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Assessing the quality of public services: For-profits, chains, and concentration in the hospital market

Johannes S. Kunz[1] | Carol Propper[1,2] | Kevin E. Staub[3] | Rainer Winkelmann[4]

[1]Monash Business School (Centre for Health Economics), Monash University, Melbourne, Victoria, Australia

[2]Department of Economics and Public Policy, Imperial College London, London, UK

[3]Department of Economics, The University of Melbourne, Melbourne, Victoria, Australia

[4]Department of Economics, University of Zürich, Zürich, Switzerland

Correspondence
Johannes S. Kunz, Monash Business School (Centre for Health Economics), Monash University, 900 Dandenong Road, 3145 Caulfield East, Melbourne, Victoria, Australia.
Email: johannes.kunz@monash.edu.au

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Abstract
We examine variation in US hospital quality across ownership, chain membership, and market concentration. We propose a new measure of quality derived from penalties imposed on hospitals under the flagship Hospital Readmissions Reduction Program, and use regression models to risk-adjust for hospital characteristics and county demographics. While the overall association between for-profit ownership and quality is negative, there is evidence of substantial heterogeneity. The quality of for-profit relative to non-profit hospitals declines with increasing market concentration. Moreover, the quality gap is primarily driven by for-profit chains. While the competition result mirrors earlier findings in the literature, the chain result appears to be new: it suggests that any potential quality gains afforded by chains are mostly realized by not-for-profit hospitals.

KEYWORDS
affordable care act, competition, hospital chains, hospital quality, hospital readmissions

JEL CLASSIFICATION
H51, I1, I11, I18

1 | INTRODUCTION

Historically, the US hospital industry has been characterized by a large role for non-profit organizations. However, over time the share of patients treated in for-profit hospitals and hospitals that are part of systems (chains) has increased considerably.[1] From 1993 to 2017, the share of for-profits rose from 18% to over 26%. Chain hospitals have experienced a similar increase and account now for roughly 75% of hospitals (AHA, 2019). Thus, as the industry evolves, the long-standing question of whether for-profits and non-profits behave differently, in a market increasingly dominated by chains, has become highly salient (e.g., Beaulieu et al., 2020; Capps et al., 2020).

A large body of theoretical literature suggests that for-profits and non-profits have different objectives (an example which focuses on public service providers is Besley & Malcomson, 2018). Early empirical studies provided mixed evidence for quality differences between for-profit and other hospitals.[2] More recent research has indicated that there exists a sizable raw quality gap between profit-oriented and other hospitals (e.g., Aswani et al., 2018; Gupta, 2017;

Herrin et al., 2015; Jindal et al., 2018; Paul et al., 2020). While chains in the hospital sector have been less studied, Eliason et al. (2019) found that the quality of dialysis care decreased in hospitals after acquisition by a chain.

Naturally, the behaviors and outcomes of hospitals can be expected to depend on the environment they are operating in, such as the patient pool, regulatory oversight, and also the local or regional competitiveness. Accordingly, an earlier literature has highlighted the interaction between ownership and market structure: when for-profits and non-profits operate in competitive environments, they may behave similarly, but this is not the case in non-competitive markets (Duggan, 2002; McClellan & Staiger, 2000; Sloan et al., 2001).

We contribute to this line of research by studying how these empirical regularities are affected by chain status. Given the large changes in the industry, this is a timely question. Our analysis uses publicly available data on all market participants for the period 2012–2016. Our preferred measure of quality is the non-time-varying latent risk of being fined under a flagship program designed to incentivize hospital quality. This is the national Hospital Readmission Reduction Program (HRRP), one of the largest and most successful schemes linking financial penalties to hospital performance. It imposed financial penalties on hospitals that had annual (risk-adjusted) readmission rates (RRs) for three emergency conditions above a threshold: acute myocardial infarction [AMI], heart failure [HF], and pneumonia [PN], for which over 70% of patients are admitted through the emergency room (Chandra et al., 2016).[3]

When considering hospital behavior, measures of quality that relate to incentivized metrics such as those in HRRP should reflect heterogeneity in strategic decisions (Mehta, 2019). This may differ by for-profit status. While penalties affect the trade-off between treatment cost and readmission probability, zero—or very few—readmissions may not be optimal from the point of view of hospital management. If the costs of avoiding readmissions are high, hospitals engaging in optimizing behavior will tolerate some penalties up to the point where marginal costs are equalized. Thus, systematic differences in the penalty likelihood between hospitals can be indicative of differences in the trade-off, or the way it is evaluated, between for-profits and non-profits. Competition may crowd out such strategic flexibility (Duggan, 2000; Gaynor et al., 2015; Moscelli et al., 2021).

Chain status means that hospitals are subject to central as well as local oversight. It is not immediately apparent how this might affect the difference between chain and non-chain hospitals with respect to the associations of for-profit status, local market competition, and quality. The market power derived from chain status may mean that chain hospitals can have lower quality than non-chain hospitals. However, this does not offer guidance as to the for-profit quality gap *among* chains. The negative quality gap between for and non-profits in the earlier literature was found to be driven out by competition. But again, it is not apparent the same will hold for chains. The greater national market power of chain hospitals may insulate them from this local competition.[4] Thus, whether the chain's national market power allows chain for-profit hospitals to have lower quality than non-profit chains in highly competitive *local* markets remains an open empirical question.

Our analyses show the following. For-profit hospitals on average are associated with lower quality. We also confirm the findings from the earlier literature on the importance of market structure, using more recent data and different quality measures: the for-profit quality gap for emergency condition treatments is larger in areas where there is less local competition. When we consider chain status per se, we find no quality difference. However, chain status matters, since the lower quality of for-profits is primarily driven by chain hospitals operating in less competitive markets.

Patient selection could be one factor explaining our findings. If sicker patients are treated in for-profit chain hospitals, these hospitals will appear to have lower observed quality, which, however might not reflect "true" quality differences. But our design weakens this line of argumentation implausible. First, we consider emergency conditions, where the place of treatment is by definition mostly determined by proximity and not by choice, as it would be the case for elective surgery for example, Second, we control for regional differences in population characteristics, by exploiting within-market variation that compares similar populations. Third, our findings on market structure effects are also not compatible with an explanation based on patient selection, since the quality differences increase as competition decreases, that is, in settings where there is less choice and thus less potential for selection. Fourth, and finally, if anything, for-profit hospitals should be expected to positively select their patients to avoid the readmission penalty. But this would bias our results away from finding lower quality among for-profits: we find they do have lower quality.[5]

Our results could also be affected by sorting of hospitals into different markets, based on unobserved factors that are also relevant for quality. We show that market concentration neither predicts the local for-profit share, nor the chain hospital share. The predictive effects of socio-economic characteristics sometimes suggest a negative selection of for-profits hospitals, and in other instances a positive one. The absence of a clear and strong pattern of selection-on-observables is indication that endogenous sorting on unobservables is unlikely to have a major impact on our results. We also control for the opening and closing of hospitals within the local market area in our risk adjustment measures, focus only on hospitals that did not change ownership in the sample period, and use pre-sample measures of market structure. Our results are robust to all these checks. Finally, it seems reasonable to assume that entry decisions would not be driven primarily by the HRRP quality measures we focus on.

Our findings relate to a recent literature that has started to document large adverse effects of outsourcing to private firms on the provision of quality. In the healthcare context, Knutsson and Tyrefors (2022) show that quasi-random assignment to private ambulances is associated with lower quality. Gupta et al. (2021) show that the recent rise in private-equity owners of nursing homes results in lower quality. Our finding of market structure heterogeneity in quality also echos the analysis of price by Cooper et al. (2019) who find that market concentration is strongly associated with price in hospital markets, with similar findings in Craig et al. (2021).[6] Our results also complement a study of quality provision in nursing homes (Hackmann, 2019), which finds that financial reimbursements are more important than competition in improving patient outcomes. Finally, our finding of heterogeneity by chain status and competition is related to a small but growing literature on chain status and private equity in the healthcare market. For the dialysis market, Eliason et al. (2019) found that chain status lowers quality, but quality does not react to local competition. However, that paper does not distinguish between the for-profit and non-profit status of the firms. For the nursing home market, Gandhi et al. (2020) find that private equity-owned nursing homes' quality provision can be more sensitive to competition, and in the retail pharmacy market, Janssen and Zhang (2020) find some evidence that quality improves with chain affiliation. Finally, the issue of market power has recently attracted renewed attention in many contexts (Benkard et al., 2021).

2 | ESTIMATION AND DATA

2.1 | Measures of quality

We begin by discussing our measures of quality. As noted above, our preferred measures are derived from the HRRP. This has several benefits. First, "excess readmissions" are the measure the government uses to incentivize higher quality. Second, the penalties for having excess readmissions can be considerable: the Centers for Medicaid and Medicare Services [CMS] expected to recover $526 million in 2017, or 0.3% of overall Medicare payments going to hospitals. The penalty per excess readmission is about five to six times the Medicare base payment for a hospital stay for the particular condition (MedPAC-Report, 2018), and therefore much greater than the revenue to be gained from the readmission (Gupta, 2021). Thus, these quality measures are likely a choice variable for hospitals (Garthwaite et al., 2020). Third, the usefulness of these performance metrics is further underscored by them being predictive of market-shares (Chandra et al., 2016) and, at the regional level, are correlated with deaths from COVID-19 (Kunz & Propper, 2022).

The HRRP (detailed in Appendix A) takes the raw admission rates for three incentivized emergency conditions (AMI, HF, PN) and adjusts these for potential differences in patient populations to derive the excess readmission ratio [ERR]. This is the probability of readmissions relative to the average hospital with a similar case-mix (known as *peer-benchmarking*, Zhang et al., 2016). The penalty is applied if the ERR exceeds one in any of the three conditions. This cut-off is the policy-relevant discontinuity introduced into the hospital's cost function (Gupta, 2021).

These measures have been criticized because risk-adjustment is only performed on age, sex, and other health conditions (co-morbidities) of the patients and does not take into account the differences in socioeconomic characteristics of the patients these hospitals serve (e.g., Aswani et al., 2018; Gu et al., 2014). Further, these measures are likely affected by regression to the mean (Joshi et al., 2019) and are over-reliant on small disturbances (Chandra et al., 2016). To address all these points, instead of using the raw measures directly, we perform an additional risk adjustment by extracting latent quality as measured by fixed effect for each hospital, and each condition (such approaches are often called *profiling*, *cf*. Normand et al., 2016). This approach adjusts for additional covariates and deals econometrically with the issue of the small number of only five annual observations for each hospital.

We use OLS for the RR and the ERR and probit for the penalty status of the form.

$$E(y_{itc}|\alpha_{ic}, x_{it}) = \alpha_{ic} + x_{it}'\beta \tag{1}$$

$$E(Penalty_{itc} = 1|\alpha_{ic}, x_{it}) = \Phi(\alpha_{ic} + x_{it}'\beta), \tag{2}$$

Where y_{itc} denotes the different outcomes we consider: the patient survey, raw 30-day mortality, raw 30-day RR, or the adjusted ERR. $Penalty_{itc}$ is an indicator of hospital i being penalized in year t for exceeding readmissions in emergency condition c, that is, $ERR_{itc} > 1$, and $\Phi(\cdot)$ denotes the standard normal CDF. The vector x_{it} contains time-varying covariates at the hospital, Hospital Referral Region [HRR], and county level (detailed in Section 2.3 below), as well as year indicators to control for common time shocks. We cluster standard errors at the hospital level.

Our interest lies in the fixed effects (FE), α_{ic}, which represent measures of the underlying hospital quality over the whole sampling period. We estimate several variants of the models: first, we pool across conditions resulting in one fixed effect per hospital, $\alpha_{ic} = \alpha_i$ for all i (3917 FE); second, interacted condition×hospital FE, α_{ic} (8713 FE); third, estimating the regressions separately by condition.[7]

To deal with large and imprecise outliers, researchers often shrink the estimated FE toward their mean using Empirical Bayes.[8] We follow this literature for the OLS FE estimates in Equation (1).[9] For the penalty status measure—equation (2)—we use a bias-reduced fixed effect probit approach (Kunz et al., 2021). This method's bias-reduction shrinks the α_{ic} during estimation. Intuitively, it achieves this by adding a particular penalty term to the probit score function, which results in the FE being shrunk toward zero. While serving the same purpose as Empirical Bayes for the linear model, this method also removes incidental parameter bias and it avoids the perfect prediction problem that affects the estimation of these types of nonlinear models. In our context, the perfect prediction problem means that any information in the covariates would be discarded when hospitals are always or never fined, as the corresponding predicted fixed effect (α_{ic}) would be infinite. For such cases, shrinkage after estimation, such as with Empirical Bayes, would obviously not be possible as no estimates are obtained. In our application, the problem of hospitals being either always or never fined is particularly relevant since roughly 50% of hospitals did not change their penalty status during our 5-year sample period.[10] In addition, Empirical Bayes often involves assumptions such as homogeneity, which cannot be satisfied with binary outcomes (Frederiksen et al., 2020). In contrast, the bias-reduction approach we pursue avoids any additional assumptions used for Empirical Bayes: the method automatically shrinks the FE toward the conservative benchmark of the marginal hospital with neither positive nor negative relative quality.

The predicted FE from Equation (2), $\hat{\alpha}_{ic}$, are used to calculate the marginal penalty propensities, $MPP_{ic} \equiv \Phi(\hat{\alpha}_{ic})$ (and $MPP_i \equiv \Phi(\hat{\alpha}_i)$ respectively), which can be thought of as the propensity to be fined if the hospital would otherwise be marginal, in the sense of being equally likely to be fined or not fined $\left(x_{it}'\hat{\beta} = 0\right)$. These estimated MPP_{ic} are model-consistent as they respect the [0; 1] bounds without any ad hoc adjustments. More details on the estimator can be found in Appendix B.

2.2 | Assessing quality differences

In a second step, we use the OLS and probit FE in order to estimate the quality differences between for-profit and other hospitals, and how they interact with market structure and chain status.[11] Rather than making simple mean comparisons, we seek to account for further potential confounding factors that characterize the hospital, the county or the referral region but that are time-invariant, so could not be included in the first-step models.

We therefore estimate cross-sectional OLS regressions of the form:

$$MPP_{i,hrr,c} = \gamma_1 \text{For - profit}_i + \gamma_2 \text{For - profit}_i \times \text{HHI}_{hrr} + z_i'\beta + \delta_c + \theta_{hrr} + \varepsilon_{i,hrr,c} \tag{3}$$

where MPP is our preferred measure of hospital quality, z_i contains time-invariant hospital and county level controls (see Section 2.3 below), δ_c denote emergency-condition FE and θ_{hrr} are hospital-referral-region (HRR) FE. Note that county level effects can be estimated despite the presence of HRR FE, because there are on average about 10 counties per HRR.

To examine whether the quality difference between for-profit and non-profit hospitals changes with market conditions, we interact the for-profit indicator with a measure of market concentration, the Herfindahl-Hirschmann Index (HHI), computed for the HRR using contemporaneous as well as "pre-treatment" market structure, that is, in 2008 before the penalty program was introduced. Equation (3) is a cross-section equation without time dimension. While HHI itself is perfectly collinear with the regional FE, and the HHI main effect must therefore be dropped from the equation, identification of the interaction effect γ_2 is possible, because in any HRR there is a mix of hospitals, some of them for-profit and others non-profit. Multiplying ownership status with a non-varying HHI index allows us to identify the competition effect even if HHI only varies across HRRs and HRR FE are included.[12]

We repeat the analysis replacing the for-profit indicator in (3) with an indicator for the hospital belonging to a chain. Finally, to test for the impact of being part of a hospital chain, we stratify our analysis by whether or not the hospital is part of a (large) chain, defined as being in the top tercile of the size distribution.

It is important to point out that our empirical strategy for estimating the for-profit quality gap relies on a three-level adjustment for risk-differences in the patient pool. The first level uses individual level risk factors, such as age and co-morbidities, and is already accounted for in the readmission penalty measure we use. The second level, based on longitudinal models (1) and (2), takes out time-varying socio-economic differences in the patient pool, and the third level, based on cross-sectional model (3), accounts for further potential confounders that are time-invariant but vary by hospital, county or referral region. While remaining quality relevant for-profit/non-profit differences in unobserved characteristics cannot be ruled out, our approach substantially limits the scope for such selection-on-unobservables.

2.3 | Data and explanatory variables

Our data are from the administrative Hospital Compare dataset provided by the Centers for Medicare and Medicaid Services [CMS], which gives information on penalties for the period 2012–2016. Reporting is delayed by one year, so the data relating to the 3-year aggregates of readmissions during 2011–2015. For each of the 3197 included hospitals, each of the three emergency conditions, and every year, we know whether or not a penalty was issued (there are 8713 hospital×condition and 41,095 hospital×condition×year observations). As noted above, using profiling for Equations (1) and (2), we extract from the outcomes the latent hospital quality that is not driven by aggregate changes over time and local area characteristics beyond the hospital's control. We follow the extant literature (Chandra et al., 2016; Gu et al., 2014) to select relevant covariates. In Equations (1) and (2), we use the following HRR- and county-level controls. Measures defined at the HRR-level are taken from the Dartmouth Atlas of Health Care. We use the number of discharges for ambulatory-care-sensitive conditions (ACSC), indicating the lack of accessible primary health care facilities in the area (Gu et al., 2014), as well as changes in the number of hospitals in the region (Chandra et al., 2016), via changes in the hospital market (i.e., opening and closing of hospitals in the HRR). At the county level, we use the Federal Information Processing Standard and the American Community Survey to add community characteristics, such as the poverty rate, the unemployment rate as well as the median household income, which have been discussed as determinants of RRs outside the control of the hospital (Herrin et al., 2015). Another control variable is the number of discharges in the emergency conditions, in order to account for the different sizes of the hospitals and the populations they serve.

Most hospital-level variables display little or no variation over time, and while it is essential to control for these (Normand et al., 2016), they can only be included in the second step estimation. We therefore add the following additional time-invariant controls not included in Equations (1) and (2) to Equation (3): two hospital variables, namely an indicator for teaching status and the number of beds, plus several county level level controls, in addition to those already included in the profiling Equations (1) and (2): the population share of medicare recipients, the ethnic composition as well as the education level (all for 2010). We also include an urban/rural dummy as it is known that people living in rural areas face disproportionately poorer health outcomes compared to those living in urban areas.

To measure local market (HRR-level) concentration, we construct a standard measure of competition, the HHI, based on the number of beds. We also examine sensitivity of results to alternative concentration measures, such as: (1) HHI based on discharges in the respective emergency conditions; (2) treating hospitals that belong to the same chains as one hospital (Hausman & Lavetti, 2021); (3) calculating the HHI from discharges before the HRRP (in 2008) to address concerns over endogeneity of location (our preferred specification).

In addition to the marginal penalty propensity, we also examine four other quality measures. These are patient satisfaction (the share that would recommend the hospital), the 30-day mortality rate; the 30-day raw RR; and the risk-adjusted ERR (i.e., the basis for our penalty propensity measure).[13] The variables and data sources are in Appendix D, and the descriptive statistics are in Table C1.

2.4 | Association of quality measures and spatial distribution

We begin by graphically showing our extracted quality FE (the risk-adjustment regressions are presented in the Appendix C2). Figure 1 shows the association of our quality measure with the other less incentivized hospital-wide quality metrics (for this, we pool across the three condition-specific hospital estimates to obtain a single hospital-level quality measure). The three graphs show that the rank ($Rank(\alpha_i)$) in the hospital quality measure (grouped into 100 bins) correlates, respectively, with the overall RR,[14] the average hospital mortality (in the same condition) and patient satisfaction. While these three measures are not risk-adjusted, all three correlate positively with our quality measure; the RR and patient satisfaction, very strongly so. The strong correspondence between our objective and subjective measures (the patient survey responses) is notable, as *ex-ante* it is not obvious that patients would value the same quality dimensions as those related to readmissions or even mortality. These results suggest that our penalty propensity measures a common hospital quality. In the Appendix, we show that our penalty status measure is strongly correlated across the three different penalized conditions, further suggesting that the measure picks up overall hospital quality rather than department-specific quality (cf. Figure C3).

Next we turn to MPP_i, our penalty propensity measure of hospital quality. Figure 2, Panel A, shows its substantial spatial heterogeneity across the 307 HRRs (see also Finkelstein et al., 2016). The estimated propensity of being penalized varies from 15% to 95%, with an interquartile penalty-propensity difference of nearly 15% points (p.p.). Panel B shows the distribution of for-profit hospital shares. Panel C shows that of chain shares.[15] Panel D shows the distribution of market concentration. Overall, the maps show considerable dispersion in all three measures and no obvious mapping in geographical space between quality, for-profit status, and market concentration. Further, a comparison of Panels A and B shows that for-profits are not necessarily more likely to be located in higher-penalty areas.

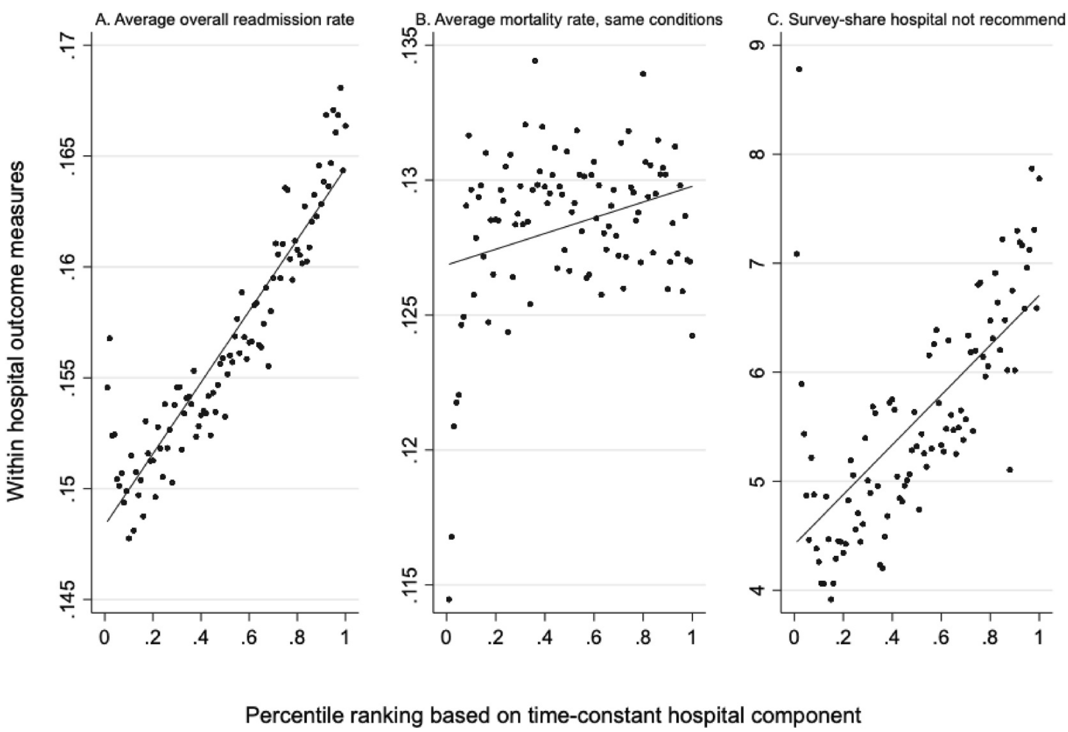
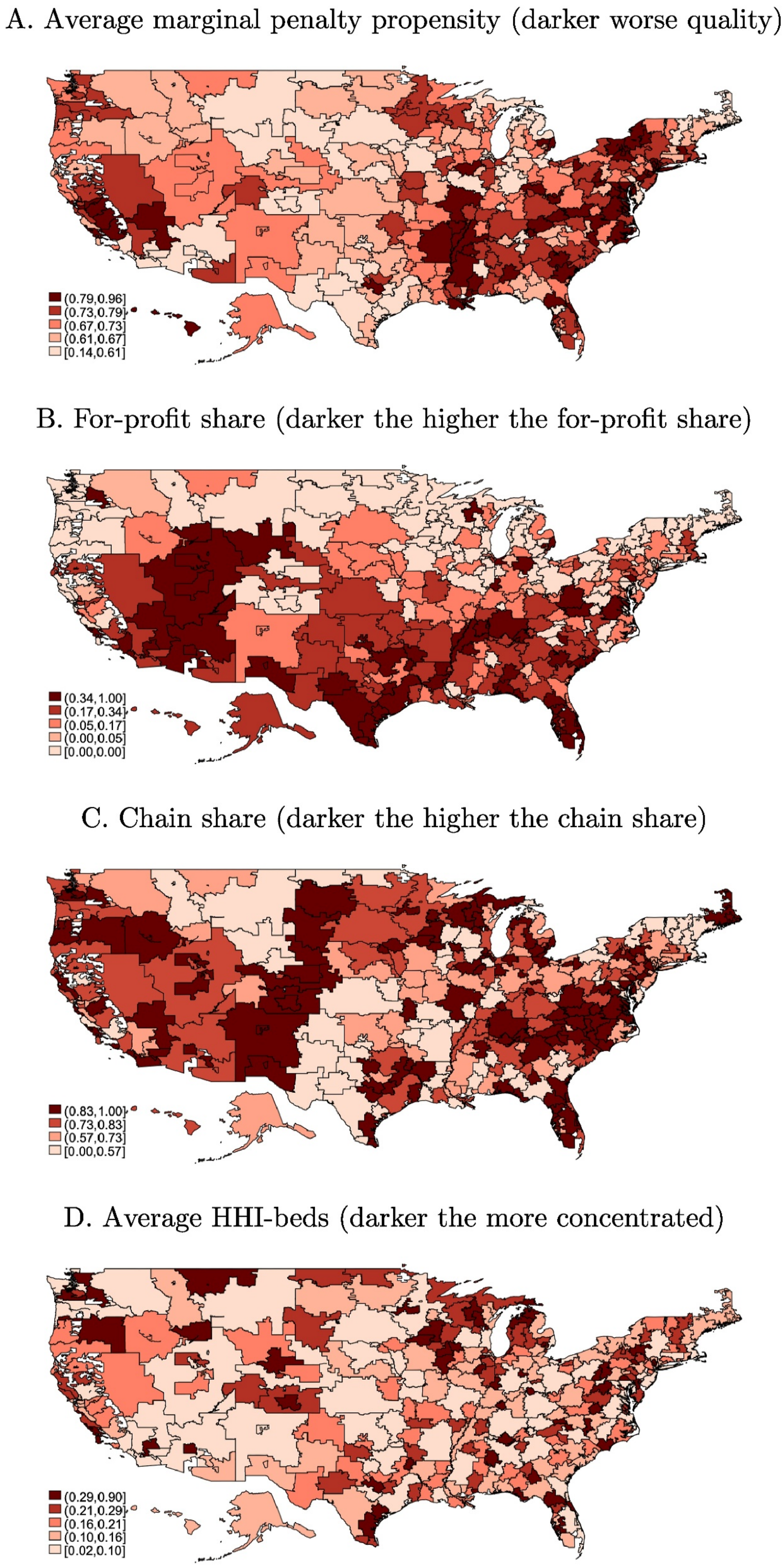


FIGURE 1 Within hospital readmission penalty propensity across diagnosis-related groups, binned. Figure plots bins of hospital FE and corresponding averages of other quality measures: overall readmission rate, mortality rate in respective emergency conditions, patient survey responses. The x-axes are identical and based on the pooled regression model (Column 4, Table 2). These estimated FE are ranked and binned into 100 equal-sized percentile ranks. Within each rank, the y-axis quality measures are averaged. (a) overall readmission rate in the hospital (b = 0.0161(se 0.0001) R2: 0.856), (b) the average mortality across time and the 3 diagnosis groups (b = 0.002(se 0.00017) R2: 0.080), and (c) the survey based share of people answering they would not recommend this hospital (b = 2.285(se 0.045) R2: 0.447). *Source*: Centers for Medicaid and Medicare Services [CMS] 2011–2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations. ACS, American Community Survey; FE, fixed effects.

FIGURE 2 Average hospital adjusted readmission penalty propensities, for-profit share, and average Herfindahl-Hirschmann Index (HHI) across hospital referral regions. Figure plots, (a) average hospital penalty-propensity (for the marginal hospital) across the map of hospital referral regions (HRR), based on averages of marginal penalty propensity using the interactive FE of Table 2, Column 5. (b) depicts the share of for-profit hospitals in HRRs, (c) is the share of chain hospitals, and D is the average HHI based on the number of beds. *Source*: Centers for Medicaid and Medicare Services [CMS] 2011–2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations. ACS, American Community Survey; FE, fixed effects.



2.5 | Predicting for-profit and chain status

In this section, we provide evidence on the sorting of hospitals ownership types into different markets. Markets are characterized by the health fundamentals of their local population as well as by the industry structure, that is, the level of competition. If, for example, for-profit hospitals were serving primarily richer urban neighborhoods, whereas non-profits are equally present everywhere, we would expect to find a lower re-admission rate, on average, among for-profit hospitals.

It is simple to check for differences in *observed* market characteristics by ownership status. In this spirit, Figure 3 examines whether for-profit or chain status is associated with local market (HRR) concentration. The left panel shows the unconditional association between the share of for-profits in a local market and local market HHI, within percentile bins. The right-hand panel shows the same association for the share of chains. There is virtually no association between the share of for-profits in a local market and market concentration (slope coefficient −0.0002, s.e. 0.0004), nor between the share of chains and market concentration (slope 0.0004, s.e. 0.0005). Both associations are far from being economically or statistically significant at conventional levels. This provides evidence that (lagged) market concentration does not predict for-profit status or chain status.

This is confirmed by the predictive regressions in Table 1. We see again that local competition (Average HHI in discharges) does not predict for-profit ownership or chain status. There are a number of socio-economic factors that predict ownership type (as judged by statistical significance), but there is no uniform pattern in these partial associations: for example, being a rural area with high unemployment predicts a *lower* for-profit share, while a lower household median income and a higher share of highschool dropouts predict a *higher* for-profit share. There is no systematic evidence of cream skimming here.

Our analyses below control for all the predictors appearing in Table 1 (and others). Of course, there may still be residual confounding. For example, the concentration index at the HRR level may be too crude to capture the true competitive environment a hospital finds itself in, and similarly, the county-level socio-demographics hospital ownership may be endogenous to unobserved characteristics of patients in the nearby market that are not captured by our county-level socio-demographics. However, the lack of systematic selection-on-observables makes us feel more comfortable with the assumption that selection-on-unobservables is not driving our results.

Another concern might be that for-profits and/or chains may target hospitals whose quality is declining. We address this by restricting our analysis sample to hospitals with constant ownership through the 2012–2016 period. We also repeat our analysis constraining the sample to only hospitals which have not changed ownership in 10 years and find similar results to those using the full sample. Finally, it seems reasonable to assume that ownership decisions are not driven primarily by the HRRP quality measures that we are studying as an outcome.

Nevertheless, in Figure 4 we present an exploratory event study of the hospitals that change to for-profit ownership in our sample period. While we discard these observations in our main analysis due to the concerns mentioned above, the different sample and the different source of variation —within hospitals but over time— provide an alternative and complementary empirical lens through which to look at the issue of ownership and quality. The figure plots the average quality of these hospitals from 4 years before to 4 years after they become for-profits, as measured by the penalty and ERR. While it is important to keep in mind the much smaller sample size (139 unique hospitals) and relatively short time dimension, looking at the pre-acquisition trend, the graphs do not support the idea of private firms acquiring

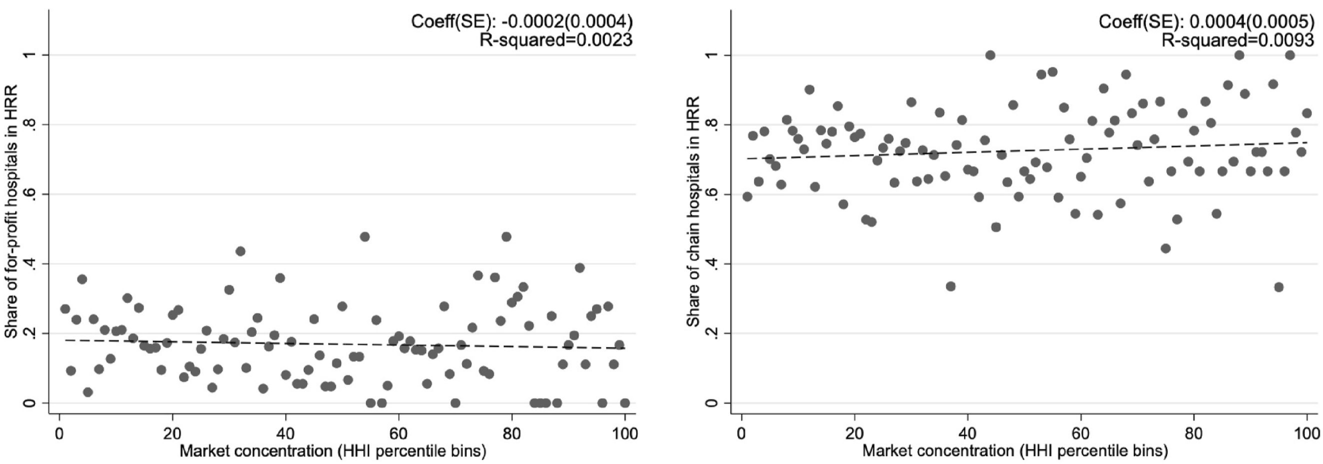


FIGURE 3 Share of for-profit and chain hospitals by local competition. The left panel shows the HRR-level share of for-profit hospitals for each percentile bin of the average Herfindahl-Hirschmann Index (HHI) in discharges (averaged across conditions and years), as well as the slope and the R2 of the fitted line, and in the right panel analogously for the share of chain hospitals. *Source*: Centers for Medicaid and Medicare Services [CMS] 2011–2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations. ACS, American Community Survey.

TABLE 1 Predicting ownership: For-profit, chain, and for-profit chain status.

	For-profit (1)	Chain (2)	For-profit chain (3)
Percent ages 65 and older (2010, county)	0.004	−0.001	0.004
	(0.002)	(0.003)	(0.002)
Rural area (county)	−0.010	−0.049	−0.012
	(0.005)	(0.006)	(0.005)
Percent unemployed, in county	−0.009	0.003	−0.004
	(0.004)	(0.004)	(0.003)
Total population in 100′000, in county[a]	0.039	0.025	−0.015
	(0.050)	(0.056)	(0.047)
Household median income in 10′000$, in county	−0.018	−0.013	−0.015
	(0.010)	(0.012)	(0.010)
Percent living in poverty, in county	−0.003	0.006	−0.002
	(0.003)	(0.003)	(0.002)
Discharges ACSCs per 1′000 enrollees, in HRR	0.003	−0.002	0.002
	(0.001)	(0.001)	(0.001)
Average HHI in discharges	−0.058	0.047	−0.072
	(0.061)	(0.068)	(0.057)
Hospitals per head in HRR	−0.005	−0.009	−0.003
	(0.007)	(0.008)	(0.006)
Percent less than high school (2010, county)	0.008	−0.006	0.006
	(0.002)	(0.002)	(0.002)
Percent black non-hispanic (2010, county)	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)
Percent hispanic (2010, county)	0.003	−0.001	0.002
	(0.001)	(0.001)	(0.001)
N	3197	3197	3197
R^2	0.046	0.055	0.029

Note: Table presents coefficient estimates (and standard errors in parentheses) from OLS regressions. Columns (1) regresses the For-profit status indicator on the area-level covariates indicated in the rows; Col. (2), the chain status indicator; and Col. (3), the For-profit chain status indicator.

Abbreviation: ACS, American Community Survey.

[a]further standardized by 100 for expositional purposes.

Source: CMS 2011–2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

hospitals whose quality is deteriorating, nor –looking at the post-acquisition trend– the quality of the hospitals increasing after acquisition.

3 | RESULTS

3.1 | Readmission performance by hospital ownership

Table 2 presents the quality differences between for-profits and other hospitals for the five quality measures. Columns (1)-(3) show the unconditional means and raw differences pooled across years and conditions. Quality is unconditionally

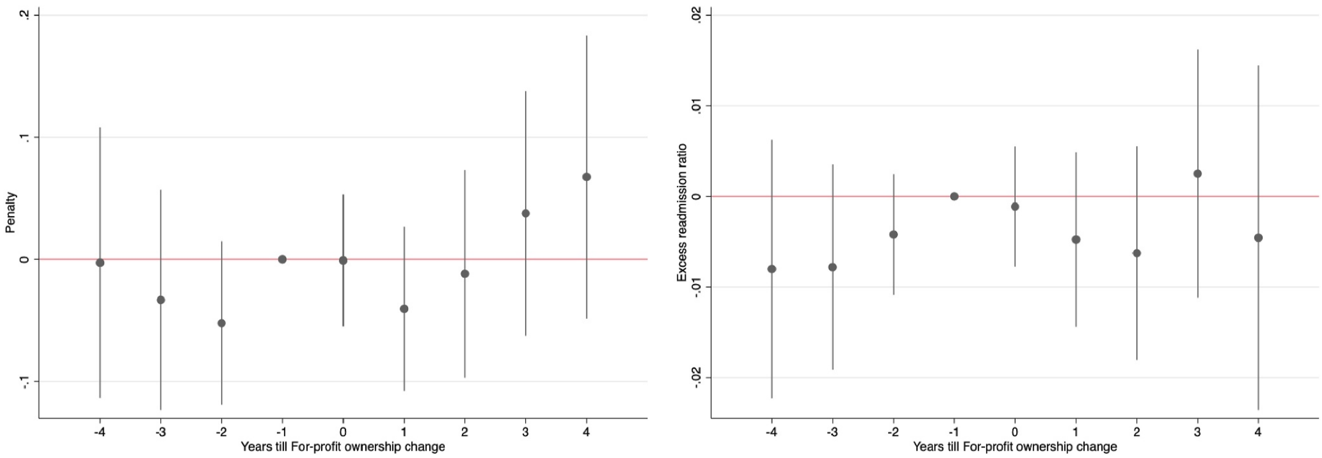


FIGURE 4 Quality measures before and after ownership change to for-profit. Regression estimates and 95% confidence intervals of the average quality of hospitals changing ownership from non-profit to for-profit, from 4 years before to 4 years after the change, relative to the quality in the year before takeover (normalized to zero). Dependent variables: penalty (left) and excess readmission ratio [ERR] (right). Total number of observations (condition-hospital-years): 1716 (139 unique hospitals, 652 hospital-years). *Source*: Centers for Medicaid and Medicare Services [CMS] 2011–2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations. ACS, American Community Survey.

TABLE 2 For-profit differential in hospital performance.

	Unconditional means			Covariate-adjusted for-profit difference	
	For-profit (1)	Other (2)	Difference (3)	Hospital-level (4)	×condition (5)
Share would not recommend this hospital	7.327	5.213	2.114	1.471	
	(0.160)	(0.060)	(0.170)	(0.132)	
30-day mortality rate×100	12.920	12.878	0.043	0.039	0.067
	(0.051)	(0.023)	(0.055)	(0.044)	(0.069)
30-day raw readmission rate (RR)	0.199	0.196	0.003	0.001	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Risk-adjusted excess readmission ratio (ERR)	1.012	0.999	0.013	0.007	0.008
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Penalty	0.545	0.474	0.071	0.023	0.030
	(0.012)	(0.006)	(0.013)	(0.010)	(0.010)
Observations[a]	7997	33,098	41,095	3197	8713
Hospital and area characteristics				✓	✓
Diagnosis indicators					✓

Note: Table presents various measures of readmission performance: survey share would not recommend the hospital, the 30-day mortality rate (×100), Raw readmission rate - RR, excess readmission ratio - ERR (CMS-risk-adjusted based on age, gender and co-morbidities), and an indicator for penalty status, whether ERR >1, by ownership status (for-profit and other hospitals). Column (1) presents averages (and standard error, clustered on hospital-level, in parentheses) across hospital×condition(AMI,HF,PN)×year(2011–2015) for For-profit and Column (2) for other hospitals. In Column (3), we present the unconditional mean difference of Columns (1) and (2) for RR as well as ERR and the marginal effect from a Probit model. Columns (4) and (5), present the coefficient of a regression of FE obtained from models (1) and (2) on the for-profit[5] indicator plus the time constant covariates (urban setting, teaching status, chain status, etc.). For the mortality rate, raw readmission rate, and ERR, we first run an OLS regression on time-varying covariates (number of discharges, median household income in the county, etc.) and extract the FE, which are then shrunken via Bayes-adjustment (Chandra et al., 2016), for the Penalty status we use an analogous procedure via bias-reduced FE probit model that embeds a shrinkage (Kunz et al., 2021).

Abbreviations: ACS, American Community Survey; FE, Fixed Effects.

[a]Note that observations refer to ERR as well as Penalty; for the RR, six hospitals did not have an RR, and about 1000 have no condition-specific mortality rate by condition (i.e., not reported due to small counts). Also, survey results are available only at the hospital level. Table C1 presents descriptive statistics by penalty status. More on the construction and definition of the variables used can be found in Appendix Table D1.

Source: CMS 2011–2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

lower in for-profits on all measures. These differences are statistically significant for all measures except the 30-day mortality rate.[16] So, for example, the third row of the table shows for-profits have a statistically significant 0.3 p.p. higher rate of readmissions, which corresponds to around 10% of the total reduction in readmissions over the sample period, which fell from 21.5% to 17.8% (and was considered a success, e.g. Zuckerman et al., 2016). The fourth row presents the raw CMS measure, which adjusts for gender, age, and co-morbidities, and compares the adjusted rate to expected readmissions using comparable hospitals. Column (3) shows a 1.3 p.p. for-profit difference, indicating that the quality gap is not driven by differential coding of co-morbidities (one strategy by which hospitals reduce their penalty risk, Ody et al., 2019).[17] The final row shows the quality difference measured by our preferred penalty status measure. Column (3) shows that for-profits have a 7.1 p.p. higher probability of being penalized.[18] Using these measures, for-profit hospitals appear to provide lower quality services.

However, these measures have been criticized for insufficiently accounting for risk and market-level factors. Columns (4) and (5), therefore, use FE estimated from the linear Equation (1) (α_i and α_{ic}) and marginal penalty propensities from the probit Equation (2) ($MPP_i = \Phi(\alpha_i)$ and $MPP_{ic} = \Phi(\alpha_{ic})$), as the outcome measures, regressed on the for-profit indicator and additional time-constant covariates. As discussed above, these measures are risk-adjusted for a large number of time-varying covariates and include shrinkage. Column (4) pools the three target conditions (α_i or MPP_i, respectively). The for-profit gap in all measures (except, again the 30-day mortality) remains large and statistically significant, although smaller than without the additional adjustments. We estimate a 0.1 p.p. higher readmissions rate, a 0.7 p.p. higher ERR, and a 2.3 p.p. higher marginal penalty propensity. Using the expected $526 million penalties as a benchmark (MedPAC-Report, 2018), this amounts to 12 million per year expected to be paid in excess by for-profits. Column (5) shows the results estimating one fixed effect for each hospital×condition (α_{ic} or MPP_{ic}), which allows for inherent differences across the three conditions. The for-profit gap is slightly larger than in Column (4). For example, the difference is three p.p. In the marginal penalty propensity, corresponding to a 6.3% increase from the mean of 47.4%.[19] That all these measures, adjusted or not, point in the same direction makes it unlikely that this conclusion is driven by hospital coding choices.

3.2 | Quality, ownership, and concentration

Since Table 2 shows qualitatively similar results across the different quality measures, our subsequent analyses use only our penalty propensity measure as it contains the most correction for patient selection and measurement error. Table 3 examines the interaction between for-profit status, chain status, and market concentration. It shows the differences in quality associated with competition by profit (Panel A) and chain status (Panel B).

Column (1) uses MPP_{ic}, and all time-constant covariates, the coefficient in Panel A is, therefore, the same as that in the last row of Column (5) in Table 2, as a benchmark. The marginal probability of incurring a penalty (i.e., having lower quality) is three p.p. higher for for-profit hospitals. As noted above, a small number of hospitals changed their for-profit status during the observation period. Column (2) omits these hospitals from the estimation sample. The for-profit gap remains the same (3.1 p.p.). Column (3) additionally controls for HRR FE. Once we include those FE, the gap increases to 5.2 p.p.; this means that for-profit hospitals are over-represented in regions where time-invariant regional characteristics (including potentially a high level of competitiveness, see e.g. Figure 3) would predict a high quality, and thus a low marginal penalty propensity. Comparing for-profits and non-profits within a referral region, this effect is differenced out.

In Columns (4)-(7), we test the hypothesis that competition may drive out the for-profit differential by interacting the for-profit indicator with the market-level HHI for the respective penalized condition while continuing to condition on HRR FE (which absorb the baseline level of competition). Column (4), Panel A, shows that the for-profit gap drops back to 3.3 p.p. for hospitals in markets with zero concentration. For the average HHI value, based on bed numbers ($mean(HHI) = 0.14$), the for-profit differential in the penalty propensity equals 5.4 p.p. (shown in the "For-profit + interaction" row) with a corresponding p-value smaller than 0.001. These results are robust to another measure of HHI based on discharges in respective emergency conditions only (Column 5), treating chains as one competitor in the local market (Column 6), and using market concentration before the period our data covers (Column 7). Using this last (and our preferred) specification to benchmark, these differences would imply that 47% of the mean raw For-profit quality difference can be attributed to the lack of competition in the average market.[20]

TABLE 3 Marginal penalty propensity by for-profit, competition, chain status.

Dependent variable: Marginal penalty propensity MPP_{ic}							
			Local hospital market				
				Competition: HHI based on			
	All (1)	Constant Ownership (2)	HRR FE (3)	-Beds (4)	-Discharges (5)	-Chain (6)	2008 (7)
Panel A: For-profit status							
For-profit hospital (Yes/No)	0.030	0.031	0.052	0.033	0.035	0.020	0.036
	(0.010)	(0.011)	(0.009)	(0.015)	(0.014)	(0.017)	(0.013)
× HHI-measure				0.180	0.138	0.168	0.140
				(0.107)	(0.082)	(0.071)	(0.071)
For-profit + interaction				0.055	0.054	0.055	0.055
				$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
Panel B: Chain status							
Chain hospital (Yes/No)	0.006	0.009	0.005	0.010	0.011	0.007	0.008
	(0.009)	(0.009)	(0.008)	(0.014)	(0.013)	(0.016)	(0.012)
× HHI-measure				−0.046	−0.051	−0.010	−0.034
				(0.088)	(0.074)	(0.068)	(0.067)
Chain + interaction				0.005	0.004	0.005	0.004
				$p = 0.586$	$p = 0.598$	$p = 0.568$	$p = 0.678$
Observations	8713	8072	8072	8072	8072	8072	7987
Hospitals characteristics	✓	✓	✓	✓	✓	✓	✓
Area demographics	✓	✓	✓	✓	✓	✓	✓
HRR FE			✓	✓	✓	✓	✓

Note: Table presents OLS coefficients (standard errors clustered on hospital level in parentheses). Column (1) reprints Column (5) from Table 2. Column (2) restricts the sample to hospitals that did not change ownership status. Column (3) conditions on HRR FE. Columns (4)-(7) interact for-profit status with various measures of local competition via HHI: (4) based on the concentration in the number of beds, (5) based on discharges, (6) based on discharges but on the chain level rather than individual hospital-level, and (7) uses lagged HHI on chain level in 2008. For-profit + Interaction gives the interaction evaluated at the mean HHI measures $(\gamma_1 + \gamma_2 * \overline{HHI})$, and the p-value for the corresponding F-test. Panel B repeats the analysis for the chain status instead of the for-profit indicator.

Abbreviations: ACS, American Community Survey; FE, fixed effects.

Source: CMS 2011–2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

Panel B repeats this analysis focusing on the difference between hospitals that are part of a chain and those that are not. It shows that, in contrast to for-profit status, chain status per se is not associated with a significant difference in quality, nor is there an interaction with a market concentration in any of the specifications.

Table 4 presents several robustness tests. These all use market concentration measured in 2008 to reduce dynamic equilibrium-adjustment concerns. Panel A examines the effect of for-profit status. Column (1) reprints Column (7) of Table 3, the baseline specification. Column (2) examines potential non-linearities in local market concentration, replacing the continuous measure with a binary indicator variable for being above the median. This shows that being in an above-median HHI region essentially doubles the for-profit marginal penalty propensity relative to other hospitals. Next, we assess whether monopoly markets are driving the results by dropping fully-monopolistic HRR markets (Column 3) and dropping hospitals operating in markets in the highest 10th percentile of the HHI distribution (Column 4). Excluding these highly concentrated markets yields similar—even slightly larger—results.

Our period coincided with the insurance expansions mandated by the Affordable Care Act. This differentially impacted markets, and hospitals within markets, by improving hospital finances and changing their mix of patients and services. To address whether this policy change is driving our results, we include as an additional covariate the

TABLE 4 Robustness and specification tests.

Dependent variable: Marginal penalty propensity MPP_{ic}	Base (1)	Above Median HHI (2)	Non-Monopol Markets (3)	Non-Mono-polistic (4)	County Share Uninsured (5)	Overall Hospital (6)	HSA FE (7)	HHI(HSA) HSA FE (8)
Panel A: For-profit status								
For-profit hospital (Yes/No)	0.036	0.037	0.036	0.030	0.036	0.034	0.029	0.004
	(0.013)	(0.013)	(0.013)	(0.016)	(0.013)	(0.014)	(0.020)	(0.026)
×HHI-measure (2008)	0.140	0.036	0.140	0.229	0.140	0.127	0.248	0.165
	(0.071)	(0.018)	(0.071)	(0.126)	(0.071)	(0.075)	(0.103)	(0.058)
For-profit + interaction	0.055	0.073	0.055	0.061	0.055	0.051	0.062	0.118
	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
Panel B: Chain status								
Chain hospital (Yes/No)	0.008	0.002	0.008	0.007	0.007	0.010	0.001	−0.023
	(0.012)	(0.011)	(0.012)	(0.014)	(0.012)	(0.012)	(0.022)	(0.028)
×HHI-measure (2008)	−0.034	0.006	−0.034	−0.034	−0.035	−0.046	−0.035	0.063
	(0.067)	(0.016)	(0.067)	(0.120)	(0.068)	(0.068)	(0.136)	(0.062)
Chain + interaction	0.004	0.008	0.004	0.003	0.002	0.004	−0.003	0.021
	$p = 0.678$	$p = 0.804$	$p = 0.678$	$p = 0.789$	$p = 0.779$	$p = 0.684$	$p = 0.822$	$p = 0.408$
Observations	7987	7987	7970	7184	7987	2918	7985	7919
Hospitals characteristics	✓	✓	✓	✓	✓	✓	✓	✓
County demographics	✓	✓	✓	✓	✓	✓	✓	✓
HRR FE	✓	✓	✓	✓	✓	✓		
HSA FE							✓	✓

Note: Table presents OLS coefficients (standard errors clustered on hospital level in parentheses), see Table 3 notes. Column (1) corresponds to Table 3 Column (7) - 2008 HHI measure, provided as reference. Column (2) replaced the interaction by using an indicator for the above median HHI. Column (3) drops fully monopolistic markets, and (4) hospitals in areas in the top (10th) percentile of the HHI distribution. Column (5) includes the hospital county share of uninsured people from the County Health Rankings (see Davis et al., 2020), (6) uses the overall hospital quality (instead of the condition-specific quality measures), (7) replaces the HRR FE with the smaller HSA FE where, HSA is a collection of ZIP codes whose residents receive most of their hospitalizations from the hospitals in that area, and (8) measures the HHI on the HSA level and includes HSA FE.

Abbreviations: ACS, American Community Survey; FE, fixed effects.

Source: CMS 2011–2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

hospitals' county-level share of uninsured in 2011 (see Davis et al., 2020).[21] The results are unaffected by this additional control variable (Column 5). Our main analyses are at the condition-specific level to allow hospitals to respond to market power in that condition. However, as noted above, our quality measures are correlated and so pick up overall hospital quality, and decision-making about quality will be at the hospital level as well as at the condition level (as suggested by Figure C3). We therefore repeat our analysis using the average quality at the hospital level in Column (6) of Table 4. This shows little difference from the baseline analysis that is at the condition level.

Finally, although we believe the HRR is the appropriate market level, hospitals may respond to (even) more local competition. To examine this, we re-estimate within the smaller health service area (HSA) markets by replacing the HRR FE with HSA FE (Column 7). The results are very similar to those of Table 3. For-profit hospitals are of lower quality and this quality is lower in more concentrated markets. As a final check, in addition to the HSA FE, we also define the local competition measure —the concentration as measured by HHI— based on the much smaller HSA level (Column 8). This reduces the variation in HHI affecting the precision of the estimation. But even at this finer level a lack of competition is associated with a statistically significantly larger for-profit quality differential.

Panel B shows that, across all these robustness checks, chain hospitals, on average, do not differ from non-chain hospitals in terms of quality, nor do they differ in response to local market concentration.

3.3 | Heterogeneity by chain status

We define a hospital to be part of a chain if it has any formal affiliation with another hospital. This classification, therefore, includes both large national as well as small local chains, and hospitals with a loose affiliation as well as those with much tighter chain-level managerial control. But it is possible that the quality of for-profit hospitals and the interaction with local market concentration varies within chain status, particularly with the size of the chain.

To examine this, Table 5 presents the estimated for-profit quality difference for various sub-samples defined by chain status. As before, all analyses use market concentration measured in 2008. Column (1) shows again our previous baseline estimates for all hospitals. Column (2) examines only non-chain hospitals. It shows that among non-chain hospitals, there is no significant for-profit difference in quality, nor does it significantly vary with market concentration. Column (3) shows that if we focus only on chain hospitals there is a sizable and significant for-profit gap and an interaction with the market concentration. The two terms are also jointly significant ($p = 0.006$).

Columns (4) and (5) split chain hospitals into those belonging to nationally small chains and large chains, where small and large are defined by not belonging or belonging to the highest tercile of the chain size distribution (which equates to more than 20 hospitals) respectively. Column (4) shows that for-profits that are part of small chains have lower quality, but the interaction coefficient with market concentration is estimated imprecisely. Column (5) shows that for hospitals that are part of large chains, the for-profit gap is completely crowded out in fully competitive markets (i.e., evaluated at $HHI = 0$ the gap is just 0.009) but increases strongly the more concentrated the local market is, as can be seen from the interaction coefficient (0.239).[22]

TABLE 5 Marginal penalty propensity by for-profit, competition, chain status: Sub-samples.

Dependent variable: Marginal penalty propensity MPP_{ic}			Chain		
	All (1)	Non-Chain (2)	All (3)	Small (4)	Large (5)
For-profit hospital (Yes/No)	0.036	−0.059	0.044	0.049	0.009
	(0.013)	(0.042)	(0.014)	(0.026)	(0.021)
×HHI-measure (2008)	0.140	0.216	0.145	0.121	0.239
	(0.071)	(0.306)	(0.078)	(0.209)	(0.101)
For-profit + interaction	0.055	−0.034	0.065	0.066	0.043
	$p = 0.000$	$p = 0.228$	$p = 0.000$	$p = 0.005$	$p = 0.005$
Observations	7987	2144	5843	3441	2402
Hospitals characteristics	✓	✓	✓	✓	✓
County demographics	✓	✓	✓	✓	✓
HRR FE	✓	✓	✓	✓	✓

Note: See Table 3 - Column (7) Panel a - notes for details. Column (1) shows this for reference again. Column (2) restricts the sample to hospitals not organized in the chain, and (3)-(6) to those in the chain. Column (3) uses all chain organised hospitals, and (4) and (5) split them further by the highest tercile (33% - 20 or more hospitals in the chain). The full set of results across the different sub-samples is presented in Appendix Table C5.

Abbreviations: ACS, American Community Survey; FE, fixed effects.

Source: CMS 2011–2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

3.4 | Further robustness checks

Appendix Table C3 presents a series of checks on the precise definition of the quality measure. Columns (2)-(4) show that our results hold for the percentile ranking in our quality measure (which does not depend on the magnitude of the penalty propensity) and for a definition of being in the high-quality tail (defined as an indicator for being in either the top 10% or 25% hospitals).[23] Column (5) uses the raw penalty (i.e., without our adjustments for the socioeconomic environment and small samples). The results are similar to our preferred specification but are less precise, showing that the various fixed-effect profiling approaches are beneficial. The final three columns examine the Empirical Bayes OLS penalty measure, raw readmissions, and the published ERR measure. The use of these different measures also does not affect our qualitative conclusions regarding the for-profit-concentration gap among all hospitals and large chain hospitals.

Appendix Table C4 shows further tests of robustness. Panel A is for all hospitals and Panel B for hospitals which are part of a large chain. In Column (2) we weight hospitals by their size; in Column (3) we drop government hospitals from the analysis. The results are robust to these changes. To further assuage endogeneity concerns, we restrict the sample to have constant ownership for the 10 years before the end of our sample period (Column 4) and use only data for the first 2 years after HRRP enactment (Column 5). Our qualitative conclusions are unaffected, although some precision is lost due to the reduced sample sizes. In Column (6), we use a fractional response model (Papke & Wooldridge, 2008) for the second stage of our preferred estimator, as the *MPP* is bounded between 0 and 1. The results are robust to this change. The full results for all chain and non-chain sub-samples (analogous to Table 3) are presented in Table C5. This shows robustness across all the specifications.

4 | DISCUSSION AND CONCLUSION

The differences in the behavior of for-profits and non-profits in public service provision are well documented. Examples include technology adoption (Horwitz et al., 2018), the provision of free care (Garthwaite et al., 2018), and the need for financial incentives to motivate workers (Besley & Ghatak, 2005). Non-profits have historically played a large role in the US hospital industry, but the role of for-profits, and hospital chains, has been steadily increasing. As the ownership and market structures of the hospital market have changed, it is essential to understand how these changed conditions are associated with differences in hospital quality.

To address this, we examine differences in quality between for-profit and non-profit hospitals using the distribution of latent heterogeneity in quality derived from the underlying penalty risk of being fined under a flagship program designed to incentivize hospital quality.[24] This quality measure is strongly correlated across diagnostic conditions within a hospital, suggesting a common hospital-wide quality, which is further supported by the strong association of our quality measure with a hospital's overall RRs in non-incentivized and non-emergency conditions, mortality rates in incentivized conditions, and patient satisfaction.

We use our measure to examine quality differences by for-profit status, chain status, market structure, and the interaction between these. Our findings show for-profit hospitals are around 5% points more likely to be penalized than other hospitals. There is no such quality gap by chain status. We find a substantial gradient in the negative for-profit gap in quality by market structure, but the chain-non-chain quality gap does not differ by market concentration. However, there is an interaction between for-profit status, chain status, and market structure. We find that the competitive pressure disciplines the for-profit gap largely among hospitals that are part of large chains.

Our finding that competition in local markets is associated with a smaller for-profit gap chimes with earlier findings in the literature. Our finding that (large) chain hospitals are responsive to competition contrasts with Eliason et al. (2019), who find that competition does not affect chain hospital quality in the dialysis market. Instead, it is chain status per se that drives lower quality. There are (at least) two possible reasons for this difference. First, dialysis patients have little choice over where they are treated, meaning competition may play little role. Second, performance for dialysis outcomes is not part of the measures published in patient-oriented quality metrics such as Hospital Compare. In contrast, the penalty rates we examine were heavily publicized. Thus, it seems probable that hospitals are more likely to compete for patients on HRRP signals than on dialysis outcomes. Poor performance on HRRP metrics might be expected to be related to loss of business (Chandra et al., 2016). An increase in competition will exacerbate this, which may be particularly the case for those hospitals at the lower end of the quality distribution (Jones et al., 2017). We show that large-chain hospitals operating in markets that lack competition—and therefore allow for flexibility in quality—

have lower quality. But for hospitals operating in highly competitive markets the gap between for-profit and non-profit chain hospitals disappears.

An alternative explanation for our findings is that hospitals respond to the publication of performance metrics by selecting healthy patients. They do this more in competitive markets where they are more at risk of losing business. Chain hospitals may implement chain-wide methods to do this and be more efficient than hospitals not part of a chain. We have addressed endogenous sorting of patients by using RRs published by CMS for emergency admission, which prior research has shown are not driven by patient selection (Doyle et al., 2019) and by further risk-adjusting them. Therefore we think it is unlikely that our results are only driven by patient selection. And if for-profits were more likely to select healthier patients, a tendency which might plausibly be hypothesized to be even stronger among those in large chains, our estimated for-profit-chain gap would reflect a lower bound on the true gap. We have also addressed concerns about the differential location by hospital type and our results are robust to this.

Finally, while our results are not causal, our findings document that when located in markets in which they can exploit their market power, for-profits, particularly those that are part of a large chain, have lower quality. This finding holds across different outcomes that are more or less risk-adjusted or incentivized and a very large number of checks and sensitivity analyses. Thus, the correlation between lower quality and lower competition should form part of any regulatory assessment of proposed mergers and acquisition behavior in the hospital industry, especially in markets with high market concentration.

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CONFLICT OF INTEREST STATEMENT

None of the authors has any conflict of interest to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ENDNOTES

[1] System is defined as either a multi-hospital or a diversified single hospital system. A multi-hospital system is two or more hospitals owned, leased, sponsored, or contract managed by a central organization (AHA, 2019); we will refer to them in the following as *chains*.

[2] Earlier literature which found a lack of difference between for-profit and non-profits focused largely on readmissions or mortality (Gaynor & Town, 2011), often based on acute myocardial infarction. Eggleston et al. (2008) provide a systematic review of 31 observational studies and find that studies representative of the US tend to report lower quality among for-profits than private non-profits, but the size and significance depend on the populations and samples considered (cf. also, Baltagi & Yen, 2014; Colla et al., 2016; Cooper et al., 2018; Dranove & Satterthwaite, 2000; McClellan & Staiger, 2000; Paul et al., 2020; Picone et al., 2002).

[3] The scheme was introduced in 2012. The penalty mechanism was modified substantially after 2016: further conditions such as hip replacement were added, and the risk adjustment was modified. To assure comparability over time, we limit our analysis to the period 2012–2016.

[4] Hausman and Lavetti (2021) find that the effects of local competition and chain level competition on prices can even have opposing signs in physician markets, though they do not study quality.

[5] Doyle et al. (2019) come to a similar conclusion that there is little evidence of patient selection in the context of our setting (see also Doyle et al., 2015, 2017).

[6] Note that in our setting Medicare sets the prices (Cubanski et al., 2015).

7 Each approach leads to qualitatively similar conclusions.

8 This approach has become ubiquitous in the literature on hospital quality (Chandra et al., 2016; Propper et al., 2008) and in other pay-for-performance metrics (Bonhomme & Weidner, 2019; Chetty et al., 2014). Although the HRRP aims to account for small counts by requiring at least 25 discharges in the respective emergency condition and corrects the excess readmission ratio using Empirical Bayes when estimating hospital FE over five years and using them in secondary analysis, the inherent estimating error needs to be accounted for.

9 Other approaches include random effects, using the residual of the quality equation, or fitting a normal distribution around the FE estimates (see MacKenzie et al., 2015, for an overview of shrinkage approaches). Appendix Table C3, which contains results for a linear probability model with *ex-post* Empirical Bayes, shows that our results for (2) are robust to the employed methodology.

10 One natural reason for the high level of persistence in the dependent variable over time is that a 3-year reference window is used to determine the penalty status. We further account for this overlap when computing standard errors by clustering at the hospital level.

11 We keep government hospitals in our analysis but present estimates excluding them in Appendix Table C4.

12 In specifications where we do not pool across conditions *c*, even the HHI main effect is identified, in principle: the competition which a given hospital in a given HRR faces varies over the three different chronic conditions. However, as explained, our interest lies in the interaction term (For-profit×HHI) rather than in the main term (HHI).

13 These three dimensions make up 66% of the publicized Hospital Compare metric, which is a five-star rating based on latent factor analysis. The metric has more than 20% missing observations in most years; it is also extracted from different mixes of indicators (prone to strategic reporting) based on availability for other hospitals and years. These issues compromise its comparability, and therefore, we do not use them here as a measure of quality in our analysis.

14 This partially addresses concerns whether hospitals used observational stays to reduce readmissions in targeted conditions. For heart failure, this hypothesis has also been dispelled more directly in Albritton et al. (2018).

15 Roughly 50% of the HRRs (164) contain both (at least one) for-profit and non-profit hospitals. For chains and lone-standing hospitals, 70% (226) share an HRR. These numbers are lower estimates of the mixing within HRR as they exclude hospitals that changed their status in the observation period.

16 This is the noisiest of our measures as it is a relatively low probability event compared to the other measures we use here.

17 Note that in our setting and time period, Buxbaum et al. (2019) find "changes in the coding of inpatient pneumonia admissions do not explain readmission reduction following the HRRP"; they also compare explicitly for-profit and other hospitals and find no differential coding behavior between the two types of hospitals.

18 Consequently, the significant gap in readmissions translates into penalties, which suggests that there is little bunching at the penalty cut-off. This is perhaps a result of the peer bench-marking embedded in the ERR and penalty status, which is unobserved by the individual hospital (Gupta, 2017; Zhang et al., 2016).

19 Table C2 presents the covariates in the regressions.

20 That is, the quality difference at the average market concentration ($HHI = 0.233$) versus a fully competitive market ($HHI = 0$) relative to the raw mean quality difference (7 p.p.): $0.47 = (0.235 \times 0.14)/0.07$.

21 We do not observe the share of Medicare or Medicaid patients in the local market in our data; but, to address this, our specifications include the share of county population living in poverty and the share of the population older than 65 in our standard set of controls as noted above.

22 In addition, we explored whether *national* market power matters (by replacing the local market measure with the average HHI across all markets in which the chain operates) and we also used discharges-weighted average HHI. The results are qualitatively the same as those using the local concentration measure: the for-profit gap is significantly larger in markets with greater market power.

23 See also the densities of the quality measure for both BRGLM-penalty and EBayes-OLS-ERR approaches shown in Figure C1, and by ownership in Figure C2).

24 Many attempts to incentivize the provision of public services share with the HRRP a similar structure of being based on annually published metrics and using nonlinear policy cut-offs (e.g., penalty/no-penalty), which may frequently change as the basis for reward or penalization of providers. While our findings are specific to the HRRP, our approach to the extraction of a medium-run measure of quality from an observed binary signal of performance could be applied in similar settings to understand the factors associated with quality (Mehta, 2019).

25 Hospitals in Maryland are exempted from the policy due to a special Medicare agreement.

26 In FY 2015, the conditions were extended to include *chronic obstructive pulmonary disease* (COPD), *elective hip or knee replacement*, and in FY 2017 to *coronary artery bypass graft* (CABG) and an extended pneumonia definition was put in place.

27 Since our measure is based on the penalty, rather than the readmission ratio or penalty amount, regression to the mean is much less problematic. Almost half of the hospitals are either always or never fined, indicating a strong persistence in penalty status incompatible with regression to the mean. Our approach further circumvents regression toward the mean by explicitly accounting for the longitudinal dimension in estimation.

[28] We tested whether there is evidence for additional condition-specific variation or whether all or most of the quality is constant within the hospital using a randomization test Abrams et al. (2012) that accounts for the uncertainty in the estimated FE (results available on request). We find that PN differs significantly from HF but both are too similar to AMI to be distinguished, see also Kunz and Propper (2022).

[29] downloaded from http://www.nber.org/ssa-fips-state-county-crosswalk/ (accessed 26.03.17).

[30] downloaded from https://www.ers.usda.gov/data-products/atlas-of-rural-and-small-town-america/download-the-data/ (accessed 26.03.17).

[31] downloaded from https://www.census.gov/data-tools/demo/saipe/saipe.html (accessed 26.03.17).

[32] downloaded from http://www.dartmouthatlas.org/tools/downloads.aspx?tab=39 (accessed 26.03.17).

[33] downloaded from http://www.dartmouthatlas.org/tools/downloads.aspx?tab=41 (accessed 26.03.17).

[34] downloaded from https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/index.html (accessed 26.03.17).

[35] downloaded from https://data.medicare.gov/data/archives/hospital-compare (accessed 26.03.17).

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