The Role of Hospital Ownership under Universal Health Insurance: Evidence from Stroke Treatment in Taiwan*

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Abstract:

The adoption of universal health insurance (UHI) inevitably reduces the need of uncompensated care, one important reason to grant subsidies to nonprofit hospitals. To what extent nonprofits should be subsidized in the universal insurance regime is thus in question. This paper compares cost and quality of new stroke cases across hospitals of different ownership status in Taiwan, the latest country adopting UHI. Our results show that stroke patients admitted to nonprofit hospitals receive better quality. We find no differences on cost by hospital ownership, but for-profit hospitals have shorter length of stay, and incur higher per-day expenditure than other hospitals.

Keywords: Ownership; University Health insurance; Quality of care; Instrumental variables

JEL codes: I11; L15; L31

Introduction

Recently there have been increasing supports of reducing the number of the uninsured, either through the expansion of public insurance programs or the adoption of universal health insurance (UHI). In a series of reports, for instance, Institute of Medicine concludes that the lack of insurance results in negative impacts to the uninsured and their families, and urges the government to seek to achieve universal insurance by 2010 (IOM, 2004). Indeed, U. S. is the only developed county without universal insurance. More than 43 millions are reported uninsured throughout 2002, of which eight out of ten are members of working families (IOM, 2004).

Implementing UHI inevitably affects the existing health care system, however. Currently, substantial subsidies are made to nonprofit hospitals through favorable tax treatments.[1] It is argued that the presence of nonprofits not only provides the charity care for the uninsured, but also the quality care for all since nonprofits are less motivated to skimp on patients' needs or take advantage of uninformed patients due to the non-distributional constraint (Arrow, 1963; Weisbrod, 1988; Hirth, 1999; For a comprehensive survey, see Sloan, 2000). Once UHI is adopted, however, the need for uncompensated care is greatly reduced, and the risk of quality distortion due to price competition is largely mitigated. To what extent the special treatment on nonprofits should be kept under UHI is therefore an important question. Unfortunately, studies of hospital ownership are largely restricted to U. S. experiences. Even for studies drawing from countries adopting UHI, their hospital industries are often comprised predominantly of public or nonprofit hospitals.[2] Without being able to compare the hospital performance by ownership under UHI, it is therefore difficult to properly address this question.

In this article we consider how the ownership status affects the program cost and quality of stroke treatment in Taiwan. We use Taiwan data because Taiwan implemented National Health Insurance (NHI) in 1995, the latest country adopting UHI. In addition, as shown below, each ownership status (nonprofit,

[1] Those treatments include the exemption of state and federal corporate income tax, the exemption of state and federal property tax, as well as the access of tax-exempt bonds and the availability of charity deduction.
[2] In Canada, 98 percent of hospitals are public facilities. In Germany, public facilities own 51 percent of beds, while private not-for-profit hospitals own 35 percent. In Netherlands, private for-profit hospitals are even prohibited by law. For more discussions on the proportion of hospitals by different ownership, see Sloan (2000) Sec. 1.

public, and for-profit) plays a significant role in Taiwan's hospital market. We analyze the stroke disease---hemorrhage strokes as well as ischemic strokes---in part because of its importance and cost----stroke is a leading cause for hospital admission, and inpatient expenditures in Taiwan----but also because the severity of the illness is unlikely to be known by an individual prior to its occurrence.[3] Therefore, the distribution of disease severity is likely to be independent of an individual's residence location, which, as demonstrated below, is essential for instrumental variable estimation in the analysis.

We use longitudinal hospital claims of NHI receipts diagnosed as new stroke cases during 1996 and 2002, matched with comprehensive hospital data over the same period. Since NHI covers almost all stroke related treatment, the hospital's charged expenditure is very close to the actual treatment cost. Therefore, our cost measure is the health expenditure spent during the treatment episode. Because stroke is the second leading cause of death in Taiwan, we measure the quality of care by the incidence of death within 1, 6, and 12 months after discharge. Conceptually, we could compare medical expenditure and time of death after discharge among new stroke patients admitted to hospitals of different ownership. In practice, however, such a comparison may be misleading since hospitals may be selected based on various differences related to ownership status. To overcome this selection issue, we employ two alternative methods: propensity score-matching (PSM) method to correct for sample selection bias due to observable differences, and instrumental variable (IV) method to correct for unobservable differences between the control and treatment groups.

Adjusting for endogeneity, we find that new stroke cases admitted to nonprofits receive lower mortality rates than those admitted to other hospitals. On average, 1, 6, and 12 month survival rates of nonprofits are at least 3% higher than that of for-profit hospitals. By contrast, the quality difference is less obvious between public and for-profit hospitals. In addition, we find no discernible differences in the medical expenditure by hospital ownership; in other words, the lower mortality is not associated with the higher expenditure. Furthermore, we find evidence showing ownership status affects treatment style:

[3] Inpatient expenditure for cerebrovascular disease (stroke) is 4.78% in 2003, next to heart disease (7.18%) and cancers (12.40%).

patients admitted to for-profit hospitals experience shorter length of stay, and incur higher expenditure per day. Given that nonprofits supply the better care at the cost no significantly higher than for-profit hospitals, our results indicate that the special treatments toward nonprofits could still be supported even under UHI.

This reminder of this article is organized as follows. We continue in Section 2 with a discussion on theories of nonprofit organization and empirical studies of nonprofit hospitals. Section 3 briefly introduces NHI and the hospital market in Taiwan. Section 4 describes the data and the sample we analyze, and Section 5 shows the econometric strategy we adopt. In Section 6, we present results of OLS, IV and PSM estimations. We discuss the robustness checks and mechanisms affecting program cost and outcome in Section 7. We conclude in Section 8.

I. Theories and Empirical Studies on Ownership

A. Theories on the Impact of Ownership

Starting with Arrow (1963), one line of theoretical studies emphasized the importance of the asymmetric information between the consumer and producer in explaining the existence of nonprofits. According to Arrow, the dominance of private nonprofit hospitals is in part due to lower transactions costs between hospitals and patients. Because the hospital care usually involves complex technology and complicated medical knowledge, patients have difficulties in judging the quality of care in advance. Nondistribution constraint embedded in nonprofit organizations---owners of for-profits have legitimate residual claimants while controllers of nonprofits are prohibited from distributing earnings---reduces the incentives to engage opportunistic behaviors, and fill a market niche where consumers are not able to judge effectively the quality of received care.[4]

[4] Hansmann (1980) first generalizes this notion and term it the “contract failure theory”. Easley and O’Hara (1983) formally incorporate the idea into the contract failure theory where they argue that for-profit organizations will produce no output and the manager will simply pocket the whole purchase price in situations where the outputs are unobserved. Consequently, the nondistribution constraint will be valuable and nonprofits may be superior to for-profits. Similar arguments have been made by Hart et al. (1997) and Glaeser and Shleifer (2001) in which they argue that there are so many possible contingencies *ex ante* that it is impossible to anticipate all of them when forming a contract. Thus, for-profit firms are more likely to exploit non-contractible quality by cutting non-contractible cost to maximize return under incomplete contracts. The nodistribution constraint embedded in nonprofit organizations, on the other hand, softens this incentive and assures higher quality of care.

Another line of research postulates various sets of objectives such as quality of care (Newhouse, 1970) or charity care (Frank and Salkever, 1991) for the nonprofit firms assuming that the equity capital has been obtained through philanthropic donations, debt, and retained earnings. Newhouse (1970) emphasizes that the quality/quantity-maximizing nonprofit firms will result in productive inefficiency because nonprofit firms set average revenue equal to average cost, rather than marginal revenue equal to marginal cost.

Other studies (e. g. Weisbrod, 1988; Gentry and Penrod, 2000; Lakdawalla and Philipson, 1998) attempt to provide a theoretical justification for the proliferation of nonprofit firms by stressing the decision to trade off between tax advantage allowed under nonprofit status, and unconstrained profit making under for-profit status. Hansmann (1980, 1987, 1996) further argued that the availability of extensive privileges, including various tax exemptions and charitable deduction, to nonprofits is neither necessary nor sufficient for the initial development of nonprofits. In any case, they all agree that the various subsidies to nonprofits may influence the overall extent of nonprofit activity thereafter.

B. Previous Empirical Studies

The empirical literature on the impact of hospital ownership predominately focuses on the health care market in the United States. Sloan et al. (2001) suggest that payments on behalf of Medicare patients admitted to for-profit hospitals during the first 6 months following a hospitalization due to stroke, hip fracture, coronary heart disease or congestive heart failure were higher. Their findings are consistent with Granneman et al. (1986) that for-profit hospitals had costs higher than not-for profit hospitals and Silverman et al. (1999) that total per capita Medicare spending was higher in markets dominated by for-profit hospitals, but contradicts with earlier results that indicate nonprofit hospitals have higher average expenses per day than for-profits but similar average expenses per patient (i.e. Institute of Medicine 1986; Becker and Sloan, 1985).

On the quality front, several studies have suggested the similarities between for-profits and nonprofit hospitals in the health outcomes (Keeler et al. 1992; Sloan et al. 2001; Ettner and Hermann 2001).

McClellan and Staiger (2000) find that for-profits have higher mortality among elderly patients with heart disease, but they explain that the difference could be confounded by the market characteristics. Nevertheless, their results are consistent with some recent studies on hospital conversion (e.g.: Shen 2002; Picone et al. 2002) which found adverse health outcomes increases after conversion from nonprofit to for-profit status. Overall, the empirical evidence has yielded mixed findings regarding the ownership effect on cost and quality of care. See Sloan (2000) for a detailed review on the impact of ownership status.

II. **Background**

A. Brief introduction of NHI

In March 1995, Taiwan implemented national health insurance that provides health insurance coverage to the entire population. Prior to this, the availability of health insurance was primarily provided through three social insurance programs covering different populations: Labor Insurance for employees in the private sector, Government Employee Insurance for workers in the public sector, and Farmer Insurance for farmers. In total, these programs cover health insurance of 12.3 millions or 57% of the total population in 1994. Since nearly half of the total population is still uninsured, of which the majority were children under fourteen or the elderly over sixty-five, universal health insurance was implemented in 1995.

The effect of the adoption of NHI is by any measure enormous. While the insured rate was a little over a half in 1994, it jumped to 92% at the end of 1995, and has stayed over 97% since 1997. Each enrollee pays a premium equaling to the product of: (i) NHI insurance rate (ii) the enrolled salary and (iii) the share of enrollee's contribution, determined by one's enrolled type.[6] Non-enrollee's contribution is paid by the private employer for the employed, and by the government for the public employees or the unemployed.[7] In return, every enrollee enjoys a standard package of benefits that charges a fixed

[6] The insurance rate was set as 4.25% from the inauguration of NHI, and raised to 4.55% since 2003.
[7] A person's enrolled type is primarily determined by his employment and occupation, with different contribution rules applied to different enrolled types. For instance, public employees pay 40% of premium while the government pays the rest; in the private sector, workers pay 30% while employers and the government pay 60% and 10% respectively. See Cheng (2003) for a detailed description.

registration fee (about $5) and a low coinsurance rate (20% for the primary care; 10% for inpatient care) for incurred services. And they are free to go to any NHI contracted health providers.

The introduction of NHI results in an even larger impact on the health industry as a whole. Since its inception, almost all hospitals and clinics have had contracts with NHI.[9] Every clinic receives a standard payment package paid on the fee-for-service basis. Hospitals are paid similarly, although some inpatient services are reimbursed on the capitation basis.[10][11] Additionally, hospitals are categorized into four levels of accreditations: medical centers, regional hospitals, area hospitals, unaccredited hospitals, with hospitals with better accreditations being paid more generously.[12] Not surprisingly, with the nearly full enrollment rate, NHI soon becomes the single and largest payer for health providers.

<u>B. Hospital Market in Taiwan</u>

Figure 1 displays the number of acute care hospitals in Taiwan since 1989. It is clear from the figure that the hospital number reduces substantially over the years: more than 200 hospitals or roughly one quarter of hospitals exit the market in the past fourteen years. On 2002, there are only 571 hospitals left. Although the declining trend started before 1995, the exiting pattern does seem to accelerate after NHI is implemented (year 1995).

Despite of the rapid decline in hospital number, the hospital industry actually *grows* over time. The number of total beds in acute care hospitals rises from 62,900 in 1989 to 109,640 in 2002, about 80% increase over a period of fourteen years. As a result, the average bed per hospital almost triples---from 76

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[9] The contracting rate for hospitals is 96.72% and 96.90% in 1996 and 2002 respectively; the rate for clinics is 92.49% in 1996 and 92.90% in 2002. (data source: http://www.doh.gov.tw/statistic)

[10] Selective procedures, such as vaginal delivery, cesarean section or artery bypass surgery, are reimbursed on the capitation basis. There are in total fifty case payment procedures up to 2002, of which stroke is not included.

[11] Beginning in 2002 for clinics and 2003 for hospitals, in order to contain the medical expenditures, NHI introduces Global Budget---the maximum cap that a government imposes on the increase of medical spending.

[12] For instance, the daily rate for an ordinary bed (4 occupancies in a room) is NT 512 for medical centers, NT456 for regional hospitals, and NT395 for area and unaccredited hospitals. NHI does not differentiate the rate between area and unaccredited hospitals.

[14] Payment for outpatient and inpatient care to hospitals in 2002 is about $3.5 billions and $3.1 billions respectively. The hospital share of medical expenditures is calculated from Financial Resource and Allocation of National Health Expenditure, Year 1997 and Year 2002 obtained from Ministry of Health (data source: http://www.doh.gov.tw/statistic)

in 1989 to 192 in 2002. And the hospital industry plays a more important role in providing health care: its payment share rises from 2.14% of GNP in 1997, to 2.46% in 2002.[14]

Figures 2 and 3 show the total number of public and nonprofit, and that of for-profit hospitals respectively. According to Taiwan's medical law, hospitals are broadly defined into three ownership categories: public hospitals managed by the government or public enterprise or universities; nonprofit hospitals established by private universities or donations for purposes of charity or medical research; and for-profit hospitals owned by physicians.[15] In contrast with the conventional ownership definition, companies or enterprises whole sole purpose is to make profits are prohibited from owning hospitals in Taiwan. Nevertheless, the non-distribution constraint remains intact. As a result, we continue to separate hospitals according to the conventional definition. Further clarifications of these distinctions are provided in Table 1.

It is clear from Figures 2 and 3 that closeouts mostly occur among for-profits, decreasing from 691 in 1989 to 412 in 2002. By contrast, the number of public hospitals is almost unchanged, while that of nonprofits increases from 59 in 1989 to 72 in 2002. To explore its effect on the provided services, Figure 4 further displays the share of hospital beds by ownership status. Although the majority of hospitals are for-profit status, they are in general smaller. Thus, each ownership status ends up enjoying almost an equal share. Over time, however, since many for-profits exit the market and new nonprofits entered the market, the share of nonprofits gradually take up that of for-profits.

III. **Data**

A. Sources

We use four data sources in the study; all, except the last one, are obtained from National Health Research Institute (NHRI). The first is the longitudinal hospital claims of NHI enrollees between 1996 and 2002. Because NHI covers almost the entire population, we essentially have every stroke case in Taiwan. The claim data include diagnoses of diseases, dates of admission and discharge, along with detailed

[15] See Medical Treatment Law Articles 3, 4 and 5.

descriptions of medical expenses (e.g. food, room, diagnoses, surgery, etc.) a hospital charges for reimbursement (before and after co-payment). Since NHI covers all stroke related treatment, and few adjustments were made on the hospital's charges, the actual reimbursement was very close to the charges.[16] More importantly, each discharge record consists of three scrambled but unique IDs: Patient ID, Doctor ID, and Hospital ID. As we will see blow, these IDs enable us to link information of patients and hospitals from other sources.

The second source combines several different NHRI hospital datasets spanning from 1996 to 2002.[17] From these datasets, we obtain a hospital's accreditation, ownership status, teaching status, location geo-code, as well as details of facilities (e.g. departments and beds) and man-power (e.g. doctors, nurses, and technicians). Moreover, we are able to calculate a hospital's provided services in a given year, either in terms of the total number of discharges, inpatient stays, or the total NHI charges.

The third source is the eligibility file of all NHI enrollees covering between 1996 and 2002. The eligibility file reports an enrollee's basic demographics (sex and age), his supporter's enrolled type and salary, the supporter's enrolled unit's geo-code, as well as the enrollee's and the supporter's personal IDs, where the supporter refers to the one paying the enrollee's premium.[18] Because the file is kept in the log format----a new entry is added once there is a change in the enrolled unit, salary, or type---a covering period comprising of starting and ending dates is also included for each entry. For convenience, we match a patient's hospital claim with the last entry of eligibility file in the admitted year if multiple entries are found in that year.

Three important pieces of information are extracted from the eligibility file. First of all, we obtain the enrollee's basic demographics, namely, sex and age. Second, we obtain the ending date of an enrollee's

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[16] The difference between the charged payment and the actual reimbursement is less than 3% for inpatient services over the sample years.

[17] Specifically, we use "Registry for Contracted Medical Facilities," "Supplementary Registry for Contracted Medical Facilities," "Registry for Contracted Beds," Registry for Medical Personnel," and "Registry for Contracted Specialty Services." For hospitals with incomplete or missing information in the data, we supplement with Hospital Registry Files and Hospital Service Files obtained from Ministry of Health.

[18] Note that, unless one's premium is self-covered, an enrollee's personal ID is not identical to the supporter's ID. For instance, if a father covers the premium of the whole family, his personal ID will appear in the supporter's ID of every family member.

insurance coverage. Because NHI is compulsory, only on very few cases a person, especially a seriously ill one, is left uninsured, of which death is the most probable event.[19] Moreover, since NHI premium is paid on the monthly basis, the coverage is easily dropped shortly after the death of an enrollee. Thus, the date of ending coverage is used as the proxy of one's death date.[20] Third, we obtain the enrolled unit's geo-code in the admission year. Below, we discuss how the supporter's enrolled unit's geo-code can be used as the proxy of an enrollee's residence geo-code.

Lastly, we obtain the population figure of every geo-code between 1980 and 2002 from Population Registry, Ministry of Internal Affairs. Because a person may not live at the place listed in the household registry, there is a difference between the "actual", and the "registered" population residing in the geo-code. To reduce the gap, we use three waves of population census conducted in 1980, 1990, and 2000 respectively to adjust the registered numbers. Therefore, the numbers obtained from population registry accurately reflect the number of residents of that geo-code.[22]

B. Sample

Our study uses stroke cases who were aged over 35 years old at the admission between 1997 and 2001, and who had stays less than 91 days at short-term general hospitals and medical payments amounted less than NT500,000.[23] We focus on these sample years because we need to ascertain a new stroke case using a year look-back period, and ensure the mortality after discharge using a year looking-forward

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[19] According to NHRI data manuals, an enrollee loses his coverage in one of the following five conditions: (1) died (2) sentenced or jailed (3) disappeared for over six months (4) served in the army (5) exceed the permitted stay or working permits; the last condition applies only to foreigners.

[20] In another study, we merged new stroke patients with their death records. We found that, for those who died within one year after discharge, 90% of the sample has no differences between dates of death and dates of ending coverage; less than 5% has differences larger than a week; and less than 2% has differences larger than a month. See Lien, Chou, and Liu (2004) for details.

[22] Specifically, we calculate the ratio between the "actual" and the "registered" number residing in every geo-code from three waves of population census, and then use the ratios to adjust the population figure of every year accordingly.

[23] We distinguished between hemorrhagic and is chemic strokes from the first three digits of their ICD-9 codes: 430-431 for hemorrhagic strokes and 434 ischemic strokes.

period. Moreover, we restrict to stroke cases in accredited hospitals having at least 20 strokes cases in that year to reduce the effect of small hospitals, as well as the impact of extreme cases in a hospital.

About half of the sample is dropped to ascertain residence information. While the enrolled unit's geo-code could be used as the proxy of an enrollee's residence, there are several practical difficulties to apply this information directly. First, the eligibility file records the supporter's residence information, not that of the enrollee. Second, some types of enrollments require supporters obtaining coverage from places away from household registries. Hence, the enrolled unit's geo-code may be different from one's household registry. [24] Third, enrollees may choose to live differently from their household registries, even though from which they obtain the coverage.[25] In light of these difficulties, it is not easy to locate one's residence, and subsequently calculate the distances from one's residence to his admitted hospital or nearby hospitals, the important information for constructing instruments in the analysis.

We take three steps to ensure the residence information. First, we select enrollees whose premiums are paid by themselves or spouses only, excluding the ones covered by third parties not necessarily living together (e.g. children or relatives).[26] Second, we choose enrollees whose geo-codes of enrolled units are identical to that of household registries or working places.[27] Specifically, we use only enrollees who obtain their coverage through office of household registry or farmer associations or private employers. Third, we restrict to the ones whose traveling distances to admitted hospitals are less than 30-km. Therefore, enrollees whose residences are distantly from their registries are to a large extent eliminated. As seen below, these restrictions substantially reduce our sample size.

Table 2 lists the observation number by each additional sample selection. In total, there are 173,221 new strokes cases with valid hospital and patient information. About 5% of sample is eliminated due to hospital restrictions. By comparison, one third of the sample is dropped due to constraints of enrolled

[24] Recall that the geo-code of enrolled unit reflects the supporter's enrolled unit, not the insured one. Therefore, the residence information is incorrect once the support does not live together with the insured one.
[25] The discrepancy rate is around 17%, that is, 17% of the households do not live at their registered addresses. See Shih et. al. (2004) for details
[26] Specifically, we choose the ones whose supporter IDs are identical to his own or spouse's personal ID.
[27] Enrollees obtaining coverage from farmers' associations or household registry offices in general have their enrolled units' geo-codes identical to that of household registries. Enrollees working in the private sectors by the large have their enrolled units' geo-codes identical to that of working places.

types and premium payers, and a further 15% is dropped due to 30-km distance constraint. The remaining observation number is 84,385, roughly half of the original size, of which very few are repeated observations of the same patient.

C. Sample Statistics

Before describing the sample statistics, we first discuss the cost and quality measure used in the study. Our cost measure is the total NHI charges for the index hospitalization, converted to 1990 dollars using Consumer Pricing Index, health related items. Since almost all stroke treatment is covered by NHI, the medical payment is a good measure for program cost. Our quality measure is survival time after discharge, measured in terms of the probability of an enrollee ending his coverage within 1, 6, and 12 months after discharge respectively.[28] Table 3 displays program cost and outcome of patients with hemorrhagic and ischemic strokes respectively. On average, an ischemic stroke costs about NT37,000 or roughly $1,100 per case, less than half of the medical expense spent on a hemorrhagic stroke case.[29] The difference in mortality is even larger---the 1-month death rate after having hemorrhagic strokes is 32%, roughly four times than that of ischemic strokes. Clearly, hemorrhagic stroke is a more serious illness.

Table 3 further separates cost and quality measures by ownership. Overall, the mortality rates were lowest for cases admitted to nonprofits, while that of public and for-profit hospitals were mixed. For instance, the 6 month mortality among hemorrhagic stroke patients in public and for-profit hospitals were 37% and 43% respectively, at least 3 percent higher than those admitted to nonprofits. In terms of program cost, however, nonprofits are not the ones who spent the most. Public hospitals consistently spent more on the treatment of strokes---about 10-15% more than nonprofits and even higher than for-profits.

Table 4 presents variables of patient and hospital characteristics as well as the market condition. There were virtually no teaching hospitals operated by for-profit organizations. By comparison, for-profit hospitals have smaller numbers of beds and hire fewer doctors. As a result, a smaller portion of for-profit hospitals receive accreditations, of which none is classified as medical centers. In terms of location, public

[28] Some studies (e.g. Sloan et. al., 2001) use time after the index shock, i.e., time after admission, as the quality indicator. Our results are insensitive to various definitions of the quality indicator.
[29] The average payment for hemorrhagic and ischemic strokes is NT87,746 and NT36,787 respectively.

hospitals tend to locate in areas where markets are competitive and sizable, where the size is measured by the population figure located within 15-km of distance from the admitting hospital, and the competition is measured by HHI index calculated from the share of inpatient admissions for all hospitals located within 15-km of the admitting hospital.

According to the age distribution in the table, nonprofits and for-profits have a more favorable case-mix than public hospitals. To examine this observation more closely, we further calculate the total expenses and the total hospital stays for every patient, regardless of the diagnoses codes, in the previous year prior to the index admission. Again, we observe similar patterns---patients admitted to nonprofits have the lowest stays and expenses, followed by for-profits, while the case mix for public hospitals is the worst. This may explain why nonprofits have better outcomes at a moderate cost. Of course the true impact of ownership requires a multivariate analysis.

IV. **Estimation**

A. OLS estimation

Consider patient *i* admitted at year *t* for stroke treatment. Let Dep_{it} be the dependent variable that is either cost or quality measure. Because the health expenditure is heavily right-schewed, the cost variable is replaced by the natural logarithm of charged payment in the estimation. Let Own_{it} be the vector of dummies that separate ownership into three groups: public, nonprofit, or for-profit, where for-profit is the reference group. We consider the following OLS estimation:

$$(1) \qquad Dep_{ii} = a \;\; + b_o H_{it} + b_1 Z_{it} + b_2 X_{it} + g_p Pub_{it} + g_n NFP_{it} + m_i + n_t + e_{it}.$$

H_{it} is the vector of hospital characteristics, including dummies of a hospital's accreditations and size. We drop the dummy of teaching status since there are no teaching hospitals among for-profits. And we combine dummies of medical center and area hospitals for the similar reason. Z_{it} is a vector containing measures of market condition, including the total number of population (15-km radius) and HHI index

(15-km radius). X_{it} is a set of patient demographics and severity measures, including age, sex, as well as the total amount of expenditures and hospital stays in a year prior to the index admissions. The county (m_i) and year dummies (n_t) are also included to control for the regional fixed effects and time trends. Finally, the estimation allows the clustering corrections of the error (e_{it}) to account for correlated observations within hospitals and years.

B. Propensity Score Matching Method

Matching methods, pairing treatment and control units that have similar observable attributes, eliminate the potential bias due to observable differences. To reduce the difficulties of matching based on high dimensionality of the observable characteristics, Rosenbaum and Rubin (1983) show that matching on the basis of multidimensional vector of pre-treatment characteristics *X* is equivalent to matching based on the propensity score *p(X)*. The propensity score gives the conditional probability of receiving a treatment given pre-treatment characteristics X, i.e., $p(X) \equiv \Pr(D=1 | X)$. Thus, conditional on p(X), the assignment to the treatment and control groups is random (assumption of ignorability) and matching methods will yield an unbiased estimate of the treatment effect on the treated.

We first estimate the propensity scores from a multinomial logit model that a patient chooses nonprofit, for-profit or public hospital as a function of the pre-treatment characteristics (Imbens 2000). The results in the first-stage are reported in Appendix A. These models are then used to predict the propensity (probability) of entering the hospital. Then for each hospital in the treatment group (either nonprofit or public hospital), we match a for-profit hospital (control group) using the nearest neighborhood matching and kernel matching methods.

Nearest neighborhood matching requires each treated unit $i \in T$ to be matched to the nearest controlled unit, even if a controlled unit is matched more than once (Becker and Ichino 2002). That is,

$$C(i) = \min_j \| p_i - p_j \|$$

where C(i) denotes a singleton set of control unit matched to the treated unit *i*.[30] Then the matching estimator (t) can be written as follows:

$$t = \frac{1}{N^T} \sum_{i \in T} \left[Y_i^T - \sum_{j \in C(i)} w_{ij} Y_j^C \right],$$

$$\begin{cases} w_{ij} = \dfrac{1}{N_i^C}, \text{if } \ j \in C(i) \\ w_{ij} = 0, \text{otherwise.} \end{cases}$$

where N^T denotes the number of observations in the treatment group, and N_i^C denotes the number of controls matched with observation $i \in T$. In practice, N_i^C is likely to be one. Y_i^T and Y_j^C are the observed outcomes of the treated and control units, respectively. The advantage of using a single controlled unit for each treatment unit is to ensure the smallest propensity-score distance between the treatment and controlled units; that is, we will be comparing very similar control and treatment units. However, the precision of the estimates will be improved if more controlled units are matched, but at the cost of increased bias (i.e. matched controlled units could be very different from the treatment unit) (Dehejia and Wahba, 2002).

Since results could be very sensitive to the matching methods, kernel matching method is also employed to reassure the robustness of our results. The kernel matching estimator is given by

$$t^k = \frac{1}{N^T} \sum_{i \in T} \left[Y_i^T - \frac{\sum_{j \in C} Y_j^C G(\frac{p_j - p_i}{h_n})}{\sum_{k \in C} G(\frac{p_k - p_i}{h_n})} \right]$$

where *G(.)* is a kernel function and h_n is a bandwidth parameter. In kernel matching, all treated as well as all controls units, will be used.

<u>C. Instrumental Variable Method</u>

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[30] In practice, multiple nearest neighbors should be very rare, especially when the propensity scores are estimated based on a large array of continuous variables.

As described above, a strong assumption made for the matching method is that conditional on p(X), the process by which units are selected into treatment or control group be unrelated to unmeasured variables. However, if unmeasured variables affecting outcomes are correlated with ownership status (e.g. patient severity), the estimation will still be biased even PSM is used. To obtain consistent estimates of ownership status, we estimate equation (1) by IV.

The instruments in the IV analysis are the distances to the nearest NFP and public hospitals and their squared terms. Distance variables have been used extensively as instruments in various articles (i.e. McClellan et. al., 1994; McClellan and Newhouse, 1997; Sloan et. al, 2001; Ettner and Hermann, 2001).[31] All other things being equal, patients generally prefer hospitals in closer proximity. Therefore, conditional on the locations of patients and hospitals, the distance measure is plausibly uncorrelated with unobserved individual characteristics, particularly a patient's severity upon admissions.

The estimation is conducted by Generalized Method of Moment (GMM). GMM is chosen in part due to its nice asymptotic properties of estimates, but also because the variance covariance matrix can be consistently estimated using a two-step procedure allowing for heteroscedasticity of unknown forms (see Davidson and Mackinnon (1993) for the discussion). More importantly, the method allows a very simple overidentification and endogenous test. Below, we performed Hansen J-test for overidentification restrictions and Durbin-Wu-Hasuman for the endogeneity test. For simplicity, we do not further specify the functional forms for cases when dependent variables are dichotomous, namely, mortality variables. In other words, they are estimated using the linear probability model.

One issue arising in the application of GMM is that it is equivalent to assume that the ownership probabilities are linear and independent, which obviously violates the fact that ownership categories are mutually exclusive. To overcome this difficulty, the IV estimation employs instruments of predicted

[31] McClellan et. al. (1994) and McClellan and Newhouse (1997) find that distance to a hospital with the capacity to provide intensive cardiac treatment is an important predictor of whether a heart attack victim is treated in such a hospital. Sloan et. al. (2001) use hospital ownership market shares as proxies for the differential distances to different types of hospitals for the patients. Ettner and Hermann (2001) use the same IVs as we do in this paper to predict the profit status of the treating hospital.

probabilities of multinominal logit, where ownership is treated as mutually exclusive (IV/MNL). In such a way, we also avoid the problem of inconsistent standard errors when applying two-stage least squares.

Before conducting IV estimation, it is important to ensure our instruments meet two important criteria : exclusion restriction and montonicity assumption (Angrist et al., 1996). Partial results of the first-stage regression of IV/MNL in Appendix A shed some lights on the quality of our instruments. All the instrumental variables have statistically significant impacts on the choice of ownership type. Montonicity seems to be valid in our estimates---increasing each of the distance to the nearest hospital, evaluated at the mean values, results in a negative marginal effect on the probability of being admitted to that type of hospital; in other words, people treated in a nonprofit hospital lived closer to nonprofit hospitals, while treated in a public hospital lived closer to public ones. The exclusion restriction might fail if some beneficiaries move closer to the treated hospitals since distance variables now affect program costs and health outcomes through channels other than ownership variables. We mitigate this concern by limiting the sample to new stroke cases.

V. Empirical Results

A. OLS Regression Results

Table 5 displays the estimated OLS result. It is clear from the table that patients diagnosed as hemorrhage have 25% higher chance to die after discharge, and incur about 70% more medical expenses. In line with our expectation, patients enrolled with higher payments or longer stays in the previous year prior to admission utilize more care, and face worse outcomes; same are for the aged (over 75 years old) and females. Hospitals with more beds as well as regional hospitals and medical centers have higher charges; this is not surprising since the reimbursement rates are higher for better accredited hospitals. However, cases admitted to these hospitals do not enjoy lower mortality: no significant differences are found in 1, 6, and 12 month death rates. Finally, hospitals located in more competitive areas incur higher payments, but no clear indications on the mortality rates.

After controlling for patient and hospital characteristics, as well as year and city/county fixed effects, nonprofits on average experienced better outcomes: the mortality rates at 1 month, 6 months and 1 year after discharge are 2% lower than for-profit ones.[33] To our surprise, patients admitted to nonprofits did not incur higher medical payments than others. On the other hand, public hospitals exercise more health care than for-profits (about 7%), but no significant differences on the mortality rates. Again, the results maybe subject to bias due to the endogeneity of ownership status. Below, we examine this more closely using IV and PSM methods.

B. Propensity Score Matching Method

If sicker patients are more likely to go to a hospital with certain ownership type, OLS will yield biased estimations even after controlling for patient, hospital and market characteristics in the model (Imbens, 2000). We apply PSM to get around with the problem that the treatment and control hospitals may differ systematically in certain dimensions.

As seen from Table 6, the signs of nonprofit's coefficients estimated under PSM are consistent with that of OLS. Nonprofit hospitals had the lowest mortality rates at 1 month, 6 month and 1 year, and their coefficients on mortality are all statistically significant at the 1% level regardless of the matching method used. Also, their incurred expenditures are no different from that of for-profits in the PSM results.

Different matching methods yield different results on the coefficients of public hospitals, particularly on the mortality rates. One important reason is that there is less overlap between the public and for-profit hospitals based on the estimated propensity scores, while there is greater overlap between the nonprofit

[33] There are in total 26 counties/cities in Taiwan. However, not every county has hospitals of three different ownership types. As a result, we combine several small counties into one and include 21 county/city dummies (instead of 25) in the estimation.

and for-profit hospitals.[34] Because of the potentially poor matching, we discount the importance of estimations of public hospitals under PSM.

C. Instrumental Variables Method

Table 6 presents the results of IV estimation, where distances to hospitals of different ownership and their squares are used as instruments. Our purpose is to examine if there is correlation between unobserved characteristics and ownership status. Indeed, the IV/GMM results reported in the lower panel of the table indicate the ownership variables are endogenous---all the Durbin-Wu-Hausman tests are strongly rejected, regardless of dependent variables. To verify the validity of instruments, we also conduct the over-identification tests (Hansen's J statistics). None of the Hansen's J statistics are rejected at the 10% level. This implies that the null hypothesis, i.e., the instruments are uncorrelated with the error terms, is to some extent confirmed.

Accounting for endogeneity, IV/GMM generates a very different result than found in OLS. In term of program quality, the chance of death of for-profit hospitals under IV/GMM is at least 7% higher or three times larger. Patients admitted to public hospitals, in relation to for-profits, also face lower mortalities, ranging between 6 and 8%. Conversely, the impact of ownership status on program cost becomes smaller. In fact, IV/GMM indicates no payment differences by hospital ownership.

As stated earlier, results without considering the mutually exclusive feature of ownership types are likely to be biased. At the bottom of the table we list results using the predicted probabilities of MNL as instruments. Comparing with IV/GMM, IV/MNL yields estimates closer to OLS. The coefficient of nonprofit status in 1, 6, and 12 month mortality is 3.2%, 4.8%, and 6.1% respectively, much smaller than IV/GMM results, but still larger than OLS results. Consistent with OLS results, dummy of public status turns insignificant on all the mortality variables. Nevertheless, we still cannot find any differences of medical payments on the coefficient of public status.

[34] The average propensity scores for public, nonprofit and for-profit hospitals are 0.378, 0.621 and 0.642, respectively.

According to IV estimates, patients admitted to nonprofits have 1-year mortality rate around 6% less than those treated at for-profits. The reduction is about one quarter of 1-year morality rate for the average stroke patient (23.1%). One likely explanation for this sizable change is that IV estimates reflect the marginal rate of return of the group affected by the instruments, as opposed to the average effect. Because different individuals may face different treatment returns due to unobserved characteristics, the marginal rate of return for those who were admitted to closer hospitals may be larger than the average population (Imbens and Angrist, 1994; Angrist et. al., 1996). This is particularly likely to stroke patients since timely treatment could extend a patient's life by a matter of years.[35][36]

VII Discussion

A. Robustness Check

To confirm our findings, we check if the results are robust to different IV instruments as well as different distance and hospital constraints. Previously, our instruments are distances to hospitals of different ownership and their square terms. Other studies (e.g. McClellan et. al., 1994; McClellan and Newhouse, 1997) have used distance differentials---the difference in the distances to hospitals of different ownership status and the distance to the nearest hospitals---as instruments.[39] Therefore, we present results of IV/GMM and IV/MNL in Table 7 using distance differentials as instruments.

[35] For example, the biggest hurdle of the use of intravenous recombinant tissue plasminogen activator (rtPA) for treatment of patients with acute ischemic stroke is time; the narrow window of opportunity is within 3 hours after stroke (Mitka, 2003).
[36] Ettner and Hermann (2001) use the same set of IVs as we did in this paper, but found IV estimates were similar to OLS results. Nevertheless, they focus on the psychiatric patients who are unlikely to benefit substantially from the immediate medical treatment due to closer hospitals; that is, the marginal return of the group affected by instruments is possibly similar to the average return of the population.
[39] See for example, McClellan et. al. (1994) and McClellan and Newhouse (1997), in which they define the differential distance as the additional distance to reach a hospital of the given characteristics (e.g. catheterization hospital) beyond the distance to the nearest hospital.

Next, we check if our results are sensitive to different distance restrictions. Our analysis restricts patients whose traveling distances to hospitals are less than 30km only. Since patients residing in different areas may be faced with different traveling distances to nearby hospitals, applying the single constraint may be inappropriate. In the upper panel of Table 8 we relax this restriction by changing the distance restriction from 30-km to 30-km plus the distance to the nearest hospital in the residing geo-code. Thus, patients living in areas distantly from hospitals are unlikely to be excluded due to the single constraint.[41]

Finally, we check if our results are sensitive to patients of different enrolled types. In the lower panel of the table, we just use those obtaining coverage through farmers' associations or household registry offices because their recorded geo-codes are identical or relatively closer to that of their residence. For the display purpose, we present OLS and IV estimates only.

As seen from Table 7, except for 1 month mortality, Hansen's J statistics are rejected and the over-identification tests are passed in all IV results. Compared with IV results of Table 6, there are three differences. First, results using distance differentials as instruments indicate nonprofits and public hospitals yield a smaller impact on the mortality. Second, the statistical level for IV/MNL result in the Table is less obvious. Third, the impact of public status on program outcome in IV/GMM turns insignificant after changing instruments. Despite of these differences, all the main findings---nonprofits provide better quality of care than for-profit hospitals, and no significant differences of medical payments by hospital ownership---remain unchanged even changing another set of instruments.

Table 8 examines if the results are robust to different residence information. From the table, it is clear that our results are robust to different distance standards or different enrolled types. Estimates using the looser distance restriction are close to that using a stricter one. Likewise, results with or without including patients obtaining coverage from private employers are also similar, although there is a reduction in the

[41] We have done other checks to examine the sensitivity of distance information. First, we dropped enrollees who worked in the private sector to see if our results are robust to patients of different enrolled types. We also changed restriction of traveling distance to less than 20-km and to less than 40-km. However, there are no significant differences in estimated results with respect to different enrolled types or distance constraints.

statistical significance for the coefficient of public status. Overall, our findings are insensitive with respect to residence information.

B. Mechanisms affecting cost and quality of care

So far our results consistently show that nonprofits produce much better quality of care at the cost no significantly higher than for-profits. The findings for public hospitals are relatively mixed, but to a large extent supports that public hospitals, in relation to for-profits, provide similar care at the same or moderately higher cost. What remains to be known is how the ownership status affects cost and quality of care; that is, what are the mechanisms resulting in such differences? To investigate the underlying factors, we break the health expense into two components: length of stay and expense per-day. Table 9 presents OLS and IV results where these two variables (in the natural logarithm expression) are dependent variables. In every result we find patients treated in nonprofits and public hospitals have longer stays than those admitted to for-profits, ranging from 14.0-18.7%. Since the average hospital stay for stroke cases is 12.06 days, the estimates suggest that the stay admitted to for-profits is about 1.54 to 2.25 days shorter than treated at other hospitals. On the other hand, for-profits have higher per-day expenditure than other hospitals, about 13.1% to 29.6%. The two findings thus explain why we found no differences in health expenditures of hospitals by ownership: for-profits have higher per-day expenses but shorter hospital stays.[42]

Our findings on mechanisms also yield important implications on theories of nonprofit organizations. Due to the availability of universal insurance, the indigent care previously supplied by nonprofits is largely replaced. Therefore, the asymmetric information hypothesis---nonprofits are less motivated to cut back services of uninformed patients due to the nondistributional constraint, becomes a more sensible reason to support the presence of nonprofits. It is thus important to examine if our findings are consistent with predictions generated by this hypothesis. Our results to a large extent support the hypothesis: nonprofits produce better quality of care, and adopt the treatment style similar to public hospitals. Overall,

[42] Our results differ from previous papers (e.g. Institute of Medicine 1986; Becker and Sloan 1985) which found that nonprofits have higher expenses per-day than for-profit hospitals.

the empirical evidence indicates there might still be reasons to subsidize nonprofit hospitals even under the universal health environment.

VIII Conclusion

Weisbrod (1988) argues that the presence of nonprofit organization is due to the inability of government to meet the demand of public good (e.g. health care to the indigent) in populations with heterogeneous preferences for public services. As a result, nonprofit organization offers an alternative to the government for providing collective goods and hence should be encouraged through favorable tax treatments. The need for uncompensated care, however, will be considerably reduced after the adoption of UHI. To what extent these subsidies should be granted toward nonprofit hospitals in the universal insurance regime is thus an important empirical question.

In this study we examine the impact of ownership status on the cost and quality of stroke treatment in Taiwan, the latest country adopting UHI. After adjusting for endogeneity of hospital ownership, we find that stroke patients treated at nonprofit hospitals receive better quality of care in terms of survival rates than admitted to for-profits. On average, the 1, 6, 12 month mortality rates for nonprofits is at least 3% lower than for-profits. Such an increase of quality, however, is not associated with an increase of the treatment cost---no differences in medical expenditure are observed between nonprofits and for-profits. Nonetheless, we find evidence showing the ownership status affecting the treatment style: for profits are more likely to have shorter hospital stays, and incur higher expenditure per day.

A key question is how general our results are. For two reasons we caution the readers planning to extend the results. First, almost every country has some unique features in its health system. Therefore, it is probably difficult to simulate the results unless the differences in health system are properly accounted for. Additionally, as seen earlier, for-profits in Taiwan differ substantially than other hospitals in sizes and accreditations. Such differences may be induced by the medical law prohibiting for-profit companies or enterprises from owning hospitals. Although our results are robust to different samples and estimation methods, we warn that the results can still be biased due to this particular restriction.

On the other hand, there are reasons to believe the findings may be more general as they look. Unless treated timely, the consequences of all strokes, particularly hemorrhage strokes, are serious. Therefore, the observed cost and quality difference should be at the low end since there should be little differences between providers' treatment practices based on hospital ownership. Additionally, there have been relatively few developments in stroke treatment. Hence, treatment discrepancies among hospitals of different ownership status should be smaller than other areas that experience rapid innovations (e.g. heart diseases), particularly when public or nonprofits are the first peers to adopt such new technologies.

Another key question is to what extent the cost and quality differences are influenced by the adoption of UHI. Our data show no signs of convergence in these differences over years after implementing UHI.[43] As a result, we suspect that UHI causes a long-lasting phenomenon. Nonetheless, it remains possible that UHI produces a one-time effect. A more careful analysis combining the data spanning before and after the implementation of UHI is necessary to determine its true impact.

Our main contribution is to provide the empirical evidence on the cost and quality differences by hospital ownership in the UHI regime. Most studies on hospital ownership are restricted to U. S., whose experiences are too unique to generalize. One important difference, for instance, is that UHI is unavailable in the states. To our knowledge our paper is the first study that analyzes the impact of hospital ownership in a country adopting UHI. Moreover, we believe the findings are also useful in testing the ownership theory. Because UHI greatly reduces the need for uncompensated care, the observed cost and quality differences, if they exist, are likely to attribute to reasons other than the provision of public good. In fact, our findings---nonprofits supply better quality care, and adopt treatment styles similar to public hospitals---are to a large extent consistent with asymmetric information hypothesis. Therefore, there might still be reasons granting subsidies to nonprofit hospitals even under UHI regime.

[43] For instance, the 12 month mortality difference between for-profits and non-profits is approximately 2% over the sample years.

References

Angrist, J.D., G. Imbens, and D.B. Rubin (1996), "Identification of Causal Effects Using Instrumental Variables", *Journal of American Statistical Association*, 91(434): 468-472.

Arrow, K. J. (1963), "Uncertainty and the Welfare Economics of Medical Care", *American Economic Review*, 53(5): 941-973.

Becker, E. R., and F. A. Sloan (1985), "Hospital Onwership and Preference", *Economic Inquiry*, 23(1): 21-36.

Becker, S. O. and A. Ichino (2002), "Estimation of Average Treatment Effects Based on Propensity Scores", *Stata Journal*, 2(4): 358-377.

Cheng T. M. (2003) "Taiwan's New National Health Insurance Program: Genesis and Experience So Far" *Health Affairs*, 22(3): 61-76

Lien, H. M, S. Y. Chou, and J. T. Liu (2004), "Hospital Competition under Universal Health Insurance: the Stroke Treatment in Taiwan", Mimeo.

Davidson, R and J. M. Mackinnon (1993), *Estimation and Inference in Econometrics*, Oxford.

Dehejia, R. H. and S. Wahba (2002), "Propensity Score-Matching Methods for Nonexperimental Causal Studies", *Review of Economics and Statistics*, 84(1): 151-161.

Easley, D. and M. O'Hara (1983), "The Economic Role of the Nonprofit Firm", *Bell Journal of Economics*, 14(2): 531-538.

Ettner, S. L. and R. C. Hermann, (2001) "The Role of Profit Status under Imperfect Information: Evidence From the Treatment Patterns of Elderly Medicare Beneficiaries Hospitalized for Psychiatric Diagnoses", *Journal of Health Economics*, 20(1): 23-49.

Frank, R. G., and D. S. Salkever (1991), "The Supply of Charity Services by Nonprofit Hopsitals: Motives and Market Structure", *Rand Journal of Economics*, 22(3): 430-445.

Gentry, W. M. and J. R. Penrod (2000), "The Tax Benefits of Not-For-Profit Hospitals", in David Cutler, ed., *The Changing Hospital Industry: Comparing Not-for-Profit and For-Profit Institutions*, University of Chicago Press, 285-324.

Glaeser, E. L. and A. Shleifer (2001), "Not-for-Profit Entrepreneurs", *Journal of Public Economics*, 81(1): 99-115.

Grabowski D. C. and R. Hirth (2003) "Competitive Spillover across Nonprofit and For-profit Nursing Home", *Journal of Health Economics*, 22: 1-22

Grannemann, T.W., R.S. Brown and M.V. Pauly (1986), "Estimating Hospital Costs: A Multiple-Output Analysis", *Journal of Health Economics*, 5(2): 107-128.

Hansmann, H. B. (1980), "The Role of Nonprofit Enterprise", *Yale Law Journal*, 89(5): 835-901.

Hansmann, H. B. (1987), "Economic Theories of Nonprofit Organization," in W.W. Powell, ed., *The Nonprofit Sector*, New Haven and London: Yale University Press, 27-42.

Hansmann, H. B. (1996), *The Ownership of Enterprise*, Cambridge, Massachusetts and London, England: The Belknap Press and Harvard University Press.

Hart, O., A. Shleifer and R.W. Vishny (1997), "The Proper Scope of Government: Theory and An Application to Prisons", *Quarterly Journal of Economics*, 112(4): 1127-1162.

Hirth, R. A (1999) "Consumer information and competition between nonprofit and for-profit nursing homes, *Journal of Health Economics*, 18(2): 219-240

Imbens, G. (2000), "The Role of the Propensity Score in Estimating Dose-Response Functions", *Biometrika*, 87(3): 706-710.

Imbens, G. and J. D. Angrist (1994), "Identification of Local Average Treatment Effects", *Econometrica*, 62(2): 467-475.

Institute of Medicine (1986), *For-Profit Enterprise in Health Care*, Washington: National Academy Press.

Institute of Medicine (2004), *Insuring American's Health: Principals and Recommendations*, Washington: National Academy Press.

Keeler, E.B., L.V. Rubinstein, K.L. Kahn, D. Draper, E.R. Harrison, M.J. McGinty, W.H. Rogers and R.H. Brook (1992), "Hospital Characteristics and Quality of Care", *Journal of the American Medical Association*, 268(13): 1709-1714.

Lakdawalla, D. and T. Philipson (1998), "Nonprofit Production and Competition", NBER Working Paper 6377.

McClellan, M., B.J. McNeil, and J.P. Newhouse (1994), "Does More Intensive Treatment of Acute Myocardial Infarction Reduce Mortality?" *Journal of the American Medical Association*, 270: 1832-1836.

McClellan, M. and J. P. Newhouse (1997), "The Marginal Cost-Effectiveness of Medical Technology: A Panel Instrumental-Variables Approach", *Journal of Econometrics*, 77: 39-64.

McClellan, M. and D. Staiger (2000), "Comparing Hospital Quality at For-Profit and Not-for Profit Hospitals", in D. M. Cutler, ed., *The Changing Hospital Industry – Comparing Not-for-Profit and For-Profit Institutions*, Chicago: University of Chicago Press, 93-112.

Mitka M. (2003), "Tensions Remain over tPA for Stroke", *Journal of the American Medical Association*, 289: 1363-1364.

Newhouse, J. P. (1970), "Toward a Theory of Nonprofit Institutions: An Economic Model of a Hospital", *American Economic Review*, 60(1): 64-74.

Picone, G.A., S-Y Chou and F.A., Sloan (2002), "Are For-Profit Hospital Conversions Harmful to Patients and to Medicare?" *Rand Journal of Economics*, 33(3): 507-523.

Rosenbaum, P. R. and D. B. Rubin (1983), "The Central Role of the Propensity Score in Observational Studies for Causal Effects", *Biometrika*, 70(1): 41-55.

Silverman, E. M., et. al. (1999) "The Association between For-Profit Hospital Ownership and Increased Medicare Spending", *New England Journal of Medicine*, 318: 1100-1107.

Shen, Y. C. (2002), "The Effect of Hospital Ownership Choice on Patient Outcomes after Treatment for Acute Myocardial Infarction", *Journal of Health Economics*, 21(5): 901-922.

Shih Y. T., Y. T. Hung, H. Y. Chang, J. P. Liu, H. S. Lin, M. C. Chang, F. C. Chang, and C. A. Hsiung (2004) "The Design, Contents, Operation and the Characteristics of the Respondents of the 2001 National Health Interview Survey in Taiwan." *Taiwan Journal Public Health*, 22: 419-430.

Sloan, F.A., G.A. Picone, D.H. Taylor Jr., and S-Y Chou (2001), "Hospital Ownership and Cost and Quality of Care: Is There a Dime's Worth of Difference?" *Journal of Health Economics*, 20(1): 1-21.

Sloan, Frank (2000), "Not-For-Profit Ownership and Hospital Behavior," in Culyer and Newhouse (eds) *Handbook of Health Economics*, North Holland.

Weisbrod, B.A. (1988), *The Nonprofit Economy*, Harvard University Press, Cambridge, MA.

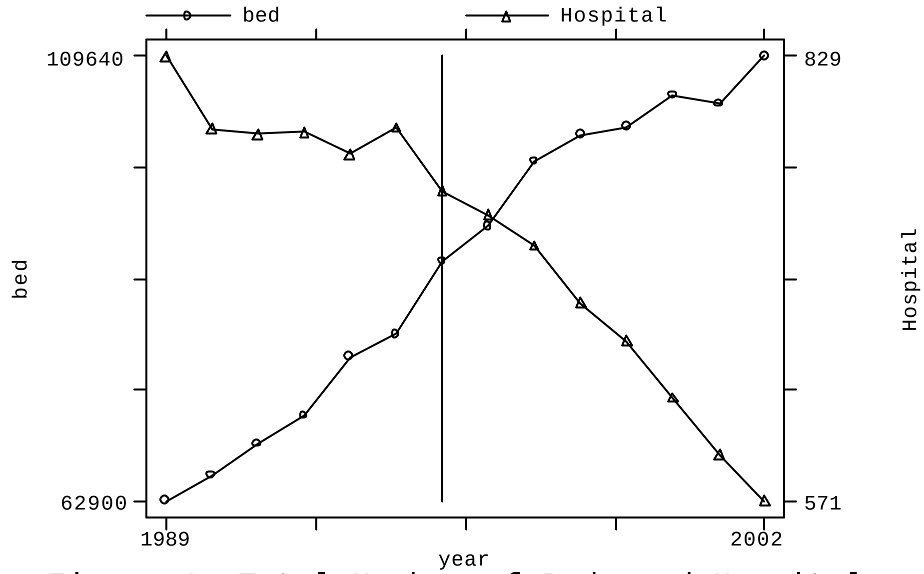

Figure 1: Total Number of Beds and Hospitals

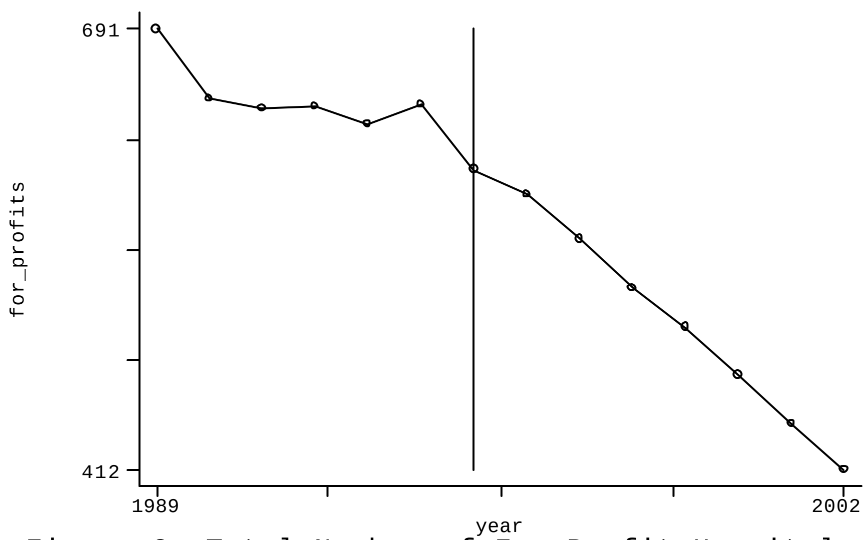

Figure 2: Total Number of For-Profit Hospitals

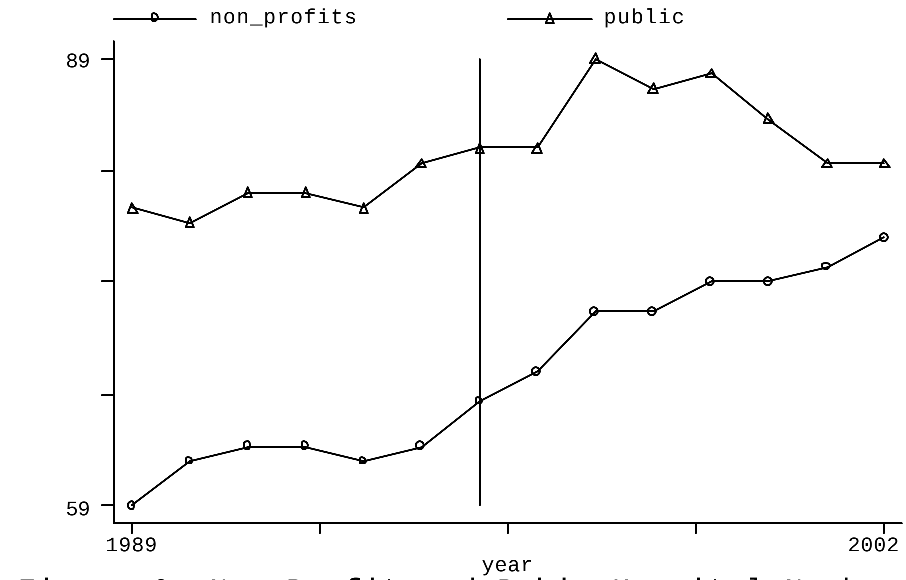

Figure 3: Non-Profit and Pubic Hospital Number

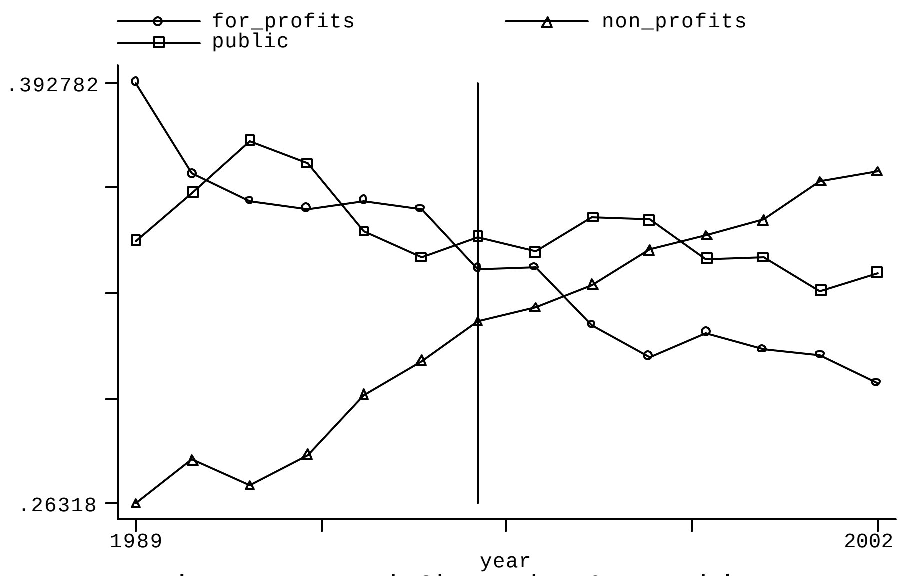

Figure 4: Bed Share by Ownership

Table 1: Distinctions between For-profit and Nonprofit Hospitals in Taiwan

	For-profit Hospitals	**Nonprofit Hospitals**
Owners of Hospitals	Medical treatment establishments owned by physicians, public organizations or business units under relevant medical regulations	Medical treatment establishments owned by juridical persons making a certain amount of donation
Right of Surplus Distribution	Can distribute some proportion of profits (net revenues less expenses) to owners, i.e., physicians will be the residual claimants	Cannot distribute surplus to those who control the organization
Tax Treatment	Owners of hospitals have to pay personal income tax from earnings Not exempted from land and property tax	Before 1995, nonprofits are exempted from corporate tax. Since 1995, corporate income tax is not exempted if less than 80% of earning are not spent on purposes consistent with founding goals of this organization Exempted from the land and property tax
Sources of Capital	Sources of capital include 1. Equity capital from establishers 2. Debt 3. Retained earnings	Sources of capital include 1. Charitable contributions 2. Debt 3. Retained earnings
Composition of Revenue	Revenues derived from sale of labor and services	Revenues derived from sale of labor and services and from charitable contributions

Table 2: Population of Patients Used in the Analysis
(Table Entries are Number of Observations Meeting Selection Criteria)

Year	new stroke cases with valid hosptial and patient information	…and enrolled into accrediated hospitals with 20 strokes a year	…with reliable residence information	…and who lived within 30 km of the index hospital
1997	31605	29981	19101	15275
1998	32792	31906	19849	15953
1999	34411	33313	20636	16431
2000	36022	34753	21641	17322
2001	38391	36968	23890	19404
Total	173,221	166,921	105,117	84,385

Table 3: Payments, Length of Stay and Mortality by Ownership Type

	Public		Non-Profit		For-Profit	
			Hemorrhagic			
Mortality						
1 Month	0.319	(0.466)	0.300	(0.458)	0.373	(0.484)
6 Month	0.373	(0.484)	0.347	(0.476)	0.429	(0.495)
1 Year	0.412	(0.492)	0.375	(0.484)	0.459	(0.498)
Medical Payments	95391	(105122)	88078	(96797)	79303	(89504)
N	5,005		9,624		4,906	
			Ischemic			
Mortality						
1 Month	0.084	(0.278)	0.069	(0.254)	0.075	(0.264)
6 Month	0.147	(0.354)	0.125	(0.331)	0.141	(0.348)
1 Year	0.192	(0.394)	0.165	(0.371)	0.186	(0.389)
Medical Payments	43887	(55681)	38199	(46996)	28962	(39714)
N	16,607		28,101		20,142	

Standard errors are in parentheses.

Table 4: Summary Statistics by Ownership Status of Hopsital of Admission

	Public		Non-Profit		For-Profit	
Hospital characteristics						
Teaching status	0.109	(0.312)	0.133	(0.3397)	0.000	(0.0000)
Accreditation						
Area Hospitals	0.206	(0.404)	0.096	(0.2943)	0.608	(0.4883)
Medical Centers	0.377	(0.485)	0.451	(0.4976)	0.000	(0.0000)
Size						
Bed number (100-300)	0.241	(0.428)	0.111	(0.3139)	0.423	(0.4940)
Bed number (over 300)	0.732	(0.443)	0.879	(0.3259)	0.298	(0.4573)
Doctor number (30-60)	0.133	(0.339)	0.069	(0.2530)	0.229	(0.4204)
Doctor number (over 60)	0.748	(0.434)	0.879	(0.3266)	0.285	(0.4513)
Demographic and pre-health status						
Male	0.685	(0.465)	0.594	(0.491)	0.580	(0.494)
Age (45-54)	0.073	(0.260)	0.099	(0.299)	0.077	(0.266)
Age (55-64)	0.144	(0.351)	0.198	(0.399)	0.175	(0.380)
Age (65-74)	0.391	(0.488)	0.360	(0.480)	0.368	(0.482)
Age (>=75)	0.361	(0.480)	0.304	(0.460)	0.351	(0.477)
Expenditure in previous year	23487	(80460)	17110	(61625)	17287	(58813)
LOS in previous year	6.295	(18.196)	4.349	(13.046)	5.042	(13.193)
Hemorraghic stroke	0.232	(0.422)	0.255	(0.436)	0.196	(0.397)
Market characteristics						
Herfindahl index (/0000, 15km)	0.116	0.088	0.147	0.086	0.137	0.070
Total population (000000, 15km)	2.351	2.038	1.874	1.910	1.261	1.324
N	21,612		37,725		25,048	

Standard errors are in parentheses.

Table 5: OLS Estimated Results

	Mortality[a]			Log(Medical Expenditure)[a]
	1 Month	6 Months	1 Year	
Ownership				
Non-Profit	-0.025***	-0.022***	-0.023***	-0.028
	(0.005)	(0.006)	(0.006)	(0.028)
Public	-0.008	-0.003	-0.001	0.071**
	(0.005)	(0.006)	(0.006)	(0.028)
Hospital characteristics				
Regional hospital and above	0.001	-0.001	-0.001	0.172***
	(0.007)	(0.008)	(0.009)	(0.035)
Bed number (100-300)	0.015**	0.009	0.011	0.228***
	(0.007)	(0.008)	(0.009)	(0.038)
Bed number (over 300)	0.017*	0.013	0.012	0.377***
	(0.009)	(0.011)	(0.012)	(0.052)
Doctor number (30-60)	0.004	0.001	0.001	0.033
	(0.006)	(0.008)	(0.008)	(0.032)
Doctor number (over 60)	0.005	-0.002	-0.006	0.006
	(0.008)	(0.010)	(0.010)	(0.051)
Demographic and pre-health status				
Male	-0.013***	-0.008***	-0.002	-0.072***
	(0.002)	(0.003)	(0.003)	(0.008)
Age (45-54)	-0.025***	-0.020**	-0.015*	-0.096***
	(0.008)	(0.008)	(0.009)	(0.022)
Age (55-64)	-0.018**	-0.005	0.006	-0.088***
	(0.007)	(0.008)	(0.008)	(0.020)
Age (65-74)	-0.003	0.027***	0.049***	-0.029
	(0.007)	(0.008)	(0.008)	(0.020)
Age (>=75)	0.064***	0.138***	0.186***	0.079***
	(0.007)	(0.008)	(0.008)	(0.021)
Previous year's payments ('0000)	0.001***	0.002***	0.002***	0.007***
	(0.000)	(0.000)	(0.001)	(0.001)
Previous year's LOS	0.001***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Hemorraghic stroke	0.258***	0.259***	0.253***	0.685***
	(0.005)	(0.005)	(0.005)	(0.016)
Market characteristics				
Herfindahl index ('0000, 15km)	-0.050*	-0.037	-0.027	-0.488***
	(0.027)	(0.030)	(0.032)	(0.126)
Total Population ('000000, 15km)	-0.004**	-0.003	-0.003	0.014*
	(0.002)	(0.002)	(0.002)	(0.007)
N	84,385	84,385	84,385	84,385
R^2	0.110	0.100	0.100	0.180

*** Significant at the 1% level (two-tail test).
** Significiant at the 5% level (two-tail test).
* Significant at the 10% level (two-tail test).
[a] All regressions include 21 city/county dummies and year dummis.
Standard errors are in parentheses.
Huber or robust standard errors on which they are based allow for hospital/year clustering.
Intercepts are not shown.

Table 6: Instrumental Variable and Propensity Score Matching Estimation Results

	Mortality[a] 1 Month	6 Months	1 Year	log(Medical Expenditure)[a]
PSM/Nearest Neightborhood				
Balanced NFP				
Non-profit	-0.050***	-0.051***	-0.048***	0.014
	(0.008)	(0.009)	(0.009)	(0.021)
Balanced GOV				
Public	-0.027***	-0.038***	-0.033***	0.227***
	(0.007)	(0.008)	(0.009)	(0.019)
PSM/Kernel				
Balanced NFP (Kernel)				
Non-profit	-0.030***	-0.030***	-0.030***	0.033**
	(0.005)	(0.008)	(0.004)	(0.018)
Balanced GOV				
Public	-0.005**	-0.009	-0.007	0.283***
	(0.002)	(0.007)	(0.005)	(0.009)
IV/GMM				
Durbin-Wu-Hausman endogeneity test $\chi^2_{(2)}$	10.809	21.590	20.225	11.990
Reject the Null?	Yes***	Yes***	Yes***	Yes***
Hansen J statistic overidentification test $\chi^2_{(2)}$	0.043	0.168	0.051	1.212
Reject the Null?	No	No	No	No
Non-Profit	-0.093***	-0.138***	-0.145***	-0.024
	(0.026)	(0.032)	(0.034)	(0.092)
Public	-0.061**	-0.080**	-0.072**	-0.109
	(0.027)	(0.033)	(0.034)	(0.091)
IV/MNL				
Non-Profit	-0.032*	-0.048**	-0.061***	0.050
	(0.017)	(0.020)	(0.022)	(0.083)
Public	-0.002	-0.018	-0.016	-0.094
	(0.017)	(0.020)	(0.021)	(0.072)
N	84,385	84,385	84,385	84,385

*** Significant at the 1% level (two-tail test).

** Significiant at the 5% level (two-tail test).

* Significant at the 10% level (two-tail test).

[a] All regressions include 21 city/county dummies, year dummis and explanatory variables reported in Table 3.
Standard errors are in parentheses.
Huber or robust standard errors on which they are based allow for hospital/year clustering.
Intercepts are not shown.

Table 7: Robustness Checks I: Different IVs for IV Estimations

	Mortality[a]			log(Medical Expenditure)[a]
	1 Month	6 Months	1 Year	
IV/GMM				
Durbin-Wu-Hausman endogeneity test $\chi^2_{(2)}$	1.793	4.238	4.780	4.134
Reject the Null?	No	Yes**	Yes***	Yes**
Hansen J statistic overidentification test $\chi^2_{(2)}$	7.553	3.320	3.694	3.942
Reject the Null?	Yes**	No	No	No
Non-Profit	-0.063***	-0.093***	-0.096***	-0.015
	(0.024)	(0.029)	(0.032)	(0.092)
Public	-0.014	-0.023	-0.003	-0.071
	(0.026)	(0.031)	(0.033)	(0.087)
IV/MNL				
Non-Profit	-0.025	-0.039*	-0.052**	0.065
	(0.017)	(0.021)	(0.023)	(0.085)
Public	0.011	0.001	0.003	-0.072
	(0.018)	(0.021)	(0.022)	(0.074)
N	84,385	84,385	84,385	84,385

*** Significant at the 1% level (two-tail test).
** Significiant at the 5% level (two-tail test).
* Significant at the 10% level (two-tail test).
[a] All regressions include 21 city/county dummies, year dummis and explanatory variables in Table 3.
Standard errors are in parentheses.
Huber or robust standard errors on which they are based allow for hospital/year clustering.
Intercepts are not shown.

Table 8: Robustness Checks II: Different Sample Composition

	Mortality[a]			log(Medical
	1 Month	6 Months	1 Year	Expenditure)[a]
Panel A: Different Distance Constraint				
OLS				
Non-Profit	-0.025***	-0.022***	-0.023***	-0.028
	(0.005)	(0.006)	(0.006)	(0.028)
Public	-0.008*	-0.003	-0.002	0.073***
	(0.005)	(0.006)	(0.006)	(0.028)
IV/GMM				
Non-Profit	-0.103***	-0.143***	-0.158***	-0.008
	(0.028)	(0.035)	(0.037)	(0.094)
Public	-0.064**	-0.082**	-0.079**	-0.106
	(0.028)	(0.034)	(0.036)	(0.087)
IV/MNL				
Non-Profit	-0.021	-0.036*	-0.049**	0.071
	(0.017)	(0.021)	(0.023)	(0.086)
Public	0.015	0.005	0.008	-0.062
	(0.018)	(0.021)	(0.022)	(0.074)
N	86303	86303	86303	86303
Panel B: Different Insurance Types				
OLS				
Non-Profit	-0.027***	-0.023***	-0.025***	-0.055*
	(0.005)	(0.006)	(0.007)	(0.028)
Public	-0.012**	-0.005	-0.004	0.061**
	(0.005)	(0.006)	(0.007)	(0.028)
IV/GMM				
Non-Profit	-0.073***	-0.120***	-0.132***	-0.057
	(0.027)	(0.033)	(0.035)	(0.099)
Public	-0.042	-0.060*	-0.05	-0.127
	(0.026)	(0.032)	(0.034)	(0.093)
IV/MNL				
Non-Profit	-0.029	-0.044*	-0.059**	0.015
	(0.019)	(0.023)	(0.025)	(0.087)
Public	-0.003	-0.007	-0.008	-0.098
	(0.018)	(0.021)	(0.022)	(0.068)
N	61,479	61,479	61,479	61,479

*** Significant at the 1% level (two-tail test).
** Significiant at the 5% level (two-tail test).
* Significant at the 10% level (two-tail test).
[a] All regressions include 21 city/county dummies, year dummis and explanatory variables in Table 3.
Standard errors are in parentheses.
Huber or robust standard errors on which they are based allow for hospital/year clustering.
Intercepts are not shown.

Table 9: Esimated Results of Hospital Stays and Per-Day Expediture

	log(Length of Stay)[a]	log(Per-Day Expenditure)[a]
OLS		
Non-Profit	0.084***	-0.112***
	(0.020)	(0.018)
Public	0.221***	-0.150***
	(0.020)	(0.017)
IV/GMM		
Durbin-Wu-Hausman endogeneity test $\chi^2_{(2)}$	7.899	13.786
Reject the Null?	Yes**	Yes**
Hansen J statistic overidentification test $\chi^2_{(2)}$	2.631	0.684
Reject the Null?	No	No
Non-Profit	0.185***	-0.209***
	(0.066)	(0.065)
Public	0.187***	-0.296***
	(0.070)	(0.063)
IV/MNL		
Non-Profit	0.181***	-0.131**
	(0.056)	(0.053)
Public	0.140***	-0.234***
	(0.052)	(0.049)
Sample size	84,385	84,385

*** Significant at the 1% level (two-tail test).

** Significiant at the 5% level (two-tail test).

[a] All regressions include 21 city/county dummies, year dummis and explanatory variables in Table 3.
Standard errors are in parentheses.
Huber or robust standard errors on which they are based allow for hospital/year clustering.
Intercepts are not shown.

Appendix A: First-Stage Multinomial Logit Results

Table A-1: First-Stage Multinomial Logit Results (IV: distance)[a]

	Mean (Std. Dev.)	Public vs. For-profits	Nonprofit vs. For-profits
Distance to the nearest government hospital	6.335	-0.067***	0.027
	(6.764)	(0.016)	(0.021)
Distance to the nearest nonprofit hospital	5.604	0.064***	0.096***
	(6.086)	(0.013)	(0.018)
Distance to the nearest government hospital squared		-0.002**	-0.001
		(0.001)	(0.001)
Distance to the nearest nonprofit hospital squared		0.000	0.000
		(0.001)	(0.001)
Log-likelihood		-61217	
N		84,385	

***Significant at the 1% level (two-tail test).

**Significant at the 5% level (two-tail test).

[a] Partial results are reported. We control for all explanatory variables listed in Table 3.

Table A-2: First-Stage Multinomial Logit Results (IV: distance differentials)[a]

	Mean (Std. Dev.)	Public vs. For-profits	Nonprofit vs. For-profits
Distance differential to the nearest government hospital	4.648	-0.080***	0.047**
	(5.865)	(0.017)	(0.020)
Distance differential to the nearest nonprofit hospital	3.916	0.067***	0.079***
	(5.209)	(0.011)	(0.018)
Distance differential to the nearest government hospital squared		-0.002**	-0.002**
		(0.001)	(0.001)
Distance differential to the nearest nonprofit hospital squared		0.000	0.000
		(0.000)	(0.001)
Log-likelihood		-61287	
N		84,385	

***Significant at the 1% level (two-tail test).

**Significant at the 5% level (two-tail test).

[a] Partial results are reported. We control for all explanatory variables listed in Table 3.