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# Endogenous Quality Investments in the U.S. Hospital Market

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## ABSTRACT

High and increasing hospital prices have led to calls for price regulation. If prices are high because of consolidation, regulating prices could enhance welfare. However, high prices could also reflect increased willingness to pay by privately insured consumers for clinical and nonclinical quality. If so, regulating prices could reduce quality. The researchers present a model of strategic quality choice where hospitals make quality investments to increase private revenue. They confirm the model's predictions across numerous quality measures including patient satisfaction, hospital processes, risk adjusted mortality, the revealed preferences of current Medicare patients, technology adoption, physician quality, and ED wait times.

# 1 Introduction

High and increasing hospital prices have ignited a vigorous policy debate with proposed solutions ranging from direct private price regulation to expanding social insurance programs (and their regulated prices). This debate has largely ignored the complex relationship between price setting and strategic quality investments. In this paper, we examine whether negotiated prices create the incentive for hospitals to invest in clinical and non-clinical quality. Our results can inform the debate over changes to pricing mechanisms by showing that such policies could affect equilibrium quality for all patients.

Healthcare pricing is complex but at a high level public insurers pay fixed prices to all providers and every private insurer negotiates different prices with each provider. In general, hospitals generating more unique value for patients can charge higher private prices. If this unique value simply results from hospital consolidation reducing the set of outside options, then reimbursement cuts may not meaningfully affect quality.[1] However, this unique value may also reflect a willingness-to-pay for quality. Across many industries, increased quality can cause meaningfully higher prices, and this could also be true in healthcare. If current quality levels result from the strategic efforts of firms to differentiate, then regulating prices could reduce quality. While a number of studies examine rising hospital prices, this literature largely does not consider the interaction between pricing and the provider's decision to invest in quality. Similarly, healthcare policy analyses largely ignore the possibility that prices and quality are jointly determined.[2]

To help understand the relationship between prices and quality, we develop and test a simple economic model of strategic hospital investments in costly quality. These investments are intended to increase the willingness to pay of privately insured patients with the goal of influencing negotiations with commercial insurers. In contrast, public insurer prices are broadly similar across hospitals and are not responsive to quality. Intuitively, if the marginal consumer is more likely to be publicly insured, then the hospital's quality choice will depend on the incentives generated by the public insurance program. By contrast, if the marginal consumer is more likely to be privately insured, then quality will reflect the incentives generated by those patients.

[1] Consolidation in hospital markets causes higher private prices, but there is no consistent evidence consolidation improves quality or reduces costs (Capps and Dranove (2004); Dafny (2009); Cooper et al. (2018)).

[2] Of the 19 papers cited in a literature review by the Kaiser Family Foundation on the determinants of healthcare pricing, only 4 evaluated quality. Perhaps more concerning, the literature review itself does not consider quality as a potential determinant of price. By contrast, the hospital bargaining literature generally takes hospital quality as fixed and models network formation and pricing, premium setting, and consumer demand for insurance and hospitals (Ho and Lee (2017, 2018); Gowrisankaran, Nevo and Town (2015)). Even those studies which document a connection between prices and quality do not examine the underlying economic mechanism. Both White and Whaley (2019) and Cooper et al. (2018) document that high-priced hospitals tend to be higher quality than low-priced hospitals but don't discuss why or how that relationship occurs. Wu and Shen (2014) show that large administrative price cuts gradually lead to slower improvement in patient outcomes. Gaynor, Ho and Town (2015) provides a review of the literature examining the effect of competition separately on prices and quality. In summarizing the literature, the authors separate studies into markets with administered prices and markets with market determined prices. Our study fills a void by exploring the interaction of the mechanism determining prices and quality investments.

Our model, when combined with institutional features of the U.S. healthcare system – where commercial prices are substantially higher than public rates and can respond to hospital quality – suggests optimal quality will be higher in markets with more private patients. In markets with a large number of private patients, hospitals may set quality sufficiently high that the cost of serving public patients exceeds the associated reimbursement.[3] Such a strategy is not viable for hospitals in markets with a greater share of publicly insured patients. Those hospitals cannot persistently lose money and must instead optimize under the fixed reimbursements offered by public insurers. Such a relationship between potential market opportunities and product quality is not unique to healthcare. Waldfogel (2003) notes that firms offer products that attract a large base of (profitable) customers. The growing literature on endogenous product design (see Crawford (2012) for a review) shows that the welfare effects of such endogenous quality choice can be comparable to that of pricing.

Since publicly insured patients can receive care at effectively any hospital and public reimbursements do not vary with quality, costly investments in quality decrease the accounting margins hospitals earn from treating those patients. As a result, hospitals investing in quality because their marginal expected consumer is privately insured should have lower Medicare accounting margins, higher quality, and higher prices from private payers. If this were true, we would predict a negative correlation between public and private accounting margins, which is precisely what we observe in the binned scatter plot in Figure 1A.[4] If these margins are a byproduct of costly quality investments in search of higher private prices[5], they imply that changes to reimbursement policy would alter the optimal quality investment.[6]

Other have noted a similar negative correlation – albeit driven by different economic mechanisms. For example, Stensland, Gaumer and Miller (2010) posit that the increased costs for hospitals receiving higher private prices solely result from a softening of pressure on hospital managers to control costs. Both this model of inefficiency and our model of strategic quality investments imply a negative correlation between Medicare and non-Medicare accounting margins. Our model, however, suggests higher costs are a byproduct of the incentive to invest in quality to increase private patient demand. The differences between these models are not merely semantic. If the potential to charge high prices creates an incentive to invest in quality, regulating prices could reduce equilibrium quality.

[3]Medicare covers elderly patients and Medicaid primarily covers the indigent and disabled. Both programs use administrative prices; Medicare is typically more generous than Medicaid. Nearly all hospitals accept Medicare and therefore these patients can receive services at hospitals with negative Medicare accounting margins.

[4]Figure 1B shows that for-profit hospitals, which can return any excess surplus to investors, also exhibit a negative correlation between Medicare and non-Medicare accounting margins.

[5]These higher prices could either be from attracting privately insured patients with higher reimbursing insurance or by demanding higher prices from the insurers of existing private patients.

[6]Such a relationship is consistent with existing literature. For example, Clemens, Gottlieb and Hicks (2020) show that changes to reimbursement affect both short-run supply and long-run physician investments; a similar phenomenon likely applies to hospitals.

Testing our model requires estimating a firm's belief about potential market opportunities. The actual payer mix at a hospital is the equilibrium outcome of, among other things, investments in quality. To avoid the endogeneity concerns that would result from using a hospital's actual payer mix as a measure of potential market opportunities, we measure a firm's beliefs about its potential patients based on the demographics of a hospital's close geographic region. This measure relies on the assumption that the geographic distance is an economically meaningful component of facility selection, as has been seen across a number of studies (McClellan, McNeil and Newhouse (1994); Kessler and McClellan (2000); Geweke, Gowrisankaran and Town (2003*a*)). It also leverages the fact that general acute care hospitals are long-standing institutions that face similar local demographics over the timescale in which quality investment decisions are considered.

In Figure 1D we demonstrate that our measure of potential private patient share is associated with lower Medicare accounting margins, in line with our predictions. To the extent private prices are generally higher than public reimbursements, this result is consistent with models of either inefficient management or costly quality investments. To distinguish between these hypotheses, we examine the relationship between the potential patient mix and a wide variety of quality measures including overall patient satisfaction, hospital processes, risk adjusted mortality, revealed patient preferences, hospital technology adoption, physician quality, and ED wait times. If the connection between Medicare and non-Medicare margins comes from waste by managers flush with resources, there should be no systematic relationship between potential private patients and quality. Our estimates are summarized in Figure 2 and Table 1. Across these quality measures, hospitals with a greater potential privately insured population provide higher quality. Where appropriate, these quality measures are risk adjusted. However, some of our measures, such as the measure of optimal hospital processes, do not require risk adjustment and therefore are immune to concerns they simply reflect some underlying characteristic of the privately insured. The consistent relationship across all of our measures provides empirical support for a model of hospitals making quality investments to increase revenue. We discuss the economic implications of this model below.

## 2 Data

We restrict our sample to general acute care hospitals filing Medicare's Hospital Cost Reports (henceforth, "Cost Reports") for which we can calculate a Medicare accounting margin; this restriction excludes small, rural hospitals.[7] We also restrict to hospitals receiving less than a one percent increase in their overall Medicare reimbursements as a result of providing graduate medical education; this restriction excludes

[7] Our measure is not price less marginal cost; accounting costs can be both fixed and marginal in nature. A large number of hospitals treating a small number of patients are rural hospitals that are designated as "critical access hospitals" by Medicare. Medicare pays these hospitals on a cost plus basis and therefore they face different incentives and reporting requirements. We also exclude a small number of "all-inclusive rate" hospitals; hospitals with this designation do not report the information we need to construct Medicare costs.

academic medical centers (AMCs). The business strategy of AMCs is not well-captured by our analyses because their quality choices (in the form of providing graduate medical education) directly affect Medicare reimbursement. By contrast, most hospitals face rigid public prices. An advantage of limiting our sample in this way is that we can be confident the relationship we estimate does not simply reflect an idiosyncratic feature of AMCs.[8] Table A.4 describes our sample restrictions in more detail.

We collected data from a number of sources described below. Unless otherwise noted, our data are from 2012.[9] Table A.5 presents summary statistics for these variables, as well as the number of hospitals with non-missing values of each measure.

## 2.1 Potential Patient Mix

We measure potential payer mix at the hospital level by combining zipcode demographics from the American Community Survey (ACS) and 2010 Census with data on the predicted share of a hospital's patients coming from each zipcode. More specifically, let $\hat{s}_{hz}$ be the predicted share of hospital $h$'s patients from zipcode $z$ given the distance between $h$ and $z$.[10] Let $Share^i_z$ be the share of patients in zipcode $z$ with insurance type $i \in \{Private, Public, Uninsured\}$.[11] The predicted share of hospital $h$'s patients with insurance type $i$ is:

$$Predicted\, Share^i_h = \sum_z \hat{s}_{hz} Share^i_z \tag{1}$$

We refer to these potential payer mix variables as *Predicted Private Share*, *Predicted Public Share*, and *Predicted Uninsured Share*. Table A.6 confirms there is strong relationship between a hospital's potential payer mix and its actual patient mix.[12] For example, we estimate a hospital predicted to draw all its patients from zipcodes that only contain publicly insured patients would have 85 percentage points more of these patients than a hospital predicted to draw all its patients from zipcodes that did not contain publicly insured patients.

[8] Table A.8 illustrates the relationship between potential patient mix and our quality remains similar if we include AMCs.

[9] We choose 2012 for two reasons. First, the quality of data on care provided to the uninsured improved after revisions to the Cost Reports that were implemented in 2010 and 2011. Second, we selected a year that predated the Affordable Care Act's insurance market reforms because those reforms changed the insurance composition of the population, but it may take time for hospitals behavior to reflect the new equilibrium.

[10] We describe the Medicare data used to calculate $\hat{s}_{hz}$ in more detail in Section 2.3.4. We predict $\hat{s}_{hz}$ using the choice model in Equation 2, except we exclude the hospital-specific fixed effects.

[11] We determine the share of the zipcodes with Medicare with the 2010 decennial Census's estimate of the share that was 65+. We approximate for the share of each hospital's patients that have Medicaid, are uninsured, and have private insurance using the ACS's zipcode-level estimate for 2009 through 2013. We re-scale the ACS estimates so they sum to one when combined with the decennial Census's estimate of the share of zipcode z's population that was 65+. We use this time frame to ensure the data predates the Affordable Care Act's 2014 insurance market expansions, but to otherwise be as proximate to the 2012 time frame for our other variables as possible.

[12] The Cost Reports report Medicare, Medicaid, and total inpatient discharges. We calculate the actual share of patients that are public as Medicare plus Medicaid discharges divided by total discharges. Because Cost Reports do not distinguish between private and uninsured discharges, we approximate for the share of patients that are uninsured by taking the share of the hospital's charges that are for uninsured patients. We only use this variable in Table A.6.

## 2.2 Accounting Margins

We measure accounting margins using the Cost Reports. We create two measures, one for traditional fee-for-service Medicare (*Medicare Accounting Margin*) and one for all other business (*Non-Medicare Accounting Margin*). To construct these measures, we determine: fee-for-service Medicare revenues, total revenues, estimated fee-for-service Medicare costs, and total costs. We subtract traditional fee-for-service Medicare costs and revenue from total costs and revenues to obtain non-Medicare costs and revenues. We produce each margin from the relevant costs and revenues. Note that *Non-Medicare Accounting Margin* includes all costs and revenues that are not from traditional fee-for-service Medicare patients, such as privately insured patients, Medicaid patients, uninsured patients, Medicare Advantage patients, and non-patient sources.[13] We use the terms "fee-for-service Medicare" and "Medicare" interchangeably.[14] More details on this process are available in Section A.2.1.

## 2.3 Quality

We construct six hospital quality measures.

### 2.3.1 Hospital Compare Composite

Using Hospital Compare we construct an aggregate quality measure based on three domains:

(i) Outcome measures, specifically, 30-day risk adjusted patient mortality rates and 30-day risk adjusted readmission rates for heart attack, heart failure, and pneumonia.

(ii) Process measures, such as whether heart attack patients receive aspirin at discharge and whether patients are given discharge instructions.[15] These process measures are collected for patients for whom the questions are relevant and are not adjusted for patient mix.

(iii) Patient experience scores, which are based on responses to the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey.[16] These measures are collected for a random sample of a hospital's adult patients (of all insurance types) and therefore the characteristics of surveyed patients will

[13] Medicare Advantage patients' insurance is administered by a private insurer.

[14] Our separation of margins into the relatively coarse categories of Medicare and non-Medicare accounting margins is driven by data availability.

[15] The complete list of measures is: 1. Heart Attack Patients Given Aspirin at Discharge Heart Failure, 2. Patients Given Discharge Instructions, 3. Heart Failure Patients Given an Evaluation of Left Ventricular Systolic (LVS) Function, 4. Heart Failure Patients Given ACE Inhibitor or ARB for Left Ventricular Systolic Dysfunction (LVSD), 5. Pneumonia Patients Given the Most Appropriate Initial Antibiotic(s), 6. Prophylactic antibiotic received within 1 hour prior to surgical incision, 7. Prophylactic antibiotics discontinued within 24 hours after surgery end time.

[16] HCAHPS includes a number of subjective measures of patient experience. We rely upon the same HCAHPS measures as in Doyle, Graves and Gruber (2018), which are: 1. Doctors always communicated well, 2. Nurses always communicated well, 3. Pain was always well controlled, 4. Patients always received help as soon as they wanted – Patients who gave a rating of 9 or 10 (high), 5. Room was always clean, 6. Room always quiet at night, 7. Staff always explained, 8. Yes, patients would definitely recommend the hospital, and 9. Yes, staff did give patients this information

vary by hospital. However, reported HCAHPS measures are patient-mix adjusted, and specifically control for respondent age and educational status.

For simplicity, we construct a single composite quality measure from Hospital Compare.[17] First, we standardize each quality measure, so that it has mean zero and a standard deviation of one, and sum the quality measures in each domain. We then create a single measure by repeating this process over the three domain specific measures.[18] Measures are correlated within a domain, but there is less correlation across domains.

While there could be a concern that non-random patient sorting may bias measures of underlying hospital quality in ways not captured by risk adjustment, we emphasize that recent research suggests these quality measures are correlated with measures of quality that account for such potential selection. Of particular relevance, Doyle, Graves and Gruber (2018) exploit random assignment of patients to validate this Hospital Compare quality measure. Furthermore, process measures are not subject to bias from non-random patient sorting.

#### 2.3.2 Emergency Department (ED) Wait Time

ED wait time, also from Hospital Compare, is calculated for all patients who are eventually admitted to the hospital and is not adjusted for patient mix. The lack of adjustment for patient mix creates some issues of interpretation. For example, we expect hospitals to expedite sicker patients within the ED, and therefore might also expect that hospitals with sicker patients would have lower ED times.

#### 2.3.3 Technology Adoption

We create a composite measure capturing adoption of technologies related to birth, cardiology, diagnostic imaging, radiation therapy, and transplantation from the American Hospital Association's (AHA) annual survey. We studentize each measure, average within technological area, studentize again, and then average across technological areas.[19] This measure is not patient-mix adjusted, but should be unaffected by patient sorting.

#### 2.3.4 Revealed Preference

We estimate a multinomial choice model to recover patient revealed preferences using Medicare's 2011 Hospital Service Area File. Medicare patients are particularly useful for this quality measure since they face

[17] In Appendix Figures A.4 and Table A.3 we provide estimates for the relationship between potential private share and each sub-domain of this composite quality measure.

[18] Some quality measures are missing for some hospitals; we interpolate missing quality measures from the measures that are present.

[19] Details are presented in Section A.2.3

effectively no insurance network based restrictions on which facilities they choose. In particular, for traditional Medicare patient $i$, visiting hospital $h$, let the distance in miles from the patient's zipcode to the hospital's zipcode be given by $m_{ih}$, let the geometric mean of the patient's zipcodes and hospital's density be given by $d_{ih}$, let mean utility for hospital h be given by $u_h$, and let $\epsilon_{ih}$ be drawn from the Type I extreme value distribution. Then the utility for patient $i$ from visiting hospital $h$ is given by:

$$U_{ih} = \beta^1 u_h + \beta^2 d_{ih} + \beta^3 m_{ih} + \beta^4 d_{ih} m_{ih} + \epsilon_{ih} \tag{2}$$

We normalize utility so that the average of $u_h$ is zero and so the average patient would be willing to travel one mile in exchange for visiting a hospital that increased $u_h$ by one.[20]

#### 2.3.5 Cardiologist Education

We measure physician quality for cardiology, a large sub-specialty practiced at most hospitals. While cardiologists are likely an important quality feature for patients when picking hospitals, they are typically not hospital employees. That said, Cutler, Huckman and Kolstad (2010) describe the variety of costly but non-pecuniary benefits hospitals provide to attract profitable physicians. Thus they represent an investment in hospital quality.[21] We calculate the percentage of a hospital's cardiologists from Medicare's Physician Compare that graduated from a medical school ranked in the top 25 of the 2018 U.S. News and World Report.[22]

#### 2.3.6 Productivity

Our final measure, "AMI survival per real resource," was developed in Chandra et al. (2016) and is described in greater detail there. It measures health outputs (i.e., survival) divided by resource inputs, and therefore serves as a measure of productivity. The numerator is a 30-day risk-adjusted acute myocardial infarction (AMI) survival rate, post-empirical Bayes shrinkage adjustment. The denominator is CMS's DRG weights for these same patients, which measure the expected resources to treat the patient based on the patient's medical condition and procedures received.

[20] Our approach is computationally tractable, robust to zero market shares, and uses a consistent outside good for comparison. See Section A.2.2 for additional details.

[21] It could be that physicians are attracted to high quality hospitals, perhaps because patients with well-reimbursing plans desire physicians with admitting privileges at such hospitals. To the extent there is correlation in preferences for high quality physicians and hospitals, this would still mean physician quality provides a measure (albeit a potentially attenuated one) of hospital quality.

[22] We use Medicare Compare data from 2014. For each physician, we select the first hospital at which the physician is recorded providing services.

# 3 Conceptual Framework and Empirical Approach

## 3.1 Model

In this section, we outline a model in which firms (hospitals) endogenously choose product quality. This classic question has been studied extensively. For example, Spence (1975) illustrates that the level of quality provided by a monopolist may deviate from the social optimum because the monopolist cannot extract the social benefits of higher quality that are obtained by infra-marginal consumers. More generally, Dorfman and Steiner (1954) illustrate that firms will jointly optimize over prices and quality such that the increase in demand from spending one more dollar to increase quality is equal to the increase in demand from cutting prices by a dollar.

In Section A.1, we extend this canonical model to consider the interaction between three economic actors: hospitals, public payers paying regulated prices, and private payers negotiating prices with hospitals. We assume market demographics are fixed and determined before hospitals choose a quality level. Hospitals first choose a level of quality and then compete in both market segments.[23] In the publicly insured segment, prices are exogenously determined by the government. In the privately insured segment, hospitals bargain with profit-maximizing insurers. Because bargaining occurs after quality is determined, prices for the privately insured may reflect higher quality.[24] Crucially, hospitals set a single level of quality for both segments. This assumption is broadly reasonable given the difficulty (both practical and political) of tailoring the quality of medical services within a hospital by payer (Grabowski, Gruber and Angelelli (2008)). This is particularly true if increasing quality requires large, fixed cost investments. Intuitively, hospitals with an expected marginal consumer that is privately insured will make investments in quality that reflect the preferences of these patients. In contrast, those with an expected marginal consumer that is publicly insured will invest in a quality level dictated by the incentives of the public program.

The model also implies a corollary: accounting margins on public patients will be lower in markets with more private patients. To see why, note that because public prices are fixed and quality is costly, higher quality leads to lower accounting margins on public patients. In turn, because optimal quality is higher in markets with more private patients, accounting margins on public patients will be declining in the number of private patients in the market. As we note above, both our model and one in which hospitals operate at an overall zero profit constraint and "waste" additional funds from private insurers generate the same prediction: Medicare and non-Medicare accounting margins are negatively correlated. However, this corollary means

[23]In the framework of Gaynor, Ho and Town (2015), we are modeling the "first stage" of a multi-stage process, taking bargaining, premium setting, consumer plan choice, and utilization as given. While we do not specify and estimate a full model of all of these stages, our results inform such a model.

[24]While we model quality investments as increasing marginal costs, the logic is easily extended for fixed cost investments in quality.

our model differs in whether more potential private patients increase hospital quality. Such a relationship will not be present in a model that connects high private prices and costs through inefficiency. Therefore, we test the validity of our model, compared to these alternatives, by examining the relationship between a hospital's exposure to public payers and observable measures of clinical and non-clinical quality. The analysis is positive, not normative, i.e. it does not comment on the optimal or efficient quality level. Given both theoretical ambiguity and market frictions, it is impossible to say whether quality is over- or under-provided in equilibrium.[25] We do, however, note that factors beyond pure clinical quality likely drive consumer willingness-to-pay and providing higher levels of that type of quality is not evidence of overprovision.

## 3.2 Estimation

Since investments in quality do not pay off instantaneously, we would ideally test our model using data on hospital quality and market demographics over long periods of time.[26] Lacking such data, our empirical approach leverages different demographics in the area around the hospitals. Such demographics evolve slowly, so hospitals face a relatively consistent potential patient population. We compare hospitals in areas with more publicly insured patients to hospitals in areas with more privately insured patients. By doing so, we leverage relatively exogenous determinants of hospital choice such as travel distances, which is similar to the approach of Kessler and McClellan (2000) and Geweke, Gowrisankaran and Town (2003*b*).

Our analysis faces four main identification threats. First, patients may sort based on insurance type to live near certain hospitals or hospitals may locate based on expected patient types. The former is unlikely; whether the latter is a concern depends on whether hospitals are differentiated prior to choosing their location.[27] This could be be problematic if, for example, certain hospital systems intrinsically provided better quality and sought out acquisition targets based on demographics. To address this concern, we replicate our results using only hospitals without ownership changes in the past decade and find the same basic relationship.[28]

Second, insurance status may be endogenous to hospital quality; i.e., if high quality hospitals have high prices, and high prices reduce private insurance take-up. In this (unlikely) case, our estimates of the effect of private insurance on quality would be biased downward.

[25] See Spence (1975) or Crawford, Shcherbakov and Shum (2019) for a recent empirical example.

[26] Unfortunately, such data are lacking. The ACS zipcode estimates were first produced in 2009, and are based on an aggregation of 5 years of data, meaning it is impossible to obtain yearly changes. Similarly, the Cost Reports have only included accurate information on the uninsured since 2010/2011.

[27] More specifically, if some hospitals would be high quality in any location but the returns to being high quality are higher in markets with more private patients, then our analyses would produce biased counterfactuals of the effect of changing the private patient share on outcomes.

[28] These results (presented in Figure A.6 and Figure A.7) are for a sample that excludes any hospital that underwent an ownership change between 2003 and 2012. We also note there is little evidence that quality is transferred across merging hospitals.

Third, local insurance types may be spuriously correlated with hospital quality. For example, states vary in Medicaid eligibility rules; states with broader Medicaid eligibility rules could also have lower quality hospitals for non-causally related reasons. To address these issues, we control for state fixed effects. To rule out concerns that our estimated relationship reflects broader cross-market differences, we confirm our results are robust to including market (HRR) fixed effects. This within-market analysis rules out the concern that certain markets have characteristics that lead to high quality that are unrelated to the market opportunities arising from varying patient demographics. As Figure A.8 shows, our empirical approach leverages the meaningful local geographic variation *within* HRRs. While data limitations prevent us from leveraging variation over time, we show that the variation across space does not predict potentially concerning time invariant features of hospitals within markets. For example, Appendix Table A.7 shows that predicted payer mix is not associated with the probability of being a Catholic-affiliated hospital.

Finally, risk adjustment for some of the quality measures may be imperfect. This final threat to identification is most substantive. Tautologically, the hospitals we study vary in payer mix in ways that may be correlated with underlying health. For this reason, we use risk-adjusted measures of quality where appropriate. That said, if risk adjustment were incomplete and privately insured patients would otherwise fare better, then some of our quality measures could directly reflect the health or other characteristics of privately insured patients rather than costly investments by hospitals. Even within patients with the same insurance status, patients could differ across markets in ways that may not be perfectly captured by various adjustments.[29] However, many of our quality measures are hospital features requiring no risk adjustment and thus are not susceptible to this concern. Perhaps most apparent are hospital process measures such as the appropriate use of aspirin for cardiology patients or antibiotics for those having surgery. As seen in Figure A.4, these process measures are strongly and positively related to the share of potential private patients. Similarly, our hospital technology and revealed preference measures require no risk adjustment and show a strong relationship with the potential private patient share. The consistency across these outcomes limits concerns our results simply reflect patient health or other non-market characteristics of privately insured patients.

There is a more subtle point related to this final identification concern. The privately insured may differ from the publicly insured in terms of their preferences. Whether this is problematic depends upon the desired interpretation of our results. Our model allows for the possibility that privately insured patient demand is more quality sensitive than publicly insured patient demand (though we have no evidence this is the case). If private patient demand would be more quality sensitive even if private patients were being reimbursed at

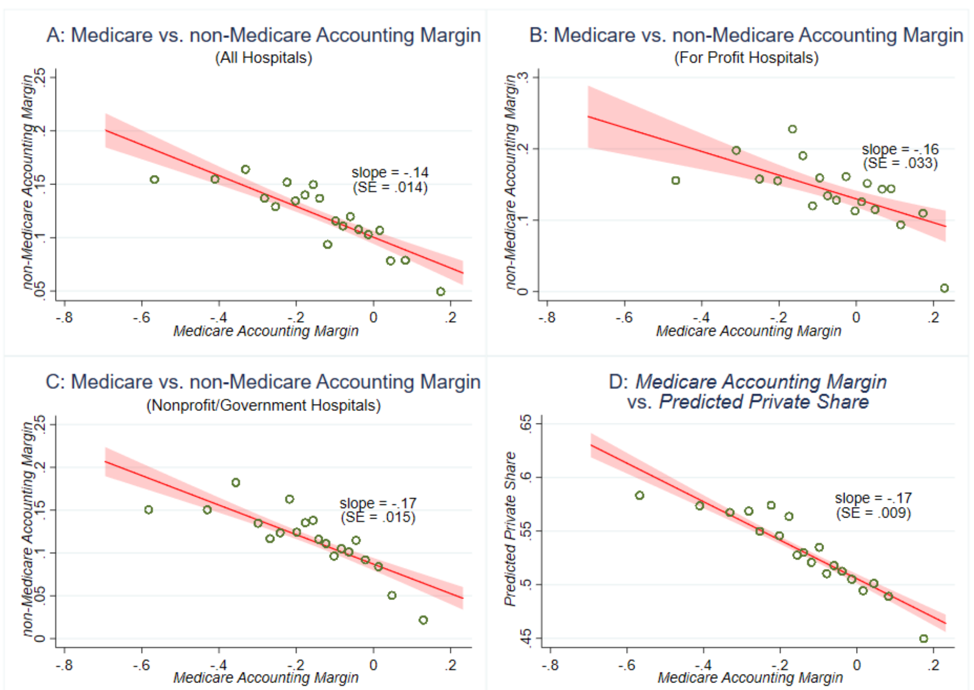
[29] For example, a Medicare patient in a market with an entirely uninsured under 65 population is likely to be very different from a Medicare patient in a market with a privately insured under 65 population.

public prices, then quality incentives under regulated prices might differ from the quality incentives hospitals currently face when treating the publicly insured. However, even if this was the case, the presence of negative Medicare margins for high private share hospitals suggests current quality levels could not be sustained. Said differently, identification concerns about imperfect risk-adjustment or different patient preferences for quality across insurance types could generate the prediction that markets with a higher private share would have higher quality, but would not generate the prediction that these market would also have lower Medicare margins (which we observe).

## 4 Analysis and Results

Figure 1D presents a binned scatterplot that confirms our prediction of a negative relationship between *Predicted Private Share* and *Medicare Accounting Margin*. This relationship is large in magnitude with a one percentage point increase in *Predicted Private Share* associated with a 0.66 percentage point decrease in *Medicare Accounting Margin*.[30]

Figure 1: Relationship Between *Medicare Accounting Margin* and Other Market Features




Notes: The dots are a binned scatterplot based of ventiles of the independent variable. The red line and shaded region are the least squares line and 95 percent confidence interval of the relationship between the variables. Analyses are weighted by costs.

[30]Table A.2 presents the relationship between potential payer mix and *Medicare Accounting Margin*.

Figure 2 presents a binned scatter plot of the relationship between our six quality measures and *Predicted Private Share*. Across all measures, a greater share of potential private patients is associated with higher quality. Table 1 contains regression estimates for the relationship between the potential patient mix and our various quality measures. We first report the coefficient on *Predicted Non-Private Share* (the inverse of the figures) and find consistent evidence that hospitals with a greater share of potential patients who are not privately insured have lower quality.

To address a possible concern that the relationship between potential private patients and various measures of quality simply reflect unobservable market characteristics, our specifications in the third and fourth columns in each panel include hospital referral region (HRR) fixed effects. These specifications are similar to those without these effects. These within-market estimates only leverage local geographic variation in potential patients while controlling for market wide features that may affect quality. To demonstrate this level of variation, Appendix Figure A.8 contains a histogram of our original *Predicted Private Share* variable as well as a demeaned version. Even after demeaning there is still meaningful variation.

With the exception of ED wait time, all specifications are robust to the inclusion of HRR fixed effects. A higher predicted non-private share is associated with less technology adoption, lower consumer surplus (as measured by our revealed preference metric), and lower quality in Hospital Compare. Crucially, the Hospital Compare Composite contains process measures unlikely to be contaminated by potentially unobserved patient selection.[31] A higher predicted non-private share is also associated with lower shares of top cardiologists and lower survival conditional on real resources. This demonstrates our estimates are robust to concerns we are simply picking up cross-market differences in quality provision. We next decompose the non-private share into *Predicted Public Share* and *Predicted Uninsured Share*. For all quality measures except ED wait time, we see that hospitals with a higher *Predicted Public Share* have lower quality. For all measures except AHA technology adoption, we see that hospitals with higher *Predicted Uninsured Share* have lower quality.

Across a range of quality measures, we show that predicted payer mix is associated with quality. Combined with the model, the patterns in the data suggest that hospitals who can attract well-reimbursed privately insured patients invest in quality to do so. Our quality estimates provide strong support for the predictions of our model and are inconsistent with a model of managerial inefficiency such as that proposed by Stensland, Gaumer and Miller (2010). Each quality measure has different strengths and limitations. Yet alternative stories, such as incomplete adjustment for patient selection, cannot explain the totality of our results: many of our measures are not directly affected by patient characteristics.

To understand the magnitude of our estimates, consider that the standard deviation of *Predicted Non-Private Share* is 9 percentage points. Recall that the technology adoption and the Hospital Compare measure

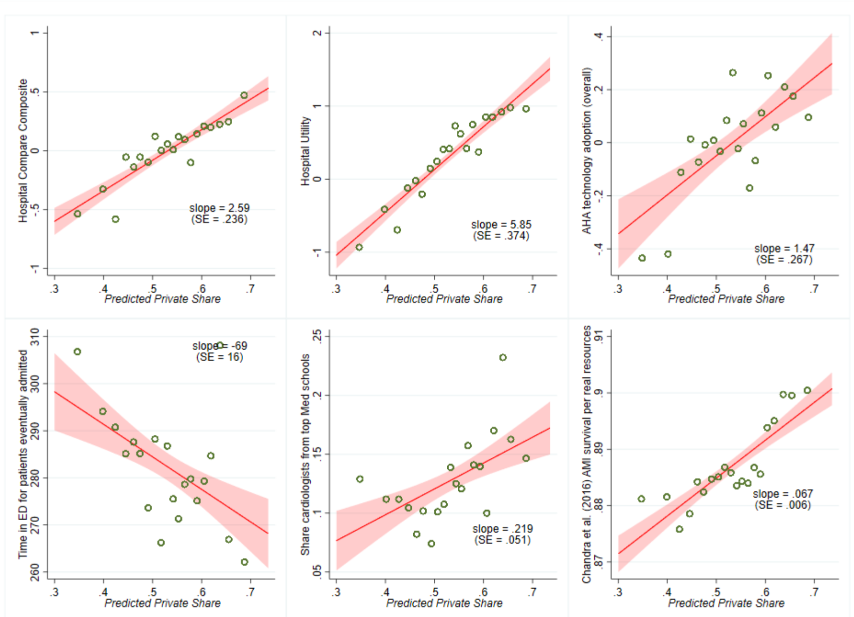
[31] We further decompose this measure into its component parts in Figure A.4 and Table A.3.

Table 1: Main regression table

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Predicted Share:* | AHA technology adoption (Overall) | | | | Hospital Utility | | | | Hospital Compare (Composite) | | | |
| *Non-Private* | -1.474*** | | -2.794*** | | -5.858*** | | -8.125*** | | -2.595*** | | -4.197*** | |
| | [0.267] | | [0.410] | | [0.374] | | [0.428] | | [0.236] | | [0.354] | |
| *Public* | | -3.139*** | | -4.374*** | | -7.427*** | | -9.775*** | | -3.525*** | | -4.110*** |
| | | [0.353] | | [0.539] | | [0.500] | | [0.559] | | [0.316] | | [0.464] |
| *Uninsured* | | 1.312*** | | 2.056* | | -3.221*** | | -3.120*** | | -1.024** | | -4.462*** |
| | | [0.472] | | [1.156] | | [0.673] | | [1.177] | | [0.426] | | [0.977] |
| *HRR FEs* | | | X | X | | | X | X | | | X | X |
| *N* | | 1,808 | | | | 2,255 | | | | 2,218 | | |
| *Predicted Share:* | Time in ED (Patients eventually admitted) | | | | Share of Cardiologists from top medical schools | | | | AMI Survival Per Real Resource | | | |
| *Non-Private* | 69.14*** | | 9.161 | | -0.220*** | | -0.172* | | -0.0673*** | | -0.0507*** | |
| | [16.90] | | [20.51] | | [0.0519] | | [0.0828] | | [0.00668] | | [0.00933] | |
| *Public* | | 20.90 | | -59.37** | | -0.320*** | | -0.228 | | -0.0597*** | | -0.0471*** |
| | | [22.61] | | [26.62] | | [0.0699] | | [0.108] | | [0.00899] | | [0.0121] |
| *Uninsured* | | 150.7*** | | 220.8*** | | -0.0544 | | -0.00341 | | -0.0799*** | | -0.0623** |
| | | [30.56] | | [56.54] | | [0.0931] | | [0.225] | | [0.0121] | | [0.0263] |
| *HRR FEs* | | | X | X | | | X | X | | | X | X |
| *N* | | 2,068 | | | | 1,535 | | | | 1,744 | | |

Notes: Unit of observation is the hospital. Observations are weighted by hospital costs. Standard errors are presented in brackets. Significance levels: * 0.10 ** 0.05 *** 0.01.

Figure 2: Relationship between *Predicted Private Share* and quality




Notes: The dots are a binned scatterplot based of ventiles of the independent variable. The red line and shaded region are the least squares line and 95 percent confidence interval of the relationship between the variables. Analyses are weighted by hospital costs.

are standardized and the coefficient can be interpreted in standard deviation units. A standard deviation in *Predicted Non-Private Share* is associated with a 0.13 and 0.23 standard deviation decrease in technology adoption and Hospital Compare measures, respectively. Share cardiologists and AMI survival range from 0 to 1. A standard deviation increase in *Predicted Non-Private Share* is associated with a 0.6 percentage point reduction in AMI survival and a 2.1 percentage point in the share of cardiologists from a top medical school. ED wait time is measured in minutes while the hospital utility metric is miles traveled. A standard deviation in *Predicted Non-Private Share* is equivalent to an additional 0.53 miles of travel to the hospital.[32]

## 5 Discussion and Conclusion

Our estimates demonstrate that changes to reimbursement policy are likely to affect strategic decisions by hospitals. While we do not fully model this strategic behavior, we note that only 20 percent of hospitals in our sample have positive Medicare accounting margins. These are not a random subset of hospitals. By construction, the average hospital in our sample has a Hospital Compare score of 0. However, the average hospital with a positive Medicare accounting margin has a score of -0.28, a quarter of a standard deviation lower in the distribution of hospitals. Table 2 shows the average Hospital Compare scores for various

[32]While this number may seem small, consumers are extremely sensitive to distance. A 5 minute increase in travel time reduces hospital market share by 17-41% (Gowrisankaran, Nevo and Town (2015)).

categories of hospitals. Column 1 contains the average score, Column 2 contains the share of hospitals with a positive Medicare accounting margin, and Column 3 combines these facts and provides the Hospital Compare composite score for hospitals with a positive Medicare accounting margin. As shown in Column 4, across all hospital categories quality scores are consistently and meaningfully lower for hospitals with a cost structure that results in a positive Medicare margin.

Table 2: Quality of Hospitals Conditional on Accounting Margins

| | | Hospital Compare Composite | | |
|---|---|---|---|---|
| **Characteristic** | **Share with Positive Medicare Accounting Margin (1)** | **Mean (2)** | **Mean \| Positive Medicare Accounting Margin (3)** | **Difference (3)-(2) (4)** |
| For profit | 0.42 | -0.20 | -0.45 | -0.25 |
| Nonprofit | 0.14 | 0.12 | -0.03 | -0.15 |
| Government | 0.17 | -0.30 | -0.64 | -0.35 |
| Small Hospital | 0.21 | -0.09 | -0.40 | -0.31 |
| Large Hospital | 0.20 | 0.14 | -0.09 | -0.23 |
| Low private share | 0.31 | -0.16 | -0.36 | -0.20 |
| High private share | 0.11 | 0.14 | -0.09 | -0.24 |
| Overall | 0.20 | 0.00 | -0.28 | -0.28 |

Notes: Restricted to hospitals with non-missing Hospital Compare Composite.

Table 2 depicts the types of trade-offs that might be necessary in a market that relies more heavily on the Medicare fee schedule, as has been proposed across numerous policy reforms. It is unclear how the 80 percent of hospitals with negative Medicare accounting margins would modify their strategies under Medicare for all. Similarly, it is unclear how hospitals would react to a large “public option” insurer that exploits the Medicare fee schedule – and therefore increased the share of patients covered by rates that are unresponsive to quality. However, the status quo of making costly investments in quality to attract higher reimbursements from private payers would not be economically sustainable for them. Finally, our results demonstrate that using Medicare rates as a measure of efficiency or as the “correct” price for bench marking provider costs ignores quality investments hospitals make in a market based system. Our results demonstrate a relationship between these costs (and the incentives to make the underlying investments) and a wide range of patient quality. At a minimum, this relationship should be considered in discussions of a greater use of direct price regulation or monopsony in the hospital market.

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# A Appendices (For Online Publication Only)

## A.1 Model

We extend Dorfman and Steiner (1954)'s model of price and quality setting to include two distinct segments of patients: one with market determined prices, and one with administratively determined prices.

Suppose that a monopolist hospital chooses one common quality level for both the public and private patients, and that quality affects marginal cost and demand. We can treat the hospital as choosing an optimal cost, rather than an optimal quality; we let c to denote marginal costs, and implicitly quality. Let $D^c(p_c, c)$ be the commercial demand curve, which is a function of commercial prices,$p_c$, and costs/quality, c. Let $D^p(c)$ be the demand curve for public patients. Prices for these patients are administratively set to a constant price of $p_p$, and demand does not depend on prices, but does depend on quality. Let the share of patients that are private in the market be given by $\alpha$. Thus, the profit function is given by:

$$\pi = \alpha\pi^c + (1-\alpha)\pi^p = \alpha D^c(p_c, c)(p_c - c) + (1-\alpha)D^p(c)(p_p - c) \tag{3}$$

Differentiating with respect to commercial prices and solving the first order condition leads to optimal commercial prices of:

$$p_c^* = c - D^c[\frac{\partial D^c}{\partial p_c}]^{-1}, \tag{4}$$

which can also be expressed in terms of the standard Lerner Index condition.

Differentiating with respect to costs/quality and solving for the optimum leads to:

$$c^* = \bar{p} - \bar{D}[\frac{\partial \bar{D}}{\partial c}]^{-1} \tag{5}$$

where $\frac{\partial \bar{D}}{\partial c} = \alpha\frac{\partial D^c}{\partial c} + (1-\alpha)\frac{\partial D^p}{\partial c}$, $\bar{D} = \alpha D^c + (1-\alpha)D^p$, $\bar{p} = \beta p_c + (1-\beta)p_p$, and $\beta = \alpha\frac{\partial D^c}{\partial c}[\frac{\partial \bar{D}}{\partial c}]^{-1}$. This expression is an analog to the single patient-type optimum, except that prices, demand, and demand elasticities with respect to cost are weighted averages of those objects for the commercial and public sectors.

Note that one can also obtain intuition about the spillover effects that public patients have on private patients by substituting optimal private prices into the first order condition with respect to quality and rearranging:

$$\frac{\partial D^c}{\partial c} = -\frac{\partial D^c}{\partial p_c}(1 + \frac{1-\alpha}{\alpha}\frac{1}{D^c}\frac{\partial \pi^p}{\partial c}) \tag{6}$$

When $\alpha = 1$ , then this reduces to: $\frac{\partial D^c}{\partial c} = -\frac{\partial D^c}{\partial p_c}$. i.e., the hospital is indifferent between lowering prices and increasing costs/quality by a dollar to stimulate demand. More broadly, at equilibrium prices and qualities $\frac{\partial D^c}{\partial c} > -\frac{\partial D^c}{\partial p_c}$ if and only if $\frac{\partial \pi^p}{\partial c} > 0$. i.e., the hospital will attract private patients on the margin by more aggressively cutting prices than increasing quality if quality is above the level that would be profit maximizing if treating only public patients.

To understand how patient mix affects quality choice, we can take the derivative of $c^*$ with respect to $\alpha$. Simplifying, we find that more private patients increase quality if and only if:

$$p_c - D^c[\frac{\partial D^c}{\partial c}]^{-1} > p_p - D^p[\frac{\partial D^p}{\partial c}]^{-1} \tag{7}$$

Thus, if private prices are weakly higher than public prices and private demand at equilibrium prices is weakly more quality elastic than public demand, then more private patients leads to weakly higher quality. Empirically, both of these conditions are thought to be true. Intuitively, this is likely to be true if public prices are set to be near costs, and if at the optimal quality level for public patients given those prices, $-\frac{\partial D^c}{\partial p_c} < \frac{\partial D^c}{\partial c}$ . i.e., private demand is more sensitive to changes in quality than changes in prices. It is also straightforward to show that if equation 7 holds, then public margins are decreasing in commercial share. By contrast, if costs are increasing in commercial share, then the effect of commercial share of private patient margins is ambiguous, and depends on the rates at which commercial prices and costs increase. Furthermore, when treating only private patients the hospital will set prices too high and quality too low; public patients worsen the distortion to private patients on quality, but alleviate it on price.

## A.2 Data Appendix

### A.2.1 Creating Accounting Margins

This Appendix details the construction of both Medicare and non-Medicare accounting margins. We collect data on costs, revenues, and margins from the Cost Reports for Medicare and non-Medicare sources separately. We are able to calculate Medicare costs and Medicare revenues from the Cost Reports. We also calculate total costs and revenues from the Cost Reports. Non-Medicare revenues and costs are calculated as total revenues and costs minus Medicare revenues and costs. The remainder of this section details the construction of Medicare revenues and costs, and then presents some additional information on the limitations of these measures, as well as some robustness checks.

**Calculating Medicare Revenues** We calculate revenue from traditional fee-for-service Medicare patients to be the sum of Medicare reimbursements and patient cost sharing over a number of sub-facilities that may be located within a hospital.[33] Note that Medicare patients can receive insurance either through traditional fee-for-service Medicare or through a Medicare Advantage plan, which is administered by a private insurer. In the Cost Reports, care provided to Medicare Advantage enrollees will not be included with fee-for-service Medicare. When we do not specify, Medicare refers solely to fee-for-service Medicare, and excludes Medicare Advantage.[34] We exclude Medicare Electronic Health Record Incentive payments from Medicare revenues because these payments were made to hospitals on only a short term basis. Other than that exception, we include all other sources of Medicare revenue as Medicare revenues, such as Medicare pass-through costs, Medicare disproportionate share payments, and Medicare graduate medical expense payments because these are revenue sources that hospitals consistently receive from Medicare.

**Calculating Medicare Costs** We use a straightforward procedure to separate hospital costs into Medicare and non-Medicare costs. The Cost Reports include accounting costs, "charges," and "Medicare charges" for each of a number of "cost centers." "Charges" are a measure of what is billed for that is meant to be correlated with costs, but that is distinct from Medicare or non-Medicare prices.[35] Cost centers can be divided into three types. First, some are patient revenue producing cost centers, such as intensive care units and operating rooms (i.e., the charges on patient bills can be assigned back to these revenue centers). Second general service cost centers, such as laundry are essential for caring for patients, but do not directly accrue charges. Finally, non-reimbursable cost centers, such as gift shops have costs and revenues that are unrelated to patient care and therefore the Cost Reports exclude these costs when calculating the costs of treating Medicare patients. The Cost Reports reallocate general service costs to patient revenue producing cost centers. We allocate a share of each cost center's charges to Medicare based on Medicare's share of charges for the cost center. We sum Medicare costs across cost centers to obtain total Medicare costs. Medicare also uses the Cost Reports to produce estimates of Medicare Costs, but follows a more complex methodology. Following Medicare's methodology, but making some basic adjustments leads to a measure of Medicare Costs that has a correlation of 0.9989 with the measure that we use. Given this very high level of correlation, we only perform analyses using our preferred, more transparently produced measure.[36]

[33] We calculate these based on Worksheet E of the Cost Reports. Medicare reconciles reimbursements to hospitals based upon submitted claims against hospital records of revenue from Cost Reports. As a result, the information on traditional fee-for-service Medicare reimbursements to hospitals as reported in Worksheet E of the Cost Reports should be very accurate.

[34] We follow MedPAC's example. MedPAC describes their margin as: "Overall Medicare margin covers acute inpatient, outpatient, hospital-based home health and skilled nursing facility (including swing bed), and inpatient psychiatric and rehabilitation services, plus graduate medical education." We aggregate over inpatient and outpatient reimbursements for the 4 types of subfacilities (Hospital, Psychiatric Facilities, Skilled Nursing Facilities, and Home Health Agencies), and any swing beds.

[35] For some cost centers, Medicare patient days and overall patient days are reported instead of charges. In such instances, we calculate Medicare's share using patient days.

[36] Specifically, we produce a version of Medicare costs that adds together the Cost Reports various "headline" cost estimates (i.e., a single number for the costs of hospital inpatient care, a single number for the costs of hospital outpatient care, etc...). We make a small number of alterations to these "headline" cost estimates to better accord with our framework. Specifically, we include costs that Medicare disallows, such as high physician salaries. These costs contribute to the cost of treating Medicare patients, even if Medicare does not recognize them for accounting purposes. Furthermore, Medicare has a complex methodology

**Limitations and robustness** This method of calculating margins has some limitations. First, we abstract away from the distinction between non-Medicare patient costs and revenues and non-patient costs and revenues. Non-patient costs are small on average, accounting for roughly 8 percent of total costs.[37] Second, there is likely some measurement error in the cost allocation process. We believe that these limitations primarily affect interpretation of the relative levels of and correlations between *Medicare Accounting Margin* and *Non-Medicare Accounting Margin*. By contrast, there are no obvious reasons that this measurement error would introduce mechanical correlations elsewhere in our analyses.

We note that the details of this process do not appear to substantively affect whether hospitals are classified as having high or low margins on Medicare patients. As a robustness check, we calculated an alternative measure of Medicare margin that has been used in a number of past studies and reports by MedPAC. In particular, the alternative measure is a Medicare margin on inpatient care, and is calculated by first producing an estimate of the inpatient costs of treating Medicare patients by taking inpatient hospital charges for traditional Medicare patients and multiplying them by Medicare's inpatient cost to charges ratio. In combination with allowed Medicare payments for these patients, one can produce an inpatient Medicare margin for each hospital. Figure A.1 illustrates that the two Medicare accounting margins are highly correlated.

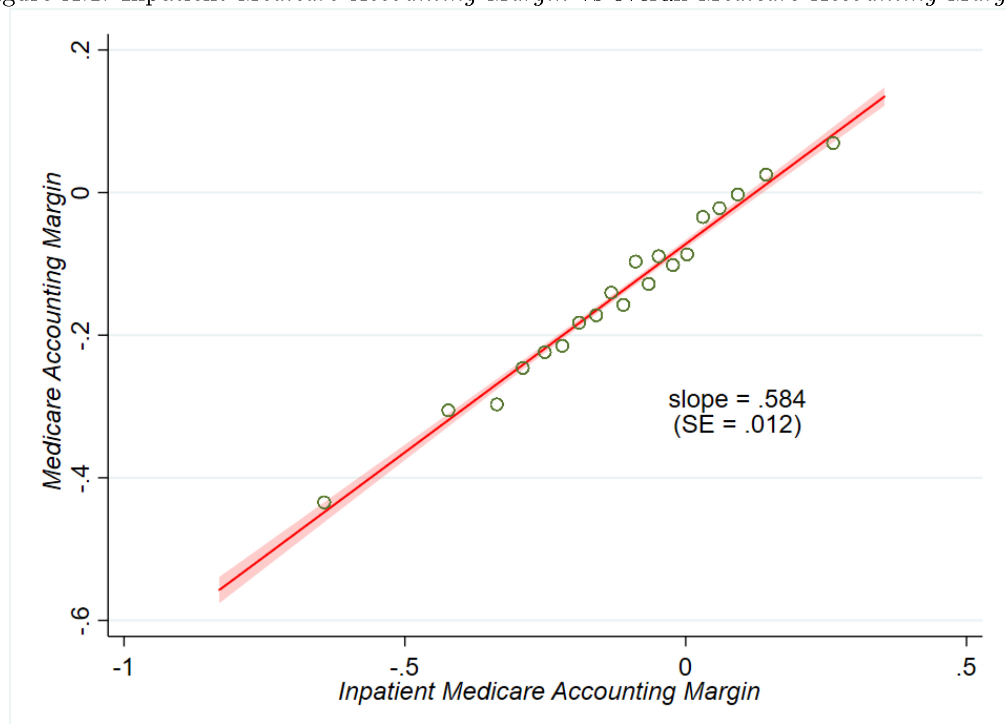
### A.2.2 Estimating patient utility

It is computationally intractable to directly estimate $u_h$ for the 4,700 acute care and critical access hospitals in the US. Therefore, we instead recover these fixed effects by running a conditional logit excluding $u_h$. Let $s_h$ be the number of discharges to hospital h and $\hat{s}_h$be the hospital's predict number of discharges based on the choice model. Then we can approximate the utility of hospital h by: $u_h = ln(s_h/\hat{s}_h)$. We produce an updated estimate of the utility of hospital h by inserting this estimate of $u_h$ into (1), re-estimating the model, and recalculating what $\hat{s}_h$would be if $u_h$ is zero. Iterating this process leads to estimates of $u_h$ that converge to a fixed point. While critical access hospitals are included in the multinomial choice model, they are not included in the paper's central analyses.

for accounting for the costs of graduate medical education, which involves "disallowing" these costs and then recalculating them using a separate methodology. Because Medicare's calculations are designed to determine reimbursements for medical education, rather than to estimate costs, we do not follow this methodology. Instead, our treatment is consistent with the fact that if a hospital was not paying salaries for residents, it would have to hire other medical staff to provide the same patient care. Economic theory suggests that these costs of training physicians or residents should be borne by those parties, rather than by the hospitals.(Newhouse and Wilensky, 2001).

[37]The main "non-patient costs are: (i) "miscellaneous", (ii) private physician offices, and (iii) research. According to the Cost Reports, research costs at hospitals are small. Medical schools, rather than hospitals, incur most of the costs of research, and receive a supermajority of research grant funding. A small number of hospitals in Massachusetts account for over one third of research costs and research revenues that are received by hospitals. By contrast, seven universities (University of Pennsylvania, Stanford, Johns Hopkins, University of Michigan, UPMC, and Yale) that collectively obtain over four times as much in NIH funding own hospitals that collectively account for under ten percent of research costs that are received by hospitals.

Figure A.1: Inpatient *Medicare Accounting Margin* vs overall *Medicare Accounting Margin*




Notes: The dots are a binned scatterplot based of ventiles of the independent variable. The red line and shaded region are the least squares line and 95 percent confidence interval of the relationship between the variables. Analyses are weighted by hospital costs.

### A.2.3 Technology adoption from the American Hospital Association

Our measure of technology adoption is based on the presence of a number of types of services in the American Hospital Association data. In particular, we study the presence of 5 categories of service offerings: transplant services, cardiology services, childbirth services, imaging services, and therapeutic radiology services. For each service category, we examine the presence of a number of specific services. The specific services that we consider for each service category are listed in Table A.1. We studentize the binary variable for each specific service, and then average over the specific services to create a service category measure of adoption. We then average over the five service categories to create an overall measure of adoption.

Table A.1: AHA technology adoption variables

| **Service Category** | **Examples of Specific Services** |
|---|---|
| births | Neonatal intermediate care |
| | Neonatal intensive care |
| | Birthing room/LDR room/LDRP room |
| | Obstetrics care |
| cardiology | Cardiac intensive care |
| | Cardiac Rehabilitation |
| | Adult cardiac electrophysiology |
| | Adult cardiac surgery |
| | Adult diagnostic catheterization |
| diagnostic imaging | Positron emission tomography (PET) |
| | Computed-tomography (CT) scanner |
| | Magnetic resonance imaging (MRI) |
| | Positron emission tomography/CT (PET/CT) |
| | Full-field digital mammography |
| | Ultrasound |
| radiation therapy | Proton beam therapy |
| | Shaped beam Radiation System |
| | Image-guided radiation therapy |
| | Intensity-Modulated Radiation Therapy (IMRT) |
| transplant | Lung transplant |
| | Bone Marrow transplant |
| | Tissue transplant |
| | Heart transplant |
| | Kidney transplant |
| | Liver transplant |

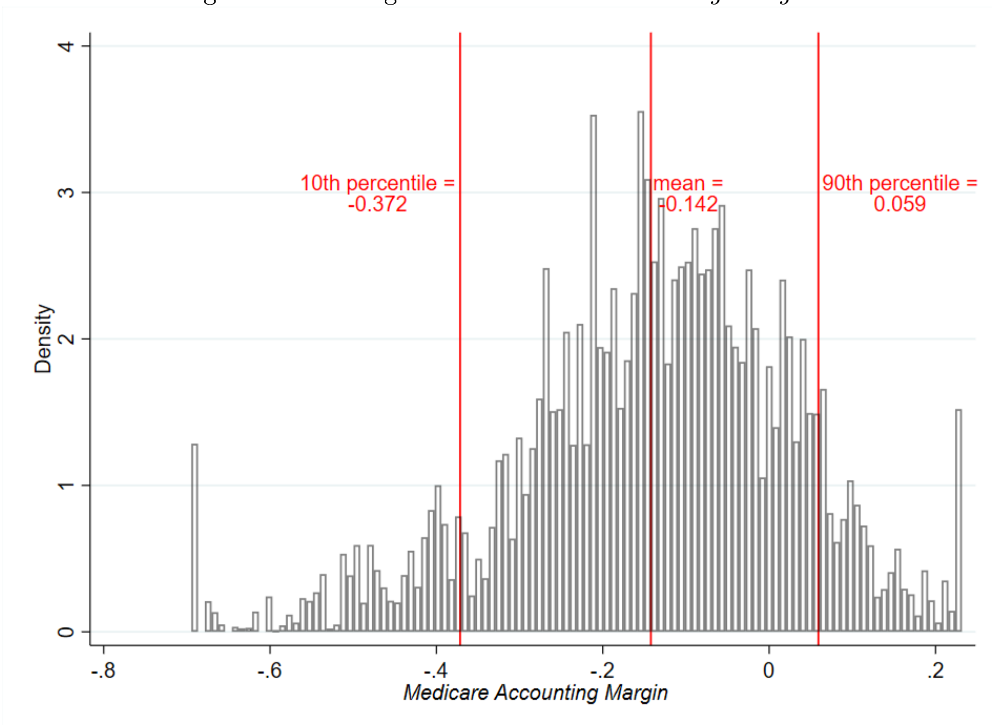
## A.3 Robustness checks by dependent variable

### A.3.1 Potential patient mix and Accounting Margins

This Appendix presents additional details on the relationship between potential payer mix and *Medicare Accounting Margin*. Figure A.2 shows the distribution of *Medicare Accounting Margin*. Consistent with

MedPAC and AHA reports, *Medicare Accounting Margin* is negative on average. The mean of *Medicare Accounting Margin* is -0.142 , the 10th percentile is -0.372, and the 90th percentile is 0.059.[38] We also find substantial dispersion across hospitals: the standard deviation is 0.173.

Figure A.2: Histogram of *Medicare Accounting Margin*




Notes: Margins are weighted by hospital costs.

Figure A.3 illustrates that in hospitals with higher values of *Medicare Accounting Margin*, have a higher *Predicted Private Share* and a lower *Predicted Public Share*; *Predicted Uninsured Share* is relatively constant across the deciles of *Medicare Accounting Margin*.

Table A.2 presents the relationship between predicated patient mix and three different margins. It confirms that *Medicare Accounting Margin* is higher when there is a higher *Predicted Public Share* and *Predicted Uninsured Share*. It also illustrates that higher *Predicted Public Share* and *Predicted Uninsured Share* lead to lower non-Medicare accounting margins and overall margins.

### A.3.2 Potential patient mix and Hospital Compare

This section explores the relationship between potential payer mix and other measures from Hospital Compare. Figure A.4 presents the relationship between *Predicted Private Share* and each of the three Hospital

[38]In recent years, MedPAC calculates that Medicare accounting margins for hospitals average roughly -0.14. Our estimates differ because MedPAC treats graduate medical expenses as a cost, whereas we do not. Furthermore, our sampling restrictions differ from MedPAC's.

Table A.2: Relationship between potential payer mix and Accounting Margins

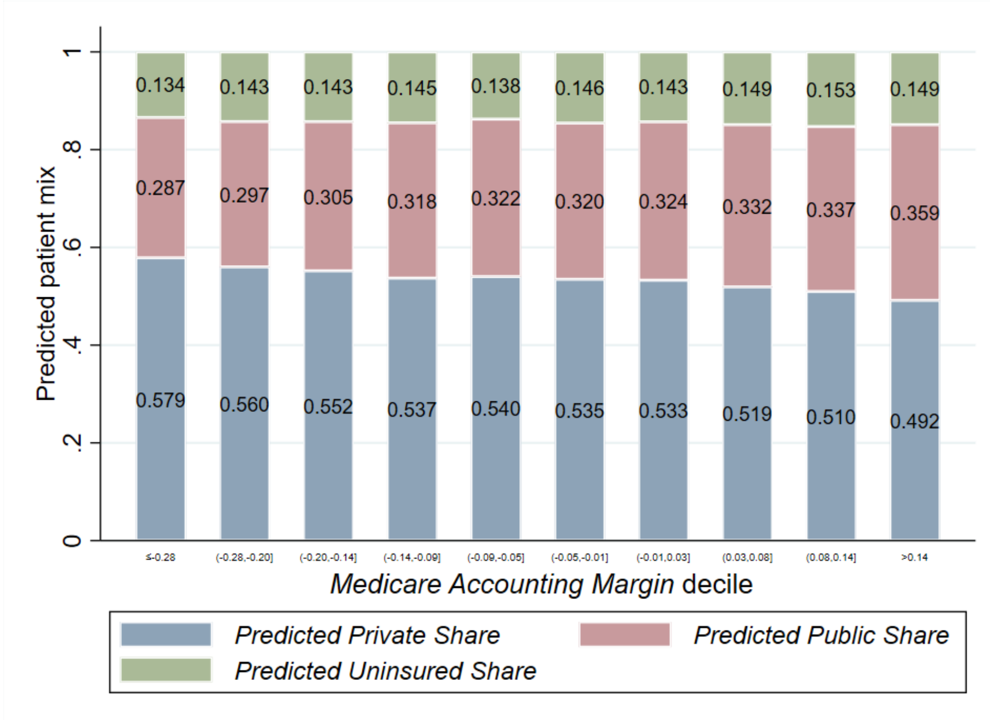
| Panel A: Medicare Accounting Margin | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Predicted Non − Private Share* | 0.697*** | | 0.656*** | |
| | [0.0388] | | [0.0562] | |
| *Predicted Uninsured Share* | | 0.775*** | | 0.481*** |
| | | [0.0521] | | [0.0734] |
| *Predicted Public Share* | | 0.567*** | | 1.185*** |
| | | [0.0701] | | [0.155] |
| HRR Fixed Effects | | | Y | Y |
| Observations | 2,255 | 2,255 | 2,255 | 2,255 |

| Panel B: non-Medicare Accounting Margin | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Predicted Non − Private Share* | -0.280*** | | -0.442*** | |
| | [0.0277] | | [0.0422] | |
| *Predicted Uninsured Share* | | -0.403*** | | -0.421*** |
| | | [0.0370] | | [0.0554] |
| *Predicted Public Share* | | -0.0730 | | -0.506*** |
| | | [0.0499] | | [0.117] |
| HRR Fixed Effects | | | Y | Y |
| Observations | 2,255 | 2,255 | 2,255 | 2,255 |

| Panel C: Total Accounting Margin | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Predicted Non − Private Share* | -0.110*** | | -0.263*** | |
| | [0.0215] | | [0.0337] | |
| *Predicted Uninsured Share* | | -0.245*** | | -0.323*** |
| | | [0.0286] | | [0.0442] |
| *Predicted Public Share* | | 0.118*** | | -0.0822 |
| | | [0.0385] | | [0.0930] |
| HRR Fixed Effects | | | Y | Y |
| Observations | 2,255 | 2,255 | 2,255 | 2,255 |

Notes: Unit of observation is the hospital. Observations are weighted by hospital costs. Standard errors are presented in brackets. Significance levels: * 0.10 ** 0.05 *** 0.01.

Figure A.3: Relationship between potential payer mix and deciles of *Medicare Accounting Margin*




Notes: *Medicare Accounting Margins* is from the Cost Reports. Section 2.1 describes the construct of hospital-level market characteristics.

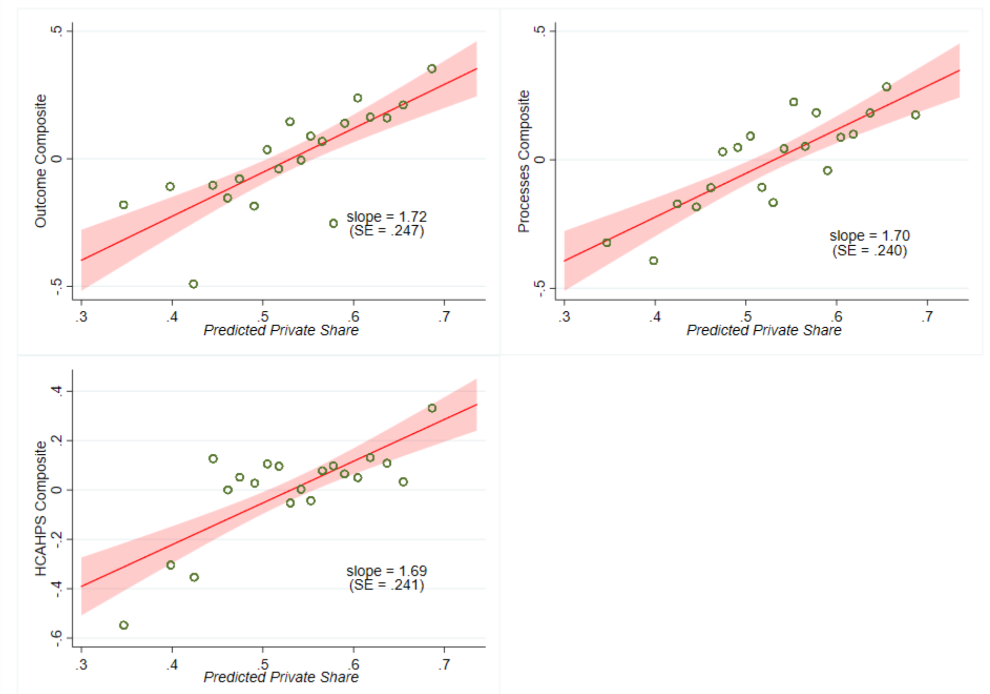
Compare sub-measures. There remains a strong and positive relationship between *Predicted Private Share* and quality across these measures. Table A.3 presents corresponding regression results.

### A.3.3 Potential patient mix and technology adoption

Figure A.5 presents the relationship between *Predicted Private Share* and each of the five technology adoption sub-measures. There remains a strong an positive relationship between *Predicted Private Share* and quality across these measures.

# B Additional Tables and Figures

Figure A.4: Relationship between *Predicted Private Share* and Hospital Compare measures




Notes: The dots are a binned scatterplot based of ventiles of the independent variable. The red line and shaded region are the least squares line and 95 percent confidence interval of the relationship between the variables. Analyses are weighted by hospital costs.

Table A.3: Relationship between potential payer mix and Hospital Compare quality

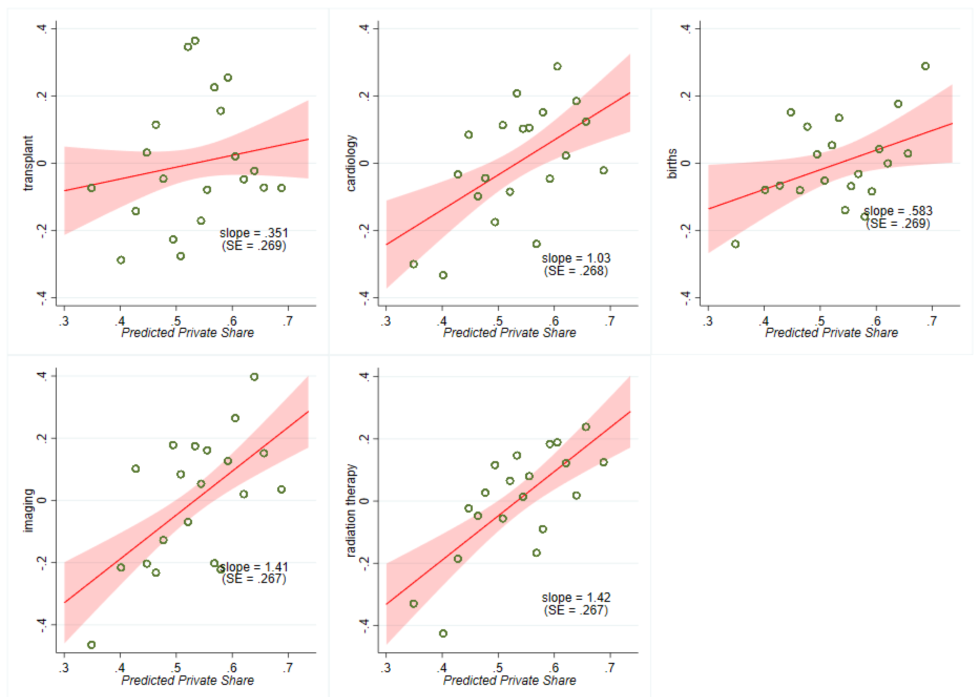
| Panel A: Outcomes Composite | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Predicted\ Non-Private\ Share$ | -1.724*** | | -2.705*** | |
| | [0.247] | | [0.363] | |
| $Predicted\ Uninsured\ Share$ | | -2.829*** | | -2.783*** |
| | | [0.331] | | [0.473] |
| $Predicted\ Public\ Share$ | | 0.141 | | -2.465** |
| | | [0.447] | | [1.002] |
| HRR Fixed Effects | | | Y | Y |
| Observations | 2,082 | 2,082 | 2,082 | 2,082 |
| **Panel B: Process Composite** | | | | |
| | (1) | (2) | (3) | (4) |
| $Predicted\ Non-Private\ Share$ | -1.702*** | | -3.284*** | |
| | [0.240] | | [0.373] | |
| $Predicted\ Uninsured\ Share$ | | -2.202*** | | -3.276*** |
| | | [0.322] | | [0.489] |
| $Predicted\ Public\ Share$ | | -0.856** | | -3.309*** |
| | | [0.435] | | [1.030] |
| HRR Fixed Effects | | | Y | Y |
| Observations | 2,212 | 2,212 | 2,212 | 2,212 |
| **Panel C: HCAHPS Composite** | | | | |
| | (1) | (2) | (3) | (4) |
| $Predicted\ Non-Private\ Share$ | -1.691*** | | -2.637*** | |
| | [0.242] | | [0.331] | |
| $Predicted\ Uninsured\ Share$ | | -1.606*** | | -2.197*** |
| | | [0.325] | | [0.432] |
| $Predicted\ Public\ Share$ | | -1.835*** | | -3.984*** |
| | | [0.438] | | [0.912] |
| HRR Fixed Effects | | | Y | Y |
| Observations | 2,189 | 2,189 | 2,189 | 2,189 |

Notes: Unit of observation is the hospital. Observations are weighted by hospital costs. Standard errors are presented in brackets. Significance levels: * 0.10 ** 0.05 *** 0.01.

Table A.4: Effect of sample restrictions on sample size

| | Number of Hospitals |
|---|---|
| Initial Sample of Hospital in Cost Reports | 6,227 |
| *Restrict to:* | |
| 49 states+DC (no MD) | 6,161 |
| General acute care hospitals | 3,499 |
| non-all inclusive rate providers | 3,432 |
| One observation per hospital | 3,373 |
| Has key variables | 3,112 |
| GME+IME $<$ 1 percent of Medicare allowed | 2,255 |

Figure A.5: Relationship between *Predicted Private Share* and technology adoption




Notes: The dots are a binned scatterplot based of ventiles of the independent variable. The red line and shaded region are the least squares line and 95 percent confidence interval of the relationship between the variables. Analyses are weighted by hospital costs.

Table A.5: Dependent variable summary statistics

| **Variable** | **Mean** | **Standard Deviation** | **Non-missing Observations** |
|---|---|---|---|
| *Medicare Accounting Margin* | -0.142 | 0.173 | 2,255 |
| *Non-Medicare Accounting Margin* | 0.121 | 0.118 | 2,255 |
| AHA technology adoption (overall) | 0.000 | 1 | 1,808 |
| Hospital Utility | 0.313 | 1.64 | 2,255 |
| Hospital Compare Composite | 0.000 | 1 | 2,218 |
| Time in ED for patients eventually admitted | 282 | 67.7 | 2,068 |
| Share cardiologists from top Med schools | 0.128 | 0.179 | 1,535 |
| Chandra et al. (2016) AMI survival per real resources | 0.887 | 0.025 | 1,744 |
| Observations | 2,255 | | |

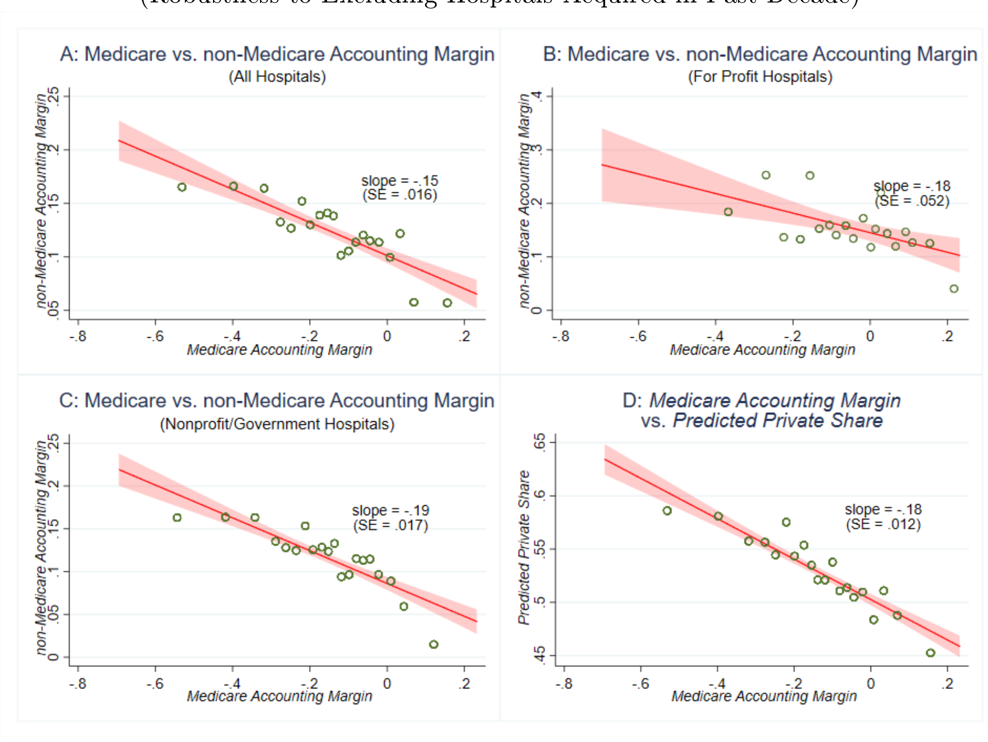
Notes: Means and standard deviations are weighted by each hospital's costs.

| | (1) | (2) |
|---|---|---|
| | Actual Public Share | Actual Uninsured Share |
| *Predicted Public Share* | 0.857*** | 0.0105 |
| | [0.0315] | [0.00931] |
| *Predicted Uninsured Share* | -0.332*** | 0.192*** |
| | [0.0424] | [0.0125] |
| Observations | 2,255 | 2,255 |

Table A.6: Relationship between potential payer mix and actual patient mix

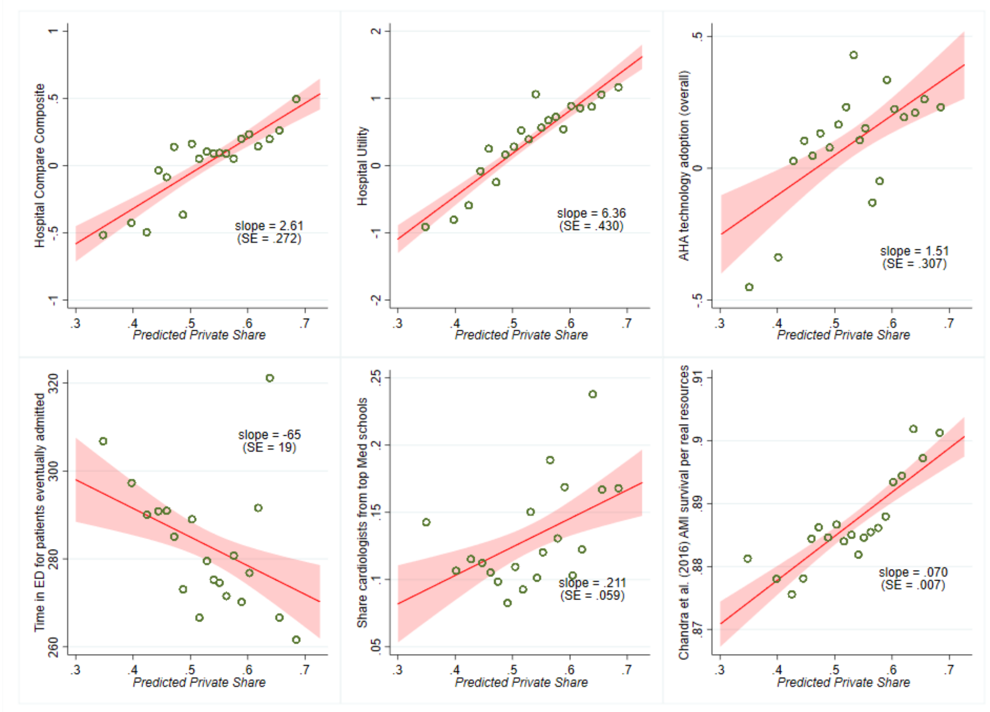
Notes: Unit of observation is the hospital. Observations are weighted by hospital costs. Standard errors are presented in brackets. Significance levels: * 0.10 ** 0.05 *** 0.01.

Figure A.6: Relationship Between *Medicare Accounting Margin* and Other Market Features (Robustness to Excluding Hospitals Acquired in Past Decade)




Notes: The dots are a binned scatterplot based of ventiles of the independent variable. The red line and shaded region are the least squares line and 95 percent confidence interval of the relationship between the variables. Analyses are weighted by costs.

Figure A.7: Relationship between *Predicted Private Share* and quality
(Robustness to Excluding Hospitals Acquired in Past Decade)




Notes: The dots are a binned scatterplot based of ventiles of the independent variable. The red line and shaded region are the least squares line and 95 percent confidence interval of the relationship between the variables. Analyses are weighted by hospital costs.

Table A.7: Relationship between potential payer mix and Catholic hospital status

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Predicted Non − Private Share* | -0.307*** | | -0.109 | |
| | [0.0909] | | [0.139] | |
| *Predicted Uninsured Share* | | -0.159 | | -0.282 |
| | | [0.122] | | [0.182] |
| *Predicted Public Share* | | -0.555*** | | 0.418 |
| | | [0.164] | | [0.383] |
| HRR Fixed Effects | | | Y | Y |
| Observations | 2,218 | 2,218 | 2,218 | 2,218 |

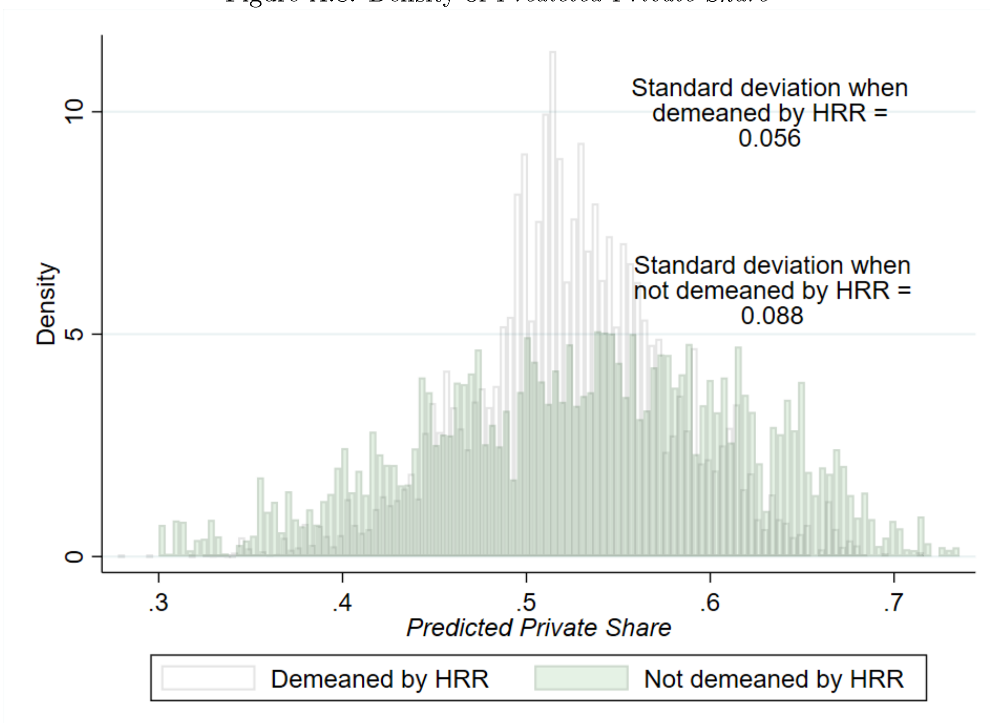
Notes: Unit of observation is the hospital. Observations are weighted by hospital costs. Standard errors are presented in brackets. Significance levels: * 0.10 ** 0.05 *** 0.01.

Table A.8: Main regression table
(Robustness to include hospitals with graduate medical education)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Predicted Share:* | AHA technology adoption (Overall) | | | | Hospital Utility | | | | Hospital Compare (Composite) | | | |
| *Non-Private* | -0.865*** | | -0.232 | | -5.959*** | | -6.318*** | | -2.520*** | | -3.998*** | |
| | [0.242] | | [0.380] | | [0.338] | | [0.369] | | [0.214] | | [0.298] | |
| *Public* | | -1.845*** | | -3.524*** | | -6.293*** | | -10.34*** | | -3.999*** | | -3.802*** |
| | | [0.335] | | [0.542] | | [0.472] | | [0.516] | | [0.296] | | [0.426] |
| *Uninsured* | | 0.467 | | 8.841*** | | -5.496*** | | 4.846*** | | -0.469 | | -4.544*** |
| | | [0.397] | | [1.142] | | [0.568] | | [1.085] | | [0.357] | | [0.897] |
| *HRR FEs* | | | X | X | | | X | X | | | X | X |
| *N* | 2,538 | | | | 3,069 | | | | 3,032 | | | |
| *Predicted Share:* | Time in ED (Patients eventually admitted) | | | | Share of Cardiologists from top medical schools | | | | AMI Survival Per Real Resource | | | |
| *Non-Private* | 197.0*** | | 171.4*** | | -0.312*** | | -0.139* | | -0.0800*** | | -0.0653*** | |
| | [21.41] | | [24.96] | | [0.0440] | | [0.0655] | | [0.00589] | | [0.00799] | |
| *Public* | | 211.7*** | | 24.83 | | -0.388*** | | -0.366*** | | -0.0598*** | | -0.0730*** |
| | | [29.78] | | [35.19] | | [0.0616] | | [0.0939] | | [0.00819] | | [0.0114] |
| *Uninsured* | | 176.4*** | | 585.3*** | | -0.209*** | | 0.480** | | -0.108*** | | -0.0434* |
| | | [35.97] | | [74.71] | | [0.0731] | | [0.195] | | [0.00983] | | [0.0244] |
| *HRR FEs* | | | X | X | | | X | X | | | X | X |
| *N* | 2,860 | | | | 2,302 | | | | 2,522 | | | |

Notes: Unit of observation is the hospital. Observations are weighted by hospital costs. Standard errors are presented in brackets. Significance levels: * 0.10 ** 0.05 *** 0.01.

Figure A.8: Density of *Predicted Private Share*




Notes: Densities are weighted by hospital costs.