Do Patients Value Uncompensated Care Provision?

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PRELIMINARY - COMMENTS WELCOME

Abstract

Our paper investigates hospitals' incentives to provide uncompensated care from a demand-side perspective. We study whether uncompensated care provision is an attribute valued by patients in their hospital choice and if the insurance status plays a role in that decision. Our results indicate that patients are less likely to go to a hospital the more uncompensated care that hospital provides. Patients could perceive this provision as a higher chance to face longer waiting times and not having hospital's resources readily available. Hospital's demand seems to be driven by location, ownership status, and quality. Counterfactual exercises showed that if nonprofit hospitals are obligated to provide a minimum amount of uncompensated care, this initiative could actually benefit nonprofit hospitals as it would tend to diminishes this type of negative externality caused by uncompensated care provision.

JEL Codes: I11, I18, L21, C35.

1 Introduction

In 2008 hospitals provided more than 60% of the uncompensated care offered by all types of health care providers (Hadley *et al.*, 2008). Uncompensated care includes both bad debt (the care provided by hospitals for which they expected but did not receive reimbursement for) and charity care (the free care provided by hospitals). Providing uncompensated care is not mandatory[1], but most hospitals, regardless of ownership type, offer this type of care.

What incentives do hospitals have to provide an unprofitable service like uncompensated care? As for public hospitals, they act as a safety net for all types of patients, including the uninsured, and are usually located in lower income areas where demand for uncompensated care tends to be greater. On the other hand, nonprofit hospitals are required to provide community benefits, which can include charity care, in order to receive tax-exempt status from the Internal Revenue Service (IRS). In fact, uncompensated care provision represents 56% of the community benefits expenditures reported by nonprofit hospitals according to the IRS (2009). For-profit hospitals, however, do not extract direct benefits from providing uncompensated care. The incentives behind the provision of uncompensated care by for-profit hospitals is the main motivation for our study.

For-profit hospitals provide a significant amount of uncompensated care compared to nonprofit hospitals. Recently, there has been much discussion about the similar levels of uncompensated care provided by nonprofit and for-profit hospitals when controlling for hospital size or revenues. Studies like Cram *et al.* (2010) and Kim *et al.* (2009) found no difference between for-profit and nonprofit provision of uncompensated care when controlling for hospital size. In addition, the IRS (2009) suggested that nonprofit provision may not have been enough to justify their tax exempt status.

Although there is some evidence linking market structure characteristics to uncom-

[1] In emergency situations, hospitals at least have to stabilize the patient's condition.

pensated care provision[2], there is no study we are aware of investigating demand-related incentives to provide uncompensated care. In particular, consumers may value how much uncompensated care is provided by hospitals. For example, they may perceive higher levels of uncompensated care as a signal of service quality or the hospital's level of social responsibility (Hirth (1997), Clement *at al* (2002)). Under these circumstances, for-profit provision of uncompensated care may be a way to mimic the behavior of nonprofit and public hospitals to attract this type of consumer.

An important aspect of the hospital market is that patients differ by insurance status. Basically, they can be privately insured, publicly insured or uninsured[3]. These types of patients may respond to hospital attributes differently. For example, privately insured patients may not care about hospital prices because insurance companies are responsible for most payments. On the other hand, for uninsured patients, price may be a decision factor if there is a small chance of paying the hospital bill. Besides that, some patients may view uncompensated care provision as a sign of quality or better reputation, while others could perceive it as a higher chance of having to wait to be admitted.

The goal of our paper is to investigate how patients value uncompensated care provision, and whether the patient's insurance status plays a role in that preference. By accounting for individual characteristics including insurance status, we are able to detect how patients perceive not only uncompensated care provision but also other hospital attributes such as price and ownership status. Being able to account for these potential differences is one of the contributions of our study.

Recent research[4] on demand for hospital care has focused on hospital characteristics like ownership status, geographic location, price and quality indicators, without investigating whether uncompensated care affects consumers' hospital choice. Moreover, there is no evidence on how hospital demand varies across different types of patients. Previous

[2]Capps, Carlton, and David (2010) found that ownership status did not influence uncompensated care provision, not even when hospitals have market power.

[3]In 2010, the US Census Bureau estimated that 16.3% of people were uninsured, comprising almost 50 million people, while there were about 256 million people with any some type of health insurance. Source: http://www.census.gov/hhes/www/hlthins/data/incpovhlth/2010/highlights.html.

[4]See, for example, Gaynor and Vogt (2003) and Tay (2003).

studies have focused on a single patient type, like privately insured people only, as in Gaynor and Vogt (2003), or only patients with a certain diagnosis, like in Tay (2003), or even patients from a specific region, as in Town and Vistnes (2001) and Capps *et al.* (2003).

Our model assumes that the choice of a hospital depends on the facilities' characteristics and also on patients' attributes, like insurance status. We worked with 2005 data on almost 1.9 million patients (classified as privately insured, publicly insured or uninsured) and 273 hospitals in California. With such a detailed patient-level dataset, our model can produce richer substitution patterns than a traditional discrete choice model and also allows us to study how uncompensated care provision affects market shares and hospitals' own-price elasticities.

Our results indicate that the incentives for-profit hospitals have to provide uncompensated care may not be driven by demand-side aspects. In fact, patients are less attracted to hospitals that provide uncompensated care, regardless of their insurance type. Estimation results showed that hospital's demand is driven by location, ownership status, and quality. Furthermore, the counterfactuals showed that hospitals market power and demand responsiveness would not change dramatically if uninsured patients became publicly insured, given the similarity in the hospital attributes these patients' value in their hospital choices. As for the possibility of mandating nonprofit hospitals to provide a minimum amount of uncompensated care, results showed that this initiative could actually benefit nonprofit hospitals as their patients become less responsive to change in uncompensated care provision.

Our paper is organized as follows. Section 2 presents some of the recent contributions to the literature on hospital demand estimation and on uncompensated care provision. Section 3 introduces the model. Section 4 explains the data and the next section describes the empirical model. Section 6 presents the results and Section 7 section concludes.

2 Previous Literature

Our study relates to the literature on hospital demand. Prior evidence indicated that hospital choice depends on hospital size, ownership status, quality measures, price, and travel distance. Tay (2003) structurally estimated hospital demand to understand how quality differentiation determines the hospital choice of Medicare patients. Her results show that Medicare patients consider both travel distance and services' quality when choosing a hospital. Patients may even be willing to travel greater distances in order to receive higher-quality treatments. Her work demonstrates the role played by several quality indicators in hospital choice and indicates that hospitals may compete on quality rather than on prices. Quality measures were also found to be a determining factor in hospital choice in Luft *et al* (1990).

Hospital choice models were also estimated by Town and Vistnes (2001). They found that hospital choice depends greatly on travel distance, which was also a result of similar models estimated by Capps *et al.* (2003) and by Ho (2006). Severity of illness, and racial characteristics were also found to be determinants of hospital choice in Town and Vistnes's (2001) model. As some implications of these results for hospitals' behavior, they found that hospital competition is driven by both product and geographic differentiation.

Another important study is that by Gaynor and Vogt (2003). They assessed the effect of mergers on hospital prices with estimates of a structural model of hospital competition which used 1995's data on privately insured patients and hospitals in California. Their estimation results showed that patients are price sensitive and prefer on average for-profit hospitals, as well as teaching hospitals and those offering high-technology services. Gaynor and Vogt's (2003) results also demonstrated there is no difference in for-profit and nonprofit hospitals' behavior after mergers. Both types of hospitals impose their market power and increase prices after a merger. These similarities in hospitals' behavior may hinder patients' perception with regards to pricing strategies. As a result, differentiation strategies based on quality, reputation or other attributes can be important mechanisms to attract more patients.

Studies of uncompensated care provision are also closely related to ours. Most of this literature has focused on the effects of hospital competition on that provision. Gruber (1994) investigated how competition among hospitals affects their provision of uncompensated care before and after a new law passed in California in 1983 which allowed selective contracting by insurance companies. With selective contracting, insurance companies could create a network of providers, and then offer better discounts to patients treated by network members. Gruber's (1994) results showed that hospitals in more competitive markets decreased their provision of uncompensated care more than hospitals in concentrated markets. He also demonstrated how uncompensated care provision depends on hospital revenues.

Recently, Garmon (2009) examined the relationship between competition and charity care provision by hospitals in Texas and Florida. The two states were chosen for having different regulatory environments. Florida regulates entry in the hospital market through a Certificate of Need requirement, whereas Texas does not control entry. No evidence was found indicating that hospitals in concentrated markets provided more charity care. This result is in line with the findings in Capps, Carlton, and David (2010). Their study questioned whether nonprofit hospitals deserve more favorable antitrust treatment because they can use their market power to provide more community benefits. Moreover, promoting competition among nonprofit hospitals may have socially undesirable effects, because being in a more competitive environment could constrain their ability to provide the community benefits they are expected to. In order to verify if this is true, Capps, Carlton, and David (2010) examined how the market structure affects the provision of uncompensated care. Their results, however, did not support the assertion that nonprofits should be treated differently by the antitrust authorities, and there was little evidence that nonprofit hospitals with market power provide more uncompensated care.

Potential differences between nonprofit and for-profit uncompensated care provision was also investigated by Needleman, Lamphere, and Chollet (1999). They examined how hospital conversions in Florida affected their provision of uncompensated care. The results showed that conversions from nonprofit to for-profit did not result in a significant change in the level of uncompensated care provided, whereas conversions of public hospitals into for-profit institutions implied less uncompensated care. Looking at different aspects of uncompensated provision, Mann et al. (1997) studied the trends on uncompensated care provision from 1983 to 1995. Their main result showed a cross-subsidization behavior from Medicaid and Medicare patients to uninsured patients.

Our paper's main motivation is to understand the incentives for-profit hospitals have to provide uncompensated care and whether this provision is perceived by patients as a sign of higher quality or better reputation. Although this question has not been answered yet, there is growing literature linking hospital behavior to quality or reputation signaling. Hirth (1999), for example, has showed that in markets where nonprofit and for-profits coexist, nonprofit status works as a sign of quality. Alternatively, provision of charity care could be thought of as a sign of better reputation or corporate social responsibility and function as a differentiation strategy. Previous works, like Baron (2010), McWilliams and Siegel (2001) and Bagnoli and Watts (2003), highlighted the strategic use of corporate social responsibility and the fact that public good provision and corporate social responsibility can have the same effects in a market. Our work is not going to be able to identify whether a positive impact of uncompensated care provision in a hospital's demand indicates higher quality or better reputation. However all these are possible reasons why consumers might value uncompensated care provision and why hospitals even when facing declining profit margins and a competitive market may opt to offer free care for their patients.

3 Model

3.1 Demand

Our model follows the literature on discrete choice random coefficients[5] where each individual i receives a utility u_{ij} from consuming product j. In addition, each hospital j offers one product, which is viewed as a bundle of hospital characteristics. Additionally, each patient i has preferences over these characteristics and chooses the hospital (product) that gives the highest utility. Each patient i gets the following utility from choosing hospital j:

$$u_{ij} = \sum_k X_{jk}\tilde{\beta}_{ik} + \xi_j + \epsilon_{ij} \tag{1}$$

where

$$\tilde{\beta}_{ik} = \bar{\beta}_k + \sum_r Z_{ir}\beta^o_{kr} + \beta^u_k v_{ik} \tag{2}$$

where X_{jk} is a vector of k observed characteristics of hospital j and ξ_j is the error term, which captures unobserved hospital characteristics; $\bar{\beta}_k$ is patients' mean taste over hospital characteristic k; Z_{ir} is a vector of r patient characteristics; v_{ik} is the error term capturing unobserved patient heterogeneity; and ϵ_{ij} is the idiosyncratic patient taste. Because patient information is available, we are able to allow for patient heterogeneity over hospital characteristics, as shown in equation 2. This equation shows that a patient's taste over a hospital attribute k can be decomposed into an average taste for this attribute ($\bar{\beta}_k$), and patient preferences according to his or her characteristics. The patient taste depends on characteristics that are observed by the econometrician and captured by β^o_{kr}, as well as unobserved attributes captured by β^o_{kr}. Therefore, depending on the patients' characteristics, they may value differently each hospital attribute k.

[5]For example: Dubin and McFadden (1984), Berry, Levinsohn and Pakes (1995, 2004), and Gaynor and Vogt (2003).

Re-writing the two equations above yields:

$$u_{ij} = \delta_j + \sum_{kr} X_{jk} Z_{ir} \beta^o_{kr} + \sum_{k} X_{jk} v_{ik} \beta^u_k + \epsilon_{ij} \tag{3}$$

$$\delta_j = \sum_k X_{jk} \bar{\beta}_k + \xi_j \tag{4}$$

Equation (3) allows patients to vary in their preferences for each hospital characteristic, whereas δ_j captures a mean utility for each hospital attribute k. This hospital-specific term is included to allow each attribute to have a direct effect on demand regardless of patient characteristics, as shown in equation (4). According to Berry, Levinsohn and Pakes (2004), it is not necessary to introduce the term δ_j if it was assumed that hospital characteristics do not have a systematic effect on hospital's demand.

Because we worked with micro data, our study observes several patient characteristics. By including interaction terms between patient and hospital attributes in equation (3), the model produces substitution patterns that take into account this patient heterogeneity. This observable patient heterogeneity also helps in the identification of the model and produces more reasonable cross-price elasticities of demand even if random coefficients were not introduced in the model (and instead a standard logit model was estimated assuming that ϵ_{ij} is i.i.d. extreme-value distributed). Although the model may still suffer from the Independence of Irrelevant Alternatives (IIA) problem, Gaynor and Vogt (2003) have shown that controlling for observed patient heterogeneity produces fairly reasonable substitution patterns.

When micro data is not available, it is still possible to estimate discrete choice models that produce richer substitution patterns than a standard logit model. Berry's (1994) nested logit model is one example of framework that employs only aggregate data, although it requires market shares to be observed prior to the estimation, which may not be applicable to markets where the geographic location is an endogenously determined decision. Alternatively, Berry, Levinsohn and Pakes (1995) proposed a random coefficient discrete choice model where consumer heterogeneity is included by allowing certain consumer attributes to follow a specific distribution. With this assumption, their model is able to produce substitution patterns that allow patients to differ in their preferences over product characteristics. Finally, Berry, Levinsohn and Pakes's (1995) model can also be estimated when information on the distribution of consumer demographics or secondary data on consumers is available, which produces even richer substitution patters. This type of application can be found in many studies like Berry, Levinsohn and Pakes (2004), Nevo (2001), Petrin (2002) and Goldberg (1995).

3.2 Supply

On the supply side, hospitals compete in a differentiated-product oligopoly setting. Suppose each hospital j is a single-product firm. The profit function of firm j, π_j, is given by:

$$\pi_j = (p_j - mc_j)s_j(p) - cf_j \tag{5}$$

where p_j and mc_j are hospital j's price and marginal cost, $s_j(p)$ is hospital j's market share, and cf_j is hospital j's fixed cost.

The profit function in equation (5) does not assume a functional form for mc_j. However, uncompensated care provision increases hospital costs, since it is a type of care for which the hospital was not reimbursed. Furthermore, it is expected that the cost of uncompensated care for a hospital is not a fixed cost, since it varies depending on how much uncompensated care is provided. In this sense, one can argue that uncompensated care affects a hospital's marginal costs. Therefore, if one explicitly assumes a linear functional form for mc_j, it is possible to obtain a measure of that provision on marginal costs. By doing that, it is possible to compare the effects of uncompensated care provision on hospitals' market share and marginal cost, which helps to give us an overall understanding of hospitals' incentives to provide uncompensated care.

Re-writing equation (5), hospital j's profit is expressed as:

$$\pi_j = (p_j - mc_j)s_j(p) - C_j \tag{6}$$

where $mc_j = \psi_1 + \psi_2 UC_j$. Or,

$$\pi_j = (p_j - (\psi_1 + \psi_2 UC_j))s_j(p) - C_j \tag{7}$$

Assuming hospitals set price and the amount of uncompensated care, the first-order conditions are:

$$\frac{\partial \pi_j}{\partial p_j} = s_j(p) + (p_j - (\psi_1 + \psi_2 UC_j))\frac{\partial s_j}{\partial p_j} = 0 \tag{8}$$

$$\frac{\partial \pi_j}{\partial UC_j} = -\psi_2 s_j(p) + (p_j - (\psi_1 + \psi_2 UC_j))\frac{\partial s_j}{\partial UC_j} = 0 \tag{9}$$

Dividing equation (8) by equation (9) produces:

$$-\frac{1}{\psi_2} = -\frac{\partial s_j/\partial p_j}{\partial s_j/\partial UC_j} \tag{10}$$

From equation (10) it is possible to recover ψ_2 and consequently ψ_1, giving an estimate for marginal cost and how it depends on the level of uncompensated care. With this estimate, one can assess how hospitals, depending on their ownership status, differ with respect to their marginal costs and especially with respect to the effect of uncompensated care on their marginal costs. Whether or not there is a difference in this effect can provide insight into the incentives hospitals have to provide uncompensated care. The estimation procedure that allows recovering ψ_1 and ψ_2 is presented in Section 5.

4 Data

Our study uses data from California, since patient-level and hospital data are not available nationwide. The information was provided by the Office of Statewide Health Planning and Development (OSHPD) in three datasets for 2005: Quarterly Financial Data Report, Annual Financial Data Report, and Patient Discharge Data Report[6].

The Quarterly Financial Data Report was the source of all information on revenues and expenses by type of payer, capacity and utilization, and income statements. In turn detailed information on hospital organization structure as well as a description of the services available in each hospital was obtained from the Annual Financial Data Report.

The Patient Discharge Data Report contains all hospitals' discharges, with information on patient age, race, gender, zip code, Diagnosis Related Group (DRG), Major Diagnostic Category[7](MDC), type of admission, expected payer, and length of stay. Total patient charge is also available, which is the total amount of each patient's bill, not detailed by procedure. This charge is based on full price, which is the list price before any of the discounts and deductions that are usually given to patients or insurance companies.

In 2005, there were 453 hospitals in California and more than 3.9 million discharges. For the purpose here, patients with a length of stay of more than 30 days were not kept in the sample, as well as patients with missing information regarding selected variables, and patients with charges less than US$ 500 and more than US$ 800,000. Only patients receiving treatment at a general acute care hospital were kept in the sample. Patients who looked for treatment outside their own Health Service Area (HSA) were also dropped. HSA is a geographic boundary comprising one or more counties, defined by the Department of Human and Health Services for health planning purposes (Makuc *et al.* (1991)). In California, there are 14 HSAs. It is important to mention that this criterion of dropping patients who looked for care outside their own HSA eliminated only

[6] Information on hospitals' casemix was also provided by the OSHPD, in a separate file

[7] According to the OSHPD, "MDCs are mutually exclusive categories containing all possible principal diagnosis areas". There are 25 different MDCs.

3% of the observations, which is good indication that if HSA was adopted as a market definition, it would not lead to underestimating the market's size. Hospital financial data include only general acute care facilities with more than 100 discharges in 2005. The final sample included 273 hospitals and 1,899,183 discharges.

For our model's identification, an important source of variation is the travel distance between the patient's and the hospital's zip code. The travel distance was obtained using the great circle distance formula, which calculates the distance between two points based on their geographic location[8]

The descriptive statistics are presented in Table 1. Among hospitals, 57% are nonprofits and 24% are for-profits. These numbers are slightly higher than the national average, which are 51% and 20% respectively according to AHA (2008). Teaching hospitals comprise 7% of the sample. On average, hospitals provided US$17 million in uncompensated care in 2005, 42% reported as charity care. Table 2 shows uncompensated care provision by ownership type. In 2005, nonprofit hospitals provided around US $20 million in uncompensated care, whereas for-profits offered approximately US $11 million. However, when taking into account hospital size, by dividing uncompensated care by numbers of beds, the difference diminishes considerably, with nonprofits providing US $80,090 in uncompensated care per bed and for-profit hospitals providing US $66,116.

5 Empirical Model

5.1 Demand

The utility patient i gets from going to hospital j is expressed as:

[8]Information on latitude and longitude by zip code was obtained at: www.boutell.com/zipcodes/.

$$
\begin{aligned}
u_{ij} = \delta_j + d_{ij}\alpha_1 + d_{ij}^2\alpha_2 + \sum_k d_{ij}X_{jk}\gamma_{1k} + + \sum_k d_{ij}^2 X_{jk}\gamma_{2k} + \sum_{\ell k} Z_{i\ell}X_{jk}\beta_{\ell k} \\
+ \sum_\ell d_{ij}Z_{i\ell}\gamma_{3k} + \sum_\ell d_{ij}^2 Z_{i\ell}\gamma_{4k} + \sum_\ell p_j UC_j Z_{i\ell}\theta_\ell + \varepsilon_{ij}
\end{aligned}
\tag{11}
$$

where d_{ij} is the distance between patient i's zip code and hospital j's zip code, $Z_{i\ell}$ is a vector of ℓ different patient i characteristics: male ($Male$), unscheduled admission ($Unsch$), privately insured ($Priv$), uninsured ($Unin$), and senior citizen ($Senior$); X_{jk} is a vector of k hospital j characteristics: for-profit status (FP), public status (Pub), teaching status ($Teach$), technology index[9] ($Tech$), number of beds ($Beds$), uncompensated care as percentage of patient revenue[10] (UCR), price (p), nurses per bed ($NursePerBed$), and casemix ($casemix$).

The mean utility, δ_j, is given by:

$$
\begin{aligned}
\delta_j = \phi_0 + \phi_1 p_j + \phi_2 UCR_j + \phi_3(p_j * UCR_j) + \phi_4 FP_j + \phi_5 Pub_j + \phi_6 Teach_j \\
+\phi_7 Tech_j + \phi_8 Beds_j + \phi_9 NursePerBed + \phi_{10} Casemix_j + \zeta_j
\end{aligned}
\tag{12}
$$

Before estimating equations (11) and (12), it is necessary to define the choice set for each patient. As noted in the previous section, there are about 1.9 million patients in the sample and 273 hospitals. Estimating a model allowing each patient to choose from the 273 hospitals in California is not only unrealistic but also computationally burdensome. Therefore it is necessary to restrict each patient's choice set. Hence, it is assumed that a patient is only allowed to choose from hospitals located in the same HSA in which he or she lives. As already mentioned in the previous section, in the sample patients that

[9]Following Gaynor and Vogt (2003), a technology index was calculated by summing over 36 dummies that indicate the availability within the hospital of a specific service. Among them are: diagnostic image services, laboratory services, and surgery services. The construction of this index follows a procedure similar to Gaynor and Vogt (2003).

[10]Because uncompensated care is reported based on list prices, the amount reported by each hospital has to be scaled in terms of costs or revenues in order to represent the actual cost for each hospital. We represent uncompensated care relative to gross patient revenue.

went to a hospital in a different HSA represented less than 3% of the observations. This small percentage confirms that restricting the choice set to each HSA does not cause an underestimation of the hospitals actually considered by each patient[11]. Table 3 presents the sample's description with number of patients and hospitals by HSA.

Given this choice set restriction, equation (11) represents the utility patient i, from HSA h, obtains when choosing hospital j, also located in HSA h. Therefore, equation (11) is estimated by HSA. The mean utility, δ_j, is recovered from this estimation and used as the dependent variable in equation (12). However, because equation (12) is estimated at the hospital level and includes all 273 hospitals, it is important to take into account that hospitals are located in different HSAs in order to control for the fact that hospitals from one HSA may share an unobserved attribute that affects the demand for all hospitals in this HSA. Hence, equation (12) needs to express hospital j's mean utility as a function of its characteristics and a dummy variable, HSA_h, representing the HSA h where hospital j is located. Then:

$$\begin{aligned} \delta_j = \phi_0 + \phi_1 p_j + \phi_2 UCR_j + \phi_3(p_j * UCR_j) + \phi_4 FP_j + \phi_5 Pub_j + \phi_6 Teach_j \\ + \phi_7 Tech_j + \phi_8 Beds_j + \phi_9 Nurse + \phi_{10} Casemix_j + \omega HSA_h + \zeta_j \end{aligned} \tag{13}$$

Following Gaynor and Vogt (2003), to identify the model, and estimate equations (11) and (13), it was necessary to assume there is no outside good and that patients do not have the ability to change the quantity consumed once they have chosen a hospital. If an outside good was considered, information on consumers that needed health care treatment and did not look for care at a hospital would have to be available. Unfortunately, not even demographic characteristics about this population is available. Given the lack of data and following previous literature about structural estimation on hospital competition, like Tay (2003) and Gaynor and Vogt (2003), it is assumed there is no

[11] As a robustness check, hospitals' prices were estimated including these observations and no significant difference was found.

outside good, implying that once a consumer gets sick, he or she will look for care at a hospital.

Another assumption necessary for identification purposes is that the quantity each patient consumes at a given hospital is a fixed characteristic of that patient. Therefore, once a patient is admitted to a hospital, he or she cannot change the quantity of care consumed, regardless of any change in hospital characteristics, including price. However, if a hospital increases price, its patients can look for care in another hospital. This assumption is necessary to obtain a measure of price for each hospital from the data available, by applying Gaynor and Vogt's (2003) methodology, which is explained in the next subsection.

Finally, it is assumed that ε_{ij} follows an independent and identical extreme valued distribution. Because of this assumption, as in any conditional logit setting, the probability of a patient i going to hospital j is given by:

$$s_{ij} = \frac{e^{\delta_j + \mu_{ij}}}{\sum_{g=1}^{J} e^{\delta_g + \mu_{ig}}} \tag{14}$$

where μ_{ij} captures all the terms in equation (11) except δ_j.

These assumptions, together with the information on the distance each patient has to travel to go to each hospital, which is patient-hospital specific, identify the model. Give these assumption, equation (11) can be estimated via conditional logit maximum likelihood. The mean-utility, δ_j, in equation (11) is represented by a dummy variable for each hospital and once estimated becomes the dependent variable in equation (13). One could argue that instead of estimating equations (11) and (13) separately, equation (1) could be estimated via logit maximum likelihood. However, this procedure would not account for potential endogeneity problems between hospital price and uncompensated care and ζ_j. If one considers that ζ_j captures an unobserved quality and/or hospital reputation, then a hospital with higher quality is expected to charge higher prices, which implies a correlation between p_j and ζ_j. Similarly, if a hospital has a better reputation because it provides more benefits to its community, including uncompensated care, this would imply that UCR_j and ζ_j are also correlated. Therefore, estimating equation (1) via logit maximum likelihood would not account for this endogeneity and it would produce upwardly biased coefficients estimates. Even though equation (11) includes quality measures that could potentially minimize this bias, because quality and reputation are multi-dimension concepts and cannot be measured with a single indicator, there is no guarantee that this control will eliminate the endogeneity issue.

In order to correct for these endogeneity problems, equations (11) and (13) have to be estimated separately. Equation (11) is estimated via conditional logit maximum likelihood and equation (13) via Two Stage Least Squares (2SLS). In this case, instruments are needed for all endogenous terms in equation (13), which are p_j, UCR_j and their interaction term, $p_j * UCR_j$.

According to the standard industrial organization literature, like Berry, Levinsohn and Pakes (2004), Nevo (2001) and Gaynor and Vogt (2003), cost-shifters' and/or rivals' characteristics are suitable instruments, where rivals are all hospitals located in the same HSA. They affect the price and level of uncompensated care but are not correlated with unobserved hospital characteristics like quality and reputation. Because there are three endogenous variables in this model (p_j, UCR_j and $p_j * UCR_j$), at least three different instruments are necessary to identify the model[12]. Because information on hospital costs as well as rivals' characteristics is available, the following instruments are tested: average price of rivals ($RivalsPrice$), average uncompensated care of rivals ($RivalsUCR$), average size of rivals ($RivalsBeds$), number of uninsured patients treated ($Uninsured$), a ratio of wage expenses and total number of full time employees ($WageFTE$), a dummy variable indicating whether the hospital has a trauma center ($Trauma$), and fixed assets costs ($FixedCost$).

[12]In fact, there could be two instruments and the third one could be an interaction term between them

5.2 Market Shares and Elasticities

From equation (14), for each hospital j located in HSA h, its market share is given by:

$$s_j = \left(\frac{1}{I}\right) \sum_{i=1}^{I} s_{ij} \tag{15}$$

$$s_j = \left(\frac{1}{I}\right) \sum_{i=1}^{I} \frac{e^{\delta_j + \mu_{ij}}}{\sum_{g=1}^{J} e^{\delta_g + \mu_{ig}}} \tag{16}$$

where I is the total number of patients in HSA h. Given hospital j's market share, its own-price elasticity, η_j, can be expressed by:

$$\eta_j = \frac{\partial s_j}{\partial p_j} \frac{p_j}{s_j} \tag{17}$$

$$\eta_j = \left(\frac{p_j}{s_j}\right) \left[\frac{1}{I} \sum_{i=1}^{I} \frac{e^{u_{ij}}(\cdot)(\sum_{g=1}^{J} e^{\delta_g + \mu_{ig}}) - e^{u_{ij}} e^{u_{ij}}(\cdot)}{(\sum_{g=1}^{J} e^{\delta_g + \mu_{ig}})^2}\right] \tag{18}$$

$$\eta_j = \left(\frac{p_j}{s_j}\right) \left[\frac{1}{I} \sum_{i=1}^{I} (\cdot)(s_{ij} - s_{ij}^2)\right] \tag{19}$$

where $(\cdot)$ is equal to:

$$\begin{aligned}(\cdot) = \phi_1 + \phi_3 UCR_j + \lambda_1 d_{ij} + \lambda_2 d_{ij}^2 + \chi_1(Male) + \chi_2(Unsch) + \chi_3(Unin) + \\ \chi_4(Priv) + \chi_5(Senior) + \theta_1 UCR_j(Male) + \theta_2 UCR_j(Unsch) + \\ \theta_3 UCR_j(Unin) + \theta_4 UC_j(Priv) + \theta_5 UC_j(Senior)\end{aligned} \tag{20}$$

From equations (19) and (20), it is possible to verify that the patients' insurance type is going to affect hospital market share and own-price elasticity. Observing patients' heterogeneity also produces richer substitution patterns and therefore minimizes the IIA problem.

5.3 Hospital Prices

Information on hospitals' prices, as already mentioned, is not readily available in the data. Hospitals report only patients' full charge, without any detail on the price of procedures or discounts and deductions negotiated afterward with patients or insurance companies. Because of that, the full charge actually represents each patient's total expenditure over the entire admission period. In order to extract a measure for hospital price from this information on the patient's expenditure, this paper follows Gaynor and Vogt's (2003) methodology. Patient i's total expenditure is defined as $charge_i$, which is the full charge for patient i prior to any deduction or discount. Then, the full charge is scaled by an average discount given by hospital j for each patient based on the payer's category (pc), which can be: Medicare, Medi-Cal, indigent, or other third party. The result is a measure of "net expenditure", $p_j q_i$, defined as:

$$p_j q_i = charge_i \left(\frac{GRI_j^{pc} + GRO_j^{pc} - DED_j^{pc}}{GRI_j^{pc} + GRO_j^{pc}} \right) \tag{21}$$

$$= charge_i \left(\frac{\text{Net Patient Revenue}^{pc}}{\text{Gross Patient Revenue}^{pc}} \right) \tag{22}$$

where GRI_j^{pc} and GRO_j^{pc} are gross inpatient and outpatient revenue, respectively, from a specific payer category (pc), and DED_j^{pc} are contractual deductions given to the same payer category. As mentioned, net expenditure represents a measure of the price paid by patients or insurance companies, or a "net charge", as the full charge is adjusted by the average deduction given by hospital j. Given the model assumptions, following Gaynor and Vogt (2003), the net expenditure $p_j q_i$ can be divided into price and quantity given the identity below:

$$\ln p_j q_i = \ln p_j + \ln q_i = \sum_j I_{i \to j} \ln p_j + W_i \beta + \nu_i \tag{23}$$

$$= I_{i \to j} \alpha + W_i \beta + \nu_i \tag{24}$$

where W_i is a vector of dummy variables for the following patient characteristics: patient insurance status (privately insured, publicly insured, and uninsured), age category (4 dummies), gender, race (3 dummies), admission type (if unscheduled or not), 543 DRG dummies, number of other diagnoses (24 dummies) and interaction terms between 25 MDC dummies and all other patient characteristics except DRGs. Finally, $I_{i \to j}$ is a dummy variable that equals one if patient i went to hospital j and zero otherwise. This indicator variable is the only one in equation (24) that is hospital-specific, and it results in a coefficient estimate for each one the 273 hospitals in the sample.

Applying Gaynor and Vogt's (2003) methodology, equation (24) can be estimated via Ordinary Least Squares (OLS). After this estimation, vector W_i is fixed at its mean values and for this vector it is assumed that $E(q_i) = 1$, representing a "standard" or "average" discharge. After all, the coefficient of each hospital's dummy gives the predicted expenditure for this "standard" discharge, generating an average price (p_j) for each hospital.

5.4 Supply

With the demand estimates from equations (11) and (13), it is possible to obtain demand responses to price and uncompensated care, which are needed to recover the marginal cost's parameters as shown in equation (10). The demand response to price is given by:

$$\frac{\partial s_j}{\partial p_j} = \left[\frac{1}{I} \sum_{i=1}^{I} (\cdot)(s_{ij} - s_{ij}^2) \right] \tag{25}$$

and $(\cdot)$ is equal to:

$$
\begin{aligned}
(\cdot) = \phi_1 + \phi_3 UC_j + \lambda_1 d_{ij} + \lambda_2 d_{ij}^2 + \chi_1(Male) + \chi_2(Unsch) + \chi_3(Unin) + \\
\chi_4(Priv) + \chi_5(Senior) + \theta_1 UCR_j(Male) + \theta_2 UCR_j(Unsch) + \\
\theta_3 UCR_j(UNIN) + \theta_4 UCR_j(Priv) + \theta_5 UCR_j(Senior)
\end{aligned} \tag{26}
$$

On the other hand, the demand response to uncompensated care is given by:

$$
\frac{\partial s_j}{\partial UC_j} = \left[\frac{1}{I} \sum_{i=1}^{I} (\bullet)(s_{ij} - s_{ij}^2) \right] \tag{27}
$$

and $(\bullet)$ is equal to:

$$
\begin{aligned}
(\bullet) = \phi_2 + \phi_3 p_j + \gamma_3 d_{ij} + \gamma_4 d_{ij}^2 + \beta_1(Male) + \beta_2(Unsch) + \beta_3(Unin) + \\
\beta_4(Priv) + \beta_5(Senior) + \theta_1 p_j(Male) + \theta_2 p_j(Unsch) + \\
\theta_3 p_j(Unin) + \theta_4 p_j(Priv) + \theta_5 p_j(Senior)
\end{aligned} \tag{28}
$$

With these two demand responses it is possible to calculate ψ_2, as shown in equation (10). In addition, from the first-order equations (8) and (9), ψ_1 can be recovered, so marginal costs for each hospital can be calculated as:

$$
\widehat{mc}_j = \psi_1 + \psi_2 UC_j \tag{29}
$$

Although uncompensated care provision is assumed to affect marginal costs linearly, one can still use ψ_2 to compare the effect of uncompensated care on supply and on demand. This comparison helps to understand the incentives for hospitals' provision of uncompensated care.

The following section presents the estimation results. The steps of the estimation procedure are: (1) hospital prices are backed out after estimating equation (24) via OLS; (2) once prices are obtained, a patient-level demand equation, given by equation (11), is estimated via conditional logit maximum likelihood; (3) from estimation in step (2), hospitals' mean utilities are obtained and used as the dependent variable in a hospital-level demand equation, as shown in equation (13), being estimated via 2SLS. Once demand is estimated, the coefficients estimated from steps 2 and 3 are used to calculate the marginal cost parameters, the hospital market shares, and the own-price elasticities.

6 Results

6.1 Hospital Prices

Before estimating the model as presented in section 5, it is necessary to back out hospital prices with estimation results from equation (24). Since there are more than 1500 independent variables, coefficient estimates will not be presented. The R^2 for the OLS regression is 0.9932 and the p-value from the F-test is 0.0000, indicating very good fit. Also, all coefficient estimates on hospital dummies (which represent price) are statistically significant and positive.

Table 4 shows the descriptive statistics for the predicted price. For-profit hospitals have on average the lowest prices. For an average discharge, for-profits charged a price of US$ 7,364.92. Nonprofit hospitals have higher prices, charging US$ 8,092.36 for an average discharge. These predicted prices are over 70% higher than those obtained by Gaynor and Vogt (2003) with 1995 data. This difference in prices from 1995 to 2005 was also attested by the Bureau of Labor Statistics, which estimated that hospital service prices rose about 65% in this period[13]. This sharp increase in hospital prices was also by Antwi, Gaynor and Vogt (2009). Their work also showed that hospital prices for private patients, for example, almost doubled from 1999 to 2006. Their work showed that neither recent regulations nor market concentration could explain why there was such a significant increase in hospital prices in California.

[13] Source: *www.bls.gov/data/#prices*

6.2 Demand Estimation

Once prices are predicted, hospital demand can be estimated in two steps. The first step is to estimate a conditional logit demand regression using equation (11), which gives the patient i's utility from going to each hospital j located in the same HSA as the patient. The second step consists of estimating equation (13) via 2SLS, where each hospital's mean-utility is expressed as a function of hospital characteristics. Before presenting the results, it is important to address an estimation issue related to the three smallest HSAs. As Table 3 shows, HSA 3 and HSA 7 have only seven hospitals each, whereas HSA 8 has ten hospitals. Although the model here is identified, the estimation procedure requires having enough variation in the choice set. Estimation showed that convergence would not be achieved, even when adopting a different maximization approach or a different stepping procedure, in nonconcave regions. In order to solve this issue, it was necessary to merge HSAs so that the choice set would be more heterogeneous. In order to verify which HSAs to merge, the patient flow to other HSAs was investigated. As previously mentioned, only about 3% of patients in the sample looked for care in hospitals outside their own HSA. Therefore, we investigated how important this patient flow was when compared to the percentage of patients treated in their own HSA. The data revealed that there was a significant patient flow from HSA 1 to HSA 3[14], as well as from HSA 7 to HSA 8[15]. Based on that, HSAs 1 and 3 are considered a single one, as are HSAs 7 and 8.

For a clear understanding, we present first the 2SLS results for equation (13), which is the demand estimation at the hospital level. It represents the effect of hospital characteristics on demand, regardless of patient attributes. Table 5 presents results of four specifications, which differ in the instruments used. First-stage diagnostics are presented at the bottom of the table. We focus on the estimates presented in column IV, which is

[14]About 94% of the patients treated by hospitals from HSA 3 came from this HSA, and 5% came from HSA 1.

[15]About 97% of the patients treated by hospitals from HSA 7 came from this HSA, and 1.4% came from HSA 8.

the one that combines all instruments. Comparison of the specifications shows that specification IV produces the highest Shea's Partial R^2, which is a measure of instruments' relevance and predictive power. Regardless of the specification used, the instruments seemed to be valid, since the hypothesis of overidentifying restrictions could not be rejected as indicated by Sargan's test. Furthermore, the Wu-Hausman statistic indicates that the rejection of the null hypothesis that the instrumented variables are exogenous.

As for the estimation results, specification IV indicates an unexpected positive effect of price on hospital choice, when taking into account not only the price coefficient estimate but also the interaction term with uncompensated care[16]. This upward bias may be capturing hospital quality not fully explained by the control variables (technology index, teaching status, number of nurses per bed, and casemix). It is important to mention that this is an average price effect regardless of patient insurance status.

On the other hand, uncompensated care provision has a negative effect, on average, on hospital choice[17]. It can thus be said that for an average patient, regardless of insurance type and other characteristics, it is less likely he or she will choose a hospital the more uncompensated care is provided by this facility. It could be that patients perceive uncompensated care provision as an indication of longer waiting times, or as a type of negative externality which they are not willing to be exposed to. In either case, the model cannot identify the reason why patients associate a negative valuation to uncompensated care provision. Nevertheless, it is necessary to control for patients' attributes to have a better understanding of whether this is a conception of a single type of patient or if all patients share the same perception.

The remaining hospital characteristics, proxies for hospital quality and ownership status do not seem to affect hospital choice on average. This reinforces the need to control for patient attributes so one can have a clear interpretation on what determines hospital choice because of patient heterogeneity.

[16] I calculate this effect at the average ratio of uncompensated care over revenue, considering that: $\partial\hat{\delta}/\partial p_j = \phi_1 + \phi_3(\overline{UC})$.

[17] An analogous procedure to the one applied to calculate the average price effect was used.

The results for each conditional logit regression are presented in the Appendix. A summary of these results is presented in Table 6, which contains descriptive statistics for the coefficients of interest[18]. From Table 6, comparison of the median coefficient estimates on patient insurance status and hospital ownership type ($privfp$, $privpub$, $unifp$, $unipub$) confirms that both privately insured and uninsured patients are more likely to go to a nonprofit hospital. This result is expected since nonprofit hospitals have on average more beds available, which would attract more patients on average, and their ownership status could be understood as a sign of higher quality (Hirth (1999)). However, uninsured patients are indifferent between nonprofit and public hospitals, whereas privately insured ones are less likely to go a public hospital.

On average, privately insured patients are less sensitive to travel greater distances to go to a hospital compared to uninsured and publicly insured patients. Uninsured patients do not seem to value hospital quality and size like insured patients. Uninsured people are much more like publicly insured patients with regards to hospital characteristics such as size, casemix, nurses per beds, and travel distance.

The results in Table 6 also indicate that uninsured patients are on average as price sensitive as publicly insured patients, whereas privately insured patients are relatively more price sensitive. On the other hand, uninsured patients are more attracted to hospitals that provide uncompensated care, whereas privately insured patients have an opposite perception. These assessments were made based on the median coefficient estimates for interaction terms between insurance status (privately or uninsured) and price p_j, uncompensated care UC_j, and $p_j * UC_j$. Next, we present the market shares and own-price elasticities.

6.3 Market Shares and Elasticities

Hospitals' market share and own-price elasticities were calculated based on the demand estimates obtained in the previous section. Table 7 presents the results (median) by

[18]Statistical significance was considered when calculating the descriptive statistics

HSA and Table 8, by ownership type. The results from Table 7 show that regardless of ownership, hospital's demand is not sensitive to price. The fact that insured patients may not be aware of the actual price charged by a hospital because essentially the negotiation is mediated by the insurance company is a possible reason why consumers do not take hospital price into consideration when choosing a hospital.

On the other hand, Table 7 indicates that hospital demand seems to be affected by the amount of uncompensated care provided. Fewer patients are attracted, on average, the more uncompensated care is provided by hospitals. As Table 8 shows, this impact is similar for nonprofit and for-profit hospitals, which indicates that, although nonprofits have higher market shares on average, nonprofits' and for-profits' demands are similarly affected by how much uncompensated care they provide. This is an indication that hospital market power is not a sufficient condition to guarantee that higher levels of uncompensated care will be provided.

As for the results on own-price elasticities, Table 8 shows that for-profit hospitals' patients seem to be the only ones who are price-sensitive. The results for nonprofit and public hospitals' patients show an unexpected positive own-price elasticity. The results in Table 7 are on average similar to those in Table 8. Unreasonable own-price elasticities seem to be mainly driven by the inclusion of the interaction term between hospital price and uncompensated care, and its effect through the coefficient estimate ϕ_3. From Table 7 it is possible to verify that the HSAs where hospitals provide the highest ratios of uncompensated care and patient revenue are the ones with the highest own-price elasticities. They are the HSAs 6, 12 and 14. These HSAs are also among the ones with the lowest average prices. A possible explanation for these unexpected own-price elasticities could be that most of the patients may not be aware of hospitals' prices at the moment of admission. Studies like Tay (2003) admit that patients may not even consider price as one of the hospital's attributes that influence their choice.

6.4 Supply-side Estimation

With the demand-side coefficient estimates, it is possible to calculate hospitals' marginal cost as in equations (8) and (9). A measure of hospitals' average marginal costs is given by ψ_1, whereas the parameter of interest, ψ_2, indicates how uncompensated care affects hospitals' marginal costs. As noted in equation (25), ψ_2 is determined by the ratio of market share response to uncompensated care and market share response to price. Therefore, assuming patients are price sensitive, the sign of ψ_2 is determined by the market share responde to uncompensated care provision, given by $\partial s_j / \partial UCR_j$. If market share increases with uncompensated care provision, then marginal costs decreases as hospitals provide more uncompensated care.

The results by ownership type and by HSA are shown in Tables 9 and 10 respectively. Table 9 shows that nonprofit and public hospitals are able to reduce their marginal costs more the more uncompensated care they provide. However, these results have to be interpreted carefully since these cost savings do not necessarily represent an cost incentive to uncompensated care provision. A negative market share response to uncompensated care and a positive market share response to price are driving these results. Therefore, it is possible that nonprofit and public hospitals present some returns to scale that justify this negative effect of uncompensated care provision on marginal costs, but there are no additional incentives coming from positive valuations of patients towards uncompensated care provision.

Additionally, from a supply-side standpoint, for-profit hospitals do not seem to have incentives to provide uncompensated care, since this provision results in marginal cost increases. This is consistent with profit-maximizing behavior, as well as with their patients' negative response to the levels of uncompensated care provided. The same conclusions can be drawn from the results by HSA, presented in Table 10.

6.5 Counterfactual Analysis

With the model's estimates, it is now possible to assess the effect of two public policies through some counterfactual exercises. The first one relates to charity care provision by nonprofit hospitals. Since 2009, nonprofit organizations have been subjected to new reporting requirements according to a new Form 990 released by the IRS at the end of 2007. Nonprofit hospitals are now required to provide more detailed information regarding provision of charity care and other community benefits. This action is a result of different studies conducted by the IRS, like IRS (2009), which showed nonprofit hospitals were not providing enough charity care or at least less than what it was expected to justify their tax-exempt status. At the time the IRS introduced these changes, a report by the Senate Finance Commission minority staff suggested that nonprofit hospitals should provide a minimum of 5% of their patient revenue or expenses (whichever was greater) on charity care (Minority Staff, 2007), in order to guarantee that they provide a minimum of community benefits in exchange for tax exemptions. Although this recommendation was not included in the Patient Protection and Affordable Care Act (PPACA, 2010), passed in March 23, 2010, there is still an ongoing discussion on whether a minimum for charity care provision should be set[19]. Given this increased scrutiny on non-profits' provision of charity care, here we investigate how setting a minimum of 5% of patient revenue for nonprofit hospitals' provision of uncompensated care affects their own demand and the substitution patterns among hospitals.

The results of this counterfactual exercise are shown in Table 11 for the median changes in market shares, own-price elasticities, and demand responses to price and uncompensated care[20]. If nonprofit hospitals provide at least 5% of revenue in uncompensated care, the results show that patients' response to uncompensated care provision

[19] See, for example, Cram et al (2010) and http://online.wsj.com/article/SB122957486551517519.html and http://www.nytimes.com/2009/06/01/us/politics/01health.html?ref=politics

[20] Because each patient's choice of hospital is restricted to the hospitals within an HSA, it is more appropriate to calculate the median of the changes in market shares instead of the mean change in market share because this will be a zero-sum game where the loss in market share of one hospital represents the increment of another, implying that the mean change in market shares will be zero.

changes considerably. Nonprofit patients become less responsive to changes in uncompensated care, whereas for-profit patients become more sensitive. These results indicate that once nonprofit hospitals provide a minimum amount of uncompensated care, their demand will respond less negatively to uncompensated care. This could mean that knowing hospitals are providing more uncompensated care on average, patients become more lenient toward this hospital behavior.

Finally, the second counterfactual exercise relates to one of the changes introduced by the PPACA (2010). Beginning in 2014, individuals must be enrolled in a health insurance plan. Those that do not show a proof of enrollment will have to pay an assessment, unless they cannot afford coverage. The model's estimates allow examining how hospitals' demand and substitution patterns would be affected if uninsured patients become either publicly or privately insured. Understanding the implications of this shift from a hospital's point of view is important not only for uninsured patients, but also for insured ones, since hospital behavior is expected to change in response to greater demand. We assume that all uninsured patients become publicly insured.

The results are presented in Table 11. Because uninsured and publicly insured patients do not significantly differ in their preferences over hospital characteristics, there is no major change in market shares and elasticities. Patients continue not to value uncompensated care provision and their price sensitiveness did not change.

7 Conclusion

The purpose of our study was to investigate how hospital choice is affected by uncompensated care provision and whether patients' insurance status influences that valuation. By examining this question, it is now possible to get a better understanding on the incentives hospitals have to provide uncompensated care, especially the for-profit ones. Previous studies (Garmon (2009), Capps, Carlton, and David (2010)) have shown that uncompensated care provision does not seem to be driven by competitive pressures.

Given that, this paper looks into the demand for hospitals, and whether patients value uncompensated care provision sufficiently to justify that provision by profit-maximizing firms like the for-profit hospitals.

The results indicate that the incentives for-profit hospitals have to provide uncompensated care may not be driven by demand-side aspects. In fact, patients are less attracted to hospitals that provide uncompensated care, regardless of their insurance type. Patients could perceive this provision as a higher chance of facing longer waiting times and not having hospital resources readily available. Patients also seem to be price-insensitive, indicating that hospital demand is driven much more by location, ownership status, and quality.

The counterfactuals showed that hospitals' market power and demand responsiveness would not change dramatically if uninsured patients became publicly insured. This effect is due to the fact that uninsured and publicly insured patients value similar hospital attributes and thus their hospital choices are very much alike. As for the possibility of mandating that nonprofit hospitals provide a minimum amount of uncompensated care, the results showed that this initiative could actually benefit nonprofit hospitals as their patients would become less responsive to change in uncompensated care provision.

Overall, the results indicate that hospitals' incentive to provide uncompensated care does not seem to be driven by demand components. Hospital choice is affected by travel distance, ownership status and quality indicators, whereas provision of uncompensated care does not attract more patients. Therefore, it is not possible to argue that hospitals provide uncompensated care as a way to signal quality or better reputation. Nevertheless, hospitals' provision of uncompensated care benefits them in some fashion and understanding this benefit is a question that deserves further investigation.

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Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	N
Nonprofit	0.57	0.50	0.00	1.00	273
For-profit	0.24	0.43	0.00	1.00	273
Public	0.18	0.39	0.00	1.00	273
Teaching	0.07	0.25	0.00	1.00	273
Technology Index	67.41	23.20	0.00	100.00	273
Casemix	1.07	0.22	0.57	2.19	273
NursePerBed	1.51	0.54	0.50	3.93	273
Beds	234.72	183.38	15.00	1,395.00	273
NetPatRev[1]	168,063.42	157,345.92	4,596.99	922,365.06	273
Charity Care[1]	7,255.54	12,797.41	-512.20	108,315.01	273
Bad Debt[1]	10,105.91	9,796.06	-328.27	61,581.35	273
Uncomp. Care[1]	17,361.45	18,754.82	77.08	117,276.35	273
Uncomp. Care/Revenue	0.04	0.02	0.00	0.15	273

[1]In thousands of dollars.

Table 2: Average Values by Ownership Type

Variable	Nonprofit	For-Profit	Public
Charity Care[1]	8,921.06	3,608.04	6,946.72
Bad Debt[1]	11,042.75	7,446.87	10,746.08
Uncomp. Care[1]	19,963.82	11,054.91	17,692.81
Uncomp. Care/Revenue	0.03	0.03	0.05
Beds	234.80	165.52	205.12

[1]In thousands of dollars.

Table 3: Sample Description by HSA

HSA	**Patients**	**Hospitals**	**Observations**
1	67,840	24	1,628,160
2	83,567	14	1,169,938
3	35,281	8	282,248
4	74,479	12	893,748
5	111,485	14	1,560,790
6	97,070	16	1,553,120
7	72,362	7	506,534
8	55,661	10	556,610
9	160,606	23	3,693,938
10	82,167	12	986,004
11	488,448	63	30,772,224
12	247,899	31	7,684,869
13	170,854	22	3,758,788
14	151,464	17	2,574,888

Table 4: Descriptive Statistics for Predicted Price

Ownership Status	**Mean**	**St. Dev.**	**Min.**	**Max.**	**Observations**
Nonprofit	8,092.36	2,103.14	3,409.48	15,501.19	156
For-profit	7,364.92	2,820.72	1,368.90	23,376.50	67
Public	9,152.22	3,432.27	4,868.92	19,127.53	50
All Hospitals	**8,107.95**	**2,628.69**	**1,368.90**	**23,376.50**	**273**

Table 5: Demand Estimation - Second Stage

Variable	**I**	**II**	**III**	**IV**
Price	-3.9743	-5.3758	-4.1381	-3.4999*
UCR	-1201.7210	-1562.6820	-1245.9400	-1066.8540**
Price*UCR	132.5058	172.5105	137.4740	117.9217**
For-profit	1.2328	1.7241	1.2979	1.0797
Public	1.0161	0.8656	0.9879	1.0686
Teaching	-0.5413	0.2663	-0.4692	-0.8378
Technology	1.0348	1.3926	1.1016	0.8540
Beds	0.0107	0.0140	0.0111	0.0096
NursePerBed	-2.3205	-4.0117	-2.5385	-1.6775
Casemix	-4.7876	-6.0005	-4.9052	-4.2983
Constant	48.3743	64.2120	50.2098	42.6449*
N	273	273	273	273
First-stage Diagnotics				
Instrumented Variable F-stat (p-value)				
Price	0.0000	0.0000	0.0000	0.0000
UCR	0.0000	0.0000	0.0000	0.0000
$Price * UCR$	0.0000	0.0000	0.0000	0.0000
Set of Instruments	A	B	C	D
Exogeneity (p-value)	0.0000	0.0000	0.0002	0.0000
Overidentification (p-value)	0.2901	0.2841	0.6835	0.5638

Significance levels: $*$: 10%, $**$: 5%, $***$: 1%.

Set of Instruments:

A: Average of Rivals' Price, Average of Rivals' UCR, Ratio of Wages and Full Time Employees, and Number of Uninsured Patients Admitted.

B: Average of Rivals' Price, Average of Rivals' UCR, Average of Rivals' Beds, and Number of Uninsured Patients Admitted.

C: Average of Rivals' Price, Average of Rivals' UCR, Dummy for Trauma Center, and Fixed Costs.

D: Average of Rivals' Price, Average of Rivals' UCR, Ratio of Wages and Full Time, Employees, Number of Uninsured Patients Admitted, Average of Rivals' Beds, Dummy for Trauma Center, and Fixed Costs.

Table 6: Demand Estimation - First Stage
Descriptive Statistics For Selected Coefficient Estimates

Interaction		Mean	Median	St. Dev.	Min.	Max.
Privately Insured	UCR	-75.4732*	-40.5819	127.3998	-378.5165	60.9186
	Price	-0.2255*	-0.2399	0.4002	-1.0766	0.3316
	Price*UCR	5.2414	3.7525	13.2920	-14.2416	32.3229
	For-Profit	-0.5775**	-0.4677	0.6392	-1.9532	0.4497
	Public	0.8862	-0.5846	4.7834	-2.5598	14.6711
	Teaching	-0.8202	-0.5820	3.3873	-8.0853	3.9703
	Technology	-1.0029	-1.0702	4.4474	-9.7060	9.9115
	Beds	0.0327	0.0014	0.7117	-1.4125	1.4502
	NursesPerBed	-0.0523	0.0000	0.4186	-0.7614	0.7735
	Casemix	0.4772	1.2254	2.4654	-5.5711	4.0653
	Distance	0.0261***	0.0279	0.0262	-0.0219	0.0699
	Distance^2	-0.0003**	-0.0001	0.0004	-0.0011	0.0002
Uninsured	UCR	-34.0773	-13.2196	131.2187	-364.6240	124.1180
	Price	-0.1628	-0.0567	0.3928	-1.0076	0.3538
	Price*UCR	3.6857	2.4221	13.7864	-20.9440	31.4179
	For-Profit	-0.6304*	-0.6800	1.0115	-2.4017	1.3050
	Public	1.3960	0.0000	4.5860	-1.8175	15.0260
	Teaching	-0.2627	-0.4043	3.0457	-4.3655	6.6553
	Technology	-1.7649*	-1.4139	3.2680	-8.0672	3.6074
	Beds	0.2756	0.0000	0.7435	-0.6990	1.7154
	NursesPerBed	-0.1196	0.0000	1.2117	-1.8755	1.7044
	Casemix	-0.3262	0.0000	2.4366	-6.5962	2.9088
	Distance	-0.0070*	0.0000	0.0126	-0.0402	0.0000
	Distance^2	0.0001	0.0000	0.0003	0.0000	0.0010

Significance levels: $*$: 10%, $**$: 5%, $***$: 1%.

Table 7: Median Market Share and Own-Price Elasticities by HSA

Variable	**HSA 1&3**	**HSA 2**	**HSA 4**	**HSA 5**	**HSA 6**	**HSA 7&8**
Price (000)	8.4619	8.1273	9.3134	10.3770	7.9233	10.5799
UCR	0.0325	0.0353	0.0212	0.0291	0.0411	0.0258
Market Share	0.0167	0.0559	0.0590	0.0587	0.0364	0.0503
$\partial s_j/\partial p_j$	0.0009	-0.0015	0.0172	0.0234	0.0093	-0.0058
$\partial s_j/\partial UCR_j$	0.0129	-1.4167	-1.4247	1.4691	-0.4988	1.0262
Own-Price Elasticity	0.4621	-0.2128	1.5791	2.1417	3.2591	-1.4105
	HSA 9	**HSA 10**	**HSA 11**	**HSA 12**	**HSA 13**	**HSA 14**
Price (000)	6.8031	7.5171	7.5114	7.1376	6.0657	6.9936
UCR	0.0326	0.0354	0.0234	0.0502	0.0260	0.0393
Market Share	0.0288	0.0787	0.0123	0.0307	0.0387	0.0398
$\partial s_j/\partial p_j$	0.0011	0.0069	-0.0013	0.0109	0.0005	0.0277
$\partial s_j/\partial UCR_j$	-1.8416	-1.7983	-1.3181	-2.4231	-8.8432	-1.7494
Own-Price Elasticity	0.6293	1.2747	-0.7663	5.1009	0.0025	4.6656

Table 8: Median Market Share and Own-Price Elasticities by Ownership Status

Variable	**HSA 1&3**	**HSA 2**	**HSA 4**
Price (000)	7.4763	7.8408	8.0918
UCR	0.0213	0.0323	0.0430
Market Share	0.0123	0.0398	0.0215
$\partial s_j/\partial p_j$	-0.0027	0.0032	0.0068
$\partial s_j/\partial UCR_j$	-1.3583	-1.3011	-0.1595
Own-Price Elasticity	-1.3356	1.0790	3.0008

Table 9: Median Marginal Costs by HSA

Variable	**HSA 1&3**	**HSA 2**	**HSA 4**	**HSA 5**	**HSA 6**	**HSA 7&8**
ψ_1	3.3486	8.0911	8.9020	8.8074	7.6052	10.2079
ψ_2	39.2318	55.8166	13.2968	21.8154	-2.0641	41.2622
Marginal Cost	5.7627	7.6022	6.7323	8.9073	7.0712	10.8820
	HSA 9	**HSA 10**	**HSA 11**	**HSA 12**	**HSA 13**	**HSA 14**
ψ_1	8.8520	9.5395	8.8260	9.3990	8.1494	9.4966
ψ_2	-6.3733	-44.2897	3.7177	-38.6601	66.8766	-56.2388
Marginal Cost	5.8498	5.7778	7.6755	6.6543	5.7391	6.2238

Table 10: Median Marginal Costs by Ownership Status

Variable	**For-Profit**	**Nonprofit**	**Public**
ψ_1	8.8655	8.1412	9.2911
ψ_2	23.6311	-1.6084	-24.3862
Marginal Cost	7.8924	6.9459	7.5213

Table 11: Counterfactual 1
Median Changes in Market Shares and Own-Price Elasticities by Ownership Status

Variable	**For-Profit**	**Nonprofit**	**Public**
Change in Market Share	0.0021	-0.0020	0.0009
Change in $\partial s_j/\partial p_j$	-0.0001	0.0214	0.0000
Change in $\partial s_j/\partial UCR_j$	-0.1505	0.0510	-0.0217
Change in Own-Price Elasticity	0.0379	5.9505	0.0048

Table 12: Counterfactual 2
Median Changes in Market Share and Own-Price Elasticities by Ownership Status

Variable	**For-Profit**	**Nonprofit**	**Public**
Change in Market Share	0.0001	0.0000	0.0000
Change in $\partial s_j/\partial p_j$	0.0000	0.0000	0.0000
Change in $\partial s_j/\partial UCR_j$	-0.0053	-0.0014	-0.0012
Change in Own-Price Elasticity	-0.0029	0.0021	0.0056

A Appendix

Table A.1: Demand Estimation - First Stage - Conditional Logit by HSA

Variable		HSA 1&3	HSA 2	HSA 4	HSA 5	HSA 6	HSA 7&8	HSA 9	HSA 10	HSA 11	HSA 12	HSA 13	HSA 14
Distance		-0.2203***	0.2281***	-0.1754***	2.1289***	-0.0257	0.8472***	-0.1755***	-0.0981***	0.1881***	0.1629***	-0.4179***	-0.3045***
Distance^2		0.0002***	-0.0084***	0.0024	-0.0639***	-0.0049***	-0.0126***	0.0002***	-0.0014***	-0.0015***	-0.0017***	-0.0176***	0.0001
Privately Insured	UCR	55.3363***	17.5946	-378.5165***	-167.8170***	-46.0186***	-200.6070***	-136.6244***	-69.2752***	-21.7825***	-35.1453***	33.8529***	60.9186***
	Price	0.3316***	-0.5162***	0.0452	-0.4212***	-0.3274***	-1.0766***	-0.4817***	-0.1525**	-0.1335***	-0.4024***	0.2878***	0.1857***
	Price*UCR	-6.9710***	0.6148	32.3229***	13.8665***	2.6215***	23.1067***	9.1718***	4.8835***	1.9974***	5.9580***	-14.2416***	-9.8187***
	For-Profit	-0.5335***	.	.	-0.4018***	-0.3878***	-0.1882***	-1.9532***	0.4497***	-0.7736***	-0.1815***	-0.6751***	-1.1296***
	Public	0.2135**	2.1906***	14.6711***	-1.0575***	-1.9257***	1.4381***	-0.5846***	-1.6634***	-2.5598***	-0.8928***		-0.0816**
	Teaching	-0.5820***	.	-0.5703***	-2.4495***		-8.0853***	3.9703***		-0.9253***	-1.5788***	2.5747***	0.2645***
	Technology	-1.2780***	-0.1995***	-9.7060***	9.9115***	-1.7135***	-3.4694***	-1.4265***	-4.1651***	0.2883***	0.0219	0.5852***	-0.8624***
	Beds	0.0029***	0.8821***	1.4502***	-1.4125***	-0.0180	0.0072***	0.2061***	0.4553**	-0.1425***	-0.1722***	-0.5356***	-0.3480***
	NursesPerBed	-0.5005***	-0.3400***	-0.7614***	0.1026	0.2397***	0.0670	0.3308***	-0.1433	0.2265***	0.7735***	-0.1979***	-0.3986***
	Casemix	1.3377***	-0.7931***	-5.5711***	1.1131***	-1.6806***	1.9557***	-0.8261***	1.8223***	1.6762***	2.1676***	4.0653***	0.4599***
	Distance	0.0086***	0.0190***	0.0375***	-0.0096***	0.0362***	0.0279***	0.0496***	-0.0219***	0.0699***	0.0141***	0.0536***	0.0280***
	Distance^2	0.0000	0.0000	-0.0011***	0.0000	-0.0002***	-0.0001***	-0.0003***	0.0002***	-0.0008***	0.0000***	-0.0010***	-0.0002***
Uninsured	UCR	124.1180***	-113.6498***	-364.6240***	-26.4393***	-2.6591	-66.7423***	25.9083***	-117.6616***	13.6869***	-68.2308***	108.0805***	76.6266***
	Price	0.2325	-0.6562***	-0.2313***	-0.1785***	-0.0808	-1.0076***	-0.0701	-0.5036***	0.0931***	-0.1134***	0.2897***	0.3538***
	Price*UCR	-8.4137*	17.8500***	31.4179***	4.8441***	-0.1073	10.7223***	-1.2448	12.0055***	-1.8684***	8.0130***	-20.9440***	-9.3978***
	For-Profit	-1.0541***	.	.	-0.8291	1.3050***	-2.4017***	-0.9681***	-0.7668*	-0.5931***	-0.1855***	-1.6395***	0.2851
	Public	-0.1540	-0.0199	15.0260***	0.2536*	0.8822***	-0.4094	0.0104	-1.8175***	0.0864*	1.2963***		-0.3715***
	Teaching	-0.3751*	.	-1.3168***	0.0783		-4.3655***	-2.6312***		-0.4043***	-1.0854***	6.6553***	1.1585***
	Technology	-0.5285	0.3454	-8.0672***	3.6074***	-2.7823***	-6.8280***	-1.9318***	-2.8977*	-0.8960***	-0.6391***	-2.4679***	1.7232***
	Beds	-0.0001	0.3142**	1.6715***	-0.6990**	0.0163	-0.0015	-0.1717***	1.7154**	0.1078***	-0.0983**	0.7382***	-0.2710**
	NursesPerBed	0.1203	-0.4697***	-1.8755***	1.4426***	1.7044***	1.4379***	0.0213	-1.5805**	0.1001***	0.2393***	-1.1839***	-1.2503***
	Casemix	-0.7085	0.0719	-6.5962***	0.2656	-1.6926***	2.9088***	1.6452***	0.4754	0.7821***	0.7751***	0.9091***	-2.6463***
	Distance	-0.0019	-0.0193***	0.0233	-0.0402***	0.0026	-0.0076*	-0.0050	-0.0167*	0.0000	0.0003	0.0024	-0.0029
	Distance^2	0.0000***	0.0002***	-0.0001	0.0010***	0.0002*	0.0001***	0.0000	0.0002**	0.0000*	0.0000**	0.0001	0.0000
Male	UCR	35.6529***	8.6168	74.3048***	4.9048*	34.8022***	9.8058*	-0.3561	20.7004***	8.7582***	-0.0739	-0.4567	33.5220***
	Price	0.1047***	-0.0261	0.1698***	0.0165	0.1728***	-0.0594***	-0.0334***	0.2224***	0.0348***	-0.0124	0.0683***	0.2289***
	Price*UCR	-3.0685***	-0.0788	-7.5387***	-0.1298	-3.5641***	0.0889	0.0390	-2.6223***	-1.1173***	0.0827	-0.4694	-3.8911***
	For-Profit	0.0129	.	.	0.2035*	0.1602**	-0.0556	-0.2776***	-0.0405	-0.0259**	0.0129	0.0709***	0.1451**
	Public	0.4248***	-0.2185	-1.8114***	0.1966***	0.1042	0.0359	-0.0146	0.7123***	0.4978***	0.2839***		-0.0377

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	Variable	HSA 1&3	HSA 2	HSA 4	HSA 5	HSA 6	HSA 7&8	HSA 9	HSA 10	HSA 11	HSA 12	HSA 13	HSA 14
Male	Teaching	0.0871	.	0.2573***	0.4872***		-0.3776	0.2344		0.0993***	-0.0104	0.2566**	-0.1586***
	Technology	-0.8493***	-0.0045	-2.4199***	-0.3865	0.9349***	-0.1501	-0.2038***	0.4952	0.0957***	-0.1787***	-0.4204***	0.5009***
	Beds	0.0003*	0.1949***	-0.1903***	-0.0150	-0.0082	0.0012***	0.0878***	-0.3589**	-0.0920***	0.1470***	0.2339***	0.0045
	NursesPerBed	0.2213***	-0.0175	0.7346***	0.0077	-0.0885*	0.0218	-0.2998***	0.4657***	-0.1089***	0.0667***	-0.2416***	-0.2248***
	Casemix	1.7527***	0.5266***	1.7129***	0.9266***	0.2574**	0.8560***	0.6398***	0.9881*	0.5531***	0.5216***	0.9040***	0.7421***
	Distance	0.0056***	0.0046**	0.0012	-0.0040	-0.0039**	-0.0034***	-0.0007	-0.0101***	0.0004	0.0053***	-0.0137***	0.0002
	Distance^2	0.0000	0.0000	0.0002	0.0002*	0.0001	0.0000	0.0000**	0.0001***	0.0000	0.0000***	0.0003***	0.0000**
Unscheduled	UCR	5.1173	-13.2520	28.3096*	17.6710***	101.6138***	85.6821***	-42.2768***	-44.9365***	10.5523***	12.4505***	-107.4466***	-14.3454**
	Price	0.0456	-0.2912***	0.3157***	-0.0110	0.5107***	0.1284***	-0.1710***	-0.3604***	-0.0836***	0.0515***	-0.4682***	-0.1484***
	Price*UCR	1.1800	4.3210***	-3.7900**	-1.4148***	-9.8427***	-4.6797***	4.6447***	6.1773***	-1.1865***	-0.1957	19.9221***	4.6596***
	For-Profit	0.9005***	.	.	1.0973***	-0.2911***	0.1130***	-0.2610***	-0.3378***	-0.0162	-0.2180***	0.2435***	1.2160***
	Public	0.6941***	-1.6098***	1.8736***	0.6479***	-0.2369***	0.3537***	-0.1251***	-1.7828***	0.9971***	0.1545***		-0.1772***
	Teaching	-0.2988***	.	-0.4380***	0.0846		-2.3466***	1.3999***		0.9688***	-0.3015***	-3.5486***	-0.0512
	Technology	-1.3269***	0.0812	-1.2752**	-2.3666***	3.4336***	-0.6317***	0.8287***	-3.9117***	0.4614***	0.4323***	-0.6911***	0.0311
	Beds	0.0006***	0.3851***	-0.6203***	0.4329***	-0.1131**	0.0036***	0.1800***	1.9786***	-0.2250***	-0.0198	-0.6695***	0.0771*
	NursesPerBed	0.2313***	0.0821**	-0.5697***	0.0410	-0.3587***	0.0267	-0.8311***	-0.7030***	0.0702***	0.2238***	-0.3602***	-0.1298***
	Casemix	2.0931***	-0.0595	0.4013	0.6362***	-1.0159***	-1.0539***	0.5180***	-1.6883***	0.1577***	0.0247	2.1662***	0.3579***
	Distance	-0.0360***	-0.0469***	-0.0502***	-0.0445***	-0.0302***	-0.0214***	-0.0199***	-0.0585***	-0.0467***	-0.0055***	-0.0848***	-0.0322***
	Distance^2	0.0002***	0.0002***	0.0014***	0.0008***	0.0003***	0.0001***	0.0000***	0.0006***	0.0004***	0.0000***	0.0019***	0.0002***
Senior	UCR	73.3051***	81.4431***	-117.1857***	-125.2875***	-4.5719	-76.3907***	12.0081***	-12.3578	-13.4335***	-7.3792***	68.5010***	83.0801***
	Price	0.3270***	0.2881***	-0.3058***	-0.1393***	-0.1103**	-0.7365***	0.0924***	0.1298	-0.1034***	-0.1273***	0.4419***	0.2911***
	Price*UCR	-7.9544***	-11.8632***	8.4775***	10.1449***	-2.1019**	9.4419***	-4.4864***	-0.1989	1.5801***	1.6097***	-19.3736***	-10.5517***
	For-Profit	0.1191	.	.	-2.1959***	-0.1959	-1.6494***	-0.9476***	0.2052	-0.3551***	-0.2714***	-1.0401***	-1.2235***
	Public	1.1818***	1.8604***	1.9633**	-0.7717***	-0.7079***	-0.0718	-0.5551***	-1.2017***	-1.3913***	-0.2934***		-0.7369***
	Teaching	-0.4905***	.	1.1145***	-2.0290***		-3.1924***	-0.4317**		-0.7668***	-1.3270***	3.0292***	-0.4405***
	Technology	-2.7725***	0.4554***	-4.8217***	9.8348***	-2.1204***	-4.3331***	-2.3181***	-0.1831	-0.1748***	-1.3704***	1.8293***	3.6875***
	Beds	0.0012***	0.7451***	0.1455**	-2.7550***	-0.0412	-0.0022***	0.0113	-1.7365***	-0.4129***	-0.5093***	-0.9233***	-1.0515***
	NursesPerBed	0.3259***	0.0508	0.4122***	-0.6599***	0.4400***	0.9546***	-0.2386***	0.4447**	-0.2748***	0.0336*	-0.4483***	-1.6609***
	Casemix	2.5571***	-0.4575***	1.9501***	4.4312***	-0.0019	4.1764***	3.1650***	5.7551***	2.7479***	3.6153***	4.4690***	2.4071***
	Distance	-0.0058***	-0.0258***	-0.1073***	-0.1177***	0.0019	-0.0002	0.0109***	-0.0674***	0.0289***	-0.0067***	-0.0407***	-0.0162***
	Distance^2	0.0001***	0.0002***	0.0019***	0.0019***	0.0001	0.0001***	-0.0001***	0.0006***	-0.0002***	0.0001***	0.0009***	0.0001***
Distance	UCR	2.3341***	-0.9148***	-5.7365***	-6.2927***	2.8055***	-2.7621***	0.4886***	-0.7474***	-2.3613***	-1.8125***	2.3636***	1.2866***
	Price	-0.0024***	-0.0599***	0.0852***	0.1071***	-0.0036***	-0.0056***	-0.0038***	0.0089***	0.0242***	0.0044***	0.0001	0.0071***
	For-Profit	0.0032	.	.	-0.6872***	-0.0823***	-0.1425***	0.0206***	-0.1184***	-0.0109***	-0.0214***	-0.0793***	0.0392***
	Public	-0.0529***	0.1622***	0.9686***	-0.2655***	-0.0606***	-0.0964***	-0.0441***	0.0391***	-0.1070***	-0.0384***		0.1114***

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Variable		HSA 1&3	HSA 2	HSA 4	HSA 5	HSA 6	HSA 7&8	HSA 9	HSA 10	HSA 11	HSA 12	HSA 13	HSA 14
Distance	Teaching	-0.0353***	.	-0.2722***	-0.3222***		-0.0516***	-0.0309***		0.2160***	0.1417***	0.0537***	-0.0344***
	Technology	0.0239***	0.2049***	-0.3500***	0.8933***	0.1110***	-0.2144***	-0.0693***	0.0771***	-0.0903***	0.0234***	1.0240***	-0.0572***
	Beds	-0.0001***	-0.0245***	-0.0952***	-0.6682***	-0.0252***	0.0006***	0.0160***	0.0015	-0.0831***	-0.0163***	0.0780***	-0.0535***
	NursesPerBed	-0.0433***	0.1267***	0.0613***	-0.5805***	0.0186***	0.0774***	0.0014	0.0297***	0.1106***	-0.0335***	-0.2902***	0.0949***
	Casemix	0.1093***	-0.0479***	0.0176	0.7292***	-0.1364***	-0.7980***	0.0376***	-0.1648***	-0.2287***	-0.1221***	-0.5502***	0.1538***
Distance^2	UCR	-0.0056***	0.0228***	0.0956***	0.1864***	-0.0556***	-0.0623***	-0.0010	0.0054***	0.0154***	0.0035***	-0.3452***	-0.0112***
	Price	0.0000	0.0009***	-0.0017***	-0.0025***	-0.0001***	-0.0001***	0.0000***	-0.0001***	-0.0001***	0.0000***	0.0002***	0.0000
	For-Profit	0.0000	.	.	0.0183***	0.0024***	0.0012***	-0.0002***	0.0006***	-0.0001***	0.0000	-0.0021***	-0.0003***
	Public	0.0002***	-0.0026***	-0.0185***	0.0067***	0.0007***	-0.0007***	-0.0002***	-0.0002**	0.0005***	0.0000***		-0.0007***
	Teaching	0.0001***	.	0.0082***	0.0077***		0.0045***	0.0007***		-0.0017***	-0.0003***	0.0092***	0.0002***
	Technology	-0.0001***	-0.0046***	0.0059***	-0.0228***	-0.0042***	0.0099***	0.0008***	-0.0004	0.0002***	0.0013***	-0.0587***	0.0003***
	Beds	0.0000***	0.0009***	0.0022***	0.0169***	0.0015***	0.0000***	-0.0001***	0.0006***	0.0006***	0.0003***	0.0043***	0.0005***
	NursesPerBed	0.0002***	-0.0022***	-0.0031***	0.0152***	0.0006***	0.0017***	0.0000***	-0.0004***	-0.0008***	-0.0002***	0.0035***	-0.0007***
	Casemix	-0.0002***	0.0017***	-0.0024***	-0.0174***	0.0011***	0.0051***	0.0001	-0.0002	0.0017***	-0.0004***	0.0380***	-0.0009***

Significance levels: $*$: 10%, $**$: 5%, $***$: 1%.