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Zack Cooper
Joseph J. Doyle Jr.
John A. Graves
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Do Higher-Priced Hospitals Deliver Higher-Quality Care?
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ABSTRACT

We analyze whether receiving care from higher-priced hospitals leads to lower mortality. We overcome selection issues by using an instrumental variable approach which exploits that ambulance companies are quasi-randomly assigned to transport patients and have strong preferences for certain hospitals. Being admitted to a hospital with two standard deviations higher prices raises spending by 52% and lowers mortality by 1 percentage point (35%). However, the relationship between higher prices and lower mortality is only present at hospitals in less concentrated markets. Receiving care from an expensive hospital in a concentrated market increases spending but has no detectable effect on mortality.

Zack Cooper
Yale School of Public Health
and the Department of Economics
Yale University
85 Trumbull Street
New Haven, CT 06520
and NBER
zack.cooper@yale.edu

Joseph J. Doyle Jr.
MIT Sloan School of Management
100 Main Street, E62-516
Cambridge, MA 02142
and NBER
jjdoyle@mit.edu

John A. Graves
Vanderbilt University
2525 West End Ave.
Suite 1200
Nashville, TN 37203
john.graves@vanderbilt.edu

Jonathan Gruber
Department of Economics, E52-434
MIT
77 Massachusetts Avenue
Cambridge, MA 02139
and NBER
gruberj@mit.edu

I. Introduction

The US hospital industry accounts for 6.1% of gross domestic product (GDP) and 31% of health spending (Centers for Medicare and Medicaid Services, 2020). While public insurers in the US pay hospitals regulated reimbursements, private insurers, which cover approximately 60% of the population, negotiate prices with hospitals. Hospitals' market-determined prices vary substantially within and across regions, are growing quickly over time, and are a key driver of variation and growth in private health spending (Cooper et al., 2019*a*,*b*; Health Care Cost Institute, 2015). There is growing policy concern that in hospital markets, where concentration is rising and quality can be difficult to measure, high prices may reflect providers' market power (Pany, Chernew and Dafny, 2021).

Over the last 30 years, there has been extensive consolidation in the US hospital sector. Between 1998 and 2017, there were 1,577 hospital mergers among the nation's approximately 6,000 hospitals (American Hospital Association, 2018). At present, the majority of US hospital markets have a Herfindahl-Hirschman Index (HHI) of greater than 5,000 and are considered "highly concentrated" per the joint Department of Justice and Federal Trade Commission horizontal merger guidelines (Fulton, 2017; Department of Justice and the Federal Trade Commission, 1997). Research shows that hospital mergers can raise prices and that hospitals in more concentrated markets tend to have higher prices (Cooper et al., 2019*a*; Gowrisankaran, Nevo and Town, 2015).[1]

High prices and rising market concentration have led to a range of proposals to regulate hospital prices (Fiedler, 2020). Several prominent proposals recommend regulating hospital payments at a fixed percentage of Medicare reimbursements (e.g., Kocher and Berwick (2019) and Skinner, Fisher and Weinstein (2014)). Other proposals, like H.R. 506 and H.R. 1332, two bills released in the US House of Representatives in 2019, recommend only regulating hospital prices in concentrated markets (e.g., markets with a HHI greater than 4,000).

However, as policymakers consider price regulation, they must balance the goal of reducing prices with maintaining (and incentivizing improvements in) providers' quality. In differentiated product markets, like the markets for cars and hotels, high-quality products that generate value for consumers can command higher prices (Berry, Levinsohn and Pakes, 1995; Crawford, Shcherbakov

[1]See Handel and Ho (2021) for a detailed discussion of this literature.

and Shum, 2019). Hospital markets could operate similarly: hospitals facing competition may be making strategic investments in their clinical services in order to attract patients with high willingness to pay for quality (Garthwaite, Ody and Starc, 2020). These investments could raise costs and lead to higher prices. As a result, before moving towards price regulation, it is vital to better understand the relationship between hospital prices, market concentration, and quality.

This paper tests if receiving care from higher-priced hospitals in an emergency results in lower mortality and whether there is a price/quality relationship in concentrated and unconcentrated hospital markets. We do so to help better understand the functioning of hospital markets in the US. To date, there is scant research assessing whether receiving care from high-price hospitals (causally) results in better outcomes. This, in part, reflects the challenge of addressing selection bias—sicker patients may differentially be admitted to higher-priced hospitals—and the challenge of obtaining claims data with hospitals' prices.

We overcome the selection challenge by analyzing outcomes during health emergencies among privately insured patients who are transported to the hospital by ambulance. We utilize an instrumental variable (IV) approach, first introduced by Doyle et al. (2015) and subsequently used by Hull (2020) and Chan, Card and Taylor (2022), which exploits the fact that ambulance companies are effectively randomly assigned to emergency calls and have clear preferences over the hospitals to which they transport patients. Taken together, these features of the pre-hospital care system induce plausibly exogenous variation in hospital destination among emergency patients.

Our empirical strategy is therefore to compare the outcomes of privately insured patients from the same communities that are taken, in an emergency, to high- and low-priced hospitals as a function of the ambulance company sent to transport them. We test whether patients treated for nondeferrable conditions at high- versus low-priced hospitals have differences in in-hospital mortality and health spending during their episode of care and over the subsequent 365-days. This empirical strategy has been used previously to test the effect of receiving care from hospitals with high Medicare spending, which is driven primarily by intensity of treatment and not differences in prices. We are the first to use this strategy to assess the causal relationship between receiving care from high-priced hospitals and patient outcomes.

Our analysis relies on data from the Health Care Cost Institute (HCCI). The

HCCI database is composed of insurance claims for individuals with health insurance from Aetna, Humana, and UnitedHealthcare. The data capture claims for approximately 27.6% of individuals in the US with employer-sponsored insurance (Health Care Cost Institute, 2015). Crucially, the data include the negotiated prices insurers paid hospitals. For each hospital, we construct an inpatient price index that adjusts for the mix of patients a hospital treats and the mix of services a hospital delivers. As a result, our analysis tests whether patients taken exogenously to hospitals with higher prices for all inpatient services have lower in-hospital mortality for emergency admissions.

Our causal estimates reveal that receiving inpatient care at high-priced hospitals lowers mortality for nondeferrable conditions and raises health spending during the initial hospitalization and over the subsequent year. This is in contrast to the positive correlation between prices and mortality we observe when we do not instrument for hospital choice. Across the entire sample, being admitted to high-priced hospitals (defined as facilities with two standard deviations or $9,268 higher prices - roughly the equivalent of moving from 20^{th} percentile of the national distribution of hospital prices to the 80^{th} percentile) lowers in-hospital mortality for emergency cases by 1.02 percentage points off of a mean of 2.93%. Likewise, being admitted to high-priced hospitals raises spending during emergency admissions by 52.39% and total spending at 365 days post admission by 21.94%.

Notably, the relationship between hospital prices and survival is driven by a price/quality relationship that is only present in hospitals located in less concentrated hospital markets (i.e., markets with a HHI of less than approximately 4,000). In both more and less concentrated markets, patients who are admitted to higher-priced hospitals have roughly 50% higher spending during their index admissions than if they attended lower-priced hospitals. In less concentrated markets, they are also 1.37 percentage points (47%) less likely to die. Our point estimates suggest that in less concentrated markets, high priced hospitals save an additional life at a cost of approximately $1 million. As we illustrate, the additional spending at high priced hospitals in unconcentrated markets is likely cost-effective, even if we assume the quality improvements we observe only accrue to patients with nondeferrable conditions.

Conversely, in more concentrated markets (approximately half the markets in our sample have an HHI greater than 4,000), we do not find evidence of lower mortality among patients admitted to higher-priced hospitals. Being admitted to high-priced hospitals in concentrated markets results in substantially higher spending with no evidence of decreases in in-hospital mortality. Prices in these markets likely reflect hospitals' higher markups.

Our findings make three contributions. First, our results highlight that in unconcentrated markets, higher-priced hospitals have higher quality and that their higher prices are potentially cost-effective. These findings dovetail with work by Chandra et al. (2016) who find that higher-quality US hospitals have higher market share and grow more quickly - signposts of a functioning market. Our findings also complement work by Garthwaite, Ody and Starc (2020) who suggest that hospitals in unconcentrated markets may be making strategic investments in quality (providing a possible mechanism for our findings) and that price regulation in these markets could lower quality. Here, it is vital to note that our results do not suggest that a policy of raising hospital prices would lead to lower mortality in concentrated or unconcentrated markets.

Second, we add to the literature assessing quality differences across hospitals. Past work by Doyle et al. (2015) found that Medicare beneficiaries taken to hospitals with high Medicare spending have lower mortality. However, the Medicare program pays hospitals via regulated prices, so hospitals with high Medicare spending are those that deliver higher intensity care, not necessarily those with higher prices. Indeed, Cooper et al. (2019a) and Chernew et al. (2020) find a low correlation between regional spending on Medicare and on the privately insured. Therefore, this paper focuses on assessing differences in quality across hospitals that vary in their market-determined prices, not in the intensity of care they deliver. This comparison of high- and low-priced hospitals provides insights into the functioning on health care markets and should directly inform the current debate over price regulation.

Third, on the policy front, our work highlights that more vigorous antitrust enforcement can lead to more efficient outcomes in hospital markets where competition is geographically feasible. Our findings suggest policymakers should use caution in regulating hospital prices in less concentrated markets. Regulating prices in these markets has the scope to lower clinical quality. Finally, while we cannot rule out a positive or negative relationship between price and quality in concentrated markets, our results suggest policymakers should consider regulating providers' prices where competition is geographically infeasible.

Going forward, this paper is structured as follows. In Section II, we provide background on hospital pricing and proposals for price regulation. Section III provides insights into our empirical strategy, and IV presents the data. We describe our results in Section V and discuss implications in Section VI.

II. Hospital Pricing and Proposals to Regulate Hospital Prices

Hospitals and insurers engage in bilateral negotiations over hospitals' prices. There is significant variation in hospital prices within facilities across insurers, within markets across hospitals, and across markets (Cooper et al., 2019*a*; Craig et al., 2020). Hospital prices are growing faster than physician prices or inflation (Cooper et al., 2019*b*). From 2015 to 2019, hospital prices increased 31%, whereas physician prices increased by 13% (Health Care Cost Institute, 2020).

Theory is clear that in markets where hospitals' prices are regulated and hospitals can only differentiate themselves on non-price aspects of care (e.g., quality), competition between hospitals will lead to higher quality as long as the regulated reimbursements are greater than hospitals' marginal costs (Gaynor, Ho and Town, 2015). However, theory does not offer clear predictions about how competition will impact hospitals' quality in markets where hospital prices are market-determined. In these markets, the impact of competition will depend on patients' relative elasticities to price and quality (see Gaynor, Ho and Town (2015) for a detailed discussion). For example, prior evidence from Propper, Burgess and Green (2004) on the introduction of competition over prices and quality in the English National Health Service in the 1990s (when quality was not well-measured) found that competition led to drops in both hospitals' prices and quality.

In the face of high hospital prices, there has been a broad push for increasing antitrust enforcement in the hospital sector (e.g., The White House (2021)) and there are growing calls to regulate US hospitals' prices. Several proposals recommend strict hospital price caps that would set insurers' payments to hospitals at a fixed percentage of Medicare reimbursements. For example, Kocher and Berwick (2019) and Skinner, Fisher and Weinstein (2014) propose regulating hospital payments from insurers at 20% and 25% above Medicare prices, respectively. A number of states have also introduced direct hospital price regulation. Since 1977, Maryland has set regulated prices for all hospital services, irrespective of the payer. More recently, Montana and North Carolina have capped hospital prices for state health plans at 234% and 200% of Medicare rates, respectively.

Chernew, Dafny and Pany (2020) propose capping hospital prices at five times the 20^{th} percentile in each market. Other proposals seek to regulate hospital prices in concentrated markets. For example, two bills in the US House of Representatives, H.R. 506 and H.R. 1332, each introduced in the 116^{th} Congress, seek to set hospital prices based on the Medicare fee schedule in markets with a HHI over 4,000.

However, there are concerns that regulating hospital prices could lower hospital quality. Garthwaite, Ody and Starc (2020) posit that high hospital prices could reflect the costs of firms' strategic investments in quality. Consistent with this concern, Wu and Shen (2014) found that hospitals that experienced larger Medicare reimbursement cuts generated by the 1997 Balanced Budget Act experienced slower mortality reductions from heart attacks than did hospitals that received small price cuts.

III. Empirical Framework

A. Ambulance Referral Patterns

Our empirical strategy leverages the plausibly exogenous drivers of patients' hospital assignment that are determined by ambulance company preferences and the assignment of ambulances to emergency calls. The underlying justification for this approach is the fact that patients' treatment locations in an emergency are largely determined by pre-hospital factors.

Because local areas are generally serviced by multiple ambulance companies, the assignment of an ambulance company to a patient is ostensibly random. In some communities, ambulance calls are broadcast to multiple companies and the nearest ambulance is assigned to transport the patient (Chiang, David and Housman, 2006; Ragone, 2012). In communities with a single ambulance provider, ambulance companies from other regions can be assigned to pick up slack during periods of high demand (Doyle et al., 2015). Likewise, in most cities, private ambulance companies work in partnership with local fire departments who also provide emergency medical services and transportation (Johnson, 2001).

Ambulance companies have strong preferences for particular hospitals. Their preferences are shaped, in part, by long-term relationships that paramedics develop with local emergency departments (Doyle et al., 2015). Their preferences are also influenced by the ownership structure of ambulance firms (Skura, 2001).

In many cases, ambulances companies are operated by nonprofit hospitals, are stationed within those facilities, and tend to transport patients to these facilities in emergencies.

To operationalize these ambulance preferences, we construct a set of instrumental variables based on the average inpatient price at hospitals where each ambulance company takes other patients. This leave-out-the-mean approach is similar to jackknife IV estimators (Stock, Wright and Yogo, 2002). For patient i assigned to ambulance company a_i, we calculate the average hospital price among patients in our sample for each ambulance company.

$$Z_{a_i} = \frac{1}{N_{a_i} - 1} \sum_{j \neq i}^{N_{a_i}-1} P_{h_j} \tag{1}$$

This measure, Z_{a_i}, is the ambulance company fixed effect in a model predicting P_h that leaves out patient i. P_h is an inpatient price index constructed following Cooper et al. (2019*a*). The price index measures a hospital's average price conditional on their patients' characteristics and their mix of services delivered (see Appendix A for details).

B. Estimation

We want to analyze whether a patient-episode i, originating from five-digit ZIP code z and place of origin (e.g., home) o, treated in year t at hospital h with higher prices P_h, gets better outcomes $Outcomes_i$ (e.g., lower in-hospital mortality):

$$Outcomes_i = \pi_0 + \pi_1 P_{h_i} + \pi_2 X_i + \pi_3 A_i + \pi_4 D_i + \theta_{z_i,o_i} + \lambda_{t_i} + \epsilon_i \tag{2}$$

where X_i is a vector of patient controls including age (measured in five-year bands), sex, and a Charlson comorbidity score measured over the preceding six months. One concern is that ambulances that take patients to higher-priced hospitals could deliver more care en route. To control for this possibility, we also include a vector, A_i, of ambulance characteristics, including the payment the insurer made to the company as a summary measure of treatment intensity, indicators for distance traveled, and an indicator for whether the transport was coded as an emergency (e.g., "lights and sirens").[2] We also include a set of principal diagnosis fixed effects D_i. While our main outcome (in-hospital mortality) is binary, we prefer to rely on OLS and 2SLS because of the large number of ZIP-origin and year fixed-effects (5,832) included in our estimator.

Because patient selection will likely confound Equation (2), we estimate it using a two-stage least squared regression where we instrument for hospital price using our ambulance instrument Z_a with standard errors clustered around patients' health service area.[3] Our first stage takes the form:

$$P_{h_{i,e}} = \alpha_0 + \alpha_1 Z_{a_i} + \alpha_2 X_i + \alpha_3 A_i + \alpha_4 D_i + \theta_{z_i,o_i} + \lambda_{t_i} + \upsilon_i \tag{3}$$

Estimating Equation (3) allows us to compare the outcomes of individuals in the same ZIP code but are picked up by ambulances with different 'preferences' about where they transport their patients. Ultimately, our ambulance instrument provides plausibly exogenous variation in the location where patients are treated. As a result, we are measuring the causal effect of being taken to a high-priced hospital, not the effect of raising or lowering prices on quality at a given hospital.

We focus on whether being admitted to high-priced hospitals impacts in-hospital mortality. There is an expansive literature on using in-hospital mortality as a quality measure (see Department of Health and Human Services (2007) for a review). Past work has illustrated a high correlation between in-hospital mortality and 30-day mortality across a range of medical conditions (Rosenthal et al., 2000; Borzecki et al., 2010).[4]

We also analyze whether patients have better outcomes when treated at high-priced hospitals located in concentrated versus unconcentrated markets. Given the importance of travel times in defining markets, for each hospital registered with the American Hospital Association, including hospitals not in our analytic sample, we construct a time-invariant, hospital-specific HHI using a market around each hospital defined by a 30-minute travel time (see Appendix B for details) (Raval and Rosenbaum, 2018). We then include our baseline instrument and our instrument interacted with an indicator for being in a concentrated market.

[2]Adding these controls do not qualitatively change our results.
[3]Our results are robust to clustering around patients' home five-digit ZIP code.
[4]We cannot link the HCCI data to Medicare claims, so we cannot simultaneously analyze outcomes for Medicare beneficiaries.

We also include a specification where we separately interact our instrument with indicators for being in a concentrated market and being in an unconcentrated market. Because HHI is defined at the hospital level, an ambulance may take patients from the same neighborhood (which we control for using ZIP code fixed effects) to hospitals that vary in the level of competition they face.

IV. Data, Sample Construction, and Summary Statistics

A. Data and Sample Construction

We use HCCI data from June 2007 to 2014. The data capture insurance claims for individuals aged 18 through 64 who have employer-sponsored insurance provided by Aetna, Humana, or UnitedHealthcare. The data capture spending by all health care providers (including ambulances) but exclude spending on pharmacy-dispensed drugs.

We rely on a sample of patients admitted to the hospital via ambulance and with a "nondeferrable" condition for which treatment cannot be delayed. Admissions that are discretionary tend to occur less frequently on weekends but nondeferrable admissions do not. Dobkin (2003), Card, Dobkin and Maestas (2009), and Doyle, Graves and Gruber (2017) identify nondeferrable conditions as those with diagnoses on a weekend that is proportional to rates of admissions during the week. We utilize diagnoses they identify as nondeferrable and also include conditions designated as nondeferrable based on expert panels (Mulcahy et al., 2013). Appendix Table 4 shows the conditions we use in our analysis. Nondeferrable admissions represent 34.35% of all HCCI inpatient admissions, 23.5% of total hospital revenue from HCCI payors, and 6.20% of patients with these diagnoses are transported to the hospital via ambulance (see Appendix Table 2). On average, patients with a nondeferrable condition transported by ambulance from a given ZIP code attend 3.8 different hospitals.

We lose approximately 13% of these ambulance rides because they went to a hospital for which we do not have a price index either because the treatment location is not a general acute care hospital or because it did not perform 50 inpatient cases on HCCI beneficiaries annually. We drop a further 3.8% of rides that are associated with admissions in Maryland hospitals, where prices are regulated. We also restrict our sample to ambulance companies for which we still have at least 10 rides and patients from zip codes where we see more than 10 observations across our sample period, which excludes 4.42% and 6.70% of observations, respectively.[5] Finally, we require patients to be treated within 50 miles of their home zip code, which excludes 8.79% of cases.

B. *Summary Statistics*

Our analytic sample is composed of 202,408 admissions among 171,432 patients that occurred at 1,814 hospitals between 2007 and 2014.[6] As we illustrate in Table 1, the mean hospital price is $14,652 and varies substantially (the standard deviation is $4,634, and the interquartile range is $11,516 to $16,803). Among our sample, the mean hospital HHI is 4,327 and the HHI at the 25^{th} and 75^{th} percentile is 2,344 and 5,422, respectively. Patient-level descriptive statistics are provided in Appendix Table 1.

Table 1 shows means and standard deviations for key patient characteristics and aspects of patients' ambulance transport to the hospital. The modal patient in our sample was between 55 and 64 years of age and was transported to a hospital by ambulance from their home. The third column reports the difference in the mean of the covariate when the instrument constructed in Equation (1) is above or below its median value computed from a regression that controls for ZIP code and year fixed effects, divided by the pooled standard deviation. Relative to widely-used standardized difference thresholds for assessing sample balance (e.g., a 0.25-standard deviation difference from Rubin (2001)), these standardized differences are small across the wide range of control variables and show a pattern consistent with effectively random assignment of ambulance companies to patients.[7]

V. Results

A. *Hospital Prices, Mortality, and Spending*

Table 2 presents results from our 2SLS analyzing whether patients have lower mortality when they are admitted and receive care at higher-priced hospitals. In Panel A, we show the first stage of our 2SLS, where the dependent variable is hospitals' time-invariant inpatient price. Our point estimate in Panel A reveals

[5] Our results are not sensitive to these restrictions.

[6] 18,975 patients in our sample have multiple nondeferrable admissions. Our results are qualitatively unchanged when we exclude patient's subsequent admissions.

[7] We also find no strong relationship between our instrument and whether patients get admitted across all patients they transport.

that a one-unit increase in our instrument leads to a \$0.67 increase in hospital prices. Because hospital prices vary substantially within geographic areas and ambulance companies generally have a single preferred hospital, our instrument has considerable predictive power, with a standard error of 0.02 and first-stage F-statistic of 819.7.[8]

In Panel B of Table 2, we show the OLS relationship between being admitted to a high-priced hospital, in-hospital mortality, and spending on the index emergency admission. Unsurprisingly, we find, via our OLS, that admission to hospitals with two standard deviations higher prices (a price increase of \$9,268) raises health spending during emergency episodes by 54.11% (\$15,315). However, in our OLS specification, we also find that receiving care from hospitals with two standard deviations higher prices is associated with an increase in-hospital mortality by 0.29 percentage points off of a mean mortality rate of 2.93%. Thus, our OLS specification suggests that higher-priced hospitals are not only generating higher spending but that their patients are more likely to die. However, despite the inclusion of our controls, this OLS estimate may be biased by patient selection.

In Panel C of Table 2, we show the second stage of our 2SLS. Instrumenting this relationship has little impact on the coefficient on spending. Our results in Column (1) of Panel C illustrate that receiving care from hospitals with two standard deviations higher hospital prices raises health spending during emergency admissions by 52.39% (\$14,828). However, moving to an IV framework reverses the sign on the effect of being admitted to a high-priced hospital on mortality. In Column (2) of Panel C, we find that admission to hospitals with two standard deviations higher prices - roughly equivalent to moving from the 20^{th} percentile of the national distribution of hospital prices to the 80^{th} percentile - lowers in-hospital mortality by 1.02 percentage point off of a mean mortality rate of 2.93% (35%).

The increases in spending we observe are driven by increases in inpatient spending during the index admission and modest increases in physician spending outside the index admission. In Appendix Table 3, we show the effect of admission to a two standard deviation higher-priced hospital on inpatient, outpatient, physi-

[8]The 95% confidence interval on our first stage coefficient ranges from 0.6245 to 0.7135. This standard error does not take into account that the instrument is a generated regressor. When we bootstrap the standard error to incorporate this estimation, we find a standard error of 0.0210 and a similar 95% confidence interval of 0.6278 to 0.7102. When we shift our sample to patients we observe for 365 days, our first-stage point estimate is similarly scaled (0.6954), with a standard error of 0.0236.

cian, and post-acute spending during the index admission and from discharge to 365 days post admission. Admission to higher-priced hospitals does not lead to any statistically significant changes in inpatient spending, outpatient spending, or post-acute spending in the period after patient were discharged. Admission to higher-priced hospitals did lead to a 14.33% increase in physician spending after the initial hospitalizations.

B. Hospital Prices, Mortality, and Spending by Hospital Market Concentration

In Figure 1, we show the distribution of prices for hospitals from our sample with an HHI below or above 4,000. Notably, there are high- and low-priced hospitals on either side of this cutoff. The mean inpatient price in hospitals with an HHI below 4,000 is $14,456 and is $14,889 for hospitals with an HHI above 4,000. The hospital in the 90^{th} percentile of prices under the HHI cutoff has prices of $20,386. This value is $20,629 above the HHI cutoff.

In Table 3, we show how the relationship between receiving care from high-priced hospitals, mortality, and spending vary as a function of hospitals' market concentration. Labeling a market as "concentrated" is empirically challenging since the HHI calculated for a given market will depend on how that market is defined (Baker, 2001). While the DOJ and FTC define a market as highly concentrated if it has an HHI of 2,500 or greater, recent proposals to regulate hospital prices define concentrated markets as those with an HHI of 4,000 or greater. We begin with a cutoff for concentrated markets of 4,000, which is both close to our sample mean and the cutoff in policy proposals such as H.R. 506. We also illustrate how our results vary when we alter the cutoff used to define concentrated markets.

Column (1) in Table 3 shows our baseline results across the universe of hospitals in our sample. In Column (2), we include our baseline instrument and an interaction between our baseline instrument and an indicator for whether a hospital is in a market with a HHI of greater than or equal to 4,000. This specification reveals the relationship between admission to a higher-priced hospital and our outcome in hospital markets with a HHI of less than 4,000 and then the marginal change in the relationship between price and mortality when patients are admitted to a hospital with a HHI greater than or equal to 4,000.

When doing so, we find a small and insignificant coefficient on the interaction in the spending regression. However, we do find a highly significant interaction in the mortality regression that is identically scaled to our uninteracted coefficient but has the opposite sign. Results in Column (4) suggests that admissions to hospitals with two standard deviations higher prices that are located in markets with HHIs of less than 4,000 lead to a 1.37 percentage point reduction in mortality. Conversely, receiving care from hospitals with two standard deviations higher prices in markets with HHIs greater than or equal to 4,000 does not have a detectable impact on mortality. Our results also imply that there is a statistically significant difference in the relationship between price and mortality in markets with HHIs above and below 4,000 ($p<0.05$).

Our point estimates on the effect of receiving care from higher-priced hospitals on mortality and spending in Table 3 suggest that, in markets with a HHI of less than 4,000, each life saved comes via an additional $1.09 million in health spending.[9] This is well below the Environmental Protection Agency's (EPA's) widely accepted estimate of the value of a statistical life of $8.7 million (Environmental Protection Agency, 2020).[10] Given the high 10-year survival rates for patients under age 65 admitted to the hospital with pneumonia or heart attack (two of the most common nondeferrable conditions), this suggests that higher priced hospitals are likely saving lives cost effectively (Eurich et al., 2015; Herlitz et al., 2001).

Hospitals with high-priced care for strokes and heart attacks also have high prices for services where quality does not vary (e.g., MRI scans). The nondeferrable care we analyze accounts for 23.5% of hospitals' revenue from HCCI beneficiaries. If we assumed that the quality gains from being admitted to higher-priced hospitals only accrued to patients with nondeferrable conditions, our estimates would suggest high-priced hospitals in unconcentrated markets generate an additional life at a cost of approximately $4 million. Even at this level, high prices in these markets are still likely cost-effective.

These results are robust to alternative definitions of hospital markets and alternative HHI cutoffs. For example, while in our main results, we define HHIs using travel times, as we illustrate in Appendix Table 6, this result is robust to using an HHI measured within a circular market defined by a 15-mile radius around each hospital. Using this alternative specification, we find that in markets with

[9]We obtain this by multiplying our coefficient on spending in Column (2) by the mean sample spending and then dividing by the mortality point estimate in Column (4) for unconcentrated markets.

[10]We use the EPA's estimate of $7.4 million in 2006, which we convert into 2014 dollars using the All Urban Consumers Consumer Price Index (Federal Reserve Bank of St. Louis, 2021).

an HHI of less than 4,000, admission to a hospital with two standard deviations higher prices lowers mortality by 1.33 percentage points ($p<0.01$), whereas there is no significant relationship between price and mortality in concentrated markets (with a point estimate that is statistically different from the uninteracted coefficient).

In Table 4, we show the relationship between admission to a high-priced hospital and mortality in concentrated and unconcentrated markets defined using alternative HHI cutoffs. In each specification, we include two interaction terms: (1) an interaction between our hospital price instrument and an indicator for whether a hospital is below a HHI ; and (2) an interaction between our hospital price instrument and an indicator for whether a hospital is greater than or equal to a HHI cutoff. This specification reveals the relationship between admission to a higher-priced hospital in markets above and below the HHI cutoff and allows us to also test whether the point estimates are different from one another. We focus on markets above and below an HHI of 3,000 (1,000 points below our main cutoff and the 39^{th} percentile in the distribution of hospital HHIs in our sample), markets above and below a cutoff of 3,721 (the median market in our sample), and markets above and below a cutoff of 5,000 (1,000 points above our main cutoff and the 65^{th} percentile in our sample).

As these results illustrate, in markets below HHI cutoffs of 3,000, 3,721, 4,000, and 5,000, receiving care from high-priced hospitals lead to lower mortality ($p<0.05$). Conversely, in markets with an HHI of greater than or equal to the cutoffs, we do not observe a significant relationship between receiving care from a high-priced hospital and mortality. In Column (3), for example, the point estimate on price and mortality in markets with an HHI of greater than or equal to 4,000 is 0.0001 with a 95% confidence interval of -.0105 to 0.0107. At each threshold, we can reject the null that the point estimates between price and quality are the same in concentrated and unconcentrated markets ($p<0.06$).

VI. Discussion

In the US, hospital prices for the privately insured are market-determined and set via negotiations between hospitals and insurers. These price negotiations are largely unregulated, and the nation relies on competition to generate efficient prices. However, over the last 30 years, the US hospital sector has experienced significant consolidation (Fulton, 2017). As a result, concerns about the functioning of markets in the health sector in general and the hospital industry in particular have led to proposals to regulate hospitals' prices (Fiedler, 2020).

In this paper, we test whether patients who receive care at higher-priced hospitals get better outcomes. We do so to better understand the functioning of hospital markets and help determine if and how hospital prices should be regulated. We address issues of selection by using an instrument that exploits the fact that, in an emergency, there is quasi-random assignment of the ambulance companies sent out and that ambulance companies have strong preferences for where they transport patients. This generates plausibly random assignment of patients to hospitals. We use this instrument to generate an experiment that tests whether patients from the same five-digit ZIP code have lower in-hospital mortality during an emergency admission for nondeferrable care if they are taken to and treated at hospitals with higher prices.

We find that receiving care from hospitals with two standard deviations higher inpatient prices leads to a 35% reduction in in-hospital mortality. However, the relationship between hospital prices and in-hospital mortality is only present for hospitals located in relatively unconcentrated markets. In markets with an HHI of less than 4,000, receiving care from hospitals with two standard deviations higher inpatient prices leads to a 1.37 percentage point decrease in mortality, a 53% increase in spending on the emergency episode, and a 22% increase in one-year total health spending. This implies that hospitals in these markets spend an additional $1 million on nondeferrable emergency cases for each life saved - spending that is likely cost-effective. Conversely, receiving care from hospitals with two standard deviations higher prices in markets with an HHI of greater than or equal to 4,000 leads to substantially higher spending, but we do not detect that it leads to lower mortality.

Our analysis suggests that in unconcentrated markets, allowing hospitals to compete and prices to be market-determined is not necessarily wasteful. This is consistent with predictions by Garthwaite, Ody and Starc (2020) that, in some markets, high hospital prices may reflect strategic investments by firms to increase quality and not patients' lack of outside options. Ultimately, our findings suggest that regulating hospital prices in unconcentrated markets may lead to a reduction in quality.

Notably, however, approximately 69% of hospitals in the US are located in markets with an HHI of greater than 4,000. In many of these markets, competition is not geographically feasible. Our evidence highlights that in these concentrated markets, high prices likely reflect patients' lack of alternative options, not hospital quality. In these markets, regulating prices has scope to limit the rents hospitals collect from their bargaining power and could be successful if regulated prices were set high enough that they did not adversely impact quality.

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Table 1—Hospital- and Ride-Level Characteristics

Panel A: Hospital level

	Mean	SD	p5	p25	p50	p75	p95	N
Price Index	14,652	4,634	8,592	11,516	14,086	16,803	23,237	1,814
Hospital HHI	4,327	2,590	1,190	2,344	3,721	5,422	10,000	1,814

Panel B: Patient-ride level

	Mean	Standard deviation	Standard difference in means $\mathbf{1}$(instrument > median)
Ambulance instrument	14,615	953	0.481
Ambulance payment	814	551	0.030
Advanced life support	0.753	0.330	-0.004
Ride from home	0.638	0.410	-0.012
Emergency transport	0.950	0.190	-0.010
Male	0.511	0.437	-0.002
0–17 years old	0.046	0.181	0.002
18–24 years old	0.050	0.192	0.004
25–34 years old	0.073	0.227	0.005
35–44 years old	0.132	0.296	0.002
45–54 years old	0.270	0.389	-0.002
55–64 years old	0.430	0.428	-0.004
Comorbidity score	1.128	1.560	0.002

Note: The price index is based on all inpatient claims (adjusted for inflation) between 2007 and 2014. In Panel B, values are adjusted for year and zip code fixed effects. Our comorbidity score is measured via a Charlson Index constructed using six months of prior health claims.

Table 2—First and Second Stage Regressions

Panel A: First stage

	Inpatient price index
	(1)
Ambulance average hospital price index	0.6690***
	(0.0227)
Outcome mean	14,652
Observations	202,408

Panel B: OLS

	Log admission spending	In-hospital mortality
	(1)	(2)
Inpatient price index	0.5411***	0.0029**
	(0.0147)	(0.0012)
Outcome mean	28,304	0.0293
Observations	202,408	202,408

Panel C: Second stage

	Log Admission spending	In-hospital mortality
	(1)	(2)
Inpatient price index	0.5239***	-0.0102***
	(0.0363)	(0.0038)
Outcome mean	28,304	0.0293
Observations	202,408	202,408

Note: All models include 5-digit zip code and year fixed effects. The price index is based on all inpatient claims (adjusted for inflation) between 2007 and 2014. We control for point of origin (home, nursing home, or scene of accident), diagnoses, demographics and ambulance characteristics. Diagnostic controls include a list of 29 non-discretionary diagnoses codes. Demographic controls include indicators for age category and gender. Ambulance controls include payment to the company, whether the transport utilized advanced life support, and whether the transport was coded as emergency transport. We also control for the patient's comorbidity score, which is measured via a Charlson Index constructed using six months of prior health claims. The observations are unique at the patient-ride level. Standard errors are in parentheses, clustered at the HSA level. The outcome mean in Panel A is reported at the hospital level. We use logged spending as a dependent variable, but report the outcome mean in levels. * p <0.1; ** p <0.05; *** p <0.01.

Table 3—Effect of Price on Mortality

	Log admission spending		In-hospital mortality	
	(1)	(2)	(3)	(4)
Inpatient price index	0.5239***	0.5293***	-0.0102***	-0.0137***
	(0.0363)	(0.0401)	(0.0038)	(0.0042)
Inpatient price index * HHI above 4,000		0.0102		0.0137**
		(0.0546)		(0.0057)
Observations	202,408	202,408	202,408	202,408
Outcome mean	28,304	28,304	0.0293	0.0293

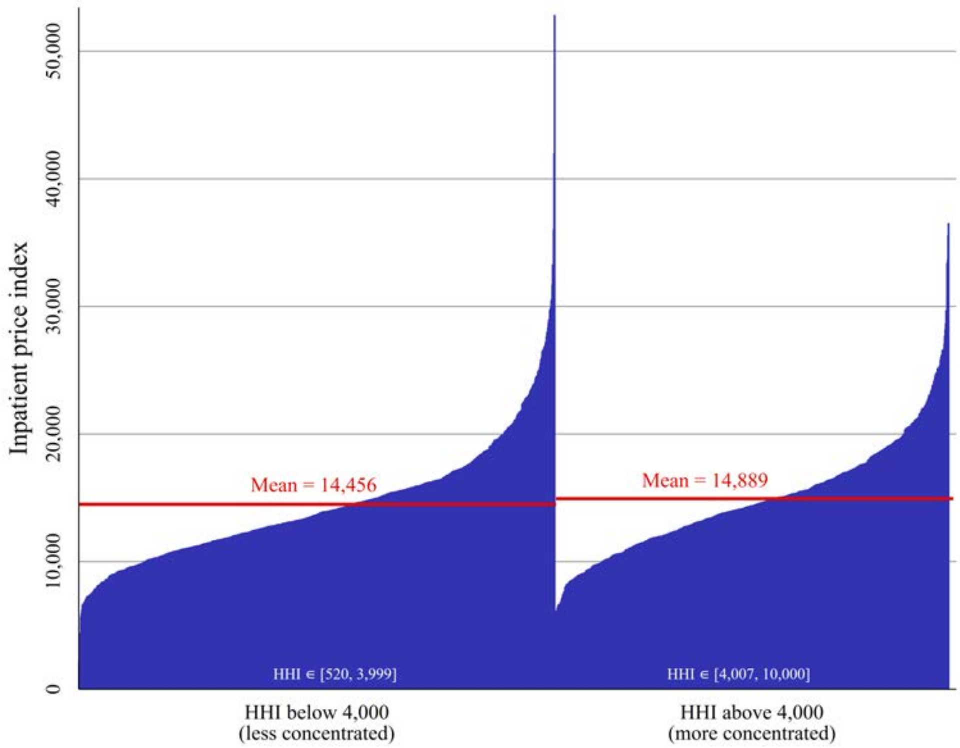
Note: All models include 5-digit zip code and year fixed effects. The price index is based on all inpatient claims (adjusted for inflation) between 2007 and 2014. We control for point of origin (home, nursing home, or scene of accident), diagnoses, demographics and ambulance characteristics. Diagnostic controls include a list of 29 non-discretionary diagnoses codes. Demographic controls include indicators age category and gender. Ambulance controls include payment to the company, whether the transport utilized advanced life support, and whether the transport was coded as emergency transport. We also control for the patient's comorbidity score, which is measured via a Charlson Index constructed using six months of prior health claims. The observations are unique at the patient-ride level. Standard errors are in parentheses, clustered at the HSA level. The HHI measure is calculated at the hospital level, and based on bed counts for hospitals accessible in under 30 minutes. We use logged spending as dependent variable in columns 1 and 2, but report the outcome mean in levels. * p <0.1; ** p <0.05; *** p <0.01.

Table 4—Effect of Price on Mortality: Different Interaction Cutoffs

	In-hospital mortality			
HHI cutoff	3,000	3,721	4,000	5,000
	(1)	(2)	(3)	(4)
Inpatient price index * HHI below cut-off	-0.0149***	-0.0130***	-0.0137***	-0.0130***
	(0.0045)	(0.0042)	(0.0042)	(0.0042)
Inpatient price index * HHI above cut-off	-0.0029	-0.0029	0.0001	-0.0006
	(0.0044)	(0.0052)	(0.0054)	(0.0059)
Test of equality between interacted coef.:				
F-statistic	5.7684	3.7251	5.8269	3.7562
P-value	0.0165	0.0538	0.0159	0.0529
Observations	202,408	202,408	202,408	202,408
Outcome mean	0.0293	0.0293	0.0293	0.0293

Note: Columns (1)–(4) report results for different HHI cutoffs, with column (2) representing the median HHI in our sample. All models include 5-digit zip code and year fixed effects. The price index is based on all inpatient claims (adjusted for inflation) between 2007 and 2014. We control for point of origin (home, nursing home, or scene of accident), diagnoses, demographics and ambulance characteristics. Diagnostic controls include a list of 29 non-discretionary diagnoses codes. Demographic controls include indicators for age category and gender. Ambulance controls include payment to the company, whether the transport utilized advanced life support, and whether the transport was coded as emergency transport. We also control for the patient's comorbidity score, which is measured via a Charlson Index constructed using six months of prior health claims. The observations are unique at the patient-ride level. Standard errors are in parentheses, clustered at the HSA level. * p <0.1; ** p <0.05; *** p <0.01.

Figure 1 Distribution of the Hospital Inpatient Price Index



Note: The HHI measure is calculated at the hospital level and based on bed counts for hospitals accessible in under 30 minutes. We compute a time-invariant measure by averaging the hospital-year level measures between 2007 and 2014.

ONLINE APPENDIX

Appendix A Inpatient Price Index

The time-invariant inpatient price index is based on Cooper et al. (2019*a*). The inpatient price sample is derived from hospital claims for all inpatient care provided to covered 18 to 64 year olds in hospitals regigsted with the AHA and classified as general and surgical facilities. For each DRG, cases above the 99^{th} percentile of length-of-stay or where the price is below the 1^{st} percentile or above the 99^{th} percentile are excluded to get rid of outliers (e.g., the million dollar knee replacement).

The inpatient price index captures the combined amount paid by patients and insurers for inpatient episode e in DRG d delivered in hospital h between 2007 and 2014. We limit the data to general medical/surgical hospitals with at least 50 cases in this period. Following Gaynor and Vogt (2003) and Gowrisankaran, Nevo and Town (2015), we regress hospital payments ($p_{e,h,d}$) on hospital fixed effects (α_h), a vector of patient characteristics ($\mathbf{X}_{e,h,d}$) comprised of indicators for patient age (measured in ten-year age bands), a dummy for the patient's sex, and a vector of DRG fixed effects (γ_d). The regression to produce our inpatient prices has the form:

$$p_{e,h,d} = \alpha_h + \mathbf{X}_{e,h,d}\beta + \gamma_d + \upsilon_{e,h,d} \tag{A.1}$$

where $\upsilon_{e,h,d}$ is the stochastic error term. We recover the vector of hospital fixed effects $\hat{\alpha}_h$ and calculate a hospital price index for each hospital at the sample means of the patient characteristics ($\overline{\mathbf{X}}$) and the DRG indicators, $\overline{d}$ (i.e., sample mean basket of DRGs):

$$\hat{p}_h = \hat{\alpha}_h + \overline{\mathbf{X}}\hat{\beta} + \overline{d}\hat{\gamma}_{\overline{d}} \tag{A.2}$$

This yields the hospital's price, adjusted for its mix of treatments and mix of patients (note the fixed effect $\hat{\alpha}_h$ is the key output: $\overline{\mathbf{X}}\hat{\beta} + \overline{d}\hat{\gamma}_{\overline{d}}$ is just a constant across all hospitals to match the mean in the data).

Appendix B HHI Calculation

For each hospital h in each year t, we calculate an Herfindahl-Hirschman Index based on the number of beds in hospital h and in all $H_{h,t}$ hospitals in the relevant market. We define the market based on the travel time from hospital h (30-minutes). The count of hospitals ($H_{h,t}$) is defined as:

$$H_{h,t} = \text{Total number of hospitals in market around hospital } h \text{ in year } t$$

$$H_{h,t} \geq 1$$

We obtain the bed-based HHI measure ($HHI_{h,t}$) in the following way:

$$HHI_{h,t} = \sum_{h=1}^{H} \left(\frac{\text{Number of beds in hospital } h \text{ in year } t}{\text{Total number of beds in all } H_{h,t} \text{ hospitals in the market in year } t} \right)^2$$

$$HHI_{h,t} \leq 1$$

We do not view other hospital sites within the same health system as competitors. We average the hospital-year level HHI across all years from 2007 to 2014 to create a time-invariant HHI.

Appendix Tables and Figures

Appendix Table 1—Summary Statistics

	Mean	SD	p5	p25	p50	p75	p95	N
In-hospital mortality	0.029	0.169	0	0	0	0	0	202,408
30-day spending	32,700	46,191	3,485	9,626	18,252	36,798	110,412	200,590
180-day spending	57,124	93,663	4,795	12,644	26,271	61,708	212,180	190,985
365-day spending	70,040	118,169	5,467	14,407	30,680	74,425	266,941	178,465
Comorbidity score	1.128	1.814	0	0	0	2	6	202,408
Male	0.511	0.500	0	0	1	1	1	202,408
0-17 years old	0.046	0.209	0	0	0	0	0	202,408
18-24 years old	0.050	0.218	0	0	0	0	0	202,408
25-34 years old	0.073	0.259	0	0	0	0	1	202,408
35-44 years old	0.132	0.338	0	0	0	0	1	202,408
45-54 years old	0.270	0.444	0	0	0	1	1	202,408
55-64 years old	0.430	0.495	0	0	0	1	1	202,408

Note: Spending is expressed in 2014 USD. The Charlson score is calculated using a 180-day claim history. The HHI measure is based on bed counts in hospitals accessible in under 30 minutes. There are 171,432 unique patients in our analytical dataset. The data are at the patient-ride level. Our comorbidity score is measured via a Charlson Index constructed using six months of prior health claims.

Appendix Table 2—Inpatient Admission Characteristics

	Total number of inpatient admissions	Percentage of non-discretionary diagnoses in all inpatient admissions (%)	Percentage of ambulance transport in in all inpatient admissions (%)	Percentage of ambulance transport in admissions with a non-discretionary diagnosis (%)	Non-discretionary admission spending as a share of total hospital revenue (%)
Inpatient admissions	15,608,555	34.35	2.76	6.20	23.51

Note: The observations are unique at the patient-ride level. Non-discretionary admission spending and total hospital revenue are obtained from inpatient and outpatient claims.

Appendix Table 3—Effect of Price on Spending Components using 2SLS

	Log spending	**Log IP spending**		**Log OP spending**		**Log PH spending**		**Log PA spending**
	365 days w/o admission	**Admission**	**365 days w/o admission**	**Admission**	**365 days w/o admission**	**Admission**	**365 days w/o admission**	**365 days**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inpatient price index	0.2194**	0.6168***	0.1658	0.0216	-0.0051	0.0514	0.1433*	0.0520
	(0.0915)	(0.0379)	(0.1445)	(0.1225)	(0.1912)	(0.0556)	(0.0849)	(0.0915)
Outcome mean	34,721	23,955	18,482	413	2,139	3,936	8,375	3,222
Observations	143,877	202,408	143,877	202,408	143,877	202,408	143,877	143,877

Note: All models include 5-digit zip code and year fixed effects. The price index is based on all inpatient claims (adjusted for inflation) between 2007 and 2014. We control for point of origin (home, nursing home, or scene of accident), diagnoses, demographics and ambulance characteristics. Diagnostic controls include a list of 29 non-discretionary diagnoses codes. Demographic controls include indicators age category and gender. Ambulance controls include payment to the company, whether the transport utilized advanced life support, and whether the transport was coded as emergency transport. We also control for the patient's comorbidity score, which is measured via a Charlson Index constructed using six months of prior health claims. The observations are unique at the patient-ride level. Standard errors are in parentheses, clustered at the HSA level. The HHI measure is calculated at the hospital level, and based on bed counts for hospitals accessible in under 30 minutes. We use logged spending as dependent variable but report the outcome mean in levels. "365-day w/o admission" spending refers to spending that occurs from the day after the discharge date to the 365 days after the ambulance ride. IP refers to inpatient, OP to outpatient, PH to physician, and PA to post-acute. * p <0.1; ** p <0.05; *** p <0.01.

Appendix Table 4—Nondeferable Admissions

	Mean	**Standard deviation**	**Standardized difference in means** $\mathbf{1}$(instrument > median)
Septicemia	0.070	0.225	0.003
Malignant Neoplasm of Trachea, Lung	0.020	0.121	-0.004
Secondary Malignant Neoplasm	0.017	0.114	-0.002
Acute Myocardial Infarction	0.085	0.247	-0.003
Intracerebral Hemorrhage	0.022	0.130	0.002
Precerebral Occlusion	0.038	0.170	-0.002
Cerebral Artery Occlusion	0.070	0.225	-0.005
Transient Cerebral Ischemias	0.046	0.188	0.001
Pneumonia, Other Bacterial	0.019	0.123	0.002
Penumonia, Unspecified Organism	0.107	0.273	-0.003
Solid, Liquid Pneumotitis	0.024	0.134	-0.001
Other Lung Diseases	0.251	0.381	0.005
Diseases of Esophagus	0.055	0.204	-0.002
Gastric Ulcer	0.012	0.095	-0.002
Dudendal Ulcer	0.007	0.075	-0.002
Vascular Insufficiency of Intestine	0.006	0.067	0.002
Other Noninfective Gostroenteritis	0.028	0.147	0.000
Intestinal Obstruction	0.030	0.152	-0.000
Other Urinary Tract Infection	0.080	0.240	0.002
Disorder of Muscle Ligament, Fascia	0.043	0.181	-0.004
General Symptoms	0.603	0.433	-0.000
Fractured Rib, Sternum, Trachea	0.023	0.132	0.005
Pelvic Fracture	0.012	0.095	0.004
Fracture Neck of Femur	0.021	0.126	-0.004
Tibia and Fibia Fracture	0.027	0.143	0.001
Ankle Fracture	0.029	0.149	0.004
Injury Neck, Nose	0.165	0.325	0.008
Analgesic, Antipyretics Poisoning	0.024	0.136	-0.000
Psychotropic Agent Poisoning	0.032	0.155	-0.002

Note: The observations are unique at the patient-ride level.

Appendix Table 5—Patient Characteristics by Price Index Quartile

	1st quartile	**2nd quartile**	**3rd quartile**	**4th quartile**	**1st vs. 4th quartile difference**
Comorbidity score	1.18	1.11	1.09	1.14	-0.04***
0–17 years old	0.03	0.04	0.05	0.06	0.03***
18–24 years old	0.05	0.05	0.05	0.05	0.01***
25–34 years old	0.07	0.07	0.07	0.08	0.01***
35–44 years old	0.13	0.13	0.13	0.13	0.00
45–54 years old	0.27	0.27	0.27	0.26	-0.01***
55–64 years old	0.46	0.43	0.42	0.41	-0.04***
Observations	50,618	50,862	50,344	50,584	

Note: The observations are unique at the patient-ride level. The last column shows a test of significance between the first and last quartile. * p <0.1; ** p <0.05; *** p <0.01.

Appendix Table 6—Effect of Price on Mortality [15-Mile HHI]

	Log admission spending		**In-hospital mortality**	
	(1)	(2)	(3)	(4)
Inpatient price index	0.5239***	0.5150***	-0.0102***	-0.0133***
	(0.0363)	(0.0392)	(0.0038)	(0.0042)
Inpatient price index * HHI above 4,000		0.0643		0.0114**
		(0.0452)		(0.0048)
Observations	202,408	202,408	202,408	202,408
Outcome mean	28,304	28,304	0.0293	0.0293

Note: All models include 5-digit zip code and year fixed effects. The price index is based on all inpatient claims (adjusted for inflation) between 2007 and 2014. We control for point of origin (home, nursing home, or scene of accident), diagnoses, demographics and ambulance characteristics. Diagnostic controls include a list of 29 non-discretionary diagnoses codes. Demographic controls include indicators age category and gender. Ambulance controls include payment to the company, whether the transport utilized advanced life support, and whether the transport was coded as emergency transport. We also control for the patient's comorbidity score, which is measured via a Charlson Index constructed using six months of prior health claims. The observations are unique at the patient-ride level. Standard errors are in parentheses, clustered at the HSA level. The HHI measure is calculated at the hospital level, and based on bed counts for hospitals within 15 miles. We use logged spending as dependent variable in columns 1 and 2, but report the outcome mean in levels. * p <0.1; ** p <0.05; *** p <0.01.