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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 using 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 (IV) 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 FP hospitals are more likely to treat high-cost patients than not-for-profit (NFP) hospitals, showing no evidence that FP hospitals engage in cream skimming. Our results may alleviate concerns surrounding the recent proliferation of FP psychiatric hospitals with regards to cream skimming.

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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[1]. 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 (i.e., those without health insurance) in public hospitals. Cheng et al. (2015) examines patterns of patient transfers among hospitals in Australia and identify that

[1] If the diagnosis-related group (DRG) system can fully account for cost differences, this statement may not always hold true since patients with more severe, resource-intensive, and complex DRGs tend to receive higher payments. However, it is less likely that the DRG system completely addresses the differences due to the heterogeneity of disease severity and treatment intensity among patients.

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 an unobserved market characteristic 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). Variations in the managerial teams' capabilities and motivations could also influence the profit margins of patient care. One study comparing the performance of psychiatric inpatient care providers indicated that NFP hospitals outperformed FP counterparts in cost reduction (Rosenau & Linder, 2003). Likewise, 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 and expected profitability can also be driven by the differential execution of healthcare delivery upon admission, signifying a dimension of productivity.

The main goal of this paper is to assess the effects of hospital ownership status on cream skimming behavior, with a particular focus on costs, using inpatient psychiatric admission data in California. Compared to the existing approaches relying on other proxy measures of cream skimming, such as insurance status and disease severity (Cheng et al., 2015; Duggan, 2000), the direct use of cost data can reduce uncertainty of estimating the patient's expected resource use. Moreover, the previous studies have relied on exogenous policy changes or detailed patient transfer records between FP and NFP hospitals to account for potential endogeneity of ownership status. We achieve the same goal uniquely by implementing multiple modeling techniques. Specifically, if we determine cream skimming by assessing the association between ownership types and patient's treatment costs through the naïve regression 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 a naïve generalized linear model (GLM) to estimate the association of the ownership type with patient-level treatment costs. Estimates from the naïve GLM comprise 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 residual inclusion (2SRI) 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 allows us to acquire the patient-level cost estimates solely derived from the hospital cost containment practices varying by the ownership type. In the final step, we extract the effect of the differential patient case mix by subtracting the 2SRI estimate (i.e., the effect of hospital cost containment) from the naïve estimate (i.e., the combined effects). The difference between the two estimates indicates the effect of hospital behavior referring to cream skimming. We construct the standard errors for all the estimates based on 1000 rounds of clustered bootstrapping at the patient-level hospital service area (HSA).

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-level and hospital-level analysis, respectively. Section 7 presents the results. Section 8 discusses the findings and concludes.

2. BACKGROUND

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 (Lutterman et al., 2017). During this period, the country experienced a steady increase in patients staying in private psychiatric hospitals. 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 (ACA) 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. 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).

2.3. 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.

2.4. 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.

3. STUDY OBJECTIVES AND HYPOTHESES

The primary objective 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. Our hypothesis, based on the patient-level analysis, posits that FP hospitals admit patients with lower costs (i.e., lower severity) without necessarily achieving higher efficiency compared to NFP hospitals.

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) using hospital-level data. Our hypothesis of the hospital-level analysis is that FP hospitals operate inpatient psychiatric units with fewer staff 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 without sacrificing demand and reputation of their services by hedging on quality. The hospital-level analysis provides implications for the quality of care.

4. DATA AND DESCRIPTIVE STATISTICS

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.

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, one for the general acute care hospitals and the other for the specialty psychiatric hospitals, are established to account for potentially different treatment and resource utilization patterns between these 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) patients are admitted from or returned to a prison/jail, (2) death in the hospital is denoted, (3) 365 days of hospital stay is exceeded, (4) patients are from state hospitals, long-term care facilities, hospitals in the Kaiser Permanente system, and public hospitals, and which are from the hospital (5) without licensed psychiatric beds and (6) without case mix index (CMI) information. In addition, we symmetrically drop (7) 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 1,092,287 (731,220 for general hospitals and 361,067 for specialty hospitals; Figure S1).

4.3. Outcomes

The dependent variables are total costs per admission, average costs per day, and length of stay (LOS). 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 average costs per day and LOS. The former represents the intensity of care, while the latter 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. Patients whose admission and discharge occur on the same day are denoted as LOS of 1 day.

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 (white/non-white), age (0-17, 18-34, 35-64, 65 years and over), 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 others, 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, number of licensed psychiatric beds, and CMI. Market characteristics include market concentration level measured by Herfindahl-Hirschman Index (HHI)[2]. 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 for inpatient psychiatric services (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.

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 patient severity and does not vary between the hospitals. Among specialty hospitals, NFPs operate a slightly larger number of psychiatric beds, maintaining bed turnover rates comparable to those of FPs. NFPs exhibit higher ratios of physicians to hospital beds and nursing staffs to hospital beds, respectively, while demonstrating minimal differences in the CMI compared to FPs.

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[2] The HHI of a hospital is measured by the sum of the squared market shares of psychiatric patients from each zip code. We defined the hospital's market share for each zip code as the proportion of psychiatric patients admitted from that zip code out of the total psychiatric patients staying at the hospital.

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 specialty hospitals than in general hospitals. About 30 percent of inpatient psychiatric admission is from this minor group in specialty 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 approximately 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 percent 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 almost two-fold higher than in their counterpart FPs. Additionally, approximately 40 to 50 percent of patients in specialty hospitals are covered by private insurance, which is notably different from general hospitals, where the proportion of those is lower than 15 percent in FP general hospital. Fourth, about 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.

5. EMPIRICAL STRATEGY FOR PATIENT-LEVEL ANALYSIS

5.1. Naïve log-link GLM

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 using the log-link GLM model with gamma distribution.

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

where $\widehat{FP}_{ijmt}$ is a dummy variable with the value of 1 for patient i in 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, 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, psychiatric bed count, CMI, and HHI. We implemented clustered bootstrapping approach (1000 times) to establish the standard errors at the patient-level HSA.

It is worth reiterating that the effect of ownership type in the naïve GLM 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 differences in patient-level 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 either FP or NFP 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.

5.2. 2SRI IV Model

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.

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 the IV model as causal treatment effects, 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 specialty psychiatric hospital samples, respectively. Below is the specification of the first stage model.

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

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.

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).

To test for random assignment, it would be ideal to check the balance of observed and unobserved variables between patients above and below median of DD. However, this is impractical because we cannot address "unobserved" factors. Instead, we report 31 patient characteristics for those groups, categorized by whether their values of DD are below or above the median (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 median 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 naïve GLM analysis.

Another evidence for randomization is to confirm that the 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 continuous 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 continuous IV measure of this study.

Lastly, we show that our continuous 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 specialty hospitals are 89 and 34, 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 continuous 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 a 10 mile increase in DD decreases the probability of going to a FP hospital by 19 and 6 percentage points for general and psychiatric hospitals, respectively.

5.2.3. Model Specification

Two-stage least squares (2SLS) and 2SRI models are widely employed approaches in IV analysis. The 2SLS estimator identifies the average treatment effects in cases where effect sizes are homogeneous; however, in reality, it is unlikely that each individual across the IV status experiences the same treatment effect. Thus, when treatment effects are heterogeneous, the 2SLS estimator with binary IV reports a local average treatment effect (LATE), while the estimator with continuous IV yields a weighted average of LATEs (Imbens & Angrist, 1994)[3]. The 2SRI estimator, on the other hand, can be interpreted as average treatment effects, particularly when a treatment variable is binary (Terza et al., 2008). We adopted the 2SRI model for our IV analysis to improve comparability with the prior analysis that would produce (biased) estimates of average treatment effects.

Based on the concept of control function methods, the 2SRI model aims to address endogeneity (i.e., unmeasured confounding) by including residuals obtained from the first-stage regression as additional regressors in the second-stage regression (Wooldridge, 2015). However, the estimate of the 2SRI model could be biased if the types of residuals and its functional form

[3] For continuous IV, the causal treatment effect 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 $Z_i = IV_j$ and $Z_i = IV_j - 1$ (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.

are not correctly specified (Basu et al., 2018). To mitigate these concerns, we used generalized residuals as the core component of the control function. Furthermore, we relied on goodness-of-fit criteria in determining the functional form of the control function. As shown in Figure S2, which presents the locally weighted smoothed plots of the outcomes against the generalized residuals by treatment groups, we observed curvilinear relationships that vary between the treatment groups. This suggests that a quadratic polynomial of the generalized residuals interacting with the treatment dummy may serve as a suitable functional form for the control function. We conducted likelihood ratio tests to compare this specification with parsimonious alternatives where either the polynomial terms or the interactions were excluded. The results of the tests indicated that our suggested functional form provides the best fit for the general hospital samples. However, among the specialty hospital samples, the simpler specification omitting the interaction between the polynomial of the residuals and the treatment indicator demonstrated a better fit than the suggested functional form. Consequently, we used different functional forms as the control function for the separate hospital sample sets.

The effect of ownership type is estimated in two stages, using Equation (3) in the first stage and Equation (4) in the second stage. In the first stage, we used a logit model, while in the second stage, a GLM with a log link function and gamma distribution was implemented.

$$ln\frac{Pr(\widehat{FP}_{ijmt})}{1-Pr(\widehat{FP}_{ijmt})} = \alpha_m + \alpha_t + DD_i + \beta X'_{iz} + \delta H'_j \quad (3)$$

$$Y_{ijmt} = exp(\alpha_m + \alpha_t + \varphi\widehat{FP}_{ijmt} + CF_{2SRI} + \beta X'_{iz} + \delta H'_j) \quad (4)$$

where our endogenous regressor of interest $\widehat{FP}_{ijmt}$ is an indicator variable with the value of 1 if patient i in HSA m selects FP hospital j in year t. DD_i is a continuous variable, indicating the DD of patient i based on zip code of residence z. 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, psychiatric bed count, CMI, and HHI. CF_{2SRI} is a group of control function[4]. Standard errors are established through 1000 times of clustered bootstrapping at the patient-level HSA 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. We perform the IV analysis separately for each hospital sample. We report marginal effects for the 2SRI estimates.

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 naïve estimates of the GLM 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 naïve 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 HSA.

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 includes information on labor resources. The list of hospital-level outcomes includes the number of physicians per bed, number of nurses per bed, and nurse hours per patient day. 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.

[4] The control function used for general and specialty hospital samples includes $\widehat{FP} \times \varepsilon^2 + \widehat{FP} \times \varepsilon + \varepsilon^2 + \varepsilon$ and $\widehat{FP} \times \varepsilon + \varepsilon^2 + \varepsilon$, respectively. Note that ε is the generalized residuals obtained from the first stage regression of 2SRI model.

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 ordinary least squares (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. We also adjust an additional set of covariates into the first stage model: profit margin and operating margin. 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 S3 shows that after the full matching, distributions of the propensity scores become almost identical between the FP and NFP hospitals. Figure S4 also confirms that the full matching method improves the covariate imbalance remarkably compared to unmatched samples except for a few variables including the cost-to-charge ratio and HHI. 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.

7. RESULTS

7.1. Naïve GLM Results

Table 5 presents the results of Equation (1) using the naïve GLM for patients admitted to general hospitals (Columns (1) to (3)) and specialty hospitals (Columns (4) to (6)). The results represent biased estimates regarding the effects of hospital ownership types on costs and utilization.

In Panel A, among patients admitted to general hospitals, the average cost per day is 45 dollars lower in FP hospitals than in NFP hospitals ($p < 0.05$). However, the LOS is 0.4 days longer in FP hospitals compared to NFP hospitals ($p < 0.05$). Among patients from specialty hospitals, the total cost per discharge is 1360 dollars lower than that of NFP hospitals. This reduction is attributed to both the decreased intensity and duration of care. Specifically, the cost per day and the LOS in FP hospital are 150 dollars ($p < 0.001$) and 0.4 days ($p < 0.05$) lower, respectively, compared to NFP hospitals.

By comparing Panel B and C, we can identify distinct treatment patterns of hospitals by their ownership type depending on payer types. Notably, there is no significant difference in hospital behaviors between private insurance and Medicare beneficiaries, except for the discharge practices. For example, compared to NFP hospitals, FP hospitals tend to discharge private insurance patients earlier while maintaining longer stays for Medicare patients.

7.2. 2SRI IV Results

Table 6 exhibits the results of Equation (4) through the 2SRI approach for patients admitted to general hospitals (Columns (1) to (3)) and specialty hospitals (Columns (4) to (6)). The results demonstrate unbiased estimates of the effects of hospital ownership types on costs and utilization.

The estimates from the 2SRI models show analogous patterns to the previous results from the naïve models but with a more pronounced impact. Particularly, within the samples from specialty hospitals, FP hospitals are more likely to reduce the total cost per discharge compared to NFP hospitals. Furthermore, the average cost per day and the LOS were 177 dollars ($p < 0.001$) and 0.6 days ($p < 0.05$) lower, respectively, in FP hospitals.

Among private insurance patients in Panel B, the effect sizes for the LOS show an increase in both hospital samples, consequently attaining statistical significance at $p < 0.05$. In contrast, among Medicare beneficiaries in Panel C, an opposite pattern is observed in specialty hospitals where the discrepancy in the LOS between FP and NFP hospitals decreases towards null.

7.3. Bootstrapped Results

Table 7 presents the results reflecting the effects exclusively derived from the unobserved differential patient case mix of FP and NFP hospitals on costs and resource utilization. Note that the estimates in Table 7 are computed by subtracting the estimates in Table 6 from the corresponding estimates in Table 5 based on patient samples admitted to the general and specialty hospitals, respectively. Figure 5 illustrates a summary of the results from the three distinct modelling approaches (i.e., naïve GLM, 2SRI, and bootstrapped results).

In Panel A, among all patients admitted to general hospitals, FP hospitals have 240 dollar higher cost per discharge ($p < 0.05$) than NFP hospitals[5]. The same observation is found in Panel C among Medicare beneficiaries admitted to general hospitals ($p < 0.05$). For all patients admitted to specialty hospitals, both the cost per discharge and the cost per day are higher in FP hospitals than in NFP hospitals by 344 and 28 dollars, respectively ($p < 0.05$). This trend also applies to private insurance patients admitted to specialty hospitals. However, among Medicare beneficiaries, there are no statistically significant differences across the costs and LOS outcomes between FP and NFP specialty hospitals.

7.4. PSM Results

Table 8 presents the results from Equation (5) based on the hospital-level data of specialty hospitals. Panel B includes estimates of the PSM model, indicating that FP hospitals invest fewer labor resources for inpatient psychiatric care. For instance, the number of physicians per bed and the number of nurses per bed in FP specialty hospitals is 2 and 0.5 are lower, respectively. Furthermore, patients in FP specialty hospitals tend to receive one hour less attention from nurses per day.

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

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[5] We derived this figure by subtracting the cost per discharge of -257.2 dollars in Table 6 from the cost per discharge of -17.4 dollars in Table 5.

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 naïve log-link GLM and 2SRI 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 naïve log-link GLM model consist of the effects of hospital cost containment strategies and differential patient case mix, we subtract the IV estimates from the combined naïve estimates to obtain unbiased estimates representing differential patient case mix only.

Our main results indicate that FP hospitals do not practice cream skimming. From both general and specialty hospitals, we find that the cost per discharge attributed to differential patient case mix is approximately 200 to 300 dollars higher in FP hospitals compared to NFP hospitals (Panel A in Table 7). Essentially, this demonstrates that FP hospitals are more inclined to treat higher cost patients, implying a lack of avoidance towards patients who require costly medical interventions. Additionally, given the higher cost per day and the absence of statistical differences in the LOS between FP and NFP hospitals, we characterize the patients admitted to FP hospitals as those who may not necessarily require extended hospitalization but do require more daily medical attention. This finding can be partly attributed to patients' comorbidity status and the presence of caregivers (Eassom et al., 2014).

The subgroup analysis focusing on patient insurance types allows us to further examine the potential variations in (unobserved) patient case mix between the hospitals. We observe that our primary finding, which suggests that both FP general and specialty hospitals tend to admit patients with higher cost profiles compared to NFP hospitals, does not uniformly hold true across different patient insurance groups (Panels B and C in Table 7). Specifically, general FP hospitals are likely to admit Medicare patients with higher costs, while overall cost measures do not reveal statistically significant differences for privately insured patients compared to NFP general hospitals. In contrast, specialty FP hospitals are associated with higher costs for private insurance patients, whereas their Medicare patients do not necessitate higher costs compared to NFP specialty hospitals.

Our IV analysis also shows that FP hospitals perform superior to NFPs in terms of containing costs (Table 6). FP general hospitals offer services at reduced costs, particularly among patients with private insurance and Medicare (Panels B and C in Table 6). Among specialty hospitals, FP hospitals also provide services at lower costs than the NFPs. These findings may suggest the possibility of attaining higher efficiency in treating psychiatric patients compared to NFP hospitals. The sources of cost savings appear to stem from both reduced intensity and duration of care, as evidenced by the lower cost per day and LOS in FP specialty hospitals compared to NFPs (Panel A in Table 6).

Based on the above findings from the patient-level analysis, we evaluate our initial hypothesis – FP hospitals admit low-cost patients (i.e., engage in cream skimming) but may not achieve higher efficiency compared to NFPs. In fact, the empirical results of this study indicate the contrary, especially among private insurance patients admitted to specialty hospitals. We view this opposing phenomenon as the combined influence of two distinct features of FP specialty hospitals: their marketing strategy and the target patients. One of the marketing strategies of FP specialty hospitals involves providing services at a reduced cost (Gaylin, 1985). Moreover, specialty hospitals reputedly focus less on treating elderly patients due to the 190-day lifetime coverage limit of specialty psychiatric hospital care set by Medicare (Ettner, 2001). Consequently, privately insured patients experiencing severe mental health conditions may disproportionately choose FP specialty hospitals for inpatient services. Furthermore, the FP specialty hospitals may actively engage with these high-cost patients to enhance their market share and competitive position in the market. Therefore, we deduce that FP hospitals are likely to implement more robust cost containment strategies than NFPs to sustain their businesses without incurring financial losses, while preserving their market dominance.

The hospital-level analysis of labor resources increases our understanding of the cost containment strategy among FP specialty hospitals (Table 8). 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 five 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.

When evaluating the efficiency of care delivery based on cost outcomes, it is crucial to consider quality measures as a whole. The hospital-level finding indicates that cost containment practices of FP specialty hospitals may not incorporate efforts to improve efficiency. Instead, our evidence suggests that FP specialty hospitals may compromise the quality of patient care by reducing costs associated with the salaries of physicians and nurses. These findings may offer a legitimate rationale for potential quality and 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).

Our study is subject to several limitations. First, despite the comprehensive inclusion of various insurance payers, our analysis does not guarantee external validity regarding geographic locations, since the OSHPD data only encompasses inpatient discharge information from hospitals in California. Second, given that the OSHPD data only covers up to 2011, this study does not fully account for potential shifts in hospital behaviors and market dynamics since the passage of the Mental Health Parity and Addiction Equity Act of 2008 and the ACA of 2010. Future research could examine whether hospitals in the inpatient psychiatric care market alter their behaviors in response to changes in market characteristics (i.e., the evolving composition of ownership status, chains and system affiliation) using recent data (Shields et al., 2021). Third, the hospital-level analysis of quality measures is susceptible to omitted variable bias because of the limitations of the PSM approach. Thus, caution should be exercised when interpreting the findings on hospital efficiency alongside patient-level cost outcomes.

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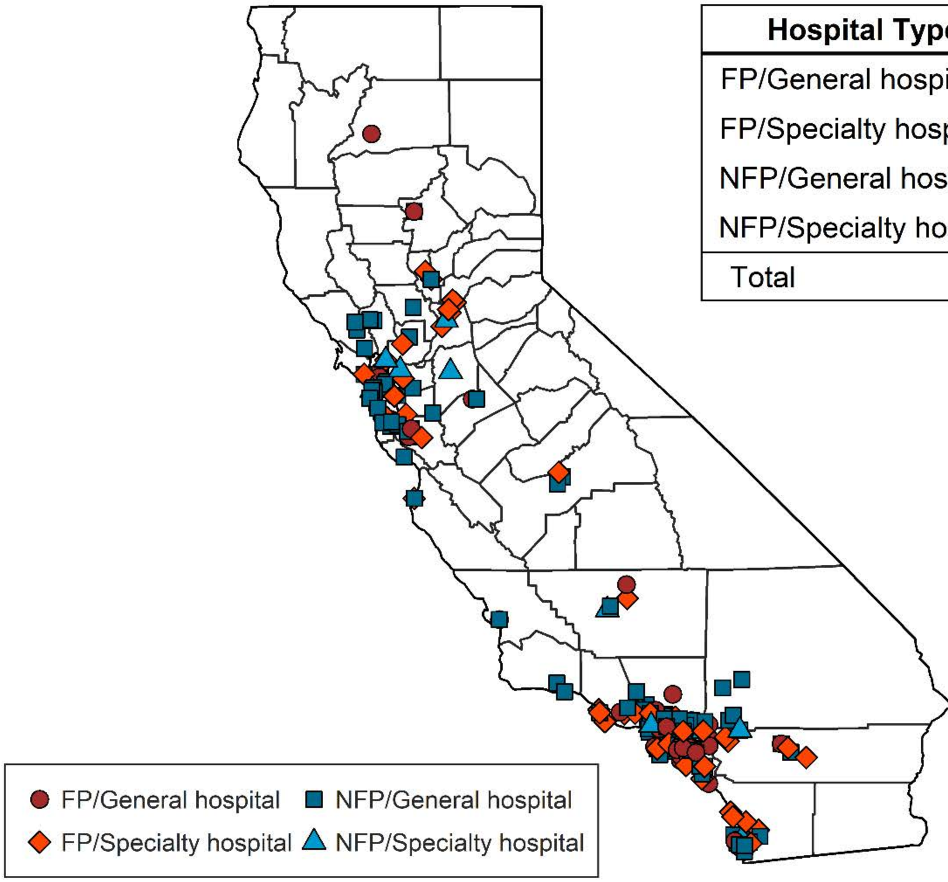
Figures and Tables

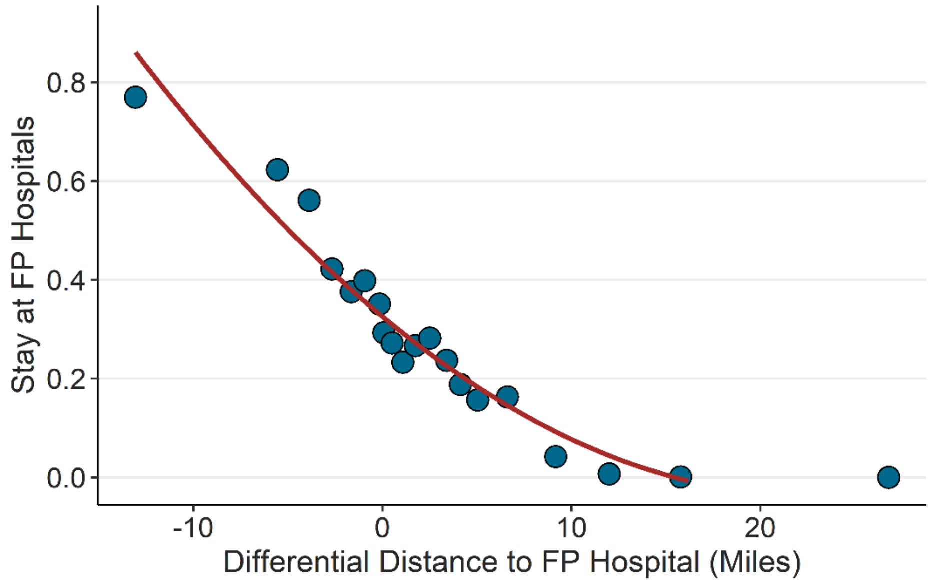
Figure 1. Geographical distribution of private hospitals with licensed psychiatric beds in California



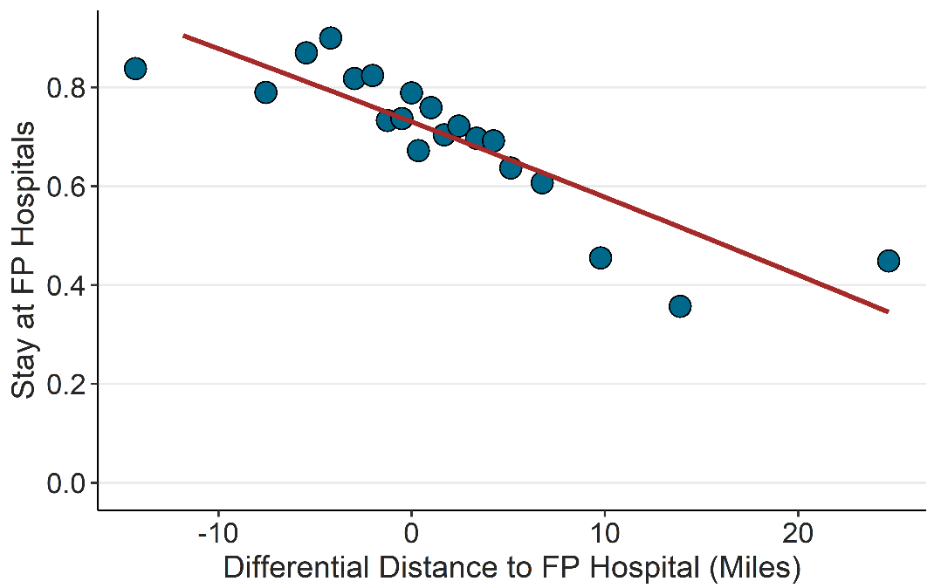
Hospital Type	N
FP/General hospital	51
FP/Specialty hospital	55
NFP/General hospital	96
NFP/Specialty hospital	13
Total	215

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

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



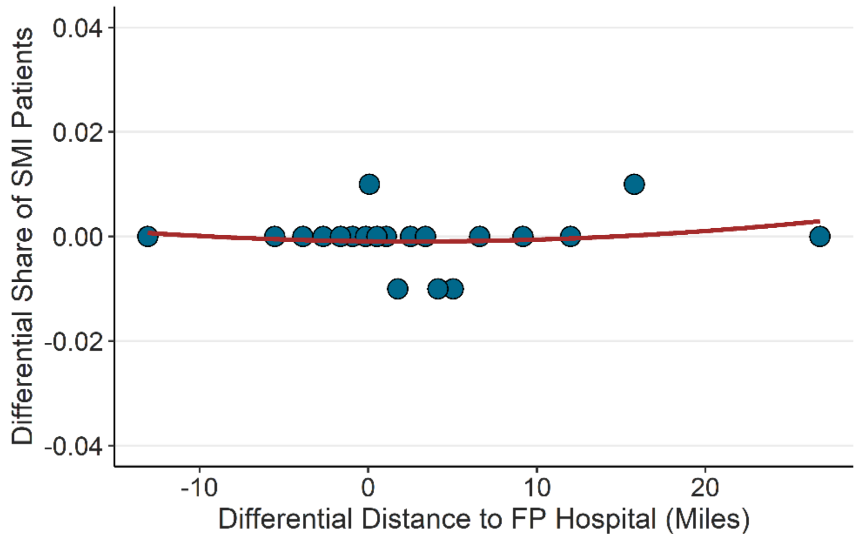
A: General hospital



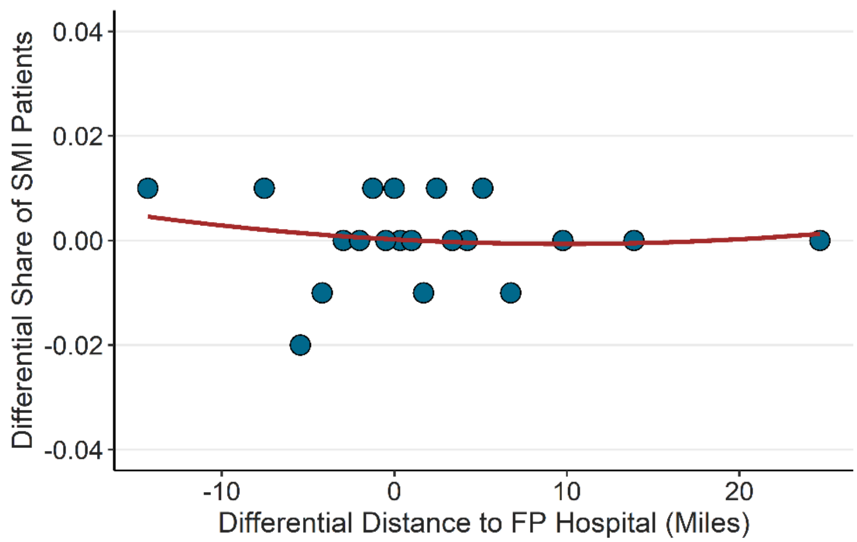
B: Specialty hospital

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



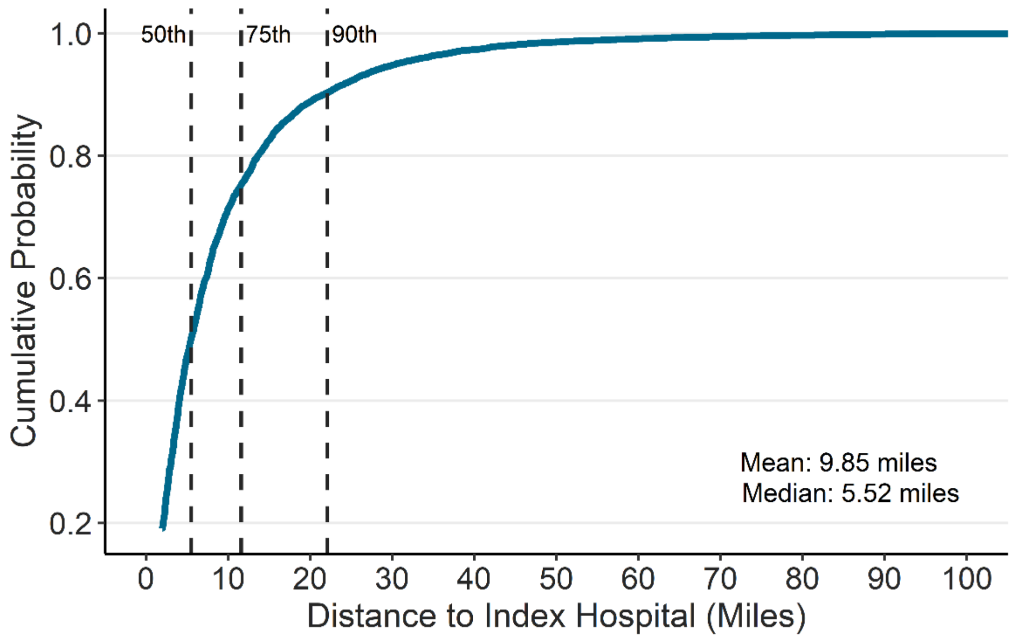
A: General hospital



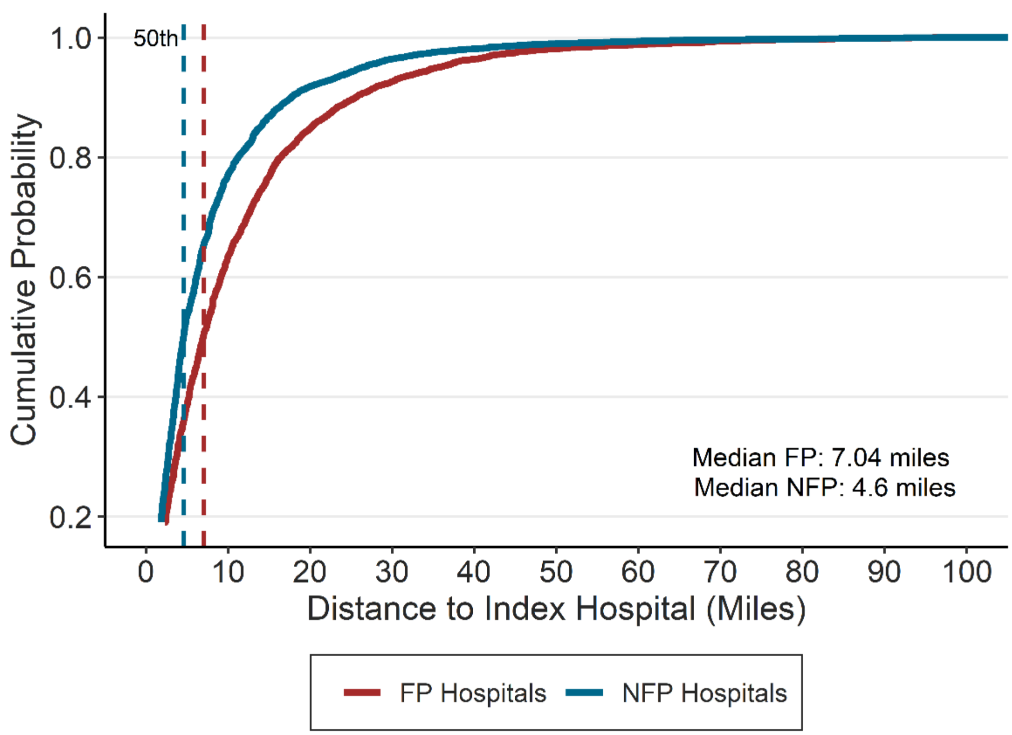
B: Specialty hospital

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 continuous DD 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 specialty hospitals. All regressions include patient- and hospital-level control variables including HHI, patient HSA and year fixed effects. The quadratic fitted lines are displayed in the figure. Specialty hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities.

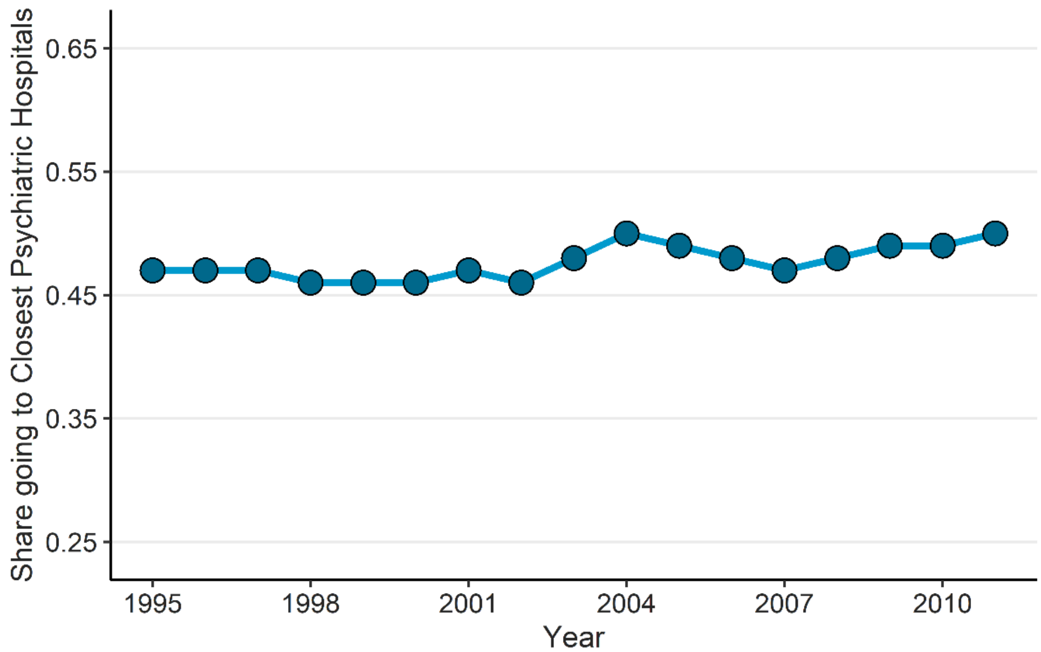
Figure 4. Distance from the patient's residence to the admitted hospital



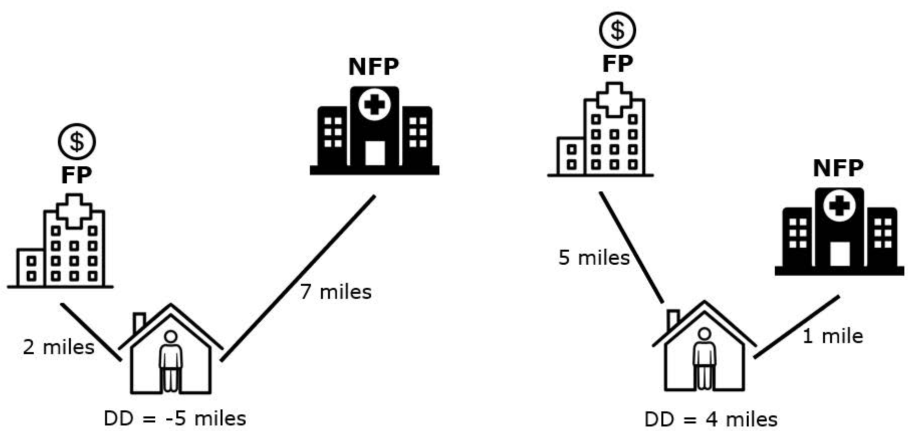
A: CDF: All patients



B: CDF: FP vs. NFP patients



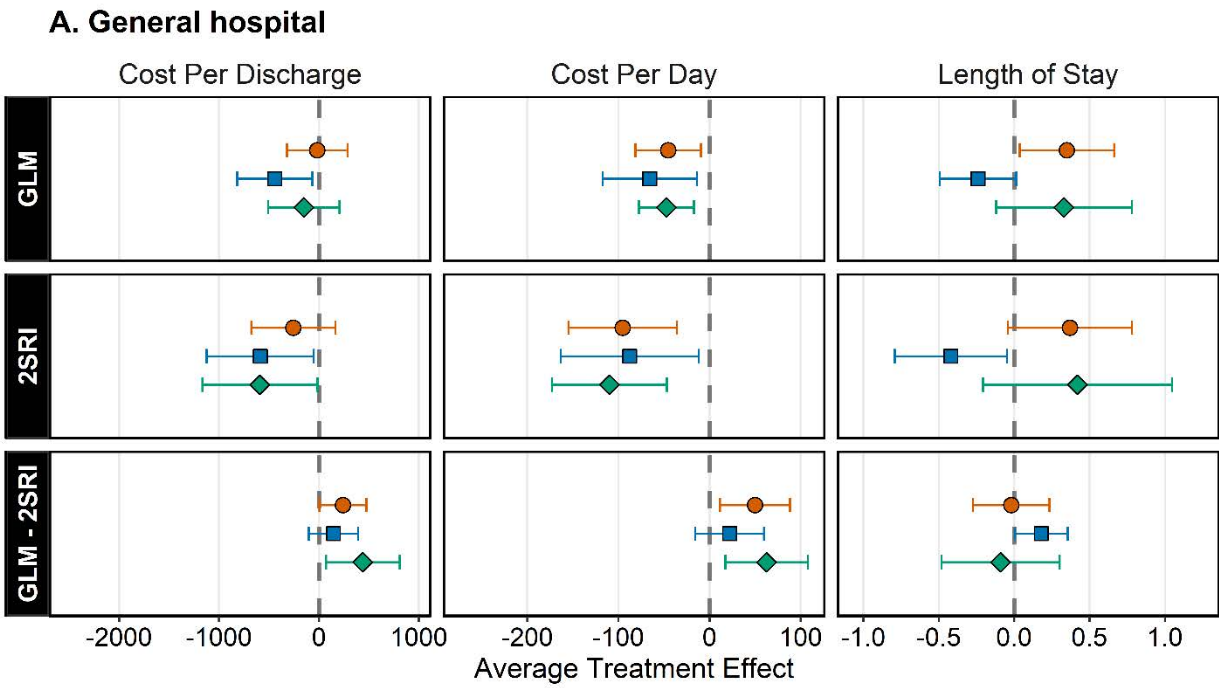
C: Share going to the nearest hospital with licensed psychiatric bed



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, 75^{th} and 90^{th} 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 results of the association between FP hospital status on spending and utilization across different modeling approaches by hospital types



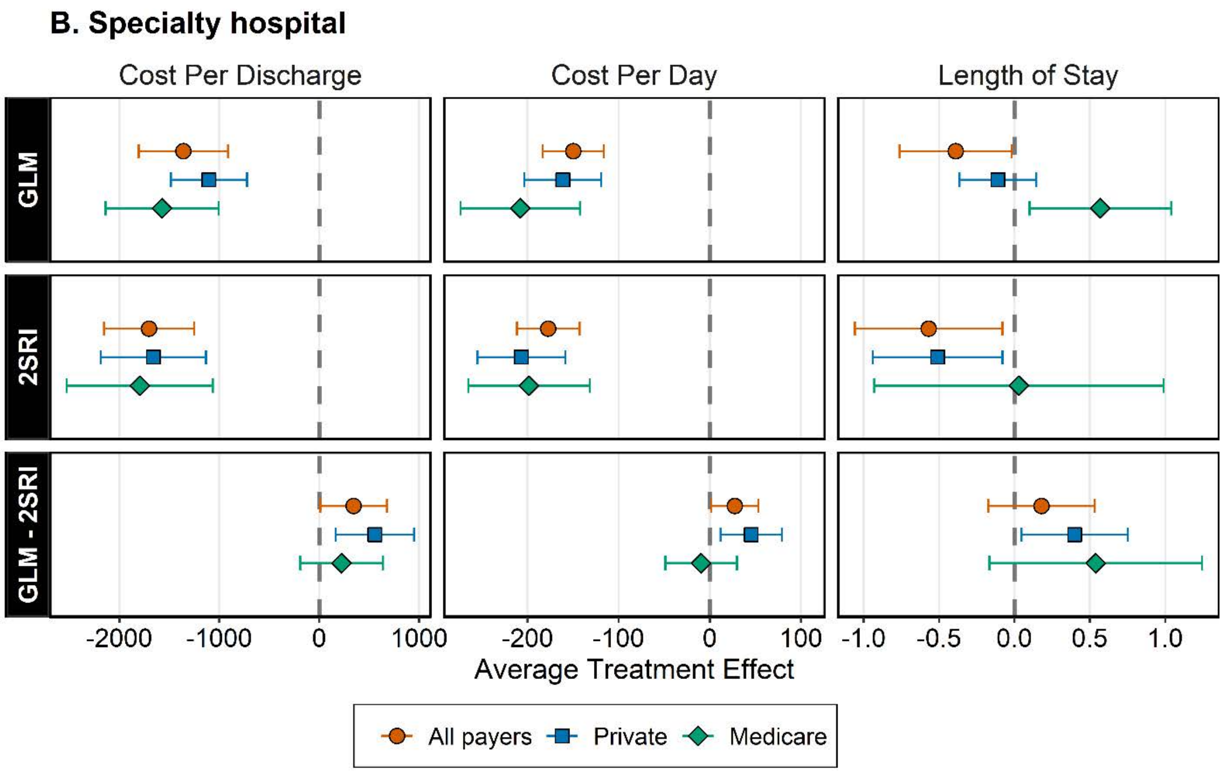


Figure S1. Flow diagram of the selection procedure for the study population

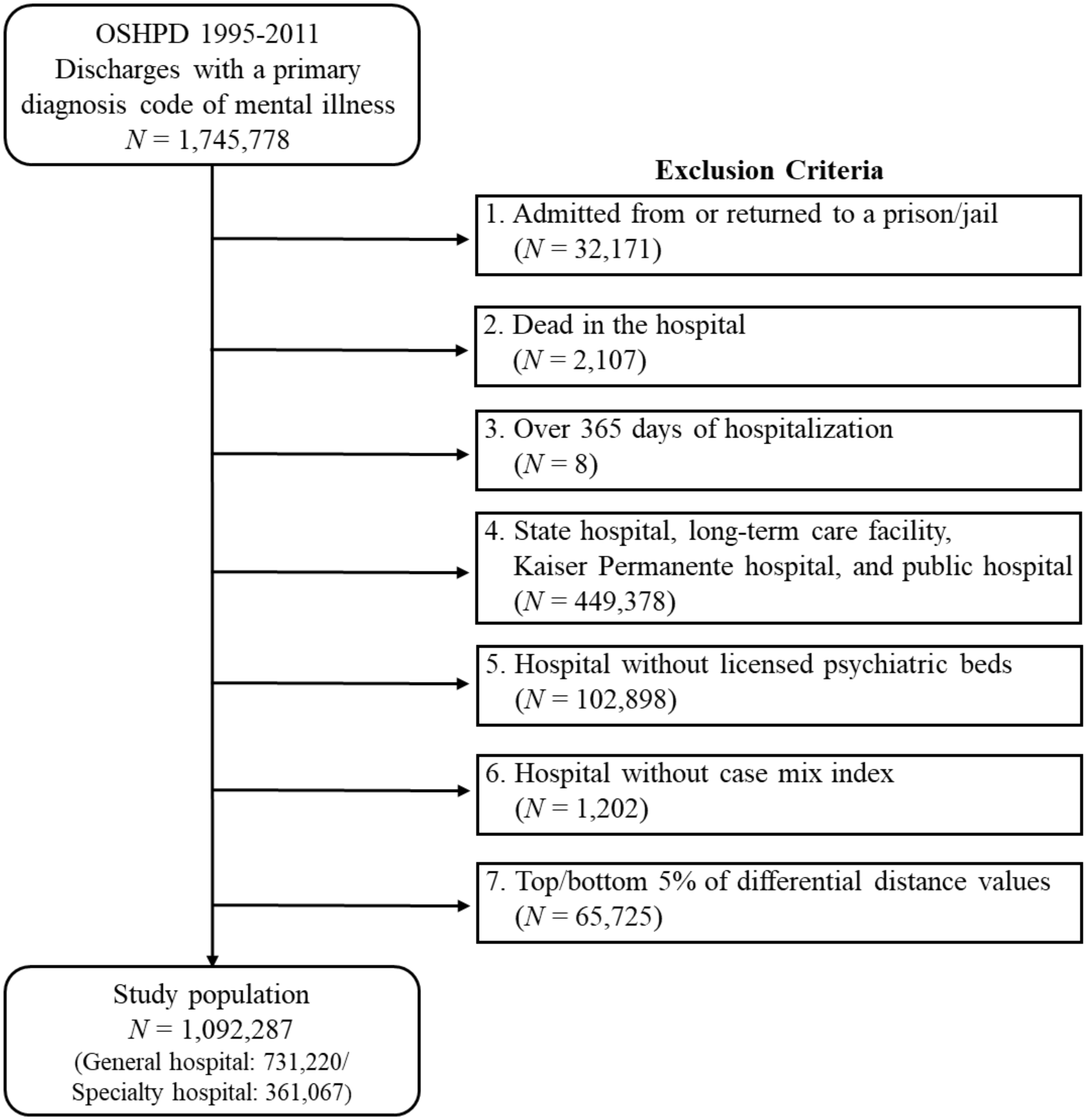
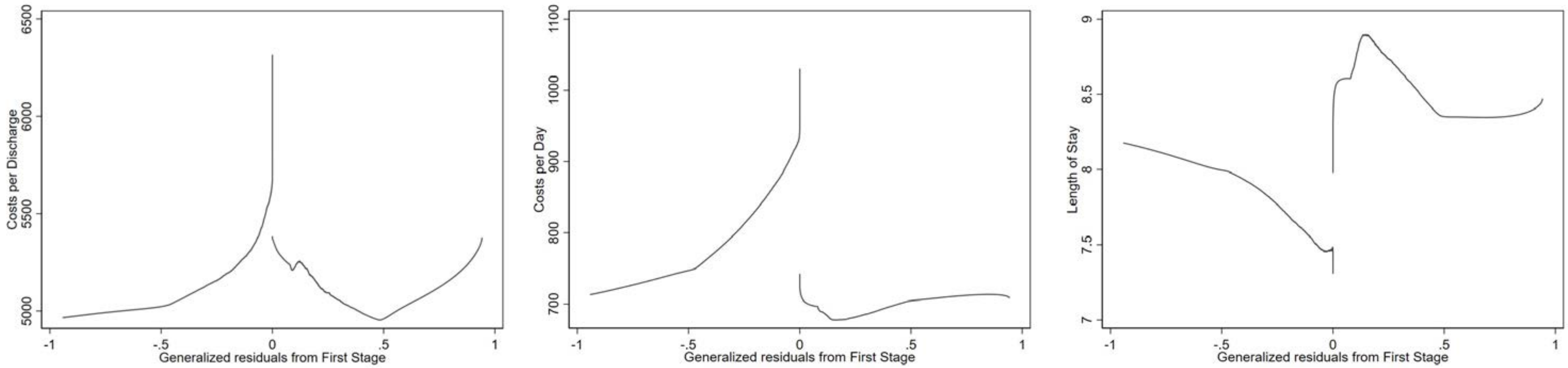
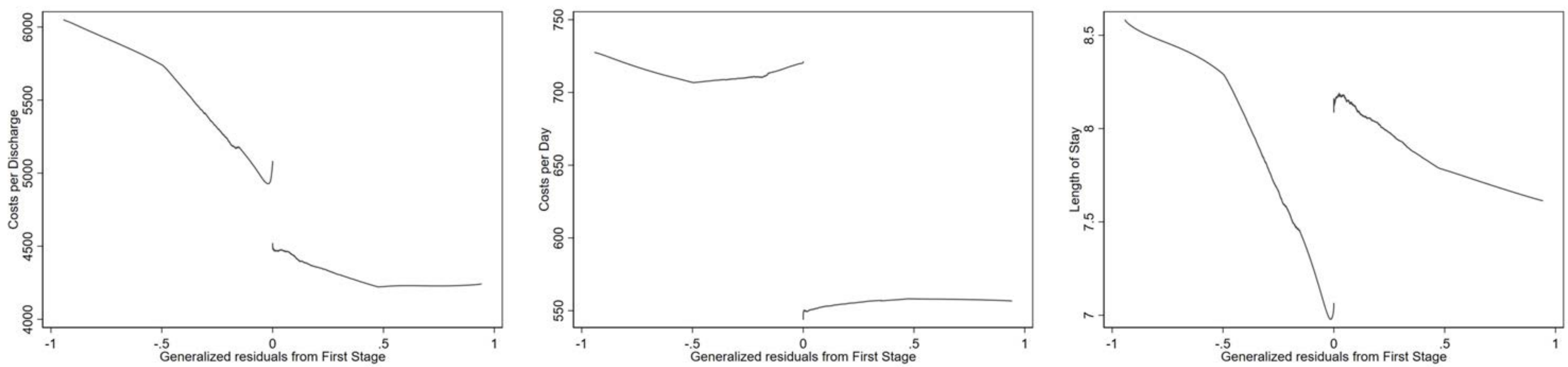


Figure S2. Diagnostics for control function specifications of 2SRI models

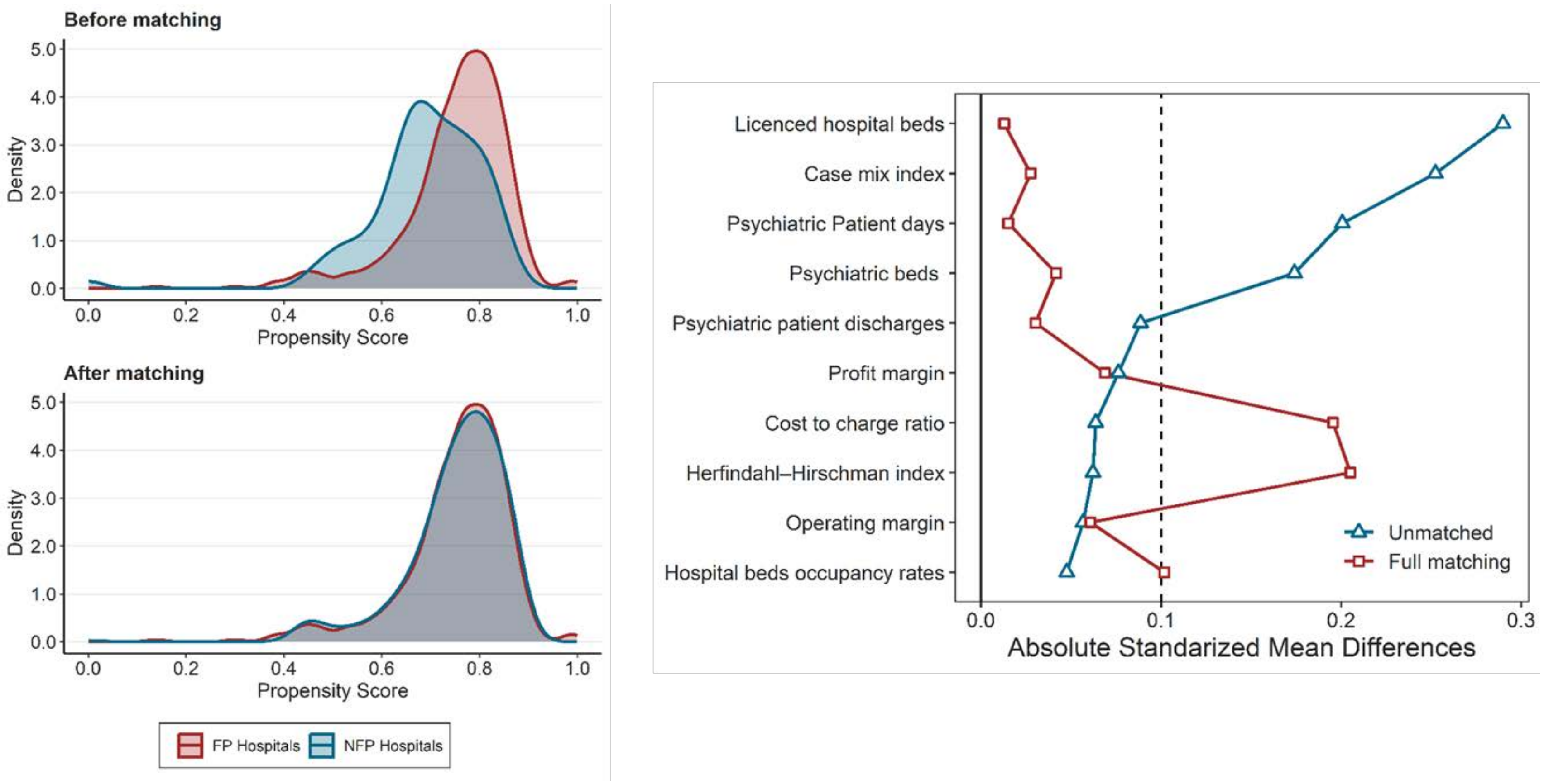


A: General hospital



B: Specialty hospital

Figure S3. Comparison of the propensity score distribution and covariate balance before and after matching



A: PS distribution B: Covariate balance

Note: The left figure presents density plots of propensity score distribution comparing before and after matching. A full matching method is used. The outcomes of labor resources encompass the number of physicians per bed, number of nurses per bed, and nurse hours per patient day. The list of covariates 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 right figure illustrates covariate imbalance between unmatched and matched samples based on the full matching method. The X-axis represents absolute standardized mean differences, and we add the dotted line on the value of 0.1. The study sample consists of freestanding specialty psychiatric hospitals only.

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

Characteristics	General hospital For-profit (N = 51)	General hospital Not-for-profit (N = 96)	Specialty hospital For-profit (N = 55)	Specialty hospital Not-for-profit (N = 13)
Teaching (%)	1	16	0	0
Hospital bed				
Number of total hospital beds	209 (104)	364 (192)	69 (40)	80 (40)
Available beds / licensed beds	0.96 (0.1)	0.9 (0.12)	0.99 (0.05)	0.95 (0.14)
Number of psychiatric beds	40 (27)	37 (22)	65 (39)	72 (36)
Discharge				
Annual discharges from psychiatric beds	1063 (1062)	967 (761)	1734 (1414)	1859 (1123)
Annual psychiatric discharges per psychiatric bed	24 (13)	27 (14)	26 (13)	27 (13)
Annual occupancy rates for psychiatric beds (%)	61.8 (23.5)	57.1 (23.1)	63.6 (20.8)	64.6 (21.4)
Human resources				
Number of physicians	274 (216)	463 (385)	24 (25)	83 (165)
Physicians per hospital bed	1.34 (0.92)	1.27 (0.82)	0.37 (0.4)	1.02 (2.32)
Number of registered nurses	278 (201)	569 (400)	52 (41)	79 (52)
Registered nurses per hospital bed	1.28 (0.52)	1.54 (0.63)	0.8 (0.54)	0.99 (0.55)
Others				
Cost-to-charge ratio	0.3 (0.12)	0.34 (0.1)	0.57 (0.24)	0.58 (0.23)
Case mix index	1.08 (0.29)	1.14 (0.21)	0.74 (0.07)	0.72 (0.08)
Herfindahl–Hirschman index	2413 (961)	3229 (1321)	2808 (787)	2759 (661)

Note: This table presents hospital-level summary statistics by hospital type (general/specialty hospital) and ownership 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 ownership 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-Hirschman 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. Specialty hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities. The sample includes only private hospitals with licensed psychiatric beds.

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

Characteristics	General hospital For-profit (*N* = 207,775)	General hospital Not-for-profit (*N* = 523,445)	Specialty hospital For-profit (*N* = 253,533)	Specialty hospital Not-for-profit (*N* = 107,534)
Female (%)	50	53	50	56
Age category (%)				
0-17 years	2.4	3.7	28.9	29.6
18-34 years	20.1	23.7	23.8	20.5
35-64 years	59.4	56.0	42.7	43.2
65 years and over	18.1	16.6	4.6	6.8
Race (%)				
White	76.1	81.7	74.4	86.8
Black	16.6	10.5	10.5	7.7
Native American/Eskimo	0.1	0.1	0.2	1.0
Asian/Pacific Islander	2.2	2.6	1.8	1.6
Other	5.0	5.1	13.1	2.7
Primary diagnosis (%)				
Serious mental illness	85	77	81	68
Schizophrenia	47	32	28	19
Bipolar disorder	16	19	22	19
Major depression	22	26	31	30
Depression	3	5	8	10
Alcohol use disorder	4	7	2	6
Drug use disorder	1	1	2	3
Other	7	11	7	14
Rural residence	2	2	2	2
Zip code-level median income	57662 (20661)	63869 (23588)	62507 (20581)	62747 (21619)
Payer category (%)				
Private	13	24	41	54
Public	78	65	47	34
Medicare	44	38	27	21
Medi-Cal	34	27	20	13
County	2	1	5	0
Charity/Self-pay	4	7	3	4
Other	3	2	4	8
Managed care	12	22	29	49
Source of admission (%)				
This hospital – emergency room	32	50	0	0
This hospital – general	7	8	0	0
Transfer from another hospital	7	5	8	8
Not a hospital	54	37	92	91
Type of licensed bed (%)				
Acute care	17	23	1	1
Psychiatric care	83	77	99	99

Note: This table presents patient-level summary statistics by hospital type (general/specialty hospital) and 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 type and 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. Serious mental illness includes schizophrenia, bipolar disorder, and major depression. Specialty hospital refers to standalone specialty psychiatric hospitals, including psychiatric health facilities.

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

Characteristics	(1) DD < Median	(2) DD > Median	(3) SMD (IV) 1(DD)	(4) SMD (GLM) 1(FP)
Female (%)	52	53	0.02	0.06
Age category (%)				
0-17 years	3	4	0.03	0.07
18-34 years	22	23	0.03	0.08
35-64 years	57	57	0.01	0.06
65 years and over	18	17	0.03	0.04
Race (%)				
White	78.9	81.7	0.07	0.13
Black	13.6	10.6	0.09	0.17
Native American/Eskimo	0.1	0.1	0	0.01
Asian/Pacific Islander	2.4	2.4	0	0.02
Other	4.9	5.2	0.01	0
Primary diagnosis (%)				
Schizophrenia	39	33	0.12	0.31
Bipolar disorder	18	18	0.01	0.06
Major depression	24	26	0.03	0.1
Depression	4	5	0.05	0.1
Alcohol use disorder	5	7	0.05	0.11
Drug use disorder	1	1	0.01	0.03
Other	9	10	0.05	0.13
Rural residence	1	3	0.11	0.01
Zip code-level median income	60252 (21692)	64445 (24252)	0.18	0.28
Payer category (%)				
Private	19	23	0.1	0.27
Public (Medicare/Medi-Cal)	71	66	0.1	0.29
County	2	1	0.01	0.03
Charity/Self-pay	6	7	0.05	0.16
Other	3	2	0.04	0.05
Managed care	16	22	0.14	0.25
Source of admission (%)				
This hospital – emergency room	42	47	0.1	0.36
This hospital – general	8	8	0.01	0.03
Transfer from another hospital	6	4	0.06	0.09
Not a hospital	43	40	0.06	0.33
Type of licensed bed (%)				
Acute care	21	22	0.02	0.14
Psychiatric care	79	78	0.02	0.14
No. observations	353,776	352,908		

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 the median miles of differential distance (DD) versus more than median miles of DD from the sample. Column 1 presents the mean values of variables for patients with DD less than the median, while Column 2 shows the mean values for patients with DD more than the median. We introduce the standardized mean difference (SMD) by the DD status (i.e., 0, DD < Median; 1, DD > Median) in Column 3 to increase comparability across different patient characteristics based on a common scale. Column 4 presents the SMD by the ownership 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 (Specialty hospital)

Characteristics	(1) DD < Median	(2) DD > Median	(3) SMD (IV) 1(DD)	(4) SMD (GLM) 1(FP)
Female (%)	52	52	0	0.1
Age category (%)				
0-17 years	28	31	0.06	0.02
18-34 years	24	22	0.04	0.08
35-64 years	44	42	0.03	0
65 years and over	5	5	0	0.1
Race (%)				
White	77.5	79.1	0.04	0.32
Black	9.8	9.8	0	0.1
Native American/Eskimo	0.2	0.6	0.06	0.12
Asian/Pacific Islander	1.9	1.5	0.03	0.01
Other	10.6	8.9	0.06	0.38
Primary diagnosis (%)				
Schizophrenia	26	24	0.05	0.21
Bipolar disorder	22	20	0.04	0.09
Major depression	30	31	0.02	0.03
Depression	8	9	0.03	0.06
Alcohol use disorder	3	4	0.03	0.19
Drug use disorder	2	3	0.02	0.1
Other	9	10	0.04	0.22
Rural residence	1	3	0.14	0
Zip code-level median income	64793 (20728)	60230 (21098)	0.22	0.01
Payer category (%)				
Private	44	45	0.01	0.28
Public (Medicare/Medi-Cal)	43	44	0.01	0.27
County	5	3	0.09	0.31
Charity/Self-pay	3	3	0	0.03
Other	5	5	0	0.16
Managed care	34	37	0.06	0.42
Source of admission (%)				
This hospital – emergency room	0	0	0	0.02
This hospital – general	0	0	0	0.06
Transfer from another hospital	8	8	0	0.01
Not a hospital	92	92	0	0
Type of licensed bed (%)				
Acute care	1	1	0	0.03
Psychiatric care	99	99	0	0.03
No. observations	174,024	174,209		

Note: This table presents the balance of patient-level characteristics by the instrument for patients from specialty psychiatric hospitals. Patients are split into two groups, less than the median miles of differential distance (DD) versus more than median miles of DD from the sample. Column 1 presents the mean values of variables for patients with DD less than the median, while Column 2 shows the mean values for patients with DD more than the median. We introduce the standardized mean difference (SMD) by the DD status (i.e., 0, DD < Median; 1, DD > Median) in Column 3 to increase comparability across different patient characteristics based on a common scale. Column 4 presents the SMD by the ownership 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 4. First stage results from the regression model of differential distance on FP status

	(1)	(2)	(3)	(4)	(5)	(6)
	1(FP)	1(FP)	1(FP)	1(FP)	1(FP)	1(FP)
Panel A: General hospital						
Differential distance	-0.0238***	-0.0224***	-0.0187***	-0.0227***	-0.0231***	-0.0189***
(Marginal effects)	(0.0023)	(0.0022)	(0.0021)	(0.0019)	(0.0019)	(0.0019)
No. observations	731,220	731,220	731,220	731,220	731,220	731,220
F-statistics	89	95	72	106	116	89
Panel B: Specialty hospital						
Differential distance	-0.0077***	-0.0073***	-0.0064***	-0.0063***	-0.0056***	-0.0063***
(Marginal effects)	(0.0015)	(0.0012)	(0.0011)	(0.0015)	(0.0015)	(0.0011)
No. observations	361,067	361,067	361,067	361,067	361,067	361,067
F-statistics	27	33	34	19	15	34
HHI						Y
Hospital-level controls			Y	Y	Y	Y
Patient-level controls		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 logit regression model is implemented. The point estimates and standard errors are converted to represent marginal effects. The hospital is defined as general acute care or specialty psychiatric hospital which has at least a single licensed psychiatric bed. We characterize the differential distance (DD) as a continuous variable. The estimates of each column present the coefficient β obtained from Equation (3). The predictor variable is the 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). 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 residence, zip code- level median income, and bed type). Column 3 adds hospital-level controls (teaching hospital, 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 to control market competition and includes patient HSA and year fixed effects. Standard errors are clustered by patient-level HSA. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 5. Association of hospital ownership type on spending and utilization (Naïve GLM)

	General hospital			Specialty hospital		
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Length of Stay	(4) Cost Per Discharge	(5) Cost Per Day	(6) Length of Stay
Panel A: All						
1(FP)	-17.4	-45.4*	0.35*	-1359.7***	-149.8***	-0.39*
	(154.1)	(18.3)	(0.16)	(227.9)	(17.1)	(0.19)
No. observations	731,220	731,220	731,220	361,067	361,067	361,067
Y-Mean	5533.4	858.4	7.81	4735.8	599.1	7.99
Panel B: Private						
1(FP)	-443.2*	-65.6*	-0.24	-1103.7***	-161.3***	-0.11
	(192.3)	(26.5)	(0.13)	(194.8)	(21.5)	(0.13)
No. observations	154,439	154,439	154,439	161,241	161,241	161,241
Y-Mean	4761.6	969.5	5.71	3951.1	612.4	6.46
Panel C: Medicare						
1(FP)	-151.9	-47.3**	0.33	-1572.6***	-207.9***	0.57*
	(181.8)	(15.4)	(0.23)	(288.5)	(33.4)	(0.24)
No. observations	291,060	291,060	291,060	91,426	91,426	91,426
Y-Mean	6954.7	810.4	10.17	6315	608.3	10.55
Hospital controls	Y	Y	Y	Y	Y	Y
Patient controls	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, urban/rural residence, 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 calculated using 1000 times of clustered bootstrapping at the level of patient HSA. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 6. Association of hospital ownership types on spending and utilization (2SRI)

	General hospital			Specialty hospital		
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Length of Stay	(4) Cost Per Discharge	(5) Cost Per Day	(6) Length of Stay
Panel A: All						
1(FP)	-257.2	-95.3**	0.37	-1703.9***	-177.3***	-0.57*
	(214.6)	(30.4)	(0.21)	(229.8)	(17.5)	(0.25)
No. observations	731,220	731,220	731,220	361,067	361,067	361,067
Y-Mean	5533.4	858.4	7.81	4735.8	599.1	7.99
Panel B: Private						
1(FP)	-587.8*	-87.6*	-0.42*	-1660.2***	-206.8***	-0.51*
	(273.6)	(38.6)	(0.19)	(268.4)	(24.6)	(0.22)
No. observations	154,439	154,439	154,439	161,241	161,241	161,241
Y-Mean	4761.6	969.5	5.71	3951.1	612.4	6.46
Panel C: Medicare						
1(FP)	-591.1*	-109.9***	0.42	-1795.9***	-198.4***	0.03
	(293.6)	(32.2)	(0.32)	(373.1)	(34)	(0.49)
No. observations	291,060	291,060	291,060	91,426	91,426	91,426
Y-Mean	6954.7	810.4	10.17	6315	608.3	10.55
Hospital controls	Y	Y	Y	Y	Y	Y
Patient controls	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 the 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, urban/rural residence, 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 calculated using 1000 times of clustered bootstrapping at the level of patient HSA. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 7. Association of hospital ownership types on spending and utilization (Naïve GLM - 2SRI)

	General hospital			Specialty hospital		
	(1) Cost Per Discharge	(2) Cost Per Day	(3) Length of Stay	(4) Cost Per Discharge	(5) Cost Per Day	(6) Length of Stay
Panel A: All						
1(FP)	239.8*	49.9*	-0.02	344.2*	27.5*	0.18
	(119.8)	(19.6)	(0.13)	(170.2)	(13.2)	(0.18)
No. observations	731,220	731,220	731,220	361,067	361,067	361,067
Y-Mean	5533.4	858.4	7.81	4735.8	599.1	7.99
Panel B: Private						
1(FP)	144.6	22	0.18*	556.5**	45.5**	0.4*
	(125.4)	(19.3)	(0.09)	(200.4)	(17.2)	(0.18)
No. observations	154,439	154,439	154,439	161,241	161,241	161,241
Y-Mean	4761.6	969.5	5.71	3951.1	612.4	6.46
Panel C: Medicare						
1(FP)	439.2*	62.6**	-0.09	223.3	-9.5	0.54
	(188.4)	(23.1)	(0.2)	(211.4)	(20)	(0.36)
No. observations	291,060	291,060	291,060	91,426	91,426	91,426
Y-Mean	6954.7	810.4	10.17	6315	608.3	10.55
Hospital controls	Y	Y	Y	Y	Y	Y
Patient controls	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 unobserved differential 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, urban/rural residence, 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 8. Association of hospital ownership types on the use of labor resources

	(1) Number of Physicians Per Bed	(2) Number of Nurses Per Bed	(3) Nurse Hours Per Patient Day
Panel A: OLS			
1(FP)	-2.17**	-0.46***	-1.14***
	(0.72)	(0.08)	(0.21)
No. observations	657	657	657
Y-Mean	0.54	0.85	2.37
Panel B: PSM			
1(FP)	-2.27**	-0.43***	-1.04***
	(0.84)	(0.07)	(0.17)
No. observations	657	657	657
Y-Mean	0.54	0.85	2.37
Hospital controls	Y	Y	Y
Fixed effects	HSA/Year	HSA/Year	HSA/Year

Note: This table presents estimates of the association between hospital ownership status and the use of labor resources. 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. The list of covariates 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. 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.