ONLINE APPENDICES

A Predicting Post-Merger Price Effects

Theory predicts that the extent to which mergers raise prices depends on the extent to which merging hospitals are good substitutes for one another, and whether their patients are unwilling to go to another hospital. As pointed out by Capps et al. (2003) and Gowrisankaran et al. (2015), since demand for hospitals is very inelastic, a standard model of Nash-Bertrand pricing would predict extremely high prices following mergers and suggest mergers could raise prices by implausibly large amounts. Instead, these prior studies have developed a theory of price-setting in which prices are bilaterally negotiated between hospital systems and insurers, which bargain on behalf of their enrollees. In these models, prices are not determined by patients' price elasticities but are instead driven by what is effectively the insurer's elasticity — in terms of how much insurers can subsequently raise premiums if the hospital system is included in the insurer's preferred network of hospitals. In this way, hospital prices are determined by patients' *ex ante* willingness to pay for the option to go to the hospital when buying an insurance plan (Ho and Lee, 2017, 2019).

A.1 Hospital-Insurer Bargaining and ΔWTP

Capps et al. (2003) model the *ex post* utility of patient i at hospital h as $U_{ih} = U(X_{ih}) + \varepsilon_{ih}$, where $U(\cdot)$ denotes expected utility at the hospital and ε_{ih} represents idiosyncratic patient preferences at specific hospitals with ε distributed i.i.d. standard Gumbel. X_{ih} contains patient and hospital characteristics that determine preferences for a given hospital, including the patient's specific health care needs as well as the distance between them and the hospital.

If a patient faces a hospital network $\mathscr{N}$ that limits what hospitals she has access to, then the patient's *ex ante* expected utility of access to a network $\mathscr{N}$ is

$$\begin{aligned} EU_i(\mathscr{N}) &= E[\max_{j \in \mathscr{N}} U_{ij}] \\ &= ln\left(\sum_{j \in \mathscr{N}} \exp(U_{ij})\right) \end{aligned}$$

Moreover, say that a hospital h is dropped from the network. Capps et al. (2003) show that the change in expected utility as a result of this network change is:

$$\begin{aligned} \Delta EU_{ih} &= EU_i(\mathscr{N}) - EU_i(\mathscr{N} \setminus h) \\ &= ln\left(\sum_{j \in \mathscr{N}} \exp(U_{ij})\right) - ln\left(\sum_{j \in \mathscr{N} \setminus h} \exp(U_{ij})\right) \\ &= ln\left(\frac{1}{1 - s_{ih}}\right) \end{aligned}$$

where s_{ih} is that hospital's expected market share from patient i under network $\mathscr{N}$. If consumers are always indifferent between receiving a 1-point increase in EU and a \$$\gamma_i$ payment, then we can describe patients' *ex ante* "willingness-to-pay' for hospital h as $W_{ih} = \gamma_i \Delta EU_{ih}$. We integrate over the distribution of consumers F_i to calculate market-level willingness to pay as $W_h = \int_i \gamma_i ln\left(\frac{1}{1-s_{ih}}\right) dF_i$. Where W_h represents the amount that the average consumer is willing to pay for access to hospital h. Both Capps et al. (2003) and Gowrisankaran et al. (2015) show that, in standard models of bargaining (either pure Nash or Nash-in-Nash), the price for h's services that will be negotiated jointly by the hospital and insurer is proportional to W_h.

The above notation assumes that all hospitals are independent. If, instead, hospitals are part of some system S, the hospitals will bargain jointly. That is, prices will be determined by the willingness to pay for the *entire system*, $W_S = \int_i \gamma_i ln\left(\frac{1}{1-s_{iS}}\right) dF_i$, with $s_{iS} = \sum_{j\in S} s_{ij}$. Systems are able to exert greater leverage than individual hospitals because they can threaten to hold out the entire system from the insurer's network if a deal on prices fails to be realized.[17]

We model the case of a merger (m) between two hospitals h and h'.[18] The impact of the merger on the bargaining leverage of the two hospitals is the difference between the willingness to pay of the merged system and the sum of the willingness to pay for h and h' individually. Due to a lack of data on individual insurance take-up, we follow Capps et al. (2003) and assume that $\gamma_i = \gamma$ for all patients. The percent change in willingness to pay due to the merger is:

$$\Delta WTP_m = \frac{\int_i \left[ln\left(\frac{1}{1-(s_{ih}+s_{ih'})}\right) - \left(ln\left(\frac{1}{1-s_{ih}}\right) + ln\left(\frac{1}{1-s_{ih'}}\right)\right)\right] dF_i}{\int_i \left[ln\left(\frac{1}{1-s_{ih}}\right) + ln\left(\frac{1}{1-s_{ih'}}\right)\right] dF_i}$$

where γ_i drops out of the equation under the assumption of homogeneity. Importantly, we focus on the joint complementarities created by a merger, excluding the effect of pure scale increases for each participating hospital. In unpublished results, we found that, particularly for mergers in which a single independent hospital was acquired by a large chain, allowing the scale effects to enter into the change in WTP predicted implausibly (and incorrectly) large post-merger price increases.

Under these assumptions, the potential price changes due to a merger should be proportional to ΔWTP_m.

A.2 Estimating Demand for Hospitals

Measuring ΔWTP_m requires us to estimate substitution patterns in the relevant market. Capps et al. (2003) underscore the importance of patient heterogeneity in this calculation — heart attack patients may care much more about hospital closeness than patients undergoing elective surgeries.

We therefore take the semiparametric approach to demand estimation developed by Raval et al. (2017). That is, we estimate $U(X_{ih})$ by assuming we can partition patients into groups $g \in G$ based on their characteristics, such that

$$U_{ih} = U_{g(i)h} = \delta_{g(i)h} + \varepsilon_{ih}$$

Patients within the same groups are assumed to have the same *ex ante* expected utility for any

[17] In practice, we consider the relevant bargaining entity to be the only the hospitals in a system within a given HRR, to avoid diffusing local changes in bargaining leverage over large acquiring systems. In unreported results, we consider the entire system and system-state to be the relevant bargaining unit and find that our results are not sensitive to this choice.

[18] This is without a loss of generality and can be replaced with systems.

particular hospital, but patients across groups may have different preferences in an unrestricted way. It is then true that, for patients within the same group, expected market shares at each hospital are equal within groups, such that:

$$s_{ih} = s_{g(i)h} = \frac{\exp(\delta_{g(i)h})}{\sum_{j \in \mathcal{N}} \exp(\delta_{g(i)j})}$$

Using this procedure, a valid partition of patients allows us to use the observed group-level market shares as an equivalent measure to individual-specific choice probabilities, and therefore patient utility for each hospital-by-group pair.

We calculate group-specific market shares for each hospital using every inpatient hospitalization for HCCI patients (in the group) during our relevant time period.[19] We exclude any hospitalization in which a patient attended a hospital more than 100 miles from their home. The Raval et al. (2017) approach provides an algorithm that partitions patients into increasingly small groups until the resulting groups are no smaller than S_{min}. This minimum group size parameter is set to balance a bias-variance trade-off: allowing for smaller groups reduces bias by allowing us to capture consumers' heterogeneous preferences for hospitals. However, smaller bins also increase variance by estimating preferences over smaller samples, where market shares may be estimated with error.

The algorithm proceeds as follows:

Step 1: The econometrician first establishes a set of discrete patient characteristics, ordered by "importance." Specifically, we group according to the following characteristics:

1. Patient home county
2. Patient home 5-digit zip code
3. Major Diagnostic Category of the patient's illness
4. Binary indicator for whether the patient's illness was such that the hospitalization was likely to be discretionary (rather than an emergency)
5. Binary indicator for whether the patient's illness was likely to require a surgical treatment (rather than a purely medical treatment)
6. Quartiles of the weight placed on the Diagnosis-Related Group for the patient's illness[20]
7. The Diagnosis-Related Group for a patient's illness (as measured by their primary diagnosis code)
8. Patient age, in 10-year buckets
9. Patient sex

[19] That is, we assume that there is no relevant extensive margin substitution to no hospitalization as a result of changes in market structure.

[20] This DRG weight is used to determine hospital payments under Medicare's reimbursement system.

Step 2: We partition patients into groups based on their unique values for every characteristic (e.g., if the characteristics are gender, race, and county, there will be one group for black female patients in New York County, another group for white male patients in Cook County, etc.).

Step 3: We assign groups based on any partitions from Step 2, as long as the partition has a size above S_{min}. Any patients in partitions with size below S_{min} are left ungrouped.

Step 4: We then disregard the lowest-priority characteristic.

Step 5: We repeat Steps 2-4 until we reach a single characteristic (the patient's home county).

The partitions this algorithm produces vary in granularity to allow for more heterogeneity among patients characteristics when larger sample sizes are available. For example, denser counties will have more groups, subdivided by illness and patient demographics. By contrast all patients will be grouped together in smaller counties where data are sparser.

We run the algorithm separately for each year of mergers in our data. To ensure that we capture finer partition of groups — and therefore flexible substitution patterns — we pool data from the two years prior for each year of mergers. We then compute patient choice probabilities for each hospital ($\hat{s}_{gh}$) for each group. To compute expected proportional changes in price, we compute the percent change in willingness-to-pay,

$$\Delta WTP_m = \frac{\sum_g P_g \left[ln\left(\frac{1}{1-(\hat{s}_{gh}+\hat{s}_{gh'})}\right) - \left(ln\left(\frac{1}{1-\hat{s}_{gh}}\right) + ln\left(\frac{1}{1-\hat{s}_{gh'}}\right)\right)\right]}{\sum_g P_g \left[ln\left(\frac{1}{1-\hat{s}_{gh}}\right) + ln\left(\frac{1}{1-\hat{s}_{gh'}}\right)\right]} \tag{4}$$

where P_g is the share of patients within group g.

B Flagging Mergers as Above or Below HSR Thresholds

To determine whether the mergers we identify as predictably anticompetitive are observable to regulators, we predict whether each merger in our sample was above HSR reporting thresholds. While the FTC publishes industry-level statistics on HSR filings, information about the filing status of individual mergers is not publicly available.

The criteria for mandating an HSR filing depend on the deal's value and the revenues and assets of the merging parties. Mergers valued at $50 million or less are exempt from reporting, whereas those exceeding $200 million must be reported. For mergers valued between $50 and $200 million, reporting is required if one party has over $100 million in net sales or assets and the other has at least $10 million. These thresholds are subject to annual adjustments, which we account for in our calculations.

Hospital revenues and assets come from HCRIS data. Transaction values are extracted from companies' 10K reports and Irving Levin Associates' Health Care Services Acquisition Reports. Transactions values are not available for 75% of mergers between 2010 and 2015. To estimate values for these transactions, we construct a value-revenue multiplier, calculated as the transaction value divided by the target's revenue in the year preceding the merger. Between 2010 and 2015, the average transaction value was 72% of the target's revenue. To impute missing transaction values, we assume the transaction value was 72% of the target's total revenue in the year prior to the merger. Using these valuations, along with revenues and assets, we predict which deals filed HSR reports per the reporting requirements.

C Addressing Staggered Timing Issues in the Difference-in-Difference Design

C.1 Matching Treated and Control Hospitals

Our primary approach to estimating our difference-in-difference is outlined in Section 3. In this section, we describe the procedure used to match treated hospitals to sets of matched comparison hospitals. We estimate a probit regression of the form:

$$\mathbb{P}\{Merger_h\} = X'\beta + \varepsilon_h \tag{5}$$

where X contains a vector of hospital characteristics — drawn from the AHA data and measured in the year before our first merger (2009) — that may meaningfully determine price trends at hospitals: total number of hospital beds; total inpatient admissions; full time equivalents; number of unique technologies; share of Medicare patients; share of Medicaid patients; whether the hospital is a teaching hospital; a non-profit hospital; or a government hospital; the distance to the hospital's nearest competitor; the distance to the hospital's nearest hospital in its system or not; and whether the hospital is independent or part of a system.

X also includes measures of local area characteristics around the hospital. First, we include the HHI, as described in the manuscript. Second, we include the share of the hospital's county covered by private insurance, which we construct using data from the Census's Small Area Health Insurance Estimates (SAHIE). Finally, we include the share of the county insured by HCCI payors specifically, using data from HCCI to form the numerator and data from SAHIE to form the denominator.

We then use the predicted values from Equation (5) as propensity scores. For each merging hospital, we find the 25 nearest neighbors that (1) never merge, or do not merge until after two years following the year of the focal merger, (2) have common support to the merging hospital in the price data from two years before and two years after the merger, and (3) are "close" to the merging hospital in propensity score space. We define close as within 20% of a standard deviation across all hospitals in the data.

C.2 Alternative Matching Approaches

In Table A.3, we present a series of robustness exercises aimed at testing sensitivity to our matching approach. In Panel A, we test alternative methods of calculating propensity scores using Mahalanobis distance and implementing the probit with a LASSO penalty. Because we include a long list of hospital characteristics in our probit, there is a risk that we might overfit the data when generating propensity scores. If this is a problem, a LASSO penalty would avoid this issue by restricting the number of coefficients admitted to the regression.[21] The resulting coefficients in Panel A are close in magnitude to our main estimates and are significantly different from zero.

In Panel B of Table A.3, we re-estimate our treatment effects using alternative restrictions to our controls — allowing only five neighbors instead of 25 and omitting our caliper restriction on our main choice of 25 neighbors. Including only five neighbors weakens our precision on the inpatient price effect, though the estimate is qualitatively similar to our main approach. All other estimates

[21] The LASSO penalty results in the exclusion of the share of patients covered by Medicaid and distance to the nearest hospital.

remain precise, and all estimates are qualitatively similar.

D Robustness Exercises

Post-merger price increases are generally thought to result from mergers increasing market power. However, hospital prices could also increase if mergers cause hospitals to expand their operations, thus raising their marginal costs. To test this, we estimate whether hospitals increased their inpatient volume after mergers. We present these results in Appendix Figure A.5 and find no evidence that hospitals increased their quantity provision post-merger.

Another possible concern is that our approach involves averaging many merger-specific estimates, each of which is estimated imprecisely over a small set of hospitals. MacKinnon and Webb (2020) discuss how this can lead researchers to over-reject null hypotheses. We therefore construct a placebo test in the spirit of randomization inference. For each match group we construct, we drop the merging hospital and randomly assign treatment status to one of the non-merging control hospitals. We then re-estimate Equation (3) to get the average "post-merger price increase" for this placebo group. The null hypothesis (that mergers have no average effect on price) is true by construction in this approach, since there is no actually treated unit. Performing this procedure many times (redrawing the placebo-treated hospital each time) simulates the distribution of estimates under the null hypothesis. We do so 1,000 times and plot the distribution of average effects for our composite price measure in Appendix Figure A.6, which includes a red vertical line reflecting our actual estimated average merger price increase. Our composite price effect estimates are larger than 99.8% of the placebo estimates (equivalent to rejecting the null hypothesis in a two-sided hypothesis test with a p-value of 0.004).[22]

We also illustrate that our estimates are robust to various perturbations of the specific analytic choices we make. In Appendix Table A.3, we show that our estimates are not sensitive to alternative matching approaches, such as not restricting potential controls or using LASSO regularization to limit the characteristics used to generate propensity scores. In Appendix Table A.4, we expand to mergers where the merging parties are less than 400 miles apart (rather than 50) and show that this does not meaningfully shift our overall effect.

[22]We include the distributions for inpatient and outpatient prices in Appendix Figure A.7.

E Estimating Aggregate Spending Changes

In Section 4, we present estimates of the aggregate spending change generated by our sample of mergers. Our general approach is to multiply the price changes we observe by the *ex ante* level of commercial revenue at each hospital. We then sum across all mergers by year to obtain an aggregate spending estimate for each year of mergers from 2010 to 2015. To calculate the average 1-year spending increase from mergers, we take the average spending increase across the six years from 2010 to 2015. Formally, the mergers in our sample imply an average 1-year spending increase of

$$S = \sum_{t} \sum_{eh} \lambda_{eht} \times s_{eh,t-1} \tag{6}$$

λ_{eht} is the hospital-specific price effect estimated for "experiment" e in year t. $s_{eh,t-1}$ is the level of commercial spending at merging hospital *eh* in the year prior to its merger, which we estimate using data from HCRIS. The HCRIS data provides information on hospital finances as a condition of hospitals' participation in the Medicare program. Although the HCRIS does not contain a direct measure of commercial revenue, it does include a measure of total revenue, as well as measures of charges (list prices) by payor type. We subtract Medicare and Medicaid charges from total charges to obtain an estimate of commercial charges. We then simulate the hospitals' average discount rate across all payors to obtain a multiplier that converts commercial charges into estimated commercial revenue.

Note that using an overall average price-to-charge ratio to convert commercial charges to revenue likely understates the level of of commercial revenue because Medicare and Medicaid typically reimburse at levels much lower than commercial payors. We therefore regard our estimates of implied spending increases to be conservative, as actual commercial revenue is likely higher.

F Heterogeneity

In this section, we group mergers by the characteristics of the counties of participating hospitals, separating counties as a function of whether they were above or below the median for three measures: population density, income per capita, and the share of the population in poverty.[23]

In Table A.10, we show the average post-merger price increases for these sets of mergers. For each measure, the estimated average post-merger price increase was larger for mergers in less privileged or less densely populated regions, with differences of 2.8 percentage points (by share in poverty), 1.0 percentage points (by median income per capita, though not statistically significant), and 7.4 percentage points (by population density). In Appendix Figure A.9, we present the relationship between the post-merger price effects we observe and continuous measures of these characteristics.

A large share of the differences in Table A.10 are a function of the relatively large increases in outpatient prices that mergers in less affluent areas generate. One potential explanation for this result is that these areas — due to low population density — have more concentrated markets for outpatient services. In these areas, mergers potentially give hospitals additional bargaining leverage over outpatient prices because there are fewer freestanding facilities (e.g., imaging or surgical centers) to constrain their price increases. Ultimately, markets for outpatient care are more local, and non-hospital outpatient facilities are more common in more densely populated areas due to economies of scale (Dingel et al., 2023). We confirm this in Appendix Figure A.10: less affluent areas, by all three measures, have fewer ambulatory surgical centers (non-hospital outpatient facilities) nearby. In Appendix Table A.9, we show that mergers involving hospitals in markets with fewer ambulatory surgical centers produce significantly larger outpatient price increases.[24]

[23]We measure county-level poverty from the American Community Survey's five-year estimates. Income per capita is measured as total county wages from the Quarterly Census of Wages and Employment divided by the total county population aged 25-64. Population density estimates are calculated as population per square mile, where county areas are measured using the Census Bureau's County and City Databook. County populations are measured using the Census Bureau's County Population Totals.

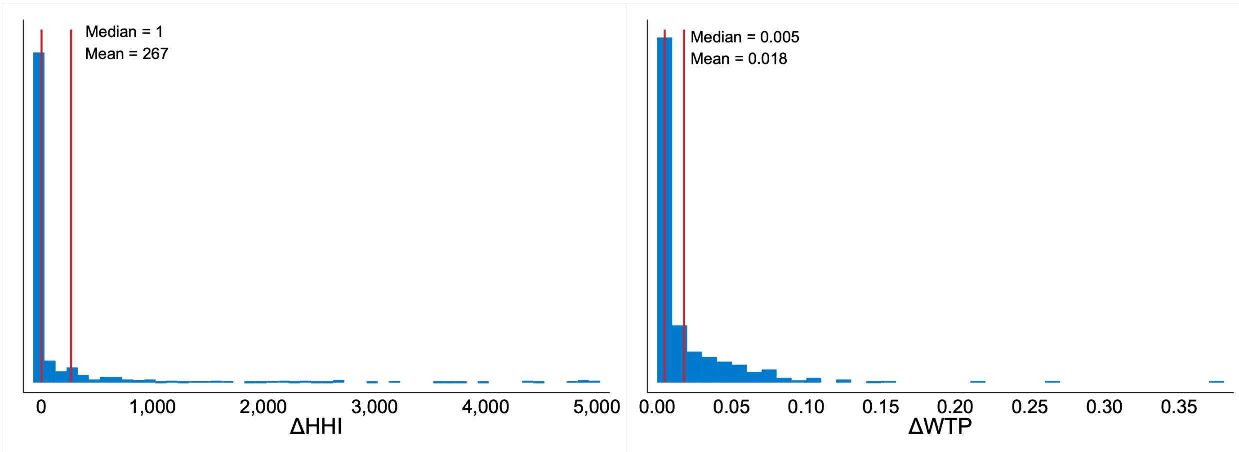
[24]This result is robust to alternative market definitions.

G Additional Tables and Figures

Figure A.1: Distributions of Change in HHI and Percent Change in WTP for Hospital Mergers in Our Analytic Sample

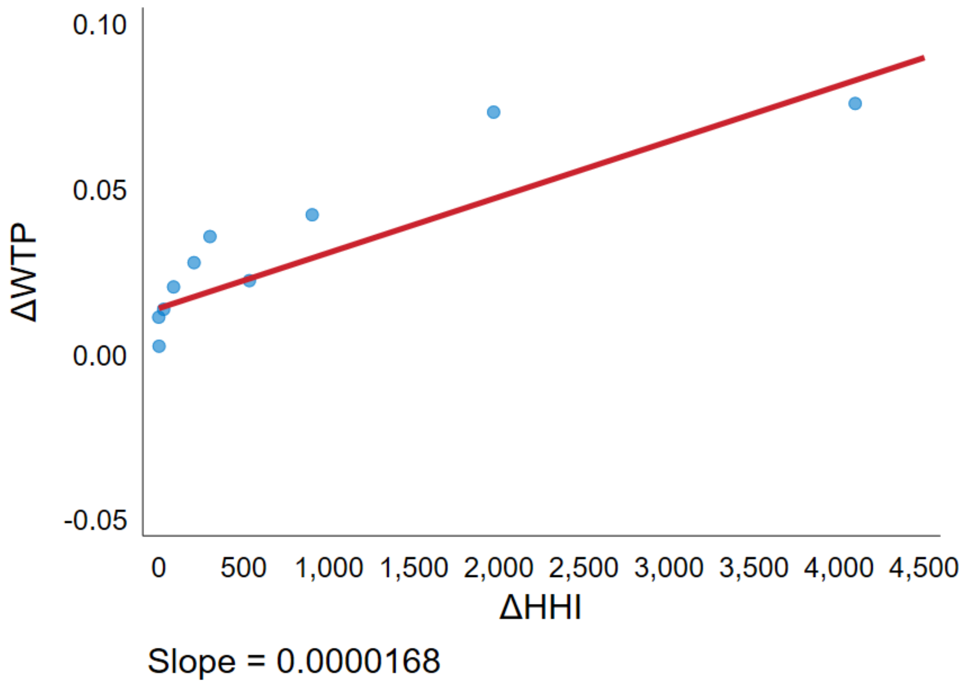
(a) Change in Hospital HHI per Merger

(b) Percent Change in Hospital WTP per Merger



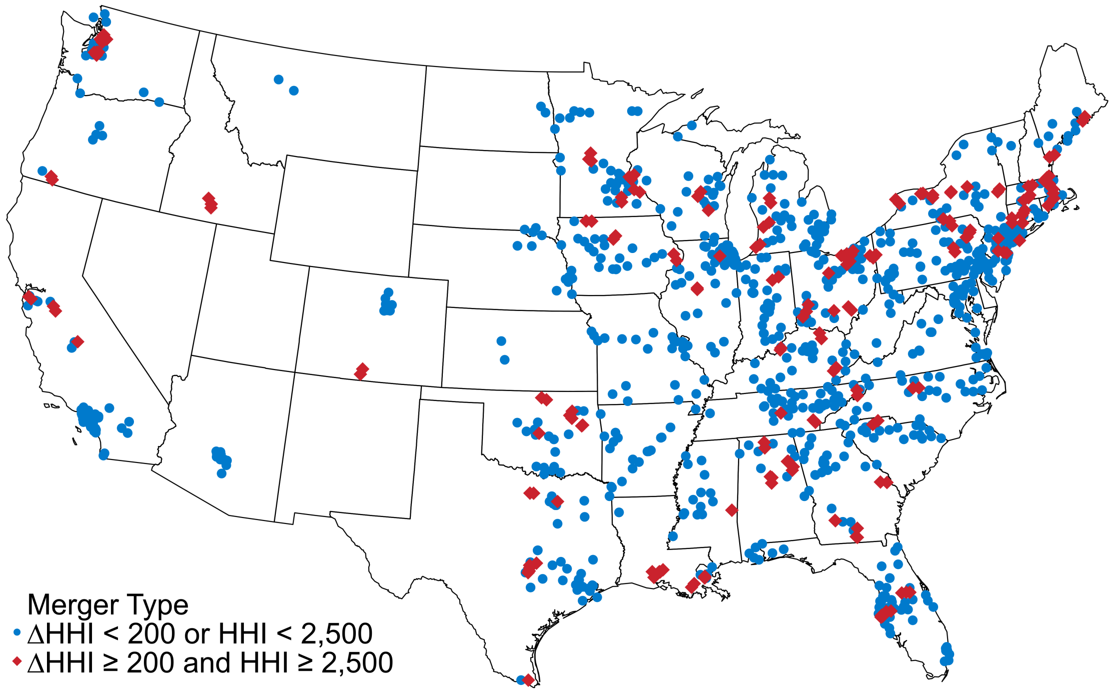
Note: This figure presents histograms of the distribution of changes in hospital HHI (Panel A) and percent changes in hospital WTP (Panel B, divided by 100) for each merging hospital. These figures are limited to the 702 merging hospitals in the analytic sample.

Figure A.2: Binned Scatter Plot of Change in HHI and Percent Change in WTP



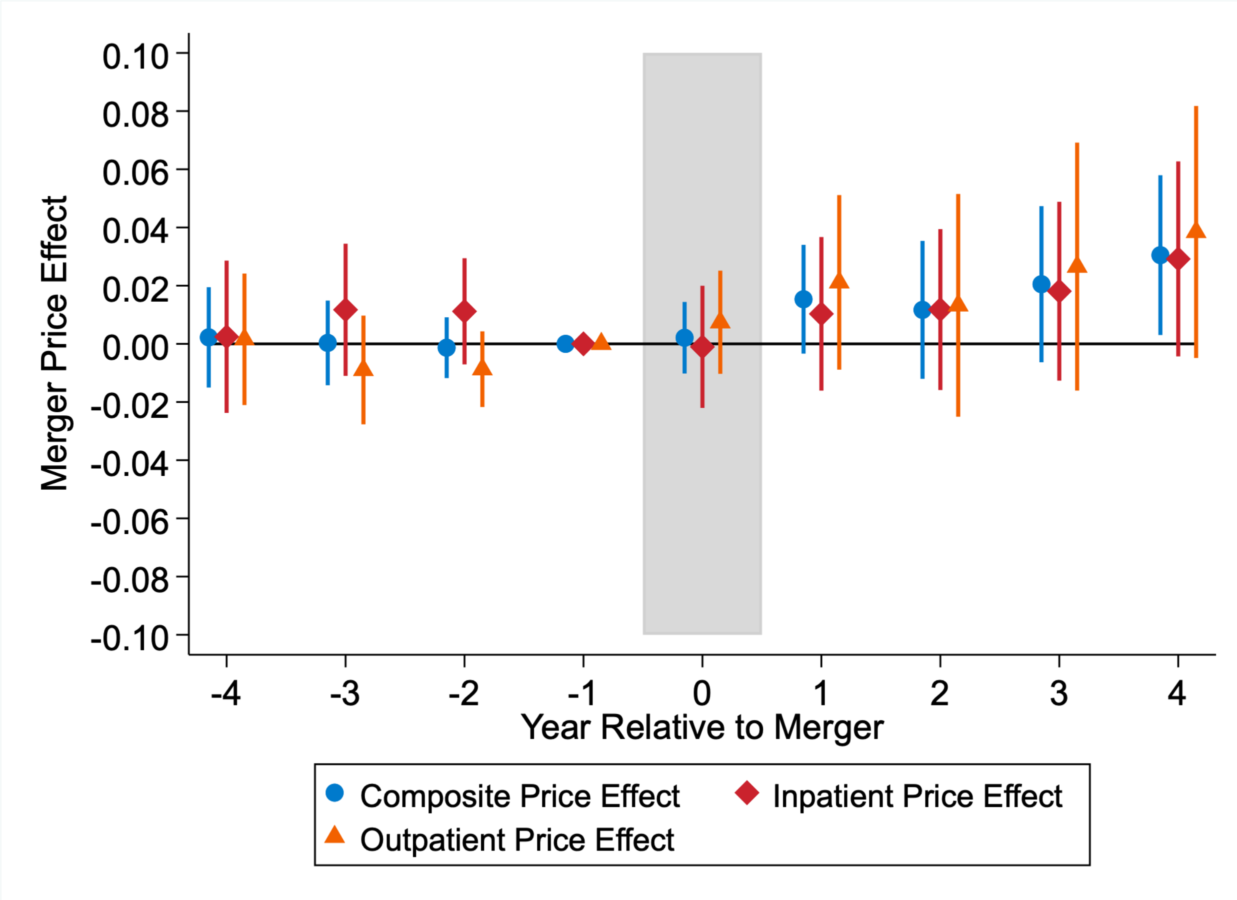
Note: This figure presents the relationship between ΔHHI and ΔWTP in a binned scatter plot. Each underlying observation is a merging hospital. The red line is the line of best fit.

Figure A.3: Hospital Mergers by Whether $\Delta HHI \geq 200$ and Post-Merger $HHI \geq 2,500$ From 2010-2015



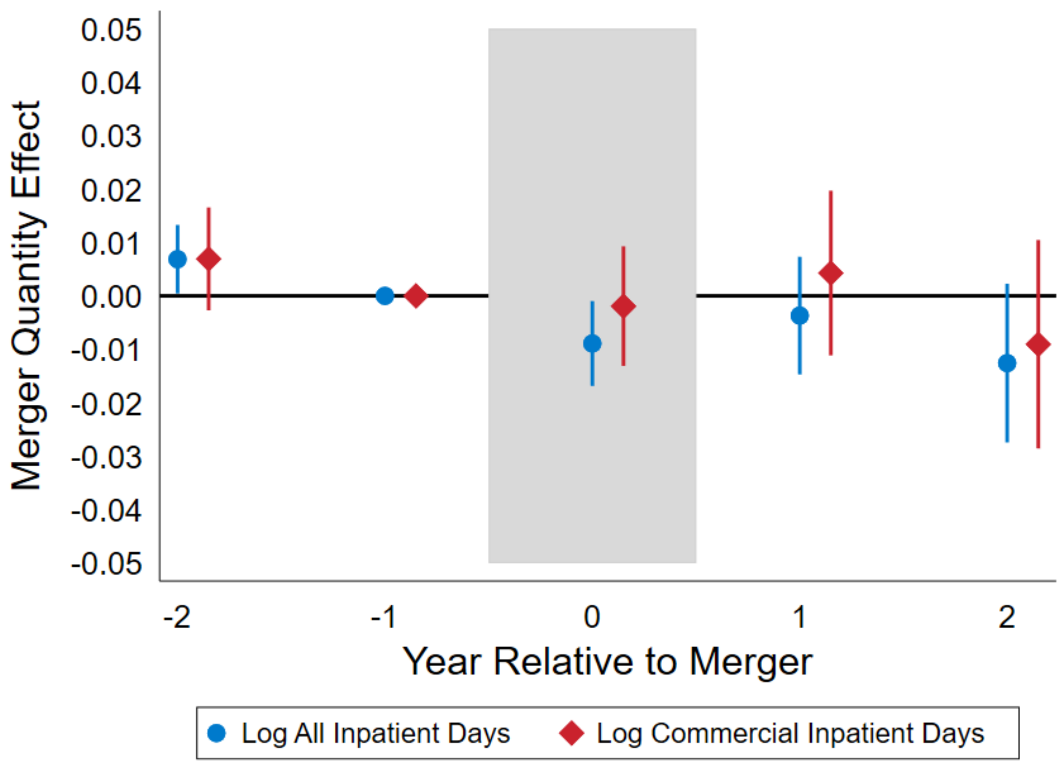
Note: The map presents all hospital mergers in our analytic sample from 2010 to 2015. We focus on hospital mergers in the continental US. The market definition used to calculate HHI is a 30-minute drive time radius around each merging hospital.

Figure A.4: Event Studies for 2012-2013 Set of Mergers (+/- 4 years)



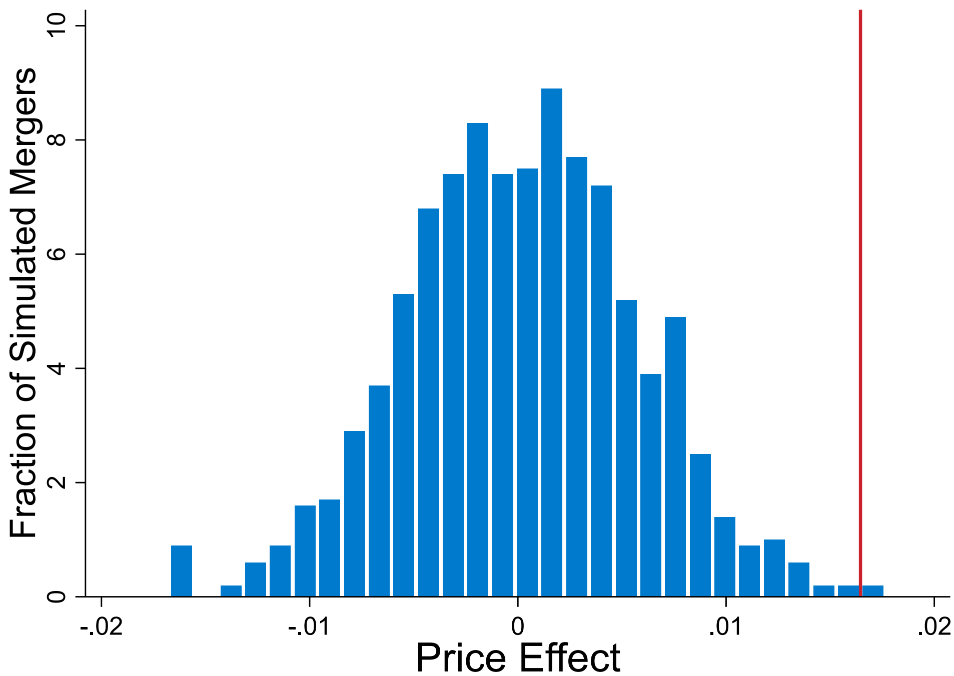
Note: This figure presents event study estimates of Equation (3) on 202 hospitals from our analytic sample from mergers that occurred in 2012 and 2013 involving 98 targets and 104 acquirers located less than 50 miles from one another. Each dot represents a point estimate and the vertical line displays the corresponding 95% confidence interval. Hospital pricing data come from HCCI. This is based on estimates from Equation (3), with standard errors clustered at the hospital level.

Figure A.5: The Impact of Hospital Mergers on All and Commercial Inpatient Days



Note: This figure shows event study estimates of total and commercial inpatient days for merging hospitals located within 50 miles of each other. The regression model used is similar to Equation (3), but the dependent variable is total inpatient days from HCRIS instead of HCCI prices. Each dot represents a point estimate, and the vertical line represents the corresponding 95% confidence interval. Our standard errors are clustered around hospitals. Commercial inpatient days are calculated as the difference between total inpatient days and the sum of Medicare and Medicaid inpatient days. To prevent duplication of inpatient days across hospitals with the same Medicare provider number, the analysis is limited to hospitals with a unique Medicare provider number.

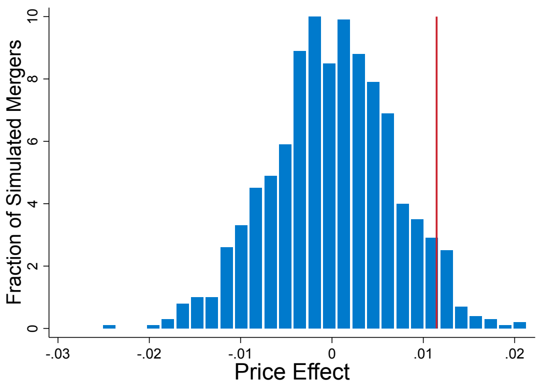
Figure A.6: The Post-merger Price Increase from Mergers Relative to a Distribution of Simulated Effects of 1,000 Simulated Mergers



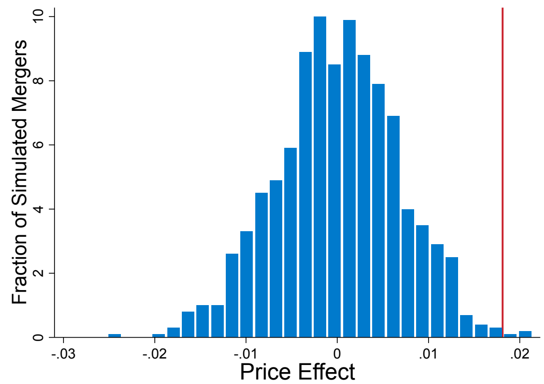
Note: This figure presents a distribution of average treatment effects for 1,000 placebo cohorts as described in Appendix D. We estimate post-merger price effects as if control hospitals had merged, rather than actual merging hospitals. We then average these placebo estimates. We plot the kernel density of the distribution of average placebo post-merger effects on the composite price index (the blue curve) and the actual estimated average post-merger price effect (the red vertical line) on hospitals' composite prices. The x-axis is the price effect in log points. The share of placebo estimates above our actual estimates is 0.2%. We present the analogous results for our inpatient and outpatient price effects in Appendix Figure A.7.

Figure A.7: The Post Merger Price Increase From Mergers Relative to a Placebo Distribution of Simulated Effects of 1,000 Mergers

(a) Inpatient Price Effect



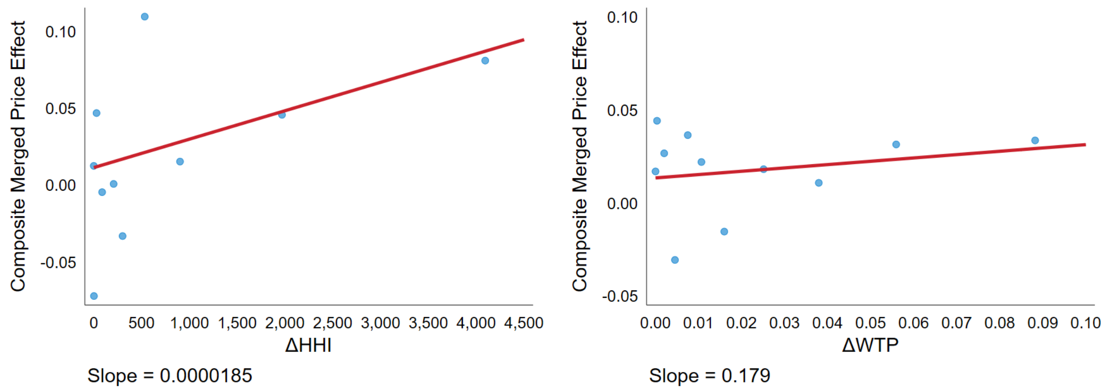
(b) Outpatient Price Effect



Note: This figure presents a distribution of average treatment effects for 1,000 placebo cohorts as described in Appendix D. We estimate post-merger price effects as if control hospitals merged, rather than actual merging hospitals. We then average over these placebo estimates. We plot the kernel density of the distribution of average placebo post-merger effects on the composite price index (the blue curve) and the actual estimated average post-merger price effect (the red vertical line) on hospitals' composite prices. The x-axis is the price effect in log points. Panels (a) and (b) contain these results for inpatient and outpatient price indices, respectively.

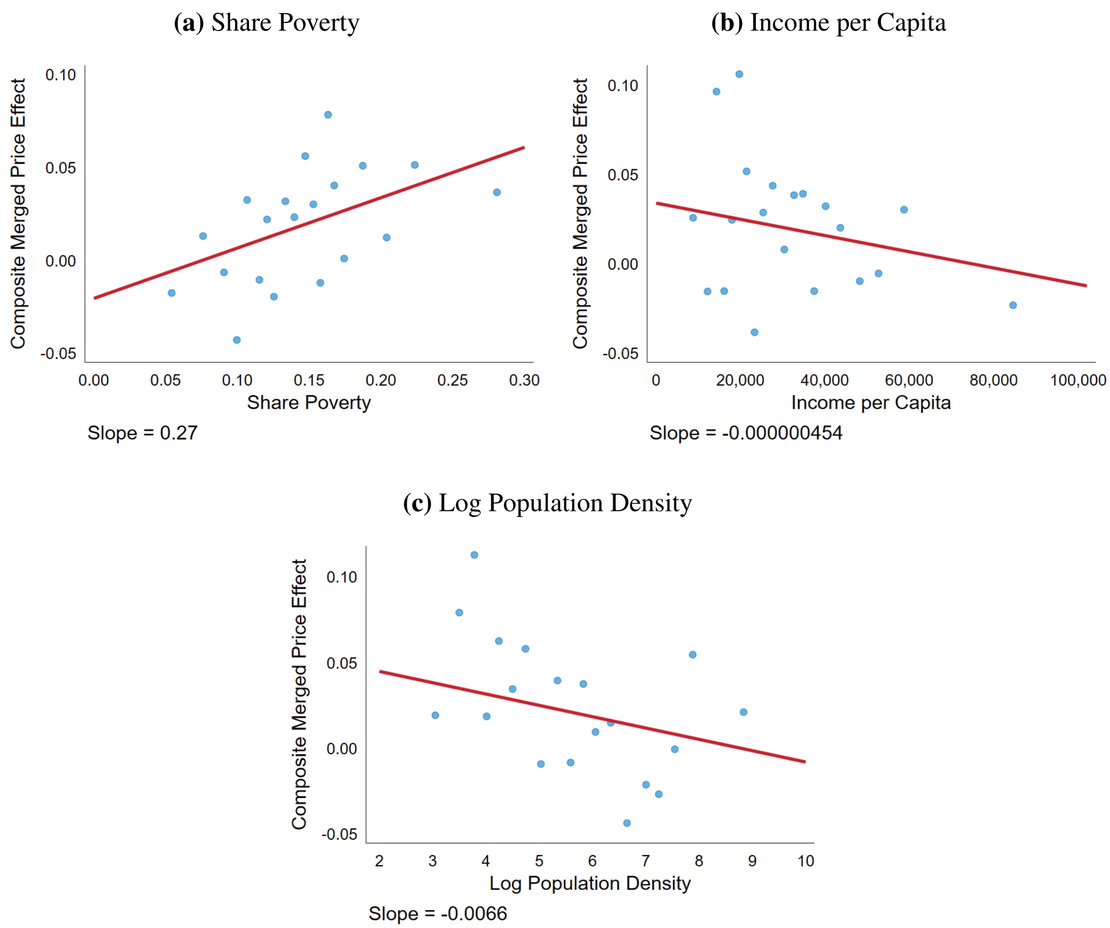
Figure A.8: Binned Scatter Plot of the Changes in Composite Price Effect and Change in HHI and Percent Change WTP

(a) Change in HHI **(b)** Percent Change WTP



Note: This figure presents the relationship between our estimated post-merger price effect for the composite hospital price index and Δ HHI and Δ WTP in a binned scatter plot. Each underlying observation is a merging hospital. The percent change in WTP is truncated at 10%. The red line is the line of best fit. Panel B presents the percent change in WTP estimated using HCCI inpatient claims data.

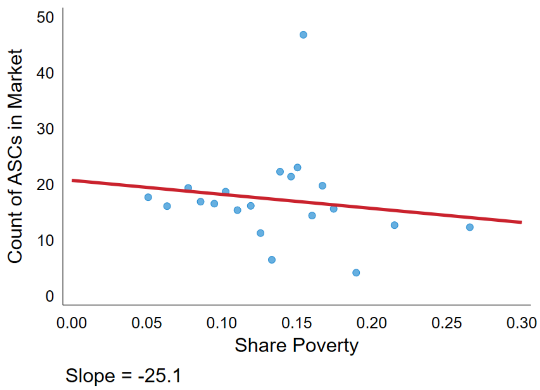
Figure A.9: Binned Scatter Plot of the Changes in the Composite Price Effect and Local Area Characteristics



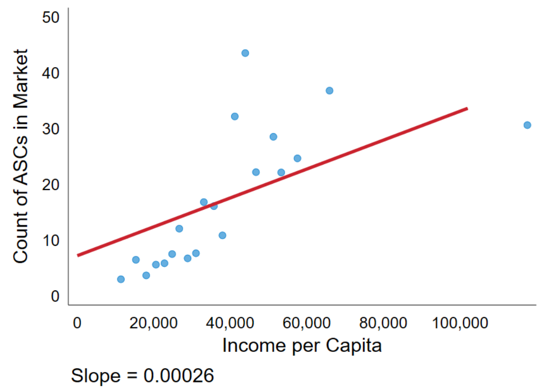
Note: This figure illustrates the relationship between the estimated post-merger price effect for the composite hospital price index and various local area characteristics. The underlying data are at the hospital level, and the local area characteristics of hospitals are determined based on the county in which each hospital is situated, using the 2010 data. County-level poverty is measured using the American Community Survey's 5-year estimates. Income per capita is calculated by dividing the total county wages from the Quarterly Census of Wages and Employment by the total county population aged 25-64. Population density estimates are determined by calculating the population per square mile, with county areas obtained from the Census Bureau's County and City Databook. County populations are measured using the Census Bureau's County Population Totals.

Figure A.10: Binned Scatter Plot of the Number of Ambulatory Surgical Centers in the Market and Local Area Characteristics

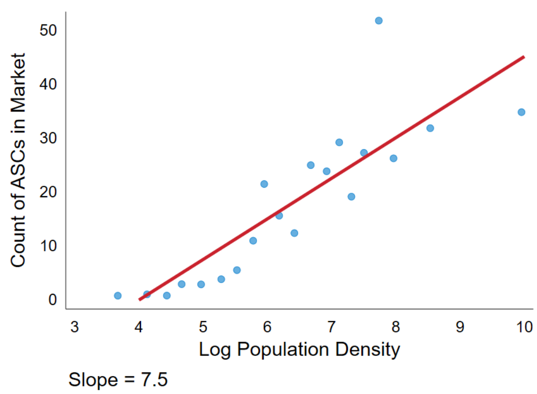
(a) Share Poverty



(b) Income per Capita



(c) Log Population Density



Note: This figure reports the relationship between the number of ASCs in the market and various local area characteristics. The underlying data are at the hospital level and are limited to the 702 merging hospitals in our analytic sample. The number of ASCs in the market is defined as all ASCs within a 30-minute drive time of the merging hospital, using the 2010 Medicare Provider of Services file. ASC locations are determined based on the centroid of their zip code. The local area characteristics of hospitals are determined based on the county in which each hospital is situated, using the 2010 data. County-level poverty is measured using the American Community Survey's 5-year estimates. Income per capita is calculated by dividing the total county wages from the Quarterly Census of Wages and Employment by the total county population aged 25-64. Population density estimates are determined by calculating the population per square mile, with county areas obtained from the Census Bureau's County and City Databook. County populations are measured using the Census Bureau's County Population Totals.

Table A.1: Merger Characteristics

	All 2002-2020 **(1)**	All 2010-2015 **(2)**	50 Mile 2010-2015 **(3)**	In Estimation 2010-2015 **(4)**
Number of Transactions	1,164	484	377	322
Average Number of Acquirer Hospitals	18.1	18.1	18.0	18.7
Average Number of Target Hospitals	1.6	1.5	1.4	1.5
Share $\Delta HHI \geq 200$ and Post-Merger $HHI \geq 2,500^{*}$	20.4%	20.0%	25.7%	25.5%
Share $\Delta HHI \geq 100$ and Post-Merger $HHI \geq 1,800^{**}$	23.2%	23.3%	30.0%	30.4%
Share $\Delta WTP \geq 5\%$		9.3%	11.7%	13.0%

Note: This table presents summary statistics of hospital mergers under various sample restrictions. Column (1) presents all hospital mergers occurring between 2002 and 2020. Column (2) restricts to mergers occurring between 2010 and 2015. In Column (3) we focus on the subset of these mergers where at least two of the prior competitor hospitals were located within 50 miles of one another. Column (4) shows how the sample changes when we restrict to the subset of merging hospitals in Column (3) for which we have sufficient data from HCCI to estimate our difference-in-difference model.

*Threshold associated with the 2010 DOJ/FTC Horizontal Merger Guidelines.

**Threshold associated with the 2023 DOJ/FTC Merger Guidelines.

Table A.2: The Effect of Mergers on Hospital Prices

	Count of Hospitals **(1)**	Composite Price Effect **(2)**	Inpatient Price Effect **(3)**	Outpatient Price Effect **(4)**
2023 DOJ/FTC Merger Guideline Threshold				
$\Delta HHI \geq 100$ and Post-Merger HHI $\geq 1,800$	135	0.043***	0.052***	0.041***
		(0.007)	(0.010)	(0.010)
$\Delta HHI < 100$ or Post-Merger HHI $< 1,800$	567	0.010***	0.002	0.013**
		(0.004)	(0.005)	(0.005)
Difference		0.033***	0.050***	0.028**
		(0.008)	(0.011)	(0.012)

Note: * *p < 0.1*, ** *p < 0.05* , *** *p < 0.01*. This table presents estimates from the regression given in Equation (3) on sub-samples of merging hospitals. The analysis compares merging hospitals with an HHI increase of over 100 points and a post-merger HHI greater than 1,800 points to merger hospitals with either an HHI increase less than 100 points or a post-merger HHI less than 1,800 points. These are thresholds set via the 2023 DOJ/FTC Merger Guidelines. A merging hospital's market is defined as all hospitals within a 30-minute drive time of the merging hospital, and market shares are defined using a hospital's share of inpatient beds in the market, measured using AHA data. The underlying regression is from a stacked difference-in-differences design comparing merging hospitals to a set of matched non-merging control hospitals before and after the merger of the focal hospital. Rows represent different sub-samples. "Difference" denotes the difference in coefficients between the two sub-samples within the panel. Our standard errors are clustered at the hospital level.

Table A.3: Robustness to Alternative Matching Algorithms and Matching Specifications

	Count of Hospitals	Composite Price Effect	Inpatient Price Effect	Outpatient Price Effect
	(1)	**(2)**	**(3)**	**(4)**
Panel A: Alternative Matching Algorithms				
Probit	702	0.016***	0.011**	0.018***
		(0.003)	(0.005)	(0.005)
LASSO Probit	702	0.016***	0.010**	0.019***
		(0.003)	(0.005)	(0.005)
Mahalanobis	702	0.021***	0.012**	0.027***
		(0.003)	(0.005)	(0.005)
Panel B: Alternative Matching Specifications				
25 Neighbors, 20% Caliper	702	0.016***	0.011**	0.018***
		(0.003)	(0.005)	(0.005)
5 Neighbors, 20% Caliper	702	0.016***	0.009	0.019***
		(0.005)	(0.006)	(0.007)
25 Neighbors, No Caliper	702	0.016***	0.012**	0.018***
		(0.003)	(0.005)	(0.005)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents estimates from the regression given in Equation (3) on various matching specifications. The first row in each panel is our baseline specification, which limits to merging hospitals within 50 miles of a former rival hospital in the merging system. The baseline specification also uses probit regression to estimate the propensity scores, and selects the 25 nearest hospitals as controls (25 neighbors) within 0.2 times the standard deviation of the propensity scores (20 calipers). Panel A presents results using a Mahalanobis distance instead of a probit regression or using LASSO regularization to limit the characteristics that enter the match. Panel B varies the number of nearest neighbors selected and the caliper restriction. Our standard errors in this table are clustered around hospitals.

Table A.4: Robustness to Alternative Maximum Distances Between Merging Parties

	Count of Hospitals (1)	Composite Price Effect (2)	Inpatient Price Effect (3)	Outpatient Price Effect (4)
50 Miles	702	0.016***	0.011**	0.018***
		(0.003)	(0.005)	(0.005)
400 Miles	949	0.013***	0.014***	0.011***
		(0.003)	(0.004)	(0.004)

Note: * *p < 0.1, ** p < 0.05 , *** p < 0.01*. This table presents estimates from the regression given in Equation (3) on various maximum distances between merging parties. The first row is our baseline specification, which limits to merging hospitals within 50 miles of a former rival hospital in the merging system. The second row shows the overall effect of mergers on hospital prices when including additional merging hospitals over 50 miles away from their closest, former rival hospital in the merging system. Our standard errors are clustered around hospitals.

Table A.5: Merger Price Effects For Deals Above and Below ΔHHI Thresholds Calculated Using Various Market Definitions

	Count of Hospitals **(1)**	Composite Price Effect **(2)**	Inpatient Price Effect **(3)**	Outpatient Price Effect **(4)**
Panel A: 30-Minute Drive Time Radius				
$\Delta HHI \geq 200$ and Post-Merger $HHI \geq 2,500$	109	0.052***	0.054***	0.045***
		(0.008)	(0.011)	(0.011)
$\Delta HHI < 200$ or Post-Merger $HHI < 2,500$	593	0.010***	0.004	0.013**
		(0.004)	(0.005)	(0.005)
Difference		0.042***	0.050***	0.032***
		(0.009)	(0.012)	(0.012)
Panel B: 15-Mile Radius				
$\Delta HHI \geq 200$ and Post-Merger HHI $\geq 2,500$	112	0.028***	0.043***	0.013
		(0.007)	(0.009)	(0.011)
$\Delta HHI < 200$ or Post-Merger HHI $< 2,500$	590	0.014***	0.006	0.019***
		(0.004)	(0.005)	(0.005)
Difference		0.014*	0.036***	–0.006
		(0.008)	(0.011)	(0.012)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents estimates from the regression given in Equation (3) on various market definitions to define HHI. The underlying regression is from a stacked difference-in-differences design comparing merging hospitals to a set of matched non-merging control hospitals before and after the merger of the focal hospital. Each panel defines HHI using a different market definition. Panel A defines the market as including all hospitals within a 30 minute drive time of the focal hospital. Panel B defines the market as including all hospitals within a 15 miles of the focal hospital. Market shares are defined using a hospital's share of inpatient beds in the market, measured using AHA data. "Difference" denotes the difference in coefficients between the two sub-samples within the panel. Our standard errors are clustered around hospitals.

Table A.6: Count of Mergers That Are Flagged as Presumptively Anticompetitive

	Count of Mergers (1)	$\Delta HHI \geq 200$ & Post-Merger HHI $\geq 2,500$ (2)	$\Delta HHI < 200$ or Post-Merger HHI $< 2,500$ (3)	Mean ΔWTP (4)	$\Delta WTP \geq 5\%$ (5)	$\Delta WTP < 5\%$ (6)
Panel A: All Mergers 2010-2015						
All Mergers	484	97	387	.024	45	439
Above HSR Reporting Threshold	207	44	163	.084	29	178
Below HSR Reporting Threshold	277	53	224	.007	16	261
Panel B: Mergers in Analytic Sample						
All Mergers	322	82	240	.034	42	280
Above HSR Reporting Threshold	153	41	112	.092	27	126
Below HSR Reporting Threshold	169	41	128	.01	15	154

Notes: Each cell contains the count of mergers flagged as presumptively anticompetitive based on the change in HHI they produce and its relation to the 2010 Horizontal Merger Guidelines or the change in willingness to pay they generate. Panel A presents all mergers we observe between 2010 and 2015. Panel B presents mergers in our analytic sample. We differentiate between mergers we think are and are not visible to regulators based on whether they exceed Hart-Scott-Rodino (HSR) filing thresholds. We provide a similar analysis using HHI thresholds relative to the 2023 Horizontal Merger Guidelines in Appendix Table A.7.

Table A.7: Count of Mergers That Are Flagged as Presumptively Anticompetitive - 2023 Merger Guidelines

	Count of Mergers (1)	$\Delta HHI \geq 100$ & Post-Merger HHI $\geq 1,800$ (2)	$\Delta HHI < 100$ or Post-Merger HHI $< 1,800$ (3)
Panel A: All Mergers 2010-2015			
All Mergers	484	113	371
Above HSR Reporting Threshold	207	55	152
Below HSR Reporting Threshold	277	58	219
Panel B: Mergers in Analytic Sample			
All Mergers	322	98	224
Above HSR Reporting Threshold	153	52	101
Below HSR Reporting Threshold	169	46	123

Notes: Each cell contains the count of mergers flagged as presumptively anticompetitive based on the change in HHI they produce or the change in willingness to pay they generate. Panel A presents all mergers we observe between 2010 and 2015. Panel B presents mergers in our analytic sample. We differentiate between mergers we think are and are not visible to regulators based on whether they exceed Hart-Scott-Rodino (HSR) filing thresholds. The HHI thresholds used in this table reflect those described in the 2023 DOJ/FTC Merger Guidelines.

Table A.8: Changes in Concentration and Competition for FTC-Litigated Mergers Compared to Consummated Mergers

	Full Sample	Flagged Mergers	FTC Enforced
Change in Concentration (HHI)	435	1,843	3,607
Change in Concentration (WTP)	2.0%	9.6%	22.9%

Note: This table presents estimates of the changes in the Herfindahl-Hirshman Index (HHI) and willingness-to-pay (WTP) for three sets of mergers: 1) The full sample of mergers in our sample, 2) The set of mergers flagged by our premerger screening approach (for HHI, mergers that changed HHI by at least 200 points and resulted in a post-merger HHI of at least 2500 points; for WTP, mergers that resulted in an estimated change in WTP of at least 5%), and 3) Mergers that the FTC took an enforcement action against during 2010-2015. For each transaction in the category, we take the maximum change in HHI/WTP across hospitals within the transaction, then average across transactions.

Table A.9: Merger Price Effects by Count of Ambulatory Surgical Centers (ASCs) in the Market Across Multiple Market Definitions

	Count of Hospitals **(1)**	Composite Price Effect **(2)**	Inpatient Price Effect **(3)**	Outpatient Price Effect **(4)**
Panel A: 30-Minute Drive Time				
Below Median ASCs in Market	327	0.027***	0.002	0.043***
		(0.005)	(0.008)	(0.007)
Above Median ASCs in Market	375	0.007	0.020***	–0.004
		(0.004)	(0.006)	(0.007)
Difference		0.019***	–0.018*	0.047***
		(0.007)	(0.010)	(0.010)
Panel B: 15-Mile Radius				
Below Median ASCs in Market	245	0.024***	0.001	0.035***
		(0.007)	(0.010)	(0.008)
Above Median ASCs in Market	457	0.012***	0.017***	0.009
		(0.004)	(0.005)	(0.006)
Difference		0.012	–0.016	0.026**
		(0.008)	(0.011)	(0.010)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents estimates from the regression given in Equation (3) subset to hospitals with different counts of ambulatory surgical centers in their local market. Panel A defines the relevant market as all ASCs within a 30 minute drive time of the focal hospital. Panel B defines the relevant market as all ASCs within 15 miles of the focal hospital. The number of ASCs is determined using the 2010 Medicare Provider of Services File and the location of ASCs is set as its zip code centroid. Our standard errors are clustered around hospitals.

Table A.10: The Effect of Mergers on Hospital Prices by Local Area Characteristics

	Count of Hospitals (1)	Composite Price Effect (2)	Inpatient Price Effect (3)	Outpatient Price Effect (4)
Panel A: Share Poverty				
Above Median Share Poverty	316	0.032***	0.024***	0.036***
		(0.006)	(0.008)	(0.008)
Below Median Share Poverty	386	0.004	0.001	0.004
		(0.004)	(0.005)	(0.006)
Difference		0.028***	0.023**	0.032***
		(0.007)	(0.010)	(0.010)
Panel B: Income per Capita				
Below Median Income per Capita	82	0.025*	–0.001	0.048***
		(0.013)	(0.021)	(0.017)
Above Median Income per Capita	620	0.015***	0.013***	0.014***
		(0.003)	(0.005)	(0.005)
Difference		0.010	–0.014	0.034*
		(0.013)	(0.021)	(0.018)
Panel C: Population Density				
Below Median Population Density	21	0.089***	0.063	0.108***
		(0.020)	(0.051)	(0.019)
Above Median Population Density	681	0.014***	0.010**	0.015***
		(0.003)	(0.005)	(0.005)
Difference		0.074***	0.053	0.093***
		(0.021)	(0.051)	(0.019)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents estimates from the regression given in Equation (3) on sub-samples of merging hospitals. The underlying regression is from a stacked difference-in-differences design comparing merging hospitals to a set of matched non-merging control hospitals before and after the merger of the focal hospital. Rows represent different sub-samples of mergers. Hospitals' local area characteristics are defined using the 2010 local area characteristic of the county each hospital is located in. Panel A segments merging hospitals by whether they are located in counties above or below median share poverty measured using the American Community Survey. Panel B reports the results by above- and below-median income per capita measured using the Quarterly Census on Employment and Wages. Panel C segments merging hospitals by above and below median population density measured using the Census's County and City Databook. The denominator for panels B and C is measured using the Census's County Population Totals files. Medians are calculated across all counties in the continental US. "Difference" denotes the difference in coefficients between the two sub-samples within the panel. Our standard errors are clustered around hospitals.