The Effects of Ownership and Competition on Psychiatric Hospital's Behavior: Implications for Cream Skimming and Heterogeneity of Causal Parameters

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Abstract

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Hospitals' ownership status and the degree of market competition are two critical factors that shape their behavior. The distinctive characteristics of the inpatient psychiatric care market may provide an ideal environment for studying the role of ownership type of hospitals (for-profit versus not-for-profit) and potential impact of competition. Using inpatient psychiatric admissions in California, we examine whether for-profit hospitals engage in cream skimming, i.e., choosing patients for some characteristic(s) other than their need for care. Next, we examine whether an increase in competition motivates hospitals to operate more efficiently. Lastly, we examine how the form of instrumental variable and the specific analysis approach can identify different causal treatment effect parameters by estimating the causal effects of hospital ownership status on total inpatient costs.

TABLE OF CONTENTS

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DEDICATION

To Jisun, Seoro, and Rogun

Chapter 1. INTRODUCTION

The ownership status of a hospital (for-profit versus not-for-profit) is a crucial determinant of its behavior. Economic models suggest that for-profit (FP) hospitals are strongly motivated to provide services efficiently, which can lead to lower costs and higher profit margins (Pauly & Redisch, 1973). However, the profit-maximizing objective of FP hospitals has given rise to several concerns, such as a lack of community benefit (e.g., uncompensated care and medical research and education), and cream skimming, i.e., choosing patients for some characteristic(s) other than their need for care (Hyman, 1998; Sloan et al., 2001). While FP hospitals can be defined by a single objective function, profit maximization, there is no consensus on economic theories for not-for-profit (NFP) hospitals. NFP hospitals' objective functions can be broadly characterized by four categories: 1) hospital output maximization, 2) market output maximization, 3) "for-profit in disguise (FPID)", and 4) a hybrid model combining hospital output maximization and FPID (Horwitz & Nichols, 2009; Moon & Shugan, 2020). The output maximization theories reflect the behavior of NFP hospitals that prioritize social values by maximizing their outputs (James, Estelle; Rose-Ackerman, 1986; Newhouse, 1970; Rose-Ackerman, 1996). Conversely, the FPID and the hybrid models highlight the profit motive of NFP hospitals (Moon & Shugan, 2020; Pauly & Redisch, 1973).

Competition within the market also plays a key role in shaping the behavior of hospitals; in particular, it provides an incentive for hospitals to modify their objectives. When NFP hospitals compete with FP hospitals in a market, the NFP hospitals tend to become more responsive to financial incentives. For example, the NFP hospitals are more likely to prioritize profitable services, limit admissions for patients with less profitable conditions, reduce spending on patient care, and potentially engage in undesirable practices, such as upcoding (Ettner & Hermann, 2001; Horwitz & Nichols, 2009; Hughes & Luft, 1990; Schlesinger et al., 1987, 1997; Silverman & Skinner, 2004). Similarly, under comparable market conditions, FP hospitals may also be influenced by the altruistic motives of NFP hospitals. For instance, the FP hospitals may be more inclined to focus on the quality of patient care and improving accountability in their services and for communities (Grabowski & Hirth, 2003; Hirth, 1999).

This research aims to deepen our understanding of how ownership status and competition impact treatment patterns of hospitals, with a specific focus on costs and quality. Using robust econometrics methods, such as instrumental variable (IV) and discrete choice framework, we overcome challenges from endogeneity associated with ownership status and market competition measures. The specific objectives of this study are as follows:

In Chapter 2, we examine whether, among inpatient psychiatric admissions in California, FP hospitals engage in cream skimming, i.e., choosing patients for some characteristic(s) other than their need for care, which enhances the profitability of the provider. We propose a novel approach to identify cream skimming with cost outcomes.

In Chapter 3, we examine the effects of competition on treatment costs and quality among hospitals in California's inpatient psychiatric care markets. We establish a market competitiveness measure using the hospital choice model among patients based on a plausibly exogenous determinant of hospital selection, i.e., travel distances.

In Chapter 4, we examine potential impacts of various IV modeling approaches on the estimation of treatment effect parameters. Differential distance has been widely used as an IV in health economics literature to investigate the causal effect of alternative interventions or utilizations where access to these options is affected by the shadow costs of travel. However, less attention has been paid in the literature on how the form of IV and the specific analysis approach can identify different causal treatment effect parameters. We present a case study to illustrate these discussions, estimating the causal effects of hospital ownership types (FP versus NFP) on total inpatient costs for psychiatric admissions in California.

Chapter 5 summarizes the findings and concludes.

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Chapter 2.

DO FOR-PROFIT HOSPITALS CREAM-SKIM PATIENTS? EVIDENCE FROM INPATIENT PSYCHIATRIC CARE IN CALIFORNIA

ABSTRACT

The paper examines whether, among inpatient psychiatric admissions in California, for-profit (FP) hospitals engage in cream skimming, i.e., choosing patients for some characteristic(s) other than their need for care, which enhances the profitability of the provider. We propose a novel approach to identify cream skimming with cost outcomes. Naïve treatment effect estimates of hospital ownership type consist of the impact of differential patient case mix (selection) and hospital cost containment strategies (execution). In contrast, an instrumental variable approach can control for case mix and establish the causal effects of ownership type due to its execution. We interpret the difference in naïve and IV treatment effects to be driven by FP hospitals' selection (cream skimming) based on unobserved patient case mix. We find that not-for-profit (NFP) general hospitals are more likely to treat low-cost patients than FP general hospitals, showing no evidence that FP general hospitals engage in cream skimming. We also find no difference in unobserved case mix between FP and NFP specialty psychiatric hospitals. Our results may attenuate concerns about the recent proliferation of FP specialty psychiatric hospitals.

2.1 INTRODUCTION

The differences between for-profit (FP) and not-for-profit (NFP) hospitals have been of interest to health economists for several decades. The debates on the role of hospital ownership type in service provision are ongoing and have yielded opposing perspectives. One side claims that the behavior of hospitals differs by ownership type; in contrast, the other side asserts that they are alike, except that NFP hospitals are qualified for various tax-related benefits (Colombo, 2006; Sloan, 2000).

Both views mainly rely on the social welfare implications of hospital ownership type under incomplete markets (Arrow, 1963). One line of research suggests that NFP hospitals may be more socially responsible and thus are more likely to supply services that improve community and social benefits (e.g., uncompensated care, unprofitable services, and medical research and education) and with a higher quality of care (Lee & Weisbrod, 1977; Newhouse, 1970; Weisbrod, 1988). On the other hand, some researchers argue that NFP hospitals do not necessarily offer more or better-quality services than FP hospitals; therefore, the distinction of hospitals on the basis of ownership type is unlikely to differentiate their performance (Pauly & Redisch, 1973). A wide range of empirical evidence supports both lines of arguments, which has fueled a long-standing policy debate as to whether NFP hospitals are eligible for tax-exempt organization status (Sloan, 2000).

Cream skimming refers to the behavior of hospitals to select patients, not based on their needs, but by their expected profitability – less ill patients with lower costs are preferred over sicker patients for treatments. Because of economic theory suggesting FP hospitals pursue profit maximizing objectives, they have long been suspected of engaging in cream skimming activities. However, the evidence from health economics literature focusing on the association between hospital ownership type and cream skimming is scant (Cheng et al., 2015; Duggan, 2000; Yang et al., 2020). Duggan (2000) investigates the effect of the change in Medicaid reimbursement policy on the behavior of hospitals in California and finds that both private FP and NFP hospitals select financially lucrative patients, resulting in a potential increase in unprofitable patients in public hospitals. Cheng et al. (2015) examines patterns of patient transfers among hospitals in Australia and identify that patients with high severity of illness experience a higher chance of being transferred from private FP to public hospitals than vice versa. These studies determine cream skimming using Medicaid status (i.e., insurance status) or the Charlson index (i.e., patient severity) as a proxy for the patient's expected costs and profitability. Also, they have exploited exogenous policy variation or patient transfers between hospitals to avoid endogeneity bias.

Identifying the causal link between hospital ownership status and cream skimming is challenging due to potential endogeneity. We cannot dismiss the likelihood that un unobserved characteristic of a market is associated with the hospital ownership and patients' profitability. For example, FP hospitals may locate in affluent areas with a greater number of better-insured patients, which may allow them to provide more profitable services (Norton & Staiger, 1994). Additionally, patients with severe medical conditions may prefer to choose hospitals affiliated with medical schools, which are often NFP. Therefore, two observably identical individuals, one going to a FP while the other to a NFP hospital, may costs more or less depending on hospital's cream skimming behavior on patient characteristics that remain unobserved in data, but observed/predictable to hospitals. This makes ownership status endogenous in the data. Differences in estimated costs can also be driven by the differential execution of healthcare delivery upon admission, signifying a dimension of productivity for these hospitals.

Our study adds to the existing literature on the causal relationship between ownership and cream skimming. Most importantly, this study offers a new approach to identifying cream skimming behavior of hospitals using the cost information. Compared to the existing approaches that rely on other proxy measures of cream skimming (e.g., insurance status, disease severity), the direct use of expenditure data may further reduce uncertainty of estimating the patient's expected resource use (Cheng et al., 2015; Duggan, 2000). Moreover, the earlier studies utilized exogenous policy changes or detailed patient transfer records between hospitals with different ownership types to address potential endogeneity of ownership status. We achieve this goal uniquely by implementing multiple modeling approaches. It should be noted that if we determine cream skimming by assessing the association between ownership types and patient's treatment costs through the single equation model, we may end up with biased cost estimates of the ownership effect. This is because the estimate from the model implies a mixture of the effects of unobserved differential patient case mix and hospital cost containment efforts. Therefore, we need to separately document the combined effects to evaluate cream skimming; otherwise, we cannot rule out the possibility that lower costs in FP hospitals are attributable to their cost containment efforts, instead of cream skimming.

To obtain unbiased cost estimates that only reflect the effects of patient case mix in the hospital, we execute the following three-step approach: First, we use an ordinary least-squares (OLS) model to estimate the association of the ownership type with patient treatment costs. Estimates from the OLS model comprises the effects of both unobserved patient case mix and hospital cost containment practice that might vary between FP and NFP hospitals. Next, we employ a two-stage least-squares (2SLS) model that applies differential distance (DD; i.e., the difference in the distances between the nearest FP and NFP hospitals from the patient's home) as an instrumental variable (IV) in the first stage. The IV analysis in this second step allows us to acquire the cost estimates solely derived from the hospital cost containment practices varying by the ownership type. In the third step, we extract the effect of the differential patient case mix by subtracting the 2SLS estimate (i.e., the effect of hospital cost containment) from the OLS estimate (i.e., the combined effects). The difference between the two estimates indicates the effect of hospital behavior referring to cream skimming.

The rest of the paper is structured as follows: Section 2 outlines the research context, the economic theory of hospital ownership type, and the characteristics of inpatient psychiatric care markets. Section 3 presents the study objectives and hypotheses. Section 4 describes the data and reports summary statistics. Section 5 and 6 illustrate the empirical strategy of patient- and hospital-level analysis, respectively. Section 7 presents the results. Section 8 discusses the findings and concludes.

2.2 BACKGROUND

2.2.1 *The Growth of For-Profit Psychiatric Hospitals in the US*

Since the 1950s, the de-institutionalization movement (i.e., moving patients with psychiatric conditions out of state-run institutions and into community care) has dramatically decreased the number of patients in government psychiatric hospitals (Bassuk & Gerson, 1978). For example, the number of patients dropped from 369,969 in 1970 to 39,907 in 2014, a 90% reduction over a half-century. During this period, the country experienced a steady increase in patients staying in private psychiatric hospitals (Lutterman et al., 2017). Notably, much of the trend recently observed in the private sector, facilitated by the passage of major federal policies (e.g., the Affordable Care Act of 2010), was driven by the increase of FP beds (Lutterman et al., 2017; Sachs, 2019; Shields, Stewart, et al., 2018). The expansion in FP hospital capacity in the inpatient psychiatric care market can be concerning if they prioritize providing services with a higher profit margin and limit the provision of evidence-based care, especially if the quality is not verifiable by patients (Hansmann, 1980; Shields, Stewart, et al., 2018). FP hospitals are also more likely to report safety violations than NFP hospitals (Mark, 1996; Rosenau & Linder, 2003).

2.2.2 *Theories of Hospital Behavior by Ownership Type*

Economic theories suggest hospital objectives are associated with organizational characteristics, including ownership status (e.g., FP vs. NFP). FP hospitals are deemed to follow a profit-maximizing model based on classical economic theory (Friedman, 2002). In most cases, FP hospitals are maintained by private equity funds or joint venture capital; thus, managers in FP hospitals may seek to maximize financial gains on their behalf as an agent. Unlike the objective of FP hospitals, there is a lack of consensus in the literature on the objective function of NFP hospitals (Sloan, 2000). Several prominent theories of NFP hospitals' behavior include 1) "for-profits in disguise" (FPID), 2) quality-quantity maximizers, 3) social welfare maximizers, and 4) a hybrid of disguise and output maximization theories.

First, the economic theory of FPID posits that FP and NFP hospitals share the same objective function, maximizing profits, thereby producing identical behaviors in equilibrium (Pauly & Redisch, 1973). Considering the latter as physician cooperatives, this model predicts that the output of the NFP hospitals will be set at the level yielding maximum income per doctor in the hospitals. Second, the quality-quantity maximizing model suggests that NFP hospitals maximize a weighted average of quality and quantity, subject to a constraint limiting the quantity to the point of zero profit (i.e., the intersection of demand and average cost curves) (Newhouse, 1970).

Third, the social welfare maximizing model characterizes NFP hospitals as total market output maximizers, indicating their preference for community benefits or altruistic motives. The NFP hospitals pursue this objective to address government failures in providing public goods (Lee & Weisbrod, 1977; Weisbrod, 1988). To achieve this, NFP hospitals create conditions to attract altruistic managers and employees (Rose-Ackerman, 1996), or behave as consumer cooperatives (Ben-Ner & Gui, 1993; Lynk, 1995). Alternatively, asymmetric information may be a key factor justifying NFP hospitals' commitments to the provision of socially optimal level of services (Arrow, 1963; Easley & O'Hara, 1983; Hansmann, 1980; Hirth, 1999; Weisbrod & Schlesinge, 1986). Under asymmetric information, FP hospitals may engage in opportunistic behaviors, such as cream skimming, to maximize profits. In contrast, NFP hospitals would not exploit their patients in favor of profit due to the non-distribution constraint.

Lastly, the hybrid model developed by Hirth (1997, 1999) combined the FPID and quality-quantity maximizing models. This model focuses on changes in hospitals' behavior, demonstrating that NFP hospitals tend to mimic the objective of FP hospitals when facing competition. Additionally, it shows that the presence of NFP hospitals not seeking profit maximization (i.e., pure NFP) affects the objective of other hospitals, including FP and FPID hospitals, such that both increase the quality of their services (i.e., positive spillover). Thus, the role of competition is crucial for understanding hospital behaviors. Another type of hybrid modeling approach is to view the objective of NFP hospitals as maximizing a weighted sum of profits and outputs (Dranove, 1988; Gaynor et al., 2015; Moon & Shugan, 2020). The important difference between this approach and Hirth (1997, 1999) is that the weight of output in the model for NFP hospitals should not be zero, while Hirth (1997, 1999) allows the zero weight for non-pure NFP hospitals (i.e., FPID).

2.2.3 *Characteristics of Inpatient Psychiatric Care Market*

Hospitals (general and specialty psychiatric hospitals) in the inpatient psychiatric care market manifest several distinctive features that set them apart from other hospitals in ordinary acute care settings. Concentrating on the treatment of patients with psychiatric conditions, inpatient psychiatric facilities provide a much narrower range of diagnostic and treatment services than acute care hospitals. Thus, psychiatric facilities handle fewer therapeutic uncertainties than general hospitals in acute care settings. Also, inpatient psychiatric services are considered to be unprofitable owing to case mix (i.e., many psychiatric patients are low-income, poorly insured, and admitted via emergency room) and uncertain reimbursement policies that might not entirely cover actual costs of the services (Horwitz & Nichols, 2009; Stensland et al., 2012). Finally, the presence of asymmetric information seems to be (arguably) more palpable in inpatient psychiatric care settings than in the rest of medical care (Shields, Stewart, et al., 2018). The level of asymmetric information between providers and patients could be potentially large because of the limited access to quality and safety information and the environment that hinders family engagement. For instance, family visits for patients generally occur outside the wards, and this restriction might prevent family members from monitoring the quality of and advocating for the patient's needs.

Additionally, compared to the patients in acute care settings, psychiatric patients face limited choices in terms of decisions for hospitalization (i.e., involuntary admission) and treatment places (i.e., a lack of available psychiatric beds). Furthermore, psychiatric patients might be often exposed to a vulnerable environment for self-advocacy during hospital stay due to their disease conditions and power inequality between the patients and health professionals (Shields, Stewart, et al., 2018). For example, the patients might worry about repercussions for speaking out against the staffs (Ortiz, 2014). The stylized nature of the inpatient psychiatric care market described above may provide the ideal environment for studying the role of ownership type of hospitals, especially whether FP hospitals actively engage in cream skimming to maximize profits.

2.2.4 *Cream Skimming Literature in Inpatient Psychiatric Care*

Cream skimming refers to the opportunistic behavior of hospitals and other providers selecting patients and/or treatment services for the sake of financial benefits (Ellis, 1998). This behavior can be divided into two distinctive activities: "vertical" and "horizontal" cream skimming (Levaggi & Montefiori, 2003). Vertical cream skimming refers to patient selection based on patient characteristics that are not indicative of their needs for care but rather higher expected profitability. Horizontal cream skimming refers to patient selection based on service selection by providers whereby the providers offer the provision of particular types of services considered to be lucrative. In this study, we only aim to address the vertical aspects of cream skimming within the limitation of our dataset.

The empirical literature on cream skimming by ownership type of hospitals is relatively lacking compared to other performance measures, especially among inpatient psychiatric care facilities. Currently, only a handful of literature addressing cream skimming of inpatient psychiatric facilities by their ownership type is available, and their conclusions are somewhat inconsistent. Among the studies using the disease severity as a proxy for cream skimming, Olfson and Mechanic (1996) report that the proportion of patients with schizophrenia was lower in the FP hospitals than their NFP counterparts. In contrast, Schlesinger and Dorwart (1984) show that FP hospitals are more likely to serve functionally impaired patients with mental illness than NFP hospitals. Additionally, findings from Ettner and Hermann (2001) demonstrate that observable characteristics (e.g., disease severity, comorbidity, income) of patient populations admitted to FP versus NFP hospitals do not differ.

2.3 STUDY OBJECTIVES AND HYPOTHESES

The main goal of this paper is to quantify the effects of hospital ownership status on treatment patterns, especially costs, using inpatient psychiatric admission data. Naïve treatment effect estimates of hospital ownership type consist of the impact of differential patient case mix (selection) and hospital cost containment strategies (execution). In contrast, an instrumental variable approach can adjust case mix and establish the causal effects of ownership type due to its execution. We interpret the difference in naïve and IV treatment effects to be driven by FP hospitals' selection (cream skimming) based on unobserved patient case mix. We also test whether FP hospitals provide inpatient treatment services more efficiently than NFP hospitals using the IV-based effects directly.

The secondary aim of this paper is to investigate the impact of ownership type of hospitals on labor use (i.e., the number of physicians and nurses and nurse hours per patient day) and financial margins (i.e., profit and operating margins) using hospital-level data. Our hypothesis of the hospital-level analysis is that FP hospitals operate inpatient psychiatric units with fewer staff and yield higher financial margins than NFP hospitals. Provision of lower-quality patient care, especially if the true quality is only partly observable, can be a potential avenue for generating profits. Hospitals can reduce costs and yield higher profits without sacrificing demand and reputation of their services by hedging on quality. The hospital-level analysis provides implications for the quality of care and hospital profitability.

2.4 DATA AND DESCRIPTIVE STATISTICS

2.4.1 *Data*

The primary data source is hospital financial and patient discharge records from the California Office of Statewide Planning and Development (OSHPD) between 1995 and 2011. As Sachs (2019) highlighted, the OSHPD data has some unique features that may further improve our understanding of the delivery system for inpatient psychiatric care. In particular, the patient discharge records encompass the hospitalization data from general acute care hospitals and freestanding specialty psychiatric hospitals. This is uncommon for other hospital discharge databases because the records from the specialty psychiatric hospitals are often omitted. However, all the hospitals in California must disclose their patient discharge records and financial information to the state agency. Also, the OSHPD data covers all payer types, such as commercial insurance, Medicare, and Medicaid. This enables us to compare potentially different treatment patterns of hospitals across the payer groups. One important limitation of our data is that it does not provide information on other providers in non-hospital settings, such as office-based psychiatrists and residential treatment centers. Thus, our analysis is restricted to hospital care provided through an emergency department or inpatient units.

2.4.2 *Study Population*

The study population comprises all patients admitted to a general or specialty psychiatric hospital with a primary diagnosis code of mental health disorder (the detailed ICD-9 codes are available in Table S1). Two separate sample sets are established according to the hospital types to account for potentially different treatment and resource utilization patterns between the general acute care and specialty psychiatric hospitals (Schneider et al., 2008). The unit of observation is the patient discharge. Since the OSHPD patient discharge data prevents the identification of the same individuals who are readmitted to the hospital, our study sample may contain more than a single observation per patient.

To augment the internal validity of our analysis and precision of data, we exclude the records of patient discharge in which (1) demographic (sex/race/age) and zip code information is omitted, (2) patients are admitted from or returned to a prison/jail, (3) death in the hospital is denoted, (4) 365 days of hospital stay is exceeded, (5) patients are from rural areas, (6) patients are from state hospitals, long-term care facilities and hospitals in the Kaiser Permanente system, and which are from the hospital (7) without licensed psychiatric beds and (8) without CMI information. In addition, we symmetrically drop (9) patients at top and bottom 5% of DD values to ensure the circumstance where FP and NFP hospitals in the choice set of the patient are reasonably accessible from the patient's residence (i.e., both hospitals are located in the same market). The total observations are 1,371,413 (986,425 for general hospitals and 384,988 for specialty hospitals; Figure S1).

2.4.3 *Outcomes*

The dependent variables are total costs per admission, average costs per day, number of procedures per admission, LOS, and whether the patient was discharged to other providers, including nursing facilities and home health services. In addition, we take a natural log transformation of the LOS and cost outcomes to compare median values. To improve comparability between the untransformed and logged outcomes, we exponentiate the coefficient of our primary regressor in the second stage of the logged model and then multiply it by the median value of respective outcomes among the patients admitted to NFP hospitals.

Total costs per admission characterize the overall use of hospital resources during the stay. As the charged amount is the only accessible expenditure information in the OSHPD inpatient discharge data, we convert it to costs by applying the hospital's cost-to-charge ratio varying across the years. To further understand the major determinant of hospital costs, we also analyze other outcome variables, such as LOS, number of procedures, and average costs per day. The last two outcomes represent the intensity of care, while the LOS reflects the duration of care. Examining these additional outcomes helps differentiate hospital strategies for cost management – whether the lower level of cost per admission in FP hospital is mainly due to shorter duration rather than the intensity of care over the hospital stay, for example. It is also possible that hospitals may transfer patients to other providers (e.g., hospitals, nursing facilities, home health services) to avoid an increase in costs caused by a prolonged hospital stay. We, therefore, examine the likelihood of patient transfer in hospitals. Patients whose admission and discharge occur on the same day are denoted as LOS of 1 day.

2.4.4 *Regressors*

Three layers of controls – patient, hospital, and market characteristics – are included in the model. The patient characteristics incorporate both sociodemographic and clinical traits. Specifically, for sociodemographic characteristics, we consider sex, race, age, urban/rural residence status, zip code-level median income of patient's residence (the reference year of 2000), insurance payment category and managed care status, and scatter/specialized psychiatric beds. Following Duggan et al. (2022), the insurance payment category is constructed and contains Private, Medicare, Medi-Cal, County, Charity/Self-pay, and others. Additionally, information on the source of admission and psychiatric diagnosis is included to address patient clinical characteristics. Based on the primary ICD-9-CM diagnosis codes, we classify patients into seven categories, Schizophrenia, Bipolar Disorder, Major Depression, Depression, Alcohol Use Disorder, Drug Use Disorder, and Other, as noted in Table S1. The source of admission determines whether the patient was admitted via an emergency room, transfer, or from home – this is a proxy for the severity of mental health conditions together with the diagnosis category.

Hospital characteristics encompass medical school affiliation, public hospital status, number of licensed psychiatric beds, and CMI. Market characteristics include market concentration level measured by Herfindahl-Hirschman Index (HHI). Among the various approaches to define hospital markets and establish market concentration estimates (Wong et al., 2005), we use the method that constructs the HHI for each zip code based on actual patient flow (Ettner & Hermann, 2001; Zwanziger & Melnick, 1988). The competition index for any given hospital is formulated by weighted averaging all of the zip code level HHIs from the areas covered by that hospital (i.e., any zip code area with an admitted patient from that hospital). The weight is calculated by dividing the number of patients in the zip code admitted to that hospital by the total number of patients who used inpatient psychiatric services dwelling in the same zip code.

2.4.5 *Descriptive Statistics*

Table 1 presents the hospital-level descriptive statistics by hospital and ownership types. Among general hospitals, NFPs are more likely to engage with medical education and locate in less concentrated markets. Hospital and service volumes between FPs and NFPs are comparable with respect to the number of psychiatric beds, psychiatric discharges per psychiatric bed, and physicians and nurses per bed. The CMI indicates few differences in patient severity between the hospitals. Among psychiatric hospitals, FPs operate a slightly larger number of psychiatric beds, and the bed turnover rate is lower than NFPs. The ratio between physician and hospital bed is higher in NFPs, whereas the ratio for nursing staff is higher in FPs. There is almost no difference in the CMI between FPs and NFPs. NFP psychiatric hospitals operate in less concentrated markets.

Table 2 shows the patient-level summary statistics by hospital and ownership types. There are many differential patient characteristics worth paying attention to across the types. First, the proportion of patients aged 17 and younger is much higher in psychiatric hospitals than in general hospitals. About a quarter of inpatient psychiatric admission is from this minor group in psychiatric hospitals, but the number is reduced to 2 to 3 percent in general hospitals. There is no particular discrepancy between FPs and NFPs regarding the distribution of the patient's age. Second, the proportion of patients with serious mental illness (Schizophrenia, Bipolar disorder, and Major depression) is ten percentage points higher in FPs than NFPs across the hospital types. This contradicts our hypothesis that overall patient severity would be lower in FPs than NFPs.

Third, about 80% of patients in FP general hospitals are under public insurance coverage, either Medicare or Medi-Cal. In contrast, the proportion of charity or self-pay in NFP general hospitals is two-fold higher than in their counterpart FPs. Additionally, 40 percent of patients in psychiatric hospitals are covered by private insurance, which is notably different from general hospitals, where the proportion of those is lower than 20 percent. Fourth, more than half of patients are admitted via an emergency department in NFP general hospitals. Fifth, among general hospitals, about 20 percent of inpatient psychiatric care is provided at scatter beds.

2.5 EMPIRICAL STRATEGY FOR PATIENT-LEVEL ANALYSIS

2.5.1 *OLS Model*

One of the typical reduced-form approaches to assessing the effect of hospital ownership type on various performance outcomes is to include a dummy variable of the hospital type (e.g., 1 for FP hospital, and 0 for otherwise) in the single equation model. The following specification, Equation (1), represents our approach to estimating the effect of the ownership type.

$$Y_{ijmt} = \alpha_m + \alpha_t + \varphi \widehat{FP}_{ijmt} + \beta X'_{iz} + \delta H'_j + \epsilon_{ijmt} \quad (1)$$

where $\widehat{FP}_{ijmt}$ is a dummy variable with the value of 1 for patient i in hospital service area (HSA) m selects FP hospital j in year t. α_m is a patient HSA fixed effect. α_t is a year fixed effect. The vector X'_{iz} is patient-level controls, including sex, race, age, psychiatric diagnosis, urban/rural residence, zip code-level median income, payment category, managed care status, source of admission, and a type of bed (scatter bed or psychiatric bed). The vector H'_j is hospital-level controls, including teaching status, public ownership, psychiatric bed count, CMI, and HHI. We cluster standard errors by patient-level five-digit zip code.

It is worth reiterating that the effect of ownership type in the OLS model, the coefficient φ, consists of two components: one component illustrates unobserved differential case mix. The other component mirrors the hospital-specific cost containment strategies. No coherent evidence exists on the different levels of treatment costs by ownership status among hospitals in an inpatient psychiatric care market (Ettner & Hermann, 2001; Mark, 1996; Schlesinger & Dorwart, 1984). Specifically, the lower costs in FP hospitals may reflect the combined effects, including unobserved patient case mix and the efficiency in hospital operation. Unmeasured patient characteristics, such as family support and supplemental insurance coverage, can be correlated with hospital ownership and the outcome variables. Thus, we must differentiate each component from the combined effects to identify whether FP hospital cream-skim low-cost patients.

2.5.2 *2SLS IV Model*

2.5.2.1 Distance Instrument

We use DD (i.e., the difference in the distances between the nearest FP and NFP hospitals from the patient's home) as an IV (McClellan et al., 1994) to control for observable and unobservable characteristics of patients that affect their decision for hospital selection. In the health economics literature, especially around the studies examining the effect of operational characteristics of health organizations, the DD instrument is a reasonably common method to address bias due to the endogeneity of treatment status, such as hospital ownership and related quality. This instrument benefits from the well-known preference among healthcare consumers for nearby medical providers (Capps et al., 2003; R. J. Ellis et al., 2020; Gowrisankaran et al., 2015; Ho, 2006). For instance, Gowrisankaran et al. (2015) find that the choice of a hospital is heavily guided by travel distance and times – additional five minutes in travel time lead to a decrease in demand for each hospital by 17 to 41 percent. Our data also support a patient's preference for closer proximity to hospital locations. Specifically, the median and 90th percentile travel distances between a patient's residence to their hospital are 5.5 (7.1 for FP hospital and 4.8 for NFP hospital) and 22 miles, respectively (Figure 4 Panel A and Figure 4 Panel B). In addition, it shows that roughly half of all patients selected the nearest hospital to their home (Figure 4 Panel C). As evidenced by these patterns, the DD instrument has been widely employed in the hospital context to control for the endogeneity of hospital selection.

To create a DD measure for inpatient psychiatric admissions, we first compute two types of distances (in miles) from a patient's home zip code to the nearest FP and NFP hospitals (with licensed psychiatric beds) zip code based on great-circle distances. We then calculate the difference between the two measures by subtracting the former from the latter. A positive value on the DD measure indicates the closest hospital to the patient is an NFP, and the patient is getting closer to the nearest FP hospital as the value decreases (Figure 4 Panel D). Along with hospital openings and closures in the market over time, DD for patients living in the same zip code area may vary over years.

2.5.2.2 Instrument Assumption and Validity

IV must satisfy the three underlying assumptions, conditional random assignment, monotonicity, and relevance, to be interpreted as causal effects (Imbens & Angrist, 1994). If applicable to our study setting, conditional random assignment refers to the situation when DD is unconfounded with the outcomes of interest conditional on covariates. This assumption incorporates the exclusion restriction, which implies the DD of a patient cannot have a direct impact on the outcomes, other than through its effect on her probability of choosing a FP hospital. The monotonicity assumption holds if patients' likelihoods of going to FP hospital increase following a decrease in their levels of DD (i.e., no defiers). The instrument relevance suggests that DD strongly predicts a patient's choice of hospital ownership type.

We begin with the validation of the monotonicity assumption. To interpret estimates from 2SLS IV as local average treatment effects (LATE), monotonicity is required. Although the assumption may be fulfilled on average, verifying it at the individual level is challenging. We present evidence that our data is generally compatible with the monotonicity assumption in Figure 2 Panel A and Figure 2 Panel B, which are binned scatter plots (i.e., each dot represents 5% of the sample) of the first stage model of general and psychiatric hospital samples, respectively. Below is the specification of the first stage model.

$$FP_{ijmt} = \alpha_m + \alpha_t + DD_i + DD_i^2 + v_{ijmt} \quad (2)$$

where FP_{ijmt} is an outcome indicator of 1 being FP hospital and 0 otherwise for patient i in hospital j. α_m is patient's HSA fixed effects. α_t is year fixed effects. DD_i is differential distance of patient i. DD_i^2 is squared differential distance of patient i.

The graph of general hospitals shows that the probability of going to a FP hospital decreases almost linearly up to the 10 miles of DD and maintains a nearly constant level after crossing the point (Figure 2 Panel A). The trend of psychiatric hospitals is comparable to that of general hospitals, besides the fact that the slope is less dramatic (Figure 2 Panel B).

We construct a binary IV measure to strengthen consistency with the monotonicity assumption based on the revealed trend of the probability across the range of DD: Above and below 10 miles of DD. This approach is advantageous because using the binary IV improves the interpretability of LATE. IV estimator can identify the average treatment effects (ATE) of those induced to shift a behavior according to the change of their IV status, also called compliers (Imbens & Angrist, 1994). For continuous IVs, the LATE is a weighted average of the effects from every possible instrument case (Angrist & Pischke, 2009). In other words, it is the weighted average of the estimates gained from numerous pairwise comparisons between the patient subgroups with $Z_i = DD_j$ and $Z_i = DD_j - 1$ (i.e., one unit apart from the comparator across $j \in J$ subgroups of compliers). Note that the sum of the weights is equal to 1. However, one caveat of this approach is that the weight for each complier subgroup may differ depending on group sizes. Without applying the structural approach, the conventional IV method cannot determine the individual weights to separate each effect from the combined effects of the complier subgroups (Heckman & Urzúa, 2010). As such, the extent to which the ATEs of complier subgroups evenly contribute to the LATE derived from continuous IV is less clear. We avoid this limitation with binary IV. With this approach, we can specify a single complier group sharing the same treatment effect based on a certain IV threshold of 10 miles of DD in this study.

To test for random assignment, it would be ideal to check the balance of observed and unobserved variables between patients above and below 10 miles of DD. However, this is impractical because we cannot address “unobserved” factors. Instead, we report 32 patient characteristics for those groups by the IV status following the standard in the economics literature (Table 3A and Table 3B). We also compute standardized mean differences between the groups to enhance comparability across the characteristics. Specifically, column (3) shows the difference between the patients above and below 10 miles of DD, while column (4) presents the difference between the patients choosing a FP and NFP hospital. The patient-level characteristics are similar across the two groups in most cases. Additionally, evidence from columns (3) and (4), especially for primary diagnosis, payer category and admission source, confirms that the potential imbalance of patient characteristics is less of concern in the IV analysis than the OLS analysis.

Another evidence for randomization is to confirm that the binary IV has no association with covariates, some of which may impact health utilization and costs, such as the severity of a patient’s psychiatric conditions. We test the assumption two-fold. First, we compare the estimates from the first stage model with and without patient-level controls. Columns (1) and (2) of Table 4 show that adding patient-level controls barely affects the coefficients on the binary DD, thereby supporting random assignment. Second, we inspect whether there is an association between patient disease severity and the instrument. We plot the residuals of the model against DD in Figure 3 Panel A and Figure 3 Panel B. This visual inspection shows little correlation between the severity of a patient's mental health conditions and DD, supporting the validity of the binary IV measure of this study.

Lastly, we show that our binary DD achieves the relevance assumption. The F-statistics that evaluate the association's strength are reported in Table 4. Column (6) demonstrates the estimates from the specification of the selected model. The F-statistics for general and psychiatric hospitals are 30 and 22, respectively, both of which are beyond the conventional threshold of 10 (Staiger & Stock, 1997). To document variations of F-statistics by the change of market fixed effects, we include the results from different specifications in Columns (3) through (5). The results demonstrate the robustness of the binary IV measure, consistently satisfying relevance in any market fixed effects, such as hospital referral region (HRR) and county. The estimates in column (6) suggest that residing beyond 10 miles of DD decreases the probability of going to a FP hospital by 6 and 10 percentage points for general and psychiatric hospitals, respectively.

2.5.2.3 Model Specification

The effect of ownership type is estimated in two stages, using Equation (3) in the first stage and Equation (4) in the second stage.

$$FP_{ijmt} = \alpha_m + \alpha_t + 1(DD)_i + \beta X'_{iz} + \delta H'_j + v_{ijmt} \quad (3)$$

$$Y_{ijmt} = \alpha_m + \alpha_t + \varphi \widehat{FP}_{ijmt} + \beta X'_{iz} + \delta H'_j + \epsilon_{ijmt} \quad (4)$$

where our endogenous regressor of interest FP_{ijmt} is an indicator variable with the value of 1 if patient i in HSA m selects FP hospital j in year t. $1(DD)_i$ is a binary instrument taking the value of 1 if the DD of patient i based on zip code of residence z exceeds 10. α_m is a patient HSA fixed effect. α_t is a year fixed effect. The vector X'_{iz} denotes patient-level controls, including sex, race, age, psychiatric diagnosis, zip code-level median income, payment category, managed care status, source of admission, and a type of bed (scatter bed or psychiatric bed). The vector H'_j denotes hospital-level controls, including teaching status, public ownership, psychiatric bed count, CMI, and HHI. Standard errors are clustered by patient-level five-digit zip code to account for unobserved correlation in error terms within the same residence. We implement subgroup analysis by two specific payment categories – private payer and Medicare. Similar to the OLS analysis, we perform the IV analysis separately for each hospital sample.

2.5.3 *Identification of Cream Skimming Behavior*

Given that cream skimming occurs upon the strategic selection of low-cost patients by hospitals, whether FP hospitals practice cream skimming can be detected by examining the association of ownership type with the treatment costs of patients in the hospitals. In the previous sections, we discussed that estimates of the OLS model are mainly derived via the two channels – unobserved differential patient case mix and hospital cost containment strategies. Also, we present that the IV analysis using DD balances different patient case mix between FP and NFP hospitals and yields unbiased estimates of the effect of hospital's cost containment effort. Therefore, to obtain the effect of patient case mix on treatment costs (i.e., note that this effect implies the evidence of cream skimming), we subtract the IV estimates from the OLS estimates across all the outcome variables. Standard errors for the subtracted estimates are formulated using 1000 times of clustered bootstrapping at the level of patient zip code.

2.6 EMPIRICAL STRATEGY FOR HOSPITAL-LEVEL ANALYSIS

To supplement our findings on patient-level service utilization and expenditure, we explore other operational characteristics of hospitals by their ownership type, using the hospital-level OSHPD data that include information on labor use and various financial outcomes. The list of hospital-level outcomes includes the number of physicians per bed, number of nurses per bed, nurse hours per patient day, profit margin, and operating margin. The version of the hospital-level data we use in this study does not allow us to disaggregate information by acute and/or psychiatric care units. Thus, we cannot identify inpatient psychiatric care-specific information from general hospitals. For this reason, our hospital level analysis focuses on specialty psychiatric hospital samples.

2.6.1 *Empirical Strategy and Model Specification*

To identify ownership effects based on the hospital-level data, we implement the model employing the propensity score matching (PSM) method. We choose this method because adjusting hospital and market characteristics in the OLS model may not sufficiently attenuate bias in the effect estimates for the following reasons – 1) the adjusted variables can be nonlinearly confounded with the main regressor, ownership type of the hospital, and 2) the distribution of the covariates might significantly differ with little overlap between FP and NFP hospitals (Imbens, 2000; Rubin, 1979). Our approach using the PSM method ensures that the covariate distribution balance is similar between FP and NFP hospitals.

Using the probit model, we first estimate the conditional probability of being a FP hospital (i.e., propensity score) given a vector of observable hospital characteristics. The hospital-level controls included in the first stage are the number of licensed beds, number of licensed psychiatric beds, number of total discharges from psychiatric beds, number of total patient days in psychiatric beds, the occupancy rate of psychiatric beds, cost-to-charge ratio, CMI, and HHI. With the two different types of outcomes, labor use, and hospital finance, we adjust additional separate sets of covariates into the respective first stage model: profit margin and operating margin for labor use outcomes and the number of physicians and number of nurses for financial outcomes. In the next stage, we match FP and NFP hospitals using the full matching method, which performs well in reducing bias from observable confounders (Hansen, 2004; Stuart & Green, 2008). Figure 5 shows that after the full matching, distributions of the propensity scores become almost identical between the FP and NFP hospitals. Figure 6 also confirms that the full matching method improves the covariate imbalance remarkably compared to other methods, including the nearest matching. Our model estimates reflect the average treatment effect on the treated as denoted below.

$$ATT = E_{P(\boldsymbol{X})FP=1}\{E[Y^{FP}|FP = 1, P(\boldsymbol{X})] - E[Y^{NFP}|FP = 0, P(\boldsymbol{X})]\} \quad (5)$$

where ATT is the average treatment effect on the treated for outcome Y. FP denotes for-profit hospital while NFP denotes not-for-profit hospital as the control. $P(\boldsymbol{X})$ is the probability of being a FP hospital based on a vector of covariates $\boldsymbol{X}$. Additionally, we include facility HSA fixed effects and year fixed effects, as well as the matched covariates used for generating propensity scores to mitigate potential remaining imbalance (Nguyen et al., 2017). Robust standard errors are applied to address heteroskedasticity.

2.7 RESULTS

2.7.1 *OLS Results*

Table 5A shows the results by estimating Equation (1) based on the patients admitted to general hospitals. Column 1 indicates the mean cost per discharge is about 470 dollars lower in FP hospitals than in NFP hospitals ($p < 0.001$). Columns 2 and 3 and Column 4, each of which represents intensity and duration of care, respectively, suggest that the lower cost per discharge in FP hospitals is associated with reducing the intensity of care. Particularly, the cost per day and the number of procedures in FP hospital are 93 dollars and 0.12 units lower ($p < 0.001$), respectively, than in NFP hospital, while their LOS is 0.2 days longer ($p < 0.01$). FP hospitals tend to transfer their patients to other providers four percentage points more than NFP hospitals (Table 5A Column 5). Columns 6, 7, and 8 imply that the median values hold similar trends to the mean values.

Table 5B presents the results from Equation (1) for the patients admitted to psychiatric hospitals. Similar to the above findings from general hospital samples, the mean cost per discharge in Column 1 demonstrates that it decreases by 1790 dollars in FP hospitals compared to NFP hospitals ($p < 0.001$). However, we find that the LOS in FP hospital is about a half day lower ($p < 0.001$) than that of NFP hospitals. The referral rate in FP psychiatric hospitals is two percentage points lower ($p < 0.001$) than in their counterparts.

By comparing Panel B and C, we can identify different treatment patterns of hospitals by their ownership type depending on payer types. There is no notable difference in hospital behaviors between private insurance and Medicare beneficiaries except that compared to NFP hospitals, FP hospital discharge private insurance patients earlier while keeping Medicare patients longer.

2.7.2 *2SLS IV Results*

Table 6A presents the results from Equation (4) using the patient sample from general hospitals. Column 1 suggests that the mean cost per discharge is approximately 10300 dollars lower ($p < 0.05$) in FP hospitals than in NFP hospitals. However, Column 6, the median cost per discharge, does not yield the same result. We cannot determine the driver of decreasing costs between intensity and duration of care, given that none of these measures shows statistically significant differences between FP and NFP hospitals. Panel B presents the results from the private insurance patient sample, which shows FP hospital is more likely to reduce the intensity of care than NFP hospital.

Table 6B estimates from Equation (4) using the patients admitted to psychiatric hospitals. Both mean and median cost per discharge in FP hospital is 1500 and 1100 dollars lower ($p < 0.01$) than that of NFP hospital, respectively. With the lower mean and median daily costs in FP hospitals (Column 2 and 7 in Panel A), we view that a decrease in intensity of care may contribute to their lower mean and median total costs than NFP hospitals. For the private insurance and Medicare beneficiaries in Panel B and C, we notice that the way that FP hospitals reduce the cost per discharge differs by the insurance type. That is, although treating both patients in FP hospitals occurs with fewer mean costs per discharge, FP hospitals do so by reducing the intensity of care for the patients covered by private insurance. In contrast, they discharge Medicare patients earlier than NFP hospitals.

2.7.3 *Bootstrapped Results*

Table 7A demonstrates the estimates computed by subtracting Equation (4) from Equation (1) based on the general hospital sample. In Panel A, for all patients, FP hospital has 9800 dollar higher mean cost per discharge ($p < 0.01$) than NFP hospital. The same observation is found in Panel C among Medicare beneficiaries ($p < 0.05$).

Table 7B presents the estimates calculated in the same manner as above from the psychiatric hospital sample. In Panel A for all patients, there are no differences in the outcomes except the number of procedures – FP hospital has 0.6 unit less procedures ($p < 0.01$) than NFP hospital. This trend also applies to private insurance patients similarly. In Panel C for Medicare beneficiaries, FP hospital has 4 days longer length of stay ($p < 0.01$) and 870 dollar higher median cost per discharge ($p < 0.05$) than NFP hospital.

2.7.4 *Robustness Check*

Using different model specifications, we repeated the above patient-level analysis. In the first stage, we implemented the generalized linear model with log link function with gamma distribution as a naïve estimator. Then, we conducted the two-stage residual inclusion (2SRI) analysis using generalized residuals obtained from the first stage logistic regression model. The results from each step are presented in Tables 8, 9, and 10, respectively. The outcomes from the robustness check also demonstrate that FP hospitals treat patients with higher costs.

2.7.5 *PSM Results*

Table 11 presents the results from Equation (5) based on the hospital-level data of psychiatric hospitals. Panel B includes estimates of the PSM model, indicating that FP hospitals invest fewer human resources for inpatient psychiatric care. Additionally, for labor use outcomes, the effect sizes of the PSM model in Panel B are larger than the estimates of the OLS model in Panel A.

2.8 DISCUSSION AND CONCLUSIONS

Few empirical research has investigated the relationship between hospital ownership type and cream skimming among inpatient psychiatric admissions. Furthermore, none of these studies use treatment costs as a proxy for cream skimming. Our study is novel and distinguished from the prior literature. We integrate multiple statistical modeling techniques, such as OLS and 2SLS models, to detect the evidence of cream skimming. More specifically, we explicitly account for the two different channels of effects (i.e., selection of patient case mix and execution of cost containment practice) combined within the regression-based estimates. After instrumenting ownership type by the DD, we can gain unbiased estimates indicating the hospital's execution of cost containment, primarily driven by efficient resource allocation of the hospital. Then, considering that estimates from the OLS model consist of the effects of hospital cost containment strategies and differential patient case mix, we subtract the IV estimates from the combined OLS estimates to obtain unbiased estimates representing differential patient case mix only.

Our main results suggest that FP general hospitals do not practice cream skimming (Table 7A). Conversely, we found that NFP general hospitals are more likely to treat low-cost patients, meaning that they may cream skim patients who do not require costly medical interventions. The duration of hospitalization is correlated with total treatment costs. This also supports the evidence of cream skimming in the NFP general hospitals because patients' lower costs are influenced by patient severity. No difference in the median measures (e.g., log cost per discharge) between FP and NFP general hospitals provides additional information on the distribution of patient severity in the hospitals – the proportion of patients with more serious psychiatric conditions is higher in FPs than in NFP hospitals. The subgroup analysis by insurance coverage indicates that NFP general hospitals practice cream skimming, particularly among Medicare beneficiaries, and do not cream skim among patients with private insurance. Compared to general hospitals, the evidence of cream skimming for psychiatric hospitals is inconsistent (Table 7B). It is worth highlighting that the median cost per discharge of Medicare patients in the FP hospitals is higher than those in the NFP hospitals, with no difference in their mean costs per discharge. This finding implies that NFP hospitals may practice cream skim among the psychiatric patients with low or medium severity.

In addition to the evidence of cream skimming, our analysis also shows that FP hospitals perform superior to NFPs in terms of containing costs. Among the general hospitals, the FP hospitals provide services with fewer costs (Table 6A), which suggests that they may achieve higher efficiency when treating psychiatric patients than the NFP hospitals. Given that the median cost per discharge does not differ between the FP and NFP hospitals, it seems that FP hospitals are particularly more efficient in treating patients with high severity. However, when they treat patients with private insurance or Medicare, the efficiency of the FP hospitals is not maintained; thus, it becomes indifferent compared to the NFP hospitals. Among the psychiatric hospitals, the FP hospitals perform more efficiently than the NFPs (Table 6B). Particularly, the FP hospitals are more likely to discharge Medicare patients four days earlier than the NFPs, which might be their primary cost saving strategy. However, this treatment pattern is not observed among patients with private insurance; instead, the FP hospitals save treatment costs by reducing treatment intensity via daily costs.

The hospital-level analysis of labor use and financial margins increases our understanding of the cost containment strategy among FP psychiatric hospitals (Table 11). The FP hospitals tend to employ fewer clinical personnel than the NFP hospitals. Particularly, the degree of difference in the number of physicians per bed is approximately eight times larger than the number of nurses per bed. The lower number of nurses per bed is naturally connected to the lower nurse hours per patient day, a proxy measure for the quality of inpatient care. The commonly used patient-level quality measures, such as 30-day readmission rate and mortality, may reflect the treatment quality more precisely than the hospital-level proxy measure; however, due to the limitation of our data (i.e., cross-sectional data without the individual identification code) and distinctive characteristics of inpatient psychiatric care, we cannot introduce those outcomes to our patient-level analysis. Yet, these findings may offer a legitimate rationale for potential safety concerns against the recent growth of FP facilities in the inpatient psychiatric care markets (Shields, Reneau, et al., 2018; Shields, Stewart, et al., 2018).

Regarding profit and operating margins, although none of them show a statistically significant association with ownership type, these financial outcomes also highlight the FP psychiatric hospital's cost containment strategy. Specifically, our results show that the FP hospitals yield higher operating margins, whereas profit margins are lower than the NFP hospitals. Considering that the operating margin represents the mark-up obtained after deducting all the labor costs (e.g., salaries and payments) from total revenue and that the operating margin of FP hospitals will be shared with shareholders as a dividend, FP psychiatric hospitals may sacrifice the quality of care to maximize their financial gains.

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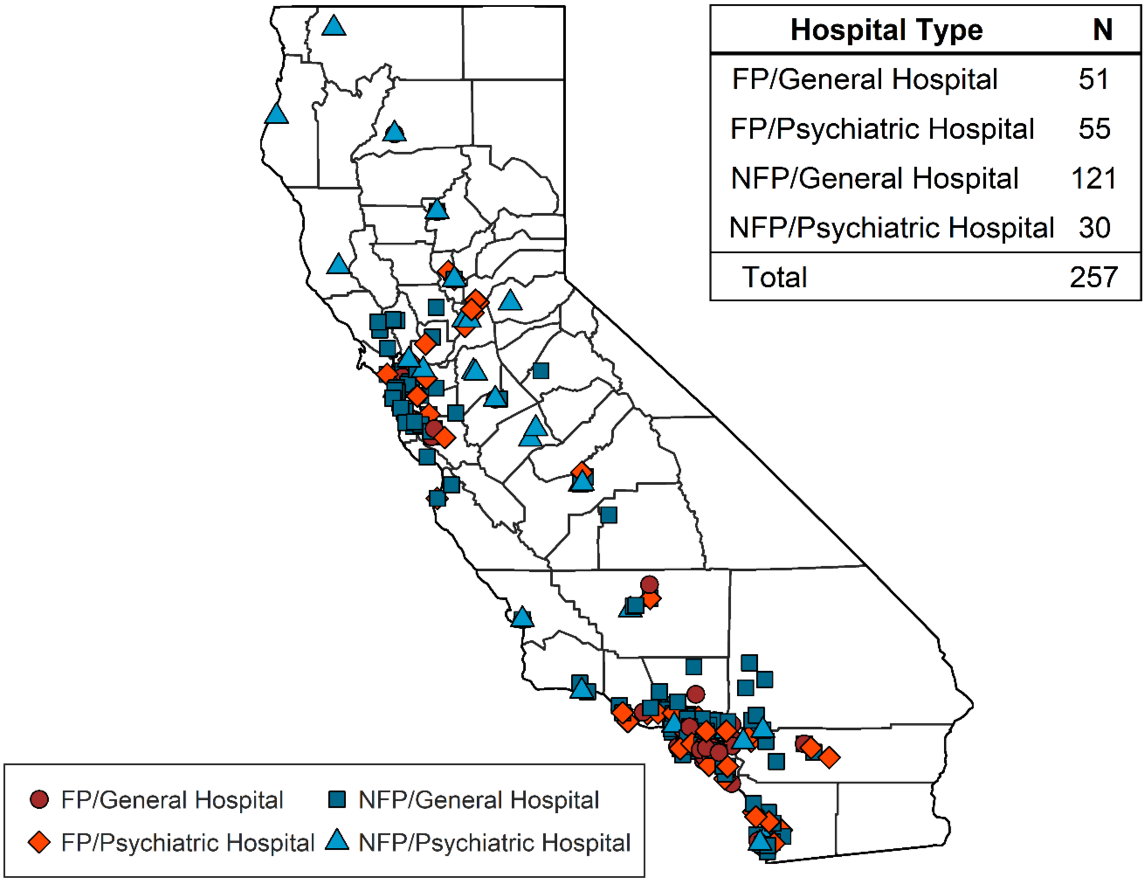
FIGURES AND TABLES

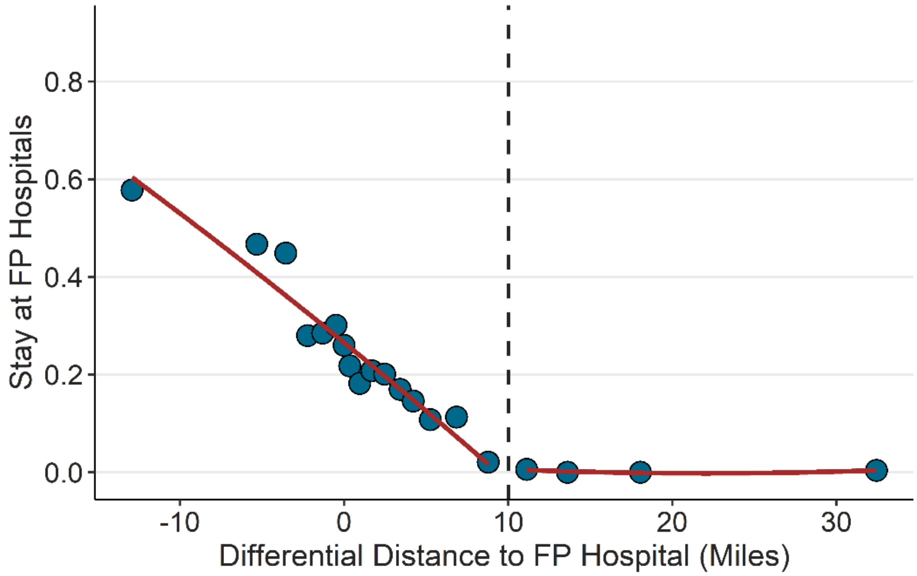
Figure 1. Geographical distribution of hospitals with licensed psychiatric beds in California



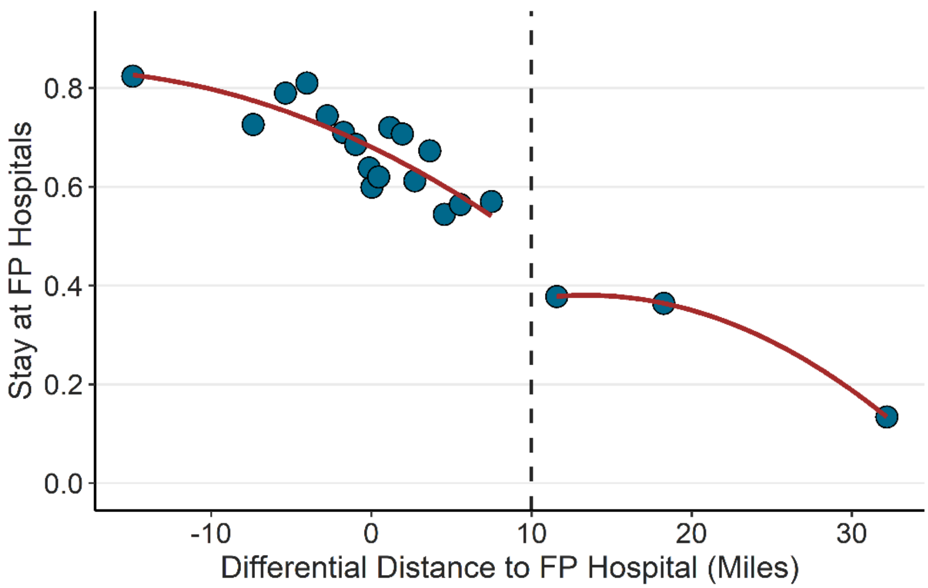
Hospital Type	N
FP/General Hospital	51
FP/Psychiatric Hospital	55
NFP/General Hospital	121
NFP/Psychiatric Hospital	30
Total	257

Note: This map illustrates the locations of California hospitals with licensed psychiatric beds. General Hospital refers to general acute care hospitals available at least a single licensed psychiatric bed. Psychiatric Hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities.

Figure 2. Probability of staying at FP hospital with differential distance



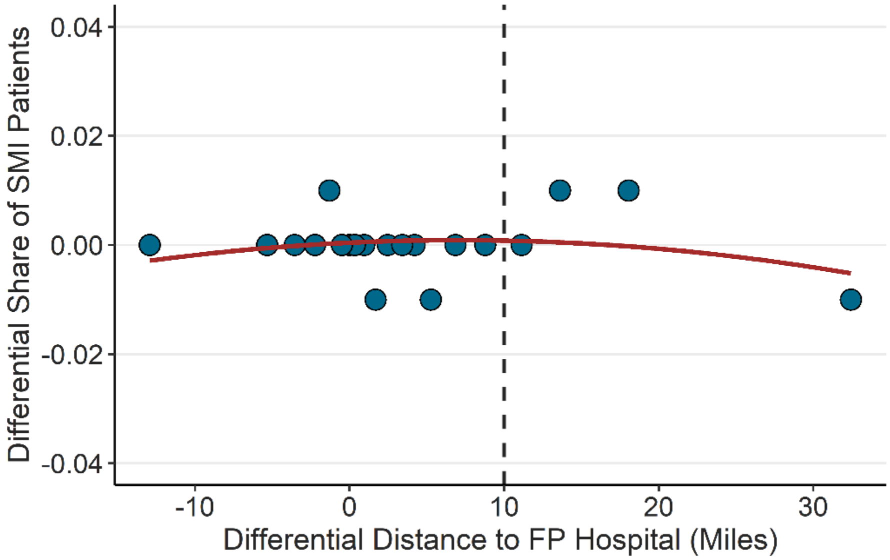
A: General hospital



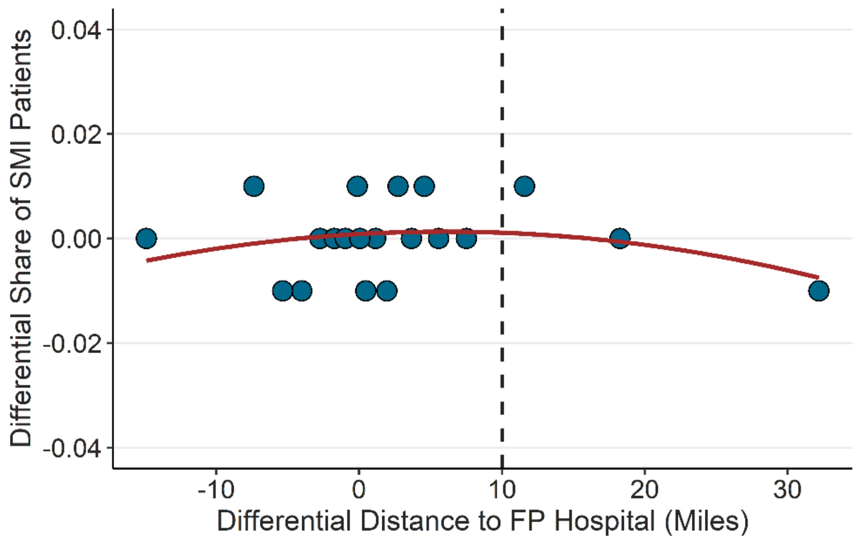
B: Psychiatric hospital

Note: This figure presents binned scatter plots of the probability of staying at the FP hospital against differential distance. The predictor variables are the linear and quadratic DD calculated based on distances between centroid points of zip code for the patient and the nearest FP and NFP hospitals. The outcome variable is an indicator of whether the patient is admitted to the FP hospital. We obtain residuals from the model for each patient and take an average of the residuals by 20 equal sized bins based on continuous DD. Each dot represents 5% of the sample. Panel A presents outcomes from the patients admitted to general hospitals, while Panel B presents outcomes from those admitted to psychiatric hospitals. All regressions include patient HSA and year fixed effects without adjusting other patient and hospital characteristics. The quadratic fitted lines are displayed in the figure. Psychiatric hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities.

Figure 3. Distribution of SMI patients with differential distance



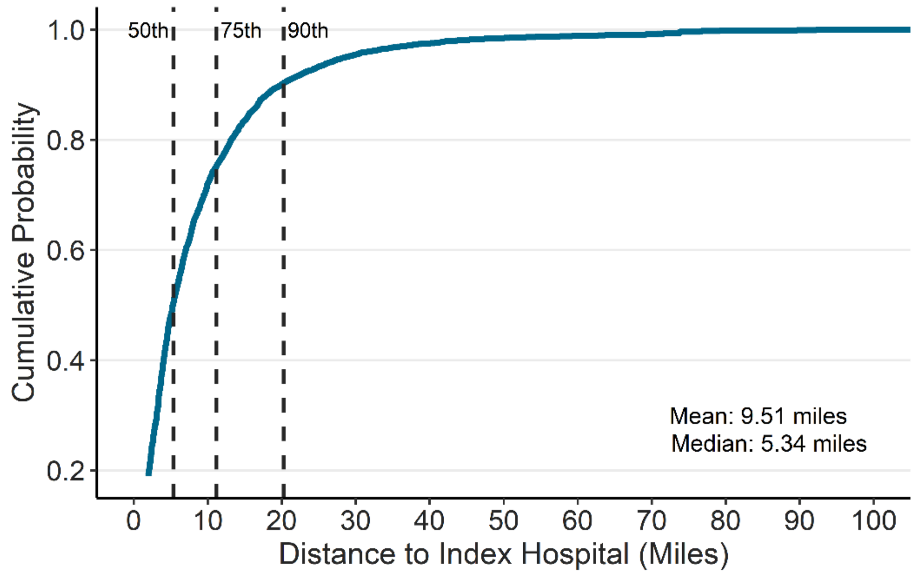
A: General hospital



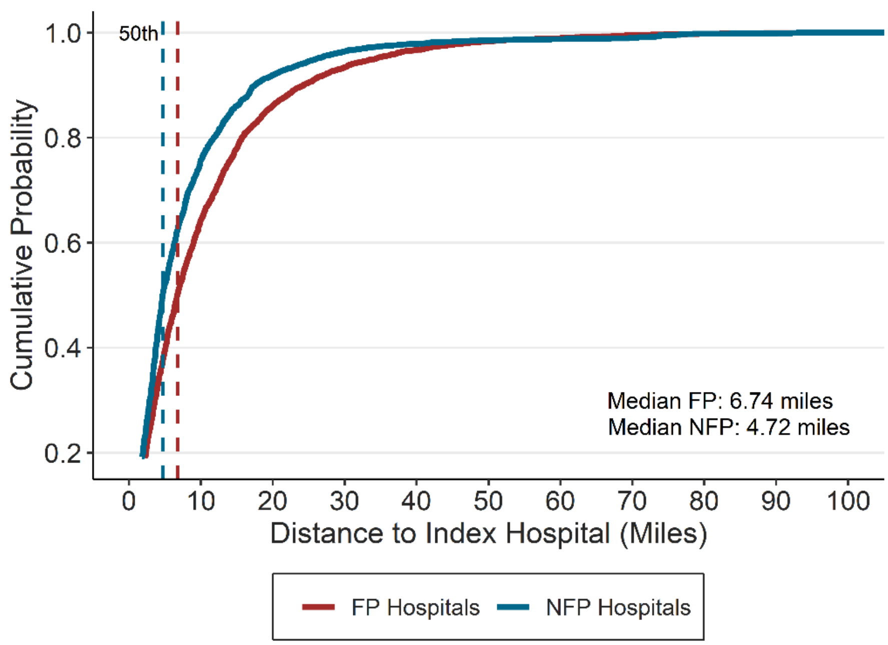
B: Psychiatric hospital

Note: This figure presents binned scatter plots of the differential share of patients with serious mental illness (SMI) against differential distance to the closest FP hospital with licensed psychiatric beds. Patients with SMI are defined as those with a primary diagnosis of Schizophrenia, Bipolar disorder, or Major depression. The predictor variable is the binary DD (i.e., DD > 10 miles) calculated based on distances between centroid points of zip code for the patient and the respective hospitals. The outcome variable is an indicator of whether the patient is diagnosed with SMI. We obtain residuals from the model for each patient and take an average of the residuals by 20 equal sized bins based on continuous DD. Each dot represents 5% of the sample. Panel A presents outcomes from the patients admitted to general hospitals, while Panel B presents outcomes from those admitted to psychiatric hospitals. All regressions include patient-, hospital-, and market-level control variables, patient HSA and year fixed effects. The quadratic fitted lines are displayed in the figure. Psychiatric hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities.

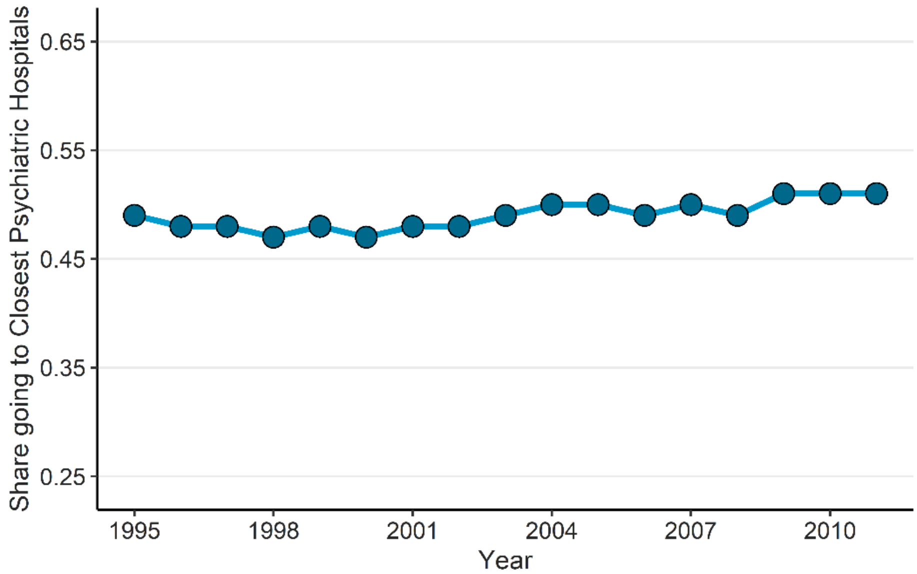
Figure 4. Distance from the patient's residence to the admitted hospital



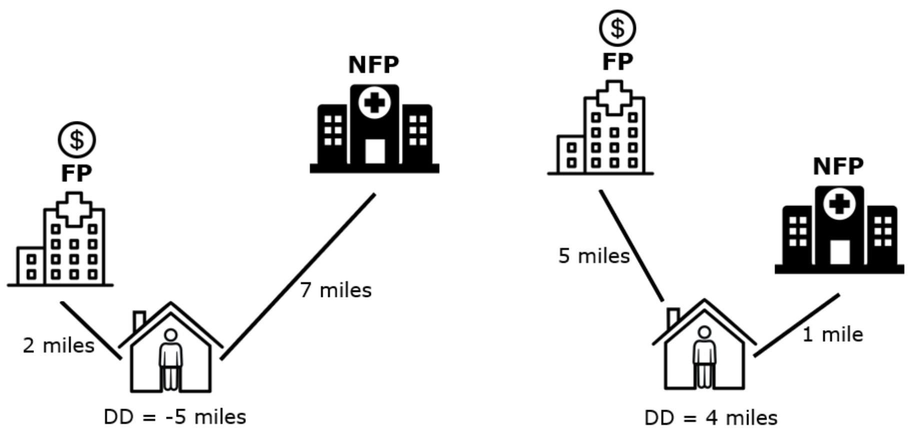
A: CDF: All patients



B: CDF: FP vs. NFP patients



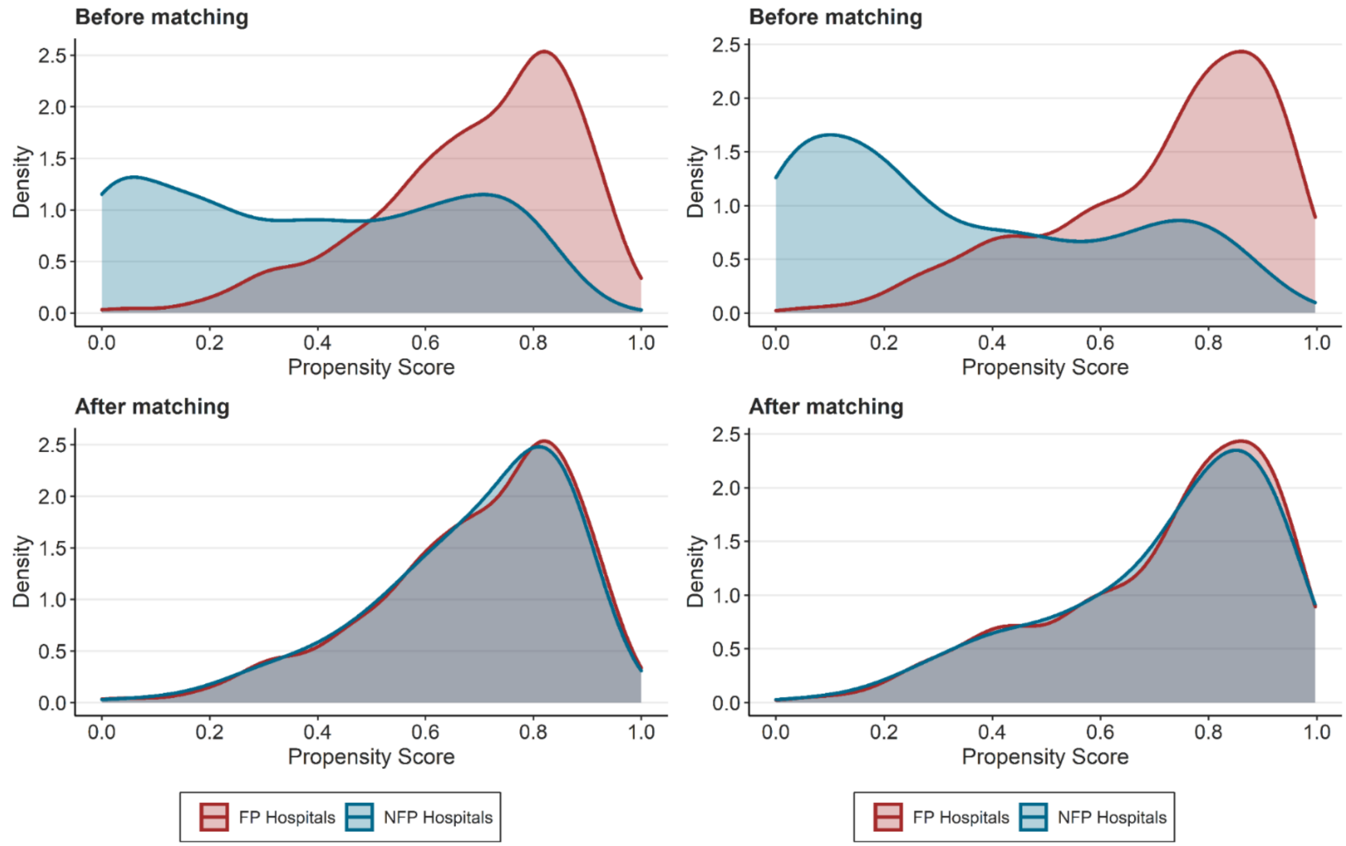
C: Share going to the nearest hospital with licensed psychiatric bed



D: Calculation of differential distance between nearest FP and NFP hospital

Note: This figure provides general information on the patient's distance to the admitted hospital calculated based on the difference between centroid points of zip code for the patient and the index hospital. Panels A and B illustrate cumulative density functions (CDF) of distance from the patient's residence to the admitted hospital. The CDF in Panel A shows the trend from the patient sample and describes the mean, median, 75th and 90th percentile values. The CDF in Panel B presents the separate trend by admitted hospital status and describes their respective mean and median values. Panel C illustrates the proportion of patients going to their nearest hospital with licensed psychiatric beds over the sample period, 1995-2011. Panel D provides two examples of differential distance calculations.

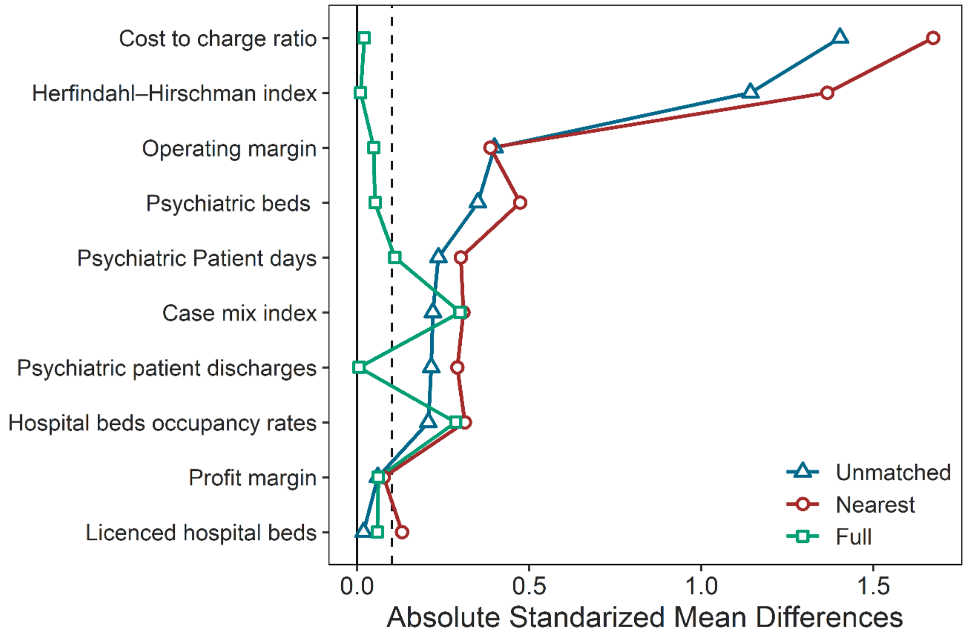
Figure 5. Comparison of the propensity score distribution before and after matching



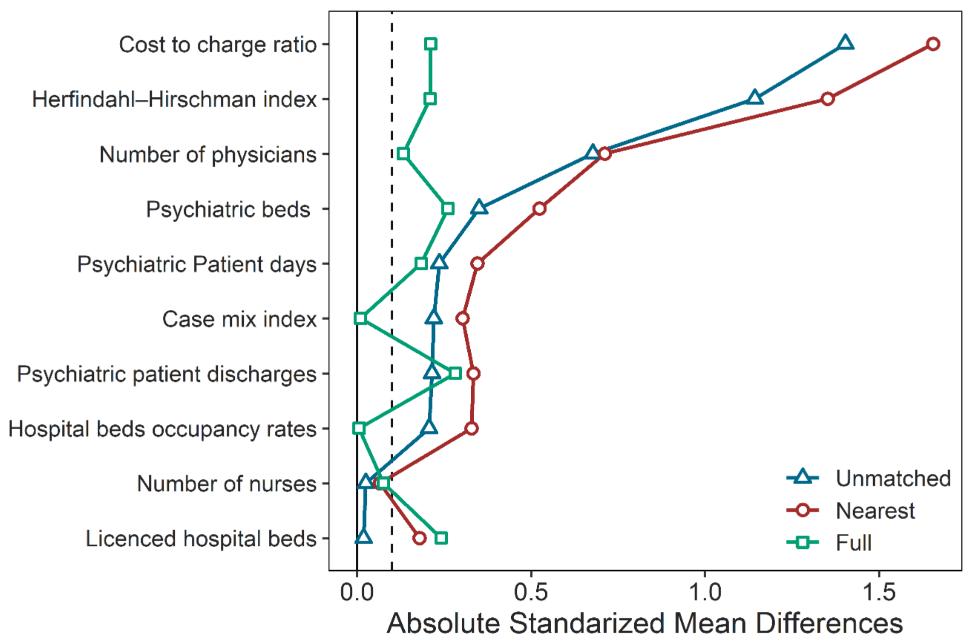
A: Labor resources (left) B: Financial outcomes (right)

Note: This figure presents density plots of propensity score distribution comparing before and after matching. A full matching method is used. The outcomes of labor resources in Panel A encompass the number of physicians per bed, number of nurses per bed, and nurse hours per patient day. The financial outcomes in Panel B are profit and operating margin. The list of covariates included in Panel A is the number of licensed beds, number of licensed psychiatric beds, number of total discharges from psychiatric beds, number of total patient days in psychiatric beds, the occupancy rate of psychiatric beds, cost-to-charge ratio, case mix index, profit margin, operating margin, and HHI. The list of covariates included in Panel B is the same as above, except the number of physicians and nurses replace profit and operating margin. The study sample consists of freestanding specialty psychiatric hospitals only.

Figure 6. Comparison of covariate imbalance



A: Labor resources



B: Financial outcomes

Note: This figure illustrates covariate imbalance among matched samples using three approaches, including the nearest and full matching methods. The X-axis represents absolute standardized mean differences, and we add the dotted line on the value of 0.1. The Y-axis shows the covariates adjusted in the models for labor resources and financial outcomes, respectively.

Figure S1. Flow diagram of the selection procedure for the study population

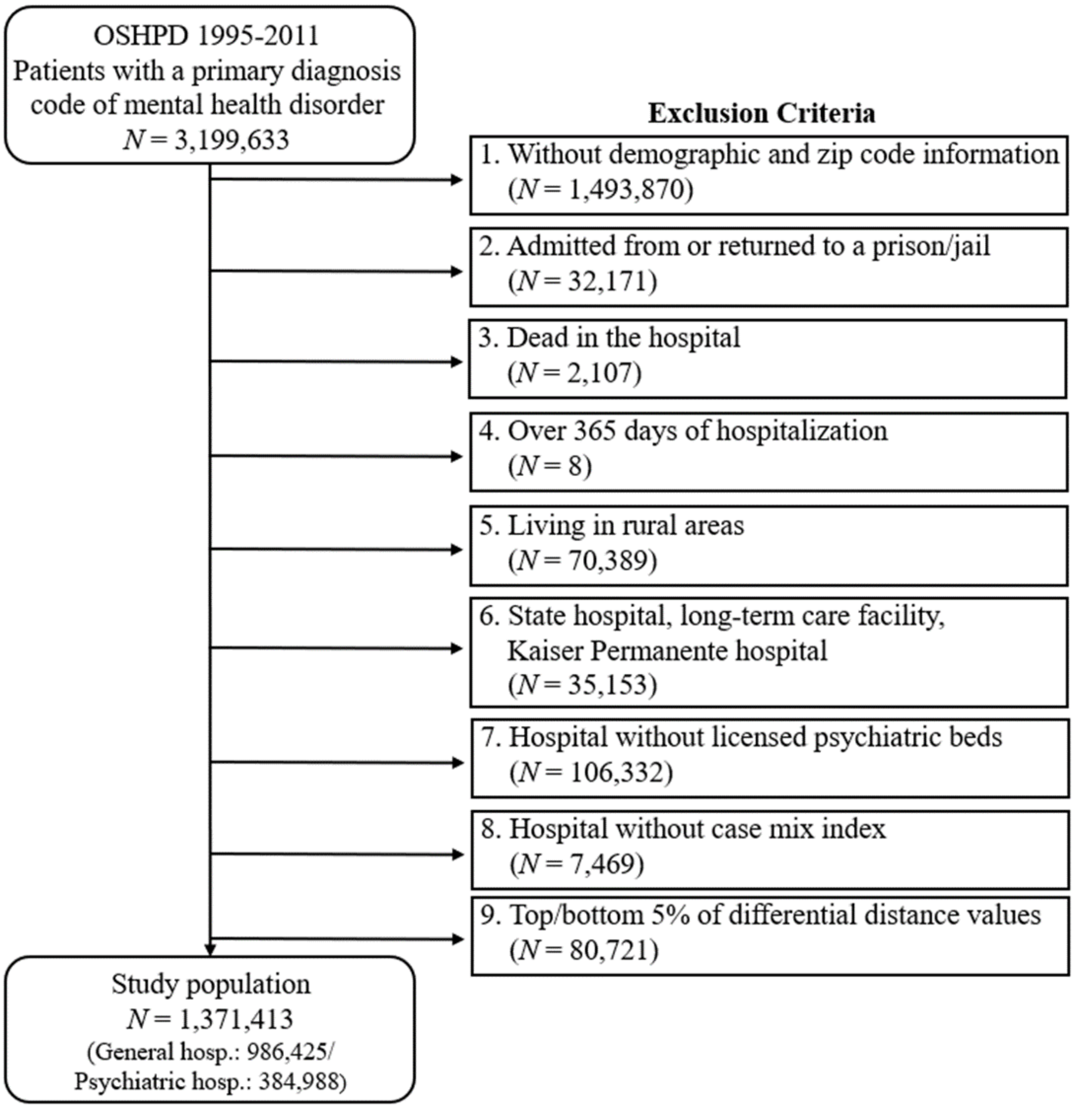


Table 1. Hospital-level summary statistics by hospital type and profit status

	General hospitals		Psychiatric hospitals	
	For-profit (N = 51)	Not-for-profit (N = 121)	For-profit (N = 55)	Not-for-profit (N = 30)
Teaching (%)	1	23	0	0
Hospital bed				
Number of total hospital beds	209 (104)	378 (215)	69 (40)	69 (83)
Available beds / licensed beds	0.96 (0.1)	0.9 (0.12)	0.99 (0.05)	0.96 (0.12)
Number of psychiatric beds	40 (27)	41 (32)	65 (39)	52 (38)
Discharge				
Annual discharges from psychiatric beds	1063 (1062)	1046 (843)	1734 (1414)	1448 (1043)
Annual psychiatric discharges per psychiatric bed	24 (13)	27 (14)	26 (13)	33 (16)
Annual occupancy rates for psychiatric beds (%)	61.8 (23.5)	59 (23.1)	63.6 (20.8)	67.8 (21)
Human resources				
Number of physicians	274 (216)	428 (352)	24 (25)	42 (118)
Physicians per hospital bed	1.34 (0.92)	1.18 (0.79)	0.37 (0.4)	0.57 (1.63)
Number of registered nurses	278 (201)	601 (410)	52 (41)	54 (78)
Registered nurses per hospital bed	1.28 (0.52)	1.59 (0.63)	0.8 (0.54)	0.56 (0.63)
Others				
Number of procedures	0.6 (0.6)	0.6 (0.7)	0.4 (0.7)	0.7 (1)
Cost-to-charge ratio	0.3 (0.12)	0.37 (0.14)	0.57 (0.24)	0.91 (0.61)
Case mix index	1.08 (0.29)	1.11 (0.2)	0.74 (0.07)	0.72 (0.07)
Herfindahl–Hirschman index	2413 (961)	3377 (1391)	2808 (787)	3669 (1472)

Note: This table presents hospital-level summary statistics by hospital type (general/psychiatric hospital) and profit status (for-profit/not-for-profit) over the sample period of 1995-2011. A unit of observation is a hospital-year. The number of hospitals represents uniquely identified hospitals in the sample (i.e., the hospital which shifted profit status during the sample period is counted separately). The number in parenthesis indicates the standard deviation. Among the listed variables, we use teaching status, psychiatric bed count, case mix index, and the Herfindahl index for hospital-level controls in the regression model. The number of physicians includes both hospital- and non-hospital-based physicians. A more detailed description can be found in the glossary of active medical staff in the OSHPD Hospital Annual Financial Data document. Psychiatric Hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities.

Table 2. Patient-level summary statistics by hospital type and profit status

	General hospitals		Psychiatric hospitals	
	For-profit (*N* = 196,690)	Not-for-profit (*N* = 789,735)	For-profit (*N* = 239,636)	Not-for-profit (*N* = 145,352)
Female (%)	50	51	50	53
Age category (%)				
0-17 years	2.4	3.4	28.8	21.7
18-34 years	20.1	27.7	23.8	26.9
35-64 years	59.0	56.2	42.9	46.0
65 years and over	18.4	12.6	4.5	5.5
Race (%)				
White	76.3	76.7	74.3	82.9
Black	16.3	13.1	10.8	9.1
Native American/Eskimo	0.1	0.2	0.2	1.3
Asian/Pacific Islander	2.2	2.9	1.8	2.1
Other	5.1	7.1	12.9	4.6
Primary diagnosis (%)				
Seriou mental illness	85	74	81	70
Schizophrenia	47	34	28	28
Bipolar disorder	16	18	22	18
Major depression	22	22	31	24
Depression	3	6	8	9
Alcohol use disorder	4	7	2	5
Drug use disorder	1	1	2	3
Other	7	12	7	13
Zip code-level median income	57885 (20828)	61633 (22614)	62607 (20842)	58781 (20978)
Payer category (%)				
Private	14	18	40	41
Public	78	60	47	34
Medicare	44	31	27	18
Medi-Cal	34	29	20	16
County	2	5	5	7
Charity/Self-pay	4	9	3	5
Other	3	8	4	13
Managed care	12	17	29	36
Source of admission (%)				
This hospital – emergency room	33	55	0	1
This hospital – general	8	7	0	0
Transfer from another hospital	7	4	8	9
Not a hospital	53	34	92	90
Type of licensed bed (%)				
Acute care	18	23	1	1
Psychiatric care	82	77	99	99

Note: This table presents patient-level summary statistics by hospital type (general/psychiatric hospital) and profit status (for-profit/not-for-profit) between 1995-2011. A unit of observation is a patient discharge from psychiatric admission. The total patient number is calculated by summing over discharge events according to the type and profit status. The zip code-level median income is dollars in 2000, and the number in parenthesis indicates the standard deviation. All variables included in this table are used as patient-level controls in the regression model. Please note that categories of the variables reflect the types of variables (i.e., continuous/binary/categorical) in the model. Serious mental illness includes Schizophrenia, Bipolar disorder, and Major depression. Psychiatric Hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities.

Table 3A. Balance of patient characteristics (General hospital)

	(1) DD < 10 miles	(2) DD > 10 miles	(3) SMD (IV) 1(DD)	(4) SMD (OLS) 1(FP)
Female (%)	50	52	0.04	0.01
Age category (%)				
0-17 years	3	3	0.02	0.06
18-34 years	26	29	0.07	0.18
35-64 years	57	58	0.02	0.06
65 years and over	15	11	0.11	0.16
Race (%)				
White	75.8	80.0	0.1	0.01
Black	14.5	10.8	0.11	0.09
Native American/Eskimo	0.1	0.2	0.02	0.02
Asian/Pacific Islander	2.5	3.6	0.06	0.04
Other	7.1	5.4	0.07	0.09
Primary diagnosis (%)				
Schizophrenia	38	33	0.1	0.26
Bipolar disorder	18	18	0.01	0.05
Major depression	22	22	0.01	0
Depression	5	7	0.08	0.15
Alcohol use disorder	7	7	0.01	0.13
Drug use disorder	1	1	0.02	0.01
Other	10	12	0.06	0.15
Zip code-level median income	59887 (22086)	64810 (22795)	0.22	0.17
Payer category (%)				
Private	17	21	0.11	0.12
Public (Medicare/Medi-Cal)	64	62	0.03	0.4
County	4	4	0.05	0.19
Charity/Self-pay	8	7	0.02	0.22
Other	7	6	0.06	0.22
Managed care	15	21	0.16	0.13
Source of admission (%)				
This hospital – emergency room	48	60	0.24	0.47
This hospital – general	7	6	0.06	0.03
Transfer from another hospital	5	3	0.11	0.12
Not a hospital	40	31	0.18	0.39
Type of licensed bed (%)				
Acute care	23	19	0.1	0.14
Psychiatric care	77	81	0.1	0.14
No. observations	786,309	200,116		

Note: This table presents the balance of patient-level characteristics by the instrument for patients from general hospitals. Patients are split into two groups, less than 10 miles of differential distance (DD) versus more than 10 miles of DD. Column 1 presents the mean values of variables for patients with DD less than 10 miles, while Column 2 shows the mean values for patients with DD more than 10 miles. We introduce the standardized mean difference (SMD) by the binary DD status in Column 3 to increase comparability across different patient characteristics based on a common scale. Column 4 presents the SMD by the profit status of hospitals that served the patient. Comparing Columns 3 and 4, we can determine how much the IV analysis mitigates influences from an endogenous regressor.

Table 3B. Balance of patient characteristics (Psychiatric hospital)

	(1) DD < 10 miles	(2) DD > 10 miles	(3) SMD (IV) 1(DD)	(4) SMD (OLS) 1(FP)
Female (%)	51	54	0.07	0.06
Age category (%)				
0-17 years	26	26	0.01	0.16
18-34 years	25	25	0	0.07
35-64 years	44	43	0.02	0.06
65 years and over	5	6	0.04	0.04
Race (%)				
White	76.8	82.3	0.14	0.21
Black	10.4	8.8	0.05	0.06
Native American/Eskimo	0.5	1.3	0.09	0.13
Asian/Pacific Islander	1.8	2.4	0.04	0.03
Other	10.5	5.3	0.19	0.3
Primary diagnosis (%)				
Schizophrenia	28	29	0.02	0.01
Bipolar disorder	21	18	0.09	0.1
Major depression	28	28	0	0.15
Depression	8	9	0.04	0.06
Alcohol use disorder	3	3	0.04	0.14
Drug use disorder	2	2	0.02	0.08
Other	9	11	0.09	0.19
Zip code-level median income	61995 (21162)	56188 (19084)	0.29	0.18
Payer category (%)				
Private	41	40	0.02	0.01
Public (Medicare/Medi-Cal)	43	38	0.09	0.28
County	5	13	0.29	0.07
Charity/Self-pay	4	5	0.06	0.08
Other	8	4	0.17	0.36
Managed care	31	36	0.1	0.14
Source of admission (%)				
This hospital – emergency room	0	0	0.05	0.13
This hospital – general	0	0	0.04	0.06
Transfer from another hospital	8	8	0.02	0.04
Not a hospital	91	92	0.04	0.06
Type of licensed bed (%)				
Acute care	1	0	0.07	0.01
Psychiatric care	99	100	0.07	0.01
No. observations	329,827	55,161		

Note: This table presents the balance of patient-level characteristics by the instrument for patients from psychiatric hospitals. Patients are split into two groups, less than 10 miles of differential distance (DD) versus more than 10 miles of DD. Column 1 presents the mean values of variables for patients with DD less than 10 miles, while Column 2 shows the mean values for patients with DD more than 10 miles. We introduce the standardized mean difference (SMD) by the binary DD status in Column 3 to increase comparability across different patient characteristics based on a common scale. Column 4 presents the SMD by the profit status of hospitals that served the patient. Comparing Columns 3 and 4, we can determine how much the IV analysis mitigates influences from an endogenous regressor. Psychiatric Hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities.

Table 4. First stage results from the regression model of FP status on differential distance

	(1)	(2)	(3)	(4)	(5)	(6)
	1(FP)	1(FP)	1(FP)	1(FP)	1(FP)	1(FP)
Panel A: General hospital						
Differential distance	-0.044***	-0.042***	-0.043***	-0.102***	-0.079***	-0.040***
(> 10 miles)	(0.008)	(0.008)	(0.007)	(0.01)	(0.009)	(0.008)
No. observations	986,425	986,425	986,425	986,425	986,425	986,425
Y-Mean	0.2	0.2	0.2	0.2	0.2	0.2
F-statistics	34	32	35	102	71	25
Panel B: Psychiatric hospital						
Differential distance	-0.193***	-0.192***	-0.162***	-0.202***	-0.147***	-0.164***
(> 10 miles)	(0.021)	(0.021)	(0.021)	(0.032)	(0.034)	(0.022)
No. observations	384,988	384,988	384,988	384,988	384,988	384,988
Y-Mean	0.62	0.62	0.62	0.62	0.62	0.62
F-statistics	87	83	59	39	18	58
HHI						Y
Hospital cont.			Y	Y	Y	Y
Patient cont.		Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HRR/Year	County/Year	HSA/Year

Note: This table presents estimates from the first stage regression model showing the relationship between the hospital's for-profit (FP) status and the difference in distance to the closest FP hospital and the nearest NFP hospital for the patient. The hospital is defined as general acute care or specialty psychiatric hospital which has at least a single licensed psychiatric bed. We dichotomize the differential distance (DD) on the basis of 10 miles. The estimates of each column present the coefficient β obtained from Equation (3). The predictor variable is the binary DD calculated based on distances between centroid points of zip code for the patient and the respective hospitals. The dependent variable is an indicator taking the value of 1 if the patient is admitted to FP hospital (0; otherwise). Column 1 only includes patient HSA and year fixed effects. Column 2 adds patient-level controls (sex, race, age, payment and managed care status, psychiatric diagnosis, urban/rural status, zip code- level median income, and bed type). Column 3 adds hospital-level controls (teaching hospital, public ownership, psychiatric bed count, and case mix index). Columns 4 and 5 alter area-based fixed effects from patient HSA to patient HRR and patient county, respectively. Column 6 (our preferred specification) adds the Herfindahl–Hirschman index of the hospital as a market-level control and includes patient HSA and year fixed effects. Standard errors are clustered by patient-level zip code. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 5A. Effects of being a FP hospital on spending and utilization (OLS/General hospital)

	Mean					Median		
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Number of Procedures	(4) Length of Stay	(5) Referral to Other Providers	(6) Log Cost Per Discharge	(7) Log Cost Per Day	(8) Log Length of Stay
Panel A: All								
1(FP)	-471.8***	-92.6***	-0.12***	0.22*	0.04***	-134.3*	-53.1***	0.19***
	(93.6)	(11.7)	(0.03)	(0.09)	(0.004)	(66.0)	(11.1)	(0.05)
No. observations	986,425	986,425	986,425	986,425	986,425	986,425	986,425	986,425
Y-Mean/Median	6093.3	934.5	0.47	7.75	0.1	3668.3	716.6	5
Panel B: Private								
1(FP)	-612.3***	-106.9***	-0.03	-0.25**	0.03***	-591.1***	-107.4***	-0.24***
	(94.6)	(17.9)	(0.02)	(0.08)	(0.003)	(51.5)	(11.5)	(0.05)
No. observations	170,892	170,892	170,892	170,892	170,892	170,892	170,892	170,892
Y-Mean/Median	4701.3	976.7	0.47	5.59	0.06	3040	775	4
Panel C: Medicare								
1(FP)	-450.6***	-70.1***	-0.15***	0.24	0.06***	-84.9	-38.2***	0.28**
	(108.6)	(8.9)	(0.03)	(0.13)	(0.006)	(92.8)	(9.7)	(0.09)
No. observations	332,424	332,424	332,424	332,424	332,424	332,424	332,424	332,424
Y-Mean/Median	7307	854.2	0.54	10.02	0.17	4850.6	666.2	7
Hospital cont.	Y	Y	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents estimates of the association between for-profit (FP) status and patient utilization and expenditure among the patients admitted to general hospitals. The estimates of each column present the coefficient β obtained from Equation (1) by OLS. The coefficients of logged outcomes in Columns 6, 7, and 8 are exponentiated and then multiplied by median values of the respective outcomes from patients admitted to NFP hospitals. The predictor variable is an indicator of the patient served by a FP hospital. In Panel A, patients from all payer categories are included in the analysis. Panel B presents estimates from the patients covered by commercial private insurance, while Panel C presents estimates from Medicare beneficiaries. All regression models include patient- and hospital-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, source of admission, zip code-level median income, and bed type. The hospital-level controls include teaching hospitals, public ownership, psychiatric bed count, case mix index, and the Herfindahl–Hirschman index of the hospital. Standard errors are clustered by patient-level zip code. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 5B. Effects of being a FP hospital on spending and utilization (OLS/Psychiatric hospital)

	Mean					Median		
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Number of Procedures	(4) Length of Stay	(5) Referral to Other Providers	(6) Log Cost Per Discharge	(7) Log Cost Per Day	(8) Log Length of Stay
Panel A: All								
1(FP)	-1790.8***	-177.1***	-0.31***	-0.62***	-0.02***	-917.2***	-164.2***	-0.18*
	(106.3)	(12.0)	(0.05)	(0.15)	(0.003)	(59.7)	(8.7)	(0.07)
No. observations	384,988	384,988	384,988	384,988	384,988	384,988	384,988	384,988
Y-Mean/Median	4767.4	597.7	0.34	8.13	0.06	3161.4	548.1	6
Panel B: Private								
1(FP)	-1490.1***	-186.7***	-0.18***	-0.14	-0.01***	-748.6***	-185.4***	-0.03
	(113.1)	(9.7)	(0.03)	(0.09)	(0.002)	(41.9)	(7.4)	(0.04)
No. observations	156,393	156,393	156,393	156,393	156,393	156,393	156,393	156,393
Y-Mean/Median	3939.3	612.7	0.27	6.44	0.03	2782.1	556.5	5
Panel C: Medicare								
1(FP)	-2129.9***	-250.3***	-0.51***	0.60***	-0.05***	-936.9***	-168.2***	0.45***
	(157.8)	(13.7)	(0.04)	(0.17)	(0.008)	(84.5)	(10.9)	(0.12)
No. observations	91,469	91,469	91,469	91,469	91,469	91,469	91,469	91,469
Y-Mean/Median	6279.3	608.3	0.31	10.52	0.1	4471.4	544.6	8
Hospital cont.	Y	Y	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents estimates of the association between for-profit (FP) status and patient utilization and expenditure among the patients admitted to psychiatric hospitals. Psychiatric Hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities. The estimates of each column present the coefficient β obtained from Equation (1) by OLS. The coefficients of logged outcomes in Columns 6, 7, and 8 are exponentiated and then multiplied by median values of the respective outcomes from patients admitted to NFP hospitals. The predictor variable is an indicator of the patient served by a FP hospital. In Panel A, patients from all payer categories are included in the analysis. Panel B presents estimates from the patients covered by commercial private insurance, while Panel C presents estimates from Medicare beneficiaries. All regression models include patient- and hospital-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, source of admission, zip code-level median income, and bed type. The hospital-level controls include public ownership, psychiatric bed count, case mix index, and the Herfindahl–Hirschman index of the hospital. Standard errors are clustered by patient-level zip code. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 6A. Effects of being a FP hospital on spending and utilization (2SLS IV/General hospital)

	Mean					Median		
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Number of Procedures	(4) Length of Stay	(5) Referral to Other Providers	(6) Log Cost Per Discharge	(7) Log Cost Per Day	(8) Log Length of Stay
Panel A: All								
1(FP)	-10277.3*	-995.7	-0.14	-3.59	-0.1	-1659.5	-194.8	-1.27
	(4514.0)	(639.9)	(0.52)	(2.55)	(0.07)	(1072.7)	(273.3)	(1.1)
No. observations	986,425	986,425	986,425	986,425	986,425	986,425	986,425	986,425
Y-Mean/Median	6093.3	934.5	0.47	7.75	0.1	3668.3	716.6	5
Panel B: Private								
1(FP)	-2872.0	-752.9*	-2.57***	0.39	0.0001	-833.8	-231.8	0.15
	(2625.2)	(381.6)	(0.61)	(1.81)	(0.05)	(710.3)	(132.4)	(1.04)
No. observations	170,892	170,892	170,892	170,892	170,892	170,892	170,892	170,892
Y-Mean/Median	4701.3	976.7	0.47	5.59	0.06	3040	775	4
Panel C: Medicare								
1(FP)	-11091.4	-945.7	0.14	-5.44	0.08	-2103.8	-135.0	-2.07
	(6344.1)	(666.2)	(0.62)	(3.92)	(0.12)	(1782)	(303.7)	(1.78)
No. observations	332,424	332,424	332,424	332,424	332,424	332,424	332,424	332,424
Y-Mean/Median	7307	854.2	0.54	10.02	0.17	4850.6	666.2	7
Hospital cont.	Y	Y	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents estimates of the association between for-profit (FP) status and patient utilization and expenditure among the patients admitted to general hospitals. The estimates of each column present the coefficient β obtained from Equation (4) by 2SLS. The coefficients of logged outcomes in Columns 6, 7, and 8 are exponentiated and then multiplied by median values of the respective outcomes from patients admitted to NFP hospitals. The predictor variable is an indicator of the patient served by a FP hospital, instrumented by a differential distance indicator by the 10 miles threshold. In Panel A, patients from all payer categories are included in the analysis. Panel B presents estimates from the patients covered by commercial private insurance, while Panel C presents estimates from Medicare beneficiaries. All regression models include patient- and hospital-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, source of admission, zip code-level median income, and bed type. The hospital-level controls include teaching hospitals, public ownership, psychiatric bed count, case mix index, and the Herfindahl–Hirschman index of the hospital. Standard errors are clustered by patient-level zip code. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 6B. Effects of being a FP hospital on spending and utilization (2SLS IV/Psychiatric hospital)

	Mean					Median		
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Number of Procedures	(4) Length of Stay	(5) Referral to Other Providers	(6) Log Cost Per Discharge	(7) Log Cost Per Day	(8) Log Length of Stay
Panel A: All								
1(FP)	-1486.3*	-219.4*	0.3	-0.51	-0.02	-1087.8*	-179.2*	-0.36
	(708.2)	(95.5)	(0.28)	(0.87)	(0.02)	(369)	(65.0)	(0.4)
No. observations	384,988	384,988	384,988	384,988	384,988	384,988	384,988	384,988
Y-Mean/Median	4767.4	597.7	0.34	8.13	0.06	3161.4	548.1	6
Panel B: Private								
1(FP)	-1536.7*	-209.7**	0.35	0.01	-0.05**	-468.8	-151.3*	0.2
	(609.3)	(75.7)	(0.29)	(0.57)	(0.02)	(334.7)	(63.0)	(0.33)
No. observations	156,393	156,393	156,393	156,393	156,393	156,393	156,393	156,393
Y-Mean/Median	3939.3	612.7	0.27	6.44	0.03	2782.1	556.5	5
Panel C: Medicare								
1(FP)	-3699**	-252.7	-0.15	-3.56*	-0.09	-1807.7*	-124.5	-1.64*
	(1394.1)	(144.9)	(0.28)	(1.72)	(0.06)	(594.3)	(86.0)	(0.7)
No. observations	91,469	91,469	91,469	91,469	91,469	91,469	91,469	91,469
Y-Mean/Median	6279.3	608.3	0.31	10.52	0.1	4471.4	544.6	8
Hospital cont.	Y	Y	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents estimates of the association between for-profit (FP) status and patient utilization and expenditure among the patients admitted to psychiatric hospitals. Psychiatric Hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities. The estimates of each column present the coefficient β obtained from Equation (4) by 2SLS. The coefficients of logged outcomes in Columns 6, 7, and 8 are exponentiated and then multiplied by median values of the respective outcomes from patients admitted to NFP hospitals. The predictor variable is an indicator of the patient served by a FP hospital, instrumented by a differential distance indicator by the 10 miles threshold. In Panel A, patients from all payer categories are included in the analysis. Panel B presents estimates from the patients covered by commercial private insurance, while Panel C presents estimates from Medicare beneficiaries. All regression models include patient- and hospital-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, source of admission, zip code-level median income, and bed type. The hospital-level controls include public ownership, psychiatric bed count, case mix index, and the Herfindahl–Hirschman index of the hospital. Standard errors are clustered by patient-level zip code. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 7A. Effects of differential case mix between FP and NFP hospital on spending and utilization (General hospital)

	Mean					Median		
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Number of Procedures	(4) Length of Stay	(5) Referral to Other Providers	(6) Log Cost Per Discharge	(7) Log Cost Per Day	(8) Log Length of Stay
Panel A: All								
1(FP)	9805.5*	903.1	0.02	3.81*	0.14*	1525.2	141.7	1.46
	(4260.5)	(613.02)	(0.48)	(2.31)	(0.07)	(1123.5)	(286.5)	(1.0)
No. observations	986,425	986,425	986,425	986,425	986,425	986,425	986,425	986,425
Y-Mean/Median	6093.3	934.5	0.47	7.75	0.1	3668.3	716.6	5
Panel B: Private								
1(FP)	2259.7	646.01	2.54**	-0.64	0.03	242.7	-107.1	-0.34
	(2548.8)	(358.02)	(0.6)	(1.84)	(0.06)	(671.4)	(121.2)	(1.1)
No. observations	170,892	170,892	170,892	170,892	170,892	170,892	170,892	170,892
Y-Mean/Median	4701.3	976.7	0.47	5.59	0.06	3040	775	4
Panel C: Medicare								
1(FP)	10640.8	875.63	-0.29	5.68*	-0.019	2018.9	-38	2.38
	(6341.5)	(637.99)	(0.57)	(3.45)	(0.11)	(2028.2)	(345.1)	(1.6)
No. observations	332,424	332,424	332,424	332,424	332,424	332,424	332,424	332,424
Y-Mean/Median	7307	854.2	0.54	10.02	0.17	4850.6	666.2	7
Hospital cont.	Y	Y	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents outcomes reflecting the effects solely derived from the case mix of FP hospitals for the patients admitted to general hospitals. To obtain the estimates, we subtract the estimates of 2SLS IV models from the estimates of OLS models. In doing so, we disentangle the effects of case mix and hospital operation behavior from the OLS outcomes. In Panel A, patients from all payer categories are included in the analysis. Panel B presents estimates from the patients covered by commercial private insurance, while Panel C presents estimates from Medicare beneficiaries. All regression models include patient- and hospital-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, source of admission, zip code-level median income, and bed type. The hospital-level controls include teaching hospitals, public ownership, psychiatric bed count, case mix index, and the Herfindahl–Hirschman index of the hospital. Standard errors for the subtracted estimates are calculated using 1000 times of clustered bootstrapping at the level of patient zip code. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 7B. Effects of differential case mix between FP and NFP hospital on spending and utilization (Psychiatric hospital)

	Mean					Median		
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Number of Procedures	(4) Length of Stay	(5) Referral to Other Providers	(6) Log Cost Per Discharge	(7) Log Cost Per Day	(8) Log Length of Stay
Panel A: All								
1(FP)	-304.5	42.3	-0.61*	-0.11	0.001	170.6	15	0.18
	(677.1)	(80.2)	(0.25)	(0.82)	(0.02)	(297)	(42.9)	(0.4)
No. observations	384,988	384,988	384,988	384,988	384,988	384,988	384,988	384,988
Y-Mean/Median	4767.4	597.7	0.34	8.13	0.06	3161.4	548.1	6
Panel B: Private								
1(FP)	46.6	23.0	-0.53*	-0.15	0.04*	-279.8	-34.049	-0.23
	(535.7)	(63.11)	(0.26)	(0.54)	(0.02)	(282.6)	(41.1)	(0.4)
No. observations	156,393	156,393	156,393	156,393	156,393	156,393	156,393	156,393
Y-Mean/Median	3939.3	612.7	0.27	6.44	0.03	2782.1	556.5	5
Panel C: Medicare								
1(FP)	1569.1	2.40	-0.36	4.16*	0.04	870.8	-43.7	2.09**
	(1391.5)	(132.62)	(0.26)	(1.78)	(0.06)	(500.3)	(68.6)	(0.7)
No. observations	91,469	91,469	91,469	91,469	91,469	91,469	91,469	91,469
Y-Mean/Median	6279.3	608.3	0.31	10.52	0.1	4471.4	544.6	8
Hospital cont.	Y	Y	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents outcomes reflecting the effects solely derived from the case mix of FP hospitals for the patients admitted to psychiatric hospitals. Psychiatric Hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities. To obtain the estimates, we subtract the estimates of 2SLS IV models from the estimates of OLS models. In doing so, we disentangle the effects of case mix and hospital operation behavior from the OLS outcomes. In Panel A, patients from all payer categories are included in the analysis. Panel B presents estimates from the patients covered by commercial private insurance, while Panel C presents estimates from Medicare beneficiaries. All regression models include patient- and hospital-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, source of admission, zip code-level median income, and bed type. The hospital-level controls include public ownership, psychiatric bed count, case mix index, and the Herfindahl–Hirschman index of the hospital. Standard errors for the subtracted estimates are calculated using 1000 times of clustered bootstrapping at the level of patient zip code. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 8. Effects of being a FP hospital on spending and utilization (GLM log link with gamma distribution)

	General hospitals			Specialty hospitals		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cost Per Discharge	Cost Per Day	Length of Stay	Cost Per Discharge	Cost Per Day	Length of Stay
Panel A: All						
1(FP)	-35.8	-49.2**	0.35*	-1337.2***	-148.3***	-0.38*
	(145.4)	(16.5)	(0.15)	(213.5)	(16.7)	(0.20)
No. observations	723,874	723,874	723,874	360,324	360,324	360,324
Y-Mean	5511.9	853.7	7.82	4726.4	598.6	7.97
Panel B: Private						
1(FP)	-472.0*	-69.3*	-0.26*	-1087.3***	-160.4***	-0.10
	(195.2)	(27.4)	(0.13)	(198.6)	(20.3)	(0.15)
No. observations	147,540	147,540	147,540	159,817	159,817	159,817
Y-Mean	4755	967.7	5.71	3946.2	612.5	6.45
Panel C: Medicare						
1(FP)	-178.3	-50.2***	-0.33	-1555.3***	-203.9***	0.52*
	(176.5)	(13.7)	(0.21)	(257.9)	(29.3)	(0.23)
No. observations	284,323	284,323	284,323	87,482	87,482	87,482
Y-Mean	6925.4	806.4	10.16	6324.8	608	10.56
Hospital cont.	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents estimates of the association between for-profit (FP) status and expenditure and utilization among the patients admitted to general or specialty hospitals. Specialty hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities. The estimates of each column present the coefficient β obtained from the naïve estimator, the GLM log link with gamma distribution. The predictor variable is an indicator of the patient served by a FP hospital. In Panel A, patients from all payer categories are included in the analysis. Panel B presents estimates from the patients covered by commercial private insurance, while Panel C presents estimates from Medicare beneficiaries. All regression models include patient- and hospital-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, source of admission, zip code-level median income, and bed type. The hospital-level controls include teaching hospitals, psychiatric bed count, case mix index, and the Herfindahl–Hirschman index of the hospital. Standard errors are clustered by patient-level HSA. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 9. Effects of being a FP hospital on spending and utilization (2SRI)

	General hospitals			Specialty hospitals		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cost Per Discharge	Cost Per Day	Length of Stay	Cost Per Discharge	Cost Per Day	Length of Stay
Panel A: All						
1(FP)	-294.7	-103.1**	0.38	-1681.3***	-177.0***	-0.54*
	(212.6)	(30.3)	(0.20)	(220.6)	(16.0)	(0.26)
No. observations	723,874	723,874	723,874	360,324	360,324	360,324
Y-Mean	5511.9	853.7	7.82	4726.4	598.6	7.97
Panel B: Private						
1(FP)	-625.4*	-93.0*	-0.44*	-1643.7***	-205.8***	-0.49
	(291.5)	(41.1)	(0.20)	(311.4)	(24.8)	(0.26)
No. observations	147,540	147,540	147,540	159,817	159,817	159,817
Y-Mean	4755	967.7	5.71	3946.2	612.5	6.45
Panel C: Medicare						
1(FP)	-627.9*	-115.4**	0.44	-1725.2***	-187.0***	-0.07
	(296.0)	(33.5)	(0.31)	(316.1)	(25.9)	(0.50)
No. observations	284,323	284,323	284,323	87,482	87,482	87,482
Y-Mean	6925.4	806.4	10.16	6324.8	608	10.56
Hospital cont.	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents estimates of the association between for-profit (FP) status and expenditure and utilization among the patients admitted to general or specialty hospitals. Specialty hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities. The estimates of each column present the coefficient β obtained from the 2SRI estimator with generalized residuals, instrumented by a continuous differential distance variable in the first stage using logit regression. The predictor variable is an indicator of the patient served by a FP hospital. In Panel A, patients from all payer categories are included in the analysis. Panel B presents estimates from the patients covered by commercial private insurance, while Panel C presents estimates from Medicare beneficiaries. All regression models include patient- and hospital-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, source of admission, zip code-level median income, and bed type. The hospital-level controls include teaching hospitals, psychiatric bed count, case mix index, and the Herfindahl–Hirschman index of the hospital. Standard errors are clustered by patient-level HSA. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 10. Effects of differential case mix on spending and utilization (Naïve estimator - 2SRI estimator)

	General hospitals			Specialty hospitals		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cost Per Discharge	Cost Per Day	Length of Stay	Cost Per Discharge	Cost Per Day	Length of Stay
Panel A: All						
1(FP)	258.9*	53.9**	-0.03	344.1*	28.7*	0.16
	(119.8)	(19.6)	(0.13)	(170.2)	(13.2)	(0.18)
No. observations	723,874	723,874	723,874	360,324	360,324	360,324
Y-Mean	5511.9	853.7	7.82	4726.4	598.6	7.97
Panel B: Private						
1(FP)	153.4	23.7	0.18*	556.4**	45.4**	0.39*
	(125.4)	(19.3)	(0.09)	(200.4)	(17.2)	(0.18)
No. observations	147,540	147,540	147,540	159,817	159,817	159,817
Y-Mean	4755	967.7	5.71	3946.2	612.5	6.45
Panel C: Medicare						
1(FP)	449.6*	65.2**	-0.77**	169.9	-16.9	0.59
	(188.4)	(23.1)	(0.20)	(211.4)	(20.0)	(0.36)
No. observations	284,323	284,323	284,323	87,482	87,482	87,482
Y-Mean	6925.4	806.4	10.16	6324.8	608	10.56
Hospital cont.	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents outcomes reflecting the effects solely derived from the case mix of FP hospitals for the patients admitted to general or specialty hospitals. To obtain the estimates, we subtract the estimates of 2SRI models from the estimates of naïve models. In doing so, we disentangle the effects of case mix (selection) and hospital cost containment efforts (execution) from the estimates of naïve models. The predictor variable is an indicator of the patient served by a FP hospital. In Panel A, patients from all payer categories are included in the analysis. Panel B presents estimates from the patients covered by commercial private insurance, while Panel C presents estimates from Medicare beneficiaries. All regression models include patient- and hospital-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, source of admission, zip code-level median income, and bed type. The hospital-level controls include teaching hospitals, psychiatric bed count, case mix index, and the Herfindahl–Hirschman index of the hospital. Standard errors for the subtracted estimates are calculated using 1000 times of clustered bootstrapping at the level of patient HSA. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 11. Effects of being a FP hospital on the use of labor resources and financial outcomes

	Labor Resources			Financial Outcomes	
	(1) Number of Physicians Per Bed	(2) Number of Nurses Per Bed	(3) Nurse Hours Per Patient Day	(4) Profit Margin	(5) Operating Margin
Panel A: OLS					
1(FP)	-0.75*	-0.06	-0.35*	-0.03	1.46
	(0.31)	(0.06)	(0.16)	(0.05)	(1.2)
No. observations	871	871	871	871	871
Y-Mean	0.46	0.69	1.93	-0.05	-0.33
Panel B: PSM					
1(FP)	-2.53**	-0.31***	-0.54*	-0.19	0.12
	(0.82)	(0.08)	(0.25)	(0.14)	(0.22)
No. observations	871	871	871	871	871
Y-Mean	0.46	0.69	1.93	-0.05	-0.33
Hospital cont.	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents estimates of the association between for-profit status and the use of labor resources and financial outcomes. The outcomes in Panel A are estimated by OLS using the unmatched data. The estimates in Panel B present the coefficient β obtained from Equation (5) by PSM. To calculate the profit margin of hospitals, we divide net income by the sum of net patient revenue total, other operating revenue, and non-operating revenue. The operating margin is formulated as follows: we divide net income from operation by the sum of net patient revenue total and other operating revenue. The list of covariates included in the labor resources outcomes model is the number of licensed beds, number of licensed psychiatric beds, number of total discharges from psychiatric beds, number of total patient days in psychiatric beds, the occupancy rate of psychiatric beds, cost to charge ratio, case mix index, profit margin, operating margin and HHI. The list of covariates included in the financial outcomes model is the same as above, except the number of physicians and nurses replace profit and operating margin. Facility HSA and year fixed effects are included in the OLS and PSM models. Robust standard errors are obtained to address heteroskedasticity. The study sample consists of freestanding specialty psychiatric hospitals only. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Table S1. Primary psychiatric diagnosis classification

Type	ICD-9 CM codes
Schizophrenia	295.xx , 298.1x - 298.9x
Bipolar disorder	296.0x - 296.1x , 296.4x-296.9
Major depression	296.2x - 296.3x
Depression	298.0x , 300.4x , 301.12 , 309.0x - 309.1x , 311.xx
Alcohol use disorder	291.xx , 303.xx , 305.1x
Drug use disorder	292.xx , 304.xx , 305.2x - 305.9x
Other	Other codes between 290.xx and 319.xx

Note: This table presents psychiatric diagnosis codes that we use for this study. We follow the categorization implemented by Stensland et al. (2012) and include Major depression as a separate category.

Chapter 3.

COMPETITION IN INPATIENT PSYCHIATRIC CARE MARKETS: IMPLICATIONS FOR COSTS AND THE QUALITY OF CARE

ABSTRACT

The paper examines the effects of competition on treatment costs and quality among hospitals in California's inpatient psychiatric care markets. We establish a market competitiveness measure using the hospital choice model among patients based on a plausibly exogenous determinant of hospital selection, i.e., travel distances. Our main findings suggest that the effects of competition on the costs are highly heterogeneous across the hospital (general/specialty) and ownership types (for-profit/not-for-profit), patient's insurance coverage (private/Medicare), and reimbursement methods (cost-based/prospective payment). However, the results of the quality analysis in specialty hospitals indicate that competition may improve the quality of care in FP hospitals; in contrast, it may have the opposite effect on the quality in NFP hospitals.

3.1 INTRODUCTION

The impact of hospital competition on costs and quality has been extensively studied and debated in the health economics literature. One line of research suggests that higher competition leads to lower costs and greater quality of care (Dranove et al., 1992; Gaynor & Town, 2011; Kessler & McClellan, 2000). Another line of research claims that achieving such benefits of competition is challenging due to the idiosyncratic nature of the hospital market. Compared to conventional markets, the information on prices for services and products is not transparent to patients. Moreover, the patients with health insurance coverage are less responsive to differences in prices and costs among hospitals (Feldstein, 1971; Held & Pauly, 1983; Robinson & Luft, 1985). Thus, hospitals may engage in non-price competition, such as medical arms race, which can result in excess capacity in the market and higher expenditure. Given the monopolistically competitive nature of hospital markets, competition may negatively affect patient health outcomes (Volpp et al., 2003).

Previous research on the effects of hospital competition has often relied on biased measures of competitiveness or specific policy events (Cooper et al., 2011, 2018; Meltzer et al., 2002; Zwanziger & Melnick, 1988). However, a few studies have taken a different approach by using a hospital choice model based on travel distances, which provides a plausibly exogenous determinant of hospital selection. Using this model, they establish a Herfindahl-Hirschman index (HHI) to measure hospital concentration (Gowrisankaran & Town, 2003; Kessler & Geppert, 2005; Kessler & McClellan, 2000; Town & Vistnes, 2001). This approach allows us to avoid possible endogeneity bias in assessing the impact of the competition on quality and costs. For example, hospitals with higher quality or efficiency are more likely to sustain their operation in a competitive market, while those with lower quality or efficiency may have already exited the market (i.e., self-selection). Thus, the regression model including the HHI based on actual patient flows as a primary regressor may produce biased estimates of competition in a market. However, the HHI formulated by the hospital choice model is based on predicted patient flows. Therefore, researchers can obtain unbiased estimates of the competition by exploiting the exogenous source of variation (e.g., distance from home to the nearest hospital) in hospital selection.

Our study contributes to the existing literature in several ways. First, it provides empirical evidence helping to assess conflicting theoretical predictions regarding the effect of competition on costs and quality. Second, the findings may enhance our understanding of the distinct effects of competition, such as whether it has a uniform impact on all patients and hospitals, or if it primarily benefits certain types of insurance coverage (private/Medicare) and hospital ownership [for-profit (FP)/not-for-profit (NFP)]. Third, the analysis of patient- and hospital-level data in this study sheds light on the impact of competition on both cost and quality measures, providing a deeper understanding of how they interact in competitive markets. Fourth, to date, no studies have utilized the predicted patient flow approach to investigate the effect of competition in the inpatient psychiatric care market.

The rest of the paper is organized as follows: Section 2 begins with a brief overview of economic theory and empirical evidence on competition, quality, and costs and documents various methods of defining the market and competition. Section 3 introduces the study objectives and hypotheses. Section 4 describes the data and reports summary statistics. Section 5 illustrates the hospital choice model, the predicted patient flow approach for competition measures, and the empirical strategies of patient- and hospital-level analysis. Section 6 presents the results. Section 7 discusses the findings and concludes.

3.2 BACKGROUND

3.2.1 *Theory and Empirical Evidence on Competition, Quality and Costs*

Standard economic theory suggests that increased competition in the market generally results in an improvement in the quality of hospital services. In their in-depth survey of the related literature, Gaynor and Town (2011) divide the evidence into two stylized cases based on a factor that exogenously governs pricing. These cases indicate that when a regulator sets prices, competition will increase quality; however, if prices are determined by the interplay of supply and demand, it is unclear whether greater competition would result in improved quality or even potentially lead to a decline in quality.

The economic rationales supporting the cases are straightforward (Propper, 2018). In a market where both price and quality are competitive factors, hospitals' responses to competition hinge on the characteristics of market demand, specifically the degree of price sensitivity among consumers. If the demand is highly price elastic, the hospitals may compromise (unobservable) quality to increase their bargaining power over the consumers. On the other hand, if the market demand is not price sensitive, quality becomes more influential in selecting hospitals by patients, and therefore the hospitals would prioritize enhancing the quality. Similarly, in a market where prices are set by an external body (e.g., Medicare, United Kingdom National Health Service), competition via quality would become the only channel on which the hospitals can compete for patients, and as a result, quality will increase. Some empirical studies have provided evidence supporting the economic theories that suggest a positive association between competition and quality (Cooper et al., 2011; Kessler & McClellan, 2000; Sari, 2002). In contrast, other studies have found results that do not conform to these theories (Gowrisankaran & Town, 2003; Mukamel et al., 2002).

Similar to the relationship between competition and quality, the impact of competition on costs is contingent on price. Empirical evidence has shown that costs may either rise or fall depending on the influence of prospective payment systems (PPS). In the absence of the PPS, increased competition raises costs of hospital care (Meltzer et al., 2002; Robinson & Luft, 1985); in contrast, in the presence of the PPS, the costs decrease with increased competition levels (Kessler & Geppert, 2005; Meltzer et al., 2002; Zwanziger & Melnick, 1988). For instance, Meltzer et al. (2002) find that higher competition under cost containment pressures leads to a decrease in overall costs of care; patients with high risk (i.e., high costs) experience a higher reduction in the costs than those with low risk (i.e., low costs). However, the study by Kessler and Geppert (2005) demonstrates that hospitals in competitive markets spend more on high-risk patients; however, hospital's overall net expenditure decreases due to the higher reduction of costs among low-risk patients.

Moreover, economic theories propose that the effect of competition on costs would differ by reimbursement methods (Meltzer et al., 2002). Under the PPS, hospitals must bear financial risk for the additional costs that exceed a predetermined fixed rate of services. Ceteris paribus, the hospitals have an incentive to take financial responsibility for the marginal costs of additional interventions, which implies that the provision of unnecessary services would likely be discouraged. This trend is expected to be intensified under competition. In contrast, hospitals are incentivized to offer more services under the retrospective payment systems to gain an extra markup over costs. Likewise, competitive pressures in the market may augment the tendency.

The empirical evidence on the relationship between the quality and cost of care is widely inconsistent, varying across different study settings and patient characteristics (Hussey et al., 2013; Jamalabadi et al., 2020). This underscores the fact that quality and costs can be interconnected in numerous ways. In their systematic review of the quality-cost relationship, Jamalabadi et al. (2020) outline several possible mechanisms: First, an increase in costs improves quality. Second, improved quality reduces costs. Lastly, quality and costs are not necessarily related as linear or directional; instead, (inverted) U-shape may represent their relationship.

3.2.2 *Reimbursement Methods for Inpatient Psychiatric Care*

Prior to January 2005, hospitals treating Medicare psychiatric patients primarily relied on cost-based reimbursement as a payment method, until the implementation of the inpatient psychiatric prospective payment system (IPPPS) (Lave, 2003). An exception to this was for psychiatric patients who were treated in ordinary units (as opposed to psychiatric units) within general hospitals, as they were already reimbursed through the PPS. The cost-based reimbursement system refers to the methodology of the Tax Equity and Fiscal Responsibility Act (TEFRA) of 1982. Under TEFRA, reimbursement amounts for the treatment provided in specialty psychiatric hospitals (and general hospitals' psychiatric units) are determined by a target amount per discharge, updated annually based on operating costs and the number of discharges for Medicare patients. This creates a financial incentive for the hospitals to cut their average costs below the target amount because they would be entitled to an additional payment (Cromwell et al., 1992). However, the target amount can be adjusted and set higher if the hospitals under TEFRA provide evidence of escalating costs, such as worsening patient case mix.

Since 2005, a payment method for inpatient psychiatric care for Medicare patients has been shifted to the PPS, which provides a fixed rate regardless of the treatment duration and intensity. While both payment methods, the cost-based reimbursement under TEFRA and IPPPS, intended to control costs of providing care, TEFRA offers hospitals the potential to receive higher rates that more closely align with their actual costs compared to the IPPPS. Therefore, the impact of competition in cost reduction may be more pronounced following the implementation of the IPPPS. Furthermore, given the different objective functions of FP and NFP hospitals (Sloan, 2000), the divergence in their behaviors is expected to become more apparent under the IPPPS (Ettner & Hermann, 2001).

3.2.3 *Various Approaches to Defining the Market and Competition*

The health economics literature employs various approaches for defining hospital markets, which can be broadly categorized as follows: geopolitical boundaries, distances (e.g., fixed or variable radius from the hospital), and patient flows based on actual or predicted service utilization. Likewise, there are multiple ways to measure the intensity of hospital competition in the defined market, such as the number of hospitals and HHI. The outcomes of the models depend on the choice of market and competition measures, leading to varying results (Wong et al., 2005).

The geopolitical boundary approach defines the hospital market based on the administrative division (e.g., a county or metropolitan statistical area), hospital service areas (HSA), or hospital referral regions (HRR); HSA and HRR reflect local and regional health care markets for tertiary hospitals, respectively. Thus, this approach treats the hospitals in the same geographic market as potential competitors. This approach has several advantages and disadvantages in examining competition among hospitals. The primary benefit is simplicity – researchers use preexisting information without administering any additional computation. In addition, this approach improves compatibility with other data sources that provide demographic and socioeconomic information since most of these data are aggregated by geopolitical units. However, it is unlikely that the markets are circumscribed by administrative boundaries if the hospital is located near the border. Therefore, this method does not differentiate the intensity of competition across the hospitals within the same unit.

In the distance approach using fixed or variable radius, each hospital is assigned to a distinctive market based on its location at the center of a circle that defines the market (Luft & Maerki, 1984; Phibbs & Robinson, 1993). The fixed and variable radius approaches differ in that the former uses a predetermined radius (e.g., 15 miles) to define the market, while the latter allows for more flexibility in determining the market size. The fixed radius approach addresses one of the weaknesses of the geopolitical boundary approach; specifically, the method allows the hospitals located near the geopolitical boundaries to incorporate multiple administrative units into the market. Nonetheless, this approach fails to account for the potential heterogeneity of market powers across different hospital types (e.g., secondary vs. tertiary or general vs. specialty hospitals). The variable radius approach updated by Gresenz et al (2004) mitigates this challenge using patient discharge records (Gresenz et al., 2004; Phibbs & Robinson, 1993). They formulate the length of radius per hospital based on the patient utilization data, providing the list of the predicted radius that encompasses 90% and 75% of hospital discharges for the US community hospitals. Despite its advancements, the variable radius approach still has some limitations; the hospital's potential competitors are likely to be omitted from the defined market. Furthermore, it is unrealistic to characterize the hospital market as a circle.

The actual patient flow approach differs from the variable radius approach regarding the shape of the hospital market. Instead of defining the market as a circle, this method constructs the market with a collection of geographic areas, such as zip codes (Wong et al., 2005). However, with the actual patient information being used, this approach is also susceptible to the limitation of ignoring potential competitors in the defined market. The predicted patient flow approach can overcome this problem (Gowrisankaran & Town, 2003; Kessler & McClellan, 2000; Town & Vistnes, 2001).

In particular, this method uses a hospital choice model to predict the probability of selecting each hospital in the patient's choice set, including all the potentially competing hospitals in the market.

Once the market is defined, the degree of competition within the market needs to be evaluated. Two approaches, counting hospital numbers and HHI, have been commonly used in the hospital competition literature (Wong et al., 2005). The former approach is particularly useful because it is easy to implement, and if hospital's behavior is determined by the number of competitors in the market rather than their relative size (Baker, 2001). However, given that market shares are unlikely to be identical across the hospitals in the same market, this approach fails to reflect the market characteristics completely.

Using HHI allows us to incorporate the differences in market shares across the hospitals. In the context of health care, the HHI is considered to be the sum of squared market shares of all the hospitals in the market (i.e., the number of discharges (admissions) from (to) the hospital divided by the total number of discharges (admission) from (to) all the hospitals in the market). Thus, a higher value of the HHI indicates a more concentrated (i.e., less competitive) market. It is worth noting that the HHI was originally proposed to measure the competition in the industry with a homogenous product based on a non-cooperative oligopoly model. Therefore, there have been theoretical challenges in applying HHI to the hospital markets with varying products (Gaynor & Vogt, 2003; Tay, 2003). Despite these challenges, no other alternative measures have replaced the HHI, mainly because its usage for hospital competition is computationally efficient and has been set to a norm in policy making. For example, the Federal Trade Commission continues to use the HHI for hospital antitrust cases.

3.3 STUDY OBJECTIVES AND HYPOTHESES

The primary aim of this paper is to assess the effects of competition on costs among hospitals treating inpatient psychiatric patients using patient-level data. We hypothesize that an increase in competition provides an incentive for hospitals to cut their costs. We also investigate the effects of competition on the use of labor resources (i.e., quality) and financial margins using facility-level data. We expect a higher level of competition would be associated with reduced numbers of physicians and nurses and increased financial margins.

3.4 DATA AND DESCRIPTIVE STATISTICS

3.4.1 *Data*

This analysis uses data from the California Office of Statewide Planning and Development (OSHPD) patient discharge and hospital finance database between 1995 and 2011. The OSHPD data is advantageous for studying hospital behavior, especially around how hospital and market characteristics shape the provision of inpatient services and determine patient outcomes. Notably, the data provides a unique opportunity to investigate the realm of inpatient psychiatric care because it documents all inpatient discharge records (i.e., the patient records from all payer types are available) from general acute care and specialty psychiatric hospitals in the state. This feature helps distinguish potentially different behavioral responses of hospitals against varying incentive mechanisms of the patient’s insurance coverage.

3.4.2 *Study Population*

From the OSHPD patient discharge data, we select the patients whose primary diagnosis contain any ICD-9 code of mental illness between 290 and 319 (the detailed categories of mental health disorders are available in Table S1). We further restrict the sample eligibility criteria to those with private insurance or Medicare beneficiaries. The patient samples from each payer group are established independently. We introduce additional exclusion criteria of the sample as follows: 1) patients without demographic (sex/race/age) and zip code information, 2) whose length of stay (LOS) in the hospital is over 365 days, 3) who died in the hospital, 4) who are admitted to a state hospital, long-term care facilities and hospitals in the Kaiser Permanente system, and 5) who used inpatient services from the hospital located more than 35 miles away from their residence. Throughout these processes, 798,011 patients are selected for our study population (348,182 private insurance patients and 449,829 Medicare beneficiaries). The unit of analysis is a patient discharge record. Due to the limitation of the OSHPD data that does not provide the patient identification code, the same patient might contribute to more than a single discharge record.

3.4.3 *Outcomes*

To examine the effects of competition on hospital expenditure and resource utilization, we assess the four sets of outcomes: 1) total costs per discharge, 2) average costs per day, 3) number of procedures per discharge, and 4) LOS. Our primary outcome is the total costs occurring over the inpatient stay, which reflect how hospitals manage their overall resources for treating patients in response to market competition. The three additional outcomes help further explain the strategic behavior of hospitals towards more (less) competitive market conditions. In particular, we can identify underlying causes of variations in total costs by analyzing the outcomes of average costs per day and number of procedures per discharge, both of which illustrate the level of care intensity. Alternatively, exploring the LOS of patients allows us to determine another cost driver, the duration of care. The LOS of patients whose admission and discharge occur on the same day is labeled as one day. We convert the charged amount to cost estimates using the cost-to-charge ratio in the OSHPD hospital financial reports.

3.4.4 *Regressors*

Our models consider various covariates to control for different patient, hospital, and market characteristics, all possibly associated with outcomes and primary regressors. The patient characteristics account for their sociodemographic status and clinical conditions. For example, we include sex, race, age (category), whether the patient lives in a rural area, median income of the patient's zip code residence (continuous), enrollment status of managed care plans, primary psychiatric diagnosis, source of admission, DRG code (the information after 2007 is not available in our data), and bed type (scatter or psychiatric bed) in the model. Moreover, the included variables representing hospital characteristics are ownership type (FP or NFP), public hospital status (private or public), medical school affiliation, number of licensed psychiatric beds, predicted number of patients admitted to the hospital, and the case mix index. Lastly, the proportion of FP hospitals within the same HSA is adjusted to address the likely change in hospital behavior depending on the prevalence of FP hospitals in the same market.

3.4.5 *Descriptive Statistics*

Table 1 describes the hospital-level summary statistics by hospital type (general/specialty hospital) and ownership type (for-profit/not-for-profit). The number of psychiatric beds among general hospitals is similar between FP and NFP hospitals. In contrast, FP specialty hospitals operate a slightly larger number of psychiatric beds – the bed counts for FP and NFP specialty hospitals are 65 and 51, respectively. The predicted number of patients suggests that general hospitals have more patients with private insurance, albeit the difference is small among FP general hospitals. In contrast, specialty hospitals are likely to receive more Medicare beneficiaries than patients with private insurance. The case mix indicates no difference in patient severity between FP and NFP hospitals; however, specialty hospitals, on average, have a lower score for the case mix index than general hospitals. The estimates of the proportion of FP hospitals in the same market, HSA, or county, imply that FP hospitals tend to locate in markets where other FP hospitals are more prevalent.

Table 2 presents the patient-level summary statistics by hospital type (general/ specialty hospital) and insurance coverage status (private/Medicare). The standard deviation of the average zip code-level HHI suggests that the index scores are largely spread out from the mean. Based on the four categories of HHI proposed by FTC, less than 40% of the patients live in the zip code areas where the level of hospital competition is either high or very high for both hospital and insurance groups. Almost half of Medicare beneficiaries are admitted to hospitals primarily due to schizophrenia, regardless of hospital type. Moreover, about 70% of the patients covered by private insurance are enrolled in managed care plans, whereas only 2 to 3% of the Medicare beneficiaries are under managed care. Half of the patients staying in general hospitals are admitted via an emergency department regardless of their insurance coverage status.

3.5 EMPIRICAL STRATEGY

3.5.1 *Hospital Choice Model*

We model patient behavior of hospital choice based on observable characteristics of the patients and hospitals through a discrete choice model framework. We use an alternative-specific conditional logit model (i.e., McFadden's choice model) to estimate the parameters of patient i's indirect random utility from choosing hospital $j \in J$ for inpatient psychiatric admission (McFadden, 1973). Our specification of the hospital choice model complies with the approach by Gowrisankaran and Town (2003); their model includes the hospital-level characteristics, such as distance from the patient's home and number of hospital beds, while employing the patient-level characteristic of emergency room admission as interaction terms only. The emergency room admission status of the patient, an alternative-specific variable of the choice model, is interacted with the distance and indicator of whether the selected hospital is the nearest. Here we present details of our hospital choice model.

$$u_{ij} = \lambda_1 d_{ij} + \lambda_2 Type_j + \lambda_3 FP_j + \lambda_4 Close_{ij} + \lambda_5 PsyBed_j + \lambda_6 d_{ij} \times emerg_i + \lambda_7 close_{ij} \times emerg_i + \varepsilon_{ij} \quad (1)$$

where d_{ij} is the distance (miles) from the patient's home to each hospital in the choice set based on the center of their zip codes, $Type_j$ is an indicator variable with 1 as a specialty hospital and 0 as a general hospital, FP_j is an indicator variable with 1 as a for-profit hospital and 0 as a not-for-profit hospital, $Close_{ij}$ is an indicator variable with 1 if the hospital is the nearest alternative in the choice set and 0 otherwise, $PsyBed_j$ is the number of licensed psychiatric beds, $emerg_i$ is an indicator variable with 1 for patients admitted through an emergency department and 0 otherwise. The error term, ε_{ij} is presumed to be independently and identically distributed (i.i.d.) following Type I extreme value distribution. Note that we suppress an alternative-specific constant term to obtain a single parameter for each model variable.

We establish the hospital choice set for private insurance enrollees and Medicare beneficiaries separately. The choice set comprises the hospitals with at least a single licensed psychiatric bed and within the range of 35 miles from the patient's home based on the centers of their zip codes. Our data shows that 95% of the patients in both groups, private insurance and Medicare, are admitted to hospitals satisfying these conditions. We estimate the parameters of (1) independently varying years across the sample period to account for the changes in hospital characteristics (e.g., ownership status) and market environment (e.g., hospital openings and closures). Then, we derive the expected mean utility of patient i choosing hospital j, u_{ij}, as proposed in model (1) without including ε_{ij}.

3.5.2 *Formulating Measures of Hospital Market Concentration*

Under the logit assumption, McFadden (1973) demonstrates that the predicted probability of patient i selecting hospital j at year t, $\hat{P}_{ijt}$, can be estimated by

$$\Pr(Y_{ijt} = 1) = \hat{P}_{ijt} = \frac{\exp(u_{ijt})}{\sum_{j \in J} \exp(u_{ijt})} \quad (2)$$

where J is the hospital choice set of patient i in zip k.

Note that the summation of $\hat{P}_{ijt}$ over the choice set J is equal to 1.

$$\sum_{j=1}^{J} \hat{P}_{ijt} = 1 \quad (3)$$

Following Kessler and McClellan (2000), we apply a three-step approach to formulate zip code-specific competition indices for every patient residence based on the predicted probabilities of the individual's hospital selection. Aggregating over the predicted probabilities, we can construct a predicted share of hospital j for each zip k at year t, defined as

$$\hat{\alpha}_{jkt} = \frac{\sum_{i\, from\, zip\, k} \hat{P}_{ijt}}{\sum_{j=1}^{J} \sum_{i\, from\, zip\, k} \hat{P}_{ijt}} \quad (4)$$

where $\sum_{i\,from\,zip\,k} \hat{P}_{ijt}$ indicates the predicted number of patients admitted to hospital j for each zip k at year t. $\sum_{j=1}^{J} \sum_{i\,from\,zip\,k} \hat{P}_{ijt}$ indicates the sum of predicted number of patients admitted to any hospital $j \in J$ for each zip k at year t.

Using the predicted share of hospital j per zip k at year t, $\hat{\alpha}_{jkt}$, we then calculate the patient-level predicted HHI for each zip k at year t as follows:

$$HHI_{kt}^{pat} = \sum_{j=1}^{J} \hat{\alpha}_{jkt}^{2} \qquad (5)$$

This first-step patient-level HHI demonstrates the level of competitiveness over inpatient psychiatric care for patient i living in zip k at year t. Also, this measure implies that hospital $j \in J$ encounters different levels of competitiveness based on the patient's residence. Thus, if using the first-step patient-level HHI for our analysis examining the effect of competition, we must rely on the unrealistic assumption that hospitals can distinguish the demand function of admitted patients according to their zip code (Kessler & McClellan, 2000). Given that hospitals attract all the patients living in their nearby service areas, the nature of competition the hospitals would face is likely to be the weighted average of the patient-level predicted HHI based on a predicted patient flow.

For this reason, in the next step, we first create a predicted share of patients from zip k for each hospital j at year t, $\hat{\beta}_{kjt}$, denoted as

$$\hat{\beta}_{kjt} = \frac{\sum_{i\,from\,zip\,k} \hat{P}_{ijt}}{\sum_{i=1}^{N} \hat{P}_{ijt}} \quad (6)$$

where $\sum_{i\ from\ zip\ k} \hat{P}_{ijt}$ indicates the predicted number of patients selecting hospital j for each zip k at year t. $\sum_{i=1}^{N} \hat{P}_{ijt}$ indicates the predicted number of patients in hospital j (i.e., the sum of the numerator) at year t.

Then, using the predicted share of patients from zip k for hospital j at year t, $\hat{\beta}_{kjt}$, we establish the hospital-level predicted HHI for each hospital j as follows:

$$HHI_{jt}^{hosp} = \sum_{k=1}^{K} \hat{\beta}_{kjt} \cdot (\sum_{j=1}^{J} \hat{\alpha}_{jkt}^{2}) = \sum_{k=1}^{K} \hat{\beta}_{kjt} \cdot HHI_{kt}^{pat} \quad (7)$$

This hospital-level predicted HHI suggests the weighted average of the patient-level HHI. Note that the weight is the predicted share of patients from each zip code for hospital j. As pointed out by Kessler and McClellan (2000), the direct use of HHI_{jt}^{hosp} as a competition measure is subject to endogeneity bias if assigned to patients based on their actual hospital choice since unobserved characteristics of patients (e.g., disease severity) could be correlated with their decision of hospital selection. To avoid the bias, we re-formulate the patient-level zip code-specific HHI weighted by the predicted share of the hospital in the patient's residence as follows:

$$HHI_{kt}^{pat^*} = \sum_{j=1}^{J} \hat{\alpha}_{jkt} \cdot \left[\sum_{k=1}^{K} \hat{\beta}_{kjt} \cdot (\sum_{j=1}^{J} \hat{\alpha}_{jkt}^{2})\right] = \sum_{j=1}^{J} \hat{\alpha}_{jkt} \cdot HHI_{jt}^{hosp} \quad (8)$$

This patient-level predicted HHI calculated in the three steps indicates the weighted average of hospital-level HHI, weighted by the predicted share of each hospital in the patient's residence. We repeat the above procedures independently to formulate the separate weighted average of hospital-level HHI for private insurance and Medicare patients.

Establishing the competition indices using McFadden's choice model and Kessler and McClellan's three-step approach has some merits in determining the causal effects of competition (Kessler & McClellan, 2000). First, it avoids endogeneity bias from the patient's actual hospital choice, which is potentially related to unobservable characteristics of the patients and hospitals (e.g., disease severity, quality of care). Instead, it only relies on predicted patient flows based on exogenous variables, such as the patient's residence. Second, it characterizes hospital markets to such an extent that every hospital potentially competing within the same zip code area should be included. This may allow us to avoid the issue that defining the markets based on geopolitical boundaries or a fixed distance can misguide our estimation of predicted patient numbers for hospitals. Third, regarding the competition measures finally assigned to the patients, since we use the weighted average of hospital-level HHI that employs an exogenous factor (i.e., the predicted share of each hospital in the patient's zip code) for the weight, remaining likelihoods of endogeneity bias would be further mitigated.

3.5.3 *Modeling the Effect of Competition on Expenditure and Utilization*

3.5.3.1 Patient-level Analysis

Using the ordinary least-squares (OLS) model, we evaluate the effect of hospital competition on inpatient psychiatric service expenditures and utilization among private insurance and Medicare patients in California. The model includes zip-code fixed effects to absorb any time-invariant unobservable heterogeneity across small local areas, such as the characteristics of patient populations and hospitals. Thus, our model estimates are attributed to any changes in the competitiveness of hospital markets. Additionally, we use year fixed effects and add controls for observable patient and hospital characteristics. The patient-level controls include sex, age, race, psychiatric diagnosis, managed care status, admission source, urban residence, median income of the patient's zip code, DRG code, and bed type. The hospital-level controls encompass ownership status (FP or NFP), public hospital status, number of psychiatric beds, the case mix index, and the logged predicted number of private insurance and Medicare patients admitted to the hospital. Note that the predicted number of each insurance group is employed differently depending on the study population of the model. The market-level control includes the proportion of FP hospitals in the same HSA for the hospital. We subgroup the samples according to their insurance coverage (private/Medicare), hospital ownership type (FP/NFP), and the period before and after the implementation of IPPPS in 2005. The introduction of IPPPS creates a new financial incentive for the hospitals treating Medicare psychiatric patients, thus may induce a change in their treatment patterns. This change may also lead to an adjustment in treating patients under private insurance (i.e., spillover effect). To address a potential delay in adopting the policy by the hospitals, we omit the samples collected in 2005 from the analysis. Our OLS model is denoted by,

$$Y_{ijkt} = \delta_k + \sigma_t + \beta ln\left(HHI_k^{pat^*}\right) + \gamma X_i + \delta H_j + \lambda S_{HSA} + \varepsilon_{ijkt} \quad (9)$$

where δ_k is a zip-code fixed effect. σ_t is a year fixed effect. X_i is a vector of patient-level controls. H_j is a vector of hospital-level controls. S_{HSA} is a vector of HAS-level controls. ε_{ijkt} is an error term.

3.5.3.2 Hospital-level Analysis

In addition to the patient-level cost outcomes, we investigate hospital-level labor resources (physicians per bed, number of nurses per bed, and nurse hours per patient day) and financial performance measures (profit and operating margins). In doing so, we explore to what extent the findings from the cost outcomes are reflected in the service quality and hospital margins.

Constructing the hospital-level competition indices is analogous to those at the patient-level but with a few differences: First, instead of using separate patient samples by their insurance coverage status, the hospital-level indices are developed from the whole patient sample without restricting the insurance type. Second, the hospital-level predicted HHI in Equation (7) is employed in the hospital samples. The hospital-level controls include public ownership, psychiatric bed count, case mix index, and logged predicted numbers of patients for the hospital. The market-level control is the proportion of FP hospitals in the same HSA for the hospital. Below is the model specification for the hospital-level analysis:

$$Y_{ijmt} = \delta_m + \sigma_t + \beta ln\left(HHI_j^{Hosp}\right) + \delta H_j + \lambda S_m + \varepsilon_{ijmt} \quad (10)$$

where δ_m is an HSA fixed effect. σ_t is a year fixed effect. H_j and S_m is a vector of hospital-and market-level controls, respectively. ε_{ijmt} is an error term.

Since our OSHPD data contains the hospital financial information in an aggregated format, we cannot distinguish the use of labor resources and financial outcomes solely derived from the inpatient psychiatric admissions. To maintain our study context focusing on inpatient psychiatric care, we only conduct the analysis using specialty psychiatric hospital samples.

3.6 RESULTS

3.6.1 *Patient-level Results*

Table 3A presents the results of the effects of competition on spending and resource utilization by estimating Equation (9) out of the patients admitted to general hospitals. Among the private insurance patients and prior to the IPPPS, we find that a 10% increase in HHI is associated with an increase in the cost per discharge by 13300 and 5090 dollars for FP and NFP hospitals, respectively (Column (1) in Panels A and B). The same degree of increase in HHI also leads to a decrease in the number of procedures by three units among FP hospitals (Column (3) in Panel A), while it increases the cost per day by 850 dollars among NFP hospitals (Column (2) in Panel B). After the IPPPS, spending and utilization outcomes in FP hospitals (Columns (1) through (4) in Panel C) are not associated with varying degrees of the HHI; however, for NFP hospitals, a 10% increase in HHI is associated with a decrease in the cost per discharge by 12500 dollars and an increase in the number of procedure by five units, respectively (Columns (1) and (3) in Panel D).

Additionally, among the Medicare beneficiaries and before the implementation of the IPPPS, we do not observe any association between the varying degrees of HHI and the four outcomes in FP hospitals; in contrast, for those in NFP hospitals, a 10% increase in HHI is associated with an increase in the two cost measures and a decrease in the number of procedures and LOS (Columns (5) through (8) in Panel B). After the implementation of the IPPPS, both FP and NFP hospitals experienced a decrease in the cost per day by 2010 and 4010 dollars, respectively (Column (6) in Panels C and D), following a 10% increase in HHI.

Table 3B shows the same set of spending and resource utilization outcomes from Equation (9) but using the different patient samples admitted to specialty hospitals. Among the private insurance patients and prior to the IPPPS, a 10% increase in HHI is associated with decreases in all of the four outcomes in FP hospitals (Columns (1) through (4) in Panel A). However, this observation does not apply to NPF hospitals; notably, the estimates in the cost per discharge and cost per day between FP and NFP hospitals indicate the opposite direction. After the IPPPS, higher levels of HHI are associated with increases in the LOS in FP hospitals (Column (4) in Panel C) and the cost per day in NFP hospitals (Column (2) in Panel D), respectively.

Moreover, among the Medicare patients and prior to the IPPPS, the cost per discharge in FP hospitals increases by 15300 dollars if the HHI escalates by 10% (Column (5) in Panel A). Furthermore, the number of procedures and LOS contradicts each other in response to a 10% increase in the HHI since the former decreases by four units, while the latter increases by twenty days (Columns (7) and (8) in Panel A). After the introduction of the IPPPS, an increase in the HHI level is associated with rises in the cost per discharge and cost per day in NFP hospitals (Columns (5) and (6) in Panel D).

3.6.2 *Hospital-level Results*

Table 4 reports the estimates from Equation (10) evaluating the association between the market competition and the use of labor resources and financial margins. Before the implementation of the IPPPS, a 1% increase in HHI is associated with a decrease in the nurse hours per patient day by two hours in FP hospitals (Column (3) in Panel A) and an increase in the number of physicians per bed by one unit in NFP hospitals (Column (1) in Panel B), respectively. After the IPPPS, NFP hospitals experience increases in the number of nurses per bed and nurse hours per patient day by one unit and five hours, respectively, following a 1% increase in HHI (Columns (2) and (3) in Panel D). The evidence shows no association between competition levels and hospital financial outcomes.

3.7 DISCUSSION AND CONCLUSIONS

Despite the existing literature on the effects of competition on costs and the quality of care, only a limited number have analyzed the effects on both of these measures simultaneously (Kessler & Geppert, 2005; Kessler & McClellan, 2000; Mukamel et al., 2002). Furthermore, there is a gap in the literature since no studies have specifically investigated competition in the market for inpatient psychiatric care. This paper represents the first study to our knowledge that evaluates the effects of competition on both costs and quality among hospitals that offer inpatient psychiatric services in the US. Based on the OSHPD data and the implementation of IPPPS in 2005, our study sheds light on the behavioral responses of hospitals providing inpatient psychiatric services in California to varying degrees of competition and different insurance coverage and payment mechanisms.

Our analysis's primary findings suggest that competition's effects on hospitals' medical expenditures are highly heterogeneous across their hospital and ownership types, patient insurance coverage characteristics, and reimbursement methods. From the samples of psychiatric patients treated in general hospitals (Table 3A), we observe opposite trends in the cost per discharge – the introduction of the IPPPS in 2005 is a key to describing the differences. For example, before the IPPPS, the costs per discharge for private insurance patients in NFP hospitals were reduced when the level of competition intensified; in contrast, after the IPPPS, the costs in NFP hospitals increased with a higher degree of competition. Likewise, the costs per day for Medicare patients in NFP hospitals declined due to an increased competition in the market prior to the IPPPS; in contrast, the same outcome increases when the market becomes more competitive after the IPPPS. Given that the shift of reimbursement method from TEFRA to IPPPS was only relevant for Medicare beneficiaries in specialty units, we did not anticipate any changes from private insurance patients due to the IPPPS implementation. The evidence demonstrating similar changes in both insurance groups after the IPPPS provides two important policy implications. First, it shows the presence of spillover effect of the IPPPS from Medicare to private insurance patients. Second, NFP hospitals do not discriminate against patients by their insurance coverage when providing inpatient psychiatric services. This latter part is particularly contrasting to the finding from FP general hospitals showing opposite treatment patterns between private insurance and Medicare patients when competition increases. Although a formal statistical test is not performed on the differences in the costs between private insurance and Medicare patients across the hospitals, comparing the signs of the cost estimates may partly support our assessment.

Our findings on the association between competition and costs per discharge in Table 3A do not agree with the prior evidence by Meltzer et al. (2002), which suggests that before the PPS, treatment costs for Medicare patients increase in the more competitive markets, but after the PPS, the costs decrease with an increase in competition. Economic theories also propose that hospitals minimize the provision of unnecessary clinical interventions when PPS fixes the service rate to earn higher profits. However, our analysis of the Medicare patient samples provides a mixed picture varying by hospital ownership types – FP hospitals, albeit without statistical significance, follow the theory and empirical finding; in contrast, NFP hospitals behave opposite to FP hospitals by dropping their cost containment efforts after the IPPPS. This variation between FP and NFP hospitals may be attributed to their difference in objective functions, but this remains the topic for future studies.

We also observed a decrease in divergence between FP and NFP hospitals when comparing the period before and after the implementation of the IPPPS. One possible explanation of this phenomenon is that transition to the IPPPS from the cost-based reimbursement system limits the extent to which hospitals exhibit distinct behaviors based on their objective functions, thus resulting in a convergence in their behaviors.

In the samples of patients treated in specialty hospitals (Table 3B), we identify coherent patterns among FP and NFP hospitals in response to increased competition. In addition, unlike general hospitals, specialty hospitals are mostly consistent in their behaviors when comparing the outcomes of the patient's insurance coverage before and after the implementation of the IPPPS.

The only exception is the cost estimate from private insurance patients treated in FP hospitals before the IPPPS; whereas all the remaining cost estimates generally show a decreasing trend when competition increases, their costs escalate along with an increased level of competition. This finding may indicate the potential presence of non-price competition targeting private insurance patients among FP hospitals. Considering that hospitals typically receive higher reimbursement rates from private insurance patients compared to Medicare beneficiaries, this evidence illuminates the profit maximizing strategies adopted by FP hospitals in response to increased competition. Importantly, the opposite patterns observed between the private insurance and Medicare patients in FP hospitals further reinforce this analysis.

Other outcome measures, including the daily costs and LOS, offer additional details in this finding. For instance, when the market becomes more competitive, the cost per day, the number of procedures, and LOS also increases in FP hospitals treating private insurance patients. These findings provide that both increased intensity and duration of treatment contribute to the increase in total costs. Comparing the outcomes of private insurance patient samples to those of Medicare patients may reveal a distinct treatment pattern based on the patient's insurance coverage in FP hospitals prior to the IPPPS. Particularly, FP hospitals shorten the LOS of Medicare patients when facing higher competition, which may reduce overall costs per discharge. However, after the IPPPS, we do not observe the differences in the treatment pattern between private insurance and Medicare patients in FP hospitals.

The outcomes of the labor resources in the hospital-level analysis provide information on the changes in quality among specialty psychiatric hospitals with respect to varying degrees of competition in the market (Table 4). We notice that specialty hospitals respond to the changed market environment very differently according to their ownership types. For example, when competition becomes more intense, FP hospitals tend to hire more physicians and nurses, but NFP hospitals are likely to reduce the number of clinicians. Considering that the nurse hours per patient day is a widely used quality indicator for inpatient care, this finding implies that competition may improve quality of care in FP hospitals, while diminishing it in NFP hospitals. Moreover, the evidence on quality of care allows us to differentiate whether the decreased treatment costs among specilaty hospitals in the more competitive markets are attributable to improved efficiency or sacrifice in quality. In particular, we find that NFP hospitals will likely decrease costs by compromising their quality of care.

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FIGURES AND TABLES

Table 1. Hospital-level summary statistics by hospital type and profit status

	General hospitals		Specialty hospitals	
	For-profit (N = 51)	Not-for-profit (N = 121)	For-profit (N = 55)	Not-for-profit (N = 30)
Teaching (%)	1	23	0	0
Rural (%)	0	2	0	0
Hospital bed				
Number of total hospital beds	209 (104)	376 (216)	69 (40)	68 (82)
Number of psychiatric beds	40 (27)	41 (32)	65 (39)	51 (38)
Occupancy rates for psychiatric beds (%)	62 (24)	59 (23)	64 (21)	68 (21)
Predicted number of patients				
Private	515 (284)	705 (408)	267 (160)	396 (299)
Medicare	493 (253)	509 (250)	656 (382)	619 (403)
Case mix index	1.1 (0.3)	1.1 (0.2)	0.7 (0.1)	0.7 (0.1)
Proportion of for-profit hospitals				
HSA	0.66 (0.27)	0.15 (0.21)	0.55 (0.24)	0.15 (0.18)
County	0.48 (0.15)	0.28 (0.19)	0.37 (0.14)	0.2 (0.16)
Herfindahl–Hirschman index	1725 (1554)	2898 (2190)	2573 (1611)	4487 (2796)

Note: This table presents hospital-level summary statistics by hospital type (general/specialty hospital) and profit status (for-profit/not-for-profit) over the sample period of 1995-2011. A unit of observation is a hospital-year. The number of hospitals represents uniquely identified hospitals in the sample (i.e., the hospital which shifted profit status during the sample period is counted separately). The HHI is computed using the predicted patient flow approach. The higher HHI indicates a more concentrated market (i.e., a lower competition level). The number in parenthesis indicates the standard deviation.

Table 2. Patient-level summary statistics by hospital type and insurance coverage status

	General hospitals		Specialty hospitals	
	Private (N = 183,935)	Medicare (N = 351,416)	Private (N = 164,247)	Medicare (N = 98,413)
For-profit hospital (%)	15	26	58	66
Distance from home (miles)	7.4 (7.1)	6 (6.3)	10.6 (8.2)	8.9 (7.7)
Herfindahl–Hirschman index (HHI)	2742 (2148)	2477 (2032)	2563 (1871)	2984 (2180)
HHI ≤ 1000 (%)	20	22	19	14
1000 < HHI ≤ 1500 (%)	15	22	9	14
1500 < HHI ≤ 2500 (%)	27	22	33	23
HHI > 2500 (%)	37	34	38	49
Female (%)	60	50	58	45
Age category (%)				
0-17 years	7.45	0.01	28.99	0.11
18-34 years	29.14	10.98	25.60	19.73
35-64 years	57.66	53.58	42.97	65.34
65 years and over	5.75	35.44	2.43	14.81
Race (%)				
White	87.50	81.90	84.15	83.01
Black	4.24	11.27	5.14	8.82
Native American/Eskimo	0.09	0.14	0.18	0.26
Asian/Pacific Islander	2.95	2.30	1.89	1.46
Other/Missing/Unknown	5.22	4.38	8.64	6.44
Primary diagnosis (%)				
Schizophrenia	12	42	14	46
Bipolar disorder	21	17	21	21
Major depression	34	22	35	20
Depression	7	3	11	3
Alcohol use disorder	11	4	5	2
Drug use disorder	3	1	3	2
Other	13	12	10	6
Rural (%)	3	2	2	3
Zip code-level median income	72424 (24494)	61143 (21961)	66981 (21698)	57520 (18787)
Managed care	66	6	67	5
Source of admission (%)				
This hospital – emergency room	48	44	0	0
This hospital – general	6	10	0	0
Transfer from another hospital	5	4	7	8
Not a hospital	41	41	92	91
Type of licensed bed (%)				
Acute care	27	21	1	1
Psychiatric care	73	79	99	99

Note: This table presents patient-level summary statistics by hospital type (general/specialty hospital) and insurance coverage status (Private/Medicare) between 1995-2011. A unit of observation is a patient discharge from psychiatric admission. The total patient number is calculated by summing over discharge events according to the type and insurance coverage status. The zip code-level median income is in 2000 dollars, and the number in parenthesis indicates the standard deviation. The regression model uses all variables included in this table as patient-level regressors. Please note that categories of the variables reflect the types of variables (i.e., continuous/binary/categorical) in the model. The HHI is computed using the predicted patient flow approach. HHI ≤ 1000, 1000 < HHI ≤ 1500, 1500 < HHI ≤ 2500, and HHI > 2500 indicate a highly competitive, unconcentrated, moderately concentrated, and highly centered market, respectively.

Table 3A. Effects of competition on expenditure and resource utilization among general hospitals

	Private				Medicare			
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Number of Procedure	(4) Length of Stay	(5) Cost Per Discharge	(6) Cost Per Day	(7) Number of Procedure	(8) Length of Stay
Panel A: FP/Before IPPPS								
Log HHI	1330.3*	114.2	-0.31*	0.41	-1224.4	-118.3	0.05	-0.21
	(530.8)	(70.2)	(0.15)	(0.73)	(1128.3)	(96.1)	(0.19)	(1.16)
No. observations	18507	18507	18507	18507	51566	51566	51566	51566
Y-Mean	3410.4	696.8	0.57	5.46	6012.7	608.8	0.53	10.96
Panel B: NFP/Before IPPPS								
Log HHI	508.8*	84.5***	-0.12	0.02	1118.5*	201.2***	-0.39***	-1.23*
	(209.2)	(24.7)	(0.07)	(0.25)	(514.6)	(58.3)	(0.07)	(0.51)
No. observations	92645	92645	92645	92645	164637	164637	164637	164637
Y-Mean	4059.8	831.9	0.47	5.71	6828.8	765.8	0.6	10.23
Panel C: FP/After IPPPS								
Log HHI	-186.5	-351.1	0.16	2.04	562.2	-201.2*	-0.13	1.18
	(1590.9)	(194.1)	(0.14)	(1.5)	(1071.7)	(78.6)	(0.16)	(1.41)
No. observations	7980	7980	7980	7980	33876	33876	33876	33876
Y-Mean	4554.4	1063.3	0.25	4.97	6845.4	793.5	0.23	10.03
Panel D: NFP/After IPPPS								
Log HHI	-1249.1*	-77.7	0.48**	-0.49	-387	-401.4***	-0.06	1.00
	(580.6)	(88.9)	(0.15)	(0.41)	(706)	(61.3)	(0.07)	(0.57)
No. observations	53789	53789	53789	53789	79999	79999	79999	79999
Y-Mean	6002.4	1298.2	0.44	5.25	9309.3	1251.5	0.47	8.78
Market cont.	Y	Y	Y	Y	Y	Y	Y	Y
Hospital cont.	Y	Y	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	Zip code/Year	Zip code/ Year	Zip code/ Year	Zip code/ Year	Zip code/ Year	Zip code/ Year	Zip code/ Year	Zip code/ Year

Note: This table presents estimates of the association between the market competition level and spending and resource utilization among the patients admitted to general hospitals. The outcomes are displayed by the patient's insurance coverage (private/Medicare), the hospital's profit status (FP/NFP), and the period before and after the implementation of IPPPS. The Medicare PPS for inpatient psychiatric care was introduced in 2005. The estimates of each column present the coefficient β obtained from Equation (8) by OLS. The predictor variable is the logged patient-level HHI, formulated separately according to the patient's insurance coverage status (private/Medicare). In Panel A, the patients from FP hospitals are included in the analysis. Panel B presents estimates from the patients admitted to NFP hospitals. All regression models include patient-, hospital-, and market-level control variables, as well as patient zip code and year fixed effects. The patient-level controls include sex, race, age, managed care status, psychiatric diagnosis, DRG code, source of admission, urban/rural status, zip code-level median income, and bed type. The hospital-level controls include teaching affiliation, public ownership, psychiatric bed count, case mix index, and logged predicted numbers of the patients by their insurance coverage status. The market-level control is the proportion of FP hospitals in the same HSA for the hospital. Standard errors are clustered by patient-level zip code. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 3B. Effects of competition on expenditure and resource utilization among specialty hospitals

	Private				Medicare			
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Number of Procedure	(4) Length of Stay	(5) Cost Per Discharge	(6) Cost Per Day	(7) Number of Procedure	(8) Length of Stay
Panel A: FP/Before IPPPS								
Log HHI	-695.5***	-53.7**	-0.63***	-0.68*	1530.6**	34.0	-0.36**	2.34**
	(191.2)	(17.2)	(0.15)	(0.31)	(497.5)	(36.0)	(0.13)	(0.84)
No. observations	57541	57541	57541	57541	42737	42737	42737	42737
Y-Mean	3329.7	512.2	0.12	6.52	5486.9	515.8	0.2	10.63
Panel B: NFP/Before IPPPS								
Log HHI	775.1**	166.2***	-0.002	0.03	681.2	128.1*	0.34	1.04
	(263.7)	(39.3)	(0.13)	(0.36)	(546.6)	(58)	(0.29)	(0.95)
No. observations	43403	43403	43403	43403	23030	23030	23030	23030
Y-Mean	3538.5	601.6	0.39	5.92	5482.2	611	0.44	9.31
Panel C: FP/After IPPPS								
Log HHI	671.7	-1.0	0.03	1.64*	730.7	-51.0	0.12	2.11
	(590.1)	(68.2)	(0.12)	(0.72)	(680.5)	(30.9)	(0.1)	(1.11)
No. observations	33107	33107	33107	33107	18588	18588	18588	18588
Y-Mean	3934.8	617.4	0.22	6.37	6981.6	643.5	0.23	10.87
Panel D: NFP/After IPPPS								
Log HHI	1101.8	392.9*	0.1	1.42	9570*	2014.3***	-0.002	0.85
	(840.1)	(161.1)	(0.1)	(0.74)	(4029.4)	(513.1)	(0.22)	(1.67)
No. observations	21179	21179	21179	21179	8953	8953	8953	8953
Y-Mean	5528.8	996.1	0.49	6.04	9680.9	1188.8	0.94	9.5
Market cont.	Y	Y	Y	Y	Y	Y	Y	Y
Hospital cont.	Y	Y	Y	Y	Y	Y	Y	Y
Patient cont.	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	Zip code/ Year	Zip code/ Year	Zip code/ Year	Zip code/ Year	Zip code/ Year	Zip code/ Year	Zip code/ Year	Zip code/ Year

Note: This table presents estimates of the association between the market competition level and spending and resource utilization among the patients admitted to psychiatric hospitals. The outcomes are displayed by the patient's insurance coverage (private/Medicare), the hospital's profit status (FP/NFP), and the period before and after the implementation of IPPPS. The Medicare PPS for inpatient psychiatric care was introduced in 2005. The estimates of each column present the coefficient β obtained from Equation (8) by OLS. The predictor variable is the logged patient-level HHI, formulated separately according to the patient's insurance coverage status (private/Medicare). In Panel A, the patients from FP hospitals are included in the analysis. Panel B presents estimates from the patients admitted to NFP hospitals. All regression models include patient-, hospital-, and market-level control variables, as well as patient zip code and year fixed effects. The patient-level controls include sex, race, age, managed care status, psychiatric diagnosis, DRG code, source of admission, urban/rural status, zip code-level median income, and bed type. The hospital-level controls include public ownership, psychiatric bed count, case mix index, and logged predicted numbers of the patients by their insurance coverage status. The market-level control is the proportion of FP hospitals in the same HSA for the hospital. Standard errors are clustered by patient-level zip code. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 4. Effects of competition on the use of labor resources and financial outcomes

	Labor Resources			Financial Outcomes	
	(1) Number of Physicians Per Bed	(2) Number of Nurses Per Bed	(3) Nurse Hours Per Patient Day	(4) Profit Margin	(5) Operating Margin
Panel A: FP/Before IPPPS					
Log HHI	-0.28	-0.79	-1.79*	-5.73	-5.5
	(0.28)	(0.69)	(0.71)	(3.71)	(3.71)
No. observations	305	305	305	305	305
Y-Mean	0.41	0.82	2.13	-0.2	-0.2
Panel B: NFP/Before IPPPS					
Log HHI	1.3*	0.1	0.21	-0.03	-0.19
	(0.53)	(0.21)	(0.38)	(0.02)	(0.13)
No. observations	240	240	240	240	240
Y-Mean	0.66	0.62	1.84	0.0004	-0.14
Panel C: FP/After IPPPS					
Log HHI	-0.05	-0.06	-0.59	0.13	-0.02
	(0.07)	(0.28)	(0.68)	(0.07)	(0.11)
No. observations	154	154	154	154	154
Y-Mean	0.29	0.76	1.88	0.1	0.09
Panel D: NFP/After IPPPS					
Log HHI	0.68	0.93***	4.75***	0.04	5.83
	(0.35)	(0.26)	(1.3)	(0.12)	(8.31)
No. observations	130	130	130	130	130
Y-Mean	0.41	0.43	1.78	-0.03	-1.54
Market cont.	Y	Y	Y	Y	Y
Hospital cont.	Y	Y	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year	HSA/Year	HSA/Year

Note: This table presents estimates of the association of the market competition level with the labor resources and financial outcomes. The outcomes are displayed by the hospital's profit status (FP/NFP) and the period before and after the implementation of IPPPS. The Medicare PPS for inpatient psychiatric care was introduced in 2005. The estimates of each column present the coefficient β obtained from Equation (9) by OLS. The predictor variable is the logged hospital-level HHI, formulated using all the patient samples (regardless of their insurance coverage). Panels A and B include FP and NFP hospitals, respectively. All regression models include hospital-, and market-level control variables, as well as HSA and year fixed effects. The hospital-level controls include public ownership, psychiatric bed count, case mix index, and logged predicted numbers of patients for the hospital. The market-level control is the proportion of FP hospitals in the same HSA for the hospital. Robust standard errors are reported in parentheses. The study sample consists of freestanding specialty psychiatric hospitals only. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table S1. Primary psychiatric diagnosis classification

Type	ICD-9 CM codes
Schizophrenia	295.xx , 298.1x - 298.9x
Bipolar disorder	296.0x - 296.1x , 296.4x-296.9
Major depression	296.2x - 296.3x
Depression	298.0x , 300.4x , 301.12 , 309.0x - 309.1x , 311.xx
Alcohol use disorder	291.xx , 303.xx , 305.1x
Drug use disorder	292.xx , 304.xx , 305.2x - 305.9x
Other	Other codes between 290.xx and 319.xx

Note: This table presents psychiatric diagnosis codes that we use for this study. We follow the categorization implemented by Stensland et al. (2012) and include Major depression as a separate category.

Table S2. Parameter estimates from the McFadden choice model (Private insurance)

Year	(1) Distance	(2) Freestanding hospital	(3) For-profit	(4) Close	(5) Psychiatric bed	(6) Distance × Emergency	(7) Close× Emergency
1995	-0.15	-0.43	-0.18	0.24	0.008	-0.07	0.12
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0003)	(0.005)	(0.05)
1996	-0.15	-0.55	-0.41	0.33	0.009	-0.09	0.13
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)
1997	-0.16	-0.85	-0.22	0.19	0.006	-0.12	0.08
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)
1998	-0.16	-0.97	-0.32	0.21	0.007	-0.11	0.18
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)
1999	-0.15	-0.99	-0.22	0.21	0.006	-0.13	0.07
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)
2000	-0.15	-1.22	-0.39	0.05	0.006	-0.13	0.24
	(0.002)	(0.02)	(0.02)	(0.03)	(0.0002)	(0.005)	(0.05)
2001	-0.15	-1.26	-0.47	0.16	0.006	-0.11	0.38
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)
2002	-0.15	-1.25	-0.26	0.06	0.008	-0.12	0.3
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.05)
2003	-0.14	-1.19	-0.414	0.15	0.008	-0.13	0.14
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.05)
2004	-0.13	-1.68	-0.48	0.34	0.005	-0.13	0.3
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)
2005	-0.13	-1.07	-0.36	0.16	0.012	-0.14	0.4
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)
2006	-0.14	-0.89	-0.38	0.09	0.012	-0.12	0.64
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)
2007	-0.14	-1.08	-0.43	0.01	0.01	-0.13	0.65
	(0.002)	(0.02)	(0.02)	(0.03)	(0.0002)	(0.005)	(0.05)
2008	-0.15	-1.13	-0.51	-0.22	0.009	-0.13	0.58
	(0.002)	(0.02)	(0.02)	(0.03)	(0.0002)	(0.005)	(0.05)
2009	-0.15	-1.09	-0.61	-0.15	0.011	-0.13	0.61
	(0.002)	(0.02)	(0.02)	(0.03)	(0.0002)	(0.005)	(0.05)
2010	-0.13	-0.92	-0.59	0.04	0.015	-0.14	0.26
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)
2011	-0.14	-0.84	-0.64	0.08	0.015	-0.11	0.22
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.05)

Table S3. Parameter estimates from the McFadden choice model (Medicare)

Year	(1) Distance	(2) Freestanding hospital	(3) For-profit	(4) Close	(5) Psychiatric bed	(6) Distance × Emergency	(7) Close× Emergency
1995	-0.18	0.25	-0.02	0.53	0.005	-0.09	-0.17
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
1996	-0.18	0.27	-0.04	0.53	0.005	-0.11	-0.31
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
1997	-0.17	0.14	-0.03	0.65	0.004	-0.13	-0.52
	(0.002)	(0.02)	(0.01)	(0.02)	(0.0002)	(0.004)	(0.04)
1998	-0.18	-0.001	-0.11	0.56	0.002	-0.12	-0.43
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
1999	-0.18	0.05	-0.03	0.48	0.001	-0.12	-0.33
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
2000	-0.2	0.29	-0.11	0.31	0.002	-0.11	-0.16
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
2001	-0.2	0.3	-0.09	0.35	0.003	-0.11	-0.09
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.04)
2002	-0.19	0.3	-0.11	0.35	0.005	-0.09	-0.05
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
2003	-0.18	0.49	-0.053	0.47	0.005	-0.12	-0.29
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
2004	-0.18	0.36	0.04	0.41	0.006	-0.1	-0.1
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
2005	-0.18	0.44	0.06	0.38	0.007	-0.11	-0.01
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
2006	-0.17	0.56	0.07	0.26	0.01	-0.11	0.08
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.005)	(0.04)
2007	-0.17	0.47	-0.07	0.1	0.008	-0.11	0.18
	(0.002)	(0.02)	(0.02)	(0.02)	(0.0002)	(0.004)	(0.04)
2008	-0.18	0.63	0.18	0.09	0.009	-0.1	0.37
	(0.002)	(0.02)	(0.02)	(0.03)	(0.0002)	(0.004)	(0.04)
2009	-0.18	0.62	0.16	0.16	0.009	-0.1	0.29
	(0.002)	(0.02)	(0.02)	(0.03)	(0.0002)	(0.004)	(0.04)
2010	-0.16	0.65	0.19	0.27	0.007	-0.12	0.06
	(0.002)	(0.02)	(0.02)	(0.03)	(0.0002)	(0.004)	(0.04)
2011	-0.16	0.81	0.24	0.24	0.008	-0.09	0.2
	(0.002)	(0.02)	(0.02)	(0.03)	(0.0002)	(0.004)	(0.04)

Chapter 4.

ALTERNATIVE APPROACHES TO EMPLOY DIFFERENTIAL DISTANCE AS AN INSTRUMENTAL VARIABLE

ABSTRACT

Differential distance (DD) has been widely used as an instrumental variable (IV) in health economics literature to examine the casual effect of alternative interventions or utilizations where access to these options is affected by the shadow costs of travel. However, less attention has been paid in the literature on how the type of DD variable and the specific analysis approach can identify different causal treatment effect parameters. We present a case study to illustrate these discussions, estimating the causal effects of hospital ownership types (for-profit versus not-for-profit) on total inpatient costs for psychiatric admissions in California. The six different IV approaches are evaluated: 1) 2SLS with binary IV (DD > 10 miles), 2) 2SLS with continuous IV, 3) 2SRI with binary IV, 4) 2SRI with continuous IV, 5) Local IV approaches, and 6) Fuzzy regression discontinuity design. Our analysis indicates that how effect heterogeneity leads to identifying different treatment effects with varying IV specifications. More generally, it indicates that we should avoid using binary IVs that are not policy related.

4.1 INTRODUCTION

Instrumental variable (IV) approaches are popular econometric techniques to address both observed and unobserved confounding bias in observational research. An appropriate instrumental variable is one that is strongly associated with the endogenous exposure variable but has no association with any of the risk factors of the outcome or with the outcomes directly. With such an IV at hand, one can use the variation in the exposure induced by the IV as exogenous variation (i.e., independent of the potential outcomes for each exposure level) and use this exogenous variation to establish causal effect of the exposure on the outcome. The strength of association between an IV and the exposure variable is testable. Typically, this test is conducted, conditional on other confounders in the data. The absence of association between IV and all risk factors or outcomes is not fully testable since the analysts do not observe all the risk factors in the data. Instead, analysts rely on substantive knowledge to defend this assumption, and importantly, back up this assertion by demonstrating the lack of association between IV and the observed risk factors in the data.

While these standard approaches are fundamental to any IV analysis, less attention has been paid in the health economics and health services research literature on how the form of IV variable (e.g., binary, categorical, continuous) and the specific analysis approach [e.g., two-stage linear squares (2SLS), two-stage residual inclusion (2SRI), local instrumental variable (LIV), regression discontinuity design (RDD)] can identify different causal treatment effect parameters. The basis of this concern lies in the fact that treatment effects are expected to be heterogenous (Basu et al., 2007; Heckman, 1997; Heckman et al., 2006). Moreover, this heterogeneity spans not only the observed levels of risk factors, but also unobserved levels. That is, unobserved confounders not only bias a naïvely estimated treatment effect, but it also moderates the level of the true causal effects. Consequently, different forms of the same instrumental variable, and different IV approaches identify a different effect parameter, varying both in interpretation and magnitude. There is a large econometric literature demonstrating these issues (Angrist et al., 1996; Basu et al., 2007, 2018; Heckman et al., 2006; Heckman & Urzúa, 2010; Heckman & Vytlacil, 2005; Imbens & Angrist, 1994). A classic example where all of these concerns can be illustrated in the health economics and health services research literature is the use of distance-based measures to instrument for certain utilizations, and then estimating the causal effect of those utilizations on outcomes. In this paper, we present a scoping review of the literature where differential distance (DD) has been used as an IV and identify differences in interpretation of their estimated effects. Next, we use a case study on estimating the causal effects of going to a for-profit (FP) hospital versus a not-for-profit (NFP) hospital on the total cost of inpatient stay, using DD to the nearest FP hospital as an IV, to illustrate the issues.

4.2 LITERATURE REVIEW

To characterize the methodological practices of DD use in health economics and health services research literature, we performed a scoping review of relevant articles via PubMed and EconLit research databases. In total, 25 studies were selected for review, and 6 and 19 articles were from medical and health economics and policy journals, respectively (Table 1).

Our analysis starts with a discussion of a seminal paper by McClellan et al. (1994), which is widely recognized as one of the earliest and most significant applications of DD as an IV. The authors examined the effect of intensive treatments for acute myocardial infarction (AMI) on mortality rates. The study defined DD as the distance from a patient's residence to the nearest catheterization hospital[1] minus the distance to the any other nearest hospital. This method allowed them to avoid biases arising from differential selection of treatment alternatives. The likelihood of receiving more intensive treatment procedures, such as catheterization and revascularization, may depend on patient's severity at admission. Thus, it is difficult to correctly estimate the impact on mortality in the presence of such endogeneity. McClellan et al. addressed this issue by exploiting the random variation of patients' residence closer to one type of hospital or the other.

Since the original application of DD by McClellan et al. (1994), three additional studies have utilized the identical IV measure to investigate other economic implications of catheterization use (Brooks et al., 2000; Chandra & Staiger, 2007; Cutler, 2007). For example, Brooks et al. (2000) extended the study population from Medicare beneficiaries to different insurance subgroups, such as patients under Medicaid or private health maintenance organization. Cutler (2007) further studied the long-term impact of catheterization (revascularization) on costs and life expectancy. Chandra and Staiger (2007) tested the presence of productivity spillovers of catheterization in high-use areas of the surgery.

DD has been extensively utilized in other research areas beyond the clinical setting of AMI. We categorized them on the basis of the characteristics of endogenous exposure variables: 1) different types of nursing homes (Bowblis & McHone, 2013; Burke et al., 2022; Grabowski et al., 2013; Huang & Bowblis, 2018, 2019; Joyce et al., 2018; Konetzka et al., 2018; Rahman et al., 2013, 2016; Werner et al., 2019), 2) different types of hospitals (Brooks et al., 2006; Daysal et al., 2015; Ettner & Hermann, 2001; Kahn et al., 2009; McConnell et al., 2005; Swanson, 2021;

[1]The authors defined a catheterization hospital as a facility that conducted a minimum of five catheterization procedures for elderly patients with AMI.

Valley et al., 2015; Xian et al., 2011), 3) different types of surgical procedures (Neuman et al., 2014; Tan et al., 2012) and 4) other (Frogner et al., 2018).

Our analysis of these categories revealed that most of DD applications focused on evaluating the effects of receiving services in different nursing home and hospital settings. For example, the nursing home studies analyzed the mortality and quality of care, comparing various types of facilities, such as home health agencies versus skilled nursing facilities, hospital-based versus freestanding facilities, and traditional facilities versus continuing care retirement communities. Similarly, the hospital studies compared the effectiveness of different types of hospitals, including admission to stroke center, transfers to different levels of trauma centers, and FP versus NFP hospitals.

We also observed that calculating DD is more straightforward when the study's objective is to compare patient outcomes between two alternative health providers, such as in nursing home and hospital studies. This is because researchers do not need to establish their own definitions for treatment and comparator. In contrast, when studying the effect of a specific medical intervention (e.g., surgical or anesthesia technique), researchers must create their classification of the treatment and comparator for the DD. For instance, the study by Neuman et al. (2014), which examined the effect of regional versus general anesthesia on mortality, used the average median rate of regional anesthesia in the sample as a threshold value to categorize hospitals into either those specialized in regional or general anesthesia.

In terms of selecting the DD form, continuous DD is the most commonly used form (17 studies; 68%), followed by binary (7 studies; 28%) and categorical (1 study) forms. Regarding the IV analysis methods, the majority of the selected studies used the 2SLS (17 studies; 68%) or

2SRI (5 studies; 20%) approach. Two studies employed the bivariate probit model (Bhattacharya et al., 2006), and one study used the near-far matching method (Baiocchi et al., 2012).

Additionally, we noticed that the authors used a range of causal parameters to interpret their IV estimates. They encompassed easily interpretable ones, such as the average treatment effect (ATE) and average treatment effect on the treated (ATT), to less intuitive ones, such as the local average treatment effect (LATE), weighted local average treatment effect (W-LATE), and marginal effect at the means (MEM).

4.3 THE CASE STUDY

4.3.1 *Data*

Our main data sources were from the California Office of Statewide Planning and Development (OSHPD) patient discharge and hospital finance database between 1995 and 2011. Detailed patient discharge information and hospital characteristics, including charged amounts, the five-digit zip codes for both the patient's residence and hospital, and information on hospital types and ownership status are all available within this dataset. We also used the National Bureau of Economic Research zip code distance database to compute the DD of the patient between the nearest FP and NFP hospitals based on great-circle distances.

4.3.2 *Study Population*

The study sample consists of all inpatient psychiatric admissions to a general or specialty psychiatric hospital in California. We defined psychiatric admissions based on primary diagnosis of the patient using the ICD-9 codes of mental health disorders. Due to the limitation of our data, we cannot identify the same individual longitudinally. Thus, it is possible that a single patient contributes to the study sample multiple times. The sample size is 1,083,461.

4.3.3 *Outcome*

Our dependent variable is total costs of inpatient stay. Using the OSHPD hospital financial reports, we formulated the cost-to-charge ratio of each hospital and converted the charged amounts to costs.

4.3.4 *Control Variables*

All models incorporate the three types of control variables, such as patient-, hospital-, and area-level characteristics. For the patient-level characteristics, we include race, sex, age, urban/rural residence, median income of patient's zip code, psychiatric diagnosis, payment category, managed care status, bed types (scatter bed or psychiatric unit), and source of admission (e.g., emergency department). Hospital-level characteristics are hospital type (general/specialty psychiatric hospital), teaching status, number of licensed psychiatric beds, and case mix index. The level of market competition measured by Herfindahl-Hirschman index are included in the area-level characteristic (Zwanziger & Melnick, 1988). Moreover, we add year and patient-level hospital service area (HSA) fixed effects to all models. The year fixed effects control for secular time trends in the data while the patient HSA fixed effects control for non-time-varying differences across HSAs. The inclusion of patient HSA fixed effects implies that the model estimates represent the effect of hospital ownership status on the total costs of inpatient stay within the group of patients from the same HSA. Our data suggests that all patient-level HSAs contain at least more than a single inpatient psychiatric admission from FP and NFP hospitals, respectively.

4.4 MOTIVATING DIFFERENTIAL DISTANCE AS AN IV

4.4.1 *Instrument Validity and Strength*

We first evaluated the balance of patient-level covariates to assess the validity of our DD measure as an IV in the study sample. Figure 1 illustrates z-score distributions for each covariate across the exposure status and binary and continuous DD. These z-scores were derived based on the residuals from the regression models, including hospital- and area-level characteristics and HSA and year-fixed effects. We found that the characteristics of covariates between the group of patients who selected the FP versus NPF hospitals are distinguishable (Figure 1A). However, the imbalances were considerably diminished across the binary DD status (Figure 1B). Furthermore, Figure 1C provides additional evidence supporting the random distribution of z-scores for the covariates across patients' continuous DD.

We also tested the monotonicity assumption by graphing the probability of selecting an FP hospital as a function of patients' DD percentiles (Figure 2). As patients' DD levels increased, there was a corresponding decrease in the probability of selecting an FP hospital, which provides evidence supporting the assumption (Figure 2; Table 2). In particular, we chose a cut-off value of 10 miles for the binary DD based on the presence of a slope discontinuity at this point. Lastly, we investigated the strength of binary and continuous DD as an IV across alternative first-stage models (Table 2). The F-statistics for all models exceeded 10 (i.e., a commonly used rule of thumb for assessing weak IV), supporting a strong association between DD and selecting an FP hospital (Staiger & Stock, 1997).

The distribution of predicted probabilities for selecting FP hospitals overlapped for patients who ultimately selected FP versus NFP hospitals and spanned the full support of the probability distribution, as illustrated in Figure A1 (Appendix). This suggests that the estimation of mean treatment effect parameters would not require extrapolation when following a local instrumental variable approach (Basu et al., 2007).

4.4.2 *Alternative Treatment Effects*

In most analyses, analysts claim to estimate an estimate of the ATE parameter. For example, under the assumption of unconfoundedness, which implies that there are no unobserved confounders, a regression analysis, adjusting for observed confounders, aims to establish an ATE. Alternatively, alternative estimators of parameters such as ATT or average treatment effect on the untreated (ATUT) can also be established using the same model. Once IVs are introduced to deal with unobserved confounding, a series of treatment effect parameters can be defined, some of which are easy to interpret, while others are not so easy. A description of alternative models and the assumptions under which they can provide consistent estimators for different treatment effects are summarized in Table 3. All differences between treatment effect parameters arise because they represent the ATE for slightly different subpopulations. Interpretation becomes easy if this subpopulation can be identified and targeted, but it becomes difficult otherwise. Interpretation can also become straightforward if there is no heterogeneity in treatment effects, in which case, all treatment effect parameters converge to be the same as ATE. The LIV approach is perhaps the most intuitive of all the approaches to establish the differences between these parameters. An LIV approach can help identify Marginal Treatment Effects (MTE) parameters, which are building blocks for all other mean treatment effect parameters (Basu, 2014; Heckman & Vytlacil, 1999, 2001, 2005). We use the LIV approach to build the profile of MTEs to illustrate what other estimators are identifying under different empirical specifications.

The 2SLS IV estimators are typically interpreted as identifying either LATE with binary IV or W-LATE with continuous IV. These estimators represent the ATE among marginal patients whose treatment status is determined solely by their proximity to one type of facility over another. However, unlike naturally dichotomous IVs, such as policy intake, identifying marginal patients and attributing ATE to them can be challenging in the IV analysis with DD. This is because knowing the individuals' threshold values of DD that dictate their choice of a facility is necessary but not always available.

Lastly, whether the estimators that claim to estimate the interpretable ATE or ATT parameters actually identify them remains uncertain and contingent upon whether the underlying assumptions are met or not.

4.5 ESTIMATORS AND MODELS

The list of estimators we compare is detailed in Table 3, along with the specific models used and the effect parameters that each of these estimators identify under different structural assumptions.

For 2SRI and LIV approaches, the first stage comprised a logistic regression model of the treatment indicator on covariates and the DD.

In our data, we implemented the second stage of 2SRI using a generalized linear model (GLM) with a log link function with gamma distribution. Generalized residuals from the first stage were used as the control function's building block. Goodness-of-fit criteria drove the functional form of the control function. Figure 3a shows the non-parametrically locally weighted smoothed plot of the outcome against the generalized residuals by treatment groups. It illustrates curvilinear relationships that were different across treatment groups. This indicated that a second-order polynomial of the generalized residuals interacting with the treatment indicator might be an appropriate functional form for the control function. We performed likelihood ratio tests comparing this specification to simpler specifications where either the polynomial or the interactions were omitted. All these tests were significant at the 0.001 level, indicating that our chosen function form produced a significantly better fit. As illustrated in Figure 3a, the same functional form was used with both the binary IV and continuous IV.

We implemented LIV approaches using a linear model or a log link function with gamma distribution in the second stage (i.e., outcomes model). Figure 3b illustrates the non-parametrically locally-weighted smoothed plot of the outcome against the predicted probability of treatment choice from the first stage. It highlights that a third-degree-polynomial may approximate this relationship appropriately. We performed likelihood ratio tests comparing this specification to simpler quadratic or linear specifications of the treatment probability in the second-stage model. All these tests were significant at the 0.001 level, indicating that the third-degree polynomial produced a significantly better fit. In addition to this polynomial specification, the predicted treatment probabilities also entered the control function through interactions with individual-level characteristics.

The LIV approach using continuous DD allows us to estimate the distribution of treatment effects in the study population more completely. The linear model second-stage specification of the LIV method was used to establish an MTE profile over the resistance (i.e., 1 – propensity) to select FP hospitals based on unobserved factors, along with weights to aggregate MTEs into different mean treatment effect parameters. This includes the W-LATE identified in 2SLS with a continuous DD approach.

The GLM second-stage specification of the LIV method was used to establish person-centered treatment effects (PeTE), which were an aggregated form of MTEs, but reflected an individualized estimate of the ATE for every individual in our sample (Basu, 2014). The marginal distribution of PeTE helps identify the treatment effect heterogeneity at the individual level in the population. These PeTEs can also be averaged over any observable characteristics for individuals to obtain estimates for conditional average treatment effects (CATEs and CATTs).

Standard errors for effects from each estimator were based on 1000 times of bootstrapping clustered by patient-level HSA.

4.6 RESULTS

Table 4 presents descriptive statistics for an outcome and other covariates used in the empirical models by hospital ownership status. We found that FP hospitals had a higher proportion of patients aged 0-17 years and non-white patient groups compared to NFP hospitals. Additionally, we noticed a slightly higher patient severity in FP hospitals, given a greater proportion of patients with schizophrenia or bipolar disorder compared to NFP hospitals (56% vs. 48%). There was little variation in payer categories among the patients between FP and NFP hospitals. However, we observed that the difference in the source of admission, especially via the emergency room, was significant since its proportion in NFP hospitals was three times higher than in FP hospitals. As discussed above and illustrated in Figure 1, all of these risk factors were found to be evenly distributed across the DD levels.

The results of the estimators with different approaches are provided in Table 5.

The treatment effect estimate for the naïve linear model (estimated via ordinary least squares (OLS) model) was -\$679. The naïve GLM log link with gamma variance, estimated using quasi-likelihood, yielded a treatment effect of -\$867. The GLM model fitted the data better than the linear model (Appendix Figure A2). The results from either naïve model suggest that the treatment costs for inpatient psychiatric patients in FP hospitals were lower than in NFP hospitals. However, cost estimates from the naïve estimators may be subject to bias arising from the endogeneity of hospital ownership status (i.e., differential patient case mix and hospital cost containment strategies).

For IV-based methods, we start with the LIV approach. The estimated mean treatment effect parameters, such as the ATE, ATT, and ATUT, were almost identical across the linear model or the GLM specification of LIV second stage. The linear model specification estimated values are -$2010, -$2359, and -$1925, for ATE, ATT, and ATU, respectively. The nonlinear model specification estimated values of -$2128, -$2391, and -$1928 for ATE, ATT, and ATU, respectively.

The MTE profile over the unobserved resistance to choosing an FP hospital is illustrated in Figure 4a. It shows that the MTEs were negative for those least likely to resist going to a FP hospital (based on unobserved factors) and negative for those most likely to resist going to a FP hospital. It seems likely that different confounders may be at play here. We do not conjecture what those confounders could be. Figure 4(b) shows the estimates of MTE weights used to aggregate MTE to estimate ATT and W-LATE. The ATT weights, by definition, increase as the resistance to select FP hospitals based on unobserved factors decreases. The W-LATE weight, however, decreases on both ends of the resistance, generating an W-LATE estimate of -$1860, which is much lower (in absolute value) than ATT.

The nonlinear second-stage specification in the LIV approach was used to generate the density of patient-centered treatment effects (PeTE) shown in Figure 5. It shows FP hospital would produce cost-savings over NFP hospitals for a majority of individuals hospitalized for psychiatric conditions. Additionally, these PeTEs were used to compute CATEs for different percentiles of DD in Figure 6. Figure 6(a) revealed that estimates of the CATE remained stable across the percentiles of DD, which corresponded with the fact that DD was an IV and that the population of patients across DD was similar. However, the CATT estimates in Figure 6(b) suggest that for patients who opted for FP hospitals, even when DD exceeded 10 miles, FP hospitals generated a larger cost reduction than average. Whether such selection was driven by anticipated gains or endogenous heteroscedasticity remains unknown.

We now turn our attention to other IV estimators. The 2SLS approach with binary DD produced a treatment effect estimate of -\$2899, whereas the size of the effect estimate decreased to -\$1416, representing a 50% reduction when continuous DD was used instead. The 2SLS IV estimator is designed to provide unbiased average treatment effects on individuals whose treatment selection is solely based on their IV status (i.e., marginal individuals). We could interpret the result of our 2SLS binary IV estimator as LATE, which implies the ATE within the subgroup of patients who would have been chosen to be admitted to FP hospitals if only their DD was lower than 10 miles. Conversely, our 2SLS continuous IV estimator captured overall IV effects, a weighted average of LATEs (W-LATE) across the marginal patients at every possible pair of values of DD in our data. The evidence from our analysis demonstrates a sizeable disparity in the treatment effects estimated by the 2SLS with binary versus continuous DD. This highlights that when using the 2SLS estimator with binary IV, analysts need to carefully assess the potential consequences associated with the selection of a particular cut-off value. Note the closeness of the estimate W-LATE with 2SLS and that from our LIV approach.

Both the 2SRI approaches using binary and continuous DD yielded similar estimates of the treatment effects, with -\$2512 and -\$2274, respectively. Both of these estimates were close to the ATE estimate generated by LIV approaches. Since the estimates from the 2SRI model can identify ATE under specific assumptions (Table 3), our findings suggest that 2SRI methods can identify ATE when control functions are appropriately specified. It is important to note that the 2SRI approach with a binary IV would only work if sufficient variation in other covariates generates a continuous control function.

The first stage in the RDD approach at the 10-mile mark was a weak instrument (Table 2). Consequently, the estimate from the fuzzy RDD was severely biased and did not correspond to any of the other mean treatment effect parameter estimates.

4.7 CONCLUSIONS

Our analysis based on the case study using inpatient psychiatric admissions in California showed that the magnitude of the treatment effect estimates varies depending on the use of different forms of IV and analytic approaches. Since the interpretation of treatment effect estimates from IV models are often nuanced, it requires careful consideration to avoid unintentionally misleading inferences and erroneous conclusions. We hope that our work can assist researchers in comprehending the potential effects of various IV approaches on different causal parameters, as well as encourage discussion on accurately identifying the subset of the population pertinent to treatment effects.

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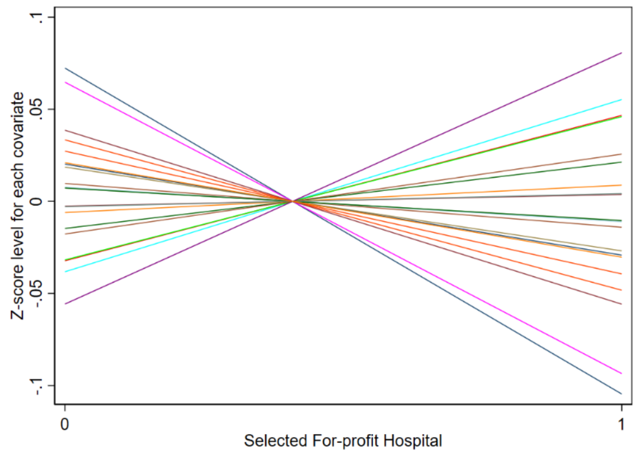
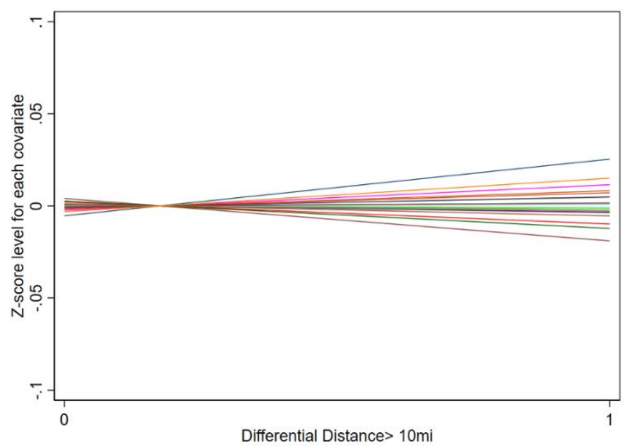
FIGURES AND TABLES

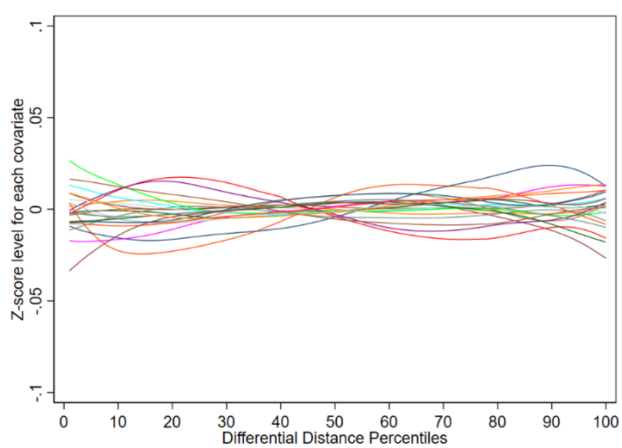
Figure 1. Balance of covariates across (a) exposure (for-profit vs not-for-profit hospitals) versus balance across (b) binary and (c) continuous differential distance IV



(a)



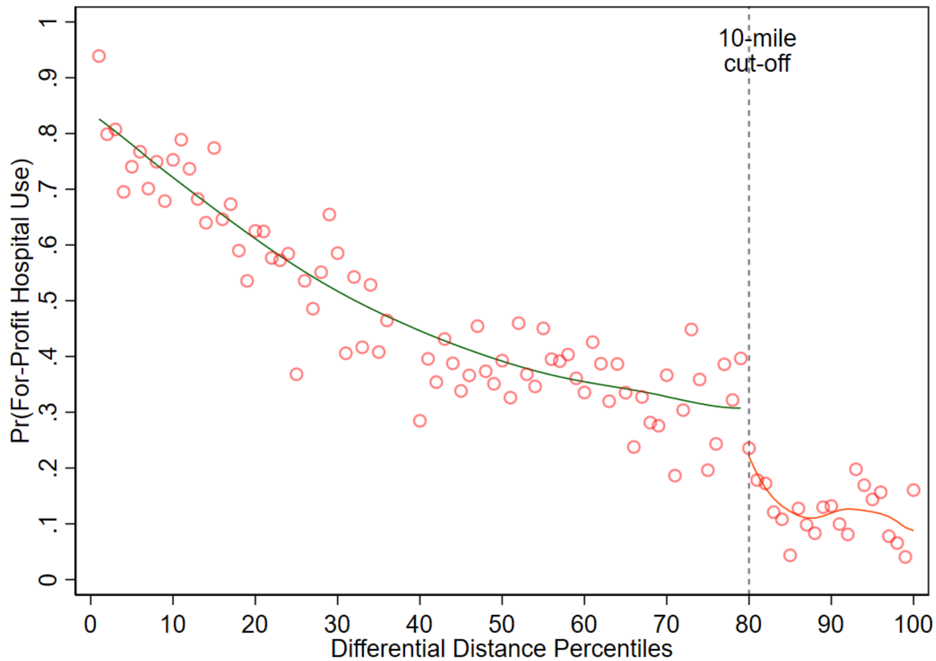
(b)



(c)

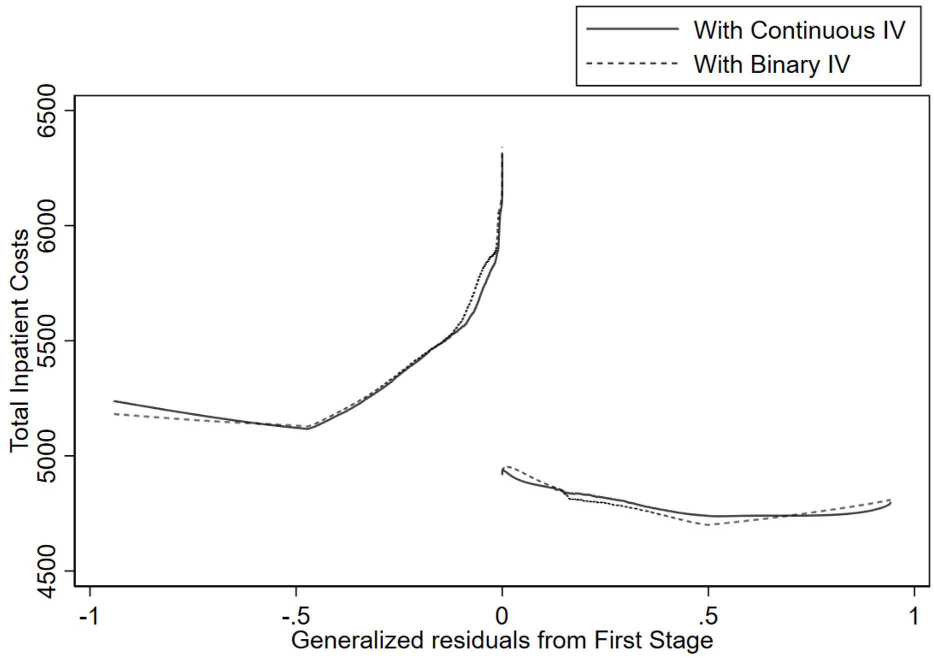
Note: Each covariate was converted to a Z-score. It was then regressed over area-level characteristics, hospital-level characteristics, HSA, and year fixed effects. The residuals were plotted against exposure or instrument levels.

Figure 2. Illustration of the probability of selecting FP hospital across the differential distance

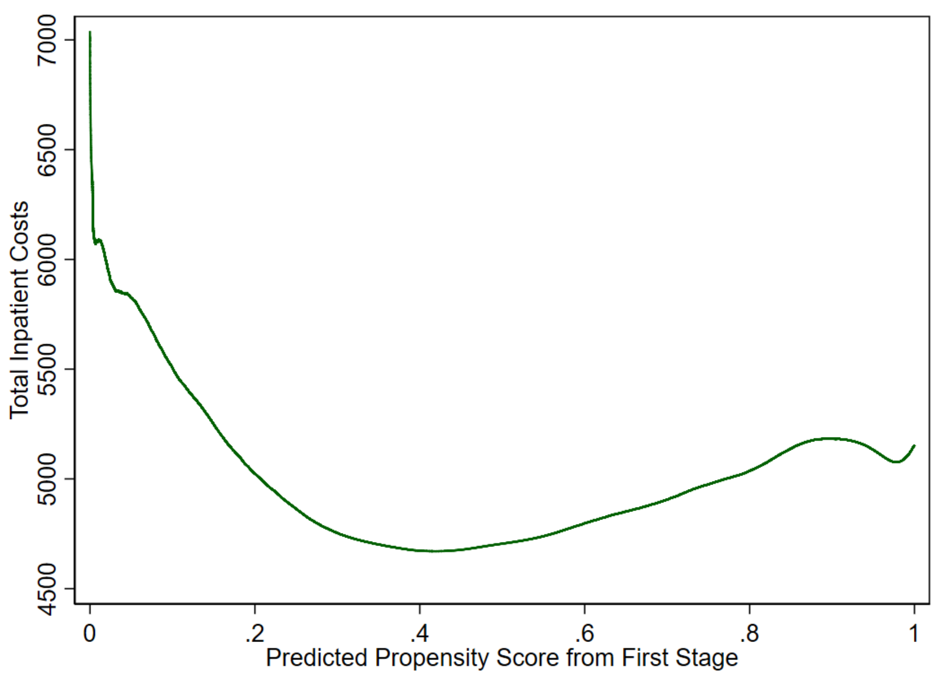


Note: This figure presents binned scatter plots and the locally smoothed relationship of the probability of selecting the FP hospital across the percentiles of differential distance (DD) of the patients. Smoothing done separately for 1st -79th percentiles and 80th-100th percentiles. 80th percentile marks the 10-mile cut-off. No other adjustment was made.

Figure 3. Diagnostics for control function specifications of 2SRI and LIV

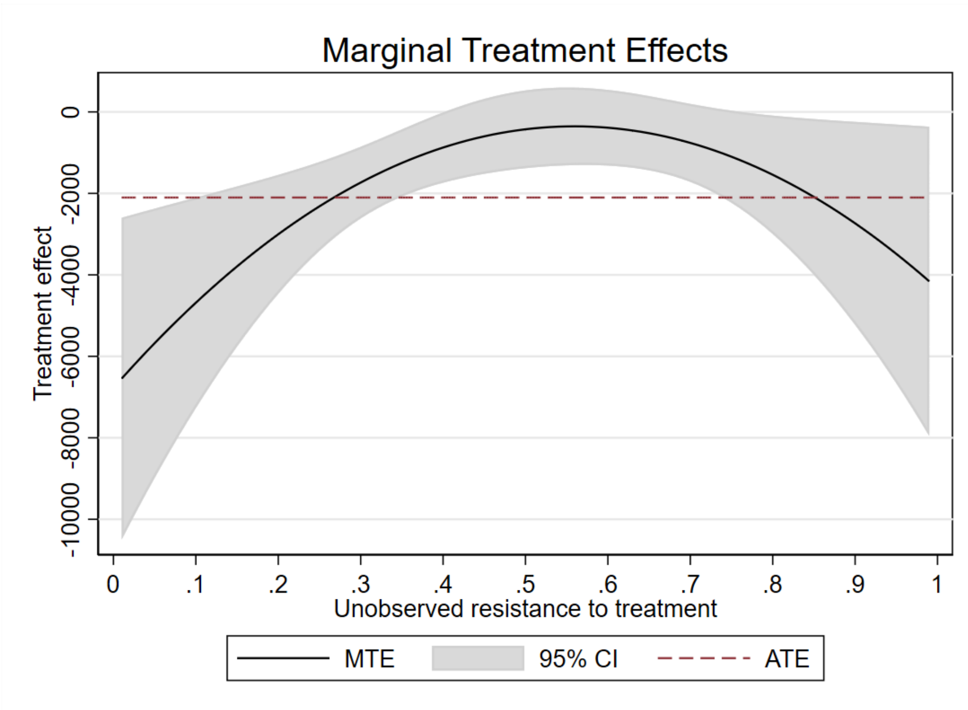


(a) 2SRI



(b) LIV

Figure 4. Heterogeneous treatment effects using local instrumental variable approach. (a) Marginal treatment effect (MTE) distribution over the unobserved resistance to choose for-profit hospitals (based on linear LIV model (b) LIV weights for ATT and LATE



(a) Distribution of MTE

(b) LIV weights

Figure 5. Distribution of person-centered treatment (PeT) effects (based on GLM log-link model)

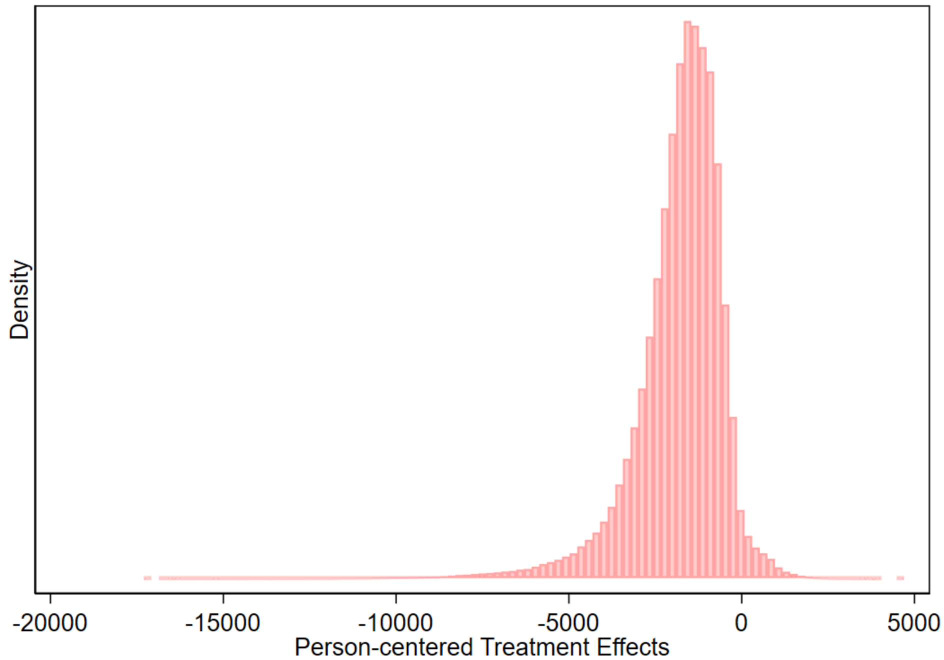
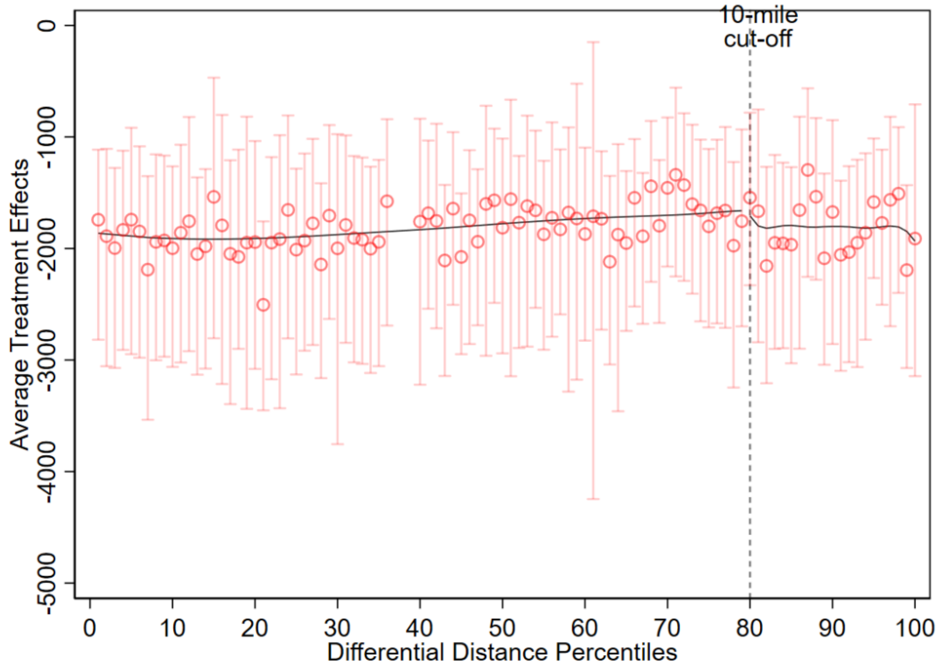
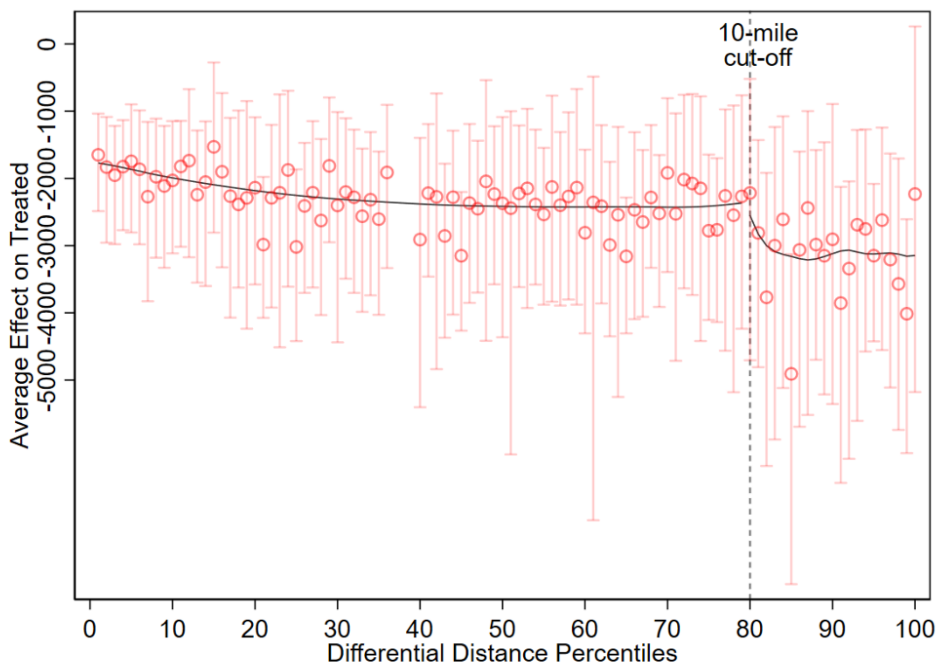


Figure 6. PeT-based treatment effects at each level of differential distance

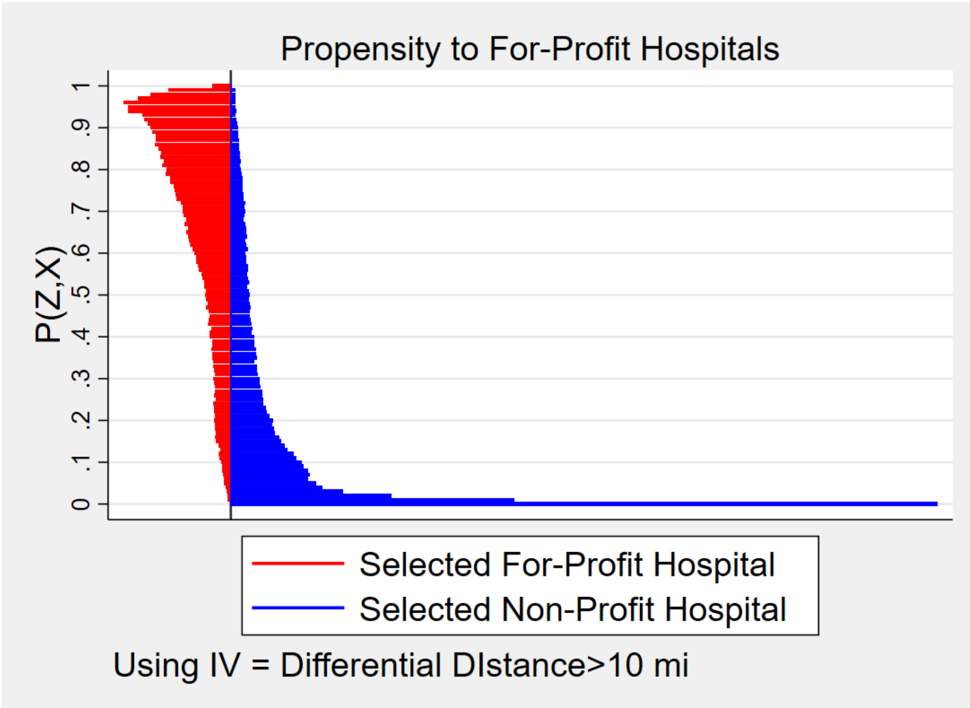


(a) ATE

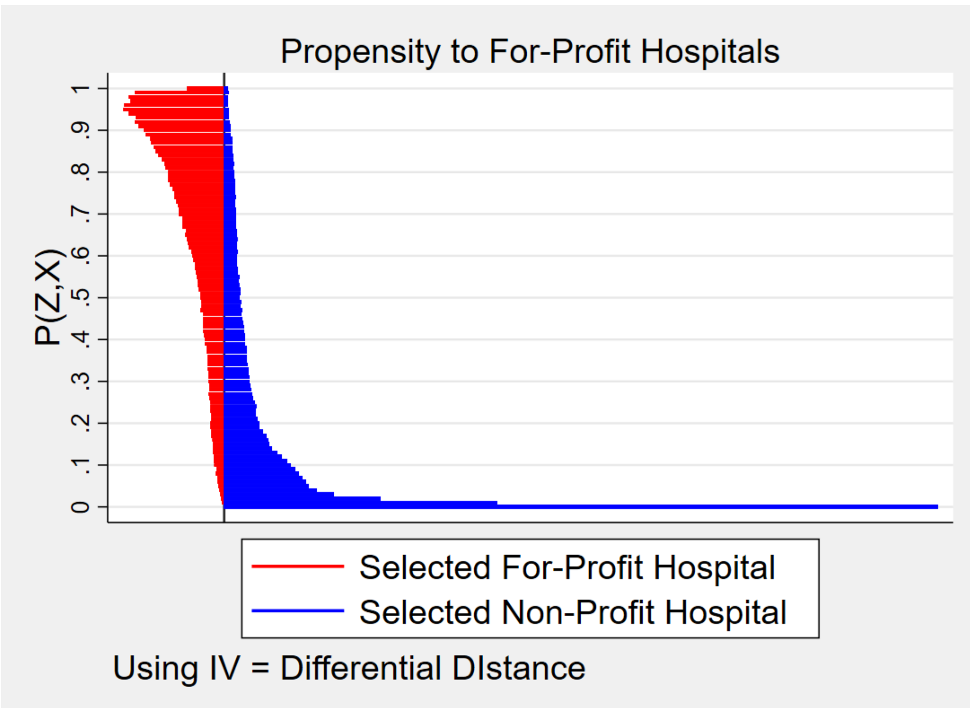


(b) ATT

Figure A1. Predicted probability distribution of selecting for-profit hospital among those who selected for-profit versus not-for-profit hospitals



(a) Binary IV



(b) Continuous IV

Note: The range of propensity score is from 0.001 to 0.999 for both figures, (a) and (b).

Figure A2. Residual analysis for goodness-of-fit for naïve linear model versus log-link GLM model

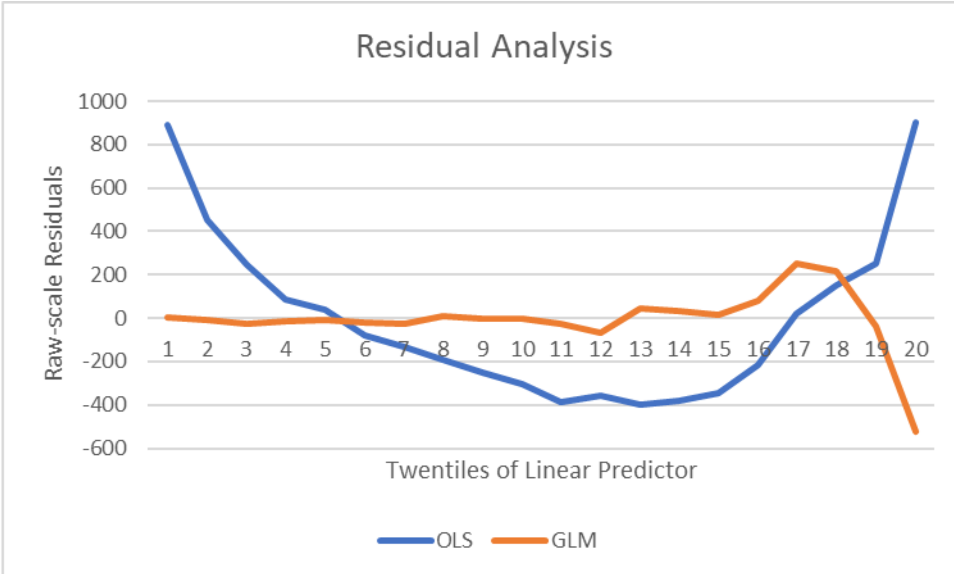


Table 1. Medical and health economics/policy articles using differential distance (DD) as instrumental variable

Authors (Year)	Endogenous Exposure Variable	Instrumental Variable: DD Treatment	DD Comparator	DD Form	Method	Primary Outcomes	Interpretation of Effects
Medical Journals							
McClellan et al. (1994)	Catheterization use	Catheterization hospital[1]	Hospital of any other type	Binary[+]	2SLS	Mortality	W-LATE
Xian et al. (2011)	Admission to stroke centers	Stroke center	Hospital of any other type	Continuous	Bivariate probit	Mortality	AME
Tan et al. (2012)	Surgical treatment (Partial vs. radical nephrectomy)	Physician performing partial nephrectomy	Surgeon performing any kidney cancer surgery	Categorical	2SRI	Mortality	AME
Neuman et al. (2014)	Anesthesia technique (Regional vs. general)	Regional anesthesia hospital*	General anesthesia hospital*	Continuous	Near-far matching	Mortality/ LOS	ATT
Valley et al. (2015)	Admission to ICU	Hospital with high ICU admission*	Hospital of any other type	Continuous	2SLS	Mortality/ Payment/Cost	W-LATE
Werner et al. (2019)	Different post-acute care settings (Home vs. SNF)	SNF	Home health agency	Binary	2SLS	Readmission/ Mortality/Payment	LATE
Health Economics and Policy Journals							
Brooks et al. (2000)	Catheterization use	Catheterization hospital[1]	Hospital of any other type	Binary[+]	2SLS	Mortality	W-LATE
Ettner and Hermann (2001)	Hospital ownership type	FP hospital	NFP hospital	Continuous	2SLS	Cost/LOS/ Readmission	W-LATE
McConnell et al. (2005)	Transfer to different trauma centers (level I vs. level II)	Level II center (From the initial center)	Level I center (From the initial center)	Continuous	Bivariate probit	Mortality	AME
Brooks et al. (2006)	Dialysis center profit status	FP dialysis center	NFP dialysis center	Binary[+]	2SLS	Mortality	W-LATE
Chandra and Staiger (2007)	Catheterization use	Catheterization hospital	Hospital of any other type	Continuous	2SLS	Mortality	ATT
Cutler (2007)	Revascularization use	Revascularization hospital*	Hospital of any other type	Binary[+]	2SLS	Mortality/Cost	W-LATE
Kahn et al. (2009)	Volume of mechanically ventilated patients	Large volume hospital	Small volume hospital	Continuous	2SLS	Mortality	W-LATE
Bowblis and McHone (2013)	Different NH settings (CCRC vs. traditional)	CCRC NH	Traditional NH	Continuous	2SLS	Quality	W-LATE
Grabowski et al. (2013)	NH ownership type	FP NH	NFP NH	Continuous	2SRI	Readmission/ Quality	MEM
Rahman et al. (2013)	Proportion of SMI residents	Psychiatric hospital	General acute care hospital	Continuous	2SLS	Facility quality	W-LATE
Daysal et al. (2015)	Birth at a NICU	Hospital with a NICU	Hospital without a NICU	Continuous	2SLS	Mortality	W-LATE
Rahman et al. (2016)	Different NH settings (Hospital-based vs. freestanding)	Hospital with a SNF	Hospital without a SNF	Continuous	2SLS	Readmission	W-LATE
Frogner et al. (2018)	Access to physical therapist	Provider seen at the index date	Any provider within the same insurance plan	Binary	2SRI	Mortality/LOS/ Cost/Opioid prescriptions	MEM
Huang and Bowblis (2018)	Different NH settings (Owner- vs. salaried-manager)	NH with an owner-manager	NH with a salaried manager	Continuous	2SRI	Quality	AME
Joyce et al. (2018)	Admission to NHs with a dementia SCU	NH with the SCU	NH without the SCU	Continuous	2SLS	Quality	MEM
Konetzka et al. (2018)	Integration of hospitals with post-acute care providers	Integrated hospital	Non-integrated hospital	Continuous	2SLS	Payment/LOS/ Readmission	W-LATE
Huang and Bowblis (2019)	Private equity ownership of NH	FP NH owned by a PE firm	FP NH not owned by a PE firm	Continuous	2SRI	Quality	AME
Swanson (2021)	Admission to physician-owned hospital	Physician-owned hospital	Non- physician -owned community hospital	Continuous	2SLS	Mortality	W-LATE
Burke et al. (2022)	Different post-acute care settings	Home health agency	SNF	Binary	2SLS	Readmission/	LATE

(Home vs. SNF)			Mortality

Note: 2SLS, two-stage least squares; 2SRI, two-stage residual inclusion; ICU, intensive care unit; SNF, skilled nursing facility; FP, for-profit; NFP, not-for-profit; NH, nursing home; CCRC, continuing care retirement community; NICU, neonatal intensive care unit; SCU, special care unit; LOS, length of stay; AME, average marginal effect; ATT, average treatment effect on the treated; LATE, local average treatment effect; W-LATE, weighted average of local average treatment effect; MEM, marginal effect at the means.

+ The regression model features multiple binary DD variables, rather than a single one.

Table 2. Strength of different forms of Differential Distance as an instrument in alternate first stage models

	First stage: OLS		First stage: Logit GLM		First stage
	Binary IV	Continuous IV	Binary IV	Continuous IV	RDD (10 mi)
Differential Distance					
Marginal Effect	-0.14	-0.012	-0.19	-0.014	0.016
Std.Err. (ME)	0.027	0.001	0.03	0.002	0.144
95% CI	[-0.15, -0.09]	[-0.015, -0.009]	[-0.24, -0.13]	[-0.017, -0.011]	[-0.27, 0.30]
F-stat	27	69	41	114	-
Other covariates					
Patient-level cont.	Y	Y	Y	Y	Y
Hospital-level cont.	Y	Y	Y	Y	Y
Area-level cont.	Y	Y	Y	Y	Y
HSA fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
N	1,083,461	1,083,461	1,083,461	1,083,461	1,083,461
R^2	0.45	0.46	0.49	0.51	-
Clustering	HSA	HSA	HSA	HSA	HSA

Note: This table presents estimates from the first stage regression model showing the relationship between the hospital's for-profit (FP) status and the difference in distance to the closest FP hospital and the nearest not-for-profit (NFP) hospital for the patient. For binary IV, we dichotomize the differential distance (DD) on the basis of 10 miles. The predictor variable is the binary or continuous DD calculated based on distances between centroid points of zip code for the patient and the respective hospitals. The dependent variable is an indicator taking the value of 1 if the patient is admitted to FP hospital (0; otherwise). The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, urban/rural status, zip code-level median income, and bed type. The hospital-level controls include general/specialty psychiatric hospitals, teaching hospitals, psychiatric bed count, and case mix index. The area-level control is the Herfindahl–Hirschman index of the hospital. Standard errors are clustered by patient-level HSA.

Table 3. List of estimators and model specifications used in the study

Estimator	Exposure Model (First stage)	Outcomes Model (Second stage)	Parameters Identified	Structural assumptions required for parameter identification
Naïve Linear regression without IV	-	Linear Regression	ATE	• No unobserved confounding • Constant treatment effects
Naïve Non-Linear regression without IV	-	Gamma Log-Link GLM	ATE, ATT, ATUT	• No unobserved confounding
2SLS with binary IV	Linear Regression	Linear Regression	ATE	• Constant treatment effects
			LATE	• Heterogeneous treatment effects
2SLS with continuous IV	Linear Regression	Linear Regression	ATE	• Constant treatment effects
			W-LATE	• Heterogeneous treatment effects
2SRI with binary IV-based generalized residual	Logit Regression	Gamma Log-Link GLM	ATE	• Generate continuous control function when binary IV combined with other X's • IV-based propensity spans close to full support
2SRI with continuous IV-based generalized residual	Logit Regression	Gamma Log-Link GLM	ATE	• Generate continuous control function • IV-based propensity spans close to full support
LIV approach with continuous IV	Logit Regression	Linear Polynomial Regression	MTEs, ATE, ATT, ATU	• IV-based propensity spans close to full support
LIV approach with continuous IV	Logit Regression	Gamma Log-Link GLM	MTEs, PeTE, ATE, ATT, ATU	• IV-based propensity spans close to full support
Fuzzy RDD	Local Linear Regression	Local Linear Regression	ATE	• Constant treatment effect
			LATE	• Heterogeneous treatment effect

Table 4. Summary statistics of the inpatient psychiatric admissions in the OSHPD dataset

	Not-for-profit (N = 640,543)	For-profit (N = 442,918)
Outcome		
Cost per discharge	5667.7 (7172.6)	4815.2 (5487.8)
IV		
Differential Distance (continuous)	6.6 (10.8)	-1 (8.7)
Differential Distance (> 10 miles, %)	26.3	4.7
Covariates		
Female (%)	54	50
Age category (%)		
0-17 years	8	17
18-34 years	23.2	22.2
35-64 years	53.9	50.0
65 years and over	14.9	10.8
Race (%)		
Black/Hispanic/Other	17.1	24.3
Primary diagnosis (%)		
Schizophrenia	29	36
Bipolar disorder	19	20
Major depression	27	27
Depression	6	6
Alcohol use disorder	7	3
Drug use disorder	2	2
Other	11	7
Rural (%)	2	2
Zip code-level median income	63648 (23047)	60181 (20829)
Payer category (%)		
Private	30	29
Medicare	59	61
Medi-Cal	35	35
County	24	26
Charity/Self-pay	1	4
Other	7	3
Managed care	27	22
Source of admission (%)		
This hospital – emergency room	41	15
This hospital – general	7	4
Transfer from another hospital	5	7
Not a hospital	47	74
Type of licensed bed (%)		
Scatter bed	20	9
Psychiatric unit	80	91
Specialty psychiatric hospital (%)	17	55
Teaching affiliation (%)	19	0
Number of psychiatric beds	51 (32)	73 (36)
Case mix index	1.06 (0.24)	0.86 (0.2)
Herfindahl–Hirschman index	3193 (1254)	2774 (1013)

Note: This table presents patient-level summary statistics by hospital ownership status (for-profit/not-for-profit) between 1995-2011. A unit of observation is a patient discharge from psychiatric admission. The total patient number is calculated by summing over discharge events according to the ownership status. The zip code-level median income is dollars in 2000, and the number in parenthesis indicates the standard deviation. All variables included in this table are used as patient-level controls in the regression model. Please note that categories of the variables reflect the types of variables (i.e., continuous/binary/categorical) in the model. The Herfindahl–Hirschman index is established using actual patient flows based on patient-level zip code.

Table 5. Effects of for-profit hospital status on total inpatient costs

Estimators	Parameters	Mean (SD) [95% CI]	
Naïve			
OLS	ATE	-679*** (161) [-1003, -389]	
Log-Link-Gamma QL	ATE	-867*** (168) [-887, -288]	
2SLS			
Binary IV	LATE	-2899** (1231) [-5561, -1039]	
Continuous IV	W- LATE	-1416*** (427) [-2290, -787]	
2SRI+(Logit/Log-Link-Gamma)			
Binary IV	ATE	-2512*** (656) [-3799, -1226]	
Continuous IV	ATE	-2274*** (542) [-3257, -1443]	
LIV with Continuous IV			
		Logit/Linear polynomial	Logit/GLM Log link polynomial
	ATE	-2101*** (470) [-2991, -1300]	-2128*** (427) [-3101, -1447]
	ATT	-2359*** (542) [-3633, -1469]	-2391***(589) [-3852, -1352]
	ATU	-1925*** (479) [-2923, -1096]	-1928***(420) [-2809, -1208]
	W-LATE	-1860*** (404) [-2712, -1174]	
RDD Fuzzy	LATE	-12992 (57245) [-125192, 99208]	
N		1,083,461	

Note: This table presents estimates of the effects of for-profit hospital status on total inpatient costs. All regression models include patient-, hospital-, and area-level control variables, as well as patient HSA and year fixed effects. The patient-level controls include sex, race, age, payment and managed care status, psychiatric diagnosis, urban/rural status, zip code-level median income, and bed type. The hospital-level controls include general/specialty psychiatric hospitals, teaching hospitals, psychiatric bed count, and case mix index. The area-level control is the Herfindahl–Hirschman index of the hospital. Standard errors and Central 95% CI are obtained via 1000 bootstrap replicates, clustered by patient-level HSA. The number in parenthesis indicates the standard errors. The number in bracket indicates the 95% confidence intervals. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

+ Two-stage residual inclusion approach, using generalized residual and its square from first stage, and interactions of treatment with both. Control function specification obtained via goodness-of-fit tests.

OLS, ordinary least squares; GLM QL, generalized linear model quasi-likelihood; 2SLS, two-stage linear squares; 2SRI, two-stage residual inclusion; LIV, local instrumental variable; ATE, average treatment effect; ATT, average treatment effect on the treated; ATU, average treatment effect on the untreated; LATE, local average treatment effect; RDD, regression discontinuity design.

Chapter 5. CONCLUSIONS

In Chapter 2, we investigated whether FP hospitals practice cream skimming among inpatient psychiatric admissions in California. We have developed a novel approach based on the IV method to determine the evidence of cream skimming. This approach allows us to explicitly account for the two different channels of the ownership effects, patient selection and execution of cost containment strategy, combined within the estimates. Our analysis indicates that FP hospitals do not practice cream skimming. Conversely, our evidence suggests that NFP hospitals are likely to engage in cream skimming.

In Chapter 3, we examined the effects of competition on costs and the quality of care within the inpatient psychiatric care market in California. To mitigate the potential endogeneity bias associated with competition measure established by the patient's actual hospital selection, we employed a discrete choice framework to model patient's hospital choice – we relied on a plausibly exogenous source of variation, travel distance to the hospital from patient's home. Our main findings revealed a significant heterogeneity in the impact of competition on costs across different types of hospitals, patient insurance coverage characteristics, and reimbursement methods. Particularly, we found that when competition was intensified, costs in NFP general hospitals decreased before the introduction of the IPPPS; in contrast, the costs increased after the implementation of the IPPPS. Among specialty hospitals, however, the impact of competition on NFP hospitals consistently resulted in decreased costs.

In Chapter 4, we provided insight into the heterogeneity of causal parameters obtained from various IV approaches using DD. Notably, there has been a lack of attention to investigating the variations in different causal treatment effects produced by different forms of DD variables and the specific IV approaches. Our analysis provided compelling evidence that different forms of DD and IV approaches yielded heterogeneous estimates for various causal parameters. Additionally, this evidence suggests that use of binary IV unrelated to policy implementation should be discouraged.

VITA

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