\cdot)$ | $0.871 \\ (\cdot)$ | $0.913 \\ (\cdot)$ | |
| Forward-Looking $(\eta \text{ from MLR})$ | $0.826 \\ (\cdot)$ | $0.864 \\ (\cdot)$ | $0.874 \\ (\cdot)$ | $0.891 \\ (\cdot)$ | $0.892 \\ (\cdot)$ | |
| Forward-Looking (Inpat. Share GFT Weight) | 0.722 (·) | 0.881 (·) | $0.905 \\ (\cdot)$ | 0.897 (·) | 0.847 (·) | |
| Forward-Looking $(\beta = 0.99)$ | $\begin{array}{c} 0.99\\ (\cdot) \end{array}$ | $0.854 \\ (\cdot)$ | $0.875 \\ (\cdot)$ | $0.881 \\ (\cdot)$ | 1 (\cdot) | |
| Forward-Looking (Hospital TIOLI) | $0.696 \\ (\cdot)$ | $0.001 \\ (\cdot)$ | $0.001 \\ (\cdot)$ | $0.001 \\ (\cdot)$ | (•) | |
| Forward-Looking $(\tau = 0.5)$ | $0.817 \\ (\cdot)$ | $\begin{array}{c} 0.5 \ (\cdot) \end{array}$ | $\begin{array}{c} 0.5 \ (\cdot) \end{array}$ | $\begin{array}{c} 0.5 \\ (\cdot) \end{array}$ | (•) | |
| Forward-Looking (MCO TIOLI) | $\begin{array}{c} 0.52 \\ (\cdot) \end{array}$ | $\begin{array}{c} 0.999 \\ (\cdot) \end{array}$ | $0.999 \\ (\cdot)$ | $0.999 \\ (\cdot)$ | \cdot (·) | |
| Myopic (No Hosp. Size) | \cdot (·) | 0.863^{***} (0.006) | 0.845^{***} (0.016) | 0.631^{***} (0.027) | \cdot (·) | |
| Forward-Looking (No Hosp. Size) | $\begin{array}{c} 0.714^{***} \\ (0.032) \end{array}$ | $\begin{array}{c} 0.852^{***} \\ (0.012) \end{array}$ | 0.86^{***} (0.008) | 0.685^{***} (0.028) | \cdot (·) | |
| Only-2015 (Baseline) | (\cdot) | 0.487^{**} (0.191) | -7.54 (17.204) | 0.694^{***} (0.175) | 3.354 (22.875) | |
| Only-2015 (No Hosp. Size) | · (·) | 0.365^{***} (0.011) | 0.278^{*} (0.143) | 0.16^{***} (0.048) | · (·) | |

Table 4: Comparison of estimated bargaining parameters with other potential modeling choices. I describe the rows in Appendix B.5.

Note:

*p<0.1; **p<0.05; ***p<0.01

B.6 Other Empirical Estimates and Results

I present diagnosis category frequencies in Table 5. Labor and cardiac discharges are the largest share of actively defined categories. Medicare patients are more likely to have cardiac discharges and less likely to have labor discharges than the commercially insured sample I use in estimation.

I present estimated hospital demand distance parameters in Table 6. Regardless of diagnosis, consumers prefer closer hospitals and have a diminishing loss from distance. Consumers with neurological conditions are relatively insensitive to distance. Patients travel less far for emergency care outside labor cases. In the 201 hospital-diagnosis fixed effects I estimate but omit for space, consumers place the highest value on Ruby Memorial, the West Virginia University (WVU) Health system's flagship hospital. Hospitals near the state's border like Cabell Huntington and Mon Health Medical Center are generally higher value than their state-level share would suggest, consistent with border hospitals also competing for patients from neighboring states. Hospital fixed effects are comparable for most diagnoses but are smaller for labor discharges.

The insurer demand estimates are presented in Table 7 and Table 8. Table 7 includes insurer mean $\delta_{j,m}^M$ fixed effects inclusive of premiums. Consumers are more likely to choose Highmark BCBS than can be explained by the insurer's inpatient network alone, which may reflect a better outpatient network, better perceived quality, inertia, or Highmark BCBS's nonprofit status. The regional HPUOV is also nonprofit and has a larger fixed effect than the three national for-profit insurers, which in part reflects lower premiums. Appendix Table 8 presents the estimated WTP coefficients. Consumers are more likely to purchase insurance with a better network. The network value coefficients differ substantially by age in absolute terms. The scale of network valuation reflects age differences: younger consumers are less likely to get sick and so have a smaller variation in WTP across networks.

Discount Contract List Budgeted Discounts for FY 2016 Hospital Name Charleston Surgical Hospital



Figure 8: Discount Contract List (DCL) scan, with white space and handwritten notes omitted, for Charleston Surgical Hospital in fiscal year 2016 The top panel of contracts lists smaller contracts that are only included in the DCLs, while the bottom panel lists contracts with detailed information reported in the DC scans (Figure 9).

Table 5: The percent of discharges by diagnosis category for all inpatient discharges (top row), the commercial nonnewborn discharges I use for estimation (middle row), and the Highmark BCBS subset of commercial discharges I use for hospital demand estimation (bottom row).

| Discharges | Labor | Cardiac | Digestive | Neurological | Cancer | Other |
|---------------|-------|---------|-----------|--------------|--------|-------|
| All | 16.86 | 15.42 | 8.29 | 7.47 | 1.04 | 50.16 |
| Commercial WV | 19.85 | 12.41 | 9.97 | 5.60 | 1.33 | 50.11 |
| Highmark BCBS | 20.22 | 12.49 | 9.84 | 5.52 | 1.49 | 49.72 |

| 1 | Name of Purchaser or Third Party Payor | Total | = | Combined Contracts | + 1 | Mt State-PPO | Mt State-Indemnity | Aetna |
|----|---|--|---|--|-----|-------------------|--------------------|--|
| 2 | Date of Contract | particular and a second state of a state of the second state of th | | a man di fin che dana in cale ana anti antana dana any any any any any any any any any | | 8/1/2015 | 8/1/2015 | 11/1/1994 |
| 3 | Date Contract Expires | | | | | 12/31/2018 🗸 | 12/31/2018 | Auto Renewal |
| 4 | Projected Inpatient Discharges | 92 | _ | 16 | | 50 | 2 | 17 |
| 5 | Projected Gross Inpatient Revenue | 2 878 926 | | 417 403 | | 1 627 278 | 65 091 | 567 464 |
| 6 | Inpatient Discount Percent | 31 54% | | 12 00% | | 43 38% | 43 38% | 18 00% |
| 7 | Projected Amount of Inpatient Discount | 908 049 | | 50 088 | | 705 865 | 28 235 | 102 144 |
| 8 | Projected Net Inpatient Revenue | 1 970 877 | | 367 315 | | / 921 413 | / 36 857 | / 465 320 |
| 9 | Projected Inpatient Cost | 1 079 592 | | 156 525 | | -610 226 | 24 409 | 212 798 |
| 10 | Projected Inpatient Charge per Discharge | | | | | 32 545 55 | 32 545 55 | 33 380 24 |
| 11 | Projected Inpatient Cost per Discharge | providence and the second s | | ne sanageren ander en san en | | 12 204 52 | 12 204 52 | 12 517 53 |
| 12 | Projected Cost to Charge Ratio | 37 50% | | S. A. A. Frank, W. Million & And | | 37 50% | 37 50% | 37 50% |
| | | | | | | | | and the second sec |
| 13 | Projected Outpatient Visits | 3 985 | | 619 | | 2 594 | 136 | 388 |
| 14 | Projected Gross Outpatient Revenue | 12 312 629 | | 1 276 012 | | 8 755 454 | 459 037 | 1 162 818 |
| 15 | Outpatient Discount Percent | 34 27% | | 12 00% | | 41 58% | 38 45% | 15 00% |
| 16 | Projected Amount of Outpatient Discount | 4 219 778 | | 153 121 | | 3 640 518 | 176 500 | 174 423 |
| 17 | Projected Net Outpatient Revenue | 8 092 852 | | 1 122 890 | | <u>/5 114 936</u> | 282 537 | 988 395 |
| 18 | Projected Outpatient Cost | - 4 617 213 | | 478 502 | | 3 283 279 | 172 138 | ¹ - 436 055 |
| 19 | Projected Outpatient Charge Per Visit | and the column and the second se | | | | 3 375 27 | 3 375 27 | 2 996 95 |
| 20 | Projected Outpatient Cost Per Visit | | | | | 1 265 72 | 1 265 72 | 1 123 85 |
| 21 | Projected Cost to Charge Ratio | 37 50% | | A superior and the second seco | _ | 37 50% | 37 50% | 37 50% |
| 22 | Uncompensated Care Percent of Gross Patient Revenue | | | and the second se | | | | |
| 23 | Will Contract(s) Provide a Quantifiable Economic Benefit to the Hospital? Circle | | | Yes | | Yes | Yes | Yes |
| 24 | Is the Discount Amount Below Actual Cost of Service? Circle | | | No | | No | No | No |
| 25 | Will Cost Be Shifted to Any Other Purchaser of Third Party Payor as a Result of this Contract? Circle | | | No | | Na | No | Νο |
| 26 | Date contract submitted to HCA | | | a na si salaman mana a dagana any salaman ang aga a | | 7/8/2015 | 7/8/2015 | 10/31/2014 |
| 27 | the Authority? (If yes please submit revised contracts) Circle | | | No | | No | No | No |

NOTE This page should include only the total combined and 3 (three) separate contract columns Use this form in its current version only Any modifications will be returned

Figure 9: The first page of detailed contract (DC) data for Charleston Surgical Hospital in fiscal year 2016. The data includes unusual information on contract formation and scale.

| Dependent variable: | | | | | | | | |
|---|---|--|---|--|--|--|--|--|
| | choice | | | | | | | |
| Cancer | Cardiac | Digestive | Labor | Neurological | Other | | | |
| (1) | (2) | (3) | (4) | (5) | (6) | | | |
| -0.115^{***} (0.014) | -0.113^{***} (0.004) | -0.117^{***} (0.005) | -0.121^{***} (0.004) | -0.077^{***} (0.003) | -0.108^{***} (0.002) | | | |
| $\begin{array}{c} 0.0004^{***} \\ (0.0001) \end{array}$ | $\begin{array}{c} 0.0004^{***} \\ (0.00002) \end{array}$ | $\begin{array}{c} 0.0004^{***} \\ (0.00002) \end{array}$ | $\begin{array}{c} 0.0003^{***} \\ (0.0001) \end{array}$ | $\begin{array}{c} 0.0002^{***} \\ (0.00002) \end{array}$ | 0.0003^{***} (0.00001) | | | |
| -0.010 (0.015) | -0.012^{***} (0.003) | -0.024^{***} (0.004) | 0.020^{***} (0.005) | -0.013^{***} (0.004) | -0.015^{***} (0.001) | | | |
| $284 \\ 0.555 \\ -286.987$ | 2,469 0.577 -2,722.077 | 2,048 0.615 -2,324.572 | $4,143 \\ 0.646 \\ -3,923.918$ | 1,094 0.497 -1,297.677 | 10,053 0.555 -12,578.030 | | | |
| | Cancer (1) -0.115^{***} (0.014) 0.0004^{***} (0.0001) -0.010 (0.015) 284 0.555 -286.987 | $\begin{array}{c ccc} Cancer & Cardiac \\ (1) & (2) \\ \hline -0.115^{***} & -0.113^{***} \\ (0.014) & (0.004) \\ \hline 0.0004^{***} & 0.0004^{***} \\ (0.0001) & (0.00002) \\ \hline -0.010 & -0.012^{***} \\ (0.015) & (0.003) \\ \hline 284 & 2,469 \\ \hline 0.555 & 0.577 \\ \hline -286.987 & -2,722.077 \\ \hline \end{array}$ | $\begin{array}{c c c c c c c c c c c c c c c c c c c $ | $\begin{array}{c c c c c c c c c c c c c c c c c c c $ | $\begin{array}{c c c c c c c c c c c c c c c c c c c $ | | | |

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 6: Estimated consumer valuation of distance in hospital choice (in utility units) by diagnosis category. Consumers generally are admitted to closer hospitals, have a diminishing loss from travel, and — with the exception of labor cases — are especially unlikely to travel distances for emergency care.

| | MCO: | | | | | | | | |
|-------|-------------------------|---|------------------------|-------------------------|-------------------------|--|--|--|--|
| | Aetna | Highmark BCBS | HPUOV | Cigna | UnitedHealth | | | | |
| | -1.39^{***} (0.13) | $ \begin{array}{c} 1.33^{***} \\ (0.13) \end{array} $ | -0.8^{***} (0.13) | -3.54^{***} (0.11) | -2.43^{***} (0.11) | | | | |
| Note: | | | * | p<0.1; **p< | 0.05; ***p<0.01 | | | | |

Table 7: Estimated average 2016 insurer value including premiums $(\tilde{\delta}_{j,m}^M)$ after accounting for variation in inpatient network quality.

Table 8: Insurer demand coefficient on network willingness to pay by age group. Consumers are generally more likely to purchase insurance from insurers with better networks. The coefficients are largest for young groups with smaller standard deviations in network quality.

| | | W | WTP Coefficient | | | | | |
|-------------------|-----------------|------------------|------------------|------------------|----------------|--|--|--|
| | γ_{0-17} | γ_{18-44} | γ_{45-64} | γ_{65-74} | γ_{75+} | | | |
| | 26.6*** | 4.94*** | 2.76*** | 2.79*** | 2.05*** | | | |
| | (2.65) | (0.67) | (0.33) | (0.27) | (0.15) | | | |
| Note: | | | *p<0.1; | **p<0.05; * | ***p<0.01 | | | |
| +09 - | | | | | _ • 1 | | | |
| +08 - | | | | | ar see | | | |
| ∍+07 - | | | 20- APR 4 | ·· - | | | | |
| e+06 - | | 2000 - 25000 | | | | | | |
| e+05 | | | | | | | | |
| 1e | +05 | 1e+06 | 1e+07 | 1e+0 | 3 | | | |

Figure 10: For the 63 estimation bargains, the predicted (x axis) and realized (y axis) NPV payment within the finite horizon used in estimation. Net present values are calculated using the estimated $\beta = 0.899$. Axes are log-scaled for comparability. Perfect prediction fit is indicated with the dashed line. There may be some bias for small contracts (generally non-Highmark-BCBS contracts at small-to-medium hospitals) that get little weight in the estimation procedure, but otherwise the model fit seems to be quite good.

Table 9: Additional estimated bargaining parameters with estimated τ^{Size} hospital size coefficient (top) and with τ^{Size} set to zero (bottom) in calculating hospital-insurer bargaining weights. BCBS parameters correspond to Highmark BCBS. "Data" corresponds to average difference between MLR-implied costs per life and estimated average inpatient payments per life insured, and would exactly set the MLR moment to zero for the myopic and forwardlooking models. The estimated β would be similar if η were constrained to exactly fit MLR reports (Appendix Table 4). The r^M net negotiation costs are close to their starting point of \$10,000 and may weakly identified or unidentified.

| | | Parameter (τ^{Size} Estimated) | | | | | | | | |
|-----------------------------------|------------------------|--------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-------------------------|---|--|--|
| | η_{BCBS} | η_{HPUOV} | η_{Aetna} | $\eta_{UnitedHealth}$ | η_{Cigna} | $\eta_{Carelink}$ | r^M_{yBCBS} | r^M_{nBCBS} | | |
| Only-2015 (Nash/Kalai) | 3657^{***} (45) | 3404^{***} (85) | 3658^{***} (116) | 2008^{***} (29) | 4627^{***} (32) | 3139^{***} (39) | 10000^{***} (2614) | 99999^{***} (1441) | | |
| Myopic (Nash/Kalai) | 4640^{***} (14) | 4036^{***} (650) | 3659^{***} (37) | 3197^{***} (374) | 4624^{***} (26) | 3139^{***} (463) | 10000^{***} (1444) | 10000^{***} (1) | | |
| Forward-Looking $(Pay_{IRT} = 0)$ | 4638^{***} (130) | 3631^{***} (302) | 3660^{***} (37) | 3284^{***} (69) | 4626^{***} (30) | 3140^{***} (45) | 9999^{***} (29) | 9999^{***} (65) | | |
| Data | 3600 | 3356 | 3554 | 1999 | 4635 | 3114 | | | | |
| Note: | | | | | | *p<0 | 0.1; **p<0.05 | ;***p<0.01 | | |
| | | | | Parameter | $(\tau^{Size} = 0)$ | | | | | |
| | η_{BCBS} | η_{HPUOV} | η_{Aetna} | $\eta_{UnitedHealth}$ | η_{Cigna} | $\eta_{Carelink}$ | r^M_{yBCBS} | r^M_{nBCBS} | | |
| Only-2015 (Nash/Kalai) | 3639^{***} (14) | 3412^{***} (28) | 3660^{***} (37) | 2010^{***} (27) | 4622^{***} (26) | 3139^{***} (36) | 10001^{***} (1143) | 23581^{***} (1415) | | |
| Myopic (Nash/Kalai) | 4639^{***} (14) | 3412^{***} (349) | 3659^{***} (37) | 2008^{***} (28) | 4624^{***} (26) | 6176^{***} (493) | 17779^{***} (904) | 10000^{***} (0) | | |
| Forward-Looking $(Pay_{IRT} = 0)$ | 4638^{***} (1546) | 3413^{***} (295) | 3659^{***} (487) | 2008^{***} (447) | 4624^{***} (390) | 5972^{***} (521) | 10000^{***} (761) | $ \begin{array}{c} 18098^{***} \\ (699) \end{array} $ | | |
| Data | 3600 | 3356 | 3554 | 1999 | 4635 | 3114 | | | | |

Note:

*p<0.1; **p<0.05; ***p<0.01



Figure 11: Predicted (x axis) and realized (y axis) bargain starting share of list prices under myopic (left, $R^2 = -0.116$) and forward-looking (right, $R^2 = 0.027$) bargaining models. R^2 can be negative because model predictions are chosen to minimize NPV payment residuals, while this R^2 reflects list price share residuals.



Figure 12: Estimated effects on payments by insurer from a one percentage point annual increase in Medicare rates.



Figure 13: Estimated effects of increased Medicare cost reimbursement on each hospital's received payments in 2015. There is some indication that smaller hospitals would see larger private payment increases.



Figure 14: Estimated effects on premiums by insurer for Highmark BCBS (red), HPUOV (green), and the other modeled insurers (blue). Among the other modeled insurers, only Carelink and Aetna have large payment effects, and those effects are reduced after 2012 (see Figure 12).



Figure 15: Comparison of estimated effects to a same-multiple model (green) in which bargainers keep their original benchmark multiple in place. The models mainly diverge due to contracts renegotiating a lower initial share of Medicare prices (present myopic model, red) and firms responding to expected future price increases by negotiating lower starting prices (present only in forward looking model, blue). There are also equilibrium spillover effects in both the forward-looking and myopic models, but the magnitudes are smaller than the forward-looking response needed to hold NPV payments constant.