The Price Effects of Cross-Market Mergers: Theory and Evidence from the Hospital Industry*

Leemore Dafny† Kate Ho‡ Robin S. Lee§

July 27, 2016

Abstract

So-called "horizontal mergers" of firms whose products are direct substitutes at the point of sale have garnered significant attention from researchers and regulators alike. We consider the effect of mergers between firms whose products are not viewed as direct substitutes by consumers, but are bundled by a common intermediary. Focusing on the case of hospital mergers across distinct geographic markets ("cross-market" mergers), we show that such combinations can reduce competition among the merging firms for inclusion in intermediary insurers' networks, leading to higher prices (or lower-quality care). The result derives from the presence of "common customers" (i.e. purchasers of insurance plans) who value both hospitals, as well as (one or more) "common insurers" with which price and network status is negotiated. We test our theoretical predictions using two samples of cross-market hospital mergers, focusing exclusively on hospitals that are bystanders rather than the likely drivers of the transactions in order to address concerns about the endogeneity of merger activity. We find that hospitals gaining system members in-state (but not in the same geographic market) experience price increases of 7-10 percent relative to control hospitals, while hospitals gaining system members out-of-state exhibit no statistically significant changes in price. The former group are likelier to share common customers and insurers; indeed the price effect is absent for merging hospitals that lack common insurers. The results suggest that cross-market, within-state hospital mergers appear to increase hospital systems' leverage when bargaining with insurers.

1 Introduction

Merger analysis is a staple of antitrust enforcement. When a merger eliminates current or potential "head to head" competition for a relevant product or service, enforcers may sue to block or unwind the transaction. Per the most recent release of the "Horizontal Merger Guidelines," which articulate

*We thank Cory Capps, David Balan, Gautam Gowrisankaran, Aviv Nevo, Bob Town, Nathan Wilson, and numerous conference and seminar participants for useful comments and discussion; and Matthew Schmitt and Victoria Marone for exceptional research assistance. All errors are our own.

†Northwestern Kellogg & NBER

‡Columbia University, NBER & CEPR

§Harvard University & NBER

the principles followed by the federal antitrust enforcement agencies, merger analysis is a "fact-specific process," one in which the particulars of the relevant market(s) and merging parties is integral to enforcement decisions. One such particular is the presence (or absence) of intermediaries in the chain of production or distribution. In this study, we evaluate mergers of upstream suppliers to intermediaries that bundle products or services for sale to customers who in turn may aggregate the preferences of multiple individuals. We argue that the presence of intermediaries selling to such customers can affect both the likelihood and margin of harm from a merger of suppliers, even if the products being supplied are not direct "head to head" rivals at the point of sale. Examples of such settings include: cable TV, where different content producers offer channels that are not direct substitutes but negotiate prices with distributors that market a bundle of channels to multi-person households; and retail product markets where products may be targeted to different consumers but are stocked by retailers offering one-stop family shopping.

Health insurance is another relevant example. Private (commercial) insurers bargain with providers over reimbursement rates (prices); the insurers then bundle these services, adding in administrative and oversight features—as well as risk-bearing in the case of "full insurance" products—and sell insurance plans to employers and individual households. Hospitals are critical upstream suppliers to health plans, accounting for nearly one-third of health care spending in the U.S. today.[1] In recent years, the Federal Trade Commission (FTC) has successfully challenged several proposed mergers of hospitals that are direct substitutes at the point of care (i.e. in the same geographic and product market), informed by an economic literature showing that these "within-market" mergers tend to lead to increases in negotiated prices for privately-insured patients without significant quality improvements (Gaynor and Town, 2012; Gaynor, Ho and Town, 2015; Farrell et al., 2011).

In contrast there has been very little regulatory activity regarding hospital mergers across distinct markets. This gap is notable in light of the significant pace of such "cross-market" mergers in recent years.[2] More than half of the 871 hospital mergers between 2000 and 2012 involved hospitals or systems without facilities in the same CBSA.[3] As we describe below, current methods of assessing the anticompetitive threat from hospital mergers assume there can be no increase in bargaining leverage unless the merging parties are vying to provide the same set of services to the same set of patients. These methods implicitly assume that insurance markets do not impact upstream market power; more formally, the models typically assume insurers face demand that is separable across product and service markets (as in Capps, Dranove and Satterthwaite (2003)).

We argue that an extension to the current methodology is warranted in light of the role and realities of intermediary markets. Insurers negotiate with and pay hospitals for their services, and demand for insurance may not, in fact, be separable across service markets. We show that the presence of "common customers" (e.g., employers or households) who purchase insurance products

[1] CMS National Health Expenditure Accounts.

[2] Examples include the $3.9 billion acquisition of Health Management (71 hospitals) by Community Health Systems (135 hospitals) in 2014, and the 2013 merger of Dallas-based Baylor Health Care System and Temple-based Scott & White Health; post-merger the combined entity comprised 43 hospitals and more than 6,000 affiliated physicians.

[3] A CBSA is defined as a metropolitan statistical area in larger cities, and a "micropolitan" area in smaller towns; see Figure 2 for details.

and value the services of both merging hospitals can give rise to greater post-merger bargaining leverage for the merging hospitals even when those hospitals operate in distinct patient markets. These common customers are likely to be large employers that demand insurance products covering hospital services in multiple distinct geographic markets, i.e. areas where their employees live and work. Since insurers service employers across multiple geographic regions, a merged cross-market hospital system that covers those regions can demand higher reimbursement rates from insurers.[4]

Consider for illustrative purposes a simple setting where a state-wide employer chooses insurance products to offer to employees who are evenly distributed across the state. Assume there are ten local markets, each of which contains three evenly-sized, competing hospitals. Insurers engage in pair-wise bargaining with hospitals over prices. Under current antitrust practice, authorities would be likely to object to mergers of hospitals *within* a local market on the grounds that they would "substantially lessen competition or tend to create a monopoly," per Section 7 of the Clayton Act.[5] They would be less likely to object to cross-market mergers—even repeated mergers that created three large hospital systems, each owning a hospital in every market. However, the cross-market presence of the large employer implies a potentially large effect of these mergers on negotiated hospital prices. While the employer would be unlikely to drop an insurance plan that removed just one of the thirty hospitals from its network (since this would affect few of its employees), it would be much more likely to move away from a plan that lost a large hospital system representing a third of all hospitals. Thus, competition among insurers for inclusion in employers' plan menus provides the large hospital system with greater bargaining leverage than individual hospitals to negotiate higher prices, even if no two hospitals in the system operate in overlapping service markets.

The first part of this paper uses a theoretical model of bargaining between upstream suppliers and downstream intermediaries to formalize the intuition outlined above. Building on the model in Ho and Lee (2015), we show that a sufficient condition for a market power effect of an upstream merger between hospitals is that the insurer's objective function, typically represented by its profits, is *submodular* in the set of upstream hospitals—i.e., the value of a hospital to an insurer is decreasing in the size of the insurer's hospital network. This condition can be satisfied under standard formulations for consumer demand and insurer profits if the hospitals are valued by a common customer (e.g. employer or household) even if they operate in different service markets. Our model formalizes some of the arguments in Vistnes and Sarafidis (2013), which includes numerical examples illustrating how price effects may arise when employers recruit employees from different geographic areas. We also provide conditions under which a merger between hospitals negotiating with a common insurer, even absent common customers, is sufficient to generate a price effect. However, depending on the precise mechanism, such common insurer effects alone may not give rise to an antitrust violation.

The second part of the paper explores the predictions of our model using panel data on hospital

[4]Common customers for insurance products can also be households that demand services of hospitals in the same geographic area but different product markets, e.g. pediatric and cardiac hospitals.

[5]Throughout this manuscript, we refer to "price effects," but our theoretical and conceptual observations apply equally to other potential merger effects, such as effects on quality or innovation.

prices and system acquisitions, supplemented with data on local insurance market shares. We examine two distinct samples of acute-care hospital mergers over the period 1996-2010, and compare the price trajectories of three groups of hospitals: (i) hospitals acquiring a new system member in the same state but not the same narrow geographic market ("adjacent treatment hospitals"); (ii) hospitals acquiring a new system member out of state ("non-adjacent treatment hospitals"); and (iii) hospitals that are not members of target or acquiring systems. To minimize concerns about the exogeneity of which hospitals are parties to transactions, we focus on hospitals that are likely to be "bystanders" rather than the drivers of transactions. Our first sample of transactions comprises mergers investigated by the FTC due to potential horizontal overlap among the merging parties. We argue that hospitals outside of the areas of concern fall into the bystander category. Our second sample comprises the set of all system mergers over the period 2000-2010. Here we limit the treatment group in two ways: first, to hospitals that are not the "crown jewels" of each deal and are neither party to nor located near another merger over a 5 year period spanning the transaction of interest. Second, we remove target hospitals altogether and consider the effect of the merger on *acquirers'* prices.

We find that prices for adjacent treatment hospitals increase by 7-10 percent relative to control hospitals. The estimates for non-adjacent treatment hospitals are small, generally negative, and statistically insignificant. Our results also show that *acquirers* are raising their own prices, suggesting that significant quality improvements (such as might arise for targets following a takeover) are unlikely to be the source of price increases. Extensions of our model reveal that price effects are largest when the acquirer shares common insurers with the target system, and when the merging parties have hospitals in closer geographic proximity (i.e., 30-90 minutes' drive from one another). We argue that these findings support the common customer model and suggest that alternative mechanisms are less empirically plausible.

A small number of previous papers consider the impact of cross-market mergers in the health care setting. Lewis and Pflum (2014) use a difference-in-difference analysis to empirically analyze the impact of cross-market hospital mergers on prices of targets. They focus on cases where an out-of-market hospital system purchases a single independent hospital. Lewis and Pflum find evidence suggesting that these acquisitions lead to price increases, and argue that system membership may influence hospitals' bargaining power. Gowrisankaran, Nevo and Town (2015) estimate a model of hospital-insurer bargaining and use it to predict the price effects of within-market hospital mergers. Their baseline model does not allow for our common customer effect since it assumes that insurers do not compete for enrollees. The authors argue that in settings where patients are exposed to negotiated prices via coinsurance rates, cross-market mergers may generate price effects if insurers can utilize coinsurance rates to steer patients away from higher-priced hospitals; they also note that cross-market price effects can arise when insurers are allowed to compete with one another.

Our contribution to this literature is two-fold. We provide a formal theoretical model that is more broadly relevant for markets with intermediaries, and that illustrates how cross-market mergers between upstream suppliers can generate price effects. Importantly, the common customer effect results from a change in parties' outside options (or threat points) when bargaining. The intermediary suffers a larger profit reduction if both suppliers leave its network than the combined sum of profit reductions that would arise from removing each supplier separately. It is not predicated on an assumption that suppliers' bargaining skill (or bargaining parameter in a Nash bargaining game) is affected by a merger (as in Lewis and Pflum, 2014, 2015), or on the existence and magnitude of coinsurance (as in Gowrisankaran, Nevo and Town, 2015), and generates a conceptually straightforward and actionable antitrust offense. We also provide robust empirical evidence of price effects of cross-market mergers, expanding the sample considered in Lewis and Pflum (2014), employing an empirical strategy to address concerns regarding endogenous choice of merger targets, and isolating effects on acquirers rather than targets. We find evidence consistent with common customers driving the estimated price effect, and present empirical tests ruling out several alternative mechanisms.

2 Theoretical Model

In this section, we develop a stylized model of hospital-insurer bargaining over inclusion of the hospital in the insurer's network, and the price(s) to be paid by the insurer for care received by enrollees. Although we focus on the health care context, the model is applicable more broadly if one conceives of hospitals as "upstream" suppliers of medical services who resell their services through "downstream" insurers that, in turn, bundle those services (along with other components, such as utilization review and claims processing) into insurance products. Consequently, the effects that we highlight may also be present in other vertical markets in which upstream firms sell products through downstream intermediaries.

2.1 Overview

Our theoretical framework considers two hospitals bargaining with a common insurer over reimbursement rates. We assume that if the hospitals are independent, they bargain separately with the insurer over hospital services; if the hospitals merge, they bargain jointly with the downstream intermediary. The difference between the two settings is that when hospitals bargain separately, disagreement in one bargain results in only one hospital being removed from the insurer's network; when hospitals bargain jointly, both hospitals are removed.

We first note that a market power effect of any hospital merger—i.e., an outcome where the merged hospitals are able to negotiate higher reimbursement prices without an increase in quality or bargaining effectiveness—will arise if the sum of the marginal contributions of each hospital to the insurer's objective (e.g., profits) is less than the marginal contribution of *both* hospitals jointly to the insurer. In other words, the market power effect will arise if the insurer is harmed more by losing both hospitals jointly than the combined effect of losing each hospital separately.

We show that if the two hospitals are located in separate geographic or diagnostic markets, and the insurer's objective is *separable across markets*—i.e., there are no interdependencies that arise between these markets—then this condition cannot hold. The standard analysis employed by the FTC in hospital merger cases (Farrell et al., 2011) implicitly satisfies this separability condition, and thus does not admit the possibility for cross-market mergers to yield price effects due to an increase in market power.

However, this standard analysis can be extended to capture additional institutional details that characterize the U.S. commercial health care industry. In particular, insurers often sell plans to employers or individuals who value hospitals in multiple diagnostic and/or geographic markets. If two merging parties serve customers who value the services of both, the existence of these "common customers" creates linkages across the markets in which the parties operate. If the links are sufficiently strong (i.e., the insurer serves many common customers of the merging parties), a merger can increase the bargaining leverage of the merging parties vis a vis the insurer that sells plans to the common customers.

We provide two examples of such common customers. The first example comprises *households*; a household chooses an insurance plan that best satisfies the different medical needs of all of its members, subject to budget constraints. This objective will generate a linkage across providers serving distinct diagnostic markets. The second example comprises multi-market *employers*; an employer typically chooses an insurance plan for its employees based on the insurer's network of hospitals across all the markets in which employees work and reside, thus creating a linkage across otherwise separate geographic markets.

Finally, we discuss limiting factors for this mechanism, and the empirical patterns that help to disentangle our explanation from other potential sources of cross-market merger effects.

2.2 Basic Model

Consider two upstream suppliers (hospitals), H_1 and H_2, bargaining with a monopolist downstream intermediary (insurer). For the sake of exposition, we present a stylized version of a bargaining model that highlights our key theoretical points; see Ho and Lee (2015) for a more generalized treatment of hospital-insurer bargaining.[6]

Let $\Phi(\mathcal{G})$ represents the insurer's objective for a given "network" $\mathcal{G}$ of hospitals, where $h \in \mathcal{G}$ indicates that hospital h is in the insurer's network, and $\pi_i(\mathcal{G})$ be the hospital's profits (net of payments made from the insurer). To convey intuition, assume that each hospital bargains with the insurer over a lump sum reimbursement that satisfies the following Nash bargaining problem:

$$p_h = \arg\max_p \underbrace{\Big[\Phi(\mathcal{G}) - p_h - \Phi(\mathcal{G} \setminus h)\Big]}_{\text{Insurer's "gains-from-trade"}} \times \underbrace{\Big[\pi_h(\mathcal{G}) + p_h\Big]}_{\text{Hospital's "gains-from-trade"}} \qquad h \in \{1, 2\}\ , \tag{1}$$

where $\Phi(\mathcal{G} \setminus h)$ represent's the insurer's objective when hospital h is removed from its network $\mathcal{G}$.[7]

[6] The more general model incorporates competition among different insurers with different hospital networks, bargaining over linear per-admission reimbursement rates, asymmetric Nash bargaining, and explicitly models consumer demand for hospitals and household demand for insurers.

[7] Asymmetric bargaining weights are omitted from this equation for ease of exposition. Their omission does not

For simplicity, we assume that if hospital h is removed from the insurer's network, the rest of the insurer's network does not change and the hospital earns 0 profits.[8]

The FOC of (1) for each hospital $h \in \{1,2\}$ is

$$p_h^* = \Big(\Phi(\mathcal{G}) - \Phi(\mathcal{G} \setminus h) - \pi_h(\mathcal{G})\Big)/2 \ , \tag{2}$$

and summing across both hospitals yields total (pre-merger) payments of:

$$P^{\text{pre-merger}} \equiv \sum_{h \in \{1,2\}} p_h^* = \sum_{h \in \{1,2\}} \Big(\Phi(\mathcal{G}) - \Phi(\mathcal{G} \setminus h) - \pi_h(\mathcal{G})\Big)/2 \ . \tag{3}$$

The Impact of a Merger on Total Prices. In this simple environment, we are interested in the price effect of a merger between hospitals H_1 and H_2. To highlight the market power effects of interest, assume that there are no cost efficiencies or quality adjustments upon a merger; this implies that the hospitals' profit functions $\{\pi_h\}_{h \in \{1,2\}}$ (which are net of negotiated prices and can contain costs and other sources of revenue) are unchanged by the mergers. The new negotiated prices for each hospital within the system $\mathcal{S} \equiv \{1,2\}$ will solve the reformulated Nash bargain:

$$\mathbf{p}^M = \arg \max_{\{p_h^M\}_{h \in \{1,2\}}} \left[\Phi(\mathcal{G}) - (\sum_{h \in \{1,2\}} p_h^M) - \Phi(\mathcal{G} \setminus \mathcal{S}) \right] \times \left[\sum_{h \in \{1,2\}} (\pi_h(\mathcal{G}) + p_h^M) \right] \ , \tag{4}$$

where we have assumed that, upon disagreement with any one merging hospital, the insurer loses access to both hospitals in the system. The change in the disagreement point alters the first-order condition of the Nash Bargain: the FOC of (4) for either hospital $h \in \{1,2\}$ can be expressed as:

$$P^{\text{post-merger}} \equiv \sum_{h \in \{1,2\}} p_h^{M,*} = \Big(\Phi(\mathcal{G}) - \Phi(\mathcal{G} \setminus \mathcal{S}) - \sum_{h \in \{1,2\}} \pi_h(\mathcal{G})\Big)/2 \ . \tag{5}$$

A comparison of (3) with (5) implies that the total payment to the hospital system will be greater than the sum of pre-merger payments (ie., $P^{\text{post-merger}} > P^{\text{pre-merger}}$) if:

$$\Phi(\mathcal{G}) - \Phi(\mathcal{G} \setminus \mathcal{S}) > \sum_{h \in \{1,2\}} \Big(\Phi(\mathcal{G}) - \Phi(\mathcal{G} \setminus h)\Big) \ . \tag{6}$$

That is, payments will increase if the reduction in an insurer's objective function from losing the system exceeds the sum of the reductions from losing each hospital separately. A sufficient condition for this expression is for the insurer's objective to be strictly *submodular* in its network of hospitals;

affect subsequent analysis. Applying the bilateral Nash bargaining solution across multiple bilateral bargains was proposed in Horn and Wolinsky (1988) and used in recent empirical work (Crawford and Yurukoglu, 2012; Grennan, 2013; Gowrisankaran, Nevo and Town, 2015; Ho and Lee, 2015). See Collard-Wexler, Gowrisankaran and Lee (2015) for a non-cooperative extensive form generating this division of surplus and further discussion.

[8] If there are competing insurers (and hospitals contract with multiple insurers), the analysis can be extended to account for changes in hospitals' disagreement points upon merging (see Peters, 2014; Ho and Lee, 2015); however, the effects that we focus on here will still be present.

i.e., strict submodularity of the objective $\Phi(.)$ implies:

$$\Phi(\mathcal{G}) + \Phi(\mathcal{G} \setminus S) < \sum_{h \in \{1,2\}} \Phi(\mathcal{G} \setminus h)$$

which directly implies (6). Whether or not this necessary condition for a merger to generate a positive price effect will hold is an empirical question, and partly depends on whether the insurer views the merging hospitals as substitutes or complements from the perspective of its direct customers. If hospitals are complementary—i.e., so that the sum of the losses from losing either hospital individually is greater than the loss from losing both—then a merger may lead to a reduction in prices (see also Chipty and Snyder, 1999).[9]

2.3 No Price Effects When Markets are Separable

Assume now that h_1 and h_2 are located in different markets $m \in \{1, 2\}$. If the insurer's profits (i.e., both costs and demand) are separable across these markets so that

$$\Phi(\mathcal{G}) - \Phi(\mathcal{G} \setminus \mathcal{S}) = \sum_{m} \Big(\Phi_m(\mathcal{G}) - \Phi_m(\mathcal{G} \setminus h_m) \Big) \,, \tag{7}$$

(where h_m indicates the hospital in market m), then $P^{\text{post-merger}} = P^{\text{pre-merger}}$ and there will be no cross-market price effect arising from increased bargaining leverage.

This condition is implied by the standard approach used in the hospital merger literature (Capps, Dranove and Satterthwaite (2003), Farrell et al. (2011)).[10] In particular, these models assume that an insurer's objective function when bargaining with hospitals is a linear function of individuals' "willingness-to-pay" (WTP) for the insurer's network. This WTP variable, constructed from a model of individual demand for hospitals, represents the individual's expected utility or option value from being able to access the insurer's network of hospitals in the event of a need for hospitalization. In Appendix A, we define WTP and detail its construction.

One important feature of WTP is that it is typically submodular in the set of hospitals within the same diagnostic and geographic market. Consumers view these hospitals as substitutes, so the sum of the reduction in WTP from losing one hospital but retaining access to the other is less than the change in WTP from losing both (Capps, Dranove and Satterthwaite, 2003). Thus, if an insurer's objective were captured by the WTP it generated for potential enrollees, then a within-market merger of two hospitals (i.e., in the same diagnostic and geographic market) would be predicted to increase the hospitals' bargaining leverage and generate a higher post-merger price.

There are two additional requirements for (7) to hold: WTP must be additively separable across different diagnostic categories (e.g., for a given individual, the WTP of an insurer's network for cancer can be separated from the WTP for obstetric services); and individuals must only derive

[9] A similar mechanism can be generated if losing a merged system induces an insurer to declare bankruptcy while losing a smaller system would allow it to remain in business.

[10] Absent coinsurance rates, the model in Gowrisankaran, Nevo and Town (2015) also generates this condition.

utility from hospitals within their own geographic market. Consequently, assuming that an insurer maximizes a linear function of WTP for all of its enrollees typically implies that a cross-diagnostic market or cross-geographic market provider merger will not be predicted to yield a negotiated price increase.

2.4 Common Customers and Non-Separable Markets

The assumption that the insurer's objective Φ is linear in WTP is stylized, and was adopted for analytic convenience. It is probably more realistic to assume that insurers maximize profits, which are a function of both the WTP generated for enrollees and the nature of demand faced by the insurer. If there are *common customers* for the insurer who value both hospitals *at the time of choosing an insurance plan*, then a simple extension of the standard analysis can generate an increase in bargaining leverage arising from a cross-market hospital merger. We now present two examples of such common customers.

2.4.1 Linking Diagnostic Markets Via a Common Customer: Households

Consider first a household (or family) that chooses an insurance plan to satisfy the needs of all its members. This is the assumption made by Ho and Lee (2015), in which households f choose an insurance plan j in geographic market m to maximize a utility function similar to:

$$u_{f,j,m} = \delta_{j,m} + \sum_{k \in f} \alpha_k WTP_{k,j,m}(\mathcal{G}_j) + \varepsilon_{f,j,m} \tag{8}$$

where $\delta_{j,m}$ are plan-market fixed effects, $WTP_{k,j,m}(\mathcal{G}_j)$ is the WTP generated by plan j in market m for individual k in the household, and $\varepsilon_{f,j,m}$ is an i.i.d. demand shock. This utility specification generates demand for insurer j that is non-linear in the WTP that it offers to different individuals. If the insurer maximizes an objective, such as profit, that is a function of its demand, then this simple extension to the standard framework generates two implications. First, if a household comprises multiple individuals, then diagnostic markets that are valued by different members of the household (e.g., pediatrics and obstetrics) will be linked together when the plan choice is made. Second, even if a household comprises only a single individual, the fact that the individual values the services of two providers in different diagnostic markets *at the time of choosing an insurance plan* induces a cross-diagnostic market linkage.

In Appendix B, we provide examples of demand formulations that will satisfy (6) and generate positive price effects arising from cross-diagnostic market mergers.

2.4.2 Linking Geographic Markets Via a Common Customer: Employers

The second example of a common customer is an employer that chooses an insurance plan to offer to employees who live and/or work in multiple geographic markets. This common customer effect is discussed in Vistnes and Sarafidis (2013); we formalize it here.

In the large-group employer sponsored health insurance market, employers are typically the *direct* customers for insurance plans in that they determine the menu of plans from which their employees choose and negotiate the financial terms of those plans (e.g., premiums and cost-sharing arrangements). We provide intuition for how this competition to be included in an employer's choice set introduces cross-market linkages, and hence bargaining effects arising from cross-market hospital mergers.

Consider the simple situation where an employer offers an insurance plan j to its employees if its gains from offering the plan exceed some threshold F.[11] The employer's objective, denoted $W(\mathcal{M})$, is a function of the welfare gains that its employees receive from having access to a particular choice set of insurers $\mathcal{M}$. Thus, if $\Delta W(\mathcal{M}, j)$ is the additional welfare generated by an insurance plan j for an employer's choice set, then the employer will choose not to offer the plan to its employees if $\Delta W(\mathcal{M}, j) < F$.[12] Note that this formulation is quite general: it does not require that an employer weights the welfare generated for all employees equally; it also allows the firm to require (through appropriate market-level thresholds in $W(\mathcal{M}, j)$) that employees in a particular market all receive a minimal level of insurance coverage or access.

In this setting, hospitals located in different geographic markets can, upon merging, increase their negotiated reimbursement rates from the insurer. For example, assume that if the insurer has at least H_1 or H_2 in its network, then $\Delta W(\mathcal{M}, j) \geq F$ and it will be offered by the employer. However, if it loses both, then $\Delta W(\mathcal{M}, j) < F$ and the insurer will be dropped by the firm and earn 0. In this example the cutoff value F implies a discrete drop in the insurer's objective function upon losing the combined hospital system. Under simple conditions for the shape of the insurer's objective function, this generates the required sub-modularity with respect to the hospital network. That is, since $\sum_{h \in \{1,2\}} \Phi(\mathcal{G} \setminus h) > \Phi(\mathcal{G} \setminus \mathcal{S}) = 0$, (6) will hold and there will be a cross-market bargaining effect provided $\sum_{h \in \{1,2\}} \Phi(\mathcal{G} \setminus h) > \Phi(\mathcal{G})$.[13]

For ease of exposition, this example focused on the situation with a single employer and generated a stark prediction: a cross-market hospital merger will only generate a price effect if it creates a hospital system large enough that its removal causes the insurer to be dropped by the employer. However, in reality, insurers compete to be offered by multiple employers; furthermore, the prices and networks over which they bargain are not typically employer-specific. With a distribution of employers with heterogeneous employees and thresholds, there will generally be a non-zero impact of cross-market hospital mergers if at least some employers would be willing to switch insurers if a particular hospital system were dropped. The impact of cross-market mergers will generally increase as the importance of the system to employee welfare grows.

[11] Such a threshold can arise from a fixed cost of offering each additional plan or from competition from another insurance plan (in which case F would be an endogenous equilibrium object).

[12] This extends the model in Ho and Lee (2015) to allow employers to drop an insurer if the "gains-from-trade" from employer-insurer bargaining are negative.

[13] An alternative justification for the link between markets can be derived from agency theory. Suppose the employer hires a single negotiator who deals with the insurer and who covers multiple markets. This negotiator has to report the results of his negotiations to the principal (his supervisor). He is able to report that a hospital has been dropped in one market, or the other, but may be fired if he loses both.

2.5 Caveats and Limiting Factors

The key limiting factor to the common customer mechanism is the requirement that there must exist a customer (employer, household, or individual) that, when choosing among insurance plans, places positive value on both merging providers. We view these common customer effects as a natural extension of the horizontal theory underlying most merger challenges. However we note that, under some slightly amended versions of the model discussed above, these effects would not arise.

Inelastic Insurer Demand With Respect to the Network. A key component of the common customer effect is the large reduction in the insurer's profits if it loses the merged hospital system. In our example, this arose from an increased likelihood that employers would switch to other insurers. In settings (e.g. outside of health care) where dropping an upstream merged entity is unlikely to affect the downstream intermediary's demand, there may be no price effects of cross-market mergers. The merger between P&G and Gillette may be such an example. It is plausible that consumers would not switch away from Walmart and other major retailers even if both firms' products were removed from its shelves, implying no submodularity in the retailer's profits with respect to the merged entity and no merger price effect.

Separable Demand by Common Customers. The simple model also assumed that employers faced a fixed cost of offering additional plans. If instead employers could costlessly offer different plans in different markets, this would take us back to the case with additively separable markets and no cross-market merger price effects. However, insurers commonly design plans to cover broader geographic areas than most hospital service markets (Vistnes and Sarafidis (2013)), making this disaggregation difficult. We also note the empirical regularity that employers seem to prefer one-stop shopping. For example CalPERS, an agency which provides pension and health benefits to California state and public employees and their dependents, offers a single menu of plans across the whole of California.

Separable Bargaining. Finally our model assumes that hospital systems bargain jointly with each insurer. If systems bargain hospital by hospital, i.e. they cannot impose "all or nothing" requirements on insurers, then again the cross-market price effects will be removed. Anecdotal evidence, and estimates in papers such as Ho (2009) and Lewis and Pflum (2015), suggest that systems generally negotiate jointly, and often require insurers to include all system members in contracts. Some systems also forbid insurers to use financial incentives to steer patients away from their hospitals; this conduct is the subject of a recent lawsuit filed by the Department of Justice against Carolinas Health System.[14].

[14] See https://www.justice.gov/usao-wdnc/pr/justice-department-and-north-carolina-sue-carolinas-healthcare-system-eliminate-0

2.6 Other Cross-Market Mechanisms

We now examine several situations where cross-market hospital mergers can generate price effects even though there are no customers who value both merging hospitals. Some of these effects may not constitute antitrust violations; in fact they may work in opposite directions, and in the aggregate may lead to post-merger quality-adjusted price reductions.

"Common Insurer" Effects. We provide details of two mechanisms that require a common insurer: i.e., an insurer that operates in both markets and negotiates with both hospitals, but no common customer.[15] Under both mechanisms, a merged hospital system negotiating with a common insurer can negotiate higher (total) prices than would be possible under independent ownership.

1. Price Cap in One Market. Consider a setting in which there is an independent hospital subject to a price cap due to political or regulatory restrictions. Suppose the cap binds so that the hospital is unable to increase its price to the level implied by Nash bargaining. In our model, this would imply that the FOC given by (2) is slack, and that the LHS of (2) is strictly less than the RHS. Consider now the effect of a merger between this hospital and another in a second market that is not subject to a price cap. If there is a common insurer that negotiates with both hospitals, (5) implies that the sum of the hospital prices will be a function of the hospital system's contributions to the insurer's revenues. As a result, by merging, the hospital subject to the price cap can generate an increase in the second hospital's negotiated prices so that the merged hospital system's Nash bargaining FOC given by (5) will bind. Thus the merger can yield a price effect due to the presence of a common insurer, even if the hospitals that merged were never valued by the same customers.

2. Linear Prices and Double Marginalization. Now consider a scenario where a monopolist insurer is active in two markets A and B, there are monopolist hospitals active in each market, and negotiated prices are linear (i.e., per-patient payments). We show in Appendix C that, if premiums are set after linear fees are negotiated, then the double marginalization arising from the insurer's markup of the hospital's negotiated prices introduces an inefficiency from the perspective of the bargaining firms. There are potential industry profit gains from a hospital merger that allows the new combined system to internalize pricing effects across markets (e.g. by setting a lower price in markets with a relatively high elasticity of demand and a higher price elsewhere) in a way that independent hospitals would not. The increase in industry surplus from internalizing these cross-market differences means that a hospital merger can increase the total payments made to the hospital system. However we conjecture that this effect is empirically less relevant than the common customer effect because it requires individual hospitals to sacrifice revenues for the benefit of other system members, and industry

[15] The common customer effect also requires the presence of one or more common insurers.

interviews suggest individual hospital CEOs are compensated and rewarded on the basis of their own facility's bottom line.[16]

Cost Savings, Bargaining Spillovers, and Co-insurance. Finally, a cross-market merger can generate cost savings, managerial improvements, or "bargaining spillovers"; each of these can affect prices. Cost efficiencies, for example due to the centralized provision of particular services, could lead to price reductions. Quality improvements or increases in bargaining ability could lead to price increases (Lewis and Pflum, 2014). If enrollees face coinsurance rates (so that the cost of visiting a hospital depends on the negotiated price), mergers may lead to a change in prices as insurers and hospitals respond to the impact of hospital pricing on utilization (Gowrisankaran, Nevo and Town, 2015).[17]

2.7 Linking Theory to Empirics

In the following section we present an empirical analysis of the price effects of cross-market mergers. We also conduct analyses to explore the potential mechanisms underlying the effects we uncover. We begin by listing three testable predictions of our preferred "common customer" model.

1. *A necessary condition for a common customer effect is the existence of common insurers that operate in both acquiring and target hospital system markets.* We explore this condition empirically by measuring the extent of insurer overlap across the merging hospitals and comparing the price effects of mergers between hospitals with higher and lower insurer overlap.

2. *The more prevalent the common customers, the greater the predicted price effect.* We posit that more distant hospitals probably have fewer common customers. We compare the estimated price effects for adjacent and non-adjacent treatments, and within the adjacent treatment sample, we consider whether the effects are increasing in the proximity of acquirers and targets.

3. *In most cases, the price effect on the acquirer is predicted to be increasing in the size of the target system. However, this prediction may not hold for the largest acquirers.* In order to generate an increase in negotiated prices through a common customer effect, a cross-market merger must create a sufficiently large and attractive hospital system that its loss from the network could plausibly induce employers or households to drop that plan. For a given acquirer size, mergers with larger target systems plausibly generate a larger increase in $\Delta W(\mathcal{M}, j))$ and therefore a larger price effect. However, at the extreme, very large acquiring systems may already be very attractive pre-merger—their exclusion may bring the employer below F even absent a merger with other hospitals—so an increase in target size may generate

[16] In the words of one former hospital system executive, "every tub on its own bottom" is the guiding principle when it comes to operating margins for each hospital.

[17] The analysis in this case is similar to that related to linear prices and double marginalization; see below and Appendix C.

no additional price effect. We calculate the pre-merger share of each target system (in the set of markets where both the acquirer and target operate) and ask whether larger targets lead to larger merger price effects, controlling for acquirer system size.

We also assess the empirical plausibility of the alternative mechanisms outlined above. Here are the key competing hypotheses and the empirical analyses that help us to assess the role they might play in generating the effects we document.

1. *Cost efficiencies.* Cross-market mergers may generate cost efficiencies, e.g. due to fixed costs of insurer-system negotiations or to operational efficiencies (for example, Dranove and Lindrooth find that merging hospitals that surrender a facility license - likelier to happen if they are closer together - realize cost reductions). If these efficiencies are insensitive to distance they should affect prices for adjacent and non-adjacent mergers equally. If not, they suggest price increases should be smaller for adjacent treatments.

2. *"Common insurer" effects or coinsurance rates.* Both mechanisms that require a common insurer but no common customer—the effect of a price cap in one market and the double marginalization effect under linear pricing—are likely to generate a price increase in one market but not the other.[18] The mechanism based on co-insurance rates in Gowrisankaran, Nevo and Town (2015) has a similar prediction.[19] These explanations seem implausible if the estimates indicate significant, positive average price effects.

3. *Hospital investment in assets or quality.* Mergers may be followed by significant investments that give rise to (pro-competitive, or competitively neutral) price increases. Any distance-sensitive quality investments are likely to be focused on the *target* rather than the acquiring system. Hence, we explore the robustness of our results to excluding all target hospitals (where the sample size allows, i.e. in the broad merger sample). We also consider the evidence for changes in service or customer mix among the remaining hospitals.

4. *Transferable Bargaining Skill.* To the extent that this mechanism is insensitive to the distance between merging hospitals (at least within-state), we can assess its importance by asking whether price effects differ by proximity between acquirer and target.

5. *Market Definition.* Our broad sample analyses drop treatment hospitals gaining a system member within 30 minutes' drive since there may be within-market merger effects for these providers. If effective hospital markets are larger than these approximations the estimated cross-market price effects will be upwardly biased. We repeat our analyses using the radius

[18] In the setting with a binding price cap due to political constraints in one market, the hospital in the *second*, unconstrained market should experience a price increase, but that in the first is constrained by definition. The double marginalization scenario has the combined system setting a *lower* price in markets with a relatively high elasticity of demand and a higher price elsewhere.

[19] As noted in Gowrisankaran, Nevo and Town (2015), in a setting with coinsurance rates, the insurer "might be willing to trade off a lower price in the first market for a higher price in the second, in order to steer patients to or away from the outside option appropriately".

implied by a 45 minute drive time as a robustness test. Our limited data prevent us from extending the assumed market size further; however we note that hospital markets for antitrust enforcement are typically defined more narrowly than this.

3 Empirical Analysis: Overview and Data

We use data on hospital prices, system affiliations, and acquisitions to quantify the price effects of cross-market mergers in the hospital sector and to conduct the tests outlined in the previous subsection. Although we focus on cross-*geographic*-market hospital mergers, the conceptual arguments we assess pertain to cross-product-market mergers as well.

Our empirical strategy comprises three key elements: (i) identifying a set of hospitals whose involvement in a cross-market merger is plausibly exogenous to other determinants of hospital prices; (ii) among this set of "treatment hospitals," distinguishing between those gaining a system member nearby versus further away, as the common customer effect is likely stronger in the former case (the "further away" group should capture the aggregate effect of the "other mechanisms" described in section 2.6 above); (iii) identifying a set of control hospitals that are not affected by any transactions over the relevant study period, and whose price trajectories are reasonable counterfactuals for the set of treatment hospitals. We estimate difference-in-differences models that compare price growth for two sets of "treatment" hospitals (specifically those gaining a system member in-state versus out-of-state) with price growth for "control" hospitals during the relevant time period. Below, we discuss our transaction samples and how we identify and categorize treatment hospitals.

3.1 Defining Transaction Samples and Treatment Hospitals

Prior research suggests that assuming hospital transactions and system affiliations are exogenous can lead to a significant underestimate of price effects. For example, using a set of one-to-one hospital mergers (i.e. mergers of independent hospitals), Dafny (2009) reports IV estimates of merger price effects in excess of 40 percent, whereas OLS point estimates for the same sample of transactions are near zero. Researchers have also found that new system affiliations are correlated with factors that also affect net prices.[20]

To address the endogeneity of being party to a transaction, we focus on "bystanders" to transactions. The rationale is as follows: if a given hospital is not the driver of the transaction, and is merely "treated" by virtue of being part of an acquiring or target system, it is less likely that the acquisition is the result of omitted factors correlated with price trajectories. We consider two sets of transactions: an "FTC sample," and a "broad merger sample."

The FTC sample consists of mergers that were investigated by the FTC due to geographic overlap between the merging parties in one or more markets, and eventually consummated (with

[20]Dafny and Dranove (2009) show that independent hospitals with poor operating performance and stronger "upcoding potential" are more likely to join for-profit hospital systems, and upon joining, to engage in upcoding that yields higher net revenues per admission.

or without a legal challenge by the FTC).[21] Table 1 lists the mergers in the FTC Sample and the geographic market with the closest overlap among the merging parties. Investigations are not typically announced by competition authorities unless a complaint is issued. However, private parties may disclose if they are under investigation or are being questioned in connection with an open investigation.

Combing public sources, we identified 23 investigations of proposed mergers among general acute care hospitals over the period 1996-2011.[22] Of these 23 mergers, 3 were abandoned by the would-be merging parties, and 20 were consummated. Given the high costs associated with responding to an FTC investigation, we posit that these mergers were motivated by the combination of the hospitals in overlapping geographic markets. Otherwise, the merging systems would likely have divested the potentially problematic properties or abandoned the transaction in the face of FTC scrutiny. Hence, we consider the two hospitals closest to one another to be the "drivers" of each merger, and they are dropped from our primary analysis sample.[23] We study the impact of the (consummated) merger on other system members that are part of the transaction. We argue that the treatment of gaining a system member is plausibly exogenous because the transaction generating the treatment was motivated by considerations related to a different (and omitted) set of hospitals. As a check of this assumption, we compare pre-merger price trends in treatment and control groups.

Figure 1 summarizes our strategy for identifying treatments using the FTC investigations. It depicts the merger of system A and system B across 3 states, represented by rectangles. Members of system A and B are both present in state 1, but were not the object of the FTC investigation. In state 2, there is a clear potential horizontal overlap between the system members. In state 3, only system B is present. Our approach is as follows: (i) we drop the two merging hospitals nearest one another; (ii) we designate all remaining members of systems A and B in states 1 and 2 as "adjacent treatment" hospitals; and (iii) we designate all members of system B in state 3 as "non-adjacent treatment" hospitals.[24] Table 1 reveals there are 10 transactions in the FTC Sample that generate treatment hospitals.[25]

[21]Of the 20 consummated transactions in Table 1, five were challenged by the FTC (Tenet-Doctors Regional in Missouri, Butterworth-Blodgett in Michigan, ProMedica-St. Luke's in Ohio, Evanston Northwestern-Highland Park in Illinois, and Phoebe Putney-Palmyra Park in Georgia), and one by the California Attorney General (Sutter-Summit). In one additional transaction (the Tenet-OrNda merger of 1997), the merging parties agreed to divest a hospital located in the overlap market (French Hospital and Medical Center in San Luis Obispo, CA). As indicated in Table 1, of the transactions challenged or subject to a divestiture order, only Tenet-Doctors Regional, Sutter-mit, and Tenet-OrNda are included in our estimation sample.

[22]In 2013, the FTC issued a report stating there were 20 total hospital merger investigations conducted between fiscal years 1996-2011, pursuant to the Hart Scott Rodino (HSR) Act. These figures include transactions among non-general acute-care hospitals, e.g. psychiatric hospitals. However, they exclude investigations of so-called "non-HSR reportable transactions." Nonprofits are subject to less stringent HSR reporting requirements, so in light of the fact that many hospitals are nonprofits, the aggregate totals appear to be well-aligned with this report. We did not include mergers taking place in 2012-2014 due to the absence of a post-period in our data on hospital prices.

[23]Where available, internet research confirms these are the hospitals generating FTC scrutiny.

[24]This is an abuse of the term "adjacent," as not all markets share a border; a more accurate description would be "in-state." However, we use "adjacent" as we will relax the state border restriction in robustness tests.

[25]There are a number of reasons that all of the transactions in Table 1 cannot be included in the analysis sample. These include abandonment of the transaction, a merger between two independent hospitals (which, by definition, cannot generate effects on other system members), and ongoing litigation (inclusion of these would yield potentially

Given the small number of FTC-investigated transactions and other limitations we discuss below, we also consider a second, broader transaction sample. To create this second sample, we begin with all acquisitions and mergers involving general acute-care hospitals during the period 1998-2012, as identified by proprietary reports assembled by Irving Levin Associates, a company that gathers and sells data on transactions in a variety of sectors, including the U.S. hospital industry.[26] Our focus is again on transactions generating adjacent and non-adjacent treatment hospitals and motivated by hospitals outside of this set. By definition, this approach excludes mergers between independent hospitals, in which there can be no bystanders. We drop the "crown jewel(s)" of each transaction, defined as the largest hospital being acquired for transactions involving <= 5 hospitals, and all hospitals above the 80th percentile of beds among target systems with more than 5 hospitals. We also drop hospitals gaining a system member within 30 minutes' drive, as there may be "same market" motivations and effects in these cases. If we assume that these transactions are motivated by crown jewels and/or within-market overlaps, then the impact of the transactions on other system members are plausibly be exogenous to omitted determinants of price. As in the FTC sample, we test our assumption by including leads for the transactions in our specifications; the coefficients on these leads will reveal whether treatment hospitals have pre-treatment price trends similar to those of control hospitals. While this test cannot rule out the possibility that price trends for bystanders and controls may have diverged for unobserved reasons coincident with but independent of the merger, it is supportive of the identifying assumption.

We next describe our data sources in greater detail and discuss descriptive statistics for our two estimation samples. We also explain how control groups are defined.

3.2 Data

We assemble data for three key purposes: (1) to calculate a measure of each hospital's price for commercially-insured patients and to obtain hospital characteristics that may be associated with price; (2) to build our two samples of transactions; and (3) to identify hospital system affiliations. We describe the sources for each of these objectives in turn.

We construct an estimate of hospital-year private prices using the Healthcare Cost Report Information System (HCRIS) dataset for fiscal years 1996-2014. HCRIS is a public dataset gathered by the Centers for Medicare and Medicaid Services (CMS). We follow the methodology in Dafny (2009), calculating private price as the (estimated) net revenue for non-Medicare inpatient admissions, divided by the number of non-Medicare admissions. Net revenue for non-Medicare inpatient admissions is estimated by multiplying gross charges for these admissions by the hospital's average revenue to charge ratio. Due to the presence of implausible outlier values, we drop observations in the 5 percent tails of price in each year.[27] We make one minor modification relative to Dafny

downward-biased price effects as the merging parties have an incentive to avoid increasing price until all appeals are exhausted).

[26]As we discuss below, the broad merger sample utilized in our regression analyses reflects only transactions between 2002 and 2010, as we require pre and post-merger study periods. Merger data from earlier and later years is used to exclude hospitals affected by multiple mergers during the relvant study period.

[27]We use data on all general acute care hospitals to construct percentiles of price, and then drop the 5% tails in

(2009), in that we include the hospital's Medicare Case Mix Index (CMI) as an independent control variable, rather than multiplying the denominator by the CMI. Including CMI separately allows for a more flexible association between CMI and hospital price. Unfortunately, the data do not permit us to exclude revenues for all non-commercially insured patients. As our models include hospital fixed effects, only variations in non-commercial, non-Medicare patient admissions and revenues will impact our estimates. Medicaid is the largest source of such patients, hence we include the percent of admissions accounted for by Medicaid patients as a control variable in our specifications.[28] Critical Access Hospitals and other hospitals not paid under Medicare's Prospective Payment System are excluded from the sample. Garmon (2015) presents evidence showing that the Dafny (2009) measure of price is very tightly correlated (r=.95) with true negotiated prices (constructed from claims data) for hospitals with at least 200 commercial patients per year.[29]

As previously described, we construct two datasets of general acute-care hospital mergers: one consisting of mergers investigated by the Federal Trade Commission over the period 1996-2012 ("FTC Sample"), and a second encompassing all mergers over the period 1998-2012 ("Broad Sample"). Additional information on each sample is presented in Table 1 and Table 2, respectively. The detailed breakdown in Table 1 reveals that only two transactions generate non-adjacent treatment hospitals: Tenet/OrNda in 1997 and Banner/Sun in 2008. Given that the HCRIS data begins in 1996, we have only one year of pre-merger price data for the Tenet/OrNda transaction, which is by far the larger of the two. In light of this, we view results from the non-adjacent treatment group in the FTC sample analysis as particularly tentative.

The "Broad Sample" is derived from a list of mergers involving general acute-care hospitals provided by Irving Levin and Associates. Table 2 presents descriptive information for the set of mergers that occurred between 2002 and 2010; these are the years for which we can construct an adequate pre and post-period. In all, there are 426 transactions, 332 of which generate adjacent and/or non-adjacent treatment hospitals. This larger sample size enables us to take more steps to ensure a clean treated sample than is possible when analyzing the FTC Sample. We limit our treatment sample to hospitals experiencing a treatment only once during the 5-year period spanning the transaction generating that treatment, i.e. all treatment hospitals must be exposed to no other mergers from t=-2 to t=2. We impose this restriction to ensure that the pre and post-treatment periods do not capture the effects of other transactions. [30] [31] Relative to the set of all transactions,

each year. Across all years (1996-2012), the mean value (in CPI-adjusted year 2000 dollars) for the 5th percentile and 95th percentile of price is $1,390 and $12,966, respectively.

[28]While HCRIS includes fields for Medicaid admissions and revenues, which would ideally be excluded, these fields are often empty or contain erroneous data.

[29]The actual correlation for our version of price is likely to be lower, however, as Garmon uses CMI for commercial patients in his analysis. We lack the detailed hospital-level claims data to do the same.

[30]Requiring a longer "clean" period for all treatment hospitals - i.e for the entire 8 year period we ultimately include in our regressions (t=-3 to t=4), would exclude too many mergers from our sample. Only 8 transactions have at least one treatment hospital that is clean for this full period. Instead, after imposing the 5-year requirement, we include data for earlier and later years for treatment hospitals that are clean in those years. 35 of 48 transactions have a treatment hospital that is clean in t=-3, and 28 of 48 have a treatment hospital that is clean in t=4.

[31]We could not impose this restriction in the FTC Sample because the largest of the two transactions generating treatments occurred in 1997 and we only have merger data beginning in 2000.

transactions that are included in our final analysis sample involve smaller acquirers (as measured by the number of facilities), since larger acquirers tend to engage in multiple closely-timed acquisitions. Unchanged is the median size of targets, which is a single hospital.

Table 3 displays descriptive statistics for adjacent and non-adjacent treatment hospitals in both samples (FTC and Broad). We also note the number of hospitals in each treatment group and sample that belong to the acquiring system versus the target system. Because the modal target in the Broad Sample is 1, the crown jewel restriction implies that few targets (just 6 hospitals) are in the analysis sample. The results therefore largely reflect the impact of cross-market mergers on *acquirers*; as we suggested above this renders some alternative explanations unlikely. We report results with and without the 6 target hospitals, for ease of interpretation we drop them when estimating extensions to our main model.

Alongside the data on treatment hospitals we present summary statistics for two control groups. Control Group 1 consists of all hospitals not excluded due to same-market overlap (and not classified as treatments). Control Group 2 reflects the further restriction that control hospitals should be members of systems, and in the case of the Broad sample, that they not be located within 30 minutes of a treated hospital; if this occurs we drop the year of the treatment and the three following years.

Table 3 demonstrates that adding restrictions to the control group improves the comparability of the treatment and control samples at the cost of reducing the sample size. We estimate difference-in-differences specifications using both samples and report the results below.

4 Empirical Results: How Do Cross-Market Mergers Affect Hospital Prices?

We quantify the impact on price of becoming an adjacent or non-adjacent party to a merger, relative to a sample of control hospitals over the same relevant time period. We estimate fixed-effects models of the following form:

$$\ln(price_{ht}) = \alpha_h + \sum_l \phi_l^a \mathbb{1}_{h,t+l}^{adj} + \sum_g \phi_g^n \mathbb{1}_{h,t+g}^{nadj} + X_{ht}\theta + \tau_t + \epsilon_{ht} \tag{9}$$

where h indexes hospitals and t indexes years; $\mathbb{1}_{h,t}^{adj}$ and $\mathbb{1}_{h,t}^{nadj}$ are indicators for whether hospital h belongs to the adjacent or non-adjacent treatment group at time t; and X_{ht} are hospital characteristics including ln(case mix index), ln(beds), for-profit ownership dummy, and percent of admissions to Medicaid enrollees. Given the inclusion of hospital and year fixed effects, coefficients on these variables are identified by within-hospital changes in these factors.

In our first specification, we include the maximum number of leads and lags permitted in each sample: for the reasons discussed in Section 3, $l = -2...4$ for both the FTC and the broad merger analysis, and $g = 1...3$ for the FTC analysis and $-2...4$ for the broad merger analysis. The purpose of this model is twofold: first, to confirm the leads lack a pronounced trend (to support the contention that the price trajectory of the control hospitals is a reasonable counterfactual for the treatment hospitals absent the treatment); second, to examine how the price effect (if any) changes over time.

We also estimate a second specification where the treatment leads and lags are replaced with two variables for each treatment, an indicator variable for the year of the merger and another which takes a value of 1 in every subsequent year:

$$\ln(price_{ht}) = \alpha_h + \phi^a_{t=0}\mathbb{1}^{adj}_{h,t=m(h)} + \phi^a_{t>0}\mathbb{1}^{adj}_{h,t>m(h)} + \phi^n_{t=0}\mathbb{1}^{nadj}_{h,t=m(h)} + \phi^n_{t>0}\mathbb{1}^{nadj}_{h,t>m(h)} + X_{ht}\theta + \tau_t + \epsilon_{ht} \quad (10)$$

where $m(h)$ denotes the year of the relevant transaction for hospital h. Combining the post-merger years into a single dummy increases the precision of our estimates and provides a single point estimate for the price effect of each treatment. The specification allows for a different price effect in year $t = 0$, as mergers may close at any point during the year in which they are recorded and hence $t = 0$ does not strictly fall into the pre or post periods. In all regressions, observations are weighted by the hospital's number of discharges (averaged across all years), and standard errors are clustered by hospital.

These models assume that treatment status is exogenous to omitted determinants of price. As previously described, our sample excludes hospitals that are the likely drivers of transactions. The rationale is that "bystanders" to transactions are unlikely to differ in unobservable ways from non-bystanders, i.e. control hospitals. Threats to identification are unobservable factors that differentially influence the negotiated prices for hospitals involved in mergers during the post-merger period versus hospitals in our control groups. For example, in the broad merger sample, hospitals that are never treated may have internally focused managers who are not entrepreneurial about seeking new partners and potentially less likely to negotiate steady price increases with payers (as most hospitals did throughout this time period). To the extent this is true during the pre-period, the data will show a divergence in price trends among the treatment and control groups. However, it is possible that the price gap increases exponentially over time and this could violate our identifying assumptions.

To explore this concern, we also estimate models in which we pair each treatment hospital with its closest match in the control group, as identified using a propensity score model. We then estimate a "differenced regression" that focuses on changes in price for each treatment relative to its closest match. As we discuss below, the results are broadly similar.

We now describe the results for each of the transaction samples in turn.

4.1 FTC Sample

The results from estimating equation (9) using the FTC-investigated merger sample are presented in Appendix Table 1. As discussed above, we report findings obtained using two control groups. Control Group 1 is very broad; Control Group 2 is restricted to hospitals that are system members and hence more similar to the treatment groups (which must be system members). The results are similar across the two samples. Figure 2 graphs the coefficient estimates on the leads and lags of the adjacent and non-adjacent indicator variable from equation (9) above, as estimated using Control Group 2. Beginning with the price patterns for adjacent hospitals, we see that price jumps up for these hospitals in $t = -2$ (relative to the omitted year, $t = -3$) by about 7 percent, and then holds steady until $t = 0$. Prices increase steadily from $t = 1$ to $t = 4$, at which point the price of adjacent treatment hospitals is 17-18% higher than that of the control group, all else equal. Non-adjacent hospitals, for which we only have one year of pre-merger data, exhibit a statistically insignificant reduction in price in the year of the merger, after which prices fluctuate and ultimately end up slightly lower -albeit not significantly so - than where they started. We can reject equality of the coefficients on the adjacent and non-adjacent indicators in $t = 4$ at $p < 0.05$.

Most of the control variables have statistically significant coefficients. In both samples, increases in the complexity of a hospital's caseload, and in its number of staffed beds, are associated with higher prices. The for-profit dummy is also positive and statistically significant in both models. Given the inclusion of hospital fixed effects, the interpretation is that hospitals that convert to for-profit status experience price increases, all else equal. The Mediciad patient share is not associated with a significant change in private price.[32]

Table 4 presents coefficient estimates from the parsimonious regression equation (10), in which we include indicators for $t = 0$ and $t > 0$ (separately for adjacent and non-adjacent treatment groups). The results show that the adjacent treatment leads to a price increase of roughly 7 percent, while non-adjacent treatment is not linked to any significant price effects. The confidence interval around the non-adjacent treatment effect is very wide; this is unsurprising in light of the small number of transactions generating these treatments. As a result, we cannot reject equality of the adjacent and non-adjacent treatment effects in this sample. In addition, and as noted above, the treated hospitals experience a price surge between $t = -3$ and $t = -2$. Hence, we examine a broader set of transactions to corroborate these findings.

4.2 Broad Sample

The results obtained from estimating equation (9) using the Broad Sample are displayed in Appendix Table 2. Columns 1 and 2 correspond to control groups 1 and 2, respectively. The coefficients of interest are again insensitive to the choice of control group. Figure 3 plots the coefficients from the leads and lags of adjacent and non-adjacent indicators (relative to Control Group 2), and Table 5 presents results from the specification with a pooled post-period.

There is no significant evidence of pre-treatment trends in any of the models estimated. For both treatment groups the coefficients on $t = -2$ and $t = -1$ are very small and insignificant. Thereafter, price trends for the adjacent and non-adjacent groups diverge. The adjacent hospitals show steady price increases, with a particularly large jump between $t = 2$ and $t = 3$. The cumulative price increase is estimated at $14 - 15$ percent. By comparison, prices for non-adjacent treatment hospitals zigzag over time. All coefficients are negative but none are significantly different from

[32] As noted below, Appendix Table 4 reports results dropping all control variables, and they are very similar to the results including the controls.

zero and they end about 3 percent below their starting point (relative to controls). As we discuss below, dropping the target hospitals has virtually no impact on the estimates (results in column 3 of Appendix Table 2). The estimated coefficients on the control variables are comparable to those for the FTC-investigated sample.

The results in Table 5, which separate only $t = 0$ and $t > 0$, reveal that adjacent treatment is followed by a statistically significant price increase of roughly 10 percent. The point estimates for non-adjacent treatment hospitals during $t > 0$ are small and negative, and never achieve statistical significance. Equality of the adjacent and non-adjacent treatment effects can be rejected at $p < 0.05$ using both control groups.

4.3 Robustness of Main Results

We investigated the robustness of our results to alternative specifications. One possible concern regarding the FTC sample, given the small number of transactions in the data, is that the estimated price effects could be driven by a single merger. We repeat the main analysis excluding one merger at a time. The results are presented in Appendix Table 3. The estimates are very stable across these samples.

We also test the robustness of the results to inclusion of a for-profit indicator interacted with individual year dummies. Per Table 3 (Descriptive Statistics), treated hospitals in the FTC sample are far likelier to be for-profit than hospitals in either control group (in the broad sample, for-profit ownership is similar across the treatment group and Control Group 2). If for-profit hospitals have different price trajectories, then our estimated treatment effects could be reflecting this difference. However, the results (in Appendix Table 4, reported for both samples using Control Group 2) are exceedingly similar even allowing for different year effects for for-profit hospitals. We also estimated models excluding all control variables. The coefficients of interest, also in Appendix Table 4, are virtually unchanged; this finding alleviates the concern that omitted, time-varying hospital and market characteristics that are correlated with price (as the controls are) are also correlated with treatment status.

Last, we develop a model that involves matching treatment hospitals to specific control hospitals. We estimate regressions analogous to those described above but replacing the variables with the differences between each treatment and its matched control(s). One advantage of this approach is that it admits heterogeneous time trends for different pairs of hospitals and matched controls.

The regression is below:

$$\ln(price_{ht}/price_{c(h),t}) = \alpha_h + \sum_l \phi_l^a \mathbb{1}_{h,t+l}^{adj} + \sum_g \phi_g^n \mathbb{1}_{h,t+l}^{nadj} + (X_{ht} - X_{c(h)t})\theta + \epsilon_{ht} \tag{11}$$

We experimented with a variety of methods to determine the control hospital(s), denoted $c(h)$, for each treated hospital. For example we used a match based on observables, matching controls (in control group 2) to treatments on the basis of Census division and urban/rural status, using several different numbers of matches (with or without replacement). We also used a method relying on a propensity score to find the closest match among potential control hospitals. The variables used to calculate the propensity score were the X variables included in the regression analysis, an indicator for urban areas, and measures of the number of other hospitals in the potential control's system. We encountered some sample size issues with both of these methods: the pool of potential matches for treatment hospitals was not large, and the same control hospital was quite frequently the best match for several treatment hospitals. However, the results obtained using these samples and equation (11) were very comparable to the results from the preferred specification: adjacent hospitals increased price relative to matched controls, while non-adjacent hospitals decreased price (but not by a statistically significant amount).[33]

5 Disentangling the Sources of Price Increases From Cross-Market Mergers

Our primary specifications reveal that cross-market mergers yield substantial price effects when those mergers involve hospitals in adjacent (same-state) markets. Section 2 suggests several mechanisms by which cross-market hospital mergers could lead to price increases. In this section we discuss specifications designed to elicit more direct empirical evidence of the common customer effect.

The Importance of a Common Insurer. The common customer effect requires that the merging hospitals negotiate with at least one common insurer, while alternative explanations (such as an increase in hospitals' bargaining skill or reduction in risk-aversion post-merger) do not. We therefore investigate the importance of common insurers in generating a price effect. We create a measure of insurer overlap using MSA-level market shares for comprehensive medical insurance, constructed from 2012 data from the National Association of Insurance Commissioners.

The insurer overlap measure is hospital and transaction-specific, and is continuous and monotonic in the degree of joint significance of the same insurers to a given treatment hospital and to the target system. For ease of interpretation, we drop the 6 treatment hospitals that are members of a target system. The results of doing so (for the pooled post-period model) are reported in column 3 of Table 5: there is very little change in the estimates. To construct the overlap measure, we begin by calculating the bed-weighted average market share for each insurer and target system using the market shares of insurers located in each system member's MSA (or non-MSA portions of the relevant state, if not located in an MSA). For each treatment hospital in our sample (which now consists solely of members of acquiring systems), we compare the vector of insurer market shares in that hospital's MSA (or state, where relevant) with the vector of bed-weighted average market shares for the target system. We sum the minimum market shares for insurers common to both.

[33] Results available upon request.

The insurer overlap measure is bounded by 0 and 1, equaling 0 if the treatment hospital and target system share no insurers, and 1 if they are located in the same MSA (as there are no MSAs with exactly the same insurer market shares). We consider two different versions of this measure: *state insurer overlap*, where insurers cannot cross state boundaries (i.e. United HealthCare-Texas is considered a different insurer for negotiating purposes than United Healthcare-Oklahoma); and *national insurer overlap*, where insurers operating in multiple states are considered as one.[34] The median for *state insurer overlap* is 0.82 among adjacent treatments; it is always zero, by definition, for non-adjacent treatments. The median for *national insurer overlap* is 0.88 for adjacent treatments and 0.31 for non-adjacent treatments.

We estimate the parsimonious specification in Table 6, using Control Group 2, but this time pooling all treatments together and adding an interaction between the indicator for $t > 0$ and a measure of insurer overlap. (Because the insurer overlap measure varies at the hospital level, we do not include it directly in the model as it is collinear with the hospital fixed effects.) The coefficient on the interaction with *state insurer overlap* is positive and significant at $p <= 0.01$; in fact it absorbs all of the merger price effect (i.e., the non-interacted "post" treatment effect is small and statistically insignificant). Substituting the version of insurer overlap that presumes insurers negotiate contracts jointly for hospitals in different states yields noisy estimates. This is consistent with our priors, as it is our understanding that many systems and insurers did not negotiate national contracts during our study period. Unfortunately we lack the power to disaggregate the insurer effect separately for adjacent and non-adjacent mergers. However, the results imply that insurer overlap is necessary to generate price increases from cross-market mergers.

The Role of Common Customers We next investigate the impact of sharing common customers on merger price effects. We first attempt to construct hospital-specific measures of common customers for all treatment hospitals. An ideal measure of common customers would capture two factors: (i) the relative significance of employers who draw employees from both target and acquirer hospitals; (ii) the volume of employees who commute between both target and acquirer service areas. A proxy for factor (i) could be constructed using information on multi-site establishments and identifying which sites are in each hospital's primary service area. Regrettably, this information can only be acquired through on-site access to Census data, coupled with access to national hospital discharge data to construct hospitals' primary service areas. A second option is to use public data on commuting patterns between counties to capture factor (ii). The Census publishes such data using the American Community Survey as the primary source.[35] We consider two hospital and transaction-specific measures: an outflow-only measure (defined as the total share of county residents commuting to counties in which a hospital acquires a new system member), and an outflow and inflow measure constructed as the sum of residents commuting between counties of hospitals

[34] For example, Health Care Service Corporation operates Blue Cross and Blue Shield plans in 5 states: Texas, Oklahoma, Montana, New Mexico, and Illinois.

[35] The data are available at `http://www.census.gov/population/metro/data/other.html`. We use information on the number of commuters from county of residence to county of workplace, by county pair, averaged over the period 2006-2010.

newly linked via merger, divided by the number of county residents for the hospital in question plus inbound commuters. One issue arising for both measures is that some adjacent treatment hospitals gain a system member in the same county; such cases are captured via a separate indicator variable. Unfortunately both variables are noisy measures of the extent to which the merging hospitals' service areas are linked by commuters. The commuter data are available only at the county level, and counties may be inaccurate measures of hospital service areas. In addition, these data do not capture relevant factors such as commuters' means of transportation and the extent to which family members also commute. Perhaps not surprisingly, interactions with our measures of commuter overlap do not enter significantly in our regressions.

We therefore pursue cruder measures of the role of commuters, by estimating models comparing the magnitude of the cross-market price effects for hospitals gaining members that are geographically closer versus further apart. The closer the hospitals in terms of drive time, the more likely employers are to have locations near both hospitals or to have employees who commute from the service area of one to the service area of the other. These realities will presumably make the employer less likely to choose an insurer that offers neither hospital than a plan that offers one but not the other; this preference generates the "common customer" price effect of a merger between the two hospitals.

We modify the regression in equation (9) by interacting the leads and lags for adjacent treatments with an indicator for mergers between hospitals located within 30-90 minutes' drive time of one another and an indicator for more distant merging hospitals (recall that we interpret mergers within 30 minutes' drive time as "horizontal" and therefore exclude them). We attempted to do the same for non-adjacent treatment hospitals, as the common customer effect could potentially transcend state boundaries, however we have too few merging hospitals that are 30-90 minutes apart but in a different state to enable a test of the importance of state boundaries.[36] The results from estimating this equation are presented in Appendix Table 5 and graphed in Figure 4. Only adjacent treatment hospitals gaining a system member within 30-90 minutes experience steady price increases throughout the study period. Adjacent treatments in the 90+ category see small, imprecisely estimated price increases that tail off in t=4. Four years after gaining a nearby system member, prices for the 30-90 group are 19% higher than the controls, compared to a (statistically insignificant) 3% higher and 3% lower for the 90+ adjacent treatments and non-adjacent treatments, respectively. Pooling across the entire post-merger period, we can reject equality of the 30-90 coefficient and the non-adjacent treatment coefficient. We interpret these findings as suggestive evidence of the existence of common customer effects.

The Impact of Acquirer and Target Size In section 2.7, we outline the theoretical predictions regarding acquirer and target size. To test these hypotheses, we add interactions between the adjacent*($t > 0$) term (the "post-treatment dummy") and two separate indicators, one for "above median" acquirer size and the second for "above median" target size, where size is measured as

[36] The 104 hospitals in the adjacent treatment group are roughly evenly split between 30-90 and 90+ minutes. Only 7 of the 55 hospitals in the non-adjacent treatment group are in the 30-90 minute category.

market share of all beds in the (same-state) CBSAs where either or both acquirer and target operate. We also include an interaction between the post-treatment dummy and both indicators; the coefficient on this interaction will isolate the difference in price effects for hospitals where both merging parties are relatively large. For ease of interpretation, we exclude all target hospitals from the estimate sample. The results are reported in Table 7. Beneath the coefficient estimates we present linear combinations of the relevant coefficients (and associated standard errors). These reveal that the price effect is largest for small acquirers of large targets. (Note that the median acquirer share is 0.14, whereas the median target share is 0.07, so below-median acquirers in this sample are not "small.") Large acquirers of large targets experience a price increase of roughly zero, consistent with the hypothesis that the largest systems may already be "must have" in the relevant markets and hence acquisition of another target does not increase the chance that employers view these systems as pivotal to their decisions about health plans.[37]

Alternative Explanations. The results thus far are consistent with the acquisition and exercise of post-merger market power by acquirers of hospitals operating in the same state. The effects are present only when the acquirer and target share common insurers, and are stronger when they are closer to one another (and hence likelier to share common customers). The results are inconsistent with the alternative hypotheses numbered 1. and 2. outlined in section 2.7: cost efficiencies arising from lower negotiation costs with insurers or post-merger operational efficiencies (this would suggest smaller price effects for adjacent than for non-adjacent treatments), and changes in coinsurance rates to optimize total reimbursement to the hospital system (this may not be specific to within-state mergers, and if it is, the net price effect is unlikely to be large and positive). Here we address alternatives 3.-6.

Alternative explanation 3. refers to the possibility that mergers are followed by significant investments that drive price increases. We explore this alternative explanation in two ways: first, we confirm the results are robust to dropping targets entirely, as operational and strategic changes are likeliest for these hospitals. The coefficients of interest (reported in column 3, Table 5) are virtually unchanged. Second, we estimate models using CMI and Medicaid patient shares as dependent variables (results available upon request). We find precisely estimated coefficients close to zero for both treatment groups and dependent variables. For ease of exposition, in the extensions that follow we continue to drop target hospitals from the estimation sample.

Alternative explanation 4. is the possibility that acquirers raise price by virtue of gaining access to the target's superior bargaining skill, *and* this skill is specific to the insurer-system. This possibility is difficult to completely exclude, however given the fact that most insurers operate statewide, bargaining skill should transfer beyond the case of acquisitions involving targets with 30-90 minute overlap. We also note that targets are small relative to acquirers, so such a transfer

[37] The point estimates imply a smaller price effect of a merger between large acquirer and large target, than between large acquirer and smaller target. This may imply that larger cross-market acquisitions are more likely to generate cost savings. The prediction can also be generated from our model if an insurer's value from having the large acquirer or large target system is greater when the other system is also in the network. This complementarity can arise, e.g., if an employer will only choose an insurer if it offers both systems.

of skill would need to be substantial to generate the price effect we observe.

Alternative explanation 5. for our results is that they capture horizontal rather than cross-market effects. While the sample of transactions is too small to omit all transactions with any horizontal overlap, we tried an alternative definition of 45 minutes, i.e. excluding from the adjacent treatment group all hospitals gaining a system member within 45 minutes' drive. This model reduces the number of adjacent treatments from 104 to qq. The estimated treatment effect is of similar magnitude (i.e. nearly a 10 percent price effect using both treatment groups), suggesting that the cross-market effect is present even when market boundaries are very large, but it is estimated much less precisely (p-values < 0.15). Given that most patients strongly prefer to visit nearby providers, and the fact that recent antitrust challenges to hospital transactions have defined markets with much smaller radii, arguably authorities would treat overlap in the 30-45 minute range as "cross market."

6 Concluding Remarks

This study provides theoretical and empirical analyses of the price effects of cross-market mergers of upstream suppliers to intermediaries who bundle and sell their services. Our model emphasizes the ways in which cross-market mergers differ from within-market mergers, setting aside commonalities shared across both merger types—such as changes in bargaining skill, managerial practices, service mix, and costs. The theory demonstrates that price increases may arise when the merging parties negotiate with a common buyer, and customers of that buyer value both parties (i.e., their demand for the bundle is influenced by the inclusion of the parties). (We also show how prices can change even absent these *common customers*.)

Using data on two distinct samples of transactions - and focusing on "bystander" hospitals that are not likely to be the drivers of the transactions and are thus arguably exogenously treated - we compare price effects of gaining a system member in-state versus out-of-state. We find that hospitals acquiring another system member in-state raise price by 7-10 percent, whereas an acquisition out-of-state does not result in a statistically meaningful change in price. Further analyses provide suggestive evidence that mergers of proximate hospitals (i.e. within 30-90 minutes' drive, in state) lead to the largest price effects. These are precisely the sort of cross-market hospital mergers where common customers are likeliest to be present. We interpret these results as consistent with the presence of a common customer effect that is driving post-merger price increases. We also show the results are similar when dropping target hospitals, which suggests that changes to a target's operations are not the driver of the estimated price effects. Last, we find no changes in case mix or Medicaid patient share for acquirers, as might be expected if acquirers reposition themselves in terms services offered and customer segments.

Prior researchers have shown that mergers of nearby, similar rivals can lead to increases in market power and higher prices. The existence of a common customer effect implies that market power may arise from combinations over even broader geographic areas and across product markets.

This finding does not imply more expansive boundaries for mechanical calculations of market shares and "ΔHHI"s used to evaluate whether mergers are likely to be anticompetitive; rather, we believe it favors an emphasis on the "direct effects" likely to arise from a merger, a concept promulgated in the 2010 Horizontal Merger Guidelines. The results do suggest that combinations across broader areas should be carefully evaluated by antitrust authorities, particularly if customers (such as employers) value insurance products containing both merging parties, if there is significant commuting between the areas where the merging parties are located, and/or if the same insurers are dominant.

Cross-market mergers are an increasingly relevant phenomenon in the U.S., and particularly in the healthcare landscape. The theoretical and empirical analyses in this study illustrate that at least some of the mechanisms by which cross-market mergers generate price increases are potentially actionable antitrust offenses, i.e. price increases are generated at least in part due to a reduction in competition among the merging hospitals for inclusion in insurer networks. Additional research that explicitly models the links between and among insurance choice, insurance competition, and hospital-insurer bargaining could prove valuable to antitrust enforcers and others interested in fostering and protecting competition in healthcare markets.

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A Willingness to Pay (WTP) for an Insurer's Network

In this section, we define the "willingness-to-pay" of an individual for the insurer's network of hospitals $\mathcal{G}$, represented by $WTP(\mathcal{G})$. WTP is typically used as an argument in the insurer's objective function Φ when the insurer bargains with hospitals.

The literature (e.g., Town and Vistnes, 2001; Capps, Dranove and Satterthwaite, 2003; Ho, 2006) derives WTP from a simple model of individual demand for hospitals typically as follows. Suppose that the utility of a given individual p from visiting hospital i given diagnosis l is:

$$u_{p,i,l} = \delta_i + z_i \upsilon_{p,l} \beta + \varepsilon_{p,i,l}$$

where δ_i is the average quality of the hospital, $z_i \upsilon_{p,l}$ are interactions between observed hospital and individual characteristics (which may vary by diagnosis l) and $\varepsilon_{p,i,l}$ is an i.i.d. logit error term. This model generates a simple expression for individual p's expected utility from the hospitals in the insurer's network for diagnosis l ($EU_{p,i,l}$). These values are then weighted by the probability that individual p is admitted to a hospital and diagnosed with l ($\gamma_{p,l}$) to obtain the expected WTP for that individual:

$$WTP_p(\mathcal{G}) = \sum_l \gamma_{p,l} EU_{p,i,l}(\mathcal{G}) \ . \tag{12}$$

Furthermore, we denote by $\Delta WTP_p(\mathcal{G}, h) \equiv WTP_p(\mathcal{G}) - WTP_p(\mathcal{G} \setminus h)$ the change in individual p's WTP for an insurer's network if that insurer loses access to hospital h. Similarly we define $\Delta WTP_p(\mathcal{G}, \mathcal{S})$ for any hospital system $\mathcal{S}$.

Merger Effects on ΔWTP. First, note that if H_1 and H_2 compete for the same individual within the same *geographic market m and diagnosis l*, it will generally be the case (e.g., with logit utility for hospitals) that:

$$\Delta WTP_p(\mathcal{G}, \mathcal{S}) > \sum_{h \in \{1,2\}} \Delta WTP_p(\mathcal{G}, h) \tag{13}$$

where $\mathcal{S} \equiv \{1, 2\}$. This arises from the non-linearity in $EU_{p,i,l}$ and substitutability of the hospitals. For intuition, note that if the insurer drops only hospital 1, this may reduce WTP very little since customers can substitute to hospital 2; however, if the two hospitals merge, and there is no other close substitute in the market, dropping the combined hospital system $\mathcal{S}$ reduces customer WTP by a greater amount. Thus, the impact of the loss of hospital 1 to the WTP for an insurer's network will be greater if 2 is also absent from the network if hospitals 1 and 2 are substitutes (Capps, Dranove and Satterthwaite (2003)).

However, if hospitals 1 and 2 do not compete for the same individual—either because the hospitals are located in different geographic markets or because they serve different diagnoses—then (13) will not hold. Instead, it will be the case that $\Delta WTP_p(\mathcal{G}, \mathcal{S}) = \sum_{h \in \{1,2\}} \Delta WTP_p(\mathcal{G}, h)$ and the change in an insurer's WTP from losing both hospitals will simply be the sum of the change in the insurer's WTP from losing each individual hospital.

B A Model of Insurer Demand with Concavity in WTP

In Section 2.4.1 we note that if *households*, rather than individuals, choose insurers based on a utility equation that includes the sum of household members' WTP for the hospital network, this generates links across diagnostic markets that can generate price effects of cross-diagnostic market hospital mergers. We now provide examples of scenarios that have this property.

Note first that the insurer's objective function is likely to be its profit rather than its enrollment. Assume that profits can be represented by $\Phi = D(\cdot) \times (\phi - \eta)$, where D is the *demand* for the insurer's product, and ϕ and η are per-enrollee premiums and insurer non-hospital costs.[38] Assume in addition, for ease of exposition, that the margin per enrollee is invariant to the negotiated hospital network. Substituting this formulation for Φ into our necessary condition for a hospital merger to have a price effect ((6)) yields:

$$[D(\mathcal{G}) - D(\mathcal{G} \setminus \mathcal{S})] > \sum_{h \in \{1,2\}} D(\mathcal{G}) - D(\mathcal{G} \setminus h) \tag{14}$$

Thus, a sufficient condition for hospitals H_1 and H_2 to benefit from a merger despite being in different (geographic or product) markets would be for the change in demand for the insurer when both hospitals are dropped together to exceed the sum of changes in enrollment when each is dropped individually.

This "concavity" of demand for an insurer's product in the utility generated by its network can arise whenever the merging hospitals have one or more common customers. We provide two simple examples below:

1. First, assume that the insurer competes against an outside option (e.g., not purchasing insurance or purchasing plans offered by other insurers). This insurer delivers utility to customer c given by:

   $$v = \underbrace{g(\cdot) + WTP^c(\mathcal{G})}_{\delta} + \epsilon$$

   where $g(\cdot)$ is some function of insurer and market characteristics. Assume that the outside option delivers utility $v_0 = \epsilon_0$, where $\boldsymbol{\epsilon}$ is distributed iid Type I extreme value. Given this "logit" formulation of demand, the market share of the insurer is given by $D(\delta) = \exp(\delta)/(1 + \exp(\delta))$. For $\delta \geq 0$ (i.e., when the insurer delivers greater mean utility than the outside option), D is concave in δ ($\partial D/\partial \delta > 0$, $\partial^2 D/\partial \delta^2 < 0$), and the change in demand for the insurer upon losing any hospital is greater when δ is lower: i.e., dropping hospital i is worse for the insurer if hospital k has been dropped as well. This property implies the necessary condition given by (6).

   Note that the outside option of not purchasing insurance is not required for this example. An option provided by a different insurer would be sufficient, and we could parametrize its utility as $v_0 = g_0(\cdot) + WTP_0^c() + \epsilon_0$ while still maintaining concavity in δ.

[38] Ho and Lee (2015) contains a general analysis of this type of model.

2. The result can still hold with a non-logit demand formulation. For example, consider a stylized setting where the insurer has captive enrollees who would not switch to the outside option unless they are subjected to a reduction in utility that is large enough to outweigh the switching costs. In this case, if only hospital i or k were dropped by the insurer, a customer may not find it worthwhile to leave the insurer, and thus the insurer's loss in profits from disagreement with either i or k would be minimal. If, however, both hospitals were excluded from the insurer's network, then customers may find it worthwhile to switch to a competing insurer (or outside option). Thus, the presence of switching costs may also generate the necessary concavity in the insurer's objective function.

Whether (6) holds generally will depend not only on the properties of demand for insurers, but also on how the margins per enrollee are determined (which, for simplicity, we have assumed fixed). Adding these considerations or other complexities (e.g., choice set variation, informational frictions, etc.) to the model may change the precise behavior of D, but are unlikely to restore the linearity of the insurer's objective (Φ) in the utility of its network (WTP). More generally, we observe that moving from the simple linear insurer objective function assumed in earlier models to a more realistic function reflecting insurer profits generates non-linearities in WTP quite easily, and this is all that is needed for cross-market price effects.

C A Common Insurer Effect with Linear Fees

In our second example, we examine the potential for a cross-market merger between hospitals to generate a price effect when negotiated prices are linear (i.e., per-patient payments) and at least one insurer operates in both markets.

Consider a monopolist insurer that is active in two markets, A and B, and suppose that there are monopolist hospitals active in each market. Assume that the insurer's profit in each market $m \in \{A, B\}$, if it has an agreement with the hospital in the market, is given by $\Phi_m = D_m(\phi_m) \times (\phi_m - p_m)$ where D_m represents the demand for the insurer, ϕ_m is the insurer's premiums, and p_m is now a (linear) per-enrollee price negotiated with the hospital in that market for hospital services.[39] Thus, each hospital's profit upon agreement is given by $\pi_m = D_m p_m$. For simplicity, we assume away fixed and marginal costs; including them will not change the result. We also assume that the insurer and hospital in each market do not obtain any demand or profits without agreeing to a contract: i.e., the disagreement point from bargaining for both parties is 0.

Finally, we assume that premiums are set in each market after bargaining over hospital prices concludes. Thus, the premiums that the insurer sets in each market will satisfy:

$$\phi_m^* = \arg\max_{\phi} D_m(\phi)(\phi - p_m) \tag{15}$$

[39] For exposition and to simplify notation, we assume that the hospital is paid for all enrollees. Assuming that only some fraction of enrollees visit the hospital, and that the hospital is reimbursed only for those enrollees that visit, does not affect the spirit of the following analysis.

If the hospitals are not merged, prices in each market are assumed to satisfy the following asymmetric Nash Bargain:

$$p_m^* = \arg\max_p [D_m(\phi_m^*(p))(\phi_m^*(p) - p)]^{1-b} \times [D_m(\phi_m^*(p))p]^b \qquad m \in \{A, B\} \tag{16}$$

where $\phi_m^*(p)$ represents the solution to (15) for a given negotiated price p. The FOC of (16) can be expressed as:

$$\frac{\Lambda_m p_m}{D_m(\cdot)} = \frac{p_m - b\phi_m^*(p)}{b(\phi_m^*(p) - p_m)} \qquad m \in \{A, B\} \tag{17}$$

where $\Lambda_m = (\partial D_m/\partial \phi_m)(\partial \phi_m/\partial p_m)$ and represents the change in the insurer's demand due to an increase in its premiums brought on by an increase in the negotiated price (i.e., the effect on demand of pass-through).

On the other hand, if the two hospitals merge and prices are jointly negotiated to maximize:

$$\{p_A^{M,*}, p_B^{M,*}\} = \arg\max_{p_A, p_B} [D_A(\cdot)(\phi_A^*(p_A) - p_A) + D_B(\cdot)(\phi_B^*(p_B) - p_B)]^{1-b} \times [(D_A(\cdot)p_A + D_B(\cdot)p_B)]^b \tag{18}$$

then the FOCs of (18) can be expressed as:

$$\frac{\Lambda_A p_A}{D_A(\cdot)} = \frac{\Lambda_B p_B}{D_B(\cdot)} = \frac{[(D_A(\cdot)(p_A - b\phi_A^*(p_A)) + D_B(\cdot)(p_B - b\phi_B^*(p_B))]}{b[D_A(\cdot)(\phi_A^*(p_A) - p_A) + D_B(\cdot)(\phi_B^*(p_B) - p_B)]} \tag{19}$$

The left-hand-sides of both (17) and (19) correspond to the *elasticity of (insurer) demand with respect to the negotiated price.* Consider two cases:

1. If $\Lambda = 0$ so that these elasticities are 0—as in the case where premiums are set before or simultaneously with negotiated prices, or prices are lump sums as opposed to linear—then the prices that satisfy the non-merged Nash bargaining FOCs given by (17) would also satisfy the merged Nash bargaining FOCs in (19). In such a setting, without a merger, prices in each market would be $p_m^* = b\phi_m^*$, i.e., negotiated prices would be a fraction b of the fixed premiums; with a merger, prices $\sum_m D_m p_m^* = b \sum_m D_m \phi_m^*$, i.e. total payments to the merged entity would be the same fraction b of total insurer revenues across both markets. Although a merger could thus result in a change in prices across markets (higher in one, lower in another), total payments to the hospitals would be unchanged and there would be no merger price effects (although distributional effects may arise).

2. On the other hand, if $\Lambda_m \neq 0$—which generally will be the case when premiums are set after linear fees are negotiated[40]—the total prices that are negotiated to satisfy (17) need not be the same as those negotiated to satisfy (19). Note that the merged Nash bargaining FOC in (19) requires that the elasticities of demand with respect to the negotiated prices across both markets $m \in \{A, B\}$ are equalized, whereas this need not be the case absent a merger. Indeed,

[40] Insurance regulators require substantial documentation of expected medical spending to ensure the solvency of insurers. These projections ordinarily reflect provider rates and expected utilization.

insofar as an inefficiency is introduced (from the perspective of the insurer and hospitals) by the double marginalization arising from the insurer's markup of the hospitals' negotiated prices, there are potential industry profit gains from having a hospital system internalize the pricing effects across markets. For example, if the magnitude of the elasticity of demand with respect to p_A^* (in market A) is greater than the elasticity of demand with respect to p_B^* (in market B), so that a price increase in market A would lead to a larger reduction in demand than in market B at the negotiated prices when the hospitals are independent, then a merged hospital system would wish to adjust its prices to set a lower $p_A^{M,*} < p_A^*$ and offset this with a higher $p_B^{M,*} > p_B^*$. Due to the increase in industry surplus from internalizing these cross-market differences, a hospital merger can increase the total payments made to the hospital system.

The key to generating this type of cross-market merger price effect absent a common customer is the existence of an inefficiency from the perspective of the bargaining firms—i.e. double marginalization due to linear fees. Mitigating this inefficiency via a hospital merger can leave both the hospitals and the insurer better off. The harm to customers will differ across markets, with those facing lower premiums as a result of lower negotiated prices benefiting from the merger.

Though this stand-alone common insurer effect may be relevant in some cases, we conjecture that it is less empirically relevant than the common customer effect (which presumes a common insurer). First, for this particular effect to obtain, hospitals must be paid linear fees rather than two-part tariffs. Second, premium-setting must lag behind price negotiations sufficiently for premiums to be set in response to prices. Either assumption may fail in particular markets. Finally, the double marginalization effect may result in a weighted average decrease in hospital prices; empirically, we observe an increase.

Table 1: Hospital Mergers Investigated by the FTC

	Acquirer	Target	Area with potential horizontal concern	Year of Merger	In Sample?	Reason excluded from sample	Number of hospitals obtaining adjacent system member	Number of hospitals obtaining non-adjacent system member
1	Tenet Healthcare	OrNda Healthcorp	San Luis Obispo, CA	1997	Yes		72	23
2	Inova Health Systrem	Alexandria Health Services	Alexandria, VA	1997	Yes		2	0
3	Tenet Healthcare	Doctors Regional Medical Center	Poplar Bluff, MO	1999	Yes		5	0
4	Sutter Health	Summit Medical Center	Oakland/Berkeley, CA	2000	Yes		19	0
5	Piedmont Healthcare	Newnan Hospital	Atlanta, GA	2007	Yes	N/A	2	0
6	University of Pittsburgh Medical Center	Mercy Hospital of Pittsburgh	Pittsburgh, PA	2008	Yes		6	0
7	Banner Health	Sun Health	Sun City, AZ	2008	Yes		5	5
8	St. Elizabeth Medical Center	St. Luke Hospital	Northern Kentucky, KY	2008	Yes		1	0
9	Hartford Healthcare	Central Connecticut Health Alliance	Hartford, CT	2011	Yes		2	0
10	St. Peters Healthcare Services	Northeast Health and Seton Health	Albany/Troy, NY	2011	Yes		2	0
11	Columbus Hospital	Montana Deaconess Medical Center	Great Falls, MT	1996	No	No pre period		
12	Miami Valley Hospital	Good Samaritan Hospital	Dayton, OH	1996	No	One acquiring one		
13	Butterworth Health Corporation	Blodgett Memorial Medical Center	Grand Rapids, MI	1997	No	One acquiring one		
14	Buffalo General Health System	Millard Fillmore Health System	Buffalo, NY	1998	No	One acquiring one		
15	New Hanover Regional Medical Center	Columbia Cape Fear Memorial Hospital	Wilmington, NC	1998	No	One acquiring one		
16	Evanston Northwestern Healthcare	Highland Park Hospital	Evanston, IL	2000	No	One acquiring one*		
17	Victory Memorial Hospital	St. Therese Hospital	Waukegan, IL	2002	No	One acquiring one		
18	Scott & White Healthcare	King's Daughters Hospital	Temple, TX	2009	No	Converted into a children's hospital		
19	ProMedica Health System	St. Luke's Hospital	Toledo, OH	2010	No	Litigated beyond time period of the data		
20	Phoebe Putney Health System	Palmyra Park Hospital	Albany, GA	2011	No	Litigated beyond time period of the data		
21	Inova Health System	Prince William Hospital	Northern Virginia, VA	X	No	Transaction abandoned		
22	Lifespan	Care New England	RI	X	No	Transaction abandoned		
urer shares a	OSF Healthcare System	Rockford Health System	Rockford, IL	X	No	Transaction abandoned		

Notes:

All transactions above were investigated prior to consummation with the exception of the following four, which were evaluated during the FTC's Merger Retrospective Effort in 2008-2009: Sutter Health-Summit Medical Center, New Hanover-Columbia Cape Fear, Victory Memorial-St. Therese, Evanston Northwestern-Highland Park.

*Evanston Northwestern owned two hospitals (Evanston Hospital and Glenbrook Hospital) prior to the acquisition of Highland Park, but they report consolidated data using a single Medicare provider number.

Table 2: Hospital Merger Transaction Statistics in Broad Sample, 2002-2012

Transaction Filter	Number of Transactions	Acquirer Size (# of hospitals)		Target Size (# of hospitals)	
		Median	Mean	Median	Mean
All Transactions (from Irving Levin*)	426	9.0	24.0	1.0	1.6
Generates 1+ treatment hospitals	332	17.0	30.2	1.0	1.7
Generates 1+ adjacent treatment hospitals	270	23.0	33.8	1.0	1.8
Generates 1+ non-adjacent treatment hospitals	240	29.0	39.4	1.0	2.0
Clean in the 2 years before and after treatment and:					
Generates 1+ treatment hospitals	52	5.0	9.4	1.0	1.3
Generates 1+ adjacent treatment hospitals	43	5.0	8.8	1.0	1.3
Generates 1+ non-adjacent treatment hospitals	22	8.5	15.9	1.0	1.6

Notes:

"Clean in the 2 years before and after treatment" means that the hospital is unaffected (either directly or by being within 30 minutes' drive of an affected hospital) by *other* mergers during this period

We consider only transactions involving "consolidation", which is defined as an existing hospital or system gaining members (as opposed to, say, a transfer of assets). This definition captures 85 percent of the deals in the Irving Levin Hospital Acquisition Reports.

There are 252 transactions from 1998-2001 and 122 from 2011-2012 (the table covers 2002-2012). These transactions are used to identify "clean" hospitals.

Table 3: Descriptive Statistics

Panel A: FTC Sample

	Adjacent Treatments	Non-Adjacent Treatments	Control Group 1	Control Group 2
# of Hospitals	116	28	4,706	2,692
(acquiring/target)	88/28	21/7	N/A	N/A
CMI	1.43	1.36	1.28	1.35
Beds	207	157	151	181
% Medicaid	15.8%	16.9%	14.0%	13.6%
For-Profit	64.2%	80.4%	17.3%	25.3%
Urban	88.8%	71.4%	58.4%	69.2%
Census Region				
Midwest	6.0%	0.0%	30.5%	28.8%
Northeast	8.6%	3.6%	13.8%	13.0%
South	37.1%	57.1%	38.7%	42.4%
West	48.3%	39.3%	17.0%	15.8%

Notes: The unit of observation is the hospital-year unless otherwise noted

Panel B: Broad Sample

	Adjacent Treatments	Non-Adjacent Treatments	Control Group 1	Control Group 2
# of Hospitals	104	55	4,755	756
# of Hospitals (full data)	81	38	4,055	592
(acquiring/target)	76/5	37/1	N/A	N/A
CMI	1.31	1.26	1.29	1.32
Beds	147	148	153	174
% Medicaid	12.5%	12.5%	14.4%	13.1%
For-Profit	6.1%	6.6%	21.7%	6.3%
Urban	49.4%	44.7%	60.3%	65.2%
Census Region				
Midwest	42.0%	63.2%	26.9%	32.3%
Northeast	4.9%	2.6%	15.0%	23.1%
South	40.7%	21.1%	39.0%	31.6%
West	12.3%	13.2%	19.1%	13.0%

Notes: The unit of observation is the hospital-year unless otherwise noted. Descriptive statistics pertain to hospitals with full data available (i.e. no non-missing price).

Table 4: Pre-Post Regression Results, FTC Sample

	Dependent variable is ln(price)	
	Control Group 1	**Control Group 2**
Adj Treated*(t=0)	0.0123	0.00995
	(0.0163)	(0.0163)
Adj Treated*(t>0)	0.0676***	0.0638***
	(0.0229)	(0.0231)
Non-Adj Treated*(t=0)	-0.0488	-0.0481
	(0.0576)	(0.0577)
Non-Adj Treated*(t>0)	-0.0142	-0.0128
	(0.0537)	(0.0538)
ln(CMI)	0.291***	0.286***
	(0.0472)	(0.0623)
ln(Total Beds)	0.0906***	0.107***
	(0.0160)	(0.0203)
% Medicaid	0.0551	0.0696
	(0.0396)	(0.0523)
For-Profit	0.0475***	0.0538***
	(0.0167)	(0.0199)
Observations	59,666	33,896
Number of hospitals	4,850	2,836
R-squared (within)	0.554	0.570
p-value for H_0: coefficients for Adj*(t>0) and Non-Adj*(t>0) are same	0.158	0.187

Notes: Standard errors clustered by hospital, *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 5: Pre-Post Regression Results, Broad Sample

	Dependent variable is ln(price)		
	Control Group 1	**Control Group 2**	**Control Group 2 No Targets**
Adj Treated*(t=0)	0.0315	0.0353	0.0394
	(0.0290)	(0.0287)	(0.0296)
Adj Treated*(t>0)	0.102**	0.0930**	0.101**
	(0.0462)	(0.0457)	(0.0467)
Non-Adj Treated*(t=0)	-0.0172	-0.0188	-0.0190
	(0.0245)	(0.0266)	(0.0269)
Non-Adj Treated*(t>0)	-0.0305	-0.0323	-0.0279
	(0.0304)	(0.0337)	(0.0339)
ln(CMI)	0.258***	0.213	0.213
	(0.0557)	(0.160)	(0.161)
ln(Total Beds)	0.0923***	0.117*	0.115*
	(0.0183)	(0.0671)	(0.0673)
% Medicaid	0.103**	0.164	0.166
	(0.0510)	(0.149)	(0.150)
For-Profit	0.0404**	0.0718	0.0685
	(0.0187)	(0.0486)	(0.0485)
Observations	40,994	4,422	4,392
Number of hospitals	4,174	711	705
R-squared (within)	0.462	0.435	0.436
p-value for H_0: coefficients for Adj*(t>0) and Non-Adj*(t>0) are same	0.017	0.021	0.019

Notes: Standard errors clustered by hospital, *** p<0.01, ** p<0.05, * p<0.10

Table 6: Pre-Post Regression Results in Broad Sample, Common Insurer

	Dependent variable is ln(price)	
	Control Group 2 No Targets	**Control Group 2 No Targets**
Treated*(t=0)	0.0240	0.0261
	(0.0245)	(0.0243)
Treated*(t>0)	-0.0261	0.0265
	(0.0496)	(0.0883)
Treated*(t>0)*State Insurer Overlap	0.161***	
	(0.0611)	
Treated*(t>0)*Nat'l Insurer Overlap		0.0708
		(0.109)
ln(CMI)	0.213	0.211
	(0.160)	(0.160)
ln(Total Beds)	0.114*	0.116*
	(0.0673)	(0.0672)
% Medicaid	0.160	0.161
	(0.149)	(0.149)
For-Profit	0.0667	0.0714
	(0.0476)	(0.0478)
Observations	4,392	4,392
Number of hospitals	705	705
R-squared (within)	0.437	0.435

Notes: Standard errors clustered by hospital, *** p<0.01, ** p<0.05, * p<0.10. Target hospitals are excluded. Insurer overlap is constructed as follows: Consider a hospital in system A, which acquires system B. The hospital is in an MSA with insurer shares of 30% BC, 50% BS, and 20% U. System B has insurer market shares of 20% BC, 30% BS, and 50% U, where the shares are bed-weighted averages of the insurer shares across all markets in which System B has beds. Then when systems A and B merge, the insurer overlap of BC is min(20%, 30%)=20%, BS is 30%, U is 20%. Total insurer overlap is the sum of these = 70%. This measure will be strictly between 0 and 1, and will equal 1 by design if two systems which only operate in the same markets merge. The mean across all mergers for the state-level insurer definition is 0.54.

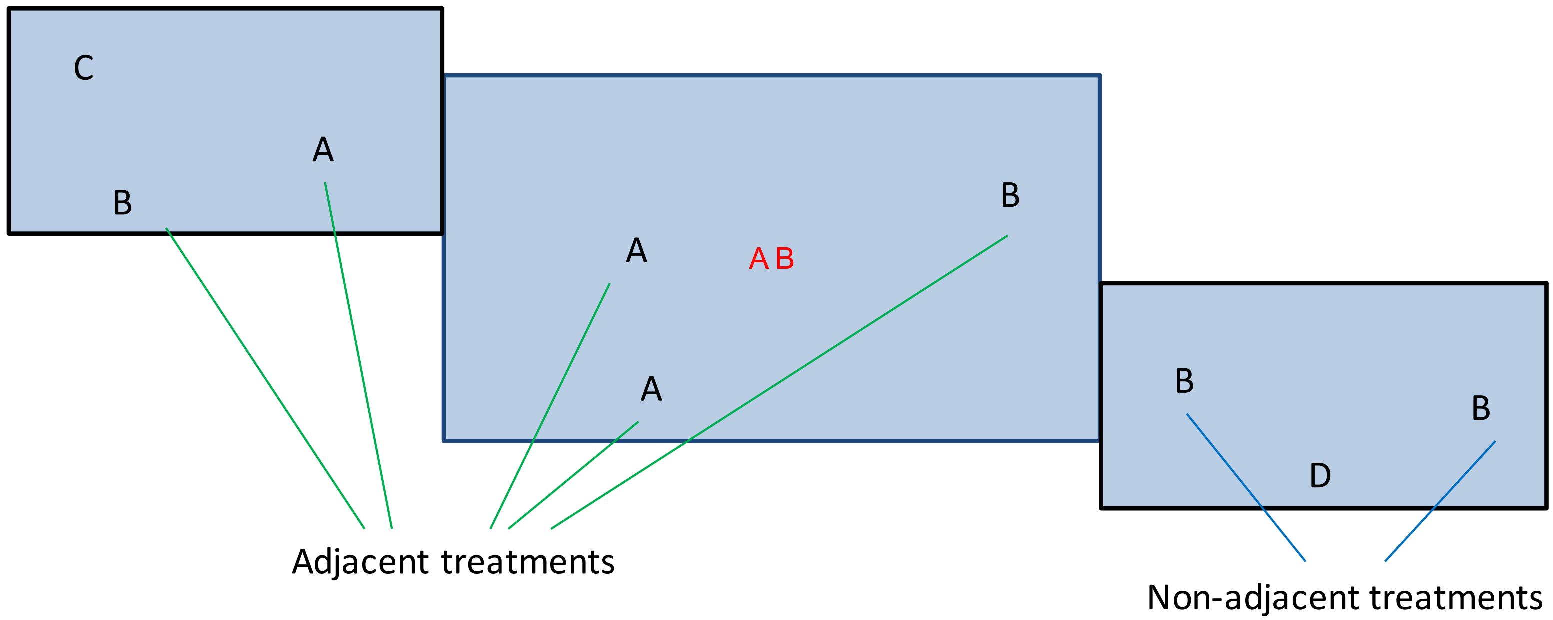
Table 7: Evaluating Alternative Explanations in Broad Sample

	Dependent variable is ln(price)			
	Control Group 2 No Targets	**Control Group 2 No Targets**	**Control Group 2 No Targets**	**Control Group 2 No Targets**
Adj Treated*(t=0)	0.0353	0.0379	0.0367	0.0330
	(0.0287)	(0.0304)	(0.0312)	(0.0315)
Adj Treated*(t>0)	0.0930**	0.167***	0.141***	0.0648*
	(0.0457)	(0.0631)	(0.0477)	(0.0353)
Adj Treated*(t>0)*Acquirer above median share beds		-0.0920		0.114
		(0.0843)		(0.0707)
Adj Treated*(t>0)*Target above median share beds			-0.0853	0.242**
			(0.0812)	(0.106)
Adj Treated*(t>0)*Acquirer above median share beds*Target above median share beds				-0.444***
				(0.138)
Non-Adj Treated*(t=0)	-0.0188	-0.0198	-0.0184	-0.0183
	(0.0266)	(0.0269)	(0.0269)	(0.0269)
Non-Adj Treated*(t>0)	-0.0323	-0.0293	-0.0268	-0.0259
	(0.0337)	(0.0340)	(0.0338)	(0.0337)
ln(CMI)	0.213	0.216	0.211	0.229
	(0.160)	(0.161)	(0.160)	(0.160)
ln(Total Beds)	0.117*	0.114*	0.113*	0.112*
	(0.0671)	(0.0671)	(0.0672)	(0.0666)
% Medicaid	0.164	0.169	0.164	0.152
	(0.149)	(0.149)	(0.148)	(0.147)
For-Profit	0.0718	0.0713	0.0656	0.0625
	(0.0486)	(0.0496)	(0.0458)	(0.0438)
Observations	4,422	4,392	4,392	4,392
Number of hospitals	711	705	705	705
R-squared (within)	0.435	0.437	0.437	0.443

Notes: Standard errors clustered by hospital, *** p<0.01, ** p<0.05, * p<0.10. Target hospitals are excluded.

	Estimated price effect among Adj Treated*(t>0)
Acquirer **below** median share beds & Target **below** median share beds	0.0648*
	(0.0353)
Acquirer **above** median share beds & Target **below** median share beds	0.1791***
	0.0615
Acquirer **below** median share beds & Target **above** median share beds	0.3064***
	0.1029
Acquirer **above** median share beds & Target **above** median share beds	-0.0228
	0.753

Figure 1. Defining Treatment Groups, FTC Sample



Notes: Figure depicts a merger between system A and system B; hospitals C and D belong to other systems. Hospitals in red generate the FTC investigation and are excluded from estimation.

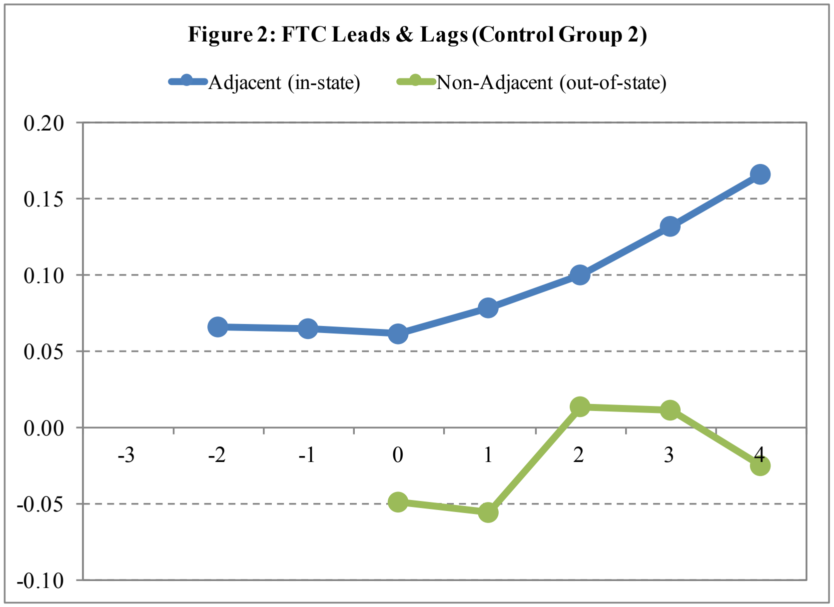


Figure 2: FTC Leads & Lags (Control Group 2)

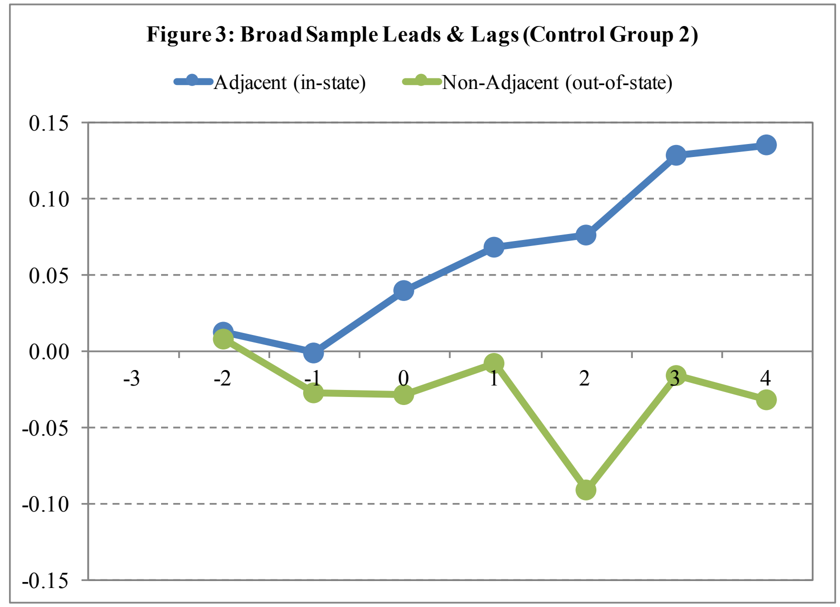
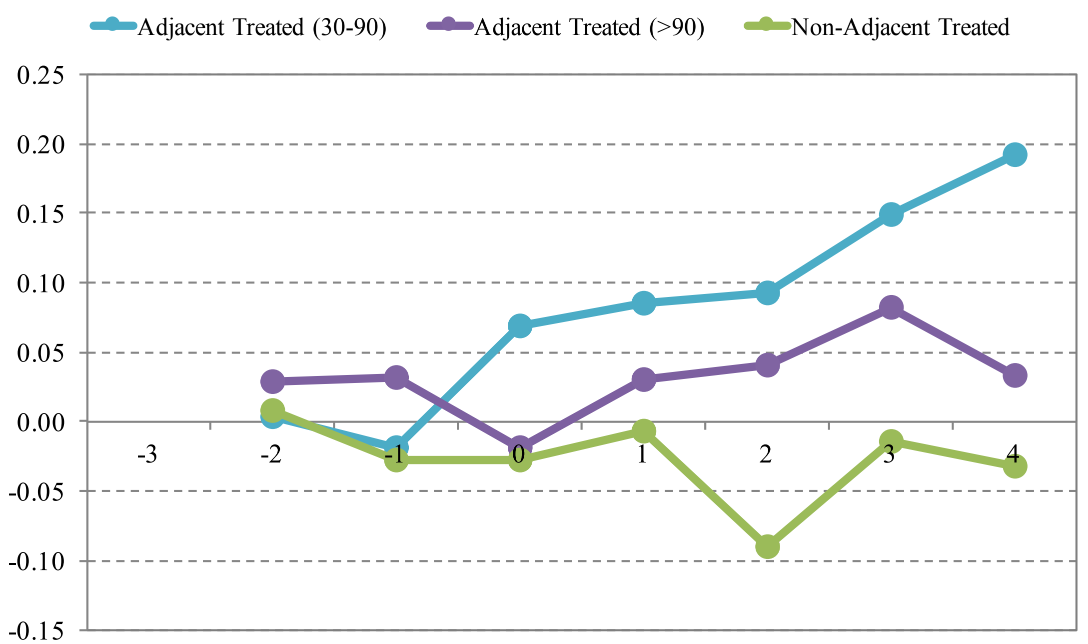


Figure 3: Broad Sample Leads & Lags (Control Group 2)

Figure 4: Broad Sample Distance Effects (Control Group 2)



Appendix Table 1:
Leads & Lags Regression Results, FTC Sample

	Dependent variable is ln(price)	
	Control Group 1	**Control Group 2**
Adj Treated*(t=-2)	0.0625	0.0659*
	(0.0400)	(0.0400)
Adj Treated*(t=-1)	0.0661**	0.0645**
	(0.0292)	(0.0295)
Adj Treated*(t=0)	0.0644**	0.0617**
	(0.0290)	(0.0290)
Adj Treated*(t=1)	0.0779**	0.0789**
	(0.0325)	(0.0324)
Adj Treated*(t=2)	0.103***	0.100***
	(0.0293)	(0.0296)
Adj Treated*(t=3)	0.138***	0.132***
	(0.0329)	(0.0333)
Adj Treated*(t=4)	0.176***	0.166***
	(0.0338)	(0.0341)
Non-Adj Treated*(t=0)	-0.0494	-0.0489
	(0.0576)	(0.0577)
Non-Adj Treated*(t=1)	-0.0625	-0.0555
	(0.0697)	(0.0700)
Non-Adj Treated*(t=2)	0.0105	0.0135
	(0.0633)	(0.0635)
Non-Adj Treated*(t=3)	0.00990	0.0116
	(0.0625)	(0.0622)
Non-Adj Treated*(t=4)	-0.0181	-0.0251
	(0.0774)	(0.0776)
ln(CMI)	0.292***	0.287***
	(0.0472)	(0.0623)
ln(Total Beds)	0.0906***	0.108***
	(0.0160)	(0.0204)
% Medicaid	0.0554	0.0701
	(0.0396)	(0.0523)
For-Profit	0.0475***	0.0538***
	(0.0167)	(0.0199)
Observations	59,666	33,896
Number of hospitals	4,850	2,836
R-squared (within)	0.554	0.571
p-value for H_0: coefficients for Adj*(t=4) and Non-Adj*(t=4) are same	0.021	0.023

Notes: Standard errors clustered by hospital, *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2:
Leads & Lags Regression Results, Broad Sample

	Dependent variable is ln(price)		
	Control Group 1	**Control Group 2**	**Control Group 2, No Targets**
Adj Treated*(t=-2)	0.0156	0.0129	0.0178
	(0.0268)	(0.0274)	(0.0285)
Adj Treated*(t=-1)	0.00929	-0.000615	0.00850
	(0.0354)	(0.0349)	(0.0362)
Adj Treated*(t=0)	0.0400	0.0394	0.0485
	(0.0335)	(0.0338)	(0.0348)
Adj Treated*(t=1)	0.0746*	0.0678*	0.0762*
	(0.0400)	(0.0409)	(0.0419)
Adj Treated*(t=2)	0.0937*	0.0762	0.0888
	(0.0530)	(0.0541)	(0.0555)
Adj Treated*(t=3)	0.144***	0.128**	0.148***
	(0.0527)	(0.0525)	(0.0527)
Adj Treated*(t=4)	0.144**	0.135**	0.143**
	(0.0582)	(0.0578)	(0.0585)
Non-Adj Treated*(t=-2)	0.00949	0.00793	0.00598
	(0.0728)	(0.0749)	(0.0749)
Non-Adj Treated*(t=-1)	-0.0185	-0.0275	-0.0302
	(0.0649)	(0.0670)	(0.0668)
Non-Adj Treated*(t=0)	-0.0219	-0.0282	-0.0306
	(0.0676)	(0.0711)	(0.0710)
Non-Adj Treated*(t=1)	0.000252	-0.00743	-0.00459
	(0.0750)	(0.0784)	(0.0784)
Non-Adj Treated*(t=2)	-0.0844	-0.0910	-0.0891
	(0.0790)	(0.0829)	(0.0830)
Non-Adj Treated*(t=3)	-0.000498	-0.0153	-0.0107
	(0.0888)	(0.0942)	(0.0948)
Non-Adj Treated*(t=4)	-0.0326	-0.0323	-0.0323
	(0.0890)	(0.0940)	(0.0941)
ln(CMI)	0.258***	0.214	0.214
	(0.0558)	(0.161)	(0.161)
ln(Total Beds)	0.0923***	0.116*	0.114*
	(0.0183)	(0.0673)	(0.0675)
% Medicaid	0.102**	0.162	0.166
	(0.0510)	(0.149)	(0.150)
For-Profit	0.0401**	0.0673	0.0638
	(0.0187)	(0.0456)	(0.0454)
Observations	40,994	4,422	4,392
Number of hospitals	4,174	711	705
R-squared (within)	0.462	0.436	0.438
p-value for H_0: coefficients for Adj*(t=4) and Non-Adj*(t=4) are same	0.096	0.119	0.103

Notes: Standard errors clustered by hospital, *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3:
FTC Pre-Post Regression Results, Dropping One Transaction at a Time (Control Group 2)

		Excluding:									
	All	**Tenet / OrNda**	**Inova / Alexandria**	**Tenet / Doctors Regional**	**Sutter / Summit**	**Piedmont / Newnan**	**UPMC / Mercy**	**Banner / Sun**	**St. Elizabeth / St. Luke**	**Hartford / Central Connecticut**	**St. Peters / Northeast / Seton**
Adj Treated*(t=0)	0.00995	0.0228	0.00971	0.00869	0.0100	0.00947	0.00481	0.0196	0.00945	0.00227	0.0102
	(0.0163)	(0.0190)	(0.0170)	(0.0168)	(0.0191)	(0.0170)	(0.0174)	(0.0160)	(0.0165)	(0.0157)	(0.0166)
Adj Treated*(t>0)	0.0638***	0.0557*	0.0646***	0.0639***	0.0560**	0.0642***	0.0628**	0.0811***	0.0619***	0.0610**	0.0655***
	(0.0231)	(0.0318)	(0.0242)	(0.0237)	(0.0224)	(0.0243)	(0.0250)	(0.0218)	(0.0233)	(0.0240)	(0.0234)
Non-Adj Treated*(t=0)	-0.0481	0.0462	-0.0481	-0.0482	-0.0487	-0.0481	-0.0482	-0.0682	-0.0481	-0.0483	-0.0481
	(0.0577)	(0.0314)	(0.0577)	(0.0577)	(0.0577)	(0.0577)	(0.0577)	(0.0707)	(0.0577)	(0.0577)	(0.0577)
Non-Adj Treated*(t>0)	-0.0128	0.00387	-0.0128	-0.0128	-0.0130	-0.0128	-0.0128	-0.0155	-0.0128	-0.0128	-0.0127
	(0.0538)	(0.0534)	(0.0538)	(0.0538)	(0.0538)	(0.0538)	(0.0538)	(0.0641)	(0.0538)	(0.0538)	(0.0538)
ln(CMI)	0.286***	0.288***	0.286***	0.286***	0.289***	0.286***	0.287***	0.287***	0.286***	0.287***	0.286***
	(0.0623)	(0.0628)	(0.0623)	(0.0623)	(0.0623)	(0.0623)	(0.0624)	(0.0623)	(0.0623)	(0.0623)	(0.0623)
ln(Total Beds)	0.107***	0.108***	0.107***	0.107***	0.107***	0.107***	0.107***	0.108***	0.108***	0.107***	0.107***
	(0.0203)	(0.0206)	(0.0203)	(0.0204)	(0.0204)	(0.0203)	(0.0203)	(0.0204)	(0.0203)	(0.0203)	(0.0203)
% Medicaid	0.0696	0.0729	0.0697	0.0698	0.0707	0.0696	0.0696	0.0698	0.0699	0.0691	0.0692
	(0.0523)	(0.0527)	(0.0523)	(0.0523)	(0.0524)	(0.0523)	(0.0523)	(0.0525)	(0.0523)	(0.0523)	(0.0523)
For-Profit	0.0538***	0.0543***	0.0538***	0.0537***	0.0539***	0.0538***	0.0538***	0.0537***	0.0538***	0.0538***	0.0540***
	(0.0199)	(0.0200)	(0.0199)	(0.0199)	(0.0199)	(0.0199)	(0.0199)	(0.0199)	(0.0199)	(0.0199)	(0.0199)
Observations	33,896	33,388	33,884	33,864	33,766	33,884	33,849	33,829	33,888	33,883	33,882
Number of hospitals	2,836	2,741	2,834	2,831	2,817	2,834	2,830	2,826	2,835	2,834	2,834
R-squared (within)	0.570	0.572	0.570	0.570	0.571	0.570	0.570	0.571	0.570	0.570	0.570
p-value for H_0: coefficients for Adj*(t>0) and Non-Adj*(t>0) are same	0.179	0.403	0.185	0.187	0.234	0.188	0.132	0.197	0.150	0.197	0.205

Notes: Standard errors clustered by hospital, *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 4:
Robustness Checks

	FTC (Control Group 2)			Broad Sample (Control Group 2)		
	In Text	Drop controls (except year effects)	For-Profit year effects	In Text	Drop controls (except year effects)	For-Profit year effects
Adj Treated*(t=0)	0.00995	0.0228	0.0115	0.0353	0.0328	0.0341
	(0.0163)	(0.0173)	(0.0168)	(0.0287)	(0.0300)	(0.0289)
Adj Treated*(t>0)	0.0638***	0.0761***	0.0785***	0.0930**	0.0932**	0.0879**
	(0.0231)	(0.0228)	(0.0244)	(0.0457)	(0.0474)	(0.0445)
Non-Adj Treated*(t=0)	-0.0481	-0.0430	-0.0317	-0.0188	-0.0131	-0.0200
	(0.0577)	(0.0583)	(0.0588)	(0.0266)	(0.0256)	(0.0265)
Non-Adj Treated*(t>0)	-0.0128	-0.0137	0.0298	-0.0323	-0.0365	-0.0411
	(0.0538)	(0.0563)	(0.0561)	(0.0337)	(0.0317)	(0.0313)
ln(CMI)	0.286***		0.285***	0.213		0.208
	(0.0623)		(0.0621)	(0.160)		(0.162)
ln(Total Beds)	0.107***		0.111***	0.117*		0.116*
	(0.0203)		(0.0204)	(0.0671)		(0.0671)
% Medicaid	0.0696		0.0670	0.164		0.170
	(0.0523)		(0.0520)	(0.149)		(0.148)
For-Profit	0.0538***			0.0718		
	(0.0199)			(0.0486)		
Observations	33,896	34,515	33,896	4,422	4,503	4,422
Number of hospitals	2,836	2,862	2,836	711	729	711
R-squared (within)	0.570	0.564	0.573	0.435	0.428	0.440
p-value for H_0: coefficients for Adj*(t>0) and Non-Adj*(t>0) are same	0.186	0.135	0.408	0.021	0.018	0.014

Notes: Standard errors clustered by hospital, *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 5:
Distance Effects, Broad Sample

	Control Group 2
Adj Treated*(30-90)*(t=-2)	0.00353
	(0.0377)
Adj Treated*(30-90)*(t=-1)	-0.0187
	(0.0477)
Adj Treated*(30-90)*(t=0)	0.0683*
	(0.0397)
Adj Treated*(30-90)*(t=1)	0.0853*
	(0.0480)
Adj Treated*(30-90)*(t=2)	0.0931
	(0.0663)
Adj Treated*(30-90)*(t=3)	0.149**
	(0.0609)
Adj Treated*(30-90)*(t=4)	0.192***
	(0.0689)
Adj Treated*(>90)*(t=-2)	0.0293
	(0.0280)
Adj Treated*(>90)*(t=-1)	0.0317
	(0.0396)
Adj Treated*(>90)*(t=0)	-0.0188
	(0.0544)
Adj Treated*(>90)*(t=1)	0.0311
	(0.0688)
Adj Treated*(>90)*(t=2)	0.0413
	(0.0849)
Adj Treated*(>90)*(t=3)	0.0819
	(0.0914)
Adj Treated*(>90)*(t=4)	0.0329
	(0.0864)
Non-Adj Treated*(t=-2)	0.00796
	(0.0749)
Non-Adj Treated*(t=-1)	-0.0275
	(0.0669)
Non-Adj Treated*(t=0)	-0.0274
	(0.0711)
Non-Adj Treated*(t=1)	-0.00696
	(0.0783)
Non-Adj Treated*(t=2)	-0.0899
	(0.0827)
Non-Adj Treated*(t=3)	-0.0148
	(0.0940)
Non-Adj Treated*(t=4)	-0.0325
	(0.0938)
ln(CMI)	0.206
	(0.160)
ln(Total Beds)	0.118*
	(0.0675)
% Medicaid	0.156
	(0.147)
For-Profit	0.0634
	(0.0432)
Observations	4,422
Number of hospitals	711
R-squared (within)	0.438

Notes: Standard errors clustered by hospital, *** p<0.01, ** p<0.05, * p<0.1

	Control Group 2
Adj Treated*(30-90)*(t=0)	0.0749***
	(0.0230)
Adj Treated*(30-90)*(t>0)	0.128***
	(0.0479)
Adj Treated*(>90)*(t=0)	-0.0419
	(0.0599)
Adj Treated*(>90)*(t>0)	0.0237
	(0.0862)
Non-Adj Treated*(t=0)	-0.0180
	(0.0265)
Non-Adj Treated*(t>0)	-0.0317
	(0.0337)
ln(CMI)	0.209
	(0.160)
ln(Total Beds)	0.116*
	(0.0671)
% Medicaid	0.160
	(0.146)
For-Profit	0.0697
	(0.0469)
Observations	4,422
Number of hospitals	711
R-squared (within)	0.436

Notes: Standard errors clustered by hospital, *** p<0.01, ** p<