The Effects of Insurers’ Hospital Choice Restrictions on the Demand for Medical Care Services

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Abstract

The rise of managed care organizations has caused a significant change in the relationship between consumers, insurers, and hospitals. Therefore, it has become increasingly important to account for the new structure of the industry when studying consumer health care demand. This paper studies how consumers choose health plans and health care providers when plans place restrictions on the available provider options.

I employ a structural empirical model of the demand for health insurance plans, hospitals, and medical care services. I model the consumer choice as a three-stage decision; health plan choice, hospital choice based on the plan choice, and utilization of medical care services based on the plan and hospital choices. This model incorporates a rich error structure that captures the effects of important unobserved factors. I explicitly model consumer uncertainty by estimating each patient's health state prior to any medical care. This uncertainty is a major factor in the selection of health insurance, and further affects the choice of hospitals and the consumption of medical care services.

Using the estimated parameters in my model, I study the welfare impact of health insurance plans with highly restrictive hospital choices. This is the first time a structural model has been used to analyze this recent trend in the market, which has generated much discussion in the health economics field.

The parameters of the model are estimated with the method of simulated maximum likelihood using the Statewide Planning and Research Cooperative System Data of 1997 from the New York State Health Department, which records the medical information of each patient, including the insurers and hospitals used.

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1 Introduction

While the determinants of hospital demand and health insurance demand have been studied widely, the function of a health insurance firm as an agent that sells hospital care to consumers has not been addressed. Because of the significant change in the U.S. health care system over the past 20 years, it has become increasingly important to account for the change in the relationship between consumers, hospitals, and insurers when studying consumer demand for health care. For instance, in the 1980’s and 1990’s, the drastic penetration of managed care organizations was observed in the U.S. medical care market.\footnote{Enrollments of Health Maintenance Organizations (HMO) increased steadily throughout the 1980s, from 9.1 million to 33.6 million in 1990. In 1980, there were fewer than 100 HMOs; less than a decade later, there were more than 600. As of the year of 2000, over 60 million of Americans were enrolled in over 500 HMOs, and more than 80 % of working Americans were enrolled in some type of managed care plan (Dranove, 2000). In such health care markets, health insurance firms demand large discounts from hospitals in exchange for steering large volumes of patients to those hospitals.} This recent diversification in the type of health insurance plans has created the need for employers and government-sponsored health insurance programs to obtain the information on systematic differences in utilization of services that are due to differences in the restrictiveness of health insurance plans. This information allows employers and government health insurance programs to contract with the plans with optimal restrictions that maximize the welfare of their employees or beneficiaries at specific per capita payment rates. The objective of this study is to estimate the effect of restrictive insurance plans in the U.S. health care market. In order to pursue this goal, I estimate a structural model of demand for health insurance plans and hospital inpatient services. I account for the determination of medical care service quality when consumers’ choices of hospitals are restricted by their insurance plans. Using the estimated demand, I will simulate the effect of restrictions of insurance plans on consumer welfare. This is the first empirical study that estimates the demand for hospital care as services obtained through insurers using the consumers’ utility maximization framework.

The structural approach of estimating the demand for health has many advantages. For example, the structural approach allows one to understand not only the demand for medical care but also the determination of health itself and the productivity of health care. It therefore provides a framework for analyzing policies such as the introduction of various government subsidy programs for HMO enrollment. Moreover, in typical reduced form models, insurance and hospital choices are
set as explanatory variables that linearly explain the dependent variable; the utilization of medical care. When evaluating the estimates from such a model, one can easily speculate scenarios behind the estimated parameters, while estimating a well-specified structural model allows one to explain causalities clearly.

Despite its theoretical appeal and wide range of potential policy applications, very few previous studies have attempted to estimate the structural model of the demand for health care. One of the first theoretical models of the demand for health by Grossman (1972) is one of the major theoretical innovations to have emerged from health economics. However, Wagstaff (1985) employs Grosman’s theoretical model for an empirical application and finds that many of the parameter estimates have unintuitive signs.² His model imposes many assumptions on functional forms in order to avoid estimating non-linear equations. Unrealistic assumptions such as constant returns to scale of the health production function could have biased his results.

The present research makes four major changes to the traditional Grossman model; the introduction of three steps of health care consumption choice, the appropriate treatment of a consumer’s uncertainty, the inclusion of the effect of deductibles and copays, and finally the development of policy analysis. Each of the contributions will be discussed below.

First, instead of assuming that a consumer purchases health care directly from a health care provider and makes continuous choices of how much health care service to consume, my model accounts for the fact that a consumer first chooses her health insurance plan (or no health insurance at all), the hospitals she visits, and finally the quantity of medical care services. A consumer may select her health insurance plan based on the information about available provider options under each insurance plan, and she may choose her insurance plan and health care provider based on her expectation of her health care consumption. On the contrary, a consumer’s choice of an insurance plan may affect her hospital choice, and the amount of health care she consumes may be affected by her choice of insurance and a hospital. Since a consumer’s choice in each of the three stages affects her choices in other stages, ignoring the selection process of insurers and hospitals in deriving the demand of health care may bias the estimation of parameters in the model. Since an insurance choice and a hospital choice are discrete choices, and a quantity choice is a continuous choice, I use the discrete-continuous model in order to model three choices in a mutually consistent manner.

²For example, his structural estimation suggests that healthier consumers consume more medical care than those who are less healthy. Likewise, it indicates that those who are more educated lose their non-market productivity.
The literature on the discrete-continuous model stems from King (1980) and Dubin and McFadden (1984) who construct specific parametric demand models for discrete and continuous decisions. Pohlmeier and Ulrich (1995) estimate a structural model of the demand for health care assuming a two-part decision-making process, the decision of whether to take medication and how much medical care to consume. The choice of insurers and hospitals, however, is not considered in their model. Dowd et al. (1991) estimate a structural model of the consumer’s choice of insurance plans and utilization of health care. When they modeled the consumer’s choice of health insurance plans, they only controlled for whether the plan is an HMO plan and did not control for differences in hospital choices as the characteristics of the insurers. Their results indicate that families enrolled in an HMO plan would use fewer inpatient days than the same families enrolled in an fee-for-service plan. Instead of the two stages employed by Dowd et al (1991), I model the three stages of consumer choices, the choice of an insurance plan, then a hospital, and then a continuous choice of medical care services. In order to apply the structural demand estimation to the health care market, including the choice set of hospitals as the second step of consumers’ health care consumption choice may better specify the model of health care demand. The present research employs the two-stage logit model that allows the consumer to choose the health insurance plan first and then the hospital.

Second, my model takes into account the uncertainty of each consumer about the future when they select an insurance plan. Cameron et al. (1988) first considered a consumer’s selection of a health insurance plan in the estimation of the demand for health care. They estimate a reduced form model of demand arguing that “a tractable structural model for insurance demand is virtually impossible due to consumers’ uncertain a priori distribution of health states”. However, in reality, even though a consumer is uncertain about the realization of her future health condition, she selects a health insurance plan based on the distribution of her a priori health status, the health status prior to any medical care treatment. Therefore, it is not the distribution of the a priori health status but the realization of it that is uncertain to each consumer. The present research overcomes the difficulty of dealing with the consumer’s uncertainty by explicitly modeling each patient’s anticipation and realization of her health state. This is an important and unique feature of my model since the uncertainty plays a big role in the consumption of health insurance, and the choice of an insurance plan affects the choice of a hospital and the consumption of medical care services. Moreover, my model estimates the consumers’ risk aversion with respect to their health and other commodity consumption separately rather than assuming that consumers’ risk aversion
towards health is the same as that towards other consumption goods. While health economists often suggest that consumers are more risk averse with respect to their health status than to consumption of other goods, previous studies either assumed they are equal or did not estimate any risk aversion parameters. Zabinski (1994) introduces a risk aversion parameter in the utility function for a consumer’s health insurance choice, and his results indicate that consumers are risk averse. However, he did not differentiate between the risk aversion towards health and other consumption. By estimating them separately, we can examine if our intuition of more risk aversion towards health is true.

The third innovation of this study is the inclusion of the effect of deductibles and copays that each consumer faces when choosing an insurance policy and the consumption of medical care services. Keeler, et al (1977) develop a model of the demand for medical care services when consumers face different price schedules with deductibles. Their model suggests that the size of the deductible affects consumers’ decisions, especially in the long run, so it is important to account for the price schedule of insurance plans when estimating health care demand. The dataset records the history of patient behavior over a year and includes patients who repeatedly visited hospitals, which allows me to impute the deductibles and copays of each insurance plan and to use them in the structural model.³

Finally, the estimated model can be used to predict welfare effects. I simulate the welfare impact of the availability of health insurance plans with highly restrictive hospital choices in the current U.S. health care market compared to the market where only traditional indemnity plans are available. First, I estimate the welfare change from having every plan contract with every hospital in the market given the current premiums and copays of each insurance plan. Second, I estimate the optimal premium and copay of each insurance plan if every insurer allows its customers to access any hospital. Using the estimated prices, I predict the change in the consumer welfare.

In the literature, many researchers have studied the effects of the diversification of health insurance services (i.e. the penetration of managed care organizations) on hospital service costs, prices, and consumers’ health care consumption. Melnick, Bamezai and Pattison (1992), Zwanziger, Melnick and Bamezai (2000), and Town and Vistness (2001) estimate the effect of selective contracting between insurers and hospitals and market power of insurers relative to hospitals on medical care prices. They use reduced form models that regress an approximation of the bargaining power of

³The method of imputation for deductibles and copay rates is illustrated in the data section.
hospitals relative to insurers on medical care prices. Although these studies accounted for the bargaining position of hospitals relative to insurers, they only model the hospital behavior and do not model the consumer’s choice of hospitals and insurers. Moreover, this approach suffers from bias due to correlation between hospital care prices and the bargaining power of each hospital. Welch et al. (1984) compare cost per enrollee of those who chose a prepaid group practice (a part of HMO plans) and those who chose a traditional fee-for-service plan using a probit health plan choice equation and an expenditure equation. The estimated fee-for-service costs per enrollee are found to be 366% higher than prepaid group practice costs. The authors find the ratio to be implausibly high and conclude that this may be due to the fact that the specification of the probit equation is inconsistent with the consumer choice. In addition, even though a large portion of the observations in the sample consumed zero health insurance, their estimation method does not control for the potential bias from treating corner solutions as interior solutions. In order to eliminate the possible bias from the endogeneity of the consumer’s health care choice, Manning et al. (1984), as part of the Rand Health Insurance Experiment, assign families randomly to an HMO and several fee-for-service plans to find the difference in the utilization and expenditure of medical care among different insurance plans. Random assignment eliminates the possibility of bias arising from endogenous health plan choice. They found that inpatient admissions were 40% lower in the HMO than the fee for service plan without coinsurance or deductibles. On the other hand, the difference between the expenditure of the randomized HMO enrollees and the self-selected HMO enrollees was insignificant. However, Welch et al. (1997) disagreed with Manning et al. (1984) noting that 29% of the consumers approached by Rand refused to participate in the study. Given these results from studies that address the potential bias arising from endogenous health plan choice, it is still not clear how restrictions of health insurance plans affect the consumers. The present research takes a different econometric approach to control for the possible problems in previous studies.

The empirical analysis uses the Statewide Planning and Research Cooperative System (SPARCS) for 1996 from the New York State Department of Health. This dataset records every inpatient incident in every hospital in New York state (nearly 2 million patients) and reports each patients’ demographic characteristics and information about patients’ hospital and insurers. Thus, the SPARCS allows me to establish a link between patients, hospitals and insurers. While the actual contracts between hospitals and insurers are unobserved, the data reports the insurer who paid the reimbursement to the hospital for each observation of a hospital stay. The data reveals a significant
variety of hospitals used by different insurers (minimum of 2 and maximum of 151 hospitals per an insurer). In addition, out of around 800 insurers observed in the data, 34 insurers are health maintenance organizations (HMO). On the other hand, the data includes many patients who used least restrictive plans such as Blue Cross and Blue Shield Plans. Additionally, I observe many uninsured patients who were free to choose any health care provider, while they had to pay a full charge for each stay. This paper assumes that consumers know which hospitals they can choose from when they purchase their health insurance plans, and the set of hospitals from which they can choose are those we observe in the data. Reporting detailed information about each individual who was hospitalized in New York gives the SPARCS incomparable richness. However, it obviously does not record information about consumers who did not experience an inpatient stay. This is the significant disadvantage of this dataset for empirical applications because treating patients in the data as randomly selected samples gives selection bias to the parameter estimates. This study overcomes the difficulty of utilizing such data by imposing constraints on the selection of the parameter estimates so that the estimated parameters are consistent not only with patients observed in the SPARCS but also with the consumers who had never been hospitalized.  

There are several variables in my model that are not included in the SPARCS. As for the data associated with patient characteristics, I do not observe each patient’s income and education in the SPARCS. I use the distribution of income and education in each county given in the Census 2000 data to simulate his or her income and education. Finally, using the identification of the provider that treated each patient, the American Hospital Association (AHA) data from 1996 will be linked to patients in the SPARCS to characterize the efficiency of medical care for each patient.

Demand functions for health care plans and the utilization of medical care services are estimated from a consumers’ utility maximization framework. The model captures the interaction between hospitals and insurance firms by restricting the choice of hospitals from each insurer. I use the maximum likelihood method to estimate the parameters in my model.

This paper is organized as follows. Section 2 provides the background of the U.S. medical care market and consumers’ insurance choices. Section 3 reviews the datasets used and the imputation methods for the variables that are unobserved in the main dataset. Section 4 analyzes the data by using a reduced form analysis in order to gain a better understanding of the data. Section 5 illustrates the theoretical model followed by the demonstration of the empirical estimation method.

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4The details of this method are described in the estimation section.
in section 6. Section 7 presents the parameters estimated from my model and discusses the results. Policy simulations are described in section 8 and section 9 concludes.

2 Industry Background

2.1 The Health Insurance Market

Every year, each insured health care consumer in the U.S. chooses either a private health insurance plan offered through his or her employer, an individual private plan, or a public health plan if he or she is qualified. The insurer contracts with hospitals and physicians to provide consumers with medical care. When consumers need medical care, they may visit any of the hospitals listed by the health insurance plan and receive services for small out-of-pocket payment. Each health plan has a different set of hospitals and physicians from which its customers can choose, and consumers choose their health plan based on the information about their provider options, plan premium, and co-insurance rates.

2.2 Consumers’ Insurance Choice

There is much variety in the choices of health insurance plans available to Americans. First of all, 15.6% of Americans have no insurance. Among those who have insurance, 81% purchase private insurance plans and 31% have government plans (some consumers have both private and government plans). 87% of privately insured consumers purchase plans through their employers, while only 13% of them directly purchase their plans. 46% of government insurance plan holders are under Medicaid, while 51% are covered by Medicare (3% of the government plan participants are members of Champus, a health benefits program that covers medical necessities only for retired military as well as dependents of active-duty, retired and deceased military).\(^5\) When choosing a private insurance plan or a Medicare plan, a consumer can typically choose her plan from a set of options, but the consumers’ freedom of provider choice depends on the following three situations. First, if one is directly purchasing a health insurance plan, she can choose any plan. Second, if her employer offers insurance plans, she may have some options but must choose from these offers or pay for the premium if choosing other plan. Although it is the employer who is directly choosing the options for the employees, my model assumes that the person takes into account the set of

\(^5\)The data source is from “The 2004 Census Annual Demographic Survey.”
insurance plan choices and each plan’s hospital choice set the employer gives to her when she takes the job, and therefore, consumers are choosing the health insurance plans even if they are in a group plan through their employers. Finally, if one is covered by Medicare, she can either choose a regular Medicare plan, a Medicare HMO, or a supplemental plan offered through Medicare.

There is significant variety in the restrictiveness of different types of health insurance plans. If an individual is insured by a HMO, he or she may visit only the hospitals in that plan’s network. Point of Service (POS) plan enrollees can visit out-of-network hospitals but only if referred by a Primary Care Physician. Preferred Provider Organizations (PPOs) and indemnity plans (such as Blue Cross Blue Shield plans) are the least restrictive insurers. Enrollees do not need a referral to visit an out-of-network hospital, although PPOs may impose financial penalties such as increased copays or deductibles for doing so.\footnote{In my analysis, it is impossible to identify patients who used out-of-network hospitals from their PPO plans or indemnity plans. Thus, I assumed every patient used in-network hospitals.} The focus of this paper is the effect of having insurance plans with different restrictiveness on consumers’ health care purchasing behavior.

3 A Preview of the Dataset

The Statewide Planning and Research Cooperative System (SPARCS) is the main data source used for this study. In addition, the American Hospital Association (AHA) data from 1996 and the Census 2000 data are used to supplement the information from the SPARCS. In section 3-1, I first provide an overview of the SPARCS and its suitability for this study. In section 3-2, I will illustrate the method for imputing the characteristics of insurers. I describe the method for imputation of data from the supplemental datasets in Appendix A for readers who are interested in the details of the calculation.

3.1 The SPARCS

The SPARCS has been provided by the New York State Department of Health annually since 1981. Although the data set consists of inpatient and outpatient data, this study uses only the inpatient data because it includes information about patients, hospitals, and insurers all together where outpatient data does not include information about insurers. Each year’s inpatient output data contains information about all of the hospital visits, about 2 million observations, in New
York State. This study uses data from 1997.

The SPARCS is well suited for this study. First, it allows one to detect connections between patients, hospitals, and insurers. In particular, for each hospital visit record, the SPARCS reports the patient’s demographic characteristics (age, race, gender, and residential zip code), the identification of the hospitals and insurers involved in the visit, the amount of the charge, the reimbursement from the patient’s insurer, and the type (DRG code) and length (days) of the treatment at the hospital. This information allows me to link patients, hospitals, and insurers, which is essential for the estimation of the parameters in my structural model. Second, since the SPARCS identifies each patient’s address up to ZIP code level, using other data sources, I can simulate important demographic characteristics included in my model that are not provided in the SPARCS. I simulate the income and education of each consumer using the distribution of income and education in each county reported in the Census 2000 data.

Out of 1,918,400 valid observations of inpatient visits in the data, I sample 2000 observations of visits randomly. If the same person has multiple stays within the same year, I account for her previous stays by calculating her cumulative expenditure in the past. Table 1 displays descriptive statistics for the 2000 observations used in this study along with the statistics for full sample. The characteristics are divided into patient characteristics in Table 1-1, insurer characteristics in Table 1-2, and hospital characteristics in Table 1-3. In Table 1-1, nearly 60% of the patients in the data are female, and approximately 26% of inpatient care patients are either black or Hispanic. The patient education was imputed from the Census 2000 data. The method of imputation of years of education and income is described in Appendix A. About half of the people in the sample have a high school diploma but did not finish college, while 33% finished college. 54.8% of the patients are admitted through an emergency visit. Table 1-2 and Figure 1 describe the insurance plans of the patients in the data. 35% of inpatient patients in New York State were enrolled in Medicare, 18% in Medicaid, 12% in Blue Cross and Blue Shield, and 28% in a commercial plan. In addition, 5.7% of the patients were uninsured. Table 1-3 summarizes the characteristics of hospitals used in the data. As seen in the standard deviation of the variables, there is a large variation in the characteristics of the hospitals. Recall that some hospitals do not report all of the variables.

\footnote{This is because of the time constraint. The evaluation of 2000 people’s log likelihood function using a high-power-computer takes about 15 minutes. Although I limit the sample of patients to 2000, each insurer’s choice set of hospitals is constructed from the full data.}
used in my analysis. I simulated the expected value of the missing variables and used them as each hospital’s characteristics when characteristics are missing. The details of the imputation are discussed in Appendix A.

3.2 Estimation Method for Insurance Characteristics

Finally, I estimate each insurers’ copay rate and deductible by the following procedure. First, for each insurer, I list each patient’s visits chronologically. Second, I calculate the ratio of the out-of-pocket expense to total charge for each patient’s visit. For each person, when the ratio becomes smaller for the visits that took place later in the data period than earlier, I assume the ratio to be the co-pay rate of the insurance plan. For example, in the SPARCS dataset, I observe a person who had three hospital stays in the data. During the first visit, she pays 100% of the total charge, the second time, she pays 7%, and then 4% for the third stay. Then, this person’s copayment rate is recorded as 4%. For each insurer, I take the average of each person’s estimated copay as $r_j$.

As the first step for deductible imputation, I calculate each patient’s cumulative previous out-of-pocket expenditure at each observation as $\iota_i$. In the last example, the person paid $1000 for the first visit, $1760 for the second visit, and $55200 for the third visit. Then, the cumulative expenditure of each visit is recorded as $0, $1000, and $1760. When I observe a patient whose out-of-pocket payment, $O_i$, is less than 100% of her total charge $T_i$, but more than her copay, I assume that the patient had not used up her deductible, $d_j$, prior to this visit, but the cumulative out-of-pocket expenditure, as of this visit, exceeds the deductible. Using the previous example, during this person’s second visit, she paid more than her copayment but less than 100%. Therefore, she pays 100% of her remaining deductible, $d_j - \iota_i$, as well as the copay rate on the remaining part of the total charge, $T_i - (d_j - \iota_i)$. Therefore, the relationship between the out-of-pocket expense $O_i$, the patient’s past expenditure $\iota_i$, and the estimated copay $r_j$ can be expressed in the following equation:

$$O_i = (d_j - \iota_i) + r_j (T_i - (d_j - \iota_i))$$

The relationship above can be manipulated to produce the following expression in order to calculate the deductible of insurer $j$ for each person,

\[8\] 98 hospitals out of 250 hospitals did not report non-payrol expenditure, while all of the hospitals reported the number of beds and non-profit status.
\[ d_j = i + \frac{O_i - r_j T_i}{1 - r_j}. \]

For each insurer, I take the average of the estimated copay rates and deductibles among all its clients in the data.

Finally, each insurer’s premium is approximated by the value that makes the firm’s profit equal to zero. In order to calculate the premium that makes the zero profit condition hold for an insurer, we need to know the cost of medical care for all of the customers in the insurance plan including those who did not utilize the inpatient care in the plan. If we use only observations in the SPARCS, the imputed premiums are overestimated because we have the information on only people who had worse health outcomes than those who did not utilize inpatient hospital services. I will estimate the premium that makes each insurer’s profit equal to zero for the entire population with the following equation,

\[ F_i = \Pr(v_i = 1) \times E(\Lambda_i | v_i = 1) \]

where \( v_i \) is a binary variable that equals one if person \( i \) utilizes any inpatient services and zero if not, and \( E(\Lambda_i | v_i = 1) \) is the expected value of the per patient cost of inpatient medical treatment, \( \Lambda_i \), for the customers who were hospitalized \( (v_i = 1) \). Following Ichimura’s (1993) method, I estimate \( \Pr(v_i = 1) \), the probability of being hospitalized for person \( i \), non-parametrically as a function of consumer characteristics, \( \bar{X}_i \), and parameters to be estimated, \( \Theta \).

\[ \Pr(v_i = 1) = P(\bar{X}_i, \Theta) = \frac{\sum \left[ v_k K \left( \frac{\bar{X}_k^\prime \Theta - \bar{X}_i^\prime \Theta}{b} \right) \right]}{\sum \sum K \left( \frac{\bar{X}_k^\prime \Theta - \bar{X}_i^\prime \Theta}{b} \right)} \]

where \( K(\cdot) \) is a kernel function defined as

\[ K(\varrho, b) = \exp \left\{ -\frac{1}{2} \times \left( \frac{\varrho}{b} \right)^2 \right\}. \]

where \( b \) is the bandwidth used for the estimation. The method I used for selecting an appropriate bandwidth is described in Appendix B.

For the estimation of \( \Theta \), I use the Medical Expenditure Survey (MEPS), which randomly samples consumers and reports their characteristics and hospital utilization. \( \Theta \) is estimated by minimizing the sum of the square of the difference between \( v_i \) and \( P(\bar{X}_i, \Theta) \).
\[ \hat{\Theta} = \arg \min_\Theta \sum_{i=1}^n (v_i - P(\bar{X}_i, \Theta))'(v_i - P(\bar{X}_i, \Theta)) \]

where \( \bar{X}_i \) includes each person’s age, sex, race, and whether she is insured.

\( E(\Lambda_i \mid v_i = 1) \), on the other hand, is the average cost of each insurer calculated from the SPARCS. Once again, I estimate \( E(\Lambda_i \mid v_i = 1) \) non-parametrically as the following function of \( \bar{X}_i \), patient characteristics from the SPARCS, and parameters, \( \Omega \),

\[ E(\Lambda_i \mid v_i = 1) = \Lambda_i (\bar{X}_i, \Omega) = \frac{\sum_{k \neq i} T_k K \left( \frac{X_{i}^{'}\Omega - X_{i}^{'}\Omega}{b} \right)}{\sum_{k \neq i} K \left( \frac{X_{i}^{'}\Omega - X_{i}^{'}\Omega}{b} \right)} \]

where \( T_i \) stands for total cost of each person’s visit, and \( \tilde{X}_i \) includes person \( i \)’s age, sex, race, whether she is insured, and the copay rate of the insurance plan used. \( \Omega \) is estimated by minimizing the sum of the square of the difference between \( T_i \) and \( \Lambda_i (\bar{X}_i, \Omega) \).

\[ \hat{\Omega} = \arg \min_\Omega \sum_{i=1}^n \left( T_i - \Lambda_i (\tilde{X}_i, \Omega) \right)' \left( T_i - \Lambda_i (\tilde{X}_i, \Omega) \right) \].

The estimated parameters, \( \hat{\Theta} \) and \( \hat{\Omega} \), are reported in Table 3. Further discussion on the method I used for controlling the selection bias will be provided in the estimation section.

### 4 Reduced Form Analyses

To better understand the data and help identify which observables are the important explanatory variables without imposing the full structure of my model, I estimate a Poisson regression (count model) analysis. The results from the estimation of the model using this method provide a standard measurement with which estimates from the structural model can be compared. The Poisson regression model is more suited for my analysis than linear regressions because the dependent variable of my model is discrete (inpatient days).

Table 2 reports estimation results from the following Poisson regression,

\[ \Pr(\tilde{q}_i = \tilde{q}_i^*) = \frac{\exp(-\lambda_i) \times \lambda_i^{y_i}}{y_i!}, \quad y_i = 0, 1, 2, \ldots \]  

(1)

where \( \tilde{q}_i \) is the number of hospital days, \( \tilde{q}_i^* \) is the corresponding observation in the data, and \( y_i \) is drawn from a Poisson distribution with parameter \( \lambda_i \), which is related to the characteristics of the patients, their hospitals and insurers, \( X_i \), as
\[
\ln \lambda_i = \beta' X_i. \tag{2}
\]

The quantity of medical care in my structural model in section 5 is the number of hospital days multiplied by the severity of the disease represented by the DRG weight.

The results in table 2 indicate that the probability of being hospitalized for a longer time increases with age, a result supported by others (Goldman (1995)). Additionally, I find that being an African American increases the likelihood of staying in a hospital for a longer time, while Hispanics decrease the likelihood of a longer hospitalization. In opposition, many previous studies have found that not only being Hispanic but also African American has a negative effect on the utilization of health care services even after controlling for the income level (National Health Disparity Report by the Agency of Health Care Research and Quality (2004), Guendelman and Schwalbe (2986)). My finding involving African Americans may be due to the fact that I am focusing on the length of inpatient stays as the medical care utilization. According to the National Ambulatory Medical Care Survey (2004) and National Hospital Ambulatory Medical Care Survey (2004), the utilization of hospital outpatient service by whites has been about 1.5 times greater than that by blacks for the last 18 years. Moreover, between 1990 and 2000, with the exception of 1998 and 1999, whites, on average, have visited a doctor for general medical exams about 40% more than African Americans have done. On the contrary, African Americans have visited hospital emergency departments almost twice as much as whites over the course of the last decade. Similarly, there have been about 10% more African Americans than whites discharged from hospital inpatient departments. This may indicate that the white population utilizes more preventive medical care than African Americans, and African Americans tend to have more severe conditions than whites once they are admitted to a hospital. As for the Poisson regressions results for Hispanics, while some studies explain that subtle personal factors such as physician bias and the willingness of patients to accept referral for subspecialty care may be important in explaining health care disparities (Ford and Cooper (1995), Rose-Lee et al. (1994)), this finding may result from the fact that more Hispanics tend to be relatively newer immigrants to the U.S. It may contribute evidence to the so-called “healthy immigrant paradox” in which first-generation Hispanic immigrants are healthier than second- or third-generation Hispanic immigrants due to the fact that healthier Hispanic people self-select themselves to migrate to another country, and newer immigrants tend to have a healthier diet that originates from their home countries. In addition, patients who were admitted to a hospital through
an emergency room are likely to stay hospitalized for a longer time. This is intuitive because an urgent condition is likely to be more severe. As for the effect of education, the regression indicates that possession of only a high school degree translate into a longer hospital stay compared to those who do not have a high school degree, while being a college graduate decreases the probability of being hospitalized compared to those with neither a high school nor college degree. This may be due to the fact that having at least a high school degree provides you with more financial resources to have a better access to medical care services while more educated consumers better understand the long term benefits of health and of preventive medical care.

The effect of types of insurers estimated from the regression is surprising. Compared to having no insurance, a plan by Medicare, Medicaid, Blue Cross Blue Shield, workers’ compensation, and a commercial insurer would decrease the likelihood of staying in a hospital for a longer time. The possible reason behind this result is that patients with no insurance tend to abstain from medical care until the condition becomes extremely severe. As I discussed in the introduction section, 15.6% of Americans are uninsured, while only 5.7% of patients who were hospitalized in New York State do not have an insurance plan, which indicates that uninsured people tend to avoid hospital care. As for the effects of hospital characteristics, higher expenditures of a hospital and more beds increase the probability for a patient to stay hospitalized for a longer time. However, larger staff, higher number of patients admitted, and higher average number of patients per day decrease the chance for a patient to stay in a hospital.

The major issue in this model is the bias caused by the endogenous choice of an insurance plan, a hospital and health care services. Consumers’ unobserved tastes for medical care services are likely to be correlated with their choice of insurance plans. For example, a consumer who expects to use more medical care services has more incentive to choose a generous plan than those who are healthier. The explanatory variables associated with health insurance and hospitals are likely to be correlated with the utilization, unexplained by the model, of medical care, which causes endogeneity biases in estimating parameters. Luft (1981) provides the evidence for this concern by estimating that prepaid health plan enrollees use 10% to 8% fewer hospital days than enrollees in other plans. To control for the bias arising from endogenous health plan choice, I model not only the choice of medical care utilization but the choice of hospitals and insurance plans and allow

9Prepaid health plans are health maintenance organization (HMO) plans, and the enrollee’s hospital choice is more restrictive than other plans.
the unobservable factors in each step of the choice process to be correlated with each other. The identification of these parameters will be discussed in the estimation section. While the Poisson regression presented here forces one to hypothesize scenarios behind the estimated parameters, by imposing reasonable structures on my model, I can estimate parameters that can better explain causalities. Finally, I observe only consumers who were hospitalized in my data. If the decision on whether one is hospitalized affects the parameters in the model, the estimated parameters are biased. In my structural model, I propose a structure that controls for this selection bias. This innovation will allow us to use rich medical care datasets that record patients who utilize the services.

5 The Model

In this section, I present a consumers’ utility maximization problem for the purpose of estimating demand for health insurance plans and hospital care service. In order to model consumers’ health care consumption behavior, I need to specify the timing of consumers’ decision making processes. The stages of my model are as follows:

1. The consumer knows her own health status and observes the medical care price of each hospital as well as each insurance plan’s hospital options, premium, and copay rate. Based on this knowledge, she chooses an insurance plan.

2. The consumer gets sick or injured, learns her actual health treatment needs, and decides which hospital in the network to visit.

3. The consumer decides how much medical care to consume.\footnote{In stage 3, I assume that the consumer decides how much medical care to consume. In reality, this decision is usually made under the advice of a physician. In the literature, it has been discussed that, after a patient decides to visit a hospital, the patient’s doctors decide how much medical care the patient should consume (See Pohlmeier and Ulrich (1995) for further discussion.). However, studies in the past have never introduced a model of physician behavior because of the lack of information on physicians and the complication that will be introduced from including physician behavior in the model. Since I have no information about physicians who treated the patients in the data, this paper also assumes that consumers decide how much to consume by themselves in stage 3.}
5.1 Consumer’s Utility Maximization Problem

5.1.1 Overviews and Notations

A consumer, $i = 1, \ldots, I$, derives utility from her health status, $H_{ijh}$, which is a function of her demographic characteristics and her medical care consumption when choosing hospital $h$ in plan $j$, and from the consumption of non-medical goods, $C_{ijh}$, which is her remaining income after consuming medical care. Specifying the utility function to be a constant absolute risk averse (negative exponential) utility function, the utility of person $i$ from choosing health insurance plan $j$ and consuming a medical care service from hospital $h$, $U_{ijh}$, is:

$$U_{ijh} = -\frac{1}{R_1} \exp (-R_1 H_{ijh}) - \frac{1}{R_2} \exp (-R_2 C_{ijh}) + e_{ijh} + \zeta_{ij}. \quad (3)$$

$R_1$ and $R_2$ are the coefficients of absolute risk aversion for health status after medical care consumption and consumption of non-medical goods respectively. I employ this utility specification because it allows me to identify the risk aversion parameters with respect to both $H_{ijh}$ and $C_{ijh}$ separately. $e_{ijh}$ is a hospital specific value of choosing hospital $h$ in plan $j$ for each person. $e_{ijh}$ is distributed $i.i.d.$ type II extreme value across the plans and the hospitals within each plan. Finally, $\zeta_{ij}$ is an insurance specific value of choosing $j$ for each person. Once again, it is distributed $i.i.d.$ type II extreme value across the plans. Since $e_{ijh}$ and $\zeta_{ij}$ are each person’s taste for a particular hospital in a particular insurance network and for a particular insurer respectively, they are independent of the person’s health status.

I assume that a consumer’s health status is determined by the following three factors; her pretreatment health status, $S_i$, her consumption of medical care, $q_i$, and the productivity of health care providers. The productivity of health care providers are determined by hospital characteristics, $Z_h$, and the interaction between hospital characteristics and the patient’s pretreatment health status, $S_i$. The value of $S_i$ depends on each person’s characteristics $X_i$, a health component that is known by the individual but not by the econometrician or the market, $\eta_i$, and a random shock $\varepsilon_i$, that is known neither by the individual, nor the econometrician, nor the market. Then, $S_i$ is specified as

$$S_i = X_i \beta + \eta_i + \varepsilon_i. \quad (4)$$

Notice that the value of $S_i$ increases as the consumer’s health worsens.

Then, I specify the health production function as
\[ \begin{align*}
    H_{ijh} &= G(Z_h, S_i)q_i - \frac{1}{2}q_i^2 - S_i
\end{align*} \] (5)

where \( Z_h \) are the characteristics of the hospitals and \( G(Z_h, S_i) \) is the productivity of the medical care service from the hospital chosen by person \( i \).

The first implication of this health production function is that, consuming more medical care \( q_i \) improves health status, \( H_{ijh} \), starting from \(-S_i\) (when \( q_i = 0 \)), and this effect increases as the productivity of the medical care service for the patient, \( G(Z_h, S_i) \), is higher. Thus, with a higher \( S_i \), the original \( H_{ijh} \) tends to be lower, but the improvement of \( H_{ijh} \) from medical care consumption \( q_i \) is higher. Second, the improvement of \( H_{ijh} \) from the incremental \( q_i \) diminishes as a patient consumes more \( q_i \). Accordingly, the marginal benefit of \( q_i \) on health,

\[ \frac{\partial H_{ijh}}{\partial q_i} = G(Z_h, S_i) - q_i, \]

diminishes as the quantity consumed increases.

I assume that the productivity of the medical care service from hospital \( h \) for person \( i \), \( G(Z_h, S_i) \), is affected by \( Z_h \), the characteristics of hospital \( h \), and the interaction between \( S_i \) and \( Z_h \). The interaction term captures the effect of people with different health status who may respond to various hospital characteristics in different ways. For instance, a sicker person may receive more benefits from her hospital’s higher expenditure than a healthier person does. To satisfy these two conditions, I specify \( G(Z_h, S_i) \) to be

\[ G(Z_h, S_i) = \gamma Z_h (1 + \alpha S_i). \] (6)

The intuition behind this equation is that health production is determined by the quality of a hospital that provided the care, \( \gamma Z_h \), and the interaction between the quality of the hospital and how sick the patient is, \( S_i \).

The consumption of non-medical care goods is the consumer’s remaining income after payment for medical care consumption. The first component of a health care expenditure is a premium. Every person who purchases a health insurance plan pays a premium, \( F_i \), to participate in the plan. Next, a consumer is likely to prefer to visit a hospital that is closer to her residence because of convenience or costs of traveling. Thus, I assume a consumer pays a cost (pecuniary or non-pecuniary cost) of traveling to a hospital and that the cost is proportional to the distance between the hospital and the patient, \( \xi_{ih} \). In addition, since hospital visits are inconvenient, I assume
that people also pay a non-pecuniary cost (such as the emotional stress of being hospitalized, the cost of not being able to look after family, and the inconvenience of not being at home), \( \vartheta \), when they consume each unit of medical care. The marginal cost of medical care utilization differs depending on how much the patient has utilized the services in the past because of her insurance plan’s reimbursement schedule. Therefore, I define four possible cases of \( C_{ijh} \), the consumption of non-medical goods, depending on how much the consumer has spent in the past for her medical care. Case 1 is when the patient’s insurance plan has no deductible or her past cumulative medical expenditure is equal to or more than the insurance plan’s deductible, case 2 is when the patient will not have used up her deductible after this visit, case 3 is when the patient’s past cumulative medical expenditure is less than her plan’s deductible but the expenditure from this visit exceeds the residual deductible, and case 4 is when the patient consumes no medical care.

\[
C_{ijh} = \begin{cases} 
    \text{(case1)} & Y_i - F_i - \rho \xi_{ih} - \vartheta q_i - r_j p_h q_i & \text{if } q_i > 0 & \iota_i \geq d_j \\
    \text{(case2)} & Y_i - F_j - \rho \xi_{ih} - (\vartheta q_i + p_h q_i) & \text{if } q_i > 0 & \iota_i < d_j \text{ and } T_i < d_j - \iota_i \\
    \text{(case3)} & Y_i - F_j - \rho \xi_{ih} - \vartheta q_i - r_j p_h (q_i + \iota_i - d_j) - p_h (q_i + d_j - \iota_i) & \text{if } q_i > 0 & \iota_i < d_j \text{ and } T_i > d_j - \iota_i \\
    \text{(case4)} & Y_i - F_i & \text{if } q_i = 0 
\end{cases}
\]

where \( Y_i \) is person \( i \)'s income, \( \rho \) is the cost of traveling to a hospital per mile, \( r_j \) and \( p_h \) are the co-insurance rate and the price of medical care service from hospital \( h \) through plan \( j \) respectively, \( q_i \) is the quantity of person \( i \)'s health care consumption, \( \iota_i \) is person \( i \)'s past cumulative medical expenditure, \( d_j \) is her plan’s deductible and \( T_i \) is the total charge for this hospital stay. I use the hospital days, multiplied by the index of severity of the disease patient \( i \) had for the visit, as the quantity, \( q_i \). In my data, I observe only consumers who stayed in a hospital. Therefore, \( q_i \) observed in my data is always positive. The solution for this selection issue will be discussed in the estimation section.

### 5.1.2 The Discrete/Continuous Choice Problem

Given the assumptions about the consumers’ utility function above, the sequence of consumers’ health care purchasing behavior is assumed to be the following: Initially, person \( i \) knows his or her own unobserved health status, \( \eta_i \), taste for hospital \( h \), \( c_{ijh} \), and the distance to hospital \( h \), \( \xi_{ih} \), in
plan \( j \), taste for plan \( j \), \( \zeta_{ij} \), and the productivity of medical care, \( G(S_i, Z_h) \), from each hospital and insurance plan. Based on this knowledge, first she picks plan \( j \) that contains the combination of hospitals that maximize his or her utility. Second, a health related incident occurs to her, and the error unobserved by the individual, \( \varepsilon_i \), is revealed. Then, the consumer picks hospital \( h \) from the network hospitals in plan \( j \). Finally, given the plan and the hospital chosen, the person chooses the quantity, \( q_i \) that maximizes his or her utility, \( U_{ijh} \).

Let us define the optimal quantity, \( q_i^* \), as \( q_i \) that maximizes the utility defined as equation (3),

\[
q_i^* = \max \left[ 0, \arg \max_q U_{ijh} \right]
\]

Substituting the optimal quantity, \( q_i^* \) (8), in the utility function (3) yields the indirect utility function when an individual purchases insurance plan \( j \) and goes to hospital \( h \) in health state \( S_i \) as

\[
V_{ijh} = -\frac{1}{R_1} \exp \left\{ -R_1 [H_{ihj}(q_i = q_i^*)] - \frac{1}{R_2} \exp \left\{ -R_2 [C_{ijh}(q_i = q_i^*)] + e_{ijh} + \zeta_{ij} \right\} \right\}
\]

\[
= \hat{V}_{ijh}(\eta_i, \varepsilon_i) + e_{ijh} + \zeta_{ij}.
\]

In equation (9), consumers have three types of errors that determine the value of insurance plans for each person; \( \eta_i \), \( e_{ijh} \), and \( \zeta_{ij} \). Healthier people with smaller values of \( \eta_i \) tend to prefer cheaper and less generous plans. On the contrary, \( e_{ijh} \) and \( \zeta_{ij} \) are each individual’s specific preference over hospitals in each plan and over insurance plans respectively, so they are not related to individual health status. Introducing these taste errors solves the statistical degeneracy problem since I may observe healthy consumers choosing generous plans or vice-versa. The identification of the parameters associated with the errors will be discussed in the estimation section.

In equation (10), \( e_{ijh} \) and \( \zeta_{ij} \) are both assumed to be distributed \( i.i.d. \) type II extreme value where \( e_{ijh} \) is \( i \)'s hospital specific value within plan \( j \), and \( \zeta_{ij} \) is \( i \)'s plan specific value. Therefore, given any insurance plan \( j \), the predicted conditional probability for person \( i \) to choose hospital \( h \) is calculated as

\[
\Pr[h \mid j, \eta_i, \varepsilon_i^*] = \frac{\exp \left( \frac{\hat{V}_{ijh}(\eta_i, \varepsilon_i^*)}{\tau} \right)}{\sum_{h'} \exp \left( \frac{\hat{V}_{ijh'}(\eta_i, \varepsilon_i^*)}{\tau} \right)}
\]

where \( \varepsilon_i^* \) is the \( \varepsilon_i \) that is consistent with the assumption that the observed quantity in the data, \( q_i^* \), is optimal and \( \tau \) is the variance of \( e_{ijh} \). Since the consumer already knows the value of \( \varepsilon_i \) when she
selects a hospital, she chooses the quantity of medical care consumption according to her knowledge of \( \varepsilon_i \). Therefore, in order to find \( \varepsilon_i^* \), I search for \( \varepsilon_i \) so that the first order condition with respect to \( q_i \) becomes zero when \( q_i \) is equal to the observed quantity, \( q_i^* \).

\[
\varepsilon_i^* = \arg \varepsilon_i \left\{ \frac{\partial U_{ijh}(\varepsilon_i | q_i = q_i^*)}{\partial q_i} = 0 \right\}.
\]

To the contrary, since the econometrician does not know the value of \( \eta_i \), the consumer’s probability of choosing hospital \( h \) given her insurance plan choice \( j \) is written as

\[
\Pr (h | j, \varepsilon_i^*) = \int \Pr[h | j, \eta_i, \varepsilon_i^*] \Pr[j | \eta_i] f(\eta_i) d\eta_i.
\] (12)

In order to derive the demand for insurance plans, I define the expected value of selecting insurer \( j \) assuming consumer \( i \) chose the hospital and quantity of medical care that maximize her expected utility as

\[
\hat{V}_{ij}(\eta_i) = E \left( \max_h V_{ijh} \right).
\] (13)

Since \( e_{ijh} \) is assumed to be distributed i.i.d. type II extreme value across plans, equation (13) has the following solution,

\[
\hat{V}_{ij}(\eta_i, \varepsilon_i) = \zeta_{ij} + \tau \ln \sum_h \exp \left( \frac{\hat{V}_{ijh}(\eta_i, \varepsilon_i)}{\tau} \right).
\] (14)

Then, the expected value of selecting insurer \( j \) given \( \eta_i \) is

\[
\int \left[ \tau \ln \sum_h \exp \left( \frac{\hat{V}_{ijh}(\eta_i, \varepsilon_i)}{\tau} \right) \right] f(\varepsilon_i) d\varepsilon_i + \zeta_{ij} = \hat{V}_{ij}(\eta_i) + \zeta_{ij}
\] (15)

The probability for consumer \( i \) of choosing insurer \( j \) can be computed as

\[
\Pr(j | \eta_i) = \frac{\exp \left( \hat{V}_{ij}(\eta_i) \right)}{\sum_j \exp \left( \hat{V}_{ij}(\eta_i) \right)},
\] (16)

which yields the demand function of insurance plan \( j \) as

\[
\Pr(j) = \int \Pr(j | \eta_i, \varepsilon_i) f(\eta_i) d\eta_i.
\] (17)

6 Estimation

In this section, I will first derive the likelihood function for my model and discuss how to control for the bias caused by the choice based sampling method in the SPARCS. Then, I outline the
method of simulation for the estimation, identification of the parameters, and the algorithm used to estimate the model presented in the previous section.

6.1 Likelihood Function

Each consumer’s likelihood contribution is the probability of his or her choosing a quantity of medical care, \( q_i \), an insurance plan, \( j \), and a hospital, \( h \), observed in the data given his or her observed characteristics and assumed distribution of unobserved characteristics. In order to illustrate the composition of the likelihood contribution, let us define three components: first, the probability of each consumer choosing the insurer observed in the data, second, the probability of the consumer choosing the hospital observed in the data, finally, the probability of the consumer choosing the quantity of medical care observed as his or her choice in the data. Then, each consumer’s likelihood contribution is the multiplication of the three components described above. Let us denote the observed characteristics and the unobservables in the model as \( \chi^O_{ihj} \) and \( \chi^u_{ihj} \) respectively, and the parameters to be estimated as \( \theta \). Recall that \( \chi^u_{ihj} \) includes error terms whose variances will be estimated in my model, \( \eta_i \) and \( \varepsilon_i \), as well as variables in my model that are not observed in the data such as educational attainment, the income of consumers, and missing variables among hospital characteristics in the AHA data, while \( \varepsilon^*_i \) belongs to \( \chi^O_{ihj} \). Then we can express the likelihood contribution \( L_i(\theta, \chi^O_{ihj}, \chi^u_{ihj}) \) as following

\[
L_i(\theta, \chi^O_{ihj}, \chi^u_{ihj}) = \Pr(j \mid \chi^O_{ihj}, \chi^u_{ihj}) \Pr(h \mid j, \chi^O_{ihj}, \chi^u_{ihj}) \Pr(q^*_i \mid h, j, \chi^O_{ihj}, \chi^u_{ihj}).
\] (18)

The first component of the likelihood contribution function (18), the probability for consumer \( i \) to choose insurer \( j \) given his or her characteristics and the characteristics of hospitals that are available through plan \( j \), is \( \Pr(j) \) as defined in equation (17). The second component, the conditional probability for a consumer to choose hospital \( h \) given he or she has chosen insurer \( j \), is \( \Pr(h \mid j, \varepsilon^*) \) as defined from equation (12). Finally, the last component, the conditional probability of consuming the quantity observed in the data given the consumer has chosen hospital \( h \) and insurer \( j \) is calculated by first finding the \( \varepsilon_i \) that is consistent with the assumption that the observed quantity in the data, \( q^*_i \), is optimal in the model and then multiplying the density of \( \varepsilon_i \) evaluated at \( \varepsilon^*_i \), \( \phi(\varepsilon^*_i) \) where \( \phi(\cdot) \) stands for the density of the normal distribution by \( \frac{de^*}{dq^*_i} \) (Jacobian). Therefore,

\[
\Pr(q^*_i \mid h, j, \chi^O_{ihj}, \chi^u_{ihj}) = \phi(\varepsilon^*_i) \frac{de^*_i}{dq^*_i}.
\] (19)
where \( \frac{d\varepsilon_i^*}{dq_i} \) can be calculated by applying the implicit function theorem using the first order condition, 
\[ \frac{\partial U_{ijh}(\varepsilon_i|q_i=q_i^*)}{\partial q_i} = 0. \]
Since my data only contains consumers who visited hospitals, there is no need to account for corner solutions. However, since we only observe consumers who were hospitalized, the probability above must be conditioned on the fact that the person has been hospitalized in order to estimate unbiased parameters. I will illustrate how to control the bias in the following estimation section.

Using the definition of the three components of the likelihood contribution, we can rearrange the likelihood contribution, (18) as
\[
L_i(\theta, \chi_{ihj}^O, \chi_{ihj}^u) = \Pr(j) \Pr(h | j, \varepsilon_i^*) \phi(\varepsilon_i^*) \frac{d\varepsilon_i^*}{dq_i} \\
= \int \Pr[h | j, \eta_i, \varepsilon_i^*] \Pr[j | \eta_i] f(\eta_i) d\eta_i \phi(\varepsilon_i^*) \frac{d\varepsilon_i^*}{dq_i}
\]

Since \( L_i(\theta, \chi_{ihj}^O, \chi_{ihj}^u) \) is still conditioned on unobservables in the model, \( \chi_{ihj}^u \), I simulate \( \chi_{ihj}^u \) over the distributions of each of the unknown characteristics. Thus, the likelihood contribution given only observable variables is calculated as
\[
l_i(\theta, \chi_{ihj}^O) = \int L_i(\theta, \chi_{ihj}^O, \chi_{ihj}^u) f(\chi_{ihj}^u) d\chi_{ihj}^u.
\]

The method of simulation of each consumer’s likelihood contribution will be discussed in the latter part of this section.

Finally, the log likelihood function of all consumers will be calculated as the sum of the log likelihood contribution,
\[
L(\theta) = \sum_{i=1}^{N} \log l_i(\theta, \chi_{ihj}^O).
\]

I estimate the parameters in my model by searching for a set of parameters \( \hat{\theta} \) that maximize the value of \( L(\hat{\theta}) \).

### 6.2 Controlling for Selection Bias

As discussed in the data section, the SPARCS only includes consumers who have been hospitalized. As discussed by Cosslett (1989), the maximum likelihood estimation procedures lead to inconsistent and asymptotically biased estimates in choice-based sampling like the SPARCS. The reason under this identification problem with a choice-based samples is the lack of information about independent
variables in the population as a whole. The estimated parameters can only be interpreted as the demand parameters for either those who had poor health status prior to medical treatment or those who had a large negative health shock. I propose a method for controlling this bias, a hybrid sampling procedure in which a choice-based sample is combined with additional survey data taken from a random sample of the entire population under study, an application of a method introduced by Judd (1989).

The goal is to select parameters in such a way that they are not only consistent with the available observations in the data but also with the whole sample. First, I divide the population into different demographic groups, \( g = 1, \ldots, G \). Using an additional randomly sampled dataset, I find the share of those who were hospitalized in the total population sample in each demographic group, \( \Psi_g \). I denote the subset of the observations that are in group \( g \) and the number of observations in \( g \) as \( \Delta_g \) and \( N_g \) respectively. Then, for each demographic group, I derive the theoretical probability of a person staying in a hospital for at least one day given her characteristics \( \chi_{Og} \) and parameters \( \theta \) in my model as

\[
\Pr(q_i > 0 \mid \theta, \chi_{Og}) = \frac{1}{N_g} \sum_{i \in \Delta_g} \left[ 1 - \Phi\left( \varepsilon_{ihj}^R \right) \right]
\]

(23)

where

\[
\varepsilon_{ihj}^R = \arg_{\varepsilon_i} \begin{cases} q_i^* (\varepsilon_i) > 0 & \forall \varepsilon_i > \varepsilon_{ihj}^R \\ q_i^* (\varepsilon_i) < 0 & \forall \varepsilon_i < \varepsilon_{ihj}^R \end{cases}
\]

(24)

and \( \Phi(\cdot) \) stands for the CDF of the normal distribution with mean 0 and variance \( \sigma_{\varepsilon_i}^2 \). In the equation above, when \( \varepsilon_i \) equals \( \varepsilon_{ihj}^R \), the consumer is indifferent between visiting a hospital and not, and if \( \varepsilon_i \) is smaller than \( \varepsilon_{ihj}^R \), the person will be better off by not being hospitalized. Therefore, \( \Phi\left( \varepsilon_{ihj}^R \right) \) is the probability for person \( i \) of not being hospitalized while \( 1 - \Phi\left( \varepsilon_{ihj}^R \right) \) is the probability for person \( i \) of being hospitalized. Notice that \( \varepsilon_{ihj}^R \) is indexed not only by person \( i \), but also by hospital \( h \) and insurer \( j \) since \( \arg_{\varepsilon_i} \max U_{ijh} (q_i^* = 0) \) from my model is calculated as a function of the characteristics of the hospital chosen and the insurer chosen by each person. However, I cannot group observations into those with different insurers or hospitals because I do not observe the individual information about insurers and hospitals used in the MEPS data. Even if there were such survey data that recorded insurers and hospitals for each consumer’s choice, it would still be impossible to observe insurers and hospitals that could have been chosen for those who had no utilization in the data. Thus, I aggregate the probability of being hospitalized for each characteristic group and do not differentiate the probability conditional on the insurers and hospitals selected.
The goal will be achieved if one selects parameters in the model that equate the theoretical probability of being hospitalized in each demographic group, \( \Psi_g \), and the actual corresponding share, \( \Psi \), which is calculated using the randomly sampled data, the MEPS. I add the constraints in the maximization problem that make the theoretical probability of hospitalization in each demographic group equal to the observed share. Instead of maximizing (22), unbiased parameters will be selected by maximizing the following equation over the parameters, \( \theta \).

\[
\max_{\theta} \left\{ L(\theta) - \lambda \left[ \Pr(q > 0 \mid \theta, \chi^O) - \Psi \right] \right\} \tag{25}
\]

where \( \Pr(q > 0 \mid \theta, \chi^O) \) and \( \Psi \) are both \( 1 \times G \) vectors. As previously discussed, \( \Psi_g \) is calculated from observations of not only people who had been hospitalized but also those who had never been hospitalized. Therefore, it cannot be conditioned on hospitals and insurance plans in the observed sample.

6.3 Simulation and the Estimated Individual Likelihood Function

There are three kinds of variables simulated in my empirical analysis; first, individual characteristics unobserved in the SPARCS (i.e. educational attainment and income), second, missing hospital characteristics in the AHA data, and finally, unobserved error terms, \( \eta_i \) and \( \varepsilon_i \). Let us denote the unobserved characteristics associated with consumers and hospitals as \( \chi^u_i \) and \( \chi^u_h \) respectively. The density of \( \eta_i, \varepsilon_i, \chi^u_i \), and \( \chi^u_h \) are defined to be \( g_1(\eta_i), g_2(\varepsilon_i), g_3(\chi^u_i), \) and \( g_4(\chi^u_h) \) respectively where \( \eta_i, \varepsilon_i, \) and \( \chi^u_i \) are assumed to be distributed normally with mean 0, while the distribution of \( \chi^u_h \) is obtained from the Census 2000. The variance of \( \eta_i, \varepsilon_i, \sigma^2_{\eta_i}, \) and \( \sigma^2_{\varepsilon_i, \chi^u_i}, \) and \( \chi^u_h \) are parameters to be estimated. Since \( \eta_i, \varepsilon_i, \chi^u_i, \) and \( \chi^u_h \) are independent with each other, the simulated likelihood contribution of each consumer is written as

\[
l_i(\theta; \chi^O_{ihj}) = \int l_i(\chi^O_{ihj}, \chi^u_i, \chi^u_h, \eta_i, \varepsilon_i)g_1(\eta_i)g_2(\varepsilon_i)g_3(\chi^u_i)g_4(\chi^u_h)d(\eta_i)d(\varepsilon_i)d(\chi^u_i)d(\chi^u_h). \tag{26}
\]

The simulator for \( l_i(\theta; \chi^O_{ihj}) \) is

\[
l^R_i(\theta; \chi^O_{ihj}) = \frac{1}{R} \sum_{r=1}^{R} l_i(\chi^O_{ihj}, \chi^u_{ir}, \chi^u_{hr}, \eta^r_i, \varepsilon^r_i), \tag{27}
\]

where \( r \) indexes \( R \) draws of \( \chi^u_i, \chi^u_h, \eta_i, \) and \( \varepsilon_i \). The simulated log-likelihood function to be maximized is the sum of all individuals’ simulated likelihood contributions,
\[
\log L^R(\theta) = \sum_{i=1}^{N} \log t^R_i(\theta, x^{O}_{ihj}).
\] (28)

The goal of the estimation is to find a set of parameters, \( \hat{\theta} \), that maximizes the simulated log-likelihood function \( \log L^R(\hat{\theta}) \).

### 6.4 Identification and Estimation Method

The parameters to be estimated, \( \theta \), are \( \theta = \{\gamma, \alpha, \beta, R_1, R_2, \rho, \vartheta, \sigma_\eta^2, \sigma_\varepsilon^2, \tau\} \). \( \gamma \) represents a vector of parameters that explain the impact of hospital characteristics on health care productivity, \( G_{jh}(S_i, Z_h) \), and \( \alpha \) is the parameter that interprets the effect of the consumer’s health status on the health care productivity. \( \gamma \) is identified by the covariation between the characteristics of the hospital chosen and the quantity of medical care consumed, while \( \alpha \) is identified by the covariation between demographic characteristics observed in the SPARCS and the characteristics of the hospital chosen. \( \beta \) is a vector of parameters that explains the effect of each consumer’s demographic characteristics on her health status, \( S_i \). \( \beta \) is identified by the covariation between the demographic characteristics and each of the following, the quantity of medical care consumption, the choice of hospitals, and the choice of insurers. \( R_1 \) and \( R_2 \) stand for risk aversion parameters with respect to health status and non-health consumption respectively in equation (3). \( R_1 \) and \( R_2 \) are identified from the variation in the relationship between budget sets given from the information on each consumer’s income as well as the price schedule of each insurer, the shape of indifference curves as affected by consumers’ demographic characteristics, and the observed consumption of medical care as well as the choice of hospitals and insurers. \( \rho \) represents the pecuniary and non-pecuniary cost, per mile, of traveling to a hospital. This parameter is identified by the covariation between the distance between patients and hospitals and their choice of medical care consumption, hospitals, and insurance plans that include particular hospitals as their network hospitals.\(^{11} \) \( \vartheta \) is the non-pecuniary cost of visiting a hospital per hospital day multiplied by the DRG weight. This non-pecuniary cost is identified from the variation in consumers’ health care consumption. \( \sigma_\eta^2 \) and \( \sigma_\varepsilon^2 \) stand for the variance of the distribution of \( \eta_i \) and \( \varepsilon_i \), respectively. The parameters associated with the error terms, \( \eta_i + \varepsilon_i \), are identified by the variation in the difference between predicted consumers’ quantity choices and actual choices. Furthermore, one can separate the variance of \( \eta_i \)

\(^{11}\)The effect of distance between patients and hospitals has not been introduced in my present results presented in Table 4. Estimation with the inclusion of this cost is work in progress.
from that of $\eta_i + \varepsilon_i$ by observing the covariation between the deviation of the predicted consumer’s quantity choices from the actual choices and the deviation of the predicted hospital-insurer choices from the actual choices. Evidence of a difference between the choice of hospitals within each insurance plan observed is displayed in Figure 2, and the variation in consumers’ choices of quantity is shown in the histograms in Figure 3-1 and 3-2. Finally, the variance of $\epsilon_{ijh}, \tau$, can be identified because $\epsilon_{ijh}$ affects not only a consumer’s hospital choice given insurance choices but it also affects a part of the value function of selecting a particular insurance plan as described in equation (27). On the other hand, the variance of $\zeta_{ij}$ cannot be identified because one can pick any variance of $\zeta_{ij}$ in equation (16) and find the same probability value. Thus, I normalize the variance of $\zeta_{ij}$ to be one.

I begin my estimation by choosing initial starting values for the parameters in $\theta$. Then, for each evaluation of the log likelihood function, I calculate the first derivative of the log likelihood contribution with respect to each parameter, $l^{R}_{i,\theta_k}(\theta, \chi^O_{ih})$ where $\theta_k$ stands for the $k$th parameter in $\theta$. Then, using Newton’s method, each time evaluating the log likelihood function, I calculate a new value of each parameter for an improved log likelihood to be

$$\theta_{k,t+1} = \theta_{k,t} + \frac{1}{N} \sum_{i=1}^{N} \left\{ \left[ l^{R}_{i,\theta_k}(\theta, \chi^O_{ih}) \right] \times \left[ l^{Ru}_{i,\theta_k}(\theta, \chi^O_{ih}) \right]^{-1} \right\} \times \frac{1}{N} \sum_{i=1}^{N} l^{R}_{i,\theta_k}(\theta, \chi^O_{ih}) \right\}. \quad (29)$$

Once the suggestion by equation (29) improves the log likelihood function, my algorithm allows $\theta$ to move in the same direction repeatedly until the update fails to improve the log likelihood function. Then, I start from the best $\theta$ to calculate equation (29) again to find the next suggested update. This iteration is continued until there is no improvement in the log likelihood.

### 7 Results

### 8 Policy Questions

The principal advantage of estimating a structural model is that it allows the econometrician to simulate changes in the underlying economic environment. Using the estimated parameters of the distribution of unknowns, I simulate potential changes in policy. Policy makers often discuss whether managed care organizations benefit consumers in order to evaluate social policies such as the introduction of subsidy programs for managed care plans or the imposition of stricter anti-trust
laws on the operations of managed care organizations. Following the estimation of the parameters in the structural model, I simulate a change in the restrictiveness of hospital choice as if all insurers had traditional indemnity plans given the current premium and copay of each plan. This provides insight into the consumer’s benefit of having more hospital choices. Second, I estimate the optimal premiums and copays of each insurance firm when every plan allows its customers to choose any hospital. Then, given the estimated premiums and copays, I simulate the impact, on social welfare, of having a health insurance market with only indemnity plans.

9 Discussion and Conclusion

This paper has made a first attempt at the estimation of a structural model that finds the effect of the rise of restrictive health insurance plans on how consumers choose health insurance plans and health care providers. The advantages of the method presented in this paper are its ease of implementation, its flexibility, and the fact that it does not rely on the behavior of consumers in restrictive health insurance plans to predict the action of the rest of the population.

In the future revision of this work, I will add the pecuniary and non-pecuniary cost of traveling to a hospital in my model since distance to a hospital is likely to be a large factor that determines the consumer’s hospital and insurance plan. After this correction, I will evaluate the policy analysis questions I introduced in the previous section.

Other limitations of the model presented in this paper suggest possibilities for future research. I estimated the parameters in my demand function using the consumer side model only, but the behavior of consumers is determined not only by the exogenous factors they observe in the market but also by their expectation of actions of suppliers. If I model not only consumers but also insurers and hospitals and simultaneously solve for the parameters built into the model, I can estimate even more consistent parameters that can analyze the entire health care market in a concrete manner.
10 Appendix

10.1 Appendix A: Estimating Consumer and Hospital Characteristics from Supplemental Datasets

From the Census 2000 data, I use the distribution of income and educational attainment levels in each county in New York state to simulate the income and education levels of the patients in the SPARCS. First, I simulate the years of education for each person, $E_i$, by the distribution of years of education given in the Census data. One may suggest that I could use the mean of the educational attainment in the county of each person’s residence as the person’s educational attainment. However, the Census data provide us with not only the mean but also distribution of years of education in each county. Thus, drawing a value of educational attainment from the distribution can better utilize the information about the distribution in the data. Then, since the educational attainment and income are typically correlated with each other, I estimate the joint distribution of income and educational attainment by using the microdata from the Current Population Survey (CPS). In particular, I regress the logarithm of income on the number of years of education as following

$$\log (I_i) = \delta + \kappa \cdot E_i + \zeta_i,$$  \hspace{1cm} (30)

in order to estimate $\kappa$ and the variance of the residual, $\zeta_i$, where $i$ indexes each observation and $I_i$ and $E_i$ are income and years of education of each person respectively. Using $\kappa$ in equation (30), the following relationship between mean the log of income, $I_c$, and education, $E_c$, in county $c$ reported in the Census 2000 data,

$$\log (I_c) = \delta_c + \kappa E_c + \zeta_c,$$  \hspace{1cm} (31)

yields the expected value of $\delta_c$ as

$$\delta_c = \log(I_c) - \kappa E_c$$  \hspace{1cm} (32)

Then, from the simulated years of education, I simulate the logarithm of income of each person in county $c$ as

$$\log(I_{ic}) = \delta_c + \kappa E_i + \zeta_i,$$  \hspace{1cm} (33)
using the simulated value of educational attainment, $E_i$, the coefficient estimated from the CPS, $\kappa$, and the constant calculated for each county, $\delta_c$ and drawing the error $\zeta_i$ from the normal distribution with mean 0 and variance estimated from the CPS in equation (30). Estimating a linear relationship between the logarithm of income and education allows me to avoid finding negative estimates of expected income since the income of person $i$ in county $c$ will be calculated as the exponent of the estimated value of the logarithm of her income.

The individual patient data from the SPARCS is supplemented by the American Hospital Association (AHA) 1996 data and the Census 2000 data. The AHA data reports information on hospital ownership, size, cost, specialization and the location of nationwide hospitals. I use the expenditure of operating the facilities, payroll amount for staff, the number of staff hired, the number of beds, the average number of patients admitted per day and the types of management (private not-for-profit or for-profit, or public) of the hospitals in New York State as hospital characteristics. The SPARCS reports the identification number of each hospital that was involved in each observation. Since the New York State Department of Health provides us with the name of the hospital corresponding to each identification number, we can match the hospital characteristics in the AHA data and the hospitals in the SPARCS data. In 1996, about 30% of the hospitals in New York State did not report some of the hospital characteristics I used in my analysis (some hospitals failed to report only one variable, others did not report as many as 6 variables used in my analysis). In order to use the AHA data, I employ the method from Lavy, Palumbo, and Stern (1997) to simulate those missing variables where the data include binary values. First, I assume that the continuous variables as well as the latent variables behind the binary variables are jointly distributed as the normal distribution. Second, using estimated the means and variances of the observed continuous variables, as well as the estimated means and variances of the latent variables implied by the observed binary variables in the data, I simulate the values of each of the continuous and latent variables. Then, I transform the latent variables into corresponding binary variables. I employ the GHK simulation method in order to update, during the simulation, the conditional means and variances of the missing variables given the variables simulated previously.

10.2 Appendix B: The Method for Estimating An Appropriate Bandwidth

Recall that I estimate the probability of each person’s being hospitalized and the expected value of total charge of each hospital visit semi-parametrically in order to estimate each person’s premium.
When using the Kernel method of non-parametric estimation, we need to select the bandwidth that are small enough to find the unbiased estimates of parameters but large enough to avoid a too large variance in the estimates. To choose appropriate bandwidths, I use the following algorithm.

Let the kernel function, \( K \left( \tilde{X}_k' \Omega - \tilde{X}_i' \Omega \right) = 0 \) if \( \frac{\tilde{X}_k' \Omega - \tilde{X}_i' \Omega}{b} > \bar{C} \). Where \( \bar{C} \) is a constant number you pick as the threshold value of the argument of the kernel function that is too large. I set \( \bar{C} \) as 4 in my analysis. Then, I pick \( b \) so that the number of observations that make the kernel function greater than 0 for each observation is no fewer than 0.5 % of the total observations. Therefore,

\[
b = \arg_b \left[ \sum_{k \neq i} 1 \left[ K \left( \tilde{X}_k' \Omega - \tilde{X}_i' \Omega \right) > 0 \right] \geq 0.005 \times N \right].
\]

References

[1] Bennahum, David A., "Managed Care : Financial, Legal, and Ethical Issues" (1936)


### Table 1

**Descriptive Statistics**

**Table 1-1: Patient Characteristics**

**Table 1-2: Insurance Share in the Data**

**Table 1-3: Hospital Characteristics**

### Table 1–1

**Patient Characteristics**

<table>
<thead>
<tr>
<th></th>
<th>Selected Small Sample (2000 observations)</th>
<th>Full Sample (1.5 million observations)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td><strong>(Standard Deviation)</strong></td>
<td><strong>Mean</strong></td>
</tr>
<tr>
<td><strong>(Standard Deviation)</strong></td>
<td></td>
<td><strong>(Standard Deviation)</strong></td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
<td>48.538</td>
<td>46.901</td>
</tr>
<tr>
<td><strong>Female</strong></td>
<td>0.583</td>
<td>0.583</td>
</tr>
<tr>
<td><strong>Black</strong></td>
<td>0.185</td>
<td>0.172</td>
</tr>
<tr>
<td><strong>Hispanic</strong></td>
<td>0.077</td>
<td>0.081</td>
</tr>
<tr>
<td><strong>Emergency</strong></td>
<td>0.548</td>
<td>0.532</td>
</tr>
<tr>
<td><strong>Length of Stays</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>(in days)</strong></td>
<td>6.405</td>
<td>6.657</td>
</tr>
<tr>
<td><strong>DRG weight</strong></td>
<td>1.132</td>
<td>1.112</td>
</tr>
<tr>
<td><strong>Total Charge</strong></td>
<td>10453.71</td>
<td>10703.85</td>
</tr>
<tr>
<td><strong>(in dollars)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Non-covered (Out-of-Pocket) Charge</strong></td>
<td>442.767</td>
<td>480.681</td>
</tr>
<tr>
<td><strong>(in dollars)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Income (in dollars)</strong></td>
<td>67504</td>
<td>50240</td>
</tr>
<tr>
<td><strong>In County</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>High School Graduate Share in County</strong></td>
<td>0.503</td>
<td>0.456</td>
</tr>
<tr>
<td><strong>College Graduate or more Share in County</strong></td>
<td>0.335</td>
<td>0.330</td>
</tr>
</tbody>
</table>
### Table 1-2

**Insurance Share in the SPARCS**

<table>
<thead>
<tr>
<th></th>
<th>Selected Small Sample (2000 observations)</th>
<th>Full Sample (1.5 million observations)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (Standard Deviation)</td>
<td>Mean (Standard Deviation)</td>
</tr>
<tr>
<td>Uninsured</td>
<td>0.057 (0.233)</td>
<td>0.061 (0.230)</td>
</tr>
<tr>
<td>Medicare</td>
<td>0.351 (0.477)</td>
<td>0.332 (0.472)</td>
</tr>
<tr>
<td>Medicaid</td>
<td>0.181 (0.385)</td>
<td>0.202 (0.398)</td>
</tr>
<tr>
<td>Blue Cross/Shield</td>
<td>0.121 (0.326)</td>
<td>0.123 (0.324)</td>
</tr>
<tr>
<td>Workers’ Compensation</td>
<td>0.005 (0.067)</td>
<td>0.012 (0.077)</td>
</tr>
<tr>
<td>Commercial Insurance</td>
<td>0.284 (0.451)</td>
<td>0.279 (0.449)</td>
</tr>
<tr>
<td>Champus (Military Insurance)</td>
<td>0.0001 (0.034)</td>
<td>0.0001 (0.039)</td>
</tr>
</tbody>
</table>

### Table 1-2

**Hospital Characteristics**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital’s Expenses including labor-related and non-labor-related costs for a 12-month period (in thousands of dollars)</td>
<td>155,068.6</td>
<td>(176345.7)</td>
</tr>
<tr>
<td>Hospital’s Payroll expenses for 12-month-period (in thousands of dollars)</td>
<td>80,521.21</td>
<td>(95507.87)</td>
</tr>
<tr>
<td>Hospital’s Number of Persons on Payroll</td>
<td>2,096.806</td>
<td>(1496.59)</td>
</tr>
<tr>
<td>Number of Patients Accepted for inpatient service during the 12 months</td>
<td>16,759.29</td>
<td>(8379.965)</td>
</tr>
<tr>
<td>Beds</td>
<td>598.1683</td>
<td>(189.9762)</td>
</tr>
<tr>
<td>Average Daily Census (Average Number of Inpatients Receiving Care Each Day during the 12 months)</td>
<td>361.453</td>
<td>(201.7453)</td>
</tr>
<tr>
<td>Share of Public Hospitals</td>
<td>0.0433559</td>
<td>(0.02037142)</td>
</tr>
<tr>
<td>Share of Not For Profit</td>
<td>0.9566441</td>
<td>(0.02037142)</td>
</tr>
</tbody>
</table>
### Table 2

**Results from Poisson Regression**

Dependent Variable = Number of Days at a Hospital

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2.493824**</td>
<td>(0.5220264)</td>
</tr>
<tr>
<td>Age</td>
<td>0.0853953**</td>
<td>(0.014667)</td>
</tr>
<tr>
<td>Age*Age</td>
<td>-0.0003146</td>
<td>(0.0015117)</td>
</tr>
<tr>
<td>Female</td>
<td>0.0283972</td>
<td>(0.0193182)</td>
</tr>
<tr>
<td>Black</td>
<td>0.2705637**</td>
<td>(0.0250136)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.1392421**</td>
<td>(0.0412109)</td>
</tr>
<tr>
<td>Emergency</td>
<td>0.0794183**</td>
<td>(0.0202875)</td>
</tr>
<tr>
<td>Medicare</td>
<td>-0.2995927**</td>
<td>(0.0661664)</td>
</tr>
<tr>
<td>Medicaid</td>
<td>-0.1914026**</td>
<td>(0.0566682)</td>
</tr>
<tr>
<td>Blue Cross/Shield</td>
<td>-0.238666**</td>
<td>(0.057067)</td>
</tr>
<tr>
<td>Worker’s Compensation</td>
<td>-0.3229636**</td>
<td>(0.171805)</td>
</tr>
<tr>
<td>Commercial</td>
<td>-0.3983725**</td>
<td>(0.0521281)</td>
</tr>
<tr>
<td>Champus</td>
<td>0.4436389</td>
<td>(0.2813706)</td>
</tr>
<tr>
<td>High School</td>
<td>1.171782**</td>
<td>(0.4681007)</td>
</tr>
<tr>
<td>College</td>
<td>-1.145115**</td>
<td>(0.4494815)</td>
</tr>
<tr>
<td>DRG weight</td>
<td>0.2891075**</td>
<td>(0.0081357)</td>
</tr>
<tr>
<td>Premium (dollars)</td>
<td>0.000021**</td>
<td>(2.86e-06)</td>
</tr>
<tr>
<td></td>
<td>Value</td>
<td>Standard Error</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------</td>
<td>----------------</td>
</tr>
<tr>
<td>Hospital’s Expenses including labor-related and non-labor-related costs for a 12-month period (in thousands of dollars)</td>
<td>0.0116849**</td>
<td>(0.0608662)</td>
</tr>
<tr>
<td>Hospital’s Payroll expenses for 12-month-period (in thousands of dollars)</td>
<td>0.1127501</td>
<td>(0.0738054)</td>
</tr>
<tr>
<td>Hospital’s Number of Persons on Payroll</td>
<td>-0.1758449**</td>
<td>(0.0860039)</td>
</tr>
<tr>
<td>Number of Patients Accepted for inpatient service during the 12 months</td>
<td>-0.0857814</td>
<td>(0.1168662)</td>
</tr>
<tr>
<td>Beds</td>
<td>0.000302**</td>
<td>(0.0000851)</td>
</tr>
<tr>
<td>Average Daily Census (Average Number of Inpatients Receiving Care Each Day during the 12 months)</td>
<td>-0.1752066**</td>
<td>(0.0783756)</td>
</tr>
<tr>
<td>Not For Profit</td>
<td>-0.1996957**</td>
<td>(0.0566004)</td>
</tr>
</tbody>
</table>
Table 3
The Preliminary Results: For the results presented on this table, I did not use the method of choosing an appropriate bandwidth suggested in my paper. The new results will be forthcoming. Standard error will be calculated once I find the final bandwidths.

Table 3-1
Parameters Estimated in the Non-Parametric Estimation of Probability of Being Hospitalized from MEPS.

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.88985</td>
<td>()</td>
</tr>
<tr>
<td>Female</td>
<td>2.001728</td>
<td>()</td>
</tr>
<tr>
<td>Black</td>
<td>-11.74539</td>
<td>()</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-3.57047</td>
<td>()</td>
</tr>
<tr>
<td>Insured</td>
<td>6.79165</td>
<td>()</td>
</tr>
</tbody>
</table>

Table 3-2
Parameters Estimated in the Non-Parametric Estimation of Total Expenditure of an Inpatient Stay in the SPARCS

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.99834</td>
<td>()</td>
</tr>
<tr>
<td>Female</td>
<td>1.16983</td>
<td>()</td>
</tr>
<tr>
<td>Black</td>
<td>6.95426</td>
<td>()</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-2.79386</td>
<td>()</td>
</tr>
<tr>
<td>Emergency</td>
<td>-6.44758</td>
<td>()</td>
</tr>
<tr>
<td>Uninsured</td>
<td>0.15054</td>
<td>()</td>
</tr>
<tr>
<td>Co-Pay (rate)</td>
<td>-1.10738</td>
<td>()</td>
</tr>
</tbody>
</table>
Figure 1

Composition of Insurance Choice in SPARCS

Uninsured 0.057  Medicare 0.351  Medicaid 0.181  Blue Cross/Shield 0.121  Workers’ Compensation 0.005  Commercial Insurance 0.284  Champus 0.0001

Figure 2

The Variation in the Number of Hospitals Used within each Plan

Insurers Ordered from Most Restrictive to Generous Hospital Options (Includes those who have more than the market share of 0.5%)

Number of Hospitals Used within each Plan
Figure 3-1
Histogram of Hospital Days in the sample from the SPARCS

Figure 3-2
Histogram of the Quantity defined in the Model, Hospital Days * DRG weight (severity), in the sample from the SPARCS