The Implication of Health Care Market Concentration on Community Benefits and Health Outcomes

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Abstract

Nonprofit hospitals with tax-exemption status are expected to promote the health of their communities to retain the tax-exemption status. Nonprofit hospitals report information regarding their financial assistance and certain other community benefit activities in dollar value during that tax year on Schedule H, which is attached to Form 990. Either the IRS or hospitals do not observe whether the community benefit activities do promote the community's health. Secondly, as a favorable tax treatment, nonprofit hospitals are expected to provide more community benefit provision once they acquire more market power or financial ability. In this paper, I examine whether the healthcare market concentration impacts the health of communities through the community benefit provisions of nonprofit. I use prevention quality indicators at population level as an outcome of interest to study the research question. Using IRS Form 990 and HCUP State Inpatient Database (SID) files for six states from 2012 and 2016, I find no evidence that nonprofit hospitals promote their communities through community benefit provisions in more concentrated markets. Unlike the hospital competition, I find evidence that prevention quality indicators improve in more concentrated insurer markets.

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1. Introduction

The Internal Revenue Services (IRS) grants tax exemption status to nonprofit hospitals with an expectation of nonprofit hospitals benefiting their communities by promoting the health (IRS, 2020). The legal justification of tax exemption status has been known as community benefit standard has evolved several times since 1969. The current community benefit standard requires nonprofit hospitals to promote the health of the community. As of 2008, the last major changed by IRS requires nonprofit hospitals to disclose community benefit expenditures in dollar value in IRS Form 990 Schedule H. The IRS categorizes community benefits based on the activity types and aims to set a standard in reporting those activities; however, neither it mandates certain amount of dollar value that tax-exempt hospitals must follow in their benefit activities nor it sets any measures on how to serve the promotion of health. Either the IRS or hospitals does not observe whether the community benefit activities promote the community's health.

Previously, a narrow definition of community benefit standard was a requirement for tax-exempt qualification between 1956 and 1969. IRS ruled 'the charity care standard' in 1956 that requires nonprofit hospitals to provide health care for free or at the rates below-cost services to those who are unable to pay (IRS, 1956). The need of charity care was reduced due to the enactment of Medicaid and Medicare as a national public health insurance in 1965. In 1969, a broader definition of community benefit replaced the previous definition and since then the definition of 'community benefit' has been considered as a legal standard for qualification of tax-exempt status (IRS, 1969). Federal tax law no longer requires nonprofit hospitals to provide only charity care for tax-exemption.

The current IRS-designed community benefit categories in Schedule H include not only charity care but also following categories: unreimbursed costs of means-tested programs, community health improvement services, health profession education and research, and contributions to community groups. An additional section of the Schedule H is dedicated to ”community building” activities which encompasses any type of activities that promote health of communities outside of the clinic. Even though the requirement of reporting community benefit activities attempted to bring a standard, the policy still requires nonprofit hospitals to report their activities in monetary value. The implication of the policy is that neither IRS nor nonprofit hospitals observe the outcome of community benefit activities. It is unclear whether charity care or uncompensated care of nonprofit hospitals improve the health of the communities and/or the hospital quality for uninsured patients is significantly different than insured patients.

In my previous chapters/studies I examine how competition in health care market affect the community benefit provision by nonprofit hospitals. In this paper, I analyze the quality of community benefit activities rather than the monetary value of community benefit provision. My starting point is that gaining more market power might raise hospital's ability to provide more community benefits and improve the health of communities by improving the health outcomes. Theoretical model by Capps et al shows that some degree of market power is a necessary condition for nonprofit hospitals to provide charity care or unprofitable services (Capps et al., 2020). Whether nonprofit hospitals do more provide more community benefits with more market power is indeed empirical question. In my previous chapter, I find no meaningful relationship between the competition level and community benefit activities.

A large body of evidence reveals that hospital quality level is compromised in concentrated markets. In their seminal paper, Kessler and McClellan (KM hereafter) examine the relationship between hospital competition and patient health outcomes, and find that competition in hospital markets is welfare-improving. Their result shows that mortality rate among Medicare patients is higher in concentrated markets compared to those in less concentrated markets. A growing body of empirical evidence supports this result that competition in health care market generally improves the quality of care (Lewis & Pflum, 2017; Kessler & McClellan, 2000; Gaynor et al., 2015; Bloom et al., 2015). If the same result applies for the community benefit provision, it implies that nonprofit hospitals may provide better quality care in competitive markets; however, it is not theoretically clear whether the quality level of community benefits is improved with competition "level." [1]

As well as setting a standard for community benefit activities is a challenging task, setting a standard for a hospital quality measure is also burdensome assessment since it has to solve the comparable measurement issue across the hospitals and communities (Joseph J. Doyle et al., 2017). One of such an initiative is launched by the Agency for Health Care Research and Quality(AHRQ) that assesses health care quality and develops quality indicators for various types of health care services. The AHRQ develops prevention quality indicators (PQI) that identify admissions with ambulatory care sensitive conditions, which could have been prevented if patients had accessed to better quality care or received high-quality care. The PQI rates as population health indicators also aim to help policymakers and hospitals to evaluate the health care needs assessments of communities.

Hospital quality is multi-dimensional, and majority of studies use mortality measures and readmission measures as a hospital quality. In this paper, I use prevention quality indicators as a hospital quality to analyze the impact of competition in health care market on the quality of community benefit provision. Due to the fact that categories of community benefit activities do not include only hospital services, I only examine charity care among all categories which falls into financial assistance category of com-

[1] better quality rate in CB does not mean that it is welfare-increasing.

munity benefit provision.

I perform empirical analysis of the impact of competition on preventable admissions using a hospital-level data that I discussed further in the data section. I create two ratios that measure preventable admissions share of both uninsured patients and all patients out of total discharges per hospital. Following KM approach, I use a form of Herfindahl Hirschman Index (HHI) that calculates the predicted market shares of hospitals to instrument for hospital competition level. for insurers, I calculate the sum of squared market shares of total enrollment plans and instrument it with demographics. I find that hospital market competition does not have a meaningful impact on the prevention quality indicators, but insurer competition improves the PQI. Several robustness checks also supports the main findings of the result.

This study contributes several strands of literature. First of all, as the main objective of the paper is to examine the outcome of tax exemption status given to nonprofit hospitals, this study contributes to the literature that examines the impact of tax-exemption status on nonprofit hospital behaviors. An extensive literature shows that nonprofit hospitals provide more community benefit activities than for-profit hospitals. CBO published an analysis before the IRS change in 2008 that examined the tax exemption status and community benefit provision and found that the distribution of community benefit provision by nonprofit hospitals vary widely (Congressional Budget Office, 2006). An important result from the analysis is that nonprofit hospitals do not provide community benefit provision as much as government hospitals do once the hospital's operation expenses are considered. Even though for-profit hospitals are not required to provide any community benefit activities, there is not significant difference between the share of operating expenses of nonprofit hospitals and for-profit hospitals for charity care.

The CBO report also highlights that there is no consensus on what is considered as community benefit. IRS requirement of Schedule H Form 990 aims to bring a standard in reporting; however, it still considers the input-based resource allocation rather than whether the community benefit expenditures turn into valuable allocations for communities. Affordable Care Act(ACA) requires nonprofit hospitals to conduct health need assessment of their communities every three year. Still it is a good progress, the content of the assessment or whether nonprofit hospitals causes any improvements does not have any legal impact of the tax exemption status. Rubin et also examined the legal process of tax exemption status after the IRS and ACA requirements, and propose an outcome-based approach for the community benefit provision of nonprofit hospitals (Rubin et al., 2015). This study aims to understand whether nonprofit hospitals' community benefit activities affect the promotion of communities' health.

The second strand of literature extensively examines the effect of hospital and insurer competition on hospital prices and quality (Dafny, 2010; Brekke et al., 2011; Colla et al., 2016; Ho & Lee, 2017; Pauly, 2019). The mechanism of hospital and insurer relationship and its impact on patient outcomes include several layer of interactions. While each hospital and insurer compete with rivals within the market, each side also negotiates with each other to set prices that health plans pay to hospitals for each patient. Each side separately has an impact of hospital quality or preventable admissions (Kolstad & Kowalski, 2012). Some empirical studies show that health maintenance organizations (HMO) penetration decreased the preventable admission rates Zhan et al. (2004) and a growing body of empirical studies also show that concentrated markets are associated with lower quality of health services as discussed above. This study contributes to this literature by analyzing how the preventable admission rates vary with competition level of the market. This literature also provides empirical evidences on behaviors of hospitals and insurers for antitrust cases. This study contributes to that literature by examining whether nonprofit hospitals exploit their market power and provide more community benefit activities once they acquire more market power.

2. Data

I primarily use the HCUP State Inpatient Database (SID) files for the years between 2012 and 2016 that contain patient discharges for the following states: Arkansas, Florida, Mississippi, New York, Utah, and Vermont. The HCUP SID data includes patient characteristics and clinical information such as diagnosis and procedures on each discharge from hospitals in participating states. Each discharge also contains payer information and the source of admissions. The data is provided by Agency for Healthcare Research and Quality(AHRQ) along with SAS software that identifies prevention quality indicators (PQIs) based on diagnosis and procedure codes. I use the same algorithm as in the SAS software to obtain PQIs for hospitals in the data sample and use those rates as dependent variables for the analysis.

The next data source I utilize for the study comes from Decision Resource Groups (DRG) Managed Market Surveyor File. The DRG data includes both public and commercial insurance enrollment for each health plan in the health insurance marketplace from 2012 to 2016. I also use the American Hospital Association's Annual Survey of Hospitals (AHA) to obtain hospital characteristics and I merge HCUP SID with AHA data using AHA hospital identifier. I supplement the data with Area Health Resource File (AHRF), and American Community Survey (ACS) to obtain market-level characteristics. I only include general short-term hospitals to obtain potentially preventable hospital admissions which are known as ambulatory care sensitive conditions (ACSCs) at the hospital level.

The data sample for the analysis contains more than 6 million discharges per year for 6 states. Following the AHRQ approach, I exclude patients who are younger than 18, or transferred from another institution, or have MDC 14 (Pregnancy, Childbirth, and the Puerperium). Then I identify discharges only having principal diagnosis of ambulatory care sensitive conditions such as diabetes with short term complications or health failure [2]. The outcome variable at the hospital level derived from HCUP data that I use for this paper is PQI rate for uninsured patients which is the ratio of the sum of uninsured patients with PQI given hospital divided by the total uninsured numbers in the service population.For robustness check, I re-examine the analysis with PQI rate for all patients.

AHRQ calculates the PQI as a population indicator which means that each indicator is considered as a fraction of the population where each patient resides. while the numerator is the related discharges with multiple exclusions, the denominator is the population in the defined geographic area (metropolitan or county). The unit level of this analysis is hospital and rather than population-level variable would be ideal for the study. For that purpose, I modified the ratio to create a hospital-level variable by changing the geographic population(denominator) with the population of service area that a hospital atracts its patients. Firstly I calculate the county-level PQIs following AHRQ approach and then I calculate the share of hospital patients from each county. In the second step, I calculate the hospital-level PQI ratio as the weighted sum of hospital-specific PQI rate, where the weight is the share of patients from that county (add a formula here). This method does not impose any geographic boundaries, instead, it defines the community that a hospital serves. The final ratio is multipled by 10000 to show how many patients with PQI per 100,000 population that hospital serves in its defined service area in fiscal quarter.

I present the mean values of each dependent variable along with all vari-

[2] See Appendix A for more details on AHRQ quality measures

Table 1: Summary Statistics

	Mean	SD	Min	Max
A.Outcome of Interest				
PQI Rate for Uninsured (per 100,000)	137.66	147.70	0	2,496.18
PQI Rate for All (per 100,000)	484.53	389.73	0	5,480.34
B.Competition Index				
Hospital HHI	0.38	0.22	0.09	1.00
Insurer HHI	0.14	0.06	0.07	0.40
C.Hospital Characteristics				
Quarterly Total Discharge	2978.61	2195.57	1.00	13040
Quarterly Uninsured Discharge	154.81	189.36	1.00	1546
Casemix IndeX	1.56	0.24	0.74	2.42
Bed Size	444.75	481.14	14	2829
For-profit Hospital	0.27	0.44	0	1
Government Hospital	0.14	0.35	0	1
D.Market Characteristics				
Private Insured Pop.(percent)	64.53	6.68	52.40	81.10
Uninsured Pop.(percent)	14.44	4.68	4.30	24.10
138 Poverty Rate(percent)	19.62	3.44	12.55	30.06
Total Medicare Pop. (percent)	18.87	4.83	7.72	37.82
Population 65+ (percent)	16.91	5.79	6.88	38.84
Unemployment Rate(percent)	0.03	0.03	0.01	0.28
Active MDs	4093.73	9854.71	131	83738
Food SNAP Recipient	210584.74	339964.24	8106	2709045
Median Income	55213.61	9844.67	35093	93144

All summary statistics are calculated for 2012-2016 time period.

Outcome of Interests, Hospital HHI and Discharges are derived from HCUP data; other hospital characteristics are from AHA survey, and market characteristics are from ACS and Health Services Area Files.

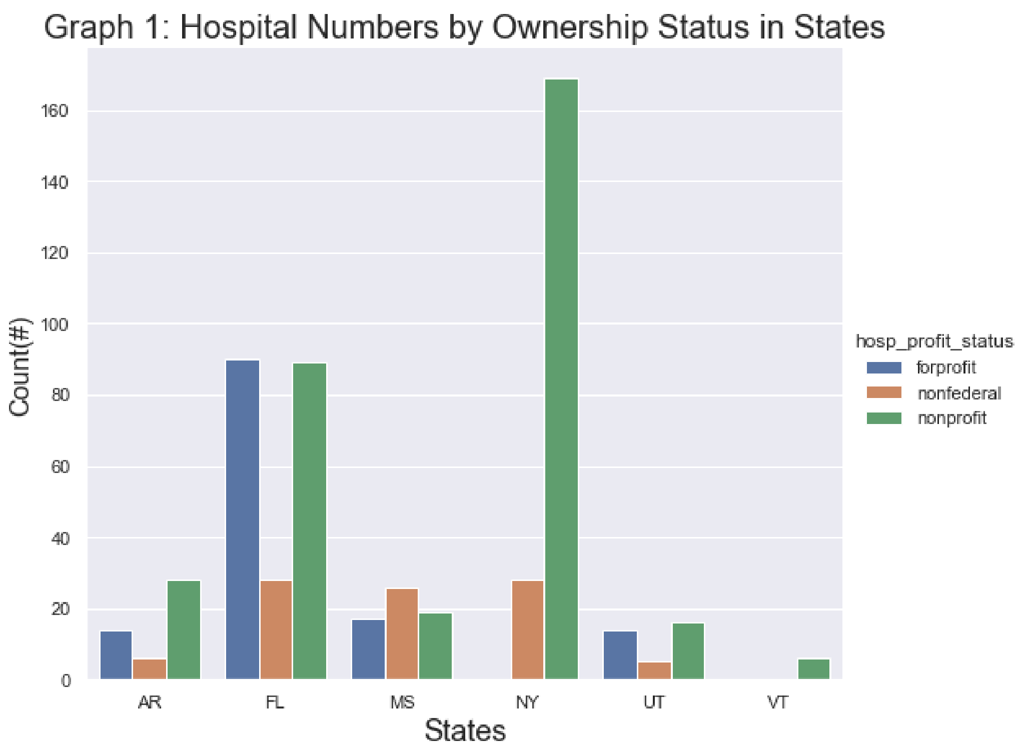


Figure 1: Number of Hospitals by Ownership Status in Six States

ables in the Table 1. The final data, which is at the hospital level, includes 417 hospitals from 6 states and the time is fiscal quarter to be consistent with the time in the HCUP SID data. The Table 1 sets out the summary statistics on the data sample and it shows that the average PQI rate for uninsured patients is nearly 15 percent of total uninsured discharges and is lower than the PQI rate for all patients. Of the six states, more hospitals are located in Florida and New York State (Graph 1) and 60 percent of total hospitals in six states have nonprofit status while 25 percent are forprofit hospitals.

It is worth noting that ICD9 codes were the national diagnosis coding system in the US before The Department of Health and Human Services (HHS) required hospitals to use ICD10 diagnosis coding as of October 1, 2015. The transition of ICD10 occurred in the last quarter of 2015 and As of 2015 q4,

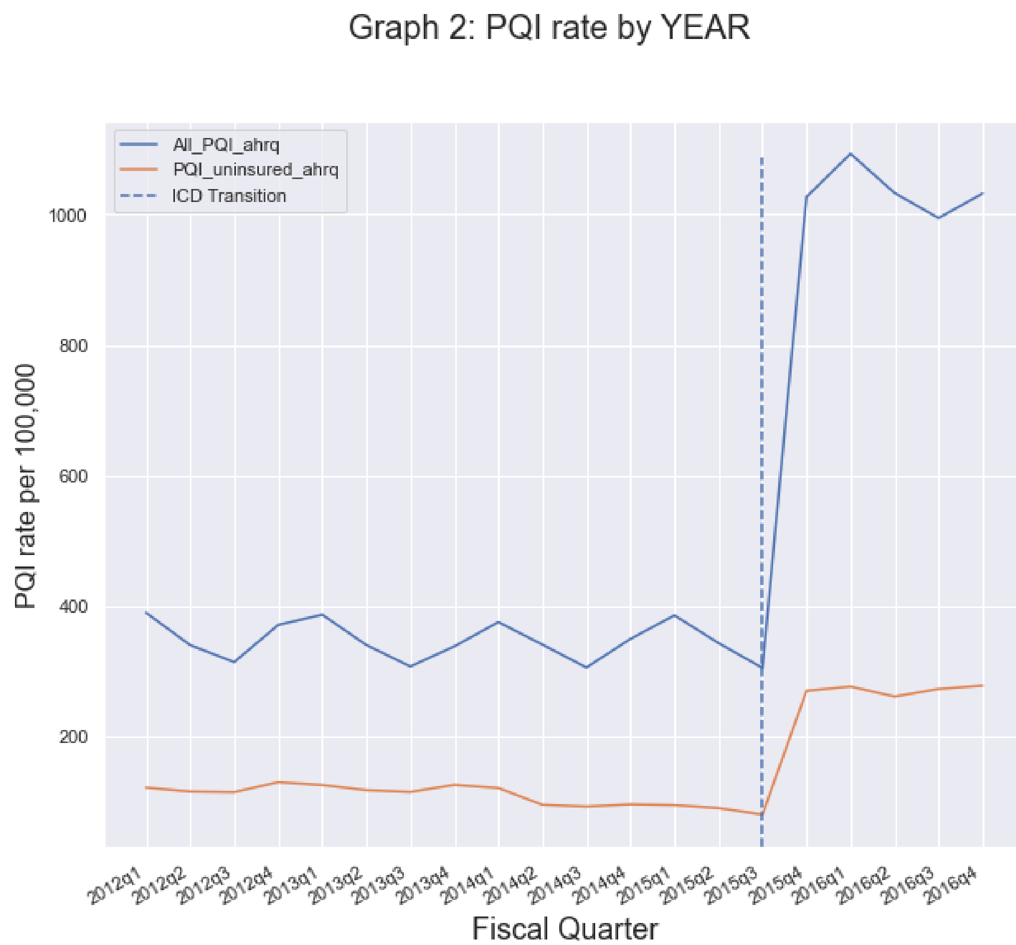


Figure 2: PQI Rate by Year

all discharges are coded in ICD-10. Compared to ICD9, the ICD10 coding system includes a higher level of detail and incorporates new codes into the health care system. The Graph 2 shows that the trend for each PQI rate increases dramatically in the last financial quarter of 2015. Since the transition requirement was applied to all hospitals, I control for the change in the analysis rather than constructing an adjusted PQI rate for each hospital. In the sensitivity analysis, I limit the data sample to only observations with ICD9.

The Graph 3 below shows how the PQI rate for each group of patients is

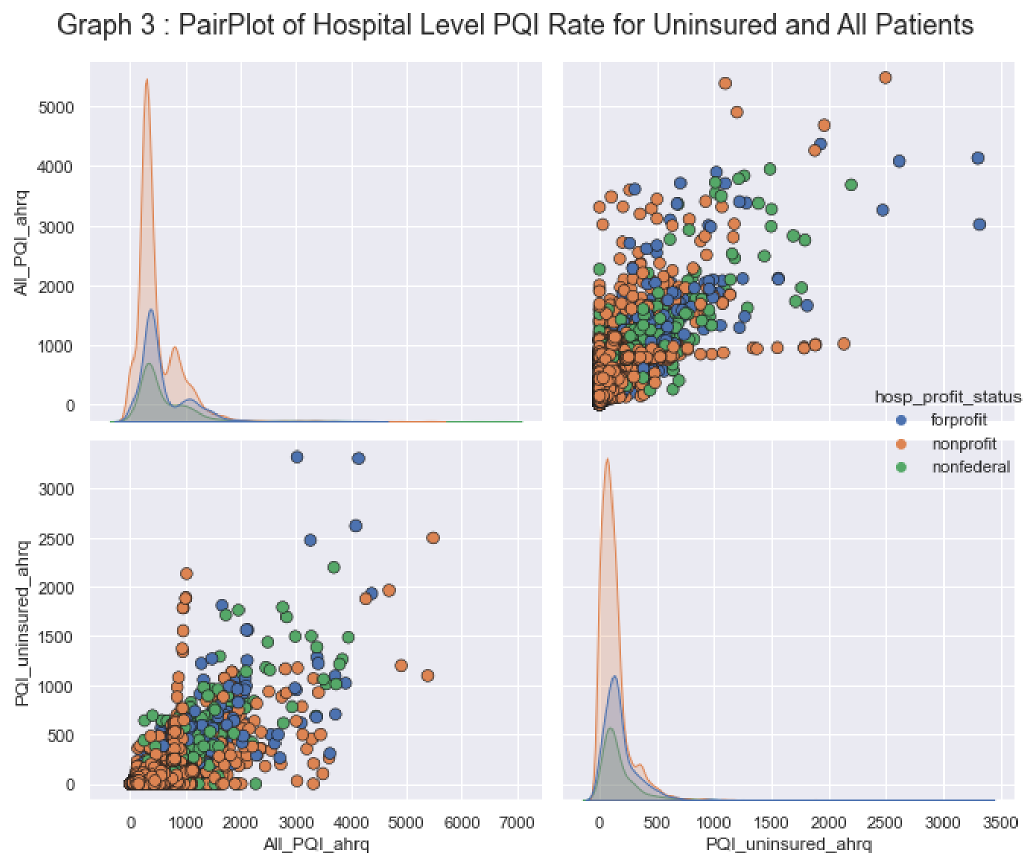


Figure 3: PairPlot of Hospital Level PQI Rate for Uninsured and All Patients

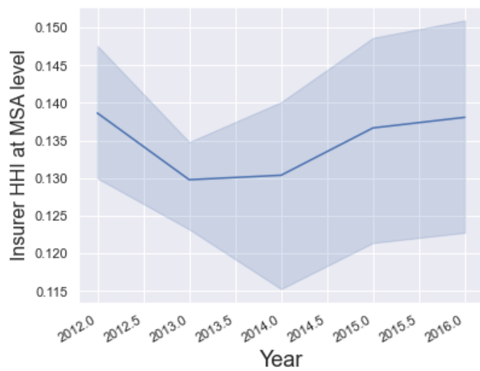
distributed and also shows the relationship between two groups of patients by ownership status of hospitals. Both PQI rates for uninsured and all patients are distributed skew right. The rate for uninsured patients is higher at nonprofit hospitals compared to other types of hospitals. As the sample size for nonprofit hospitals accounts for 60 percent of total hospital discharges from 2012 to 2016 in six states, it is probable to expect more uninsured patients to visit nonprofit hospitals compared to other types of hospitals.

2.1 Competition Measure

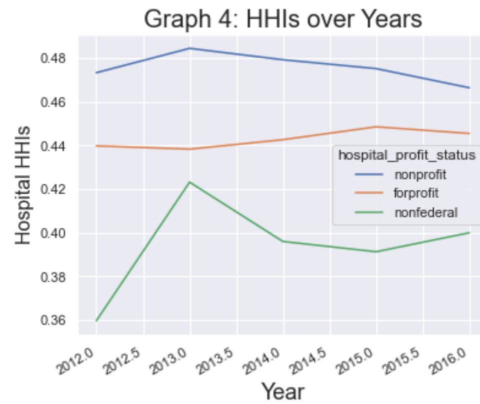
Using the HCUP SID data, I estimated the predicted Herfindahl-Hirschman Index(HHI) for each hospital which is derived from predicted market shares as I adopt Kessler and McClellan approach (Kessler & McClellan, 2000). As I discussed in Appendix A (attach it to the latex document later); due to the endogeneity of HHIs, I avoid defining the health care market based on geographical area for competition measure by estimating a demand model based on relative travel distances of hospital visits. For the demand model, I select all nonfederal general medical and surgical hospitals with nonrural Medicare patients within 80 minutes of driving from a patient location to a chosen hospital. The index is estimated between 0-1 with a higher value considering less competitive hospital.

For insurers, I calculate the HHI with shares of commercial health plan in the defined market including both fully and self-insured enrollments at metropolitan market area per year since I do not observe each patient's insurance type for either discharge data or at the population level. The index ranges from 1 (perfect competition) to 10000 (a monopoly); however, I divide the index by 10000 to be consistent with Insurer HHI calculation for analysis purposes.

The graph 4 shows how hospital HHIs and insurer HHHs at the MSA level vary over time and across hospital ownership types. There is a noticeable increase for nonfederal and nonprofit hospital HHIs by 2013; however, it decreases for these types of hospitals. On the contrary, the trend of insurer HHIs follows an opposite direction to Hospital HHIs trend over time. I also examine the relationship between hospital and insurer HHIs in the Graph 5 to observe whether insurer and hospital HHIs are correlated and how each hospital ownership type is located in a different market concentration. As the graph shows, for-profit hospitals are more competitive firms and



(a) Insurer HHI



(b) Hospital HHI

Figure 4: Insurer and Hospital HHI between 2012 and 2016

mostly located in moderately competitive insurer markets. Hospital ownership types are more normally distributed in terms of hospital HHIs (slightly right-skewed); however, the distribution of the location of different hospitals based on insurer competitiveness is highly right-skewed. It means that the majority of hospitals are located at either relatively moderate or unconcentrated insurer markets.

2.2 Econometric Specification

The main focus of this study is to examine preventable admission rates for uninsured patients given the market power of hospital and insurer concentration. I begin with a basic regression framework in which PQI rate (R) is a function of hospital and insurer HHIs along with both hospital and market-level characteristics.

$$R^m_{ht} = \Phi_h t + \alpha_h + \beta HHI_{ht} + \Gamma HHI_{it} + \theta X_{ht} + \zeta Z_t + \varepsilon^m_h t$$

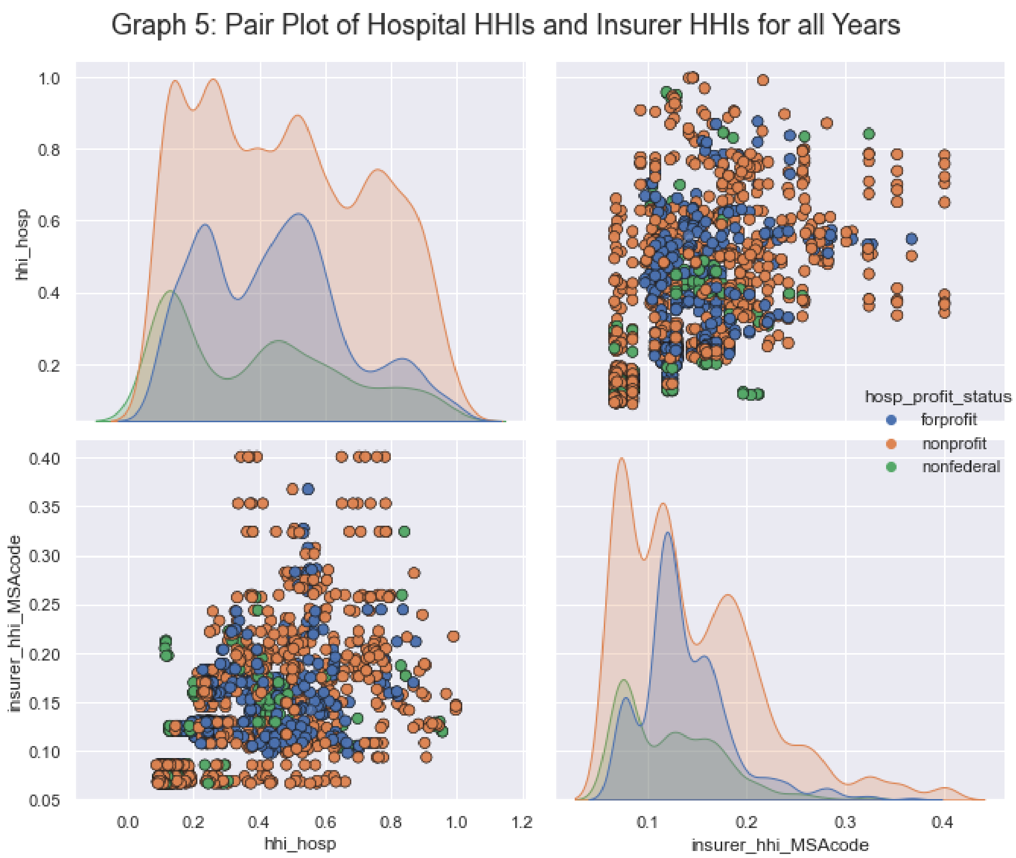


Figure 5: PairPlot of Insurer and Hospital HHI over Years

R^m_{ht} defines the type of PQI rate, R^m, at hospital h in time t and Φ_{ht} is the constant that is specific to each hospital h at time t while α_h is hospital fixed effects. β coefficient presents the hospital-specific competition index which I use predicted market shares of the hospital for HHI. X includes the hospital characteristics such as ownership and teaching status while Z is for market-level characteristics such as poverty and income level, employment rate. I also add the ICD10 version dummy variable to control for the ICD transition.

Hospitals may provide different level of quality and charge patients based on their insurance status and type (reference). Given the PQI rates are indeed a measure of hospital quality, I do not assume that hospitals provide the same level of quality for all admitted patients which is the main interest of this research. Due to the fact that hospitals set the quality level, it brings the potential endogeneity issue of quality indicators. Some hospitals also attract more patients and provide higher quality due to market size/higher market share. Since hospital market structure is endogenous, I use predicted market share of hospitals to mitigate the endogeneity bias. β and Γ capture to what extend the PQI rate changes with the market power of hospital and insurer market concentration. As a risk-adjustment, I include all-payer case-mix in the model to control for hospital performance. I, then, add hospital fixed effects to the model and compare the results with the OLS regression results.

The OLS model allows me to exploit the variation of PQI rates of hospitals in a different locations to observe how it changes with market concentration. The within and between standard deviation for the outcome of interest is nearly equal. Although the standard deviation is relatively small for within hospitals, it is high enough to examine the model with fixed effects (maybe I can display xtsum result here). I argue that adding hospital fixed effects in the model allows me to isolate unobservable hospital characteristics that might affect the quality level of uninsured patients from differences in hospitals with similar characteristics. For instance, simply adding case-mix in the model would not be enough to account for the patient type differences among uninsured patients between hospitals.

One might concern that unobserved factors might be both correlated with the preventable admission rates and insurance concentration. Unobserved effects that are related to health insurance such as health plan coverage might be correlated with the prevention admission rates. Although the concern might be valid for insured patients, the main interest of the analysis is uninsured population and the model may not suffer from endogeneity bias if the actual share of insurer concentration is control for the concentration effect. Although there is a growing evidence on the positive impact of hospital concentration on quality in health care, there is not enough empirical studies on the impact of hospital-insurer bargaining on hospital quality. Bargaining between hospitals and insurers might affect the hospital quality in a positive or negative way through the price mechanism and the health care production cost (Kolstad & Kowalski, 2012; Gaynor et al., 2015). To account for that, I instrument the insurer HHI with demographic estimates following Berry et al. and Dun et al. and find that instruments are strong with 63.3 Cragg-Donald Wald F Statistics. Instruments such as population size and employment rate in the market are factors that more directly affect the both hospital and insurance investment decisions than the hospital quality or health plans.

3. Empirical Results

The Table 2 reports the regression results on PQI rate for uninsured patients. Column(1) displays the results from the OLS model without insurer concentration index while the model in Column(2) adds the insurer concentration index. Column(3) and Column(4) shows the fixed-effect regression result for the model with no insurer concentration and both concentration indexes. Finally, Column(5) reports the results for the model with IV and fixed-effects. I display the Column 1 and Column 3 for comparison purposes.

The columns in Table 2 clearly shows that hospital HHI is statistically insignificant when insurer concentration is added in the model. I prefer the specification with hospital fixed effects and IV to mitigate bias discussed above, although the Column 4 and 5 shows that the result does not change once IV is added in the model. I also perform the specification without accounting for hospital fixed effects, the 95 percent confidence interval sug-

Table 2: Regression Results for Uninsured PQI Rate

	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE-IV
log(PQI Rate for Uninsured)					
Hospital HHI	-0.236	-0.085	0.292	0.412	-0.381
	(0.18)	(0.20)	(0.71)	(0.72)	(0.91)
Insurer HHI		2.623***		-0.858	-11.030**
		(0.69)		(0.79)	(3.80)
constant	13.851**	3.856	-1.103	-4.839	9.369
	(4.42)	(6.54)	(5.43)	(5.48)	(9.43)
N	3575	3214	3575	3214	3214.000
R2	0.64	0.67	0.58	0.58	0.46

*** indicates significance level at 1 percent, ** 5 percent, * 10 percent. Standard errors are displayed in parenthesis.

Notes: (1) The dependent variable is the log of PQI rate for uninsured patients. Column 1 and 2 are displayed for only comparison purpose. Hospital and Insurer HHI are the key explanatory variable of interest.

(2)All regressions control for time effects market and hospital characteristics. Columns 3, 4 and 5 includes also hospital-fixed effects.Standard errors are clustered by hospital.

gests that hospital HHI is not statistically significant and the result does not change.

According the columns in the Table 2, the outcome of interest is negatively associated with insurer HHI. It means that more market concentration in insurer market is associated with the improvement in the quality of preventable admissions. The same effect can be seen in Column(4) and Column(5). Even though the magnitude of insurer HHI coefficient is not close in Column (4) and Column (5), the only difference between the two models is IV. For the purpose of clear interpretation and as an illustration, consider the result in terms of elasticity. The elasticity of the coefficient shows that 10 percent increase in Insurer HHI decreases PQI rate (improves quality) by 0.3 percent (FE) and 4.3 percent (IV-FE). It is not unexpected that the coefficient of endogenous variable may increase once it is estimated with IV. Controlling for the endogeneity of insurer HHI increases the impact of insurer HHI on PQI rate.

Both Column 4 and Column 5 in Table 2 also shows that neither of different type of ownership is associated with the quality level of prevention indicators. As it is expected, nonprofit hospitals is supposed to promote the community health as a return to tax-exemption status. Either the type of ownership and hospital concentration level does not impact on the community health through PQI rate of service area. Increasing insured population through Medicaid expansion in 2014, the result shows that medicaid expansion decreased the PQI rate among uninsured patients.

Unlike insurer HHI, the hospital HHI does not produce different estimates across the columns. Adding hospital FE and IV to control the omitted variable bias I find no significant relationship between hospital HHI and PQI rate for uninsured patients. The 95 percent confidence interval around the estimate in the IV model is bounded between 0.22 percent decrease and .15 increase in the PQI rate for uninsured patients once there is a 1 percent increase in hospital HHI. It is consistent with the FE model (Column 4) in which the confidence interval around the estimate is between 0.04 decrease and .12 increase for every 1 percent increase in hospital HHI.

It shows that insurer HHI impact on PQI rate of hospital's service area is more effective than the hospital HHI. Considering the outcome of interest is only PQI rate, it seems that the relationship between insurer HHI and Hospital HHI may play a crucial role to explain the improvement of prevention quality indicators among uninsured patients. Insurers' demand of better quality of care from hospitals with a bargaining leverage of selective contracting might explain how insurer HHI positively affects the PQI rate of uninsured patients (Lewis & Pflum, 2017).

The hospital being not effective on the prevention quality indicator, in other words, not improving the community health has several plausible interpretations. The elasticity of the health care service to patients affects the hospital's decision on treatment, price and quality. Although I do not observe out-of-pocket cost of uninsured patients, providing community benefit services to uninsured patients is inherently unprofitable. Uninsured patients' ability to compensate the health care cost improves with insurance coverage.

The growing evidence in the literature also indicates that increasing health coverage among populations improves self-assessed health, decreases the hospitalization of preventable admissions and mortality rate, and increases preventive care utilization (Kolstad & Kowalski, 2012; Courtemanche & Zapata, 2014; Borgschulte & Vogler, 2020). Adequate and proper treatment for preventable admissions may be distorted by hospital decision considering the compensation of treatment and the elasticity of health care services. Inelastic treatment such as acute mycardial infarction (AMI) or stroke might be less affected by hospital decision. Finally some of studies on the impact of the hospital competition on quality shows that decrease in concentration increases non-clinical quality of hospitals rather than clinical qualities.

3.0.1 Robustness Checks

Table 3: Robustness Check for ICD-9 Only

	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE-IV
log(PQI Rate for Uninsured)					
Hospital HHI	-0.288	-0.071	-0.573	-0.878	-1.026
	(0.20)	(0.23)	(0.79)	(0.90)	(0.86)
Insurer HHI		2.272**		-1.413*	-4.522*
		(0.74)		(0.61)	(1.77)
constant	12.312**	2.170	3.905	6.593	7.796
	(4.61)	(7.34)	(5.16)	(6.27)	(6.74)
N	2630	2389	2630	2389	2389
R2	0.51	0.56	0.22	0.23	0.21

*** indicates significance level at 1 percent, ** 5 percent, * 10 percent. Standard errors are displayed in parenthesis.

Notes: (1) The dependent variable is the log of PQI rate for uninsured patients. Column 1 and 2 are displayed for only comparison purpose. Hospital and Insurer HHI are the key explanatory variable of interest. Sample includes only discharges before ICD10 transition.

(2)All regressions control for time effects market and hospital characteristics. Columns 3, 4 and 5 includes also hospital-fixed effects.Standard errors are clustered by hospital.

I conduct several robustness tests for the study. First, I test the concern that ICD10 transition might affect the estimation of the PQI rate. Although the ICD-10 transition is mandatory transition for all hospitals; I can estimate only pre-ICD10 transition time without concerning the upward bias of the coefficient on covariates by including only ICD9 period. Omitting discharges with ICD10 code, which means that 5 fiscal quarters from 2015 Q4

Table 4: Robustness Check for All Patients PQI Rate

	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) FE-IV
log(PQI Rate for All)					
Hospital HHI	-0.150	-0.020	0.158	0.164	-0.072
	(0.14)	(0.15)	(0.17)	(0.20)	(0.28)
Insurer HHI		0.168		-0.074	-3.830***
		(0.36)		(0.14)	(0.94)
constant	5.994	4.616	8.913***	9.210***	16.259***
	(3.43)	(3.64)	(1.29)	(1.53)	(2.57)
N	3845	3463	3845	3463	3463
R2	0.83	0.84	0.94	0.93	0.92

*** indicates significance level at 1 percent, ** 5 percent, * 10 percent.Standard errors are displayed in parenthesis.

Notes: (1) The dependent variable is the log of PQI rate for all patients. Column 1 and 2 are displayed for only comparison purpose. Hospital and Insurer HHI are the key explanatory variable of interest.

(2)All regressions control for time effects market and hospital characteristics. Columns 3, 4 and 5 includes also hospital-fixed effects.Standard errors are clustered by hospital.

to 2016 Q4, substantially reduces the variation in the outcome of interest; however, the results in Table 3 are close to the main result.

The second concern is that uninsured patients do not represent the all patients population and selecting uninsured patients as only one target of hospitals may not be enough to analyze hospital behavior towards preventable admissions. In Table 4, I present the result of the specification with all patients. The preferred specification with FE and IV shows similar result to my main analysis (no statistically significant relationship between PQI rate and Hospital HHI but negatively significant relationship between PQI rate and Insurer HHI).

4. Conclusion

This paper studies how hospital and insurer competition impacts on the health outcome of uncompensated care that nonprofit hospitals provide under the community benefit activities as requirement of tax-exemption status. However, IRS does not require tax-exempt nonprofit hospitals to provide certain amount of community benefits and further it does not set a target for hospital outcomes or quality of services for uncompensated care of nonprofit hospitals. There is still little understanding whether nonprofit hospitals promote their communities' health while nonprofit hospitals take the advantage of tax-exemption status. Due to the legal justification of community benefit standard, any advancement on nonprofit hospitals' ability to compensate community benefit expenses would help achieve the rationale of tax-exemption status. Nonprofit hospitals are expected to benefit their communities more once they acquire more market power or financial ability. If competition level in healthcare market restrict the provision level of community benefits by nonprofit hospitals, it is salient to understand how competition in health care market affects both the level and quality of community benefit provision.

The findings of this study provide no evidence that nonprofit hospitals promote the health of communities - improving prevention quality indicators- in more concentrated markets. The analysis also shows that the rate of prevention quality indicators decreases in concentrated insurer markets. It is plausible to think that the impact of insurer concentration might be more effective on the health outcomes of uncompensated care in nonprofit hospitals than hospital concentration. This study suggests that the behavior of nonprofit hospitals towards community benefit activities do not justify the rationale of tax exemption status given the estimates of the analysis.

This study has several limitations. Firstly, I do not directly examine the impact of insurer concentration and hospital concentration on each other. Secondly, this study employs reduced form models rather than structural models. It limits to analyze how the health outcomes of uncompensated care would have changed after exogenous changes. Third, the study period covers only 5 years data. Considering social determinant of health, longer data years would provide more variation in market characteristics and obtain better estimates in panel data analysis. The future analysis might add more quality indicators such as mortality and readmission rates to understand the improvement of communities' health better.

5. Appendix A

AHRQ calculates the numerator of population-based rate with the indicators below and the denominator is the population of defined geographic area. The geographic area is where a patient resides regardless of patient's health status.

1. TAPQ01 "PQI 01 Diabetes Short-Term Complications Admission Rate (Numerator)"
2. TAPQ02 "PQI 02 Perforated Appendix Admission Rate (Numerator)"
3. TAPQ03 "PQI 03 Diabetes Long-Term Complications Admission Rate (Numerator)"
4. TAPQ05 "PQI 05 Chronic Obstructive Pulmonary Disease (COPD) or Asthma in Older Adults Admission Rate (Numerator)"
5. TAPQ07 "PQI 07 Hypertension Admission Rate (Numerator)"
6. TAPQ08 "PQI 08 Heart Failure Admission Rate (Numerator)"
7. TAPQ10 "PQI 10 Dehydration Admission Rate (Numerator)"
8. TAPQ11 "PQI 11 Bacterial Pneumonia Admission Rate (Numerator)"
9. TAPQ12 "PQI 12 Urinary Tract Infection Admission Rate (Numerator)"
10. TAPQ14 "PQI 14 Uncontrolled Diabetes Admission Rate (Numerator)"
11. TAPQ15 "PQI 15 Asthma in Younger Adults Admission Rate (Numerator)"
12. TAPQ16 "PQI 16 Lower-Extremity Amputation among Patients with Diabetes Rate (Numerator)"

6. Appendix B

The Model of Hospital Competition Measure

I model that indirect utility that a patient receives by selecting a hospital over alternatives in a hospital choice set is a function of travel cost which increases with driving distance, hospital, and patient characteristics. It is given by:

$$\mu_{ij} = f\left(d_{ij}(D_i, D_j)\right) + g\left(X_i, Z_j\right) + \varepsilon_{ij} \tag{1}$$

where $f\left(d_{ij}(D_i, D_j)\right)$ is the driving distance to hospital j's location from patient i's location, $g\left(X_i, Z_j\right)$ is a function of hospital and patient observable characteristics, and ε_{ij} is independently and identically distributed with Weibull distribution and captures unobservable characteristics of hospital and patient. The probability of patient i selecting hospital j over the alternative choice set is given by:

$$\rho_{ij} = \frac{e^{(f_{ij} g_{ij})}}{\sum_{j=1}^{J} e^{(f_{ij}' g_{ij}')}} \tag{2}$$

I estimate the parameters of this model using multinomial maximum likelihood and then obtain predicted probabilities, $\hat{\rho}_{ij}$, of admission of each patient to hospital. For every zip code of patient location, I calculate predicted share of patients from zip code k to hospital j which is shown as:

$$\hat{\rho}_{jk} = \frac{\sum i \; living \; in \; zip \; k \; \hat{\rho}_{ij}}{\sum_{j=1}^{J} \sum i \; living \; in \; zip \; k \; \hat{\rho}_{ij}} \tag{3}$$

Due to possibility that each hospital may have different demand function from each zip code surrounding its location, it is possible that hospital might differentiate among patients from different zip code. To account for that possibility, $\hat{\rho}_{jk}$ is translated to zip code level for patients living in that zip code:

$$HHI_k = \sum_{j=1}^{J} \hat{\rho}_{jk}^2 \tag{4}$$

The next step is to calculate the hospital-level share of competition by creating a weighted average share of zip code that a hospital is predicted to serve.

$$\hat{\theta}_{kj} = \frac{\sum i\ living\ in\ zip\ k\ \hat{\rho}_{ij}}{\sum_{i=1}^{N} \hat{\rho}_{ij}} \tag{5}$$

$$HHI_j = \sum_{k=1}^{K} \hat{\theta}_{kj}.HHI_k \tag{6}$$

The $\hat{\theta}_{kj}$ is the predicted share of patients from zip code k and then HHI_j represents the weighted average of competition accounting for all zip codes a hospital serves. The concern is that unobserved factors of hospital choice might be correlated with patient health. To account for that concern, KM approach assigns hospital-level share of predicted HHI to patients depend on $\hat{\rho}_{jk}$.

$$HHI'_k = \sum_{j=1}^{J} \hat{\rho}_{jk}.HHI_j \tag{7}$$

Compared to HHI_k, HHI'_k accounts for weighted expected share of hospitals. HHI'_k in a panel data set includes variations of over time in the market such as mergers and closure, and individual preferences of hospital choice. Table 5 shows the summary statistics of demand function and HHI'_k.

Table 5: Summary Statistics of HCUP Data

State	AR	MS	UT	VT	FL	NY
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
Age (year)	77.88	77.45	77.46	78.58	78.29	79.01
	8.2	8.2	8.0	8.4	8.3	8.5
Female (%)	59%	59%	57%	55%	55%	57%
	0.5	0.5	0.5	0.5	0.5	0.5
Distance (minute)	25.93	25.04	16.09	21.72	16.16	14.65
	20.5	19.4	14.1	17.9	13.3	13.7
Choice Set	14.57	14.53	28.11	4.35	35.30	49.96
	9.5	6.4	13.5	1.3	17.2	30.5
Preferred Closest Hospital (%)	41%	35%	43%	80%	44%	46%
	0.5	0.5	0.5	0.4	0.5	0.5
Discharge	81359.64	86992.75	38942.05	11356.69	700763.75	479058.71
	3787.4	5743.6	4386.4	446.2	10654.0	19207.9
N	405893	433046	192068	56696	3503002	2391404

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