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# DO HIGHER-PRICED HOSPITALS DELIVER HIGHER-QUALITY CARE?

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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 do so to better understand the functioning and pricing patterns of the $1.3 trillion market for hospital care in the US. We address selection issues by using an instrumental variable approach that exploits the quasi-random assignment of ambulance companies to patients, which provides plausibly exogenous variation in hospital choice. We find that being admitted to a hospital with two standard deviations higher prices raises spending on patients by 53% and lowers their mortality by 1 percentage point (37%); failing to instrument for hospital prices meaningfully biases the cross-sectional relationship between hospital prices and quality. However, the relationship between higher prices and lower mortality is only present at hospitals in less concentrated markets. Receiving care from expensive hospitals in concentrated markets increases spending but has no detectable effect on mortality.

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## I. Introduction

The \$1.3 trillion US hospital industry, which accounts for 6.1% of US gross domestic product (GDP) and 31% of domestic health spending, is an international outlier (Centers for Medicare and Medicaid Services, 2020). In the US, while public insurers pay hospitals regulated reimbursements, private insurers, which cover approximately 60% of the population, negotiate market-determined prices with hospitals. By contrast, hospitals in virtually every other developed nation are paid via some form of government-regulated reimbursement. The use of regulated reimbursements in the hospital sector, rather than market-determined prices, stems from a long-standing view among policy-makers and economists, dating back to Arrow (1963), that idiosyncrasies in markets for health care services—challenges consumers face observing and responding to prices and quality, information asymmetries, large returns to scale, and the frictions associated with firms' entry and exit—impede competition between hospitals from generating efficient prices.[1]

There are growing concerns about the functioning of the market for hospital care in the US and, in particular, about the pricing of US hospital services. According to the Bureau of Labor Statistics (BLS), from 2000 to 2020, prices for hospital services increased faster than those in *any* other US industry. There is also extensive variation in hospital prices across regions, within regions, and even within hospitals. For example, Cooper et al. (2019) found that hospital prices for routine services, like joint replacements and magnetic resonance imaging (MRI) scans, varied by a factor of more than five within major US cities.

Concerns about dysfunctional hospital pricing in the US are motivated, in part, by the rise in hospital market concentration that has occurred during the last two decades. Between 2000 and 2020, there were over 1,500 hospital mergers among the nation's approximately 6,000 hospitals (American Hospital Association, 2018). At present, the majority of US hospital markets have an Herfindahl-Hirschman Index (HHI) of greater than 5,000 and are considered "highly concentrated" according to the joint Department of Justice and Federal Trade Commission horizontal merger guidelines (Fulton, 2017; Department of Justice and the Federal Trade Commission, 1997). In short, the growing concerns are that high hospital prices may reflect providers' market power or simply be a function of idiosyncrasies in

[1]There are similar, long-standing debates over regulating prices in other industries, such as the market for electricity (e.g., Cicala, 2022).

the market for health care services, rather than a reflection of providers' clinical outcomes or their strategic investments in quality (Pany, Chernew and Dafny, 2021; Garthwaite, Ody and Starc, 2020). These concerns have led to widespread, bipartisan calls from academics, policy-makers, and elected officials to regulate hospital prices.[2]

However, extensive price variation across firms need not indicate that a market is broken. A substantial literature, dating back to Stigler (1961), has documented widespread price variation, even for homogeneous products like ketchup and screws (Sorensen, 2000; Kaplan and Menzio, 2015; Pratt, Wise and Zeckhauser, 1979). In differentiated product markets, like the markets for cars and hotels, high-quality products that generate value for consumers can command higher prices, and this product differentiation can generate substantial price variation (Berry, Levinsohn and Pakes, 1995; Crawford, Shcherbakov 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 and price variation across hospitals. Alternatively, if those who support regulating hospital prices are correct, price variation in the hospital industry could reflect the growth of firms' market power or more general idiosyncrasies in health care markets that prevent efficient price setting and thus necessitate intervention.

In this paper, we test whether receiving care from higher-priced hospitals in an emergency results in higher quality, and whether the correlation between price and quality differs in concentrated versus unconcentrated hospital markets. We do so to help better understand the functioning of hospital markets in the US—one of the largest sectors of the US economy. We focus on patient mortality as our quality score both because it often dominates welfare considerations and because it is correlated with other measures of hospital outcomes, such as adherence to clinical guidelines (Doyle et al., 2015).

To date, there has been scant research assessing whether receiving care from high-price hospitals (causally) results in better outcomes. This, in part, is due to the challenge of addressing selection bias—sicker patients may differentially be admitted to higher-priced hospitals. We aim to overcome selection bias by using

[2]See, for example, Pany, Chernew and Dafny (2021); Kocher and Berwick (2019); and two bills in the US House of Representatives, H.R. 506 and H.R. 1332.

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 within neighborhoods and have clear preferences regarding the hospitals to which they transport patients. Taken together, these features of the pre-hospital care system induce plausibly exogenous variation in hospital destinations among emergency patients. Our empirical strategy is therefore to compare the outcomes of privately insured patients from the same ZIP codes that are taken, in an emergency, to high- and low-priced hospitals as a function of the ambulance company sent to transport them. Prior work that has compared hospitals in this way (e.g., Doyle et al., 2015) has all compared hospital spending measured through administratively-set prices in public programs in Medicare and the VA, where variation in spending stems from differences in the quantity of care provided. We are the first to use this strategy to assess the causal relationship between receiving care from high-priced hospitals and patient outcomes.

Our identification strategy does not test the causal effect of exogenously raising or lowering hospital prices. Rather, it allows us to test causally whether patients treated for nondeferrable conditions at high-priced hospitals have lower mortality. We then test whether this price/quality relationship is present in concentrated and unconcentrated markets. To gain further insights into why price and quality may or may not be related, we analyze the characteristics of high-priced hospitals in concentrated and unconcentrated markets, such as their cost structure, for-profit status, and characteristics of their workforce.

Our analysis relies on data from the Health Care Cost Institute (HCCI) that includes providers' negotiated prices. The HCCI database is composed of insurance claims for individuals with employer-sponsored 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). 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 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 imprecise, negative correlation between prices and quality we observe when we do not instrument for hospital choice. Indeed, we find consistent evidence that selection effects bias a simple analysis that regresses providers' quality on their prices.

In particular, using our IV strategy, we observe that being admitted to high-priced hospitals (defined as facilities with two standard deviations or $9,396 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 mortality rate of 2.75%. This 37% reduction in mortality that stems from receiving care from high-priced versus low priced hospitals is substantial and has a similar magnitude as the gains from major clinical improvements in care over the last 25 years, such as lowering the door-to-needle times for patients with heart attacks (McNamara et al., 2007). At the same time, being admitted to high-priced hospitals raises spending during emergency admissions by 53.49% and total spending at 365 days post admission by 41.72%.

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 an HHI of less than approximately 4,000).[3] In both more and less concentrated markets, patients who are admitted to higher-priced hospitals have roughly 53% higher spending during their index admissions. In less concentrated markets, they are also 1.29 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—spending per life saved that is likely cost effective.

Conversely, in more concentrated markets, 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 (e.g., rents).

We then compare the ways that high-priced hospitals in unconcentrated markets

[3]We chose this threshold because it is approximately the mean HHI in our sample and because there are two bills in the US House of Representatives, H.R. 506 and H.R. 1332, each introduced in the $116^{th}$ Congress, which seek to set hospital prices based on the Medicare fee schedule in markets with an HHI over 4,000.

differ from other hospitals in our sample. High-priced hospitals in markets with an HHI of less than 4,000 do not deliver higher-intensity care to patients admitted during an emergency, do not appear more likely to engage in surgical interventions on their emergency admissions, and do not appear to have higher cost structures (e.g., more technology or more nurses per bed). Instead, high-priced hospitals in unconcentrated markets have a substantially larger share of physicians who graduated from Top 25 US medical schools. Thus, the higher quality of high-priced hospitals in unconcentrated markets appears to be a function of the better human capital of their employees, not of observably higher marginal costs.

Ultimately, this paper makes contributions to both the academic and policy literature. First, this paper adds to the literature assessing the functioning of competition in health care provider markets. Like Chandra et al. (2016), this paper demonstrates that markets can function in the hospital sector. However, unlike prior work, this paper explores the functioning of markets where hospitals compete on price and quality. Theory and the empirical evidence show clearly 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 leads to higher quality as long as the regulated reimbursements are greater than hospitals' marginal costs (Gaynor, Ho and Town, 2015; Kessler and McClellan, 2000; Cooper et al., 2011; Gaynor, Moreno-Serra and Propper, 2013; Bloom et al., 2015). However, the theory and the empirical evidence on how competition will impact quality and prices in markets where prices and quality are market-determined is ambiguous and depends on the relative elasticities of patients to price and quality (Gaynor, Ho and Town, 2015; Propper, Burgess and Green, 2004). We show that competition can function in these markets, assuming that they are unconcentrated, and that the prices generated via competition are likely cost effective.

Second, we add to the literature assessing the drivers of price variation in hospital markets. A growing literature has documented substantial variation in US hospital prices even within narrow geographic markets (Cooper et al., 2019; Pany, Chernew and Dafny, 2021; White and Whaley, 2021). There also is clear evidence that hospitals with more market power have higher prices (Cooper et al., 2019; White, Reschovsky and Bond, 2014). The scale of the price variation in the hospital sector has led to calls to regulate hospitals' prices (e.g., Pany, Chernew and Dafny, 2021). Likewise, past work that did not address patient selection observed a negative correlation between hospital prices and hospital quality (e.g., Beauvais et al., 2020). However, as Cooper et al. (2019) demonstrate that, even after controlling for hospital characteristics, local area characteristics, and provider and insurer market concentration, there is still a substantial amount of unexplained variation in hospital prices within markets. Consistent with findings on pricing in non-health sector differentiated product markets, this paper illustrates that provider quality is also likely driving variation in hospital prices. This finding is consistent with predictions from Garthwaite, Ody and Starc (2022) that hospitals are potentially making strategic investments in quality that raise their prices.

Third, on the policy front, our findings suggest policy-makers should use caution in regulating hospital prices in less concentrated markets. At a minimum, our findings suggest that regulating hospital prices, particularly in markets where competition is geographically feasible, is complex and likely involves nuanced trade-offs between price and quality. In the past, it has been argued that the presence of extensive variation in hospital prices is suggestive that price regulation could lead to substantial cost savings without adversely affecting quality (Liu et al., 2021). Our findings suggest that indiscriminate price regulation might lower spending and could potentially also lower quality. While we cannot rule out a positive or negative relationship between price and quality in concentrated markets, our results suggest that should policymakers be interested in pursing price regulation, concentrated provider markets where competition is geographically infeasible are likely the places to begin.

Going forward, this paper is structured as follows. In Section II, we describe our empirical framework and the identification strategy we use. In Section III, we describe the data used in this, detail how we construct key variables, and present our summary statistics. We present our results in Section IV and conclude in Section V.

## II. Empirical Framework

### *A. Ambulance Referral Patterns*

The location where patients receive hospital care is seemingly nonrandom and likely correlated with patient characteristics. For example, it is highly plausible that patients with complex medical needs differentially attend higher-quality hospitals that may also have higher prices. These high prices could reflect hospitals' higher costs. As a result, the empirical challenge in this paper is overcoming the endogenous sorting of patients to hospitals that would bias cross-sectional estimates of the relationship between hospital prices and hospital quality. Indeed, past work that has regressed hospital quality against hospital prices without addressing selection has found a negative correlation between quality scores and prices (Beaulieu et al., 2020).

Our empirical strategy to address this bias leverages the plausibly exogenous drivers of patients' hospital assignment that are determined by ambulance company preferences and the manner in which ambulance companies are assigned to emergency calls. Because local areas are generally served 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, which 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). Ambulance companies' preferences are also influenced by the ownership structures of ambulance firms (Skura, 2001). In many cases, ambulance companies are operated by nonprofit hospitals, are stationed within those facilities, and tend to transport patients to these facilities in emergencies.

To operationalize the quasi-random variation driven by pre-hospital factors — the random assignment of ambulance companies to patient calls and the fact that ambulance companies have strong preferences regarding where they transport their patients — we construct a set of instrumental variables based on the average inpatient price at hospitals where each ambulance company takes other patients (i.e., not the patient they are currently transporting). This leave-out-the-mean approach is similar to jackknife IV estimators (Stock, Wright and Yogo, 2002).

In practice, 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). The price index, which we describe in more detail in Section III.C, measures a hospital's average price conditional on its patients' characteristics and its mix of services delivered.

### *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 two standard deviations higher prices $P_h$, achieves a better outcome $Outcome_{i,t}$:

$$Outcome_{i,t} = \pi_0 + \pi_1 P_{h_i} + \pi_2 X_{i,t} + \pi_3 A_i + \pi_4 D_i + \theta_{z_i} + \phi_{o_i} + \lambda_{t_i} + \epsilon_i \tag{2}$$

where $X_{i,t}$ is a vector of patient controls including age (measured in ten-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").[4] We also include a set of principal diagnosis fixed effects $D_i$. We include ZIP $\theta_{z_i}$ and place-of-origin fixed effects $\phi_{o_i}$ to compare patients from the same neighborhood and originating from the same type of location — home or nursing home — where we expect the assignment to be effectively random. While our main outcome (in-hospital mortality) is binary, we prefer to rely on OLS and 2SLS because of the over 6,000 ZIP, origin, and year fixed-effects included in our estimator.

Because patient selection will likely confound Equation (2), we estimate it using

[4] As we show in Table 6, our results are robust to excluding these ambulance characteristics as controls.

a two-stage least squares regression in which we instrument for hospital price using our ambulance instrument $Z_a$ with standard errors clustered around patients' health service area.[5] Our first stage takes the form:

$$P_{h_i} = \alpha_0 + \alpha_1 Z_{a_i} + \alpha_2 X_{i,t} + \alpha_3 A_i + \alpha_4 D_i + \theta_{z_i} + \phi_{o_i} + \lambda_{t_i} + \upsilon_i \tag{3}$$

where the the price index for the hospital chosen for patient $i$ is regressed on the instrument and the same set of controls as in the outcome equation. Estimating Equation (3) allows us to compare the outcomes of individuals in the same ZIP code who 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 Doyle et al. (2015); Department of Health and Human Services (2007) for reviews). 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).[6]

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, as we discuss in Section III.D, 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 (Raval and Rosenbaum, 2018). We then include our baseline instrument and our instrument interacted with an indicator for being in a concentrated market. We also include a specification in which we separately interact our instrument with indicators for being in a concentrated market and being in an unconcentrated

[5]As we illustrate in Table 6, our results are robust to clustering around patients' home ZIP codes or their hospital referral regions (HRRs).

[6]We cannot link HCCI data to Medicare claims, so we cannot simultaneously analyze outcomes for Medicare beneficiaries.

market.

### *C. Assumptions and Threats to Identification*

Our empirical strategy is to use the ambulance instrumental-variable strategy to generate as-good-as-random assignment of patients to hospitals. This strategy is similar in spirit to the "judge IV" literature (e.g., Kling, 2006; Doyle, 2007; Dobbie and Song, 2015; Dobbie, Goldin and Yang, 2018). Our identification strategy, like the "judge" literature, relies on a standard set of assumptions (independence, monotonicity, and exclusion) (Frandsen, Lefgren and Leslie, 2019).

Ultimately, the core identification challenge we are seeking to overcome — independence — is that potentially sicker patients differentially attend higher-priced hospitals, which would bias the uninstrumented cross-sectional relationship between hospital prices and quality. We demonstrate via balancing tests that our IV strategy does result in balanced observable characteristics of patients at high-priced and low-priced hospitals. As a summary that illustrates the appeal of our research design, we construct a measure of predicted mortality based on patient observables. We then use our predicted mortality measure as the dependent variable in OLS and IV estimates of the relationship between hospital prices and quality. If ambulance company assignment is effectively random, then this measure of patient illness severity should not be correlated with the instrumented hospital price.

We also address possible monotonicity concerns with standard checks that our instrument applies similarly across distinct patient cohorts. That is, we examine whether the coefficient on our first stage is similarly scaled and powered when we run it independently on cohorts of male patients, female patients, younger patients, older patients, sicker patients, and healthier patients. This serves as a check on whether an average monotonicity condition is met (i.e., the covariance between the ambulance-specific treatment status and the ambulance instrument is positive), which results in the IV estimates providing a local average treatment effect (Frandsen, Lefgren and Leslie, 2019).

In terms of the exclusion restriction, we return to our research question: whether high-priced hospitals differ in terms of quality compared to low-priced hospitals. We stress that we are not testing whether raising prices would raise quality. Rather, we are testing whether price and quality are positively or negatively related, which is an important consideration when crafting regulatory policy and informs the debate on the functioning of healthcare markets. We explore the potential mechanisms by which high-priced hospitals deliver higher-quality care by investigating the differences between high-priced and low-priced hospitals in concentrated and unconcentrated markets across a range of observable characteristics.

## III. Data, Sample Construction, and Summary Statistics

### *A. Data and Sample Construction*

We use HCCI data from 2008 to 2014. The data capture insurance claims for individuals aged 0 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 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 are proportional to rates of admissions during the week. We use diagnoses they identify as nondeferrable and also include conditions designated as nondeferrable based on expert panels (Mulcahy et al., 2013). Appendix Table 1 shows the conditions we use in our analysis. Nondeferrable admissions represent 34.45% of all HCCI inpatient admissions and 23.19% of total hospital revenue from HCCI payors (see Appendix Table 2). On average, patients with a nondeferrable condition transported by ambulance from a given ZIP code attend 5.92 different hospitals.

We lose approximately 2% 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 involving HCCI beneficiaries annually. We drop a further 1.77% 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 4.98% and 10.33% of remaining observations, respectively. Finally, we require patients to be treated within 50 miles of their home ZIP codes, which excludes 9.04% of cases.

### B. *Data on Hospital Characteristics*

We bring together a range of data on hospitals' characteristics (hospitals' count of technologies, bed count, for-profit status, payor mix, and count of nurses per bed) from the American Hospital Association (AHA) Annual Survey. The AHA data also contain information on whether the hospital is a member of the Council of Teaching Hospitals and Health Systems (COTH) (i.e., the hospital is a "major" teaching hospital) or is not a COTH affiliate but has a residency program (i.e., a "minor" teaching hospital). We merge in data on hospitals' publicly reported quality from the Centers for Medicare and Medicaid Services (CMS) Hospital Compare database. Finally, using a 2017 extract from the CMS Physician Compare tool, we measure the characteristics of physicians who treat patients at each hospital (e.g., gender, their average number of years since graduation from medical school, and the share of physicians practicing at a hospital who graduated from a Top 25 medical school) based on U.S. News and World Report rankings.

### C. *Measuring Hospital Prices*

We construct a measure of hospitals' time-invariant inpatient prices following the approach used in Cooper et al. (2019). Hospitals differ in the mix of patients they treat (e.g., the demographics and severity of illness of their patients) and the mix of services they offer (e.g., high-acuity versus low-acuity care and high-tech versus low-tech care). Our price measure is a hedonic price index that captures a hospital-level price conditional on the mix of patients a hospital treats and the mix of services a hospital delivers.

The inpatient price index captures the combined amount paid by patients and insurers (e.g., the allowed amounts) for inpatient episode $e$ in diagnosis related group (DRG) $d$ delivered in hospital $h$ between 2008 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 ($\alpha_h$), 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 ($\gamma_d$). The regression to produce our inpatient prices has the form:

$$p_{e,h,d} = \alpha_h + \mathbf{X}_{e,h,d}\beta + \gamma_d + \upsilon_{e,h,d} \tag{4}$$

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):

$$\hat{p}_h = \hat{\alpha}_h + \overline{\mathbf{X}}\hat{\beta} + \overline{d}\hat{\gamma}_{\overline{d}} \tag{5}$$

This yields the hospital's price, adjusted for its mix of treatments and mix of patients (note that 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).

The inpatient price sample is derived from hospital claims for all inpatient care provided to individuals age 18 through 64 who have insurance coverage from an HCCI payer and who receive care at hospitals registered 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 $30 or $1 million knee replacement).

### D. HHI Calculation

For each hospital $h$ in each year $t$, we calculate a Herfindahl-Hirschman Index based on the number of beds in hospital $h$ and in all $H_{h,t}$ hospitals in the relevant market measured via the AHA annual survey. 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 2008 to 2014 to create a time-invariant HHI. 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.

### *E. Predicted Mortality*

We create a measure of patients' predicted in-hospital, inpatient mortality based on observables measured from the HCCI data. We predict that a patient died during their inpatient stay using controls for the patient's sex, their age, interactions between sex and age, Charlson Index of Comorbidity Score, and International Classification of Disease (ICD) 9 codes. The $R^2$ on the OLS regressions used to predict inpatient mortality is 0.08.

### *F. Summary Statistics*

Our analytic sample is composed of 191,045 admissions among 162,263 patients that occurred at 1,857 hospitals between 2008 and 2014.[7] We present patient-level descriptive statistics in Appendix Table 3. As we illustrate in Panel A of Table 1, the mean hospital price is \$14,865 and varies substantially (the standard deviation is \$4,698, and the interquartile range is \$11,713 to \$17,045). Among our sample, the mean hospital HHI is 4,388 and the HHI at the $25^{th}$ and $75^{th}$ percentile is 2,366 and 5,464, respectively. As we illustrate in Appendix Table 4, because of our sample restrictions, our analytic sample of hospitals differs from the universe of hospitals registered with the American Hospital Association. Hospitals in our

[7] 17,702 patients in our sample have multiple nondeferrable admissions. Our results are qualitatively unchanged when we exclude patients' subsequent admissions.

analytic sample tend to be located in less concentrated markets, less rural areas, and larger areas.

Panel B of 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 as 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.[8]

Likewise, in Table 2, we show a balance table that illustrates how patient characteristics and patient diagnoses vary across the quartiles of our ambulance price instrument. Patients appear balanced on sex, age, diagnoses, and their comorbidity scores. Likewise, across the top 15 diagnoses in our data, there is no significant difference in incidence across quartiles of the instrument. We do not find significant differences in patient characteristics or patient diagnoses across the first and fourth quartiles of our instrument. The only characteristic that differs between the first and fourth quartile of the IV is the share of patients with an "injury of the neck and nose" (0.167 in the first quartile; 0.171 in the fourth quartile, $p < 0.1$). In Appendix Table 1, we show balance across all 29 diagnoses. These balance tests lend support to the credence of our as-good-as-random identification strategy.

## IV. Results

### *A. Hospital Prices, Mortality, and Health Spending*

Table 3 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, in which the dependent variable is

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

hospitals' time-invariant inpatient price. Our point estimate in Panel A reveals 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 a first-stage F-statistic of 877.[9] As we illustrate in Appendix Table 5, we get a strong first stage when we run our IV strategy separately on distinct patient cohorts (e.g., on younger patients separately from older patients).

In Panel B of Table 3, we show the OLS estimates of Equation (3) and show the relationship between being admitted to a high-priced hospital, spending on the index emergency admission, inpatient mortality, and predicted mortality. Unsurprisingly, we find, via our OLS, that admission to hospitals with two standard deviations higher prices (a price increase of \$9,396) raises health spending during emergency episodes by 54.27% (\$15,322). However, in our OLS specification, we also find that receiving care from hospitals with two standard deviations higher prices is associated with an imprecise increase in in-hospital mortality of 0.18 percentage points off of a mean mortality rate of 2.75% (7%). However, despite the inclusion of our controls, this OLS estimate may be biased by patient selection. Indeed, when we use our predicted mortality measure and regress it against hospital prices (and do not include our patient controls), we see that hospitals with two standard deviations higher prices receive patients with 0.26 percentage points higher predicted mortality.[10]

In Panel C of Table 3, we show the second stage of our 2SLS estimation. Instrumenting this relationship has little impact on the coefficient on spending. Our instrumented 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 53.49% (\$15,101). However, moving to an

[9]The 95% confidence interval on our first stage coefficient ranges from 0.6260 to 0.7126. This standard error does not take into account that the instrument is a generated regressor. Boostrapping our standard error to incorporate this estimation produces a standard error of 0.0205 and a similar 95% confidence interval of 0.6452 to 0.7257. When we shift our sample to patients we observe for 365 days, our first-stage point estimate is similar (0.6811), with a standard error of 0.0227. In practice, our instrument applies to patients with some hospital choice. This is the case for the vast majority of ZIP codes in our sample where patients generally attend two or more hospitals, even in rural areas. We have a large F-statistic (i.e., over 100) on our first stage when we limit our sample to patients in counties with HHIs over and under 4,000 and counties above and below the national median of population density.

[10]Indeed, as we illustrate in Appendix Figure 1, hospital prices are positively correlated with our time invariant HHI, the number of technologies at each hospital, the size of hospitals (measured using FTE employees), and hospital activity.

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 points off of a mean mortality rate of 2.75% (37%). As we illustrate in Appendix Table 7, we do not observe a precisely estimated relationship, in our IV framework, between hospital prices and patient readmissions within 30, 60, or 90-days of the initial admission. Likewise, as we illustrate in Appendix Table 7, going to a hospital with higher charges (rather than market-determined prices) does not lead to lower mortality.

Likewise, juxtapose results in Columns (2) and (3) in Panel C of Table 3. Results in Column (3) show almost no relationship between attending a higher-priced hospital and predicted mortality after we instrument for price. These results illustrate how our instrument addresses the patient selection that undermines the OLS regressions between hospital prices and quality presented in Columns (2) and (3) of Panel B in Table 3.

In Figure 1, we present our results graphically. In Panel A, we present a bin-scatter plot showing the relationship between our residualized predicted mortality measure on the Y-Axis and our residualized price IV on the X-axis. It shows virtually no relationship between our IV for price and predicted mortality. By contrast, in Panel B, we present residualized actual inpatient mortality on the Y-axis and our residualized price IV on the X-axis. The bin scatter in Panel B clearly illustrates the negative relationship between our residualized price IV and residualized inpatient mortality measure.

Results in Table 4 illustrate how attending a higher-priced hospital impacts inpatient hospital spending, outpatient hospital spending, physician spending, and post-acute spending during the index episode of care and in the 365 days following the initial ambulance trip (excluding spending on care delivered during the initial admission). Results from our 2SLS estimates of Equation 2 indicate that attending a hospital with two standard deviations higher prices raises total spending over the subsequent 365 days after the initial ambulance ride by 42%. This increase is almost entirely driven by the 63% increase in inpatient spending during the index episode. While we observe a 17% increase in inpatient spending and a 12% increase in physician spending after discharge and within the 365 days after the initial ambulance ride, and a 10% increase in post acute spending during that admission and the 365 days following, none of those changes are statistically significant. Likewise, we do not observe any evidence of statistically significant offsetting savings as a result of the higher inpatient spending during the index admission (e.g., we do not observe that the increase in inpatient spending during the initial admission is offset by lower outpatient spending post discharge).

Our results in Table 5 illustrate that the reductions in mortality following care at a high-priced hospital do not appear to be driven by marked differences in the intensity of care provided during an inpatient stay. In Table 5, we analyze whether patients taken to hospitals with two standard deviation higher prices receive more care (measured via the average DRG weight of cases—a measure of care intensity), are in the hospital for longer periods of time (measured via length of stay), or are more likely to receive a medical procedure during their admission.[11] While our OLS estimates in Panel A illustrate that patients at high-priced hospitals appear to receive more intensive care, have longer lengths of stay, and a higher probability of a procedure — results consistent with a bias generated by patient selection — when we instrument for prices in Panel B, our 2SLS results demonstrate that these point estimates shrink substantially and become statistically insignificant.

In Appendix Table 5, we show results when we construct our instrument separately for patient cohorts (e.g., for male patients, female patients, patients under age 55, patients older than 54, patients with a Charlson score of zero, and patients with a Charlson score greater than zero) and then run our analysis cohort by cohort. Our first-stage estimates are large when we focus on each cohort independently. Our second stage results in Panel B illustrates that the biggest differences in mortality between high- and low-priced hospitals occurs for patients over age 54 and those in worse health, as categorized by a non-zero Charlson severity score.

As we illustrate in Table 6, these results are robust to a number of alternative specifications, some of which we present here. All results in Table 6 present 2SLS estimates of Equation 2 in which the dependent variable is inpatient mortality. In Column (2), we run our main estimates and illustrate that our results are qualitatively similar when we exclude our ambulance controls from our analysis. In Columns (3) and (4), we show our results are robust to using ZIP-level and HRR-level clusters, respectively, rather than using the HSA-level clusters we use

[11]We measure whether a procedure was performed based on whether the patient was coded for a DRG involving a procedure or not. We identify DRGs with procedures from the Agency for Healthcare Research and Quality's Patient Safety Indicators Appendices.

in our main analysis. When we use these alternative clusters, our main estimates remain similarly precise. In Columns (5) and (6), rather than including ZIP code fixed effects, we alternatively use HSA and HRR fixed effects. This does not meaningfully shift our point estimates. In Column (7), because there may be concerns that patients' diagnoses are endogenously coded by hospitals (e.g., high-intensity hospitals might code more aggressively), we also estimate our main regression absent controls for patients' diagnoses. As we illustrate, this change does not qualitatively shift our findings. In Column (8), we loosen our count restrictions requiring ambulance and ZIP codes to have at least 10 cases across the sample period. Finally, in Column (9), rather than including ZIP and origin fixed effects separately, we include ZIP x origin fixed effects.

Another issue with leave-out instruments is the potential to have weak instruments, as the underlying variation comes from assignment to many ambulance companies. We find that the results are not affected when we implement alternative estimators, such as residualizing the instrument of the ZIP fixed effects before calculating the leave-out mean of those residuals (Kolesár, 2013). Further, our results are similar when we reduce the noise in the instrument by restricting the sample to ambulance companies with more observations (Appendix Table 6).

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

In Figure 2, we show the distribution of prices for hospitals from our sample with an HHI below or above 4,000. In addition to the sizeable variation in hospital prices across our sample — a coefficient of variation of 0.32 — notably, there are high- and low-priced hospitals on either side of this HHI cutoff. The mean inpatient price in hospitals with an HHI below 4,000 is $14,724 and is $15,027 for hospitals with an HHI above 4,000.

In Table 1, we show how the relationship between receiving care from high-priced hospitals, mortality, predicted mortality, and spending varies 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. This is close to both 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. We chose to use HHIs constructed with hospital beds to capture market shares (not actual patient flows) to define market concentration, and not willingness to pay measures, because the latter would likely be more reflective of market power due to quality and confound our analysis.

Column (1) in Table 1 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 an HHI of greater than or equal to 4,000. Panel A presents OLS estimates; Panel B presents our 2SLS estimates. Results in Table 1 reveal the relationship between admission to a higher-priced hospital and our outcome in hospital markets with an HHI of less than 4,000 along with the marginal change in the relationship between price and mortality when patients are admitted to a hospital with an 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 in Column (2). However, we do find a highly significant interaction in the mortality regression that is similar in size to our uninteracted coefficient and has the opposite sign. Results in Column (4) suggest 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 1.29 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 when adding the two coefficients. 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 ($p<0.05$).

In Columns (5) and (6), we show estimates when the dependent variable is predicted mortality. Notably, in our OLS, higher-priced hospitals have patients with higher predicted mortality. However, when we instrument for hospital prices, results in Column (6) illustrate no relationship between predicted mortality and price in either concentrated or unconcentrated hospital markets.

Our point estimates on the effect of receiving care from higher-priced hospitals on mortality and spending in Column (4) in Panel B of Table 1 suggest that in markets with an HHI of less than 4,000, each life saved comes via an additional

$1.19 million in health spending.[12] 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).[13] 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 pneumonia and heart attacks also have high prices for services where quality does not vary (e.g., MRI scans and colonoscopies) (Cooper et al., 2019). The nondeferrable care we analyze accounts for 23.19% 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 that 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 8, 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 an HHI of less than 4,000, admission to a hospital with two standard deviations higher prices lowers mortality by 1.31 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 8, 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 an HHI cutoff; and (2) an interaction between our hospital price instrument and an indicator for whether a hospital is greater than

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

[13] 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).

or equal to an 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 $37^{th}$ percentile in the distribution of hospital HHIs in our sample), markets above and below a cutoff of 3,773 (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 $63^{rd}$ percentile in our sample).

As these results illustrate, in markets below HHI cutoffs of 3,000, 3,773, 4,000, and 5,000, receiving care from high-priced hospitals leads to lower mortality ($p<0.05$). Conversely, in markets with an HHI greater than or equal to the cutoffs, we do not observe a significant relationship between receiving care from a high-priced hospital and mortality. At the 3,000, 3,773, and 4,000 thresholds, we can reject the null that the point estimates between price and quality are the same in concentrated and unconcentrated markets ($p<0.05$).

In our main estimates, we rely on a time invariant measure of hospital prices and a time invariant measure of hospital HHIs. In Appendix A, we repeat all our analysis using time varying hospital prices. In Appendix B, we repeat all our analysis using time varying hospital HHIs. In Appendix C, we repeat all our analysis using both time varying HHIs and prices.

### C. *What Are High-Priced Hospitals in Less Concentrated Markets Doing Differently?*

High-priced hospitals in markets with an HHI less than 4,000 spend 54% more during an emergency admission and have 1.29 percentage points lower mortality. What are these hospitals doing differently, and how do these hospitals themselves differ from either low-priced hospitals in less concentrated markets or high-priced hospitals in more concentrated markets?

In Table 9, we run 2SLS estimates and extend the analysis in Table 5 to see whether there are differences in the mean DRG weight, length of stay, and share of cases in which a procedure was performed at high-priced hospitals in more and less concentrated markets. In Panel A of Table 9, we show results via OLS estimates, which suggest that higher-priced hospitals in less concentrated markets provide care with higher DRG weights, longer length of stay, and more procedures. However, after instrumenting for hospital prices, our 2SLS results show that hospitals in less concentrated markets with higher prices do not provide more intense care (measured via the mean DRG weight of the care they provide), have a length of stay that's only 0.3571 days longer (7%)($p < 0.10$), and have no meaningful difference in the rate that procedures are performed.

In Table 10, we compare the characteristics of high- (above median) and low- (below median) priced hospitals in markets with an HHI of less than 4,000 and greater than or equal to 4,000. There are a range of dimensions in which high-priced hospitals differ from low-priced hospitals. For example, high-priced hospitals tend to have more technologies (e.g., MRI scanners); are bigger; are more likely to be affiliated with a medical school; provide care that, on average, has a higher DRG weight; and have higher lengths of stay. However, these differences between high- and low-priced hospitals are similarly scaled in more and less concentrated markets. Likewise, process and outcomes quality scores measured by CMS do not appear to differ meaningfully across high-priced and low-priced hospitals.

However, high-priced hospitals in unconcentrated markets do appear to differ from other hospitals in their human capital. First, high-priced hospitals in less concentrated markets are much more likely to be Council of Teaching Hospital members (a designator of being a major academic medical center). Second, high-priced hospitals in less concentrated markets have a substantially higher share of physicians working at their facilities who graduated from a Top 25 medical school in the US. Collectively, these results suggest that a core characteristic driving lower mortality at high-priced hospitals in less concentrated markets is likely to be quality of physicians offering care (e.g., more doctors from Top 25 medical schools).[14]

## V. Discussion

The majority of the US receives insurance coverage from private insurers. Unlike what occurs in most other developed countries, 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, as a result, the nation relies on competition to generate efficient prices.

However, there are broad concerns about the functioning of markets in the health sector in general and in the hospital industry in particular. A substantial

[14] We also see that at high-priced hospitals in unconcentrated markets, privately insured patients make up a higher share of admissions.

literature has highlighted a range of informational issues, market frictions, and patterns of consumer behavior that may undercut the functioning of competition in health care and hospital markets (Arrow, 1963; Cutler, 2011; Skinner, 2011; Brot-Goldberg et al., 2017; Chernew et al., 2021). Likewise, the US hospital sector has experienced significant consolidation over the last two decades (Fulton, 2017). This has prompted concerns about whether hospital markets can even support competition (Pany, Chernew and Dafny, 2021). These concerns have been bolstered by the substantial variation present in hospital prices within and across hospital markets in the US and the striking growth in hospital prices that have occurred in the 2000s (Cooper et al., 2019; U.S. Bureau of Labor Statistics, n.d.).

What drives hospital prices to vary so much in the US? On the one hand, price variation could reflect differences in providers' market power or idiosyncrasies in hospital markets. Indeed, a large body of work finds that hospitals in more concentrated markets have higher prices and that mergers can allow hospitals to raise their prices (Cooper et al., 2019; White, Reschovsky and Bond, 2014; Gowrisankaran, Nevo and Town, 2015; Gaynor and Vogt, 2003; Haas-Wilson and Garmon, 2011; Dafny, Ho and Lee, 2019; Lewis and Pflum, 2017). To the extent that high hospital prices are simply a function of market power generated by mergers or idiosycacies in the functioning of markets in the health sector, it would seem prudent to explore the scope for regulating hospital prices. However, in differentiated product markets, price variation could also reflect differences in producers' quality. Indeed, Garthwaite, Ody and Starc (2020) posit that high hospital prices could reflect firms' strategic investments in quality. Were this to be the case, regulating hospital prices, for example, could lead to reductions in quality.

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. Analyzing whether hospital prices are correlated with quality requires overcoming selection bias: sicker patients are differentially likely attend better hospitals that may have higher prices. 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 regarding 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 37% 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 1.29 percentage point decrease in mortality, a 54% increase in spending on the emergency episode, and a 59% 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.

We show that high-priced hospitals in unconcentrated markets do not perform more procedures or delivery higher-intensity care. Likewise, these facilities do not appear to rely on more nurses per bed or a greater use of technology. Instead, the most striking difference is that these high-priced hospitals in unconcentrated markets appear to have a markedly higher share of physicians who received their training from Top 25 medical schools.

Ultimately, our analysis suggests that in unconcentrated markets, allowing hospitals to compete and prices to be market-determined is not necessarily wasteful. That is, markets can function in the hospital sector, assuming those markets are not highly concentrated. This is consistent with evidence from Chandra et al. (2016) that high-quality hospitals grow more over time, and with predictions by Garthwaite, Ody and Starc (2020) that, in some markets, high hospital prices may reflect investments by firms to increase quality, and not patients' lack of outside options.

Conversely, while competition in unconcentrated markets appears to generate prices that are correlated with quality, approximately 50% of the US population lives in hospital 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. Going forward, policy-makers must consider what to do in these markets. This should include considering regulating hospitals prices and strategies to limit the rents that firms collect without adversely affecting 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 | 14,865 | 4,698 | 8,765 | 11,713 | 14,335 | 17,045 | 23,520 | 1,857 |
| Hospital HHI | 4,388 | 2,614 | 1,225 | 2,366 | 3,773 | 5,464 | 10,000 | 1,857 |

Panel B: Patient-Ride Level

| | Mean | Standard Deviation | Standard Difference in Means 1(instrument > median) |
|---|---|---|---|
| Ambulance Instrument | 14,924 | 987 | 0.468 |
| Ambulance Payment | 826 | 561 | 0.033 |
| Advanced Life Support | 0.755 | 0.330 | -0.008 |
| Ride From Home | 0.629 | 0.412 | -0.009 |
| Emergency Transport | 0.950 | 0.189 | -0.011 |
| Male | 0.511 | 0.437 | -0.002 |
| 0–17 Years Old | 0.046 | 0.182 | 0.000 |
| 18–24 Years Old | 0.051 | 0.194 | 0.003 |
| 25–34 Years Old | 0.073 | 0.228 | 0.003 |
| 35–44 Years Old | 0.131 | 0.296 | 0.003 |
| 45–54 Years Old | 0.269 | 0.389 | -0.001 |
| 55–64 Years Old | 0.430 | 0.429 | -0.004 |
| Charlson Comorbidity Score | 1.115 | 1.553 | 0.006 |

*Note:* The price index is based on all inpatient claims (adjusted for inflation) between 2008 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: Balance Test of Patient Characteristics and Diagnoses Across Quartiles of the IV

| | 1st Quartile | 2nd Quartile | 3rd Quartile | 4th Quartile | 1st vs. 4th Difference | Below vs. Above Median |
|---|---|---|---|---|---|---|
| Ambulance Instrument | 14,567 | 14,820 | 14,981 | 15,328 | 760.442*** | 461.393*** |
| Male | 0.51 | 0.51 | 0.51 | 0.51 | 0.001 | -0.001 |
| 0–17 Years Old | 0.05 | 0.05 | 0.05 | 0.05 | -0.001 | 0.000 |
| 18–24 Years Old | 0.05 | 0.05 | 0.05 | 0.05 | 0.002 | 0.001 |
| 25–34 Years Old | 0.07 | 0.07 | 0.07 | 0.07 | 0.002 | 0.001 |
| 35–44 Years Old | 0.13 | 0.13 | 0.13 | 0.13 | 0.002 | 0.001 |
| 45–54 Years Old | 0.27 | 0.27 | 0.27 | 0.27 | -0.001 | -0.000 |
| 55–64 Years Old | 0.43 | 0.43 | 0.43 | 0.43 | -0.002 | -0.002 |
| Charlson Comorbidity Score | 1.11 | 1.12 | 1.13 | 1.11 | -0.001 | 0.009 |
| General Symptoms | 0.60 | 0.60 | 0.60 | 0.60 | 0.000 | -0.000 |
| Other Lung Diseases | 0.25 | 0.25 | 0.25 | 0.25 | 0.001 | 0.001 |
| Injury Neck, Nose | 0.17 | 0.16 | 0.16 | 0.17 | 0.004* | 0.001 |
| Penumonia, Unspecified Organism | 0.11 | 0.11 | 0.11 | 0.10 | -0.002 | -0.001 |
| Acute Myocardial Infarction | 0.08 | 0.09 | 0.08 | 0.08 | -0.000 | -0.001 |
| Other Urinary Tract Infection | 0.08 | 0.08 | 0.08 | 0.08 | 0.000 | 0.000 |
| Septicemia | 0.07 | 0.07 | 0.07 | 0.07 | -0.000 | 0.000 |
| Cerebral Artery Occlusion | 0.07 | 0.07 | 0.07 | 0.07 | -0.001 | -0.001 |
| Diseases of Esophagus | 0.05 | 0.06 | 0.06 | 0.05 | -0.000 | -0.000 |
| Transient Cerebral Ischemias | 0.05 | 0.05 | 0.05 | 0.05 | 0.000 | 0.000 |
| Disorder of Muscle Ligament and Fascia | 0.04 | 0.04 | 0.04 | 0.04 | -0.000 | -0.001 |
| Precerebral Occlusion | 0.04 | 0.04 | 0.04 | 0.04 | -0.001 | -0.000 |
| Psychotropic Agent Poisoning | 0.03 | 0.03 | 0.03 | 0.03 | -0.000 | -0.000 |
| Intestinal Obstruction | 0.03 | 0.03 | 0.03 | 0.03 | -0.001 | 0.000 |
| Ankle Fracture | 0.03 | 0.03 | 0.03 | 0.03 | 0.000 | 0.000 |
| Observations | 48,052 | 47,548 | 47,739 | 47,706 | | |

*Note:* Values are adjusted for zip code fixed effects. Our comorbidity score is measured via a Charlson Index constructed using six months of prior health claims. The diagnoses listed represent 87 percent of non-discretionary diagnoses in our sample. For full list see Appendix Table 1. The data are at the patient-ride level. * p <0.1; ** p <0.05; *** p <0.01.

Table 3: First- and Second- Stage Regressions Estimating the Relationship Between Hospital Prices, Episode Spending, and Mortality

Panel A: First Stage

| | Inpatient Price Index (1) |
|---|---|
| Ambulance Average Hospital Price Index | 0.6683*** |
| | (0.0226) |
| First-Stage F Stat | 877 |
| Outcome mean | 14,865 |
| Observations | 191,045 |

Panel B: OLS

| | Log Admission Spending (1) | In-Hospital Mortality (2) | Predicted Mortality (3) |
|---|---|---|---|
| Inpatient Price Index | 0.5427*** | 0.0018 | 0.0026*** |
| | (0.0145) | (0.0011) | (0.0005) |
| Outcome Mean | 28,232 | 0.0275 | 0.0275 |
| Observations | 191,045 | 191,045 | 191,045 |

Panel C: Second Stage of 2SLS

| | Log Admission Spending (1) | In-Hospital Mortality (2) | Predicted Mortality (3) |
|---|---|---|---|
| Inpatient Price Index | 0.5349*** | -0.0102*** | 0.0005 |
| | (0.0360) | (0.0037) | (0.0013) |
| Outcome Mean | 28,232 | 0.0275 | 0.0275 |
| Observations | 191,045 | 191,045 | 191,045 |

*Note:* All models include 5-digit zip code and year fixed effects and measure the effect of a two standard deviation increase in price. The price index is based on all inpatient claims (adjusted for inflation) between 2008 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 4: Estimating the Relationship Between Hospital Prices and Spending on Outpatient Care, Physician Services, and Post-Acute Care

| | Log Spending | Log Inpatient Spending | | Log Outpatient Spending | | Log Physician Spending | | Log Post-Acute Spending |
|---|---|---|---|---|---|---|---|---|
| | 365 Days | Admission | 365 Days Without Admission | Admission | 365 Days Without Admission | Admission | 365 Days Without Admission | 365 Days |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Price index | 0.4172*** | 0.6268*** | 0.1706 | 0.0385 | -0.0335 | 0.0496 | 0.1219 | 0.1008 |
| | (0.0409) | (0.0369) | (0.1518) | (0.1230) | (0.1996) | (0.0565) | (0.0862) | (0.0902) |
| Outcome mean | 62,883 | 23,871 | 18,937 | 419 | 2,195 | 3,941 | 8,310 | 3,521 |
| Observations | 143,578 | 191,045 | 143,578 | 191,045 | 143,578 | 191,045 | 143,578 | 191,045 |

*Note:* All models include 5-digit zip code and year fixed effects and measure the effect of a two standard deviation increase in price. The price index is based on all inpatient claims (adjusted for inflation) between 2008 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. We use logged spending as a dependent variable but report the outcome mean in levels. "365-Days Without Admission" spending refers to spending that occurs from the day after the discharge date to 365 days after the ambulance ride. * p <0.1; ** p <0.05; *** p <0.01.

Table 5: Estimating the Relationship Between Hospital Prices, DRG Weights, Length of Stay, and Indicator for Whether a Procedure Was Performed

| Panel A: OLS | | | |
|---|---|---|---|
| | Mean of DRG Weights (1) | Length of Stay (2) | Procedure Preformed (3) |
| Inpatient Price Index | 0.1147*** | 0.6166*** | 0.0321*** |
| | (0.0180) | (0.0698) | (0.0034) |
| Outcome Mean | 1.6340 | 5.0825 | 0.2442 |
| Observations | 191,045 | 191,045 | 191,045 |

| Panel B: Second Stage of 2SLS | | | |
|---|---|---|---|
| | Mean of DRG Weights (1) | Length of Stay (2) | Procedure Preformed (3) |
| Inpatient Price Index | 0.0435 | 0.2802 | 0.0100 |
| | (0.0531) | (0.1767) | (0.0100) |
| Outcome Mean | 1.6340 | 5.0825 | 0.2442 |
| Observations | 191,045 | 191,045 | 191,045 |

*Note:* All models include 5-digit zip code and year fixed effects and measure the effect of a two standard deviation increase in price. The price index is based on all inpatient claims between 2008 and 2014. Procedure is an indicator equal to one if the patient has a surgical DRG. 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.

Table 6: Robustness of Mortality Analyses to Alternative Samples, Clusters, Fixed Effects, and Controls

| | Baseline Specification | No Ambulance Controls | ZIP Code Level Clusters | HRR Level Clusters | HSA Fixed Effects | HRR Fixed Effects | No Diagnoses Controls | No Count Restrictions | ZIP x Origin Fixed Effects |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Inpatient Price Index | -0.0102*** | -0.0068* | -0.0102*** | -0.0102*** | -0.0092*** | -0.0039** | -0.0100*** | -0.0071* | -0.0087** |
| | (0.0037) | (0.0037) | (0.0039) | (0.0032) | (0.0030) | (0.0020) | (0.0038) | (0.0040) | (0.0040) |
| Outcome Mean | 0.0275 | 0.0275 | 0.0275 | 0.0275 | 0.0275 | 0.0275 | 0.0275 | 0.0277 | 0.0272 |
| Observations | 191,045 | 191,045 | 191,045 | 191,031 | 191,044 | 191,031 | 191,045 | 217,476 | 189,330 |

*Note:* In Column 2, we exclude ambulance controls from the main specification. These controls include payment to the ambulance company, whether the transport utilized advanced life support, and whether the transport was coded as emergency transport. In Columns 3 and 4 we cluster standard errors at the zip code level and hospital referral region (HHR) level, respectively, opposed to hospital service area (HSA) level in the main analysis. In Columns 5 and 6, HSA fixed effects and HHR fixed effects are used, respectively, opposed to zip code fixed effects included in the main analysis. Column 7 excludes diagnoses controls which are 29 non-discretionary diagnoses codes. Column 8 no longer includes our count restrictions requiring ambulance and ZIP codes to have at least 10 cases across the sample period. Column 9 includes interactions of ZIP code and origin fixed effects. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. All columns report the effect of a two standard deviation increase in price.

Table 7: Estimating the Relationship Between Hospital Prices and Mortality in Concentrated and Unconcentrated Markets

| Panel A: OLS | | | | | | |
|---|---|---|---|---|---|---|
| | Log Admission Spending | | In-Hospital Mortality | | Predicted Mortality | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Inpatient Price Index | 0.5427*** | 0.5359*** | 0.0018 | 0.0007 | 0.0026*** | 0.0026*** |
| | (0.0145) | (0.0163) | (0.0011) | (0.0013) | (0.0005) | (0.0006) |
| Inpatient Price Index * HHI Above 4,000 | | 0.0386 | | 0.0053** | | -0.0001 |
| | | (0.0314) | | (0.0026) | | (0.0012) |
| Outcome Mean | 28,232 | 28,232 | 0.0275 | 0.0275 | 0.0275 | 0.0275 |
| Observations | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 |
| **Panel B: Second Stage of 2SLS** | | | | | | |
| | Log Admission Spending | | In-Hospital Mortality | | Predicted Mortality | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Inpatient Price Index | 0.5349*** | 0.5415*** | -0.0102*** | -0.0129*** | 0.0005 | 0.0010 |
| | (0.0360) | (0.0394) | (0.0037) | (0.0041) | (0.0013) | (0.0013) |
| Inpatient Price Index * HHI Above 4,000 | | 0.0034 | | 0.0115** | | -0.0011 |
| | | (0.0537) | | (0.0052) | | (0.0021) |
| Outcome Mean | 28,232 | 28,232 | 0.0275 | 0.0275 | 0.0275 | 0.0275 |
| Observations | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 |

*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 2008 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 regressions with Predicted Mortality do not control for patient characteristics, including: age, gender, diagnosis, and comorbidity score. 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 8: Estimating the Relationship Between Hospital Prices and Mortality at Various HHI Cutoffs

| | In-Hospital Mortality | | | |
|---|---|---|---|---|
| HHI Cutoff | 3,000 | 3,773 | 4,000 | 5,000 |
| | (1) | (2) | (3) | (4) |
| Inpatient Price Index * HHI Below Cut-off | -0.0138*** | -0.0127*** | -0.0129*** | -0.0118*** |
| | (0.0043) | (0.0041) | (0.0041) | (0.0042) |
| Inpatient Price Index * HHI Above Cut-off | -0.0040 | -0.0028 | -0.0014 | -0.0043 |
| | (0.0043) | (0.0049) | (0.0049) | (0.0050) |
| Test of equality between interacted coef.: | | | | |
| F-Stat | 4.0855 | 4.0675 | 4.9292 | 1.7927 |
| P-Value | 0.0435 | 0.0439 | 0.0266 | 0.1808 |
| Outcome Mean | 0.0275 | 0.0275 | 0.0275 | 0.0275 |
| Observations | 191,045 | 191,045 | 191,045 | 191,045 |

*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 and measure the effect of a two standard deviation increase in price. The price index is based on all inpatient claims (adjusted for inflation) between 2008 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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 9: Estimating the Relationship Between Hospital Prices and Care Delivered in Concentrated and Unconcentrated Markets

| Panel A: OLS | Mean of DRG Weights | | Length of Stay | | Procedure Preformed | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Inpatient Price Index | 0.1147*** | 0.1176*** | 0.6166*** | 0.6193*** | 0.0321*** | 0.0311*** |
| | (0.0180) | (0.0208) | (0.0698) | (0.0820) | (0.0034) | (0.0038) |
| Inpatient Price Index * HHI Above 4,000 | | -0.0087 | | 0.0100 | | 0.0062 |
| | | (0.0411) | | (0.1301) | | (0.0074) |
| Outcome Mean | 1.6340 | 1.6340 | 5.0825 | 5.0825 | 0.2442 | 0.2442 |
| Observations | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 |

| Panel B: Second Stage of 2SLS | Mean of DRG Weights | | Length of Stay | | Procedure Preformed | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Inpatient Price Index | 0.0435 | 0.0476 | 0.2802 | 0.3571* | 0.0100 | 0.0115 |
| | (0.0531) | (0.0600) | (0.1767) | (0.2006) | (0.0100) | (0.0110) |
| Inpatient Price Index * HHI Above 4,000 | | 0.0288 | | -0.1217 | | 0.0040 |
| | | (0.0879) | | (0.2397) | | (0.0165) |
| Outcome Mean | 1.6340 | 1.6340 | 5.0825 | 5.0825 | 0.2442 | 0.2442 |
| Observations | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 |

*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 2008 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 HHI measure is calculated at the hospital level, and based on bed counts for hospitals accessible in under 30 minutes.. * p <0.1; ** p <0.05; *** p <0.01.

Table 10: Hospital Characteristics by Market Concentration and Price Levels

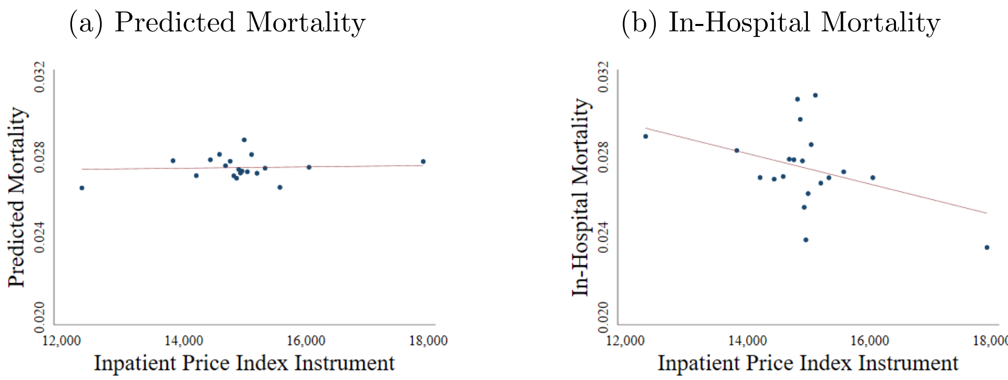
| | HHI < 4,000 | | HHI ≥ 4,000 | | Difference in Means | | |
|---|---|---|---|---|---|---|---|
| Price | Low | High | Low | High | (2) vs. (1) | (4) vs. (3) | (4) vs. (2) |
| | (1) | (2) | (3) | (4) | | | |
| Hospital Characteristics | | | | | | | |
| Number of Technologies | 60 | 66 | 53 | 61 | 5.953*** | 7.558*** | -5.418*** |
| Number of Beds | 293 | 340 | 199 | 262 | 47.271*** | 62.368*** | -78.234*** |
| Graduate Medical Education Accredited Program | 0.44 | 0.47 | 0.19 | 0.26 | 0.028 | 0.068*** | -0.211*** |
| Medical School Affiliation | 0.49 | 0.52 | 0.27 | 0.33 | 0.021 | 0.061** | -0.187*** |
| Council of Teaching Hospital Member | 0.13 | 0.22 | 0.04 | 0.06 | 0.097*** | 0.025* | -0.162*** |
| Government | 0.10 | 0.10 | 0.12 | 0.10 | 0.002 | -0.023 | -0.008 |
| Non-Profit | 0.72 | 0.67 | 0.68 | 0.72 | -0.052* | 0.037 | 0.051* |
| Medicare Share of Patient | 44.65 | 41.29 | 48.05 | 47.15 | -3.353*** | -0.898 | 5.858*** |
| Medicaid Share of Patient | 19.37 | 20.45 | 18.19 | 18.10 | 1.080 | -0.093 | -2.352*** |
| FTE Registered Nurses Per Bed | 1.63 | 1.86 | 1.48 | 1.76 | 0.232*** | 0.284*** | -0.099** |
| FTE Licensed Practical Nurses Per Bed | 0.08 | 0.07 | 0.14 | 0.12 | -0.009* | -0.013 | 0.048*** |
| Payroll Per Bed | 334,001 | 413,921 | 292,660 | 377,237 | 79,920*** | 84,576*** | -36,685*** |
| Physician Measures | | | | | | | |
| Years Since Graduation in 2014 | 21.15 | 20.33 | 20.95 | 20.67 | -0.824*** | -0.281** | 0.337*** |
| Share of Graduates From a Top 25 U.S. Medical School | 0.18 | 0.23 | 0.15 | 0.17 | 0.048*** | 0.021*** | -0.059*** |
| Share of Male Physicians | 0.74 | 0.73 | 0.78 | 0.77 | -0.013*** | -0.015*** | 0.036*** |
| Observations | 514 | 477 | 404 | 462 | | | |

Table 10: Hospital Characteristics by Concentration and Price Levels (Continued)

| | HHI < 4,000 | | HHI ≥ 4,000 | | Difference in Means | | |
|---|---|---|---|---|---|---|---|
| Price | Low | High | Low | High | (2) vs. (1) | (4) vs. (3) | (4) vs. (2) |
| | (1) | (2) | (3) | (4) | | | |
| Quality Measures | | | | | | | |
| 30-Day Acute Myocardial Infarction Survival Rate | 0.84 | 0.85 | 0.84 | 0.84 | 0.002* | 0.001 | -0.003*** |
| 30-Day Heart Failure (HF) Survival Rate | 0.89 | 0.89 | 0.89 | 0.88 | -0.000 | -0.001 | -0.008*** |
| 30-Day Pneumonia Survival Rate | 0.89 | 0.89 | 0.88 | 0.88 | -0.000 | -0.000 | -0.006*** |
| % Acute Myocardial Infarction Patient Given Aspirin at Discharge | 97.14 | 97.94 | 95.21 | 97.56 | 0.800** | 2.349*** | -0.375 |
| % HF Patient Given Discharge Instr. | 86.82 | 89.57 | 87.18 | 88.40 | 2.748*** | 1.221* | -1.174** |
| % HF Patient Tested for Left Ventricular Systolic (LSF) Function | 97.94 | 98.60 | 96.91 | 98.41 | 0.658*** | 1.503*** | -0.193 |
| % HF Patient Given ACE Inhibitor/ARB for LSF Dysfunction | 94.15 | 95.56 | 92.88 | 94.89 | 1.412*** | 2.013*** | -0.672** |
| % Pneumonia Patient Given Most Appropriate Initial Antibiotics | 92.64 | 93.49 | 91.98 | 93.72 | 0.855*** | 1.742*** | 0.228 |
| % Patient Given Antibiotic 1hr Pre-Surgery | 95.33 | 95.60 | 94.57 | 96.08 | 0.271 | 1.509*** | 0.481 |
| Sample Derived Hospital Characteristics | | | | | | | |
| Average DRG Weight for Patient in Sample | 1.54 | 1.62 | 1.40 | 1.52 | 0.077*** | 0.114*** | -0.102*** |
| Average Length of Stay for Patient in Sample | 4.80 | 5.03 | 4.43 | 4.85 | 0.232** | 0.424*** | -0.181 |
| Observations | 514 | 477 | 404 | 462 | | | |

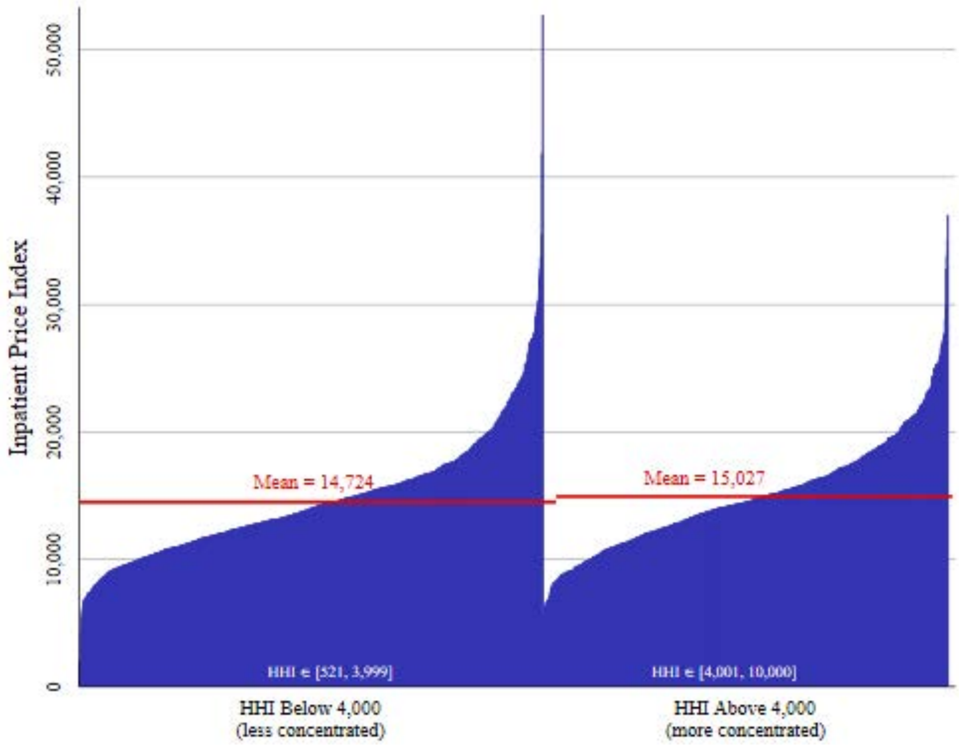
*Note:* The price index is based on all inpatient claims (adjusted for inflation) between 2008 and 2014. The observations are unique at the hospital level. "Low" (respectively, "High") price corresponds to hospitals with a price index below (above) the median price index amongst all hospitals in the AHA data. The HHI measure is calculated at the hospital level, and based on bed counts for hospitals accessible in under 30 minutes. The physicians measures are from 2017. * p <0.1; ** p <0.05; *** p <0.01.

Figure 1 : Residualized Mortality vs the Residualized Price Index




*Note:* Panel A is created by regressing predicted mortality and the inpatient price instrument on point of origin and ambulance characteristics. Panel B is created by regressing in-hospital mortality and the inpatient price instrument on point of origin, diagnoses, patients' comorbidity scores, demographics, and ambulance characteristics. 5-digit zip code and year fixed effects are included in the regressions for both panels. Each dot in the bin scatter plot represents approximately 93 hospitals.

Figure 2 : Distribution of the Hospital Inpatient Price Index In Markets with an HHI Above and Below 4,000




*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 2008 and 2014.

# ONLINE APPENDIX

Appendix Table 1: Balance Test - Full List of Non-Discretionary Diagnoses

| | 1st Quartile | 2nd Quartile | 3rd Quartile | 4th Quartile | 1st vs. 4th Difference | Below vs. Above Median |
|---|---|---|---|---|---|---|
| General Symptoms | 0.60 | 0.60 | 0.60 | 0.60 | 0.000 | -0.000 |
| Other Lung Diseases | 0.25 | 0.25 | 0.25 | 0.25 | 0.001 | 0.001 |
| Injury Neck, Nose | 0.17 | 0.16 | 0.16 | 0.17 | 0.004* | 0.001 |
| Penumonia, Unspecified Organism | 0.11 | 0.11 | 0.11 | 0.10 | -0.002 | -0.001 |
| Acute Myocardial Infarction | 0.08 | 0.09 | 0.08 | 0.08 | -0.000 | -0.001 |
| Other Urinary Tract Infection | 0.08 | 0.08 | 0.08 | 0.08 | 0.000 | 0.000 |
| Septicemia | 0.07 | 0.07 | 0.07 | 0.07 | -0.000 | 0.000 |
| Cerebral Artery Occlusion | 0.07 | 0.07 | 0.07 | 0.07 | -0.001 | -0.001 |
| Diseases of Esophagus | 0.05 | 0.06 | 0.06 | 0.05 | -0.000 | -0.000 |
| Transient Cerebral Ischemias | 0.05 | 0.05 | 0.05 | 0.05 | 0.000 | 0.000 |
| Disorder of Muscle Ligament and Fascia | 0.04 | 0.04 | 0.04 | 0.04 | -0.000 | -0.001 |
| Precerebral Occlusion | 0.04 | 0.04 | 0.04 | 0.04 | -0.001 | -0.000 |
| Psychotropic Agent Poisoning | 0.03 | 0.03 | 0.03 | 0.03 | -0.000 | -0.000 |
| Intestinal Obstruction | 0.03 | 0.03 | 0.03 | 0.03 | -0.001 | 0.000 |
| Ankle Fracture | 0.03 | 0.03 | 0.03 | 0.03 | 0.000 | 0.000 |
| Other Noninfective Gostroenteritis | 0.03 | 0.03 | 0.03 | 0.03 | 0.000 | -0.000 |
| Tibia and Fibia Fracture | 0.03 | 0.03 | 0.03 | 0.03 | 0.000 | 0.000 |
| Analgesic, Antipyretics Poisoning | 0.02 | 0.02 | 0.02 | 0.02 | -0.001 | -0.000 |
| Solid, Liquid Pneumotitis | 0.02 | 0.02 | 0.02 | 0.02 | -0.000 | -0.001 |
| Fractured Rib, Sternum, Trachea | 0.02 | 0.02 | 0.02 | 0.02 | 0.001 | 0.001 |
| Intracerebral Hemorrhage | 0.02 | 0.02 | 0.02 | 0.02 | -0.000 | 0.000 |
| Fracture Neck of Femur | 0.02 | 0.02 | 0.02 | 0.02 | -0.001 | -0.000 |
| Pneumonia, Other Bacterial | 0.02 | 0.02 | 0.02 | 0.02 | 0.000 | 0.000 |
| Malignant Neoplasm of Trachea, Lung | 0.02 | 0.02 | 0.02 | 0.02 | -0.000 | -0.000 |
| Secondary Malignant Neoplasm | 0.02 | 0.02 | 0.02 | 0.02 | -0.000 | 0.000 |
| Pelvic Fracture | 0.01 | 0.01 | 0.01 | 0.01 | -0.000 | 0.000 |
| Gastric Ulcer | 0.01 | 0.01 | 0.01 | 0.01 | -0.000 | -0.000 |
| Duodendal Ulcer | 0.01 | 0.01 | 0.01 | 0.01 | 0.000 | 0.000 |
| Vascular Insufficiency of Intestine | 0.01 | 0.01 | 0.01 | 0.01 | 0.000 | 0.000 |
| Observations | 48,052 | 47,548 | 47,739 | 47,706 | | |

*Note:* Values are adjusted for zip code fixed effects. * p <0.1; ** p <0.05; *** p <0.01.

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 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 | 13,490,137 | 34.45 | 2.86 | 6.44 | 23.19 |

*Note:* Non-discretionary admission spending and total hospital revenue are obtained from inpatient and outpatient claims.

Appendix Table 3: Summary Statistics

| | Mean | SD | p5 | p25 | p50 | p75 | p95 | N |
|---|---|---|---|---|---|---|---|---|
| In-Hospital Mortality | 0.028 | 0.163 | 0 | 0 | 0 | 0 | 0 | 191,045 |
| 30-Day Spending | 32,584 | 46,461 | 3,490 | 9,614 | 18,131 | 36,465 | 110,148 | 181,891 |
| 180-Day Spending | 53,411 | 90,486 | 4,723 | 12,232 | 24,689 | 56,322 | 196,565 | 160,045 |
| 365-Day Spending | 62,883 | 109,203 | 5,346 | 13,727 | 28,182 | 65,362 | 235,309 | 143,592 |
| Charlson Score | 1.115 | 1.803 | 0 | 0 | 0 | 2 | 6 | 191,045 |
| Male | 0.511 | 0.500 | 0 | 0 | 1 | 1 | 1 | 191,045 |
| 0-17 Years Old | 0.046 | 0.210 | 0 | 0 | 0 | 0 | 0 | 191,045 |
| 18-24 Years Old | 0.051 | 0.220 | 0 | 0 | 0 | 0 | 1 | 191,045 |
| 25-34 Years Old | 0.073 | 0.260 | 0 | 0 | 0 | 0 | 1 | 191,045 |
| 35-44 Years Old | 0.131 | 0.338 | 0 | 0 | 0 | 0 | 1 | 191,045 |
| 45-54 Years Old | 0.269 | 0.443 | 0 | 0 | 0 | 1 | 1 | 191,045 |
| 55-64 Years Old | 0.430 | 0.495 | 0 | 0 | 0 | 1 | 1 | 191,045 |

*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. The data are at the patient-ride level.

Appendix Table 4: Hospital characteristics

| | All AHA Hospitals | | Hospitals in Analytical Sample | | Difference |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | in Means |
| Total HCCI Spending | 10,036,286 | 21,508,803 | 20,853,884 | 28,197,822 | 10,817,598*** |
| Time-Invariant HHI | 6200 | 3100 | 4400 | 2600 | -1800*** |
| Bed Count | 166 | 181 | 276 | 205 | 111*** |
| For-Profit Hospital | 0.16 | 0.35 | 0.20 | 0.39 | 0.04*** |
| Rural Hospital | 0.24 | 0.41 | 0.07 | 0.24 | -0.17*** |
| Medicaid Share of Patients | 0.17 | 0.09 | 0.19 | 0.09 | 0.02*** |
| Medicare Share of Patients | 0.50 | 0.12 | 0.45 | 0.09 | -0.05*** |
| Observations | 4,463 | | 1,857 | | |

*Note:* This is based on the AHA Annual Surveys and HCCI Claims Data, 2008—2014. HCCI spending is obtained from inpatient and outpatient claims.

Appendix Table 5: Mortality Results for Subgroups, Instrument Calculated by Subgroup

| Panel A: First Stage | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Baseline Specification | Male Patients | Female Patients | Patients Age 55-64 | Patients Age 0-54 | Charlson Score of Zero | Non-Zero Charlson Score |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Inpatient | 0.6683*** | 0.6701*** | 0.6381*** | 0.5699*** | 0.7007*** | 0.7023*** | 0.6047*** |
| | (0.0226) | (0.0238) | (0.0349) | (0.0371) | (0.0250) | (0.0270) | (0.0391) |
| F-Statistic | 877 | 795 | 335 | 236 | 774 | 676 | 240 |
| Outcome Mean | 14,865 | 14,850 | 14,890 | 14,842 | 14,850 | 14,838 | 14,729 |
| Observations | 191,045 | 83,215 | 77,991 | 64,652 | 96,408 | 105,215 | 56,504 |

| Panel B: Second Stage of 2SLS | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Baseline Specification | Male Patients | Female Patients | Patients Age 55-64 | Patients Age 0-54 | Charlson Score of Zero | Non-Zero Charlson Score |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Inpatient | -0.0102*** | -0.0036 | -0.0162** | -0.0205* | -0.0061 | -0.0073* | -0.0175 |
| | (0.0037) | (0.0059) | (0.0068) | (0.0107) | (0.0045) | (0.0039) | (0.0115) |
| Outcome Mean | 0.0275 | 0.0300 | 0.0238 | 0.0355 | 0.0206 | 0.0158 | 0.0428 |
| Observations | 191,045 | 83,215 | 77,991 | 64,652 | 96,408 | 105,215 | 56,504 |

*Note:* In Column 1, we report the results of our baseline regression, with the usual controls. In the remaining columns, we restrict our sample to various subgroups and then calculate the instrument for the subgroup before preforming the regressions. In Columns 2 and 3, we restrict the sample to male patients and female patients, respectively. In these regressions, we exclude our gender control. In Columns 4 and 5, we restrict our sample based on patient age. In our main sample, the median age falls within the 45-54 age band and approximately 43 percent of our sample falls within the 55-64 age band. In these regressions, we exclude age controls. In Columns 6 and 7, we restrict our sample to patients with a Charlson Score of zero and patients with a non-zero Charlson Score, respectively. In these regressions, we do not control for Charlson Score. The observations in, for example, Columns 2 and 3 do not sum to the baseline number of observations due the 10 ambulance rides and 10 patients from a zip code count restriction being made after we restrict the sample by subgroup and calculate the instrument. Further observations are dropped due to singletons in the regressions. * p <0.1; ** p <0.05; *** p <0.01.

Appendix Table 6: Robustness of Mortality Analyses to Larger Ambulance Rides Sample Restrictions

| | At Least 10 Rides | At Least 20 Rides | At Least 30 Rides |
|---|---|---|---|
| | (1) | (2) | (3) |
| Inpatient Price Index | -0.0102*** | -0.0093** | -0.0097** |
| | (0.0037) | (0.0039) | (0.0042) |
| Outcome Mean | 0.0275 | 0.0272 | 0.0274 |
| Observations | 191,045 | 182,404 | 174,287 |

*Note:* In Column (1) we include the ambulance restriction in our main sample; ambulance companies are required to have at least 10 rides across the sample period. In each subsequent column this count restriction is increased. * p <0.1; ** p <0.05; *** p <0.01.

Appendix Table 7: Estimating the Relationship Between Hospital Prices and Readmissions

**Panel A: First Stage**

| | Inpatient Price Index (1) |
|---|---|
| Ambulance Average Hospital Price Index | 0.6683*** |
| | (0.0226) |
| First-Stage F Stat | 877 |
| Outcome mean | 14,865 |
| Observations | 191,045 |

**Panel B: OLS**

| | 30 Days (1) | 60 Days (2) | 90 Days (3) | 180 Days (4) | 365 Days (5) |
|---|---|---|---|---|---|
| Inpatient Price Index | -0.0026 | 0.0014 | 0.0038 | 0.0064* | 0.0070* |
| | (0.0039) | (0.0040) | (0.0040) | (0.0037) | (0.0039) |
| Outcome Mean | 0.2359 | 0.2865 | 0.3158 | 0.3663 | 0.4124 |
| Observations | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 |

**Panel C: Second Stage of 2SLS**

| | 30 Days (1) | 60 Days (2) | 90 Days (3) | 180 Days (4) | 365 Days (5) |
|---|---|---|---|---|---|
| Inpatient Price Index | 0.0015 | 0.0075 | 0.0058 | 0.0066 | 0.0088 |
| | (0.0114) | (0.0116) | (0.0118) | (0.0123) | (0.0124) |
| Outcome Mean | 0.2359 | 0.2865 | 0.3158 | 0.3663 | 0.4124 |
| Observations | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 |

*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 2008 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. . * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Appendix Table 8: Effect of Price on Mortality in Concentrated and Unconcentrated Markets [15-Mile HHI]

| | Log Admission Spending | | In-hospital Mortality | | Predicted Mortality | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Inpatient Price Index | 0.5349*** | 0.5272*** | -0.0102*** | -0.0131*** | 0.0005 | 0.0005 |
| | (0.0360) | (0.0388) | (0.0037) | (0.0041) | (0.0013) | (0.0013) |
| Inpatient Price Index | | 0.0587 | | 0.0111** | | 0.0007 |
| * HHI Above 4,000 | | (0.0463) | | (0.0046) | | (0.0017) |
| Outcome Mean | 28,232 | 28,232 | 0.0275 | 0.0275 | 0.0275 | 0.0275 |
| Observations | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 | 191,045 |

*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 2008 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 regressions with Predicted Mortality do not control for patient characteristics, including: age, gender, diagnosis, and comorbidity score. 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.

Appendix Table 9: First- and Second- Stage Regressions Estimating the Relationship Between Hospital Prices, Episode Spending, and Mortality using Charges to Construct Price Index

Panel A: First Stage

| | Inpatient Price Index<br>(1) |
|---|---|
| Ambulance Average<br>Hospital Price Index | 0.6864***<br>(0.0173) |
| First-Stage F Stat | 1,566 |
| Outcome mean | 28,620 |
| Observations | 190,949 |

Panel B: OLS

| | Log Admission<br>Spending<br>(1) | In-Hospital<br>Mortality<br>(2) | Predicted<br>Mortality<br>(3) |
|---|---|---|---|
| Inpatient Price Index (Charges) | 0.2538*** | 0.0030** | 0.0012** |
| | (0.0245) | (0.0012) | (0.0006) |
| Outcome Mean | 28,239 | 0.0275 | 0.0275 |
| Observations | 190,949 | 190,949 | 190,949 |

Panel C: Second Stage of 2SLS

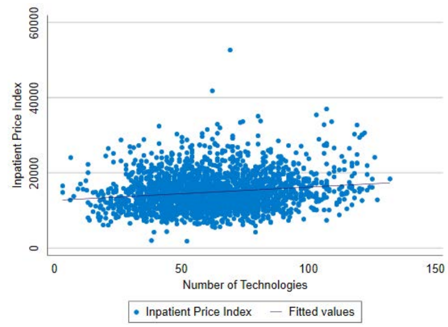
| | Log Admission<br>Spending<br>(1) | In-Hospital<br>Mortality<br>(2) | Predicted<br>Mortality<br>(3) |
|---|---|---|---|
| Inpatient Price Index (Charges) | 0.0925* | -0.0018 | 0.0003 |
| | (0.0486) | (0.0047) | (0.0013) |
| Outcome Mean | 28,239 | 0.0275 | 0.0275 |
| Observations | 190,949 | 190,949 | 190,949 |

*Note:* All models include 5-digit zip code and year fixed effects and measure the effect of a two standard deviation increase in price. The price index is based on all inpatient charges (adjusted for inflation) between 2008 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.

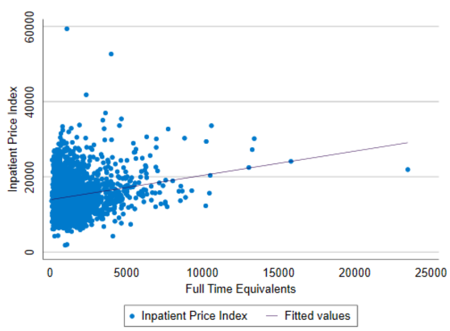
Appendix Figure 1 : Relationship Between Hospital Prices and Hospital Characteristics

(a) Price and HHI

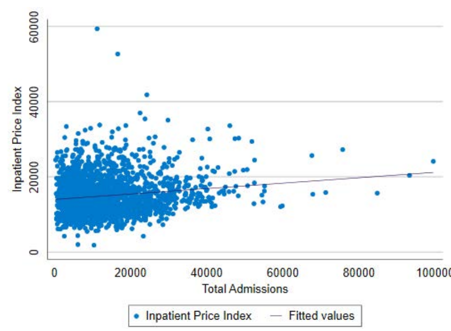

(b) Price and Technology




(c) Price and Hospital Size




(d) Price and Hospital Activity




*Note:* This figure shows the relationship between hospital prices and our time invariant HHI, the number of technologies at each hospital, the size of hospitals (measured using FTE employees), and hospital activity (measured using total admissions). The HHI measure is calculated at the hospital level, and based on bed counts for hospitals accessible in under 30 minutes.