Welfare Effects of Using Hospital Rate Setting as an Alternative to Bargaining

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Abstract

Prices paid by insurers to hospitals are determined by bilateral negotiations in all U.S. states except Maryland, where a unique all-payer rate setting health care regulation sets common prices for all insurers. Theoretical predictions on how bilateral bargaining affects total welfare are ambiguous. We empirically analyze how a Maryland style regulation would affect overall welfare relative to bilateral bargaining, using the New Jersey health care market as an example. Using hospital-, insurer-, and patient-level data from 2010, we estimate a structural model of hospital and insurer demand, and simulate consumer and insurer responses to the new price regime. We find that replacing bargaining with all-payer rate setting increases total surplus in the market. However, not all agents benefit, and the effects depend on how the largest player in our market, Blue Cross Blue Shield (BCBS), sets premiums. If BCBS sets premiums à la Bertrand Nash, consumer surplus decreases, but joint hospital-insurer surplus increases by more. The number of uninsured increases by two percent. Total surplus increases are robust to different pricing strategies of BCBS, which account for its non-profit status, but diminish the magnitude of surplus gain.

JEL: I110, I180, L1, L130, L520

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1 Introduction

Total expenditure on health care as a share of GDP increased from 5% in 1960 to 17.5% in 2014.[1] Today, hospital costs represent almost one-third of total health care expenditure, with high hospital prices and high hospital price growth being the main drivers of the increasing health care expenditure.[2,3] The increase in prices charged by hospitals to insurers has prompted a growing empirical literature that focuses on investigating the effect of hospital market power on negotiated prices. In 48 states hospitals and insurers negotiate prices bilaterally, this literature has taken the bilateral bargaining in the market as given. However, bilateral negotiation is not the only model for hospital price setting. Another model is all-payer rate setting regulation (APRS), where a state agency sets hospital prices common to all insurers. The goal of this paper is to empirically analyze the welfare effects of replacing bilateral bargaining in the health care market with all-payer regulation.

Our paper is the first to empirically assess the effects of an all-payer system on welfare in the United States health care market. Pauly and Town (2012) summarize past arguments for and against Maryland's APRS there has been no empirical work investigating possible reactions of the market. While APRS regulations were historically used in many states, today, Maryland is the only state that implements an APRS system.[4] Maryland is also characterized by below average premiums and above average quality of care compared to the rest of the United States. The success of the Maryland system and increasing policy interest in all-payer systems by other states, such as Vermont who recently voted to implement an APRS system[5]), makes it crucial to investigate the welfare effects of adopting all-payer rate setting regulations.

In this paper, we present a framework to analyze the effects of replacing bilateral bargaining with a Maryland-style all-payer regulation. In particular, we investigate the effects of implementing a Maryland-style all-payer system in New Jersey.[6] We begin by estimating consumer demand for hospitals using detailed individual discharge data. Once we have hospital demand estimates, we calculate the expected utility from an insurer's network of hospitals. This first measure of expected utility is used to account for the fact that insurers only

[1] *Source:* Centers for Medicare and Medicaid Services (CMS), Office of the Actuary, National Health Statistics Group.

[2] https://www.cdc.gov/nchs/data/hus/hus15.pdf094

[3] For a detailed breakdown of health expenditure growth in the past half century, see Catlin and Cowan (2015).

[4] While West Virginia also imposes regulation on hospital prices, the state government does so by setting price ceilings and price floors, and allowing hospitals to negotiate prices with insurers within these limits. As we investigate the impact of removal of all bargaining, we do not use West Virginia data.

[5] Vermont obtained a Centers for Medicare and Medicaid Services' (CMS) waiver for its all-payer regulation for 2017-2022

[6] New Jersey was chosen due to data availability. We show later that both patient characteristics and hospital characteristics are not significantly different. Maryland and New Jersey are also both within the northeastern market and face similar costs of capital and wages of employees.

contract with a subset of hospitals in their market. We then estimate consumers' demand for insurance, including expected utility as an insurer characteristic. Given demand estimates and hospital price estimates from a Maryland-style pricing rule, we allow insurers to re-optimize their premiums and networks of hospital. We find that if New Jersey were to switch to Maryland style APRS, it would gain more than 2.2 billion dollars in producer surplus where producer surplus is the combined surplus of hospitals and insurers.[7] The monetary value of the loss in consumer welfare would be about 700 dollars per consumer, or a loss of 1.7 billion dollars at the state level. This constitutes a gain of over 500 million dollars in total surplus. Along with these surplus changes we see a 2.5% increase in the number of uninsured.

The main driver of changes in surplus is Blue Cross and Blue Shield,[8] with this in mind, we examine two other counterfactuals based on BCBS's pricing strategy. Our second countrefactual has BCBS optimize a weighted sum of profits and consumer surplus. BCBS is a non-profit firm and may care about consumer welfare and profits jointly.[9] Under this maximization assumption the direction of change in producer, consumer, total surplus and number of uninsured are all the same, however, the magnitude of each surplus change is smaller. It is only in our third counterfactual, which does not allow BCBS to change its premiums at all, that we see gains in producer and consumer surplus simultaneously. [10] We still find an increase in total surplus as the gain for consumers dominates the decrease in producer surplus. We also see the number of uninsured decrease by 1.46%.

Our consumer surplus results suggest that when prices are negotiated through bilateral bargaining, BCBS leverages its market power to obtain lower prices from hospitals which are then passed on to consumers in the form of lower premiums. The lower premiums of BCBS help it maintain its high market share and leverage in future price negotiations with insurers. This type of behavior by firms in the presence of bargaining reflects the idea of countervailing market power, first introduced by John K. Galbraith (1952). Countervailing market power can be summarized as the ability of large downstream buyers (insurers) to extract price concessions from upstream suppliers (hospitals) which are then passed on to consumers. Hence, APRS could have a drawback. All-payer rate setting prices might limit markups less than insurers do when firms are allowed to exercise their market power through bargaining. Surplus for consumers can be broken down

[7] We do not observe prices charged between hospital-insurer pairs in New Jersey before regulation, so we cannot decompose producer surplus further.

[8] BCBS is not only the largest private insurer in New Jersey, it is the largest private insurer in the United States with almost a 40% share of the market.

[9] Lakdawalla and Philipson (2006) have a good discussion of different pricing strategies and possible advantages of non-profit firms.

[10] This third counterfactual mimics a recent attempt in New Jersey to force BCBS to be a provider of last resort.

further into 3 consumer groups: (i) stay with BCBS (ii) leave BCBS to another insurer (iii) stay with insurer other than BCBS. Type (i) consumers lose a significant amount of surplus from the higher premiums being charged by BCBS. Type (ii) consumers also lose surplus because they face a higher premium (about $30 a month more than what consumers were previously paying to BCBS) and a more restrictive network. Type (iii) consumers see a significant gain in surplus as all of their plans lower premiums more than enough to offset the loss from changes to their hospital networks.

The literature on bilateral bargaining provides evidence of many market features which prevent firms from obtaining monopoly surplus. In particular, O'Brien and Shaffer (1992), Rey and Stiglitz (1988), and Rey and Triole (1986) have each shown, respectively, that joint profit is not maximized if any of the following apply to the market: contracts are unobserved, there exist multiple upstream firms, or there is demand and cost uncertainty.[11] As there is reason to believe that these conditions all apply to the health care market, it is impossible to predict the effect that bilateral bargaining has on the joint surplus of hospitals and insurers and thus impossible to predict the effects of replacing bargaining with APRS. We find that bargaining is detrimental to the joint surplus of hospitals and insurers compared to Maryland-style all-payer rate setting. To further analyze the changes in producer surplus we break it into two broad categories, surplus from BCBS and its network and surplus from other insurers and their networks. BCBS gains in surplus come from an increase in its premiums which dominate the loss in market share from those higher premiums. BCBS increases its premiums in order to offset the higher prices it likely now must pay to hospitals and because its market share is no longer effective in obtaining discounts from hospitals. Other insurers gains come from stealing market share from BCBS, the extra revenue generated from new consumers offsets the lower premiums charged to consumers who did not switch their insurance. The other insurers also switch to lower cost hospitals increasing total producer surplus.

There is a growing literature on the formation of insurer-provider networks. Ho (2006) investigates the welfare impacts of restricted network formation and finds that consumer welfare would increase if health plans included all the hospitals in their networks keeping prices and premiums fixed. While her conclusion is intuitive, it does not allow health plans to change premiums when they widen their networks. Ericson and Starc (2015) find that individuals' preference towards network breadth gets stronger with age. Shepard

[11]Even the simple case of a monopoly supplier with unobservable contracts can reduce total surplus below that of monopoly. Once contracts have been established, even if those contracts achieve monopoly profits or the vertically integrated profits, a hospital and insurer can increase their bilateral profits by privately negotiating a reduction in their marginal transfer price which in turn lowers the retail price and shifts customers and profits away from rivals. The welfare effects of the renegotiation depend upon competition in the insurer market. See Dobson and Waterson (1997), von Ungern-Sternberg (1997), Chen (2003).

(2016) looks at the effect adverse selection has on insurers' decisions to include a single star hospital in their network and finds adverse selection provides a strong incentive to exclude a single star hospital but does not improve welfare. To our knowledge, there is no other work in the empirical literature that allows insurers to re-optimize their networks under a different price regime and set their premiums accordingly. In this paper, we follow this methodology to obtain the impacts of a counterfactual change in the price regime to an all payer rate setting system.

Our work is also related to the strand of literature that seeks to explicitly model the price negotiations between insurers and providers, normally in a Nash Bargaining framework.[12] These studies aim to uncover how surplus in the market is split between insurers and hospitals depending on their market power or leverage in the negotiation process. They find that hospitals in systems are able to set higher prices and extract a larger share of the market's surplus. More recent papers were able to show the threat of exclusion to be important in determining price. Most papers that focus on bargaining rely upon at least one of the three following assumptions: (i) hospitals negotiate as systems and not individual entities; (ii) the hospital networks of insurers remain unchanged ; (iii) premiums are fixed. While these are necessary assumptions for computational reasons, we are not as restricted in our counterfactual analysis, because prices are the same for all insurers. This grants us greater flexibility in modeling insurer choices over individual hospitals and allowing insurer networks to change. We still must make a restriction in our equilibrium search where we fix the size of insurer networks. Thus we further the analysis of bargaining and optimal decision making beyond past papers by focusing on the total changes of surplus in a market due to the removal of bargaining.

The rest of the paper is structured as follows. Section 2 discusses related literature and a brief history of rate setting in the United States. Section 3 discusses the data. Section 4 outlines the model used in estimation. Section 5 reports the estimation results. Section 6 provides welfare analysis. Section 7 concludes.

[12]For recent papers that investigate price negotiation in the health care context, see Brooks, Dor, and Wong (1997), Gowrisankaran, Nevo, and Town (2015), Lewis and Pflum (2015), Haas-Wilson and Gamon (2011), Dafny, Ho, and Lee (2016), Ho and Lee (2017), Liebman (2016), Ghili (2016) and Prager (2016).

2 Industry Background and Literature

Our paper is rooted in the literature that investigates government regulation in the hospital industry, more specifically rate setting.[13] Previous literature on hospital rate setting analyzed its impact on growth of hospital costs, mostly in a linear regression context. Findings indicate that rate setting led to a decline in hospital cost growth in states where the regulation had been implemented for three or more years.[14] The findings of Dranove and Cone (1985) indicate that states with hospital rate setting experienced 1.32 percent smaller increases in expenses per admission. Melnick et al. (1981) conclude rate regulation lowers average and total hospital expenses. Thorpe and Phelps (1990) use data from New York State's all-payer system and find an annual growth of 1.9 percent in hospital costs when the price constraint is binding as opposed to a growth of 5.5 percent when it is not binding. Different from these previous studies, we investigate rate settings effects on consumer welfare and producer surplus which was not addressed by past authors[15].

Imposing Maryland APRS removes the price competition among hospitals, thus our work is related to the literature on hospital competition. While most theoretical results on competition and quality with variable prices are ambiguous, the theoretical literature on competition and quality when prices are regulated is clear. Gaynor (2006) finds when price is above marginal cost, competition leads to more quality and improves consumer welfare but may have any impact on social welfare. Propper et al. (2004) support this theory with empirical findings showing that when the National Health Service of the United Kingdom removed price regulation and encouraged hospital competition, hospital quality decreased. Morrisey et al. (1984) and Phelps (1997) both present a theoretical framework under which rate review can be analyzed. These models see rate setting as a ceiling on the value of the service bundle produced by the hospital. If a binding ceiling is imposed, these models predict a reduction in quality while the impact on quantity is ambiguous. We refrain from the analysis of quality of care as the rate setting agencies also regulate hospital quality. Furthermore, there is little evidence in the empirical literature that DRG-based (Diagnosis-Related Group) payment systems such as APRS and prospective payment systems (PPS) reduce the quality of care.[16] We assume that hospital quality remains unchanged among the privately insured patients and investigate the change of price and network structure alone.

[13] This literature focused on three major forms of regulation: utilization review, certificate-of-need, and rate setting. For a detailed review of empirical findings in each, see Salkever (2000).

[14] Joskow (1981), Eby and Cohodes (1985), and Salkever (2000) summarize these findings.

[15] We assume authors were unable to quantify welfare due to computational restrictions of the time.

[16] See, for example, Kahn et al. (1992), Hadley (1995), Rosko (1990).

APRS also removes price discrimination between hospitals and insurers. Therefore, we also relate to the empirical literature that investigates price discrimination and vertical relationships. While this literature is large (Brenkers and Verboven (2006), Goldberg and Verboven (2001), Hellerstein (2008), Sudhir (2001), Mortimer (2008), and Villas-Boas (2009)), our paper is most related to Grennan (2013). He investigates the effects of a shift to uniform pricing of medical devices and finds uniform prices work against hospitals and for medical device producers by softening competition. He is able to model optimal pricing of medical devices producers as he observes granular price data. We have no price data from New Jersey but do have hospital costs and thus can still comment on overall producer surplus, or the combination of hospital and insurer surplus, but are not able to make comments on individual hospital or insurer profits.

2.1 A Brief History of Regulation and Competition in Health Care Markets

Federal and state governments in the United States tried both free markets and regulation as means to contain costs in response to constantly increasing national health care expenditure. While specific programs had different impacts on health care costs, neither approach consistently led to a substantial decrease in overall expenditure.

Altman and Rodwin (1988) summarize the strategies to contain health care spending both by competition and by regulation. On the competition frontier, increasing consumer co-payments and deductibles were used to offset moral hazard, HMO competition, and prudent purchaser programs where large insurance plans received discounts from providers in return for a greater volume of patients were also used. Authors conclude that while competition may increase efficiency, it does not substantially reduce health care spending. On the regulatory frontier, federal and state governments pursued certificate-of-need programs, increase in quality and safety standards, hospital rate-setting, and prospective payment systems (PPS). Among these, hospital rate setting and PPS proved to be effective in cutting costs.[17] [18] The power of PPS to cut costs is encouraging for our analysis as PPS and Maryland APRS are similar in that price per admission to a hospital for a specific DRG is fixed.

Competition, both in the hospital market and in the health plan market, is expected to drive hospital costs

[17]PPS and state rate setting are similar in nature as they are both prospective payment systems that limit revenues and charges based on diagnosis-related groups (DRGs). Davis et al. (1990), Eby and Cohodes (1985), Friedman and Coffey (1993), Sloan (1983, 1988) all emphasize the relative success of mandatory rate setting in the context of cost containment.

[18]See Hadley (1995).

down. High concentration of hospitals in the market encourages hospitals to cut costs as they compete on a price basis to be included in health plan networks.[19] Competition among health plans is also expected to restrain hospital costs and control the quantity of the services provided.[20] Since health plans have large patient populations in geographically concentrated areas, they are expected to have leverage in negotiations and drive the hospital prices down. Their incentive to oversee the quantity and quality of services provided will prevent overuse and ensure patients get the exact care they need. However, hospital mergers, formation of hospital systems, and integration of hospital and physician groups led to an increased market power of particular provider groups that increased health care prices.[21] Our paper finds evidence that bargaining between insurers and hospitals does successfully lower costs for the consumer but at the expense of producer and total market surplus. The effects of regulation, specifically hospital rate setting are discussed next.

2.2 Hospital Rate Setting

Starting in the late 1960s and early 1970s, state governments began to implement mandatory rate setting programs where hospital rates or budgets were regulated. The purpose of hospital rate setting was to control hospital cost growth while reducing price discrimination and deterring cost shifting. More than half of the U.S. states adopted such programs on either mandatory or voluntary basis, and regulated the price paid to hospitals by insurers (payers) at the state level. The first mandatory hospital rate setting at the state level was implemented in 1971.[22] Implementation of mandatory compliance varied from state to state in terms of payers covered, frequency and nature of adjustments, the administrative bodies responsible for the regulation, unit of payment (per diem, per case etc.), and methods for establishing rates (formula, budget review etc.).[23] Yet, all the mandatory rate setting programs were similar in their fundamental elements. All statewide prospective reimbursement programs had external authorities that set or approve hospital charges. The price paid by payers to hospitals per unit of service was determined on a base year and the rates in the following years were trended forward based on the base year rate, independent of actual costs of the hospital. These restricted rates created incentives for hospitals to decrease operating costs for a given service

[19] Feldman et al. (1990) show that HMOs' price elasticity of demand for hospitals is very high.

[20] See Hadley (1995).

[21] See Ho (2009) among others.

[22] The first state to adopt a mandatory hospital rate setting was New York State. In the following years, six more states also adopted this mandatory regulatory approach and rate setting commissions were established in Massachusetts (1975), New Jersey (1974), Maryland (1974), Washington (1975), Connecticut (1976), Maine (1983), Wisconsin (1983), West Virginia (1983). For the history and evolution of hospital rate setting system in the United States and particularly in Maryland, see Murray and Berenson (2015) and Murray (2009). Sloan (1981, 1983) also present the general framework for voluntary and mandatory prospective reimbursement programs and outline the early literature.

[23] See Sloan (1981, 1983).

as this resulted in higher profits. Moreover, the pre-determined rate charged by a hospital was allowed to vary across payers and services.

A common critque of rate setting is that regulated hospitals' revenues may not meet expenses and they would be forced to use capital reserves to manage shortfalls. However, the study by Schramm et al. (1986) shows that regulated hospitals improved their operating margins by reducing expenses along with revenues. Furthermore, their financial positions were not affected by unexpected expenses such as uncompensated care as rate setting programs spread these costs equitably among all hospitals. Hospitals in these states did not need to spend from their capital reserves to cover operating expenses. Moreover, with rate setting, they managed to obtain operating surpluses that became a source of accumulated capital.

Maryland's hospital rate setting program is the only remaining APRS system today. It is considered to be the most stable and most successful mandatory hospital rate setting program in the U.S. When the program was established, the cost of admission to a hospital was about 25 percent above the U.S. average while in 1993 this cost was 11 percent below the nation average. The rates in Maryland are determined by an independent state agency, the Health Services Cost Review Commission (HSCRC), in co-operation with the hospitals. By implementing an all-payer system in Maryland, HSCRC aimed to[24] constrain hospital cost growth, increase the equity and the fairness of the payment system, ensure that hospitals have the financial ability to provide efficient and high quality care to all Maryland citizens regardless of their ability to pay, improve access to hospital care by financing uncompensated care, and to make all parties accountable to the public. HSCRC was also the first to negotiate a waiver from Medicare and to set Medicare rates for each hospital within the state.[25]

2.3 Reduced-Form Evidence on Hospital Rate Setting

Most of the work in the reduced-form literature concluded mandatory hospital rate setting programs lowered hospital expenses, both on average and at the state level.[26] These early papers that regress change in hospital expenses on a regulation dummy are usually criticized in several aspects.[27] First, the dummy coefficient

[24] The goals of HSCRC can be found on their website: http://www.hscrc.state.md.us

[25] A detailed explanation of the state legislation and its evolution throughout the years can be found in Murray and Berenson (2015).

[26] Biles et al. (1980), Melnick et al. (1981), Sloan (1983) support the on average effect while findings of Morrisey et al. (1983) show that expenses go down at the state level using several measures (expenses per patient day, per admission, per capita).

[27] See, for example, Maddala (1983).

may suffer from aggregation bias as regulation intensity varies across states. Second, these settings assume that the implementation of the regulation is exogenous and does not depend on the economic conditions in the states' health markets. The inclination of states with higher hospital costs to implement regulatory policies introduces bias in these estimates and creates a self-selection problem. Third, the effect that is attributed to rate setting might exaggerate its true impact as federal and state governments implemented other regulatory programs to reduce hospital costs during the same period. Several papers in the literature addressed these issues.

Morrisey et al. (1983) compares effectiveness of rate setting programs across states and finds New York and Massachusetts were the most successful in lowering costs. Their results were challenged by Dranove and Cone (1985). They argue that the regression to the mean approach will overstate the effectiveness if the states that implement rate setting programs are the ones with transitory higher costs to begin with. To address this issue, they directly include the omitted variable in their regressions. Their findings indicate that while MA, NY, and MD have implemented such programs in response to high costs, this is not the case with WA and NJ. Therefore, regression to the mean does not greatly bias the result on the average effectiveness of the rate setting programs, however individual state results reported by Morrisey et al. (1983) are skewed. Antel, Ohsfeldt, and Becker (1995) include state fixed effects in their regressions to control for potentially endogenous timing of the regulations. They use longitudinal data to investigate the effects of different regulatory program intensities[28] on hospital costs. Their results indicate that no regulatory program lowered hospital costs on its own, however rate setting attenuated the cost increase due to Medicare.

Schramm et al. (1986) compared six rate setting states to the rest of the nation and found that cost per admission to the hospital increased 87 percent more in unregulated states compared to regulated states. Thorpe and Phelps (1990) analyzed the effect of rate-setting program in New York on inpatient cost per admission and found that costs in hospitals which received payments below average costs grew by 1.94 percent compared to the 5.5 percent cost increase in their counterparts who retrieve the average costs. Their analysis imply that the degree of regulatory intensity, measured in terms of hospital-specific disallowances and how rarely the base year is adjusted, play an important role in cost containment. Atkinson (2009) also found that costs go up less than the national average when states regulate hospital prices. Robinson and Luft (1988) compared hospital cost growth in unregulated states, four rate setting states (MA, MD, NJ, NY), and Cal-

[28]They investigate the effects of price controls such as rate setting, ESP, and PPS as well as investment and procedure controls such as certificate-of-need programs, utilization review.

ifornia during 1982-1986. Over this period, hospital competition in California was triggered by the changes of a state law.[29] Their results show that the hospital cost growth in MA, MD, and NY was significantly lower than the unregulated states while the results for NJ were insignificant. They further find that for highly competitive markets, rate setting succeeds just as much as competition does in cutting costs; while rate setting proves to be more effective in slowing down cost growth in markets with less hospital competition.

Several papers investigate the non-cost impacts of rate setting find mixed evidence. Sloan (1981) finds increase in revenue to expense ratio for mature programs while Sloan (1983) finds no impact on hospital profits. Morrisey et al. (1983) find the negative impact on revenues is smaller than negative impact on expenses, therefore hospitals' profit margins were slightly improved by rate setting. Decline in prices with rate setting and the spread of health insurance was expected to increase utilization of hospital services. Joskow (1980) and Worthington and Piro (1982) find increase in occupancy rates and length of stay for some rate setting states but negligible influence on admission per capita population overall. Melnick et al. (1981) find decrease in the rate of decrease in the average length of stay with the implementation of rate setting programs, while number of admissions do not change. Findings of Sloan (1981, 1983) indicate that rate setting did not change the growth rate of admissions, patient days, outpatient visits or average length of stay. Schramm et al. (1986) also find admissions and length of stay did not change in rate setting states as rate setting agencies and PSROs controlled hospital utilization. Lastly, a few papers investigated the impact of rate setting on the services offered. Joskow (1981) finds no change in the number of CT scanners in the state. Cromwell and Kanak (1982) find mostly no change in the services and facilities offered by hospitals, while the impact on different services varied across rate setting programs.

There are two major conclusions of this literature. First, mature mandatory rate-setting programs led to a reduction in hospital cost growth.[30] Second, state level mandatory rate setting have been more effective than other regulatory programs both in cost and non-cost aspects.[31] Morrisey et al. (1983) make the "educated guess" that rate setting programs will succeed in achieving its goals in states with similar political and regulatory environments.

[29] The changes made in 1982 increased growth of PPOs and granted permission to selective contract negotiations between third-parties, Medicaid and PPOs, and hospitals. See Hadley (1995).

[30] These programs are observed to be ineffective for three years following their implementation, although this threshold is not methodologically explained in the literature. The most common explanations are learning by doing and confounding influences of ESP. See, for example, Eby and Cohodes (1985), Morrisey et al. (1984), Sloan (1983).

[31] See Morrisey et al. (1983) and Morrisey et al. (1984) for a list of the papers that reach this conclusion.

3 Data

This paper utilizes data from various sources. Hospital characteristics come from the American Hospital Association (AHA) Annual Survey of Hospitals 2011. Consumer characteristics and discharge reports come from State Inpatient Databases (SID) 2010 provided through the Health Care Utilization Project (HCUP). Insurer characteristics come from Atlantic Information Services (AIS) with premium and enrollment data being supplemented by the WEISS Ratings Guide. Insurer characteristics from AIS include enrollment and number of enrolled by sector (commercial risk, public risk etc.). WEISS provides investment ratings of insurers, enrollment and premiums. Additional plan characteristics are taken from National Committee for Quality Assurance (NCQA) Report on Health Plan Rankings. These characteristics include the type of the insurance plan (HMO, PPO etc.), states served, an overall quality score as well as measures of consumer satisfaction, prevention, and treatment. We also use 2010 U.S. Census data on population (by age and sex) and number of uninsured by state to supplement our dataset.

We use SID data from New Jersey it covers 73 hospitals and 230,268 discharges in total. The patient zip code, diagnosis, treatment, insurance, age, sex, and charges are provided. We aggregate diagnosis to the 25 Major Diagnostic Categories (MDCs) as defined by the Centers for Medicare Services. All emergency room admissions are dropped as it is not likely these patients have any choice over the hospital to which they are admitted. This data is summarized in Table 1. We observe patients' zip codes and the hospitals they visited, therefore we are able to calculate the distance between a patient's residence location and hospital location. Average patient in our data travels 10 miles to get care at a hospital. Females constitute 66.4% of all discharges due to the large number of pregnancies and childbirths. This paper focuses only on the non-elderly population (ages between 0 and 64) as people above 65 are likely to be enrolled in Medicare plans and we are concerned with private health plans only. Since all new-borns are considered as new patients in this dataset, the average patient is younger than expected.

Table 1: Patient Characteristics

	Mean	**SD**	**Min**	**Max**
Distance (miles)	10.017	6.909	0.165	198.972
Female	0.664	0.472	0	1
Age	26.166	21.535	0	64

Notes: N = 230,268 discharges.

Table 2 provides a summary of select variables from the hospital dataset.[32] We report information on 131 hospitals that operate Maryland and New Jersey. We observe ownership type (profit, non-profit), teaching status, system membership, total inpatient days, total number of admissions and services offered by each hospital among other variables.

The health plan dataset is at the national level and is constructed using various sources. The first four variables summarized in Table 3 come from AIS and Weiss Ratings Guide. To calculate premiums, we divided total premium revenue reported by each plan by the number of enrollees. Average premium per patient per month ranges from $66.7 to $1075.6 with an average of $384.6. The range is large since all types of plans (low-premium HMOs, high-premium indemnity plans etc.) are present in the dataset. In addition to premiums, we observe the age of the plan, the number of physicians who participated in the insurer's network of providers, and the total number of enrollees. The rest of the variables are created using NCQA reports on plan performance. This source reports type of each plan, which we aggregate to two categories: HMO/POS and PPO/Indemnity. In our data, 43.4% of the plans are PPO/Indemnity. NCQA also reports a score that takes into account NCQA Accreditation standards, member satisfaction and clinical measures. While the maximum score possible is 100, the highest score we observe for a health plan is 90.5. Lastly, we use three measures of plan performance: consumer satisfaction, treatment, and prevention that range between 1 (lowest performance level) and 5 (highest performance level). For a detailed explanation of construction of these measures, see the data appendix.

4 Model and Methodology

The methodology will consist of two main stages: First, we estimate the consumers' demand for hospitals which is used to calculate the value of an insurer's network of hospitals which in turn is used as an insurer characteristic in estimation of insurer demand. Expected hospital demand is also used in tandem with predicted prices hospitals in New Jersey would charge under APRS to calculate costs associated with an insurer's hospital network. With estimates of consumer demand for health plans and insurer's expected costs we than allow insurers to optimize over premiums and hospital networks and calculate the producer surplus (for hospitals and insurers) and consumer surplus in New Jersey under the new price regime.

[32]Full list of hospital characteristics used in the analysis can be found in Table A1.

Table 2: Hospital Characteristics

	MD		NJ	
	Mean	**SD**	**Mean**	**SD**
Patient Days	67400.776	51340.834	82038.411	54282.317
Admissions	12417.672	10243.425	13605.137	11459.288
Beds	247.414	178.628	303.425	172.988
Teaching	0.138	0.348	0.151	0.360
Full Time Physicians	42.810	107.461	28.370	56.432
Full Time Nurses	325.776	366.470	347.000	307.057
Colonoscopy	0.621	0.489	0.603	0.493
Endoscopic Ultrasound	0.466	0.503	0.507	0.503
Ablation of Esophagus	0.276	0.451	0.411	0.495
Fertility Clinic	0.103	0.307	0.096	0.296
Hemodialysis	0.569	0.500	0.616	0.490
General	0.793	0.409	0.795	0.407
Obstetrics	0.603	0.493	0.616	0.490
Cardiac Intensive Care	0.379	0.489	0.493	0.503
Neonatal Intensive Care	0.293	0.459	0.315	0.468
Burn Care	0.034	0.184	0.055	0.229
Birthing Room	0.569	0.500	0.630	0.486
Blood Donor	0.207	0.409	0.137	0.346
Mammogram	0.707	0.459	0.712	0.456
Cardiac Cathederization	0.483	0.504	0.521	0.503
Cardiac Surgery	0.172	0.381	0.233	0.426
Chemotherapy	0.741	0.442	0.740	0.442
AIDS	0.431	0.500	0.507	0.503
Neurology	0.759	0.432	0.781	0.417
Oncology	0.724	0.451	0.740	0.442
Orthopedic	0.810	0.395	0.753	0.434
Diagnostic Radioisotope	0.707	0.459	0.726	0.449
Full Field Digital Mammography	0.362	0.485	0.562	0.500
Magnetic Resonance Imaging	0.655	0.479	0.726	0.449
Multislice Spiral Computed Tomography	0.707	0.459	0.699	0.462
Positron Emission Tomography	0.190	0.395	0.384	0.490
Ultrasound	0.810	0.395	0.795	0.407
Heart Transplant	0.034	0.184	0.027	0.164
Kidney Transplant	0.034	0.184	0.068	0.254
Tissue Transplant	0.086	0.283	0.055	0.229
Virtual Colonoscopy	0.241	0.432	0.151	0.360
Woman's Health Center	0.603	0.493	0.685	0.468
Number Hospitals	58		73	

Table 3: Health Plan Characteristics

	Mean	**SD**	**Min**	**Max**
Premiums	384.61	146.36	66.67	1,075.64
Age	29.896	15.821	1	78
Physicians	23,851.9	19,368.7	281	140,997
Total Enrollment	255,367.4	427,369.3	1,000	3,942,500
PPO/Indemnity	0.433	0.50	0	1
Consumer Satisfaction	2.9	1.02	1	5
Treatment	3	1.08	1	5
Prevention	2.9	1.08	1	5
Score	79.57	6.41	58.4	90.5

Notes: N = 473 health plans.

4.1 Estimation of the Demand Side

The estimation of the demand side is done in three steps following Capps et al. (2003) and Ho (2006). First, we estimate the demand of consumers for hospitals using a conditional logit model.[33] Next, we use the estimated parameters from this first step to calculate the expected utilities from a network of hospitals for consumers. Finally, we use these expected utility measures as an input while estimating the demand for health plans using the Berry, Levinsohn, and Pakes (1995, henceforth BLP) approach.

Hospital Demand:

Let the utility of patient i from visiting hospital h given diagnosis l in market m be:

$$u_{ihlm} = u(x_{hm}, v_{ilm} | \lambda, \theta) \tag{1}$$

where x_h is a vector of observed hospital characteristics, v_{il} is a vector of observed consumer characteristics such as location, age and diagnosis and (λ, θ) are parameters to be estimated. Patients choose hospitals to maximize utility, so if patient i with diagnosis l chooses hospital h, then the following inequality must hold for all other hospitals h' in the market, where the market subscript m will be suppressed for notational ease:

$$u_{ihl} = u(x_h, v_{il} | \lambda, \theta) \geq u_{ih'l} = u(x_{h'}, v_{il} | \lambda, \theta) \tag{2}$$

In particular, let the specification for the utility be:

$$u_{ihl} = \theta x_h + \lambda x_h v_{il} + \epsilon_{ihl} \tag{3}$$

[33] We use the standard conditional logit model proposed in McFadden (1974).

where the independently and identically distributed error term ϵ_{ihl} captures idiosyncratic tastes and is assumed to have a Type 1 Extreme Value distribution. Then, the hospital share equation can be written as:

$$s_h = \frac{exp(\theta x_h + \lambda x_h v_{il})}{\sum_{k \in H_j} exp(\theta x_k + \lambda x_k v_{il})} \tag{4}$$

where H_j is the set of hospitals in insurer $j's$ hospital network.

Since we observe the actual shares, we use maximum likelihood to obtain the parameter estimates $\hat{\lambda}$ and $\hat{\theta}$. Unlike our health plan demand model, this model does not account for unobserved characteristics or unobserved quality of hospitals.[34] We have very rich hospital characteristics data, therefore we assume that the 83 characteristics we use in estimation capture the quality of hospitals. Identification in this model comes from the variation in patients' hospital choice sets across insurers. In our model, patients' choice sets are defined by the set of hospitals in an insurer's hospital network. Results of this estimation are presented in Table 4.

Expected Utility:

Given the parameter estimates from the above estimation we can calculate the predicted utility of each individual of type i where types are defined by age-sex-zip code cells:[35]

$$\hat{u_{ihl}} = \hat{\theta} x_h + \hat{\lambda} x_h v_{il} + \epsilon_{ihl} \tag{5}$$

Then, we calculate expected utility for patient type i from each plan j's hospital networks. Ben-Akiva (1973) shows that, under the assumptions of Type 1 extreme value errors, expected utility reduces to:

$$EU_{ij}(H_j) = \sum_l p_{il} log\left(\sum_{h \in H_j} exp(\hat{\theta} x_h + \hat{\lambda} x_h v_{il}) \right) \tag{6}$$

where p_{il} is the probability that patient type i is hospitalized with diagnosis l and H_j is the set of hospitals in insurer plan j.

We only observe insurer networks in New Jersey and Maryland and thus must compute networks for insurers

[34] An ideal way to account for unobserved hospital characteristics would be to do the logit estimation using hospital fixed effects in the first stage and regress the estimates of the hospital-specific term on observed hospital characteristics in the second stage, as in Ho (2006). However, we are limited by a single years worth of data. Therefore, we collapsed the two-stage process into one estimating equation.

[35] Age groups are defined as 0-17,18-34,35-44,45-54,55-64

of other states. We collected hospital networks of insurers from their websites in 2017 for 16 states[36] and use those networks to calculate expected utility for insurers other than Maryland and New Jersey. For the states where we don't observe exact insurer networks, we use the number of hospitals insurers contract with and calculate the average expected utility from a hospital network of that size taking into account the number of reported insurer contracts hospitals report. The average is calculated at the level of the individual of type i.

Health Plan Demand:

As expected utility is not perfectly observed, for robustness we begin with a conditional logit model that accounts for unobserved characteristics of a plan without expected utility and then also run the same conditional logit model for Maryland and New Jersey, as these are the two states we observe hospital networks. Our third specification, uses the imputed expected utility for the single most populated zip code in combination with random coefficients to estimate a BLP style model. Finally our preferred demand specification uses expected utility at at the age-sex-zip code level as well as median income at the zip code level. We have 50 markets in total and observe 473 commercial health plans that operate in these markets. Results from the health plan demand estimation are presented in Table 5.

Conditional Logit:

The logit framework used to estimate health plan demand closely follows the specification in Berry (1994). Let utility individual i gets from plan j in market r be:

$$u_{ijr} = \sum_k x_{jkr}\beta_k + \xi_{jr} + \epsilon_{ijr} \tag{7}$$

where x_{jkr} is the k^{th} observed plan characteristic of plan j and ξ_j represents the unobserved plan characteristic (such as patients' perception about quality, status, service, reputation, past experience etc.). For simplicity, we drop the market subscripts in the rest of the analysis. Therefore, the utility function can be written as:

$$u_{ij} = \sum_k x_{jk}\beta_k + \xi_j + \epsilon_{ij} = \delta_j(x_j, \xi_j, \beta) + \epsilon_{ij} \tag{8}$$

where δ_j represents the mean utility level from plan j. The unobserved characteristics are assumed to be mean independent of x_j's and also independent across markets. The error term ϵ_{ij} is independently and identically distributed across consumers and plans and has a Type 1 Extreme Value distribution. Normalizing

[36] The states for which he have network data are Arizona, Alaska, Arkansas, Connecticut, Delaware, Rhode Island, New York, Florida, Washington, Kentucky, Colorado, Maryland, New Jersey, Oregon, Maine, Massachusetts

the mean utility from the outside good to be zero (i.e. $\delta_o = 0$), the closed-form solution for the market share equation for product j can be written as:

$$s_j = \frac{e^{\delta_j}}{1 + \sum_{g=1}^{G} e^{\delta_g}} \tag{9}$$

where G is the number of plans in the market. The share of the outside good is given by:

$$s_o = \frac{1}{1 + \sum_{g=1}^{G} e^{\delta_g}} \tag{10}$$

Dividing equation (7) by equation (8) gives:

$$\frac{s_j}{s_o} = e^{\delta_j} \Longrightarrow ln(s_j) - ln(s_o) = \delta_j \tag{11}$$

Hence, we generate δ's using the market share data. Having obtained the dependent variable, we estimate the following equation to obtain the parameter estimates:

$$\delta_j = \sum_k x_{jk}\beta_k + \xi_j \tag{12}$$

Before moving on with the estimation, the endogeneity problem caused by the premiums needs to be addressed. The unobserved plan characteristic ξ_j (the error term in equation (10)) is likely to be correlated with the plan's premium which is one of the observable plan characteristics. One would expect a high-quality, better-service plan to charge a higher premium. For this reason, we instrument for the premium variable. Traditional instruments used in the literature for price are cost shifters (these are difficult to find as they are usually correlated with ξ's), characteristics of competing products in the same market, and prices of the same product in other markets (because a shock to marginal cost will be carried to prices in other markets). We use the characteristics of other plans within the same market as instruments. These instruments and the relevant validity tests are further discussed in section 5. Given these instruments Z, we form the moment conditions as follows. First, we calculate the unobserved quality term ξ_j as a function of model parameters:

$$\xi_j = \delta_j - \sum_k x_{jk}\beta_k = ln(s_j) - ln(s_o) - \sum_k x_{jk}\beta_k \tag{13}$$

The instruments should be orthogonal to this unobserved quality term, so we form the moment conditions as

$E[\xi(\beta)'Z] = 0$. In applying iterative GMM, we use the "optimal" weighting matrix W which is the inverse of the variance of moment conditions. Therefore, the problem reduces to:

$$\min_{\beta} \xi(\beta)'ZWZ'\xi(\beta) \quad where \quad W = (E[Z'\xi\xi'Z])^{-1} \tag{14}$$

The analytical solution to this problem is:

$$\beta = (X'ZWZ'X)^{-1}(X'ZWZ'\delta) \tag{15}$$

The iterative estimation algorithm starts with $W = (Z'Z)^{-1}$ to get an initial estimate $\hat{\beta}$, and then we re-compute $W = (E[Z'\xi(\hat{\beta})\xi(\hat{\beta})'Z])^{-1}$ to get a new estimate of β. Identification in this model comes from the variation in consumers' choice sets across markets as well as the variation of health plan characteristics within a market.

BLP (1995) and Ho (2006):

The major drawback of the previous model is that it does not generate realistic substitution patterns. In this setting, cross-price elasticities between any two plans depends only on their market shares. Consider two health plans A and B whose market shares are the same. Let A be an HMO plan with low premiums, narrow hospital and physician network and low rating and B be a PPO plan with high premium, large provider network and top rating. Assume there is another PPO plan C in the market with high premiums, large provider network and high quality rating. The cross-price elasticity of the previous model implies that if plan C increases its premiums, the demand for plan A and plan B will increase equally. This is unintuitive as we expect the cross-price effect to be larger for health plans that are similar in characteristics. The model presented by BLP (1995) solves this problem and generates realistic substitution patterns. With the BLP estimation outline below, cross-price elasticities are larger for products that are closer together in terms of their characteristics.

Let the utility of patient i from plan j be:

$$w_{ijm} = \xi_{jm} + z_{jm}\lambda + \beta_2 prem_{jm} + \gamma_1 EU_{ijm}(H_{jm}) + \gamma_2 \frac{prem_{jm}}{y_i} + \eta_{ijm} \tag{16}$$

where ξ_{jm} are unobserved plan characteristics, z_{jm} are the observed plan characteristics, and $prem_{jm}$ is plan jm's premium, y_i is the median income by zipcode, EU_{ijm} is the expected utility per age-sex-zipcode cell and η_{ij} are idiosyncratic shocks to consumer tastes that are assumed to be i.i.d. Type 1 Extreme Value. It is the presence of the y_i and EU_{ijm} that allows us to capture the heterogeneity of preferences in a more flexible way. In this setting, consumers with similar characteristics prefer similar products. Therefore, if a plan is removed from the choice set, consumers will substitute to other plans that are similar in terms of characteristics and this generates more realistic substitution patterns.

Identification in this model comes from the variation in patients' plan choice sets across markets. To address the endogeneity issue, we again instrument for premiums using the BLP-type instruments mentioned above. The outside good is defined as having no insurance and its share is calculated using the Census data. In this setting, share of plan j cannot be solved analytically. While BLP (1995) uses simulation, we instead know the distribution of expected utility and thus take the weighted sum across markets.

$$s_{jm} = \sum_i \frac{n_i}{n_m} s_{ijm}(\beta, \lambda, \gamma) \tag{17}$$

Where n_i is the number of individuals in consumer type i, n_m is the number in the market, and s_{ijm} the share of type i individuals choosing plan j in market m, is defined by

$$s_{i\hat{j}m}(\lambda, \gamma, \beta) = \frac{exp\left(\xi_{jm} + \beta_1 prem_{jm} + z_{jm}\beta + \gamma_1 EU_{ijm}(H_{jm}) + \gamma_2 \frac{prem_{jm}}{y_i}\right)}{1 + \sum_{k \in P_m} exp\left(\xi_{km} + \beta_1 prem_{km} + z_{km}\beta + \gamma_1 EU_{ikm}(H_{km}) + \gamma_2 \frac{prem_{km}}{y_i}\right)} \tag{18}$$

Given the equation for predicted shares, we use the contraction mapping algorithm suggested by BLP (1995) to obtain δ, the mean utility level vector. This algorithm aims to match the predicted shares $\hat{s}$ to the observed true shares s using the following equation:

$$\delta^h = \delta^{h-1} + ln(s) - ln(\hat{s}) \tag{19}$$

We begin by evaluating the right-hand side at an initial guess of parameters and δ, obtain a new δ, put it back into the right-hand side and repeat this until convergence is reached. Once we obtain δ, we write the unobserved plan characteristics as $\xi_j = \delta_j - z_j\beta$. Therefore, we form our moment conditions as $E[\xi' Z] = 0$ and estimate via GMM.

5 Estimation Details and Results

5.1 Hospital Demand Results

Hospital choice model uses two data sources: patient characteristics come from SID New Jersey and hospital characteristics come from AHA. We estimate a conditional logit model where the utility specification is given by:

$$u_{ihl} = \theta x_h + \lambda x_h \nu_{il} + \epsilon_{ihl} \tag{20}$$

Therefore, utility of patient i who goes to hospital h with diagnosis l depends on the hospital characteristics x_h and interaction of these characteristics with patient characteristics. Table 4 presents a subset[37] of the results from the hospital demand model. Most hospital characteristics have positive coefficients that are highly significant. Same is true for the interaction terms. One of the interaction terms is distance between the patient's zip code and the zip code of the hospital he/she visited. Consistent with the previous findings in the literature, we find that having to travel an extra mile to get treated at a hospital decreases the probability that the patient will choose that hospital by about 15.8%. Remaining co-variates are interactions of services offered by the hospital with the relevant MDCs. The results are intuitive. A patient diagnosed with a circulatory system disease has a strong preference for a hospital that offers cardiac surgery, while a patient with severe burns is more likely to go to a hospital that has a burn care unit.

5.2 Health Plan Demand Results

Health plan demand model uses data at the national level. A market is defined as a state since health plans are observed to serve residents of specific states. An insurance plan is assumed to be a competitor in a market if it serves the residents of that state.

The logit framework we use takes into account unobservable plan characteristics and is estimated via GMM. The utility function is of the form:

$$u_{ij} = \sum_k x_{jk}\beta_k + \xi_j + \epsilon_{ij} = \delta_j(x_j, \xi_j, \beta) + \epsilon_{ij} \tag{21}$$

where the observable plan characteristics x_j are plan premium per person per month, age of the plan, physicians per 1000 population, Weiss rating of the plan, three measures used by NCQA to obtain the

[37]For the full set of coefficient estimates (not marginal effects) from the conditional logit model, see Table A1.

Table 4: Partial Hospital Demand Results

Variable	Coefficient	Standard Errors
Distance	-0.172***	(0.0131)
Distance^2	0.000447***	(0.00000314)
Dist*Female	0.000790*	(0.000389)
Teaching	-0.710***	(0.0241)
Beds Per Nurse	-0.676***	(0.0174)
General Med/Surgical	0.821***	(0.224)
Cardiac IC	-0.111***	(0.0254)
Neonatal IC	-0.307***	(0.0227)
Burn Care	0.0337	(0.0379)
Birth Room	2.584***	(0.0483)
Mammogram	-2.394***	(0.0359)
Adult Cardiology	-1.740***	(0.0533)
Chemotherapy	0.944***	(0.0650)
Endoscopic Ultrasound	-0.235***	(0.0269)
Fertility Clinic	-0.594***	(0.0310)
Neurological Services	-0.329***	(0.0576)
Oncology	0.894***	(0.0714)
Orthopedic	0.130***	(0.0390)
Magnetic Resonance Imaging	-1.268***	(0.0383)
Ultrasound	0.00672	(0.0533)
Kidney Transplant	-0.675***	(0.0268)
Women's Health Center	1.356***	(0.0329)
Obstetrics*Female Reproductive	0.850***	(0.0382)
Obstetrics*Childbirth	0.348***	(0.0293)
Neonatal IC*Newborn	-0.0290	(0.0161)
Burn Care * Burn	4.223***	(0.417)
Birth Room*Childbirth	1.072***	(0.0424)
Fertility Clinic*Female Reproductive	-0.0904**	(0.0294)
Hemodialysis*Kidney	0.377***	(0.0591)
Ultrasound*Birth	-0.115*	(0.0514)
Heart Transplanst*Circulatory	0.734***	(0.0358)
Kidney Transplanst*Kidney	0.968***	(0.0470)
N	230268	

Notes: $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

plan performance (consumer satisfaction, treatment, and prevention), and dummy variables for large plans, PPOs, and NCQA accreditation. We define a plan as large if it offers multiple plans in several states. According to this definition, we mark Blue Cross Blue Shield, Aetna, United Healthcare, CIGNA HealthCare, Humana Inc., and Kaiser Foundation Health Plans as large plans. Consumers' perceptions about these plans are likely to be reflected in their preferences.

Since the premiums are endogenous, we instrument for them using the average characteristics of other plans $(x_n, n \neq j)$ in the same market commonly referred to as BLP style instruments. These characteristics are age, Weiss rating, number of physicians, and the NCQA score. These instruments satisfy the three traditional conditions of instrumental variables. They are relevant as they are correlated with premiums via competition and markups[38], they are uncorrelated with the error term, and they affect utility only through their impact on premiums. To further support the choice of the instruments, we analyze two statistics. In the regression that includes both fixed effects, the first stage results report a partial R-squared of 0.77 and an F-statistic of 36.16. These statistics suggest a large portion of the unexplained variation in premiums come from the excluded instruments and the instruments are not weak since the F-statistic is greater than 10.[39]

To complete the estimation, we need to calculate the share of the outside good. Since we observe HMO/POS and PPO/indemnity plans in our data, we define the outside good as being uninsured. Census data reports number of uninsured and state population by age group. Therefore, we calculate the share of the outside good, s_0, by dividing the number of non-elderly uninsured by the non-elderly population of that state.

The parameter estimates are reported in Table 5. The first and second column implement Berry (1994) with the difference coming from sample selection based on the expected utility. As previously mentioned we only observe insurer networks in New Jersey and Maryland in 2010 and thus restrict our sample in column 2 to only those states and add expected utility as an insurer characteristic. In column 3 we instead use the full sample with a single imputed average expected utility interacted with random coefficients. The fourth column is our final and preferred specification where expected utility is calculated by age-sex-zipcode groups and premium over income by zipcode is added to the specification. All specifications with expected utility report a positive coefficients showing that individuals value hospital networks offered by insurers. The price

[38]as implied by the first order conditions in the supply side and the pricing equation

[39]See Bound et al. (1995).

Table 5: Health Plan Demand Results

	(1)	(2)	(3)	(4)
Premium ($00)	-0.209***	-0.002	-0.408**	-0.370**
	(0.042)	(-0.067)	(0.197)	(0.183)
Prem/Income ($00)	-	-	-	-0.150*
				(0.082)
Age	0.033***	0.006	0.029***	0.010**
	(0.006)	(0.006)	(0.005)	(0.004)
Number of Physicians	-0.0001***	-0.0008***	-0.013***	-0.021***
	(0.00004)	(0.0001)	(0.001)	(0.002)
PPO/Indemnity	0.339**	0.251	0.178	0.163
	(0.165)	(0.222)	(0.184)	(0.195)
Weiss Rating	0.137***	0.322***	0.111***	0.109***
	(0.039)	(0.057)	(0.038)	(0.042)
Expected Utility	-	0.261**	0.106*	-
		(0.118)	(0.062)	
Expected Utility Zip	-	-	-	0.138*
				(0.078)
Constant	-12.807**	-0.776	-12.18	-3.727**
	(5.165)	(5.248)	(7.481)	(1.449)
Large Plan FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
BCBS FE	Yes	Yes	Yes	Yes
N	447	35	447	447
R^2	0.517	0.941		

Notes: Results from GMM estimation. Clustered standard errors (at the state level) in parentheses. First two columns follow Berry (1994), last two columns follow BLP (1995). *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

elasticities of insurers range from 3 to 0.6 with the average elasticity being 1.76 implying that $100 a month increase in premiums would decrease the probability a plan is chosen by 33%.

5.3 Maryland's Pricing Rule

For our counterfactuals, we need to know what prices New Jersey hospitals would charge under a Maryland-style pricing rule. To serve this purpose, we use Generalized Linear Model (GLM) framework (McCullagh and Nelder (1989)) with log link from the Gamma family to estimate Maryland's pricing rule, and use the parameter estimates to predict what New Jersey hospitals would charge under rate setting.[40]

Maryland hospitals set their prices for 65 service categories of varying units (such as renal dialysis per treatment, burn care per patient day, anesthesiology per minute, observation per hour etc.). We use two

[40]Similar methods have been used by both Gowrisankaran, Nevo, and Town (2015) and Sheppard (2016).

Table 6: Maryland Pricing Rule

	(1) **Preset Rate**	**(2)** **Preset Rate**	**(3)** **Total Charges**	**(4)** **Total Charges**
Case-mix index (CMI)	0.078 (0.073)	0.109 (0.076)	0.280*** (0.071)	0.437*** (0.064)
Severity (Elixhauser)	0.115*** (0.029)	0.086*** (0.033)	0.076*** (0.002)	0.074*** (0.002)
Teaching Intensity	-0.120 (0.090)	0.120 (0.180)	0.442*** (0.102)	0.227*** (0.079)
Primary Care Employees	-	-0.0003 (0.001)	-	0.002** (0.0006)
Physicians	0.0004* (0.0002)	-	0.0006*** (0.0001)	-
Hospital Beds	-0.0001 (0.0002)	-0.0001 (0.0002)	0.0003** (0.0001)	0.0006*** (0.0001)
Depreciation	-0.0005** (0.0003)	-0.0004* (0.0003)	-0.0006*** (0.0002)	-0.00008 (0.0001)
For-profit	0.061 (0.057)	0.064 (0.063)	0.029 (0.047)	0.154*** (0.042)
Women's Health Center	0.002 (0.067)	0.041 (0.060)	0.032 (0.022)	0.019 (0.025)
Medical/Surgical Intensive Care	0.217*** (0.065)	0.212*** (0.063)	-1.056*** (0.082)	0.070** (0.030)
Cardiac Intensive Care	-0.003 (0.035)	-0.004 (0.036)	-0.073*** (0.027)	-0.088*** (0.026)
Birthing Room	-0.035 (0.061)	-0.014 (0.057)	-0.027 (0.020)	0.009 (0.021)
Cardiology Services (adult)	-0.078 (0.063)	-0.121 (0.076)	0.063*** (0.023)	-0.312*** (0.050)
Oncology Services	-0.036 (0.073)	-0.034 (0.070)	-0.085*** (0.038)	-0.225*** (0.046)
MRI	0.002 (0.033)	0.006 (0.043)	-0.053** (0.026)	0.011 (0.022)
Constant	4.623*** (0.185)	4.644*** (0.192)	12.245*** (0.130)	11.759*** (0.104)
Observations	1,406	1,140	113,480	194,276

Notes: Results from GLM estimation. Robust clustered standard errors in parentheses (procedure-hospital clusters used in the first two columns, DRG-hospital clusters used in the last two columns). Teaching intensity is measured by resident-to-bed ratio. Elixhauser comordibity measure is the average at the hospital level for the rate regressions, while it represents number of comordibities at the patient level for the last two columns. Omitted service category is admission services in the first two columns, omitted DRG category is DRG=3 (extracorporeal membrane oxygenation (ECMO) or tracheostomy with major operating room procedure) in column (3), and DRG=1 (heart transplant or implant of heart assist system) in column (4). Rate regressions include service/procedure fixed effects while regressions on total charges include DRG fixed effects. *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

measures of price (rates and charges), and hence run two main regressions. The first one regresses the preset hospital rates on hospital characteristics and service fixed effects. The second one regresses total charges per patient on patient severity, case-mix of the hospital, hospital beds, number of physicians, service mix, payroll expenses, teaching intensity[41], depreciation, ownership status, and DRG fixed effects.[42] Results are reported in Table 6.[43] We use the results from column (4) while predicting prices for New Jersey. While the service rates (not the total charges) are set in Maryland, all service rates are given in units of time, as we are unable to capture these specifics in our data, we use the more accurate predictions we are able to obtain through the total charges regressions.

6 Analysis of the Welfare Impact of Price Regulation

This section uses the demand and price estimates obtained in the previous section to make welfare comparisons between the counterfactual world of a single price per hospital and allowing hospitals and insurers to set prices individually.

6.1 Allowing for Re-optimization by Insurers

The first step is to take the predicted prices for New Jersey and allow insurers to re-optimize their premiums and networks offered. It is important to note that insurers only choose a single premium in this model and have no tools to individually price hospitals. This means we can make no comment about co-insurance rates and how they may affect hospital choice by consumers and insurers. Another important distinction is that insurers only account for consumer heterogeneity at the level of the premiums over median income and expected utility as these provide all the consumer heterogeneity in our market. This means we are assuming away the ability of insurers to price to the effects of moral hazard or adverse selection present among consumers choices over hospitals and we define sj, h as:

[41] We use resident-to-bed ratio as a measure of teaching intensity. Thorpe (1988) compares different teaching intensity measures used in the literature and concludes all measures perform similarly in terms of goodness-of-fit and significance.

[42] Ideally, we would use All Patient Refined Diagnosis Related Group (APR-DRG) fixed effects that are adjusted for case-mix and severity instead to capture the use of per case revenue constraints, however the 2010 SID does not report this variable for Maryland or New Jersey.

[43] The number of physicians in a hospital is a traditional explanatory variable included in price regressions in the literature. However, not all hospitals report the number of physicians to the AHA Survey. For this reason, we use an alternative/less noisy measure (the number of primary care employees) in our regressions to improve the fit of the model.

$$s_{j,h} = \sum_i \frac{n_i}{n_m} \frac{s_i h}{\sum_{k \in H} s_{ik}} \tag{22}$$

By forming the share of patients from insurer j who use hospital h in this way we are also implicitly assuming that insurers do not take the capacity constraints of hospitals into consideration when calculating expected costs of a hospital network. Furthermore we define the price of each hospital $price_h$ as:

$$price_h = \sum_l p_{il} E(Price_i l) = \sum_l p_i l s_{ihl} \hat{Price}_{ihl}^{NJ} \tag{23}$$

where p_{il} is the probability that an individual of type i is diagnosed with disease l and s_{ihl} is the share of type i individuals who visit hospital h. Now with defined costs for insurers (hospital prices) and insurer expectations of how individuals who choose their plans will utilize hospitals in their networks insurers maximize a standard profit function by choosing networks and premiums:

$$\pi_j = prem_j s_j(H_j, H_{-j}) - \sum_{h \in H_j} (s_{j,h}(H_j, H_{-j}) price_h) \tag{24}$$

Which gives us the standard first order condition as:

$$s_j(H_j, H_{-j}) + \sum_{h \in H_j} (prem_j - price_h) \frac{\delta s_{j,h}(H_j, H_{-j})}{\delta prem_j} = 0 \tag{25}$$

where H_j is insurer j's hospital network, H_{-j} are all other insurers networks.

6.2 Equilibrium

As insurers' market shares depend not only on their own premiums and hospital networks but on other insurer networks and premiums, calculation of equilibrium is computationally infeasible as we would have to check every possible hospital combination of insurer hospital networks. Not only is it infeasible but there is a possibility of equilibrium not exisiting. Instead we approach our analysis in the following way:

1. Assign a number k_j to each insurer based on the number of hospitals an insurer includes of the two largest hospital systems.
2. Define N_j to be the set of hospitals an insurer does not include in his network plus k hospitals.
3. Calculate premiums for all $\binom{N_j}{k_j}$ combinations for a single insurer leaving other hospital networks fixed
4. Assign insurer j the hospital network with highest profits

5. Iterate (3) and (4) until no change in hospital networks for any insurer

Our equilibrium search is simplified by and relies upon the following assumptions. First, this is a game with full information where every insurer observes every other insurers networks and premiums. We also observe that BCBS covers all hospitals and so will not change its hospital network as insurer hospital network sizes are fixed. As network sizes are fixed there may exist possible profitable deviations, we account for these by checking all possible single deviations in insurer networks, either the addition or subtraction of a hospital, and find that profitable deviations do exist and range from \$52,000 to \$1,700. In order to eliminate these profitable deviations we assume a yearly fixed fee of contracting to enforce our equilibrium.

6.3 Producer Surplus

Once we have the new networks and premiums offered, we can calculate the producer surplus generated by plan j when it contracts with hospital network H_j as:

$$R_j(H_j, H_{-j}) = M\left(s_j(H_j, H_{-j})\left[prem_j - \sum_{h \in H_j} s_{jh}(H_j) cost_h\right]\right) \tag{26}$$

where M is market size and $cost_h$ is the expected per-patient costs incurred by hospital h and comes from cost-to-charge ratios provided by the SID:

$$cost_h = \sum_l p_l E(cost_l) = \sum_l p_l \sum_{h \in H_J} s_{hl} cost_{hl} \tag{27}$$

We calculate the producer surplus in the presence and in the absence of bargaining by summing individual insurer surplus. However, since we do not observe the prices hospitals charge insurers in the absence of our pricing rule (we do not observe insurer-hospital pair prices in New Jersey), we can only calculate the total producer surplus, or the combination of hospital and insurer surplus.[44] The total gain in producer surplus is $\$2,239,394,865$. The main component of gain in surplus comes from BCBS increasing its premiums. BCBS likely increase its premiums to account for higher prices from hospitals as it can no longer benefit from its market power when bargaining over prices. The removal of bargaining here also removes incentives for BCBS to cut premiums in order gain market power to use as leverage against hospitals to obtain lower

[44]The ideal would be to have a claims database that reports transaction prices between insurers and hospitals. If we had such data, we could analyze whehter the individual surplus measures of hospitals and insurers go up or down once we impose rate setting in New Jersey. Several papers use such data in the literature. See Dor et al. (2013), Dor, Grossman, Koroukian (2004), and Dor, Koroukian, Grossman (2004) among others.

prices so it is no surprise we see almost a %40 increase in BCBS's monthly premiums. All other insurers, except the smallest, decrease premiums and increase market shares which also provides an increase in total producer surplus.

6.4 Consumer Surplus

The compensating variation is used to measure the change in consumer's welfare after Maryland-style pricing is implemented in New Jersey. The compensating variation refers to the amount of money a consumer would need to give up following a change in prices or product quality (hospital networks) in order to reach his pre-change utility level. The compensating variation for consumer i, following Small and Rosen (1981), may be written as

$$CV_i = \sum_i \frac{n_i}{N} \frac{-1}{\alpha_i} \left[ln \sum_j exp(V_{ij}^{post}) - ln \sum_j exp(V_{ij}^{pre}) \right] \tag{28}$$

where the superscripts *post* and *pre* refer to the post price regulation and pre price regulation time periods respectively. $-\alpha_i$ is the marginal utility of income or equivalently the negative of the price coefficient and j still represents an insurance plan. V is the observed portion of utility

$$V_{ij} = \xi_j + z_j \hat{\lambda} + \hat{\beta}_2 prem_j + \hat{\gamma}_1 EU_{ij}(H_j) + \hat{\gamma}_2 \frac{prem_j}{y_i} \tag{29}$$

Compensating variation is then the market size times the weighted sum of type i individuals whose distribution is known to us and given by

$$CV_{NJ} = M \frac{1}{n} \sum_{i=i}^{n} CV_i = M(-\frac{1}{\alpha_i}) \left[ln \sum_j exp(V_{ij}^{post}) - ln \sum_j exp(V_{ij}^{pre}) \right] \tag{30}$$

where M is market size and $\alpha_i = \beta_2 + \frac{\gamma_2}{y_i}$. Simulated compensating variation is then the weighted average of these compensating variations.

Overall, consumers lose \$693 each and the total surplus loss for consumers equals \$1.734 billion. Along with a large loss in surplus we see that the percent uninsured for all of New Jersey would increase by more than 2.5%. The loss comes partially from the shift of insurers to lower priced hospitals which generally are valued less in terms of expected utility for consumers, however the main portion of the loss comes from the increase

Table 7: Welfare Results

	Bertrand Nash	BCBS Weighted CS	BCBS No Change
Δ PS	2,239,394,865	985,464,408	107,565,067
Δ CS	-1,734,001,234	-769,046,509	7,587,403
Δ BCBS+Hospital Network	1,768,073,630	886,521,548	83,101,438
Δ Other Insurer + Hospital Network	471,321,235	98,942,880	24,463,629
Δ Total Surplus	505,393,631	216,417,899	115,152,470
Δ Uninsured	2.53%	.23%	-1.46%

in BCBS premiums and consumers unwillingness to switch from BCBS to another plan.

6.5 Blue Cross Blue Shield Counterfactuals

As mentioned previously, BCBS is the dominant firm in our market of interest, as well as the largest private insurer in the United States, and has the largest impact on both producer and consumer surplus. We therefore simulate two more counterfactuals to exposit their importance. First, we change BCBS's optimization process from Bertrand Nash to a weighted sum of consumer surplus and profits where the weight is calculated using BCBS of Maryland data. Second, we do not allow BCBS to change at all, we hold its premiums fixed.

Forcing BCBS to optimize over the weighted sum of profit and consumer surplus helps to account for BCBS acting as a nonprofit firm. Beyond BCBS being a nonprofit firm it is also the only insurer whose price elasticity is calculated as being in the inelastic region of demand. The weight for We see that the magnitudes of both changes in producer and consumer surplus lessen, although, there is still an overall gain in surplus in the market. The decrease in consumer surplus is about $769 million or approximately $307 per person and still driven by the increase in BCBS premiums. We also see that the change in producer surplus is dominated by BCBS. The amount of uninsured still increases by .23% but is lower than when all firms competed in a Bertrand Nash game.

In our the final counterfactual where BCBS is not allowed to change its premiums, the increase in total surplus now comes from an increase in consumer and producer surplus, the overall producer surplus increases by $107 million and consumers gain $7.5 million. Lastly, we observe that the percent of uninsured in the market falls by .46% percent.

7 Conclusion

As health care spending continues to increase an important question is how to control the costs and spending. This paper empirically assess one method of controlling a substantial share of those costs, specifically hospitals prices. We use a Maryland-Style all-payer system, which has proven to be successful at reducing cost growth, to investigate how a change in price regime effects welfare within health care market. We find that an all-payer system would increase total welfare and benefit producers at the expense of consumers. We argue the effects are driven by the largest insurer in the market (BCBS) losing the ability to negotiate price reductions from hospitals and pass those price savings on to consumers. While healthcare markets vary across states, and we only investigate a counterfactual change in New Jersey, the average market share of the largest private insurer is above 50% which is comparable to BCBS of New Jersey with 51%.[45] As long as the insurer is able to leverage its market power in a similar manner we would expect to see similar results from the implementation of APRS.

We conclude with possible directions for future research. The most straightforward extension would be to obtain transaction prices between hospitals and insurers in order to see how the division of surplus changes. We also focus only on a static model with no adverse selection and do not allow any hospital or insurer to exit. In general, the implementation of an all-payer system is most effective over time and generally results in exit of hospitals, evaluating the long-run effects on welfare are also of significant interest.

[45] The Kaiser Family Foundation calculates the average concentrations of insurance markets across all states in the individual,small, and large group markets. The state average across all three types of insurance markets is above %50.

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9 Appendix

9.1 Data Appendix

Dataset for Hospital Demand:

Hospital demand model combines two datasets: State Inpatient Databases (SIDs) from the Healthcare Cost and Utilization Project (HCUP) that reports patient characteristics, and 2010 American Hospital Association (AHA) Annual Survey Database that reports hospital characteristics.

We use SIDs for Maryland and New Jersey for the year 2010. SID lists patient's zip code[46], age, sex, Major Diagnostic Category (MDC), the hospital visited, and the payer[47] (the insurance plan the patient is enrolled in) for all the encounters in that particular state. AHA data reports hospitals' location, services offered, accreditation, total number of hospital beds among other variables.[48]

Distance of a patient to a hospital is calculated as the distance between two latitude and longitude coordinates which are centers of patient's zipcode and the hospital's latitude and longitude provided by the AHA. A patient's choice set consists of all the hospitals within its insurer's network.

Dataset for Health Plan Demand:

The specification of health plan demand reported in Table 5 uses nationwide health plan data. A market is defined as a state and a health plan is a competitor in a particular market if it serves to the residents of that state. Health plan characteristics used in these models come from AIS Directory of Health Plans 2011, Weiss Ratings Guide to Health Insurers 2011, and NCQA Health Insurance Plan Rankings 2010-2011.[49]

AIS data reports total enrollment and number of enrollees by sector (commercial risk, public risk etc.). This information is used to determine which plans offer commercial business. We work only with these plans as

[46]Maryland SID does not report patient zip codes. We assigned each in-state patient to a zip code using other geographic identifiers in the data. First, from the PSTCO variable which reports patient county FIPS codes, we determined which county the patient lives in. For each county, we randomly assigned individuals to the zip codes in that county based on the population weights of each zip code (the weights come from the Census data). Finally, we simulated this process multiple times to make sure the random assignment gives close to accurate results. For every simulation, we obtained similar parameter estimates. For out-of-state patients who visited a hospital in Maryland, we do not observe the county the patient resides in. Instead, we use ZIP3 variable which reports the first 3 digits of a patient's zip code. For each observation, we first assign the patient to the county most frequently occurring in those first 3 digits. Next, these patients are assigned to the zip code with the highest population percentage in that county that has the same first 3 digits. The population percentages come from the Census data. We also ran the hospital demand model excluding Maryland and obtained similar results.

[47]Available only for Maryland and New Jersey among the states we have.

[48]For a full list of variables included in the estimation, see Table A1.

[49]All these datasets report data on 2010.

we are trying to uncover the strategic decision making process of health insurers.[50] Weiss Ratings Guide provides information on number of physicians per 1000 patients, total enrollment and total health premiums earned. The premium per plan is calculated by dividing these total health premiums by the number of enrollees as reported by AIS. Whenever the enrollment data was unavailable from this source, we used the enrollment data from the Weiss Ratings Guide. The rest of our insurance plan characteristics come from NCQA's report on Health Insurance Plan Rankings.[51] These include plan type (which we aggregate to two categories: HMO/POS and PPO/Indemnity) and states served, along with different measures of plan quality. An overall score between 0 and 100 is reported for each plan that takes into account NCQA accreditation standards, member satisfaction and clinical measures. This source also reports a score between 1 and 5 for the following categories: treatment, prevention, and consumer satisfaction. The clinical quality measures (treatment and prevention) are calculated using a subset of the Healthcare Effectiveness Data and Information Set (HEDIS) measures whereas consumer satisfaction measure comes from the HEDIS survey which is overseen by the Agency for Health Care Quality (AHRQ). Consumer satisfaction measure covers patients' satisfaction with health plans (handling claims, customer service etc.), satisfaction with physicians (doctors' communication, care received etc.) and access of getting care in terms of ease and promptness. The treatment measure evaluates scores in subcategories such as asthama, diabetes, heart attack, and mental health. Finally, the prevention score assesses measures such as timeliness of prenatal check ups, breast cancer screening and early immunizations.

For the last specification used in health plan demand estimation, the above dataset was supplemented with SIDs from New Jersey and Maryland. SID is used to calculate the expected utility for patient type q, and to construct the hospital networks each health plan offers. Following Lewis and Pflum (2013), a hospital is assumed to be in a plan's network if more than 10 enrollees of that plan visited that hospital.

Dataset for Price Regressions:

Dataset for price regressions combines data from various sources: AHA, SID, CMS, and HSCRC. We use two dependent variables: preset hospital rates and total charges per patient (both in Maryland). The first one is obtained from the rate reports on HSCRC's website.[52] We use rates by hospital for the fiscal year 2010. Our second dependent variable, the total charges per patient, is available from the SID files.

[50] Using health plans that only serve to Medicare or Medicaid patients would not work as they do not set a price to maximize their profits, their price per unit of care is preset by the government.

[51] We mainly used this report for 2010-2011, missing data was filled by using the report from 2011-2012.

[52] http://www.hscrc.state.md.us/hsp$_{R}ates2.cfm$

The independent variables gather information from various sources. The case-mix index (CMI) contains information about the resource consumption of the hospital based on the complexity of treatment, diversity, and needs of its patients. CMI per hospital is calculated by applying the DRG weights specified by CMS[53] to the observed (from SID) patient base of each hospital. [54] We created the Elixhauser comordibity measure at the patient level using the International Classification of Diseases, Clinical Modification (ICD-9-CM) and DRG (version 24) codes from the SID data. The AHA data was used to obtain teaching intensity (resident-to-bed ratio), number of primary care employees, number of physicians, number of hospital beds, for-profit status, depreciation expense (divided by $100,000), and services offered.

9.2 Competition and Regulation in Health Care

The debate on how to contain health care costs offers two imperfect solutions: competition and regulation. Proponents of competition argue that market forces are capable of driving the health care prices down, therefore there is no need for the government to intervene. The efforts that used competition as a tool in the past did not result in substantial decrease in health care expenditure, primarily due to the fact that health care markets are far from being perfectly competitive. Proponents of regulation, on the other hand, argue that the incentive structure in the health care sector makes it impossible for the free markets to deliver efficient outcomes, therefore government regulation is needed.

Health care markets do not fit in the definition of perfect competition for many reasons. In particular, health care markets are characterized by asymmetric information, barriers to entry and exit, differentiated products, market power of providers and insurers. The seminal work by Arrow (1963) states that the health care markets suffer from market failures due to uncertainty and information problems. Patients know neither the care they need to receive nor the true costs of the care. They rely solely on their physicians when making choices about their treatment, and solely on their insurers when paying for the treatment they received. They are different than a consumer in a competitive market who chooses among alternatives with complete information. Furthermore, the incentive structure of the health care system leads to inefficiencies, overuse, and excessive expenditures. Providers, who determine the charges, have an incentive to provide excess care at higher prices as this will bring them more revenue. Patients, on the other hand, are not responsive to these

[53] These weights reflect the average hospital resource use by patients in that DRG category divided by the average hospital resource use by all patients. We follow the approach adopted by California's Office of Statewide Health Planning and Development (OSHPD) in applying weights for Medicare patients to all patient discharge data. See https://www.oshpd.ca.gov/HID/Products/PatDischargeData/CaseMixIndex/CMI/ExampleCalculation.pdf

[54] The case-mix index per hospital is calculated by dividing the sum of all the DRG weights in that hospital by the total number of discharges in 2010 following the formula used by CMS.

increasing charges as they are covered by their insurance plans. Lastly, the increased insurance coverage creates an artificial demand and supply for the medical services due to the moral hazard effect. All these factors result in increased health expenditure. Therefore, the *laissez-faire* approach is not likely to work in the health care market and government intervention is usually considered to improve the functioning of these markets.

Hospital markets, in particular, are far from a competitive ideal. Presence of hospital systems with market power, differentiated services and quality offered by each hospital, and possible overuse of hospital services due to expanding health insurance[55] indicate that a profit maximizing hospital will not achieve the most efficient outcome like a competitive firm, especially when the well-being of the other agents in the market is considered. Given this nature and the form of financing of the health care sector, Altman and Weiner (1978) suggest regulation to be used as a second-best choice, a necessary solution even if not the most desirable one.

Increase in health care spending in the U.S. has been influenced by price-related factors such as inflation and increase in hospital costs as well as by non-price factors such as technology, use, and intensity.[56] Federal and state governments tried both free markets and regulation as means to contain costs in response to constantly increasing national health care expenditure. While specific programs had different impacts on health care costs, neither approach led to a substantial decrease in the overall expenditure. Among the regulatory policies, state-level hospital rate setting and Medicare's Prospective Payment System (PPS) were the two major programs that proved to be effective in cutting costs.[57]

In the 1960s, expenditure growth was mostly due to increased use of medical services. Over this period, the hospital sector in the U.S. was characterized by almost no regulation. Government intervention in this decade was in the form of financing research to develop better treatment techniques, improving access to and quality of health care, renovating and building new hospitals. The increase in the growth rate of health spending led to implementation of several regulatory programs, particularly in the hospital industry, in the early 1970s.

Government intervention during this period aimed to eliminate waste and inefficiencies in the hospital business as well as to control price growth. Certificate-of-need (CON) programs were adopted at the state

[55]See for example, Feldstein (1973).

[56]For a detailed breakdown of health expenditure growth in the past half century, see Catlin and Cowan (2015).

[57]PPS and state rate setting are similar in nature as they are both prospective payment systems that limit revenues and charges based on diagnosis-related groups (DRGs). Davis et al. (1990), Eby and Cohodes (1985), Friedman and Coffey (1993), Sloan (1983, 1988) all emphasize the relative success of mandatory rate setting in the context of cost containment.

level starting at the end of 1960s. These programs restricted hospital investment decisions and made state approval necessary for expanding/modernizing capacity, purchasing new diagnostic equipment, providing new services, and even entry of new hospitals. Such programs were adopted by most states by mid-1970s with the passing of 1974 National Health Planning Act and Section 1122 review of 1972 Social Security Act Amendments.[58] These amendments also gave rise to utilization review to control the quantity and quality of medical procedures. If the Professional Standards Review Organizations (PSROs) reviewed a procedure and deemed it unneccesary, Medicare payments for that procedure could be denied to the hospital. Other controls implemented were Nixon administration's Economic Stabilization Program (ESP) and hospital rate and budget controls. ESP was implemented between 1971-1974 to slow price growth in the overall economy. Controlled hospital prices, wages, and input costs led to a decrease in expenditure. Price controls in the health care sector resulted in higher utilization and lower medical costs. Removal of ESP in 1974 along with the increase in economy-wide inflation partly due to the oil shocks resulted in a period of rapid price growth.

In the 1974-1982 period, growth in health care prices accounted for about 70 percent of the growth in nominal personal health care spending.[59] The 1983-1992 period was characterized by a slowdown in both the growth of health care spending and the growth of medical care prices. Main driving factors of this slowdown were changes in the payment systems (transition to PPS) and increased enrollment in private health plans and self-insured plans. PPS for Medicare was enacted in 1983 as previous efforts to control hospital cost inflation (comprehensive planning, the PSRO effort, second-opinion surgery etc.) were unsuccessful.[60] On the health plan frontier, HMOs and other managed care plans gained popularity in 1990s as employers saw these plans as a way to cut spending on medical care. The ability of these plans to negotiate price with providers drove the health care prices down in the 1993-1999 period and growth in health care price growth decreased to 2.5%. The trend of rapid growth of enrollment in these restricted-network plans was reversed in 2000-2002 as consumer preferences changed.[61] During this period, growth in price of health care accounted

[58] By 1979, all but three states adopted CON regulations. Different from CON regulations, Section 1122 programs were established by the federal government and adopted by state governments on a voluntary basis. These programs targeted hospital expenditures on federal programs (mostly Medicare and Medicaid) and made planning agency approval necessary to get full reimbursement on expenditures exceeding a threshold. Literature showed these programs had no effect on costs and input use. See Sloan (1981) for details.

[59] During this period, in response to federal and state governments' attempts to cap and control hospital prices, hospitals started a movement called known as "Voluntary Effort" where they promised to control prices within their own hospitals. The movement failed quickly as hospital price inflation increased from 13% in 1980 to 18% in 1981. See Mayes (2007) and Sloan (1983).

[60] See Schramm et al. (1986).

[61] Consumers were concerned about receiving constrained care under such plans. Employers also abandoned these plans as the decrease in cost was a one-time advantage and managed care plans still increased their costs due to increases in consumer demand and improvements in technology. The shift in preferences that increased enrollment in less restrictive plans (such as Preferred Provider Organizations (PPOs) and Point of Service (POS) plans) in addition to the increase in the number of hospital mergers and hospital system transferred the leverage to hospitals.

for 40 percent of the average growth in personal health care spending. Health care expenditure growth has slowed down in 2003-2013 period primarily due to increase in the number of cheaper generic drugs and severe economic recession, yet the increase in price of health care still accounted for half of the increase in the average growth of personal health care expenditure.

These historical facts reflect that health care price growth has played a major role in national health expenditure growth. Hospital costs today constitute the largest share of the total expenditure[62] which makes them an important target. In the past, the growth in health care prices was managed by market forces (such as proliferation of insurers that have bargaining power over hospitals, competition among hospitals, or recession) or by price controls (such as ESP and rate setting). In today's market, it would be a doubtful approach to rely on the market forces alone given the increased market power of hospitals and hospital systems who have profit motives. Therefore, we propose applying a regulatory approach that aims to mimic competitive outcomes by correcting disincentives and restoring missing incentives in a market that is far from a competitive ideal.[63] The rate setting rule implemented in Maryland over the past 45 years not only has been successful in cutting health expenditure, but also encouraged use of competition to serve this purpose. Our analysis shows that implementation of this rule in a similar regulatory environment results in welfare gains.

9.3 Full Model Estimates

The full set of parameter estimates from the hospital demand model are reported in Table A1.

Table A1: Hospital Demand Estimates

Variable	Coefficient	Standard Errors
Distance	-0.172***	(0.0131)
Distance^2	0.000447***	(0.00000314)
Dist*AgeCat1	0.0100***	(0.000710)
Dist*AgeCat2	0.00673***	(0.000638)
Dist*AgeCat3	0.00645***	(0.000617)

[62] CMS reports that hospital costs accounted for 30.7% of the U.S. health care spending, followed by physician services that accounted for 20% of the overall expenditure.

[63] Schramm et al. (1986) argues that regulatory and procompetitive approaches are fundamentally alike in the context of rate setting.

Dist*AgeCat4	0.00112*	(0.000569)
Dist*Teach	-0.00645***	(0.000375)
Dist*NurseRatio	-0.00135*	(0.000629)
Dist*Female	0.000790*	(0.000389)
Teaching	-0.710***	(0.0241)
NurseRatio	-0.676***	(0.0174)
Bed Size	0.287***	(0.00575)
Dist*Nervous System	0.0453***	(0.0131)
Dist*Eye Disorder	0.0272	(0.0143)
Dist*Ear/Nose/Throat	0.0383**	(0.0131)
Dist*Respiratory	0.0266*	(0.0131)
Dist*Circulatory	0.0288*	(0.0131)
Dist*Digestive	0.0257*	(0.0131)
Dist*Hepatobiliary	0.0300*	(0.0132)
Dist*Musculoskeletal	0.0409**	(0.0131)
Dist*Skin/Tissue	0.0282*	(0.0131)
Dist*Metabolic	0.0393**	(0.0131)
Dist*Kidney/Urinary	0.0315*	(0.0131)
Dist*Male Reproductive	0.0402**	(0.0132)
Dist*Female Reproductive	0.0271*	(0.0131)
Dist*Pregnancy	-0.00282	(0.0131)
Dist*Newborn	-0.00513	(0.0131)
Dist*Immunological	0.0314*	(0.0132)
Dist*Myeloproliferative	0.0536***	(0.0131)
Dist*Infectious	0.0332*	(0.0132)
Dist*Injuries/Poison	0.0368**	(0.0132)
Dist*Burns	0.0477**	(0.0151)
Dist*Other Factors	0.0446***	(0.0132)
Dist*Multiple Sig Trauma	0.0448***	(0.0132)
General Med/Surgical	0.821***	(0.224)
Obstetrics	-0.586***	(0.0435)

Cardiac IC	-0.111***	(0.0254)
Neonatal IC	-0.307***	(0.0227)
Neonatal Intermediate	-1.859***	(0.0440)
Burn Care	0.0337	(0.0379)
Birth Room	2.584***	(0.0483)
Blood Donor Hos	-0.566***	(0.0222)
Mammogram	-2.394***	(0.0359)
Adult Cardiology	-1.740***	(0.0533)
Diagnostic Catheterization	-0.416***	(0.0417)
Cardiac Catheterization	0.630***	(0.0228)
Cardiac Surgery	0.0379	(0.0320)
Cardiac Electrophysiology	-0.802***	(0.0348)
Cardiac Rehabilitation	-0.288***	(0.0242)
Chemotherapy	0.944***	(0.0650)
Optical Colonoscopy	1.485***	(0.0271)
Endoscopic Ultrasound	-0.235***	(0.0269)
Ablation of Esophagus	-0.628***	(0.0175)
ERCP	0.161***	(0.0201)
ESWL	0.461***	(0.0186)
Fertility Clinic	-0.594***	(0.0310)
Hemodialysis	-0.418***	(0.0302)
HIV-AIDS Services	0.373***	(0.0277)
Neurological Services	-0.329***	(0.0576)
Oncology	0.894***	(0.0714)
Othopedic	0.130***	(0.0390)
Diagnostic Radioisotope	-0.640***	(0.0502)
Full-field Mammography	0.472***	(0.0248)
Magnetic Resonance Imaging	-1.268***	(0.0383)
Multislice Spiral Tomography	0.680***	(0.0450)
Multislice Spiral Tomography64	1.929***	(0.0252)
Positron Emission Tomography	-0.286***	(0.0206)

Ultrasound	0.00672	(0.0533)
Heart Transplans	1.698***	(0.0511)
Kidney Transplanst	-0.675***	(0.0268)
Liver Transplanst	3.125***	(0.0492)
Lung Transplanst	-0.852***	(0.0586)
Tissue Transplanst	-0.102	(0.0524)
Virtual Colonoscopy	1.219***	(0.0281)
Women's Health Center	1.356***	(0.0329)
General Med/Surgical*Nervous	-2.452***	(0.187)
General Med/Surgical*Eye	1.456***	(0.407)
General Med/Surgical*Ear/Nose/Throat	0.648*	(0.270)
General Med/Surgical*Circulatory	-1.232***	(0.129)
General Med/Surgical*Hepatobiliary	1.823***	(0.175)
General Med/Surgical*Skin	0.325*	(0.164)
General Med/Surgical*Male Reproductive	0.732*	(0.345)
General Med/Surgical*Female Reproductive	0.210	(0.127)
General Med/Surgical*Childbirth	-1.710***	(0.0753)
General Med/Surgical*Multiple Sig Trauma	-0.108	(0.168)
Obstetrics*Female Reproductive	0.850***	(0.0382)
Obstetrics*Childbirth	0.348***	(0.0293)
Cardiac IC*Circulatory	0.225***	(0.0463)
Neonatal IC*Childbirth	0.0184	(0.0166)
Neonatal IC*Newborn	-0.0290	(0.0161)
Neonatal Intermediate*Childbirth	0.733***	(0.0309)
Neonatal Intermediate*Newborn	0.680***	(0.0293)
Burn Care * Burn	4.223***	(0.417)
Birth Room*Childbirth	1.072***	(0.0424)
Birth Room*Newborn	0.213***	(0.0309)
Blood Donor Hos*Circulatory	-0.0648*	(0.0318)
Blood Donor Hos*Blood Disorders	0.874***	(0.0715)
Mammogram*Subcutaneous Tissue	-0.104	(0.0812)

Adult Cardiology*Circulatory	1.036***	(0.125)
Diagnostic Catheterization*Kidney	0.407***	(0.0721)
Cardiac Catheterization*Circulatory	-0.255***	(0.0591)
Cardiac Surgery*Circulatory	2.292***	(0.0732)
Cardiac Electrophysiology*Circulatory	0.101	(0.0744)
Cardiac Rehabilitation*Circulatory	0.716***	(0.0428)
Chemotherapy*Ear/Nose/Throat	0.551*	(0.279)
Chemotherapy*Respiratory	-0.0913	(0.121)
Chemotherapy*Digestive	0.548***	(0.0997)
Chemotherapy*Heptobiliary	0.543***	(0.161)
Chemotherapy*Skin/Tissue	0.473***	(0.142)
Chemotherapy*Male Reproductive	1.199***	(0.287)
Chemotherapy*Female Reproductive	-0.812***	(0.103)
Chemotherapy*Blood	0.115	(0.296)
Optical Colonoscopy*Digestive	0.490***	(0.0449)
Endoscopic Ultrasound*Digestive	-0.137***	(0.0403)
Ablation of Esophagus*Digestive	0.0346	(0.0332)
ERCP*Digestive	-0.331***	(0.0395)
ERCP*Heptobiliary	-0.466***	(0.0711)
ESWL*Heptobiliary	-0.243***	(0.0550)
ESWL*Kidney/Urinary	-0.356***	(0.0475)
Fertility Clinic*Female Reproductive	-0.0904**	(0.0294)
Hemodialysis*Kidney	0.377***	(0.0591)
Neurological Services*Nervous	-0.349**	(0.121)
Oncology*Ear/Nose/Throat	-0.300	(0.271)
Oncology*Respiratory	-0.226	(0.141)
Oncology*Digestive	-0.596***	(0.0816)
Oncology*Heptobiliary	-0.754***	(0.131)
Oncology*Male Reproductive	-0.642**	(0.197)
Oncology*Female Reproductive	1.443***	(0.128)
Oncology*Blood	0.676*	(0.295)

Diagnostic Radioisotope*Ear/Nose/Throat	0.0559	(0.197)
Diagnostic Radioisotope*Respiratory	-0.649***	(0.108)
Diagnostic Radioisotope*Circulatory	-0.821***	(0.0866)
Full-field Mammography*Subcutaneoud Tissue	0.120	(0.0675)
Magnetic Resonance Imaging* Nervous	1.532***	(0.127)
Magnetic Resonance Imaging*Respiratory	0.778***	(0.0981)
Magnetic Resonance Imaging*Circulatory	0.699***	(0.0910)
Magnetic Resonance Imaging*Digestive	0.661***	(0.0679)
Magnetic Resonance Imaging*Male Reproductive	0.703***	(0.195)
Multislice Spiral Tomography*Nervous	1.326***	(0.0828)
Multislice Spiral Tomography*Respiratory	0.0334	(0.0638)
Multislice Spiral Tomography*Circulatory	-1.175***	(0.127)
Multislice Spiral Tomography64*Nervous	-0.0434	(0.0463)
Multislice Spiral Tomography64*Respiratory	0.113*	(0.0540)
Multislice Spiral Tomography64*Circulatory	-0.716***	(0.0420)
Positron Emission Tomography*Nervous	0.473***	(0.0316)
Positron Emission Tomography*Respiratory	0.284***	(0.0374)
Positron Emission Tomography*Circulatory	0.0971**	(0.0309)
Positron Emission Tomography*Subcutaneous Tissue	0.0382	(0.0415)
Ultrasound*Birth	-0.115*	(0.0514)
Heart Transplanst*Circulatory	0.734***	(0.0358)
Kidney Transplanst*Kidney	0.968***	(0.0470)
Liver Transplanst*Digestive	-0.0213	(0.0870)
Lung Transplanst*Respiratory	0.599***	(0.0921)
Tissue Transplanst*Subcutaneous Tissue	-0.0115	(0.0546)
Virtual Colonoscopy*Digestive	-0.107**	(0.0392)
Women's Health Center*Female Reproductive System	0.0215	(0.0530)
N	230268	

Notes: $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.