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JEL Classification: H51, I1, I11, I18

Keywords: A ordable Care Act, Hospital quality, Competition

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Assessing the Quality of Public Services: Does Hospital Competition Crowd Out the For-Profit Quality Gap?*

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May 2020

Abstract

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Keywords: Hospital Readmissions; Affordable Care Act; Hospital Quality, Competition

JEL classifications: H51,I1,I11,I18

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1 Introduction

Historically, the 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[1] has increased considerably in the USA. From 1993 to 2017, the share of for-profits rose from 18 to over 26 percent and system hospitals experienced a similar increase. Thus, as the industry evolves, the long-standing question of whether for-profits and not-for-profits behave differently has important implications for anti-trust regulation (Capps, Carlton and David, 2017) and attempts to increase quality in the hospital market (Doyle, Graves and Gruber, 2019). In a seminal paper, Sloan et al. (2001) found that whilst for-profits and not-for-profits may have different objectives (Besley and Malcomson, 2018), when for-profits and not-for-profits operated in competitive environments, they behaved similarly. Much of the literature which has empirically examined the relationship between market structure and hospital quality has drawn on this, arguing that when modeling the relationship between hospital behavior and market structure, it can be assumed that non-profits behave as for-profits (recent examples include Chandra et al., 2016; Zhang et al., 2016). Yet, so far the literature has found mixed results (Baltagi and Yen, 2014; Colla et al., 2016; Cooper, Gibbons and Skellern, 2018; Dranove and Satterthwaite, 2000; McClellan and Staiger, 2000; Paul, Quosigk and MacDonald, 2019; Picone, Chou and Sloan, 2002).[2] By utilizing a heavily publicized quality metric we are able to document whether such complementarities between ownership and competitive pressure exists.

In this paper we use a measure of quality derived from one of the Affordable Care Act's (ACA) signature programs, using a novel and robust estimation approach, to provide evidence on the relationship between for-profit status, membership of a hospital system, competition and hospital quality in the US. Our measure of quality is derived from the Hospital Readmissions Reduction Program (HRRP), which imposes financial penalties on hospitals that have annual (risk-adjusted) readmission rates above a threshold.[3] While readmission rates are used by many regulatory authorities as a measure of (poor) hospital quality they are contaminated by several potential sources of error. First, they are likely to be subject to idiosyncratic variation unrelated to quality. Second, they are likely to be influenced by demographic factors beyond the standard risk adjustment; and third, the readmission rate has been documented to contain some regression to the mean (Joshi et al., 2019). In addition, under HRRP, the number of conditions that were subject to the policy expanded and the size of the financial penalties was changed repeatedly. This creates empirical challenges in distilling a clean measure of the underlying stable latent quality from such a dynamic policy environment.

To overcome these problems we extract a measure of the medium-run hospital (and medical condition) latent quality from hospitals' HRRP-penalty status (whether or not a hospital was fined). We focus on the propensity to be penalized as this is observed, results in substantial fines, and remained unchanged over the five years,

[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).

[2] Eggleston et al. (2008) provide a systematic review of 31 observational studies from 1990 to 2006 and examine what factors explain the diversity of findings regarding hospital ownership and quality of care. They find that studies representative of the US as a whole tend to find lower quality among for-profits than private non-profits, and most adverse effects are located in for-profits, yet their size and significance of the differential effects depend on the populations and samples considered.

[3] The majority of evidence points towards a positive effect of this policy (see, inter alia, Dharmarajan et al. 2017, Gupta 2017, and Gupta et al. 2018).

unlike the penalty amount. We expect that hospital (and potentially demanders of care) will react to the penalty status (Gupta, 2017; Zhang et al., 2016). Simply focusing on whether a hospital is fined-or-not encounters the problem that 45% of hospitals were never or always penalized within the five-year period. Standard approaches, such as binary response panel models, would drop observations of these hospitals from the estimation and consequently disregard any environmental information for such hospitals. Thus, estimating the binary response as the outcome makes the implicit assumption that no shock could ever push the hospital over the penalty cutoff. To deal with this, we derive a straightforward metric of quality (the latent propensity to hit the penalty threshold), using a bias-reduced fixed effects generalized linear model (Kunz, Staub and Winkelmann, 2018, referred to as BRglm hereafter), which allows decomposition of the time-variant from the time-invariant heterogeneity of hospital quality, net of aggregate shocks over time and space (Baltagi and Yen, 2014), and changes in the policy, such as the numerous changes in the penalty amount over time (Zhang et al., 2016). Our measure also embeds a shrinkage property considered beneficial in the estimation of fixed effects, implemented jointly with the estimation of the latent propensity to be penalized. Using our approach, we obtain finite estimates of the quality of every hospital (one for each condition subject to penalties), including the quality of those hospitals that were never or always penalized.

Many attempts to incentivize the provision of public services share with the HRRP a similar structure in that they are yearly, involve nonlinear policy cut-offs (e.g. penalty/no-penalty), change rapidly and are used as the basis for pay-for-performance. They may have large effects on behavior.[4] It is thus important to examine whether the metrics that are published by such policies convey information about quality. While our findings are specific to the HRRP, they might provide valuable lessons for related settings.

We find quality measures extracted from readmission-penalties in emergency conditions are strongly correlated across the penalized-conditions, suggesting that they indicate an underlying latent quality at the hospital level. Our (emergency condition) measures of hospital quality are also strongly associated with a set of non-incentivized measures of quality —the overall readmission rate in all emergency conditions, mortality in the target conditions, and patient satisfaction— all these being metrics that capture more direct dimensions of quality than the propensity to be fined. We find a long positive tail in quality across all three penalized conditions, implying that some hospitals perform much better than what would be expected given the local environment they operate in.[5] There is, further, substantial spatial heterogeneity across hospital markets as defined by hospital referral regions [HRR]:[6] in some markets, the marginal hospital faces a penalty risk as low as 15 and in others as high as 95 percent (SD 0.11).

We use these measures to provide new evidence on the association of latent quality with ownership (Sloan et al., 2001), competition (Gaynor and Town, 2011; Propper, Burgess and Gossage, 2008; Sivey and Chen, 2020), and system membership (related to managerial oversight, Bloom et al., 2015).[7] At the individual hospital

[4]For example, the publishing of quality metrics may translate into larger market shares for high-quality hospitals (Chandra et al., 2016) and crowding out lower-quality hospitals, perhaps differentially by ownership (see, Jones, Propper and Smith, 2017, for example).

[5]Assessing this would be impossible with more standard measures of quality, such as raw averages of penalty rates that are often used (as discussed and referenced in Mehta, 2019).

[6]These are akin to empirically defined markets for health care and may cross state or county borders.

[7]System is defined by AHA 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).

level, we find a sizable quality gap between for-profit and other types of hospitals, echoing extant research (see, among many others, Aswani et al., 2018; Herrin et al., 2015; Jindal et al., 2018; Paul, Quosigk and MacDonald, 2019). This for-profit quality gap is consistent with a hypothesis that hospitals face different trade-offs between service provision and increases in penalty risk. While the quality gap between for-profit and other hospitals is present in regions that are characterized by high- and low-density of hospitals, it decreases strongly with local measures of competition. Furthermore, this tendency is much stronger in the high-quality tail. This finding is consistent with the idea that competition drives out differential behavior of for-profit and other firms. In a recent study based on a similar program for nursing homes, Hackmann (2019) finds that financial reimbursements are more important than competition in improving patient outcomes. Our study highlights that there might be important complementarities of such policies. We find that both the for-profit quality gap and the crowding-out by competition is driven exclusively by hospitals organized into a hospital system (roughly 75 percent of hospitals AHA, 2019). Such hospitals are likely to have a much greater managerial oversight: for example, many are Fortune 500 companies. The system or chain dimension of hospital provision has been largely overlooked to date. An exception is Eliason et al. (2019), who assess the role of chains in the market for dialysis. They also find a for-profit gap, but one that does not vary with market concentration. In contrast to performance for dialysis patients, the penalty rates we examine were heavily publicized and are among the main quality signals available to consumers of health care. It is thus more likely that hospitals compete for patients on the HRRP signals and need to exert more effort when faced with several hospitals serving the same market.

2 Policy, estimation strategy and data

2.1 Policy

Hospital readmissions have been identified as a major driver of health care costs (Jencks, Williams and Coleman, 2009).[8] While costly at the aggregate level, discharging patients too early or not offering sufficient post-discharge care can be rational from the point of view of an individual hospital when reimbursements are based on diagnosis-related groups rather than actual costs. In an attempt to have hospitals internalize the costs of readmissions, the 2010 ACA established a financial penalty for hospitals whose Medicare readmission rates exceed a certain threshold in three common emergency conditions. Since the HRRP's introduction in October 2012, thousands of hospitals were fined and billions of dollars in fines were paid. This policy is an example of a broader move towards improving the quality of health care services by adopting value-based purchasing programs. The program has received considerable attention in economic (Gupta, 2017; Mellor, Daly and Smith, 2017; Zhang et al., 2016) and health services research (Bernheim et al., 2016; Desai et al., 2016; Joynt and Jha, 2013). Here we briefly describe the relevant features of the policy environment; more detail on the timeline and the conversion of the penalty to the reductions in payments can be found in Appendix A.

Beginning in 2009, hospital readmission rates have been published publicly on an annual basis by the Center for Medicare & Medicaid Services (CMS). Announced on March 23, 2010, starting on October 1, 2012 (for the financial year 2013), eligible hospitals were penalized by up to one percent of their Medicare reimbursements

[8]It has been estimated that up to $1 billion could be saved yearly by preventing these readmissions (McIlvennan, Eapen and Allen, 2015).

if over the prior three-year period (i.e., from June 2008 to July 2011) there were higher-than-expected risk-standardized 30-day readmission rates for at least one of the three emergency conditions: *acute myocardial infarction* (AMI), *heart failure* (HF), or *pneumonia* (PN).

If a Medicare patient was initially hospitalized—based on their primary discharge diagnosis—for one of the conditions and was readmitted to the same or another hospital within 30 days after release for the same or any other condition (all-cause), the patient counted as a readmission for the initial hospital. Readmissions were then used to estimate the probability to be readmitted at a given hospital and compared to the average hospital with a similar case-mix. Thus, risk-adjustment was based on the case-mix, including age, sex, and co-existing conditions, but did not account for differences in socio-economic characteristics in the hospitals' environment. This changed after 2016, which is why we limit our sample period to before 2017. The resulting risk-adjusted *excess readmission ratio* ERR_{it}^{c} in emergency category c at year t measures the "total predicted readmissions at a hospital [i] compared with the total expected readmission if the patients were treated at an average hospital with similar patients" (McIlvennan, Eapen and Allen, 2015).

We focus on the extensive margin of a penalty—i.e., if $ERR_{it}^{c} > 1$—across any, and separately for each, of the three conditions. This penalty-cutoff is the policy-relevant discontinuity introduced into the hospitals' cost function and thought to be more relevant than the incremental changes in the penalty amount (Gupta, 2017). Other advantages of assessing the penalty status as compared to its *amount* are that it is constant across years, independent from the relative reimbursements for that emergency condition and less likely to be affected by regression to the mean (Joshi et al., 2019).[9] Increases or decreases in the reimbursement amount might confound the time-invariant performance analysis. For instance, some hospitals might do very poorly, but since they have low relative reimbursements in that category they end up with the same penalty amount.

Any measure of quality based on incentivized metrics might reflect heterogeneity in strategic decision making by hospitals (Mehta, 2019). While penalties affect the trade-off between treatment cost and readmission probability, it is by no means clear whether no, or very few, readmissions are optimal from the point of view of a hospital's management. If the costs of avoiding readmissions are high, 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, in these hospitals. Of particular interest is whether for-profit hospitals systematically differ in this regard from other hospitals (Capps, Carlton and David, 2017; Chang and Jacobson, 2017). We assess this by regressing our extracted quality metric on hospitals' time-invariant characteristics, including hospital ownership. It has been suggested that potential for-profit gaps may be due to strategic flexibility which may be crowded out by competition (Duggan, 2002; Gaynor, Ho and Town, 2015). We test whether this for-profit gap in quality varies with standard measures of local market concentration, such as the Herfindahl-Hirschman-Index [HHI]. We then assess the interaction of ownership, market concentration and managerial oversight of hospitals, the latter being measured as whether they are part of a hospital system or not (Eliason et al., 2019).

[9] 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 towards the mean by explicitly accounting for the longitudinal dimension in estimation.

2.2 Estimation strategy

We model the probability of being penalized using a probit model:

$$P(y_{it}^c = 1 | x_{it}, \alpha_i^c) = \Phi(\alpha_i^c + x_{it}'\beta), \tag{1}$$

where y_{it}^c is an indicator of hospital i being penalized in year t for exceeding readmissions in emergency condition c, i.e. $ERR_{it}^c > 1$, and $\Phi(\cdot)$ denotes the standard normal cdf. Our main interest lies in the fixed effects α_i^c, the quality measures for hospital i in condition c over the whole sample period. The vector x_{it} contains time-varying covariates at the hospital, HRR and county level, as well as year indicators to control for common time shocks. We cluster standard errors throughout at the hospital level. The fixed effects are estimated via different indicator-variable approaches: first, pooled across conditions – one fixed effect per hospital (3,917) stacking all years and conditions; second, interacted condition $\times$ hospital (8,713); and, finally, estimating the regressions separately by condition. We show below that each approach leads to qualitatively similar conclusions.

Since there are only five available years, in the constant policy environment, standard maximum likelihood approaches for binary fixed effects panel data would disregard any hospital that does not change penalty status. This would mean that a hospital in a very healthy environment could get the same ranking as one in a less advantaged area, if both are either never or always fined (this problem of *perfect prediction* is well known in the non-linear panel literature, see Maddala, 1983). In our data this issue is quite severe, as a large share of hospitals are penalized in every period or never. Since with only a short set of time periods (in our case five) it is unreasonable to assume that not observing a penalty implies that no shock could ever occur to push the hospital over the penalty cutoff and disregard any environmental information for such hospitals, this is a rather unappealing model implications for a measure of performance.

To address this, we estimate equation (1) using the bias-reduced probit fixed effect panel model as proposed by Kunz, Staub and Winkelmann (2018), which is based on a generalized linear model estimator first suggested by Kosmidis and Firth (2009). This estimator deals with the small sample (short T) problem of estimating the hospital fixed effects with few observations, and embeds an *ex-ante* shrinkage of the fixed effects towards 0 (this value implies a marginal latent hospital quality corresponding to a 50-50 propensity to be penalized net of covariates). The estimator allows decomposing the time-variant from the time-invariant heterogeneity of *all* hospitals.

The closest to our approach is a linear probability model with an ex-post shrinkage by, for example, empirical Bayes (which we present in Appendix Table B3). This type of shrinkage has become ubiquitous in the literature on hospital quality (Chandra et al., 2016; Hull, 2016; Propper, Burgess and Gossage, 2008) but also in other pay-for-performance metrics (Bonhomme and Weidner, 2019; Chetty, Friedman and Rockoff, 2014). But it has the rather unappealing property that shrinkage is ex-post and that there is little guidance on its implementation: approaches include random effects assumptions, using the residual of the quality equation, or fitting a normal distribution around the fixed effects estimates (a detailed overview between different shrinkage approaches is given in MacKenzie et al., 2015). Further, these methods often involve unappealing assumptions such as homogeneity which is impossible with binary outcomes (pointed out by Frederiksen, Kahn and Lange, 2019). Since in our approach the shrinkage is part of the estimation there is no ambiguity from choosing different forms or different target means to shrink towards: it automatically shrinks towards the conservative benchmark of the marginal hospital that has neither positive nor negative relative quality. The estimated $\Phi(\alpha_i^c)$ also bear a model-consistent interpretation as the propensity (score) of penalty for a marginal hospital which respects the 0-1 bounds without any *ad hoc* adjustments.

To assess strategic behavior embedded in these quality metrics we estimate OLS regressions of the form

$$\Phi(\hat{\alpha}_i^c) = \gamma_1 \text{For-profit}_i + \gamma_2 \text{For-profit}_i \times \text{HHI}_{i_{hrr}} + z_i'\beta + \delta_i^c + \delta_{i_{hrr}} + \varepsilon_i, \tag{2}$$

where z_i contains (almost) constant measures of hospitals' teaching status, urban, size, and county-level covariates; and emergency condition δ_i^c and hospital referral region fixed effects $\delta_{i_{hrr}}$. To test whether observed differences by for-profit status change when market conditions change, we interact the for-profit indicator with our measure of market concentration (the HHI from condition-specific discharges), and stratify by whether the hospital is part of a system.

2.3 Data

We use administrative Hospital Compare data (from the CMS) for information on penalties announced in each July of the years 2012–2016. Reporting is delayed by one year, so the data relate to the three-year aggregates of readmissions during the years 2011–2015. For each of the 3,197 included hospitals and each of the three emergency conditions, we know whether or not a penalty was issued in the five years (the full sample of hospital×condition is 8,713, and ×year is 41,095). All employed datasets are public use files to facilitate replication. Detailed variable descriptions, as well as descriptive statistics for our sample by emergency condition and penalty status, and all included variables are reported in the Appendix C and Table C1, respectively.

In the first step (1), we seek to extract the latent hospital quality—which is not driven by aggregate changes over time and local area characteristics beyond the hospital's control— from the penalty status indicator. We follow the extant literature (Chandra et al., 2016; Gu et al., 2014) to select relevant covariates. We use several measures at the HRR-level provided by the Dartmouth Atlas of Health Care. In particular, we use the number of ambulatory-care-sensitive conditions (ACSC), measuring accessibility of local primary health care (Gu et al., 2014), and changes in the number of hospitals in the region (Chandra et al., 2016).[10] At the county-level, we use the Federal Information Processing Standard to add community characteristics, such as the poverty rate and the median household income, which have been discussed as determinants of readmission rates outside the control of the hospital (Herrin et al., 2015). We then compare our extracted quality measures (fixed effects) to non-incentivized quality indicators in the CMS data: overall average readmission rate of the hospital, average hospital mortality in the respective condition, and patient satisfaction (the share of patients who would not recommend the hospital).

Most hospital- as well as regional-level variables display little or no within-hospital variation. Consequently, we include these in the second step estimation (2). In particular, we use urban/rural, teaching status of hospital, size (number of beds), for-profit, and system status from the corresponding final rule impact files. To assess

[10]Here, as is common in the literature (see Chandra et al., 2016), we define market entry and exit as changes in the hospital market, which need not be literal entries or exits.

local market concentration we construct a standard measure of competition, the HHI based on the number of discharges in the respective emergency condition in the HRR.[11]

3 Results: Heterogeneity in hospital quality

3.1 Time-variant vs time-invariant quality

Raw correlates of penalty status with hospital ownership structure suggest that there is a sizable for-profit gap in penalties of 7.2 percent, but only a minor system (chain) gap of 1.4 percent.[12] Table 1 presents the estimation results from regression (1). Column (1) shows coefficients of a simple bivariate linear regression of the penalty indicator on each of the variables indicated in the row names. A substantial HRR market-level variation is evident from, for example, the HRR-level covariates of ACSC discharges or the closing hospitals; and the (unconditional) county-level correlates of penalty risk are as expected: poverty, population and unemployment increase penalty risk; while median income reduces it.

Columns (2) and (3) present the results from our bias-reduced fixed effects probit estimator and show coefficient estimates of some selected covariates.[13] Column (2) corresponds to a restricted (pooled) model, with separate sets of hospital fixed effects (α_i) and condition fixed effects (α^c). Column (3) corresponds to equation (1), which includes one fixed effect for each hospital-condition combination (α_i^c). The results show that most of the HRR and county-level associations become statistically insignificant and/or economically small once hospital fixed effects are conditioned on. Only discharges for ACSC in the HRR seem to have a consistent effect on the penalty risk. Such discharges measure the HRR-level accessibility and effectiveness of local primary health care, which is outside the hospital's control but significantly affects their penalty propensity, confirming prior cross-sectional evidence (Gu et al., 2014).

The main objective of these estimations is to obtain predictions of the fixed effects $\hat{\alpha}_i$ or $\hat{\alpha}_i^c$, respectively, which we use to calculate marginal penalty propensities, $\Phi(\hat{\alpha}_i)$ and $\Phi(\hat{\alpha}_i^c)$. This probability can be thought of as the propensity to be fined if the hospital would otherwise be marginal ($x_{it}'\hat{\beta} = 0$). We bin these into twenty groups using 5%-penalty-probability increments, for the different conditions. Figure 1 shows their within-hospital correlations. There is a large share of always- and never-penalized hospitals, which suggest an important role for time-invariant factors (cf. Appendix, Table B1). The strong correlation across conditions is further consistent with such a non-negligible hospital-wide (or emergency-department-wide) component to quality, rather than with behavior in which there is a trade-off between investing in lowering risk in one condition at the expense of tolerating a higher risk in another.[14] Remarkably, the figure further shows that there is not only a long

[11]It makes little difference for the results whether we calculate the HHI on the number of beds (an approach more commonly taken) or on the respective (condition) and realized discharges.

[12]In Table B1, we present the sample means across penalty status.

[13]The full results by diagnosis condition, alongside OLS regressions based on the excess readmission ratio as the outcome variable, are presented in Appendix Table B2.

[14]We further 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 analogous to the test by Abrams, Bertrand and Mullainathan (2012) that accounts for the uncertainty in the estimated fixed effects. We find that only PN differs significantly (enough) from HF but both are too similar to AMI to be distinguished, which again suggests AMI is a useful summary measure of quality (results not reported).

high-quality tail in the uni-dimensional measures of quality (Figure B1), but the size of the circles confirms this across conditions. This bivariate long tail is most pronounced between AMI and heart failure which are both heart conditions perhaps most likely to exhibit strong complementarities.[15]

Figure 2 presents the association of our hospital quality measures with other hospital-wide quality metrics. Here, we use the hospital fixed effect from the restricted model of Column (2) in Table 1 to obtain a single quality measure per hospital. The three graphs in the figure show how the rank in quality measure (grouped into 100 bins) correlates, respectively, with the non-incentivized performance measures of the overall readmission rate, the average hospital mortality (in the same condition), and patient satisfaction. All three of these measures correlate positively with our quality measure; the readmission rate and patient satisfaction, very strongly so. These results, too, confirm that the proposed measure captures a broad hospital-wide rather than an (emergency) department-wide-only quality. The strong correspondence between objective measures, such as readmissions, and subjective ones, such as patient survey responses, is notable. *Ex-ante* it is by no means clear that patients would value the same quality dimensions as those relate to readmissions or even mortality.

Taken together, these results suggest a common hospital quality. In Figure 3 we show the geographic variation in the average marginal-penalty propensity within broad geographic (HRR) regions. A striking feature of the map is the substantial spatial heterogeneity in hospital quality (net of regional socio-economic indicators which were already accounted for in the first step). The estimated propensity of being penalized at HRR level varies from 15 to 95%, with an interquartile penalty-propensity difference that is as large as 14.8 percentage points. This suggests not only an individual hospital-level but also a substantial market-level role for the variation in quality. This dispersion in geography of this time-constant quality metic is remarkable. To assess determinants of this variation we correlate it at the local level with commonly hypothesized influences, ownership and competition, and a less commonly addressed one, chain status.

3.2 Quality, ownership and competition

Table 2 contains our main results for the differences in quality associated with for-profit, competition, and system-status, using functionals of our predicted hospital quality fixed effects as dependent variables in a number of linear regressions. In each of these regressions, the measure of quality (marginal propensity, percentile ranking, and being among the top 10%) is regressed on a number of hospital and county-level demographic characteristics and diagnosis-condition indicators. Column (1) uses the predicted fixed effects from the restricted model, giving one observation per hospital. Column (2) uses the full model where there is a fixed effect for each hospital-condition (standard errors are clustered at the hospital level). A small number of hospitals changed their for-profit status during the observation period: Column (3) omits these hospitals from the estimation sample.[16]

Our aim is to assess whether the for-profit gap is present using our estimated measure of quality. We begin by examining the marginal penalty propensity (Panel A). As the coefficient on for-profit in these three columns

[15] In the appendix, we present results using the raw measure α_i^c and equally spaced groups for both BRglm and OLS with empirical Bayes correction. Both show a strong correlation across conditions as well as the long tail, cf. Table B2; which is also evident in the individual densities in both BRglm as well as OLS fixed effects, see Appendix Figure B1.

[16] Column (1) and (2) uses for-profit status in the first period, i.e. before or at the time of policy change.

show, it clearly is. The coefficient in Column (3), Panel A, indicates that the marginal probability of incurring a penalty is 3 percentage points higher for for-profit hospitals. In Column (4), the regressions additionally control for the full set of hospital referral region fixed effects. As a result, the for-profit discrepancy increases to 5 percentage points when keeping the regional environment constant across hospitals. We test the hypothesis that competition can drive out the for-profit differential by interacting the for-profit indicator with the HHI based on discharges in the respective penalized condition in Column (5). We continue to condition on HRR fixed effects throughout. The results indicate that competition seems to reduce the for-profit differential substantially. The coefficient on the interaction term (0.129) is positive and statistically significant, implying that the differential increases strongly with market concentration. At the mean market concentration, HHI=0.149, the differential implies a 5.4 percentage-point larger penalty propensity for a for-profit hospital (row: For-profit + interaction). The differential is predicted to decrease to roughly 3.5 percentage points in a market with a concentration that is one standard deviation below the mean. Finally, Columns (6) and (7) assess the impact that the heterogeneity in ownership has on the for-profit differential. The sample is split into hospitals that are not part of a system (Column 6), and hospitals that are (Column 7). The for-profit gap, as well as the competition association, are not statistically significant (joint $p = 0.788$) for independent hospitals. In contrast, we estimate a significant competition effect in the system hospitals. Among system-hospitals, for-profits have a 6.6 percentage point higher penalty-risk in markets of average concentration; almost doubling their quality-gap in a fully competitive setting. A back-of-the-envelope calculation shows that roughly 17% of the interquartile range between HHR quality might be "explained" by the responses to market structure of for-profit system hospitals.[17]

Panels B and C examine functions of the predicted hospital quality measures. Panel B presents the percentile ranking of the hospital. This is based only on a relative metric and not the absolute differences between the estimated fixed effects and thus disregards the magnitude of the long high-quality tail. The effects are largely similar, if slightly stronger. Panel C assesses the long quality tail explicitly, using as the dependent variable an indicator of being in the best 10 percent of hospitals (defined for each condition). The first four columns show that, on average, there is a negative association between for-profit status and the probability of being in the top of the quality distribution, but this is statistically significant only when comparing within HRR. The results in Column (5) show that there are substantial interactions with market structure: the more monopolistic a HRR is, the less likely is it that for-profit hospitals are among the top performers. A comparison of columns (6) and (7) shows that this result is only for hospitals that are part of a system. For such hospitals, the estimated probability of a for-profit hospital being in the top 10% of performers in a HRR of average concentration is 4.4 percent lower than in a fully competitive environment. In other words, the negative for-profit gap would be completely crowded out in a fully competitive market for system hospitals.[18]

[17] This is the concentration effect times the standard deviation in concentration, divided by the interquartile range: $\frac{0.195 \cdot 0.128}{0.148}$.

[18] Appendix Tables B3 and B4 show that our results are robust to a large set of checks. Table B3 assesses different quality metrics, based on raw-average readmission rates, excess readmission ratios (risk-adjusted), or covariate-adjusted excess readmission ratios (via OLS with empirical Bayes), mean penalty or OLS-Bayes adjusted penalty. While BRglm outperforms any such metric, reassuringly, the results are not model-dependent. However, the comparison to the raw-average penalty benchmark makes it clear that some form of regional adjustment is necessary to meaningfully assess competition. B4 shows that our main results are not affected by using OLS in the second step. Panel B drops government hospitals from the comparison. Panel C uses HHI-beds (which are constant within hospital) rather than HHI-discharges. Panel D adds an additional post-estimation shrinkage to the already shrunk BRglm estimates. Panel E shows there are similar but less pronounced tendencies among the top 25% hospitals.

4 Discussion and conclusion

The differences in the behavior of for- and non-profits in public service provision are well documented, recent examples include technology adoption (Horwitz, Hsuan and Nichols, 2018), the provision of free care (Garthwaite, Gross and Notowidigdo, 2018), and the need for financial incentives to motivate workers (Besley and Ghatak, 2005). As the ownership and market structure of the hospital market changes, it is important to understand how this may be associated with hospital quality. To address this, we assess the distribution of latent heterogeneity in quality using an estimator of the underlying penalty-risk of being fined under a flagship program designed to incentivize hospital quality. We find quality to be strongly correlated across diagnostic conditions within a hospital, suggesting a common hospital-wide quality. This is further supported by a strong association of the ranking of our quality measure with hospitals' overall-readmission rates in non-incentivized and non-emergency conditions as well as mortality-rates in incentivized conditions, and even with patient survey responses.

In the raw data, for-profit hospitals are around seven percent more likely to be penalized than other hospitals. Our analysis shows that a large share of this difference remains even after extracting the medium-run quality component and adjusting for market (HRR) fixed effects. We find a substantial gradient in this for-profit gap by market structure. The gap is largely crowded out by competition, particularly amongst the best performing hospitals. We also find a large role for system ownership: both the quality gap and the interaction of for-profit status with market structure are driven by hospitals which are part of a system. These findings are consistent with the hypothesis that for-profit hospitals have a different quality-penalty trade-off which varies with market and ownership structure. Our results also show that the penalty-risk varies significantly across HRRs. A substantial part of this variation in quality is independent of common demographic indicators. Thus, our results indicate not only that there is a sizable dispersion of individual hospital quality, but it is also exhibited at the level of the region.

Our results apply to publicly insured patients. However, complementary research by Cooper et al. (2019) shows that both market concentration, as well as ownership, are associated with how hospitals price privately insured patients. This suggests that our results might extend to other patient populations. Since preventable readmissions are not only a metric of quality but also very costly, our results might further contribute to explaining the geographic variation in health care costs and its association with quality (Doyle, Graves and Gruber, 2017; Finkelstein, Gentzkow and Williams, 2016).

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Tables and Figures

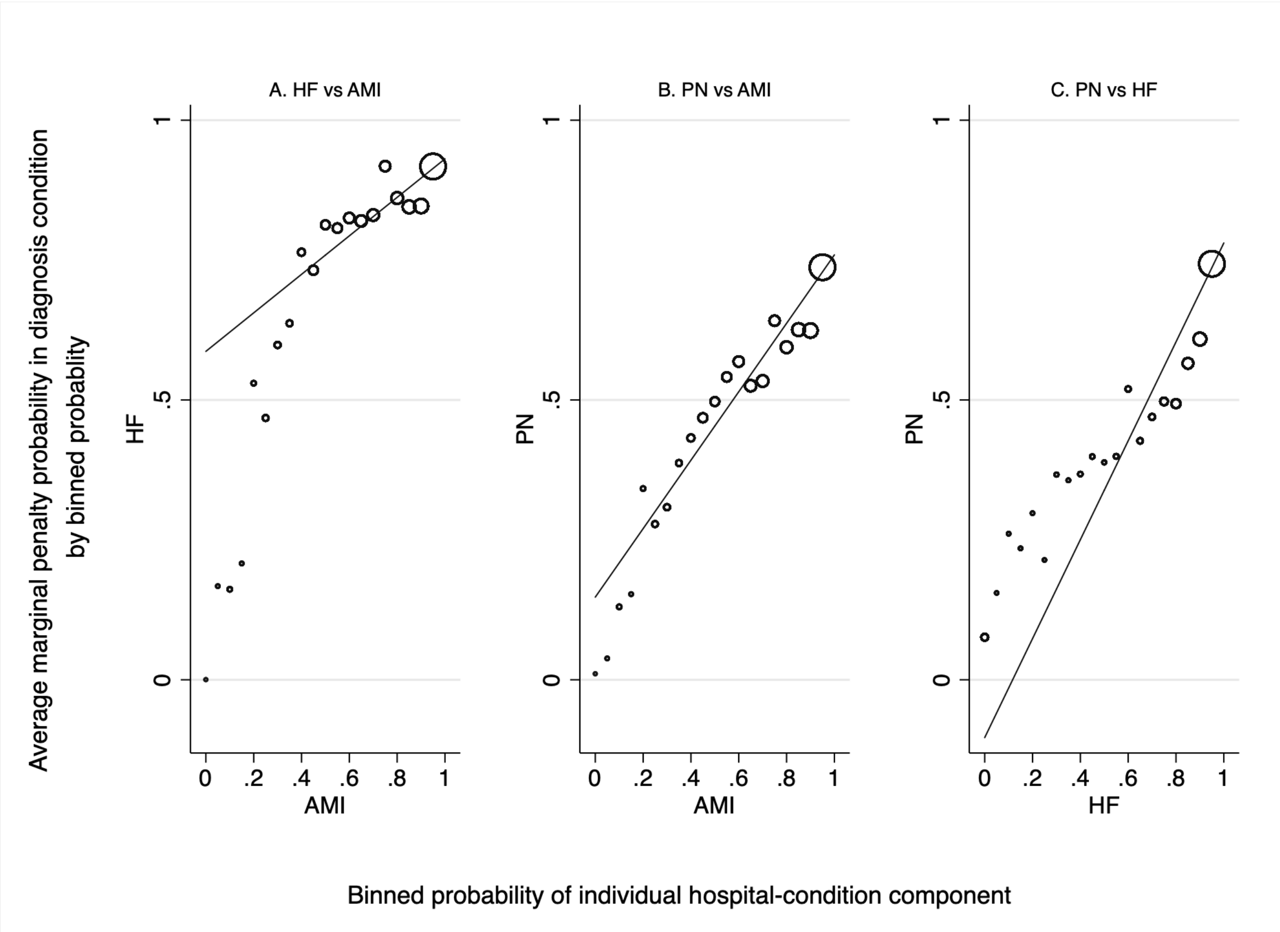

Figure 1: Within hospital readmission penalty propensity across diagnosis related groups, binned

Note: Figure plots correlation of hospital fixed effects across diagnosis conditions (AMI, HF, PN). We use the estimated fixed effects from eq.(1), ie. $\Phi(\hat{\alpha}_i^c)$ from the interacted model. We separate these into 20 bins of 5 percent increments. Then we calculate the corresponding average penalty propensity in the condition given on the y-axis. For example, the first dot in Panel A, corresponds to the 5 percent best quality hospitals in AMI. Hospitals in this bin have an average propensity for a penalty in HF of almost 0, the same hospitals in panel B, are slightly higher but still close to 0 for PN. The size of the circles show the number of hospitals in this category. It is evident that the long-quality-tail, exists across conditions rather than in separate conditions, cf. Appendix Figure B1 for the individual uni-variate density plots, based on the separated-model, Figure B2 presents the non-binned raw α version as well as those based on analogus OLS estimates.
Source: CMS 2011-2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

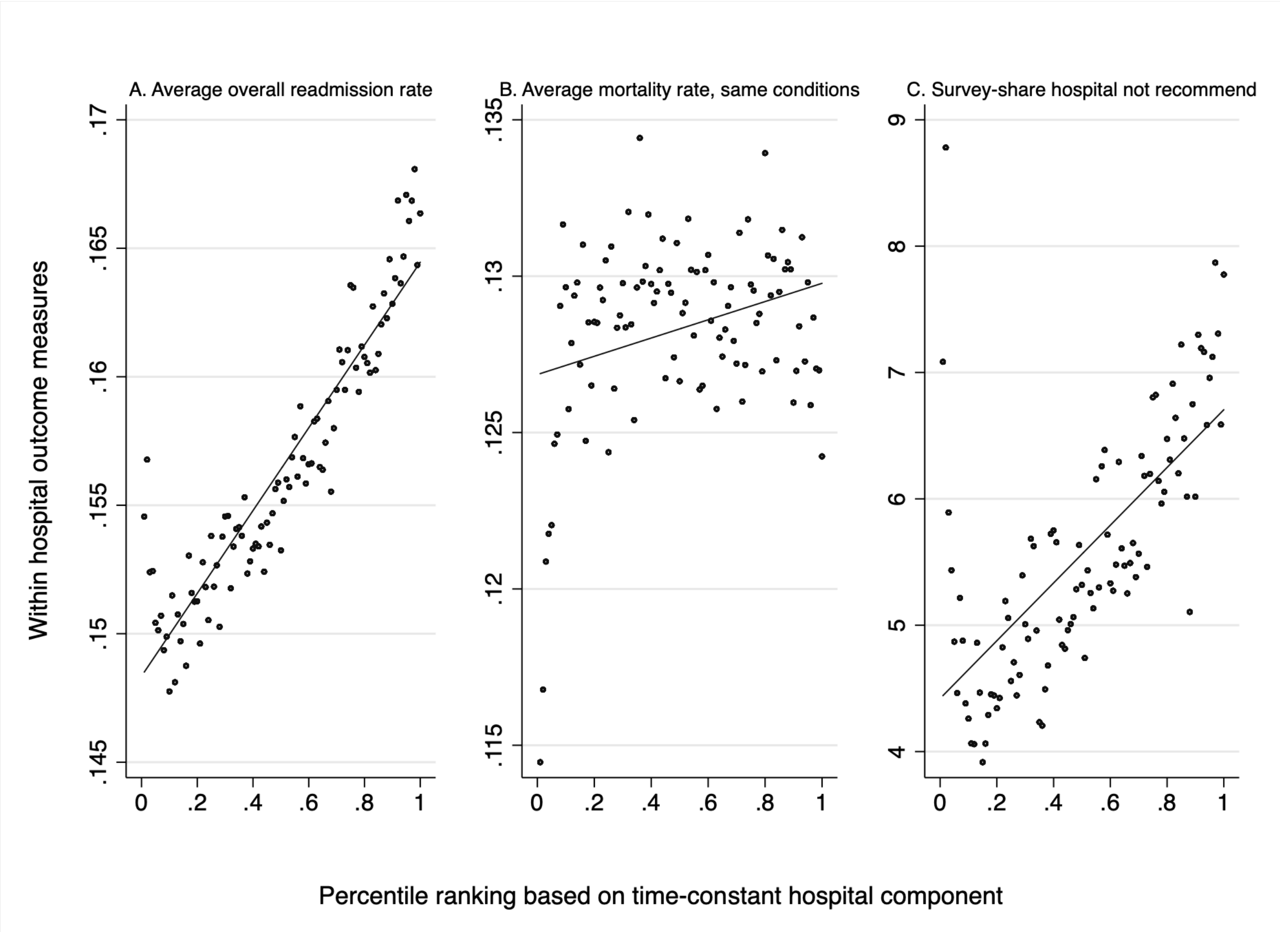

Figure 2: Within hospital readmission penalty propensity across diagnosis related groups, binned

Note: Figure plots bins of hospital fixed effects and corresponding averages of other quality measures: overall readmission rate, mortality rate in respective emergency condition, patient survey responses. The x-axes are identical, and based on the pooled regression model (Column 5, Table 1). These estimated fixed effects are ranked and binned into 100 equal sized percentile ranks. Within each rank the y-axis quality measures are averaged. In Panel A - overall readmission rate in the hospital, B- the average mortality across time and the 3 diagnosis groups, and C- the survey based share of people answering they would not recommend this hospital.

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

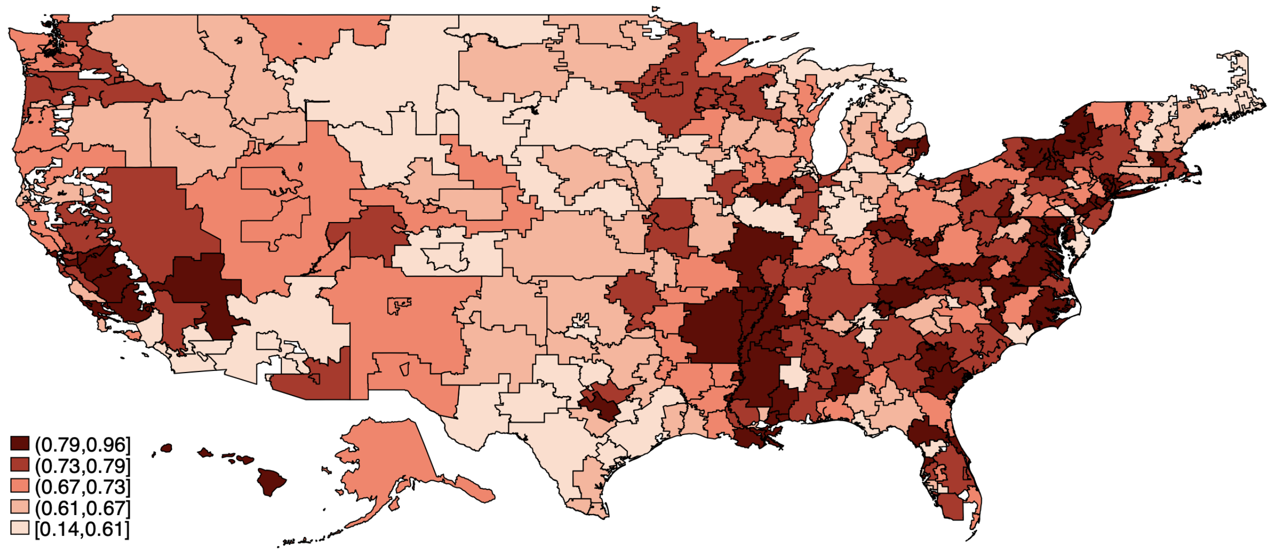

Figure 3: Average within hospital adjusted readmission penalty propensities across hospital referral regions

Note: Figure plots average hospital penalty-propensity (for the marginal hospital) across the map of hospital referral regions, based on averages of marginal penalty propensity using the interactive fixed effects of Table 1, Column 6.
Source: CMS 2011-2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

Table 1: Association of penalty-risk and selected covariates

	Regressions		
	Bivariate OLS	BR probit with α_i FE	BR probit with α_i^c FE
	(1)	(2)	(3)
HRR-level covariates			
Hospital opening	-0.005	0.007	0.008
	(0.004)	(0.022)	(0.024)
Hospital closing	0.043	-0.047	-0.046
	(0.005)	(0.018)	(0.020)
Discharges for ACSC	0.010	0.025	0.026
	(0.000)	(0.004)	(0.005)
County-level covariates			
Share in poverty (all ages)	0.008	-0.004	-0.004
	(0.000)	(0.006)	(0.006)
Median HH income (in 10T$)	-0.005	-0.028	-0.025
	(0.001)	(0.041)	(0.045)
Population (in 100T)	0.002	0.036	0.031
	(0.000)	(0.037)	(0.041)
Unemployment rate	0.026	-0.011	-0.012
	(0.001)	(0.012)	(0.013)
Observations	41,095	41,095	41,095
Hospital characteristics		✓	✓
Year fixed effects		✓	✓
Diagnosis indicators		✓	
Hospital-condition fixed effects		3,197	8,173

Notes: Table presents bivariate-OLS coefficients (robust standard errors), and BRglm panel regressions (clustered standard errors in brackets). Columns (1) presents association (bivariate regression coefficient) of mean penalty on indicated characteristics. Columns (2) and (3), show the first-step of our main results, the BRglm regressions using individual fixed effects, in (2) pooled across conditions (one fixed effect per hospital), (3) one fixed effect for each hospital-condition pair. Table B1 presents descriptive statistics by penalty status and B2 presents the full regression results for each condition separately, alongside analogous OLS regressions for the excess readmission ratio. More on the construction and definition of the variables used can be found in Appendix Table C1.

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

Table 2: Association of different measures of penalty-risk and selected covariates

Dependent variables: Measures of hospitals time-invariant penalty heterogeneity (BRglm fixed effects)							
				Local hospital market			
			Constant	HRR		Part of a system	
	Pooled	All	Ownership	FE	HHI	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Marginal hospitals penalty propensity $\Phi(\alpha_i)$							
For-profit hospital (Yes/No)	0.023	0.030	0.031	0.052	0.035	-0.056	0.037
	(0.010)	(0.010)	(0.011)	(0.009)	(0.014)	(0.044)	(0.016)
× HHI-discharges					0.129	0.106	0.195
					(0.074)	(0.221)	(0.092)
For-profit + Interaction*					0.054	-0.040	0.066
					p =.011	p =.788	p =.004
Panel B: Hospital percentile ranking							
For-profit hospital (Yes/No)	0.043	0.036	0.038	0.061	0.046	-0.064	0.050
	(0.013)	(0.011)	(0.011)	(0.010)	(0.015)	(0.046)	(0.017)
× HHI-discharges					0.111	0.077	0.186
					(0.079)	(0.235)	(0.099)
For-profit + Interaction*					0.063	-0.053	0.078
					p =.023	p =.951	p =.007
Panel C: Indicator whether hospital is in the top 10%							
For-profit hospital (Yes/No)	0.005	-0.010	-0.013	-0.036	0.001	0.053	0.003
	(0.013)	(0.011)	(0.012)	(0.011)	(0.018)	(0.063)	(0.019)
× HHI-discharges					-0.284	-0.257	-0.338
					(0.093)	(0.270)	(0.108)
For-profit + Interaction*					-0.041	0.015	-0.047
					p =.000	p =.347	p =.000
Observations	3,197	8,713	8,072	8,072	8,072	2,153	5,919
Hospitals characteristics	✓	✓	✓	✓	✓	✓	✓
County demographics	✓	✓	✓	✓	✓	✓	✓
HRR fixed effects				✓	✓	✓	✓

Notes: Table presents OLS coefficients. Columns (1) display regressions based on pooled fixed effects and robust standard errors, from Table 1(Col. 5), (2)-(7) the full set of fixed effects and accordingly cluster robust standard errors on the hospital level, corresponding to Table 1(Col. 6). All regressions contain hospital characteristics (teaching status 3-categories, size based on number of beds 3-categories, whether it belongs to a system, and whether its located in an urban area) as well as county-level demographics based on census (such as share of people older 65, share of non-hispanic whites, hispanics, blacks, share of population college educated, high school educate), and condition indicators. Column (3) reduces the estimation sample to those that did not change ownership in the sample period, (4) additionally includes HRR fixed effects, (5) interaction with HHI, (6) and (7) split the sample between hospitals that are part of a system and those that are not. For-profit + Interaction*, shows the for-profit gap for an average HHI 0.149 and the p-value whether the sum of both coefficients is significantly different from 0.

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

A Policy

Figure A1, depicts the changes in the HRRP over the sample period. The policy amount was repeatedly changed as shown by the maximum penalty cap.

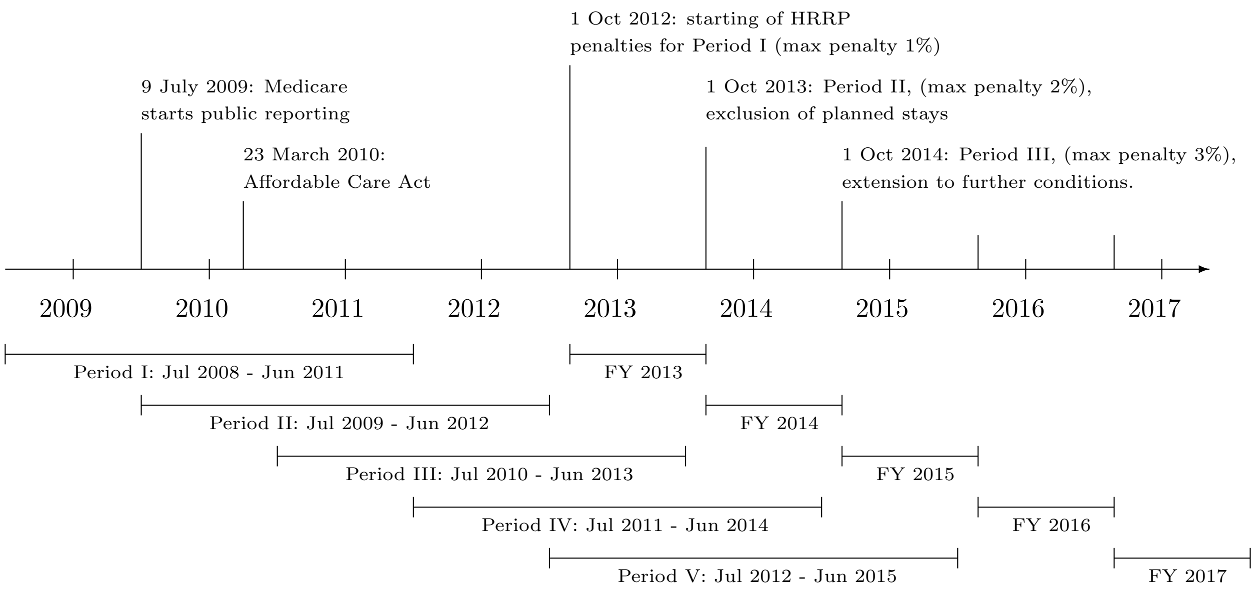

Figure A1: Event line and sample period of HRRP Policy
Source: Adapted from Figure 1 in Wasfy et al. (2017)

Hospitals with at least 25 discharges for a diagnosis and part of the inpatient prospective payment system (IPPS) were eligible.[19] Thier excess readmission ratio in emergency category c in year t measures the "total predicted readmissions [PRR] at a hospital [i] compared with the total expected readmission if the patients were treated at an average hospital with similar patients" (McIlvennan, Eapen and Allen, 2015), i.e:

$$ERR_{it}^{c} = \frac{PRR_{it}^{c}}{E(RR_{it}^{c})}.$$

A penalty was imposed if this ratio of expected versus average was strictly greater than 1, ie. $RR_{it}^{c} - 1 > 0$. The dollar amount of the penalty was calculated as 1 minus the "readmissions adjustment factor" —aggregate payments for these excess Medicare payments divided by aggregate Medicare payments for all discharges— multiplied by the hospital's base diagnosis related group payments, thus,

$$\text{Reimburstment adjustment} = 1 - \min\left[cap, \sum_{c=1}^{C} \max\{ERR_{it}^{c} - 1, 0\} \frac{Payment_{it}^{c}}{All\ payments_{it}}\right].$$

We focus on the extensive margin of a penalty—i.e., if $ERR_{it}^{c} - 1 > 0$—across any of the three conditions. The penalty-cutoff is a policy-relevant discontinuity introduced into the hospitals' cost function (see, Gupta, 2017, for a detailed discussion).

Other interesting policy metrics are the conditional-on-penalty size of the readmission ratio and the second implied cut-off, which occurs at the upper end of the excess readmissions, where the payment amount does not increase further as it is capped, this *cap* maximum rate of penalty was one percent in 2013, raised to two in 2014, and three in 2015, again complicating both the quality metrics over time.[20]

[19] Hospitals in Maryland are excepted from the policy due to a special Medicare agreement.

[20] 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.

B Additional results

First, we present the density plots separately by condition and for the BRglm and OLS estimation approach, both exhibit a long high-quality tail, and a comparable between approximative-OLS and model-consistent BRglm.

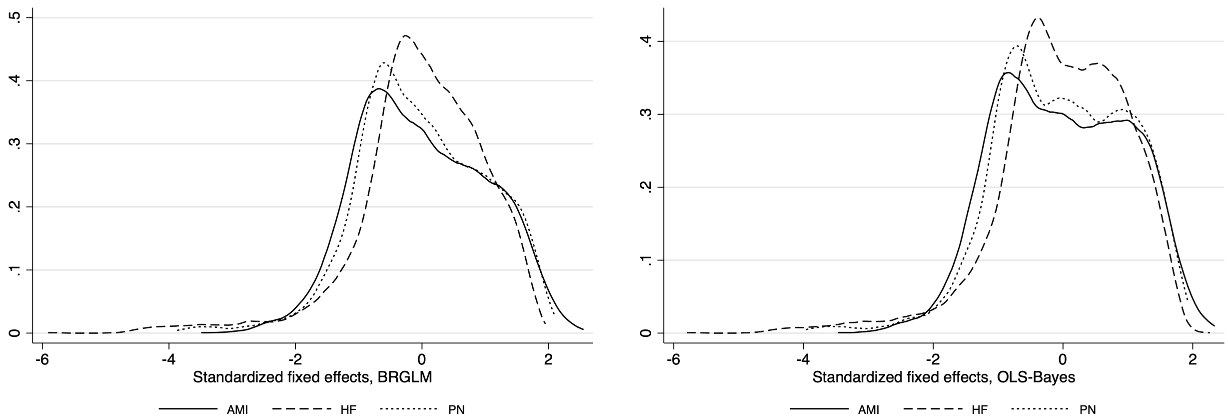

Figure B1: Density plot of separately estimated fixed effects, left Penalty-BRglm, right RR-OLS-Bayes

Note: Figure plots density plots of hospital fixed effects across diagnosis conditions (AMI, HF, PN). We use the estimated fixed effects from eq.(1), ie. $\Phi(\hat{\alpha}_i^c)$ from the separated model. Left graph is based on Penalty-BRglm model and right graph on the Penalty-OLS model.
Source: CMS 2011-2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

Second, we assess the correlation in quality between conditions. Across each, there are highly related and the long high-quality tail is evident not only in the uni-variant comparison above, but also across conditions. Again using the shrunken BRglm fixed effects or OLS with post-estimation shrinkage gives comparable results, yet, the long quality tail is much clearer when using the marginal penalty propensity (main text). Also many of the top bins in this plot actually have a marginal propensity of 100%, which would need to be converted using the OLS results but is implicit in the BRglm in the main text.

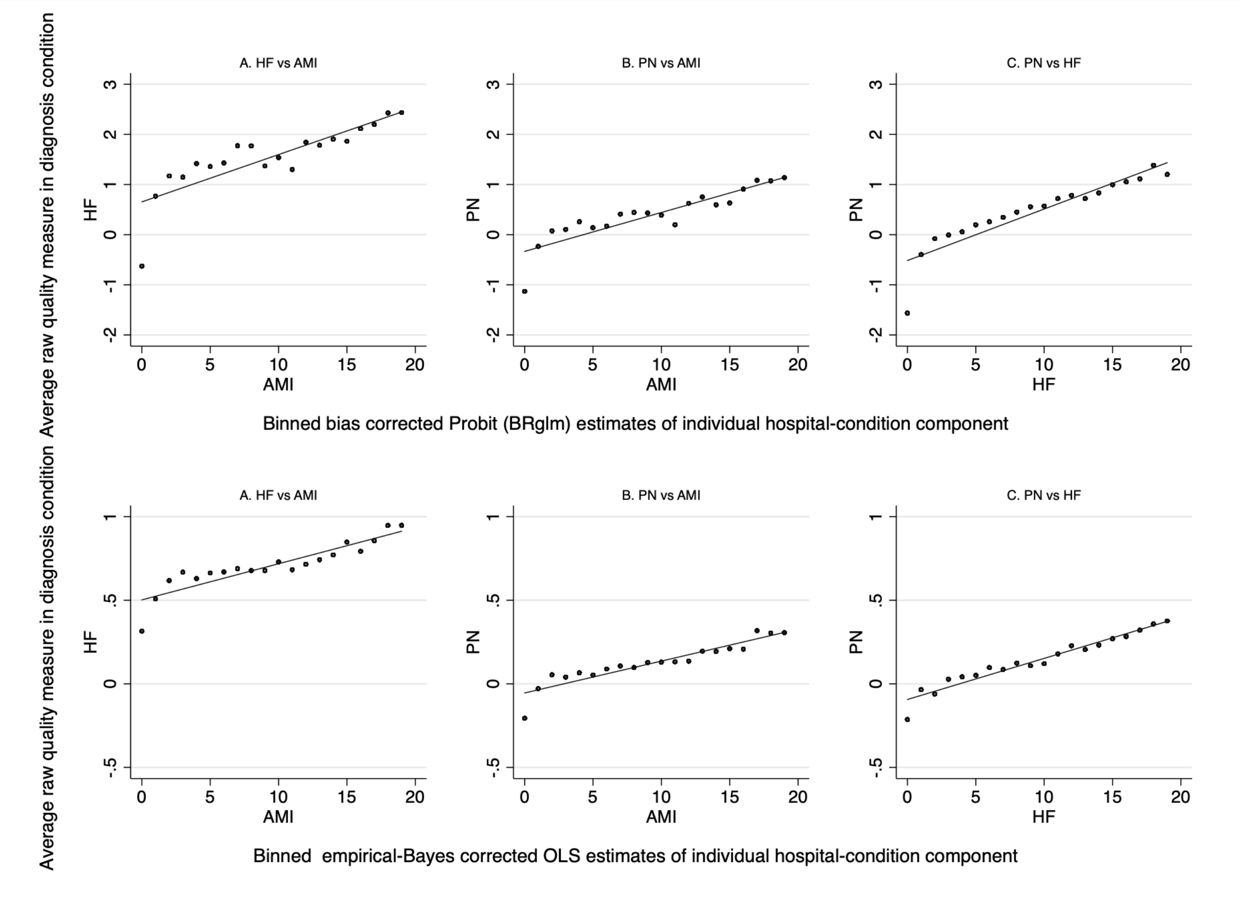

Figure B2: Robustness to Figure 1, equal sized bins of raw alpha and comparison with OLS fixed effects

Note: Figure presents the unrestricted fixed effects from regression eq (1) (top row) and analogues OLS regressions with post-estimation empirical Bayes shrinkage (bottom row). The fixed effects are clustered in 20 equal sized bins and the average performance (in the y-axis condition) is plotted.
Source: CMS 2011-2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

Table B1: Descriptives by penalty-status

	Sample means by penalty-status			Bivariate
	Never	Sometimes	Always	Correlation
	(1)	(2)	(3)	(4)
Hospital-level covariates				
For-profit hospital	0.146	0.203	0.226	0.072
	(0.004)	(0.003)	(0.004)	(0.005)
Hospital is part of a system	0.727	0.743	0.747	0.014
	(0.005)	(0.003)	(0.005)	(0.004)
HRR-level covariates				
Share of for-profit hospitals	0.178	0.202	0.199	0.115
	(0.002)	(0.001)	(0.002)	(0.011)
Number of hospitals per 100T capita	1.181	0.848	0.628	-0.045
	(0.017)	(0.008)	(0.009)	(0.001)
Hospital opening	0.273	0.271	0.260	-0.005
	(0.005)	(0.003)	(0.005)	(0.004)
Hospital closing	0.150	0.181	0.200	0.043
	(0.004)	(0.003)	(0.004)	(0.005)
Discharges for ACSC	28.493	31.834	34.632	0.010
	(0.087)	(0.058)	(0.092)	(0.000)
County-level covariates				
Share in poverty (all ages)	15.576	16.398	17.551	0.008
	(0.052)	(0.038)	(0.065)	(0.000)
Median HH income (in 10T$)	5.186	5.185	5.104	-0.005
	(0.013)	(0.009)	(0.016)	(0.001)
Population (in 100T)	6.498	8.603	11.132	0.002
	(0.147)	(0.115)	(0.208)	(0.000)
Unemployment rate	6.823	7.349	7.934	0.026
	(0.024)	(0.016)	(0.025)	(0.001)
Observations	9,772	22,428	8,895	41,095
Share	21.65%	54.57%	23.78%	

Notes: Table presents means (standard deviations). Columns (1)-(3) display averages of covariates by penalty status, Column (4) is the same as Col(1) in Table 1, for the time-invariant characteristics. Table B2 presents the full regression results for each condition separately, alongside analogous OLS regressions for the excess readmission ratio. More on the construction and definition of the variables used can be found in Appendix Table C1.

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

Table B2: Detailed regression results of penalty-risk and excess readmission ration, by diagnosis condition

Dependent variable: readmission penalty indicator						
	Penalty indicator (Yes/No) Probit-BRglm			Excess Readmission Ratio OLS		
	AMI	HF	PN	AMI	HF	PN
	(1)	(2)	(3)	(4)	(5)	(6)
Number of discharges	0.0008	0.0014	0.0002	0.0000	0.0001	0.0000
	(0.0005)	(0.0003)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Number of discharges, other ER conditions	0.0004	0.0000	0.0007	0.0000	0.0000	0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Number of beds	−0.0003	−0.0004	−0.0006	−0.0000	−0.0000	−0.0000
	(0.0008)	(0.0008)	(0.0007)	(0.0000)	(0.0000)	(0.0000)
Discarges ACSCs per 1'000 enrolles, in HRR	0.0302	0.0268	0.0205	0.0026	0.0016	0.0012
	(0.0093)	(0.0079)	(0.0073)	(0.0005)	(0.0004)	(0.0004)
Hospital opening, in HRR	−0.0215	−0.0010	0.0384	−0.0026	0.0007	0.0008
	(0.0456)	(0.0395)	(0.0388)	(0.0019)	(0.0016)	(0.0017)
Hospital closing, Hin HRRrr	−0.0683	−0.0331	−0.0428	−0.0036	−0.0012	−0.0028
	(0.0379)	(0.0321)	(0.0326)	(0.0016)	(0.0014)	(0.0014)
Percent living in poverty, in county	−0.0066	0.0008	−0.0055	−0.0006	−0.0000	−0.0008
	(0.0146)	(0.0110)	(0.0091)	(0.0006)	(0.0005)	(0.0004)
Household median income in 10'000$, in county	−0.1466	0.0574	−0.0200	−0.0054	−0.0032	−0.0032
	(0.1055)	(0.0793)	(0.0697)	(0.0051)	(0.0036)	(0.0034)
Total population in 100'000, in county	0.0187	0.0594	0.0313	−0.0010	0.0047	0.0034
	(0.0702)	(0.0665)	(0.0601)	(0.0033)	(0.0030)	(0.0030)
Percent unemployed, in county	−0.0267	−0.0130	−0.0069	−0.0019	−0.0011	−0.0011
	(0.0276)	(0.0221)	(0.0203)	(0.0013)	(0.0010)	(0.0010)
Number of observations	10,972	14,951	15,172	10,972	14,951	15,172
Number of hospitals	2,397	3,138	3,178	2,397	3,138	3,178
Share of concordant observations, 0	24.2	24.5	24.9			
Share of concordant observations, 1	23.4	23.4	21.2			
$\overline{\phi(x'\beta)}$	0.19	0.09	0.30			
Hospital fixed effects	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓

Notes: See Table notes in 1. Here, regressions are separately run for each condition in Column (1)-(3), and as comparison (4)-(6) present OLS-fixed effect regressions using the excess readmission ratio as outcome, recall that penalty is defined in this ratio is larger than 1, thus large differences between the two sets of regressions might indicate gaming.
Source: CMS 2011-2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

Table B3: Association of different measures penalty-risk and selected covariates

	Pooled	All	Constant Ownership	HRR FE	HHI	Part of a system: No	Part of a system: Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Raw mean RR							
For-profit hospital (Yes/No)	0.002	0.002	0.002	0.003	0.002	-0.002	0.002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)
× HHI-discharges					0.006	0.018	0.010
					(0.004)	(0.015)	(0.004)
For-profit + Interaction*					0.003	0.001	0.003
					p =.016	p =.220	p =.004
Panel B: Raw mean ERR, risk-adjusted							
For-profit hospital (Yes/No)	0.011	0.011	0.011	0.014	0.011	-0.010	0.009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.010)	(0.004)
× HHI-discharges					0.025	0.058	0.049
					(0.018)	(0.062)	(0.023)
For-profit + Interaction*					0.014	-0.002	0.016
					p =.027	p =.387	p =.004
Panel C: Ebayes OLS ERR							
For-profit hospital (Yes/No)	0.008	0.009	0.009	0.015	0.008	-0.024	0.009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.010)	(0.004)
× HHI-discharges					0.050	0.126	0.070
					(0.019)	(0.064)	(0.023)
For-profit + Interaction*					0.016	-0.005	0.019
					p =.000	p =.071	p =.000
Panel D: Raw mean penalty							
For-profit hospital (Yes/No)	0.056	0.065	0.065	0.076	0.074	0.034	0.064
	(0.017)	(0.013)	(0.014)	(0.013)	(0.019)	(0.060)	(0.022)
× HHI-discharges					0.020	-0.322	0.165
					(0.101)	(0.316)	(0.131)
For-profit + Interaction*					0.076	-0.014	0.089
					p =.290	p =.297	p =.047
Panel E: Ebayes OLS Penalty							
For-profit hospital (Yes/No)	0.050	0.054	0.057	0.079	0.059	-0.051	0.060
	(0.011)	(0.012)	(0.012)	(0.012)	(0.017)	(0.054)	(0.019)
× HHI-discharges					0.155	0.110	0.258
					(0.098)	(0.314)	(0.124)
For-profit + Interaction*					0.082	-0.035	0.098
					p =.013	p =.833	p =.004
Observations	3,197	8,713	8,072	8,072	8,072	2,153	5,919
Hospitals characteristics	✓	✓	✓	✓	✓	✓	✓
County demographics	✓	✓	✓	✓	✓	✓	✓
HRR fixed effects				✓	✓	✓	✓

Notes: See Table notes in 2, Panel A - shows average raw readmission rate, B - raw mean of the excess readmission ratios (accounts for basic risk adjustment), C - OLS fixed effects on ERR with post-estimation E.Bayes correction (thus adds local area risk adjustment), D - uses the raw mean of the penalty status (policy indicator), E - again compares to the OLS with post-shrinkage.
Source: CMS 2011-2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

Table B4: Association of different measures penalty-risk and selected covariates

	Pooled	All	Constant Ownership	HRR FE	HHI	Part of a system: No	Part of a system: Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Fractional response regressions, probit: $\Phi(\alpha_i)$							
For-profit hospital (Yes/No)	0.082	0.091	0.095	0.169	0.121	-0.167	0.132
	(0.035)	(0.022)	(0.023)	(0.023)	(0.035)	(0.098)	(0.040)
× HHI-discharges					0.369	0.257	0.554
					(0.190)	(0.512)	(0.235)
For-profit + Interaction*					0.176	-0.129	0.214
					p =.003	p =.840	p =.001
Panel B: Without government hospitals							
For-profit hospital (Yes/No)	0.030	0.035	0.036	0.060	0.035	-0.059	0.041
	(0.011)	(0.010)	(0.011)	(0.010)	(0.015)	(0.042)	(0.017)
× HHI-discharges					0.205	0.334	0.181
					(0.086)	(0.194)	(0.104)
For-profit + Interaction*					0.066	-0.009	0.068
					p =.001	p =.102	p =.016
Observations$^+$	2,607	7,229	6,814	6,814	6,814	1,443	5,371
Panel C: HHI based on beds (constant within hospital)							
For-profit hospital (Yes/No)	0.023	0.030	0.031	0.052	0.034	-0.054	0.039
	(0.010)	(0.010)	(0.011)	(0.009)	(0.015)	(0.051)	(0.017)
× HHI-beds					0.158	0.108	0.205
					(0.099)	(0.353)	(0.114)
For-profit + Interaction*					0.056	-0.039	0.067
					p =.028	p =.861	p =.017
Panel D: Additional post-shrinkage empirical Bayes							
For-profit hospital (Yes/No)	0.129	0.131	0.139	0.200	0.146	-0.157	0.152
	(0.030)	(0.029)	(0.031)	(0.031)	(0.043)	(0.127)	(0.048)
× HHI-discharges					0.413	0.116	0.686
					(0.242)	(0.689)	(0.306)
For-profit + Interaction*					0.208	-0.140	0.254
					p =.009	p =.946	p =.002
Panel E: Indicator whether hospital is in top 25%							
For-profit hospital (Yes/No)	-0.043	-0.022	-0.023	-0.055	-0.024	0.174	-0.045
	(0.019)	(0.016)	(0.016)	(0.015)	(0.022)	(0.072)	(0.025)
× HHI-discharges					-0.242	-0.445	-0.184
					(0.124)	(0.364)	(0.151)
For-profit + Interaction*					-0.060	0.108	-0.073
					p =.015	p =.389	p =.085
Panel F: Too few discharges - robustness whether gaming via up/down-coding or selective admission							
For-profit hospital (Yes/No)	0.031	0.040	0.041	0.005	-0.017	0.023	-0.031
	(0.014)	(0.020)	(0.021)	(0.017)	(0.024)	(0.078)	(0.026)
× HHI-discharges					0.159	0.543	0.025
					(0.126)	(0.419)	(0.139)
For-profit + Interaction*					0.007	0.105	-0.027
					p =.196	p =.120	p =.962
Observations$^+$	3,197	9,564	8,814	8,814	8,814	2,467	6,347
Observations	3,197	8,713	8,072	8,072	8,072	2,153	5,919
Hospitals characteristics	✓	✓	✓	✓	✓	✓	✓
County demographics	✓	✓	✓	✓	✓	✓	✓
HRR fixed effects				✓	✓	✓	✓

Notes: See Table notes in 2. Panel A fractional probit model, B - drops government run hospitals, C - calculates the HHI using number of beds (rather than condition-specific discharges), D - adds an additional post-shrinkage to the BRglm estimates, and E - uses as dependent variable an indicator whether the hospital-condition pair is in the top 25%, and F - shows the results for too few discharges that does not vary with ownership or competition. If Observations$^+$ are not indicated in the Panel they are the same as in the main regressions and indicated at the bottom.
Source: CMS 2011-2015, Dartmouth Atlas of Health Care, Census 2010, ACS, own calculations.

C Data sources

FIPS crosswalk

We start by performing minor corrections on the file `CBSAtoCountycrosswalk_FY13.xls`[21] to the crosswalk between county and FIPS State county, which is linkable to the hospital compare data (i.e. SAINT CLAIR we set equal to ST. CLAIR). Note, that island states such as AMERICAN SAMOA are dropped because we could not merge them to county nor HRR information.

County information

Using the FIPS indicators, we compiled for the years 2011-2015:
`Rural_Atlas_Update14/Jobs.csv` and `Rural_Atlas_Update14/People.csv` files[22] from which we get the variables such as: yearly unemployment rate, and yearly total population/100,000.

Next, we use the file `SAIPESNC_05APR17_15_02_58_98.csv`,[23] which provides yearly measures of all ages in poverty (in percent) and the median household income (in dollars/10,000). We then merge them via the FIPS crosswalk, all hospitals which could not be merged are included in the regressions with a missing indicator for county.

Hospital Referral Region information

We use zip code crosswalks:[24] `ZipHsaHrr10.xls-ZipHsaHrr14.xls` from the *Dartmouth Atlas*, which allows us to connect the Zip codes to HRRs. We use the one year lagged values as hospital data is published with a lag. We calculate the number of hospitals for each year and define two indicators, one if there are more hospitals (in HRR) than in the previous year, and one if there where less. Note, that we can not distinguish, whether these are actually openings/closings of hospitals or a result of mergers or separations.

We use the number of Discharges for Ambulatory Care Sensitive Conditions from the selected medical discharge rates files:[25] `2010_med_discharges_hrr.xls-2014_med_discharges_hrr.xls` where we subtract the conditions that are equal to our outcome measures (BacterialPneumoniaDischargesp and CongestiveHeartFailureDischar) form the total discharges (DischargesforAmbulatoryCareS). We then merge them via the zip code crosswalk, all hospitals which could not be merged are included in the regressions with a missing indicator for HRR.

Hospital Compare data

Our main data set is provided by the Centers for Medicare & Medicaid Services. More specifically, we use from the Acute Inpatient PPS:[26]

- `FY 2012 Final Rule- IPPS Impact File PUF-August 15, 2011_1.txt`
- `FY 2013 Final Rule CN - IPPS Impact File PUF-March 2013.txt`
- `FY 2014 Final Rule IPPS Impact PUF-CN1-IFC-Jan 2014.txt`
- `FY 2015 IPPS Final Rule Impact PUF-(CN data).txt`
- `FY 2016 Correction Notice Impact PUF - (CN data).txt`

The construction of these variables is taken from Gu et al. (2014). First, we use the information on the number of hospital beds which we include as 2 indicators for 100-399 beds and for more than 400. Second, we use the resident to bed or daily ratio (rday) is larger than 0.25 as indicators of major teaching hospitals and lower than 0.25 but larger than 0 as minor teaching hospitals. Also urban if either *urgeo* or *urspa* indicate an urban area. These covariates are almost always constant within hospital, for the very few minor changes we set the to the first observed state, to make them time-consistent.

[21] downloaded from http://www.nber.org/ssa-fips-state-county-crosswalk/ (accessed 26.03.17).
[22] downloaded from https://www.ers.usda.gov/data-products/atlas-of-rural-and-small-town-america/download-the-data/ (accessed 26.03.17).
[23] downloaded from https://www.census.gov/data-tools/demo/saipe/saipe.html (accessed 26.03.17).
[24] downloaded from http://www.dartmouthatlas.org/tools/downloads.aspx?tab=39 (accessed 26.03.17).
[25] downloaded from http://www.dartmouthatlas.org/tools/downloads.aspx?tab=41 (accessed 26.03.17).
[26] downloaded from https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/index.html (accessed 26.03.17).

Next, we use Hospital Compare data archive:[27]

- `HOSArchive_Revised_Flatfiles_20121001/Hospital_Data.csv` and `READMISSION REDUCTION.csv`
- `HOSArchive_Revised_Flatfiles_20131001/Hospital_Data.csv` and `READMISSION REDUCTION.csv`
- `HOSArchive_Revised_Flatfiles_20141218/Hospital General Information.csv` and `READMISSION REDUCTION.csv`
- `HOSArchive_Revised_FlatFiles_20151210/Hospital General Information.csv` and `READMISSION REDUCTION.csv`
- `Hospital_Revised_Flatfiles/Hospital General Information.csv` and `READMISSION REDUCTION.csv`

from which we get for each health conditions' READM-30-AMI-HRRP, READM-30-HF-HRRP, READM-30-PN-HRRP the excess readmission ratio, which we define as a penalty if larger than 1, we drop the hospitals with missing information in this (our key) variable. We use for each condition its corresponding number of discharges. Further, across the three conditions we calculate the total number of discharges leaving-out the current condition's discharges. Finally, the hospital's ownership is defined for-profit, if neither governmental nor non-profit (as above very minor changes, which we made time-consistent by taking the maximum observed value).

Note, that missing values in the readmission variable corresponds to "too few discharges" (less than 25). In a robustness, see appendix Table B4, we use this as dependent variable. Finally, we summarise our definitions of the key variables in the following table.

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

Table C1: Variable definitions

Variable	N	Mean	SD	Min	Max	Definition and construction	Source	Level
Main panel model, eq. (1)								
Penalty	41,095	0.49	0.50	0.00	1.00	Indicator whether there was a penalty issued in the respective condition	CMS	Hospital-condition-year
Number of discharges	41,095	320.46	295.24	0.00	3667.00	Number of discharges in hospital year condition	CMS	Hospital-condition-year
Total discharges leave out	41,095	616.35	548.44	0.00	6966.00	Sum number across ER conditions, leave out own condition	CMS	Hospital-condition-year
Number of beds	41,095	218.04	189.73	1.00	1928.00	Total number of beds	IPPS	Hospital-year
Discharges ACSC	41,095	31.65	8.95	0.00	66.36	Discharges for Ambulatory Care Sensitive Conditions - Regional measure of primary health provision, GU	DartmouthAtlas	HRR-year
Opening hospital, in HRR	41,095	0.27	0.44	0.00	1.00	Positive change in the number of ER providers one year to next	Own calculation	HRR-year
Closing hospital, in HRR	41,095	0.18	0.38	0.00	1.00	Negative change in the number of ER providers one year to next	Own calculation	HRR-year
All ages in poverty per cent	41,095	16.45	5.67	0.00	55.10	Local poverty rate	SAIPESNC	County-year
Median hhincome 10T dollars	41,095	5.17	1.39	0.00	12.59	Local median household income 10T dollars	SAIPESNC	County-year
Total population by 100T	41,095	8.65	17.25	0.00	101.70	Local total population estimate	Rural Atlas	County-year
Unemployment rate	41,095	7.35	2.42	0.00	28.90	Local unemployment rate	Rural Atlas	County-year
Other quality metrics						All averaged in hospital-condition		
Readmission rate	3,194	0.20	0.01	0.16	0.27	Condition-specific 30-day readmission rate	CMS	Hospital-condition-year
Excess readmission ratio	3,197	1.00	0.05	0.82	1.30	Condition-specific 30-day readmission rate	CMS	Hospital-condition-year
Overall readmission rate	3,154	0.16	0.01	0.12	0.20	Overall 30-day readmission rate of hospital	Sacarny-webpage	Hospital-year
Mortality rate	3,178	0.13	0.01	0.08	0.18	Condition-specific 30-day mortality rate of hospital	Sacarny-webpage	Hospital-condition-year
Patient satisfaction	3,186	5.57	3.03	0.00	29.93	Survey measure: Share would not recommend hospital	HCAHPS	Hospital-year
Fixed effect model, eq. (2)								
Measures of fixed effects	3,197	0.50	0.29	0.00	1.00	Extracted fixed effects - various standardisations, main Phi(alpha), also percentile rank,	Own calculation	Hospital-condition
For-Profit	3,197	0.20	0.40	0.00	1.00	For-profit 0/1 Indicator whether it is a for-profit hospital (voluntary and government in ref. category)	IPPS	Hospital
Changed Ownership	3,197	0.08	0.27	0.00	1.00	A change in ownership status over sample period	IPPS - Own calculation	Hospital
System hospital	3,197	0.72	0.45	0.00	1.00	0/1 Indicator whether hospital is part of a system as defined in AHA	DartmouthAtlas	Hospital
HHI-discharges	3,197	0.15	0.13	0.01	1.00	HHI based on discharges in ER condition : $Average_t(\sum_{Hrr}(dischargesincondition_t/AllDischarges)^2)$	Own calculation	HRR-condition
HHI-bed	3,197	0.14	0.11	0.02	1.00	HHI based on number of beds: $Average_t(\sum_{Hrr}(nrbeds_t/AllBeds)^2)$	Own calculation	HRR
Size	3,197	0.77	0.64	0.00	2.00	Hospital size 1/3 How many beds categories following Gu et al.: 0-,100-,400- IPPS Hospital constant	IPPS, Own calculation	Hospital
Teaching status	3,194	1.40	0.64	1.00	3.00	Whether the hospital has a high resident-to-bed or rday, 0, positive, or is larger than 0.25	IPPS, Own calculation	Hospital
Urban	3,197	0.73	0.44	0.00	1.00	Urban 0/1 Whether the hospital is located in urban area	IPPS	Hospital
Share over 65	3,193	13.66	3.54	5.57	43.38	Share of county population in 2010 that are over 65	ACS	County
Share black	3,193	12.38	13.89	0.02	85.44	black (non-hispanic white reference)	ACS	County
Share asian	3,193	3.50	5.02	0.03	43.01	asian	ACS	County
Share hispanic	3,193	13.88	15.90	0.36	95.74	hispanic	ACS	County
Share high school only	3,193	29.66	7.46	8.30	51.68	high school degree (less than HS, reference)	ACS	County
Share some college	3,193	21.25	3.59	8.67	33.76	some college	ACS	County
Share associate degree	3,193	8.03	1.97	2.04	16.66	associate degree	ACS	County
Share college and more	3,193	27.04	10.71	5.11	72.88	college or more	ACS	County